

Evolution of Nucleosome Positioning and Gene Regulation in
Yeasts: a Genomic and Computational Approach

by

Alexander Minchev Tsankov

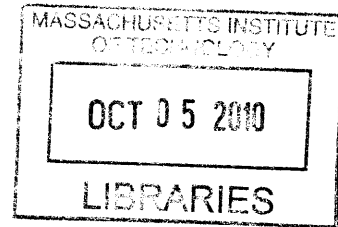
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SUBMITTED TO THE DEPARTMENT OF ELECTRICAL ENGINEERING
AND COMPUTER SCIENCE IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF

DOCTORATE OF PHILOSOPHY
AT THE
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

SEPTEMBER 2010



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Submitted to the Department of Electrical Engineering and Computer Science on August 6, 2010 in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Electrical Engineering and Computer Science

ABSTRACT

Chromatin organization plays a major role in gene regulation and can affect the function and evolution of new transcriptional programs. Here, we present the first multi-species comparative genomic analysis of the relationship between chromatin organization and gene expression by measuring mRNA abundance and nucleosome positions genome-wide in 13 *Ascomycota* yeast species.

Our work introduces a host of new computational tools for studying chromatin structure, function, and evolution. We improved on existing methods for detecting nucleosome positions and developed a new approach for identifying nucleosome-free regions (NFRs) and characterizing chromatin organization at gene promoters. We used a general statistical approach for studying the evolution of chromatin and gene regulation at a functional level. We also introduced a new technique for discovering the DNA binding motifs of *trans*-acting General Regulatory Factors (GRFs) and developed a new technique for quantifying the relative contribution of intrinsic sequence, GRFs, and transcription to establishing NFRs. And finally, we built a computational framework to quantify the evolutionary interplay between nucleosome positions, transcription factor binding sites, and gene expression.

Through our analysis, we found large conservation of global and functional chromatin organization. Chromatin organization has also substantially diverged in both global quantitative features and in functional groups of genes. We find that global usage of intrinsic anti-nucleosomal sequences such as PolyA varies over this phylogeny, and uncover that PolyG tracts also intrinsically repel nucleosomes. The specific sequences bound by GRFs are also highly plastic; we experimentally validate an evolutionary handover from Cbf1 in pre-WGD yeasts to Reb1 in post-WGD yeast. We also identify five mechanisms that couple chromatin organization to evolution of gene regulation, including (i) compensatory evolution of alternative modifiers associated with conserved chromatin organization; (ii) a gradual transition from constitutive to *trans*-regulated NFRs; (iii) a loss of intrinsic anti-nucleosomal sequences accompanying changes in chromatin organization and gene expression, (iv) repositioning of motifs from NFRs to nucleosome-occluded regions; and (v) the expanded use of NFRs by paralogous activator-repressor pairs. Our multi-species dataset and general computational framework provide a foundation for future studies on how chromatin structure changes over time and in evolution.

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Acknowledgements

The fruition of this project would not have been possible without the help of many people during my years as a graduate student. I first want to express my gratitude towards my co-advisor's Oliver Rando and Aviv Regev. Thank you Ollie for welcoming me into your lab at a time when I had just an idea for a project and very little lab experience. I really appreciate your contagious enthusiasm for science and your unfiltered, friendly advice at all times. Thank you Aviv for taking a chance on me and for your scientific guidance and loyal support during both happy times and tough moments at MIT. I also want to thank everyone in the Rando lab (John, Amanda, Marta, Ozlem, Jeremy, Lucas, Ben and others) for helping me learn laboratory science despite the broken glass and melted plastic. And finally, I want to acknowledge everyone in the Regev lab (Illan, Moran, Or, Michelle, Jason, Dawn, Amanda, Courtney, Jenna, Jay, Ana, Tal, Ido, Alon, Jimmy, and others) for both scientific and life advice.

I also want to acknowledge my friends, whose support kept me sane through this long journey. Thank you Shadi, Emanuel, Shahriar, Kayvan, Jean-Paul, Mike, Borjan, Amir, Pablo, Hisham, Ricardo, Zahi, Holly, Karti, Lisa, Anderson, Jonathan, Ben, Ilan, Adam, Mark, and Evgeny for some of the most fun years in my life. I want to thank everyone on my soccer team, the Unbelievables, for some incredible memories as we dominated MIT intramurals. I also want to acknowledge the members of AEPi for always being reliable friends and enthusiastic about life.

And finally, I want to thank my family. Thank you el Jefe for making the effort to seamlessly integrate into our family. Thanks Kake for your understanding and advice—you often know me better than I know myself. Thank you Fetzi for being a great role model and a friend, and Sparti for your undying love and care, even during my less mature years. And thank you Rosi-Mina for being so pure and cute.

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Chapter 1. Introduction

Deciphering the meaning of DNA and how the genetic code is regulated within the cell is vital for understanding human diseases as well as the evolution of different organisms. Genes are segments of DNA on chromosomes that encode a unique product with a specific cellular function. During transcription, a gene is copied (or expressed) to a more mobile molecular string of information, known as RNA. Transcription is regulated by a group of proteins known as transcription factors (TFs), which bind to the promoter of a gene (region of DNA near the start of the gene) to enhance or suppress how frequently that gene's DNA is copied to RNA. For many genes, their RNA products are mere messengers of the DNA code, or mRNA. The mRNA transports the DNA's information outside of the nucleus where it is translated into proteins, another even more functional string of amino acid molecules. The repertoire of RNAs and proteins expressed from "on" genes in each cell allows for the myriad of functions necessary for cell survival and, on a larger scale, the many different cell types found in complex organisms.

DNA in eukaryotes (nucleus-containing organisms) is assembled into a macromolecular complex, called chromatin. The basic unit of chromatin is the nucleosome, which consists of 147 base pairs wrapped around an octamer of histone proteins. Nucleosomes modulate gene regulation by affecting the ability of other proteins (such as TFs) to access DNA, which can impact gene activation and repression [1]. In particular, many genes have nucleosome-depleted "Nucleosome Free Regions" (NFRs) in their proximal promoters, providing access to sequence specific transcription factors and to the basal transcription machinery

[2-5]. Three major determinants have been proposed to impact nucleosome depletion at NFRs (Figure 1-1B-D): (1) active transcription by RNA polymerase II results in eviction of the -1 nucleosome [6, 7]; (2) Intrinsic ‘anti-nucleosomal’ DNA sequences such as Poly(dA:dT) bind histones with low affinity, and can ‘program’ NFRs constitutively [8-12]; and (3) *trans*-acting proteins can move nucleosomes away from their thermodynamically-preferred locations [13, 14].

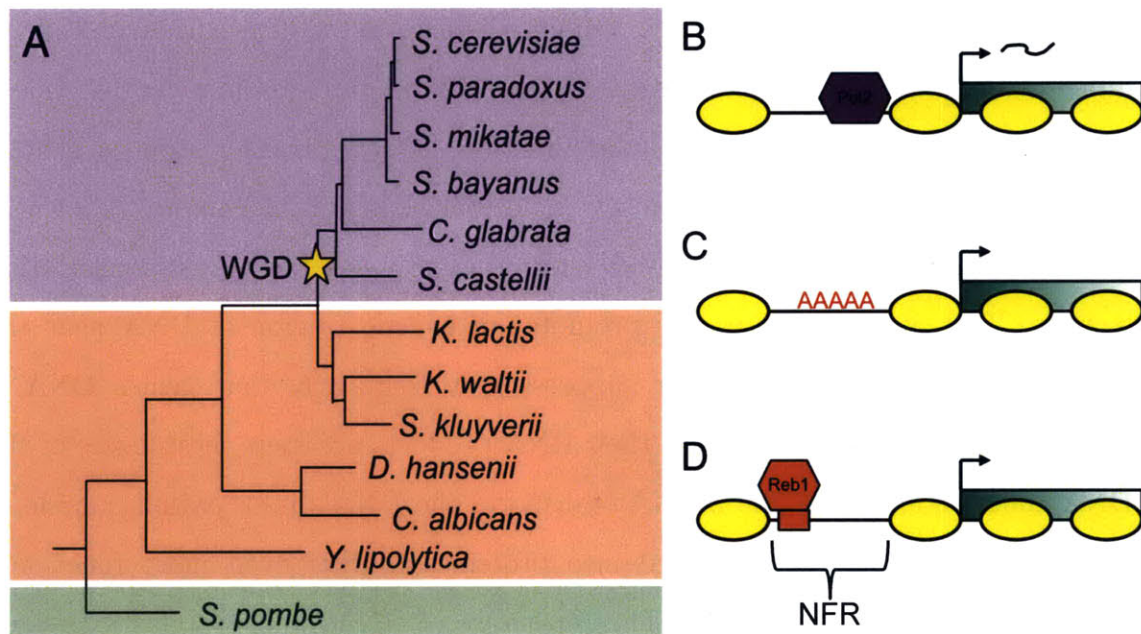


Figure 1-1: Phylogeny of species and 3 determinants of NFRs. (A) The tree above represents the phylogenetic relationship between the 13 *Ascomycota* yeast species studied in this work. Yellow star represent the Whole Genome Duplication (WGD) event. (B-D) Three major determinants of NFR occupancy, including (B) RNA Polymerase II and the transcriptional machinery, (C) intrinsic anti-nucleosomal sequences such as PolyAs, and (D) *in trans* chromatin regulators such as Reb1.

Regulatory differences affecting gene expression can play a major role in species evolution [15], and can help elucidate the functional mechanisms that control gene regulation [16, 17]. For example, several studies have shown that the variable wing pigmentation patterns in fruit flies have evolved due to gain and loss of TF DNA-binding sites at promoters of pigmentation genes [18, 19]. Although other specific examples of regulatory divergence are known in bacteria

[20], fungi [21-24], flies [25], and mammals [26], a general understanding of the evolution of gene regulation is still lacking. The recent availability of many sequenced genomes and accessibility of genomic profiling approaches open the way for genome-wide comparisons of gene regulation across multiple species.

Among eukaryotes, the *Ascomycota* yeasts (Figure 1-1A), which span over 300 million years of evolution, are particularly suitable for studying evolution of gene regulation. This is due to the genetic tractability of yeasts, the wealth of knowledge about the model organism *Saccharomyces cerevisiae*, the large number of sequenced genomes, and the diversity of yeast lifestyles [17]. Moreover, a whole genome duplication event occurred in this phylogeny [27] (WGD, Figure 1-1A), which lead to several phenotypic differences. Most notably, pre-WGD species produce energy using respiration through an oxygen-dependent (aerobic) enzymatic process called oxidative phosphorylation that takes place in the mitochondrion. In contrast, post-WGD species became respiro-fermentative, where they retained the ability to respire but often prefer to produce energy using an oxygen-independent (anaerobic) process called fermentation [28].

Recent studies in yeast suggest a broad role for chromatin organization in regulatory evolution. Most regulatory divergence between closely related *S. cerevisiae* strains is associated with divergence in unlinked (*trans*) chromatin remodelers [29, 30]. Conversely, many transcriptional differences between *S. cerevisiae* and *S. paradoxus* (Last Common Ancestor (LCA) ~2 Million years ago (Mya)) are due to linked *cis* polymorphisms predicted to affect nucleosome occupancy [31, 32]. Furthermore, a recent study suggested that changes in the regulation of mitochondrial ribosomal protein (mRP) genes between the distant species *C. albicans* and *S. cerevisiae* (LCA ~ 200 MYa) were associated with a change in nucleosome organization [33, 34]. In particular, the higher expression of mitochondrial genes in respiratory *C. albicans* is accompanied by enrichment for the PolyA-like “RGE” binding site in the mRP gene promoters [33]. These *cis*

elements appear to ‘program’ the constitutive presence of wider, more open NFRs at these genes [34] in *C. albicans*, but are absent from the promoters of mRPs in the fermentative *S. cerevisiae*. Finally, a recent study [35] compared genome-wide nucleosome positioning in *S. cerevisiae* and *S. pombe* (LCA \sim 300M - 1 BYa), finding changes in global nucleosome spacing and in the apparent sequences that intrinsically contribute to nucleosome positioning *in vivo*.

While these examples are intriguing, they are limited in their phylogenetic coverage (a pair of species) and their functional scope (one regulon). Thus, we understand little about the evolutionary interplay between gene expression, regulatory sequence elements, and chromatin organization. How does chromatin organization change over evolutionary time scales? Are the mechanisms underlying chromatin packaging of functional gene modules conserved? If not, how do they evolve and what is the role of different factors in this divergence? Are changes in chromatin organization related to changes in gene regulation? Can evolutionary changes shed light on the distinct mechanisms that help establish chromatin organization?

Here, we present the first multi-species experimental and computational study of chromatin organization across a eukaryotic phylogeny. We measured genome-wide nucleosome locations and mRNA abundance in 13 *Ascomycota* yeast species, spanning over 250 million years of evolution (Figure 1-1). In Chapter 2, we discuss the choice of our experimental system and the experimental details of the data collection process. In Chapter 3, we develop a methodology for studying the evolution of global chromatin organization, by normalizing the chromatin data, detecting nucleosome positions, finding NFRs, and characterizing the chromatin organization at all gene promoters. Chapter 4 introduces a general statistical framework for understanding how chromatin organization has evolved functionally, or between sets of related genes. In Chapter 5, we develop new methods for studying how intrinsic and *trans-*

regulated nucleosome positioning sequences have diverged in our phylogeny. We then use robust Lowess fitting to quantify the relative contribution of the three major determinants of chromatin organization (Chapter 6), and study these contributions at a global and functional level. And finally, in Chapter 7 we study the interplay between transcription factor binding sites, nucleosome organization, and gene expression.

Our approach has several limitations that are worth noting. As most works in genomics, including disease association studies, the newly discovered biological connections are often based on correlation and not causation. For example, we find that divergence in chromatin structure is accompanied by change in the underlying determinants that are known to affect it, such as gene expression, intrinsic sequences, and *trans*-acting chromatin regulators. However, with the exception of several experimental validations, we do not directly show that divergence in chromatin is a causal result of the change in these underlying determinants.

Nonetheless, our genome-wide study has several strengths that you could not attain by any other means. It allows us to obtain a general, integrative picture of evolutionary regulation. This panoramic view of the possible modes of evolutionary change in gene regulation presents us with a whole host of new hypotheses. Future experiments based on these discoveries can elucidate the causal relationships between chromatin structure and the underlying mechanisms that establish it. Here, we present several validation experiments for hypothesis related to Cbfl, Sap1 and PolyGs. Moreover, evolutionary studies are often correlation-driven, as the evolutionary path to current species is of course not accessible to direct experiment. Therefore, sometimes correlation is the best we can do.

Our analysis uncovers several major biological principles that govern the evolutionary and functional relationship between chromatin organization and

gene regulation in this phylogeny: (1) While qualitative features of chromatin organization are conserved in all species, quantitative features such as nucleosome packing, NFR length, and NFR to ATG distance have substantially diverged (Section 3.4); (2) Promoter chromatin organization and gene expression levels of ‘growth’ and ‘stress’ genes follow distinct patterns, and this dichotomy is conserved in all species (Section 4.3.1); (3) Evolutionary divergence in gene expression is often accompanied by transition of chromatin organization from a ‘growth’ to a ‘stress’ pattern (Section 4.3.2); (4) Similar to PolyAs, PolyGs also act as intrinsic antinucleosomal sequences on a global level, and their usage varies greatly between species (Section 5.2.3); (5) The specific DNA-binding sequences and identity of *trans*-acting factors that recruit nucleosome remodelers are also highly plastic (Section 5.3.3); (6) Changes in transcription levels, gain/loss of anti-nucleosomal sequences and gain/loss of binding sites for ‘general regulatory factors’ (GRFs) all accompany divergence of chromatin organization, often in a complementary manner (Section 6.2); (7) The loss of anti-nucleosomal sequences and parallel gain of binding sites for GRFs drive shifts from intrinsic to *trans*-regulated chromatin organization (Section 6.3.2). (8) Regulatory divergence can also occur by re-positioning of binding sites relative to nucleosome positions, or by expanding the use of accessible sites by paralogous transcription factors (Chapter 7). These mechanisms played a role in the evolution of respiro-fermentation, as well as in the evolution of regulation of other key regulons at different phylogenetic points, including mating, meiosis, RNA polymerase subunits, proteasomal and splicing genes. Together, they uncover novel insights into the general roles for chromatin in regulating genomic access and in the evolution of regulatory programs, and provide a rich resource for future investigation.

Chapter 2. Experimental System

To understand the effect of chromatin organization on gene regulation in our 13 *Ascomycota* species (Section 2.1) [36], we first mapped nucleosome positions genome-wide by Illumina sequencing of mononucleosomal DNA [7, 9, 37] isolated from mid-log cultures (Section 2.2). In order to compare our nucleosome data to transcriptional output, we also used species-specific microarrays to measure mRNA abundance in all species (Section 2.3) in the same mid-log cultures used for nucleosome mapping.

2.1. Strains and Growth Conditions

We chose species to provide good phylogenetic coverage of the *Ascomycota* yeasts. We included the well-studied model organisms *Saccharomyces cerevisiae* and *Schizosaccharomyces pombe*, and the independently evolved human pathogens *Candida glabrata* and *Candida albicans*. We chose six pre- and seven post-WGD species, in order to have similar number of sample points before and after the WGD event. We also sampled densely around a whole genome duplication (WGD) event, providing us with both major genomic divergence as well as a major metabolic shift to use as reference phenotypes. And finally, the large evolutionary distance (over 300 million years) of our phylogeny allowed us to gain a more complete picture of how nucleosome positions evolve. Specifically, we used the following strains (all with sequenced genomes) in the study: *Saccharomyces cerevisiae*, BY4741, *Saccharomyces cerevisiae*, Sigma1278b L5366,

Saccharomyces paradoxus, NRRL Y-17217, *Saccharomyces mikatae*, IFO1815, *Saccharomyces bayanus*, NRRL Y-11845, *Candida glabrata*, CLIB 138, *Saccharomyces castellii*, NRRL Y-12630, *Kluyveromyces lactis*, CLIB 209, *Kluyveromyces waltii*, NCYC 2644, *Saccharomyces kluyveryii*, NRRL 12651, *Debaryomyces hansenii*, NCYC 2572, *Candida albicans*, SC 5314, *Yarrowia lipolytica*, CLIB 89, and *Schizosaccharomyces pombe*, 972h.

To compare the evolution of nucleosome positions for different yeasts, it was important to choose growth conditions that induce a similar response in all species. To minimize condition- and stress-related differences, we grew all species in the same rich medium, where the growth rate of each species was at least ~80% of its maximal measured rate in any of over 40 tested media formulations. Our in-house medium adds back essential amino acids and nucleotides to nutrient-rich medium containing yeast extract, peptone and glucose, to mitigate stress responses in species that are auxotrophs for certain compounds. The recipe for the medium is the following: Yeast extract (1.5%), Peptone (1%), Dextrose (2%), SC Amino Acid mix (Sunrise Science) 2 grams per liter, Adenine 100 mg/L, Tryptophan 100 mg/L, Uracil 100 mg/L.

2.2. Measuring Genome-wide Nucleosome Positions

The technique for mapping nucleosome positions genome-wide was first developed for *S. cerevisiae* in Oliver Rando's lab [11], which we adapted to our 13 different species. Briefly, we grew cells to mid-log phase, crosslinked all protein complexes attached to the DNA, and then used micrococcal nuclease (MNase) in order to digest all DNA not wrapped by the crosslinked nucleosomes. We then isolate the DNA protected by single nucleosomes (by reverse-crosslinking and gel

purification) and sequence one of the two DNA fragment ends (single-end sequencing). Comparison of the sequenced reads against a reference genome allows us to map the genomic locations of all nucleosomes in each species. We decided to sequence our DNA samples instead of using microarrays because it has become the more cost effective option for obtaining high-resolution measurement of nucleosome occupancy.

Specifically, overnight cultures for each species were grown in 450ml of media at 220 RPM in a New Brunswick Scientific air-shaker at 30°C until reaching mid log-phase ($OD_{600} = 0.5$, WPA biowave CO 8000 Density Meter). Nucleosomes are then crosslinked to the DNA by treating the yeast with 2% formaldehyde for 30 minutes. Cells are collected by centrifugation, washed in water, and spheroplasted in order to remove the yeast's outer cell wall. Aliquots of the spheroplasted cells are then added to different concentrations of micrococcal nuclease (MNase) in order to digest the linker DNA. The remaining nucleosomal DNA is then isolated from the octamer of histone proteins by treatment with Proteinase K. The DNA is further purified by phenol-chloroform extraction, ethanol precipitation, and RNase treatment to remove RNA. Mononucleosomes were size-selected on a gel and purified using BioRad Freeze-N-Squeeze tubes followed by phenol-chloroform extraction.

Isolating nucleosomal DNA requires slight modifications to the protocol for each yeast species. The key parameters are the amount of cells collected (as measured by the optical density or OD), the MNase concentration, and the amount of time required to spheroplast cells. We chose to keep the OD constant at 0.5, since this OD was in mid-log phase of the growth curve measured for all species. Cells were spheroplasted with zymolase between 30-40 minutes for different species, depending on how much time was necessary to fully remove each species' cell wall. MNase digestion levels for all samples were uniformly

chosen across species to contain a slightly visible tri-nucleosome band (Figure 2-1).

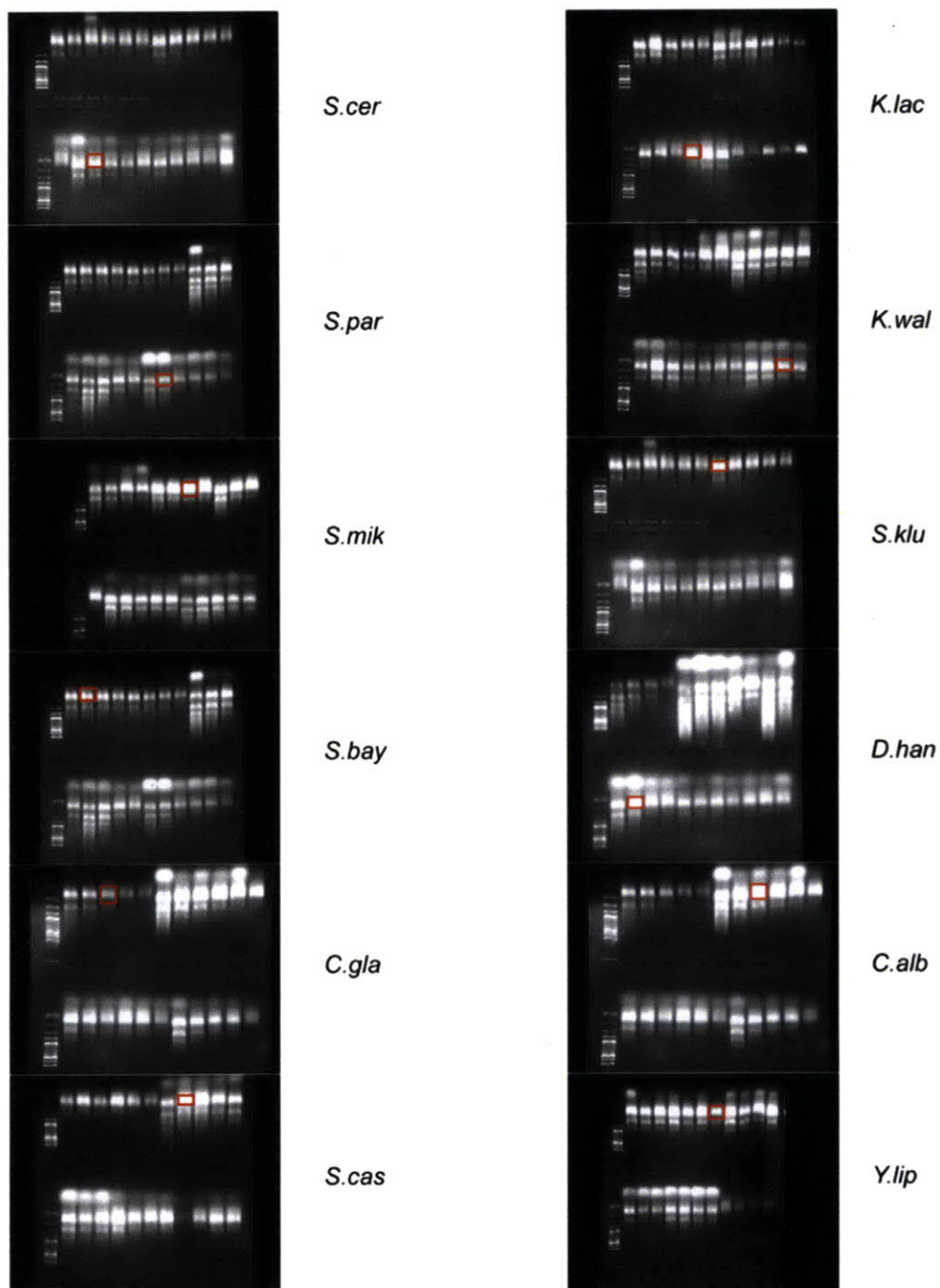


Figure 2-1: Isolation of mononucleosomal DNA from 12 species. Shown are MNase titrations from which mononucleosomal DNA (red box) was gel purified and isolated for construction of deep sequencing libraries.

Selected mononucleosomal DNA was prepared for sequencing using the standard Illumina instructions. Briefly, DNA was phosphorylated and end-repaired. The blunt, phosphorylated ends were then treated with Klenow fragment (exo minus) and dATP to yield a protruding 3'-end 'A' base. This is followed by ligation of the DNA ends with Illumina's adapters, which have a single 'T' base overhang at their 3' end. After adapter ligation, DNA was PCR amplified with Illumina primers for 19 cycles and library fragments of about 300 bp (insert plus adaptor and PCR primer sequences) were band isolated from an agarose gel using BioRad Freeze-N-Squeeze tubes followed by ethanol precipitation. Libraries were sequenced on an Illumina 1G Analyzer to generate 36bp reads. For each species, we obtained over 1 million uniquely mapped reads, which corresponds to 10x coverage or better per genomic nucleosome.

2.3. Measuring Absolute Expression Level for all Genes

To study the effect of nucleosome positions on gene regulation at the level of transcription in all species, we measured the absolute expression level of all genes using custom-designed (Agilent) microarrays with species-specific probes. A common technique for measuring absolute expression level genome-wide is to use two-color microarrays, where one channel is total RNA and the reference channel is genomic DNA. The genomic DNA channel normalizes for the melting temperature differences between probes and for other cross-hybridization effects on specific probe sequences. It is important to note that total RNA is correlated to a gene's transcriptional rate but not directly related, since mRNA molecules degrade at different rates. The following two sections explain the experimental

details of RNA and genomic DNA isolation, and microarray design and hybridization.

2.3.1. RNA and Genomic DNA Preparation

We isolated and labeled RNA by a standard procedures and DNA by a modified prototcol. Specifically, overnight cultures for each species were grown in 450ml of media as described for measuring nucleosome positions. Before formaldehyde fixation of nucleosomes, 50 ml of the culture were transferred to a 50 ml conical and spun down immediately. The isolated cell pellets were then placed in liquid nitrogen, stored at -80°C, and were later archived in RNAlater for future RNA extraction. Total RNA was isolated using the RNeasy Midi or Mini Kits (Qiagen) according to the provided instructions for mechanical lysis. Samples were quality controlled with the RNA 6000 Nano II kit for the Bioanalyzer 2100 (Agilent). Genomic DNA was isolated using Genomic-tip 500/G (Qiagen) using the provided protocol for yeast. DNA samples were sheared using Covaris sonicator to 500-1000 bp fragments, as verified using DNA 7500 and DNA 12000 kit for the Bioanalyzer 2100 (Agilent). Independently sheared samples labeled with different fluorescent dyes were highly correlated ($R > .97$ in each of 4 independent hybridizations), indicating that the shearing procedure is reproducible and unbiased. Total RNA samples were labeled with Cy3 (cyanine fluorescent dyes) and genomic DNA samples were labeled with Cy5 using a modification of the protocol developed by Joe Derisi (UCSF) and Rosetta Inpharmatics (Kirkland, WA) that can be obtained at www.microarrays.org.

2.3.2. Microarray Probe Design, Hybridization, and Data Normalization

Cy3-labeled RNA samples were mixed with a reference Cy5 labeled genomic DNA sample and hybridized on two-color Agilent 55- or 60-mer oligo-arrays. We used the 4x44K format for the *S. cerevisiae* strains (Agilent commercial array; 4-5 probes per target gene) or a custom 8x15 K format for all other species (2 probes per target gene, designed using eArray software, Agilent). After hybridization and washing per Agilent’s instructions, arrays were scanned using an Agilent scanner and analyzed with Agilent’s feature extraction software version 10.5.1.1. For each probe intensity, I_p , the median signal intensities were background subtracted for both channels and combined by taking the log2 of their ratio, as follows:

$$I_p = \log_2 \left(\frac{I_{Cy3} - B_{Cy3}}{I_{Cy5} - B_{Cy5}} \right). \quad (2.1)$$

To estimate the absolute expression values for each gene, we took the median of the log2 ratios across all probes. The experiments were highly reproducible; most biological replicates correlated at $R = 0.99$ and replicates with $R < 0.95$ were removed. For each species, we obtained at least three biological replicates that passed this reproducibility threshold. Different biological replicates were combined using quantile normalization that takes the median of the rank values to estimate the absolute expression level per gene per species.

Chapter 3. Inferring Nucleosome Positions and NFRs

In this chapter, we introduce the computational methodology we developed to quantitatively compare the chromatin structure at genes within and between species. The canonical chromatin organization at a typical gene in *S. cerevisiae* (Figure 3-1) contains a dip in nucleosome occupancy, called the ‘Nucleosome Free Region’ (*NFR*), in their upstream promoter (*5’NFR*) and following their stop codon (*3’NFR*). These regions are known to be important for binding of transcription factors and for gene activation or repression [3, 11, 38]. We term the nucleosomes at the 5’ and 3’ border of the *5’NFR* as the +1 and -1 nucleosome, respectively (Figure 3-1), and the nucleosome at the 5’ border of the *3’NFR* as the +N nucleosome.

To identify these chromatin features in the promoters of each gene, we first aligned nucleosome reads to each reference genome (Section 3.1). We then normalized each experiment for sequencing depth and MNase digestion level (Section 3.1 and 3.2.1). We then built a method for inferring nucleosome positions (Section 3.2) from the normalized data, which is based on previous work [37, 38]. Finally, we developed a new computational technique for detecting the 5’ and 3’ NFRs at each gene (Section 3.3), and evaluated its performance. We then use these computational tools to quantify a number of features of chromatin organization at each gene, and explore how these features have evolved on a global level between species (Section 3.4).

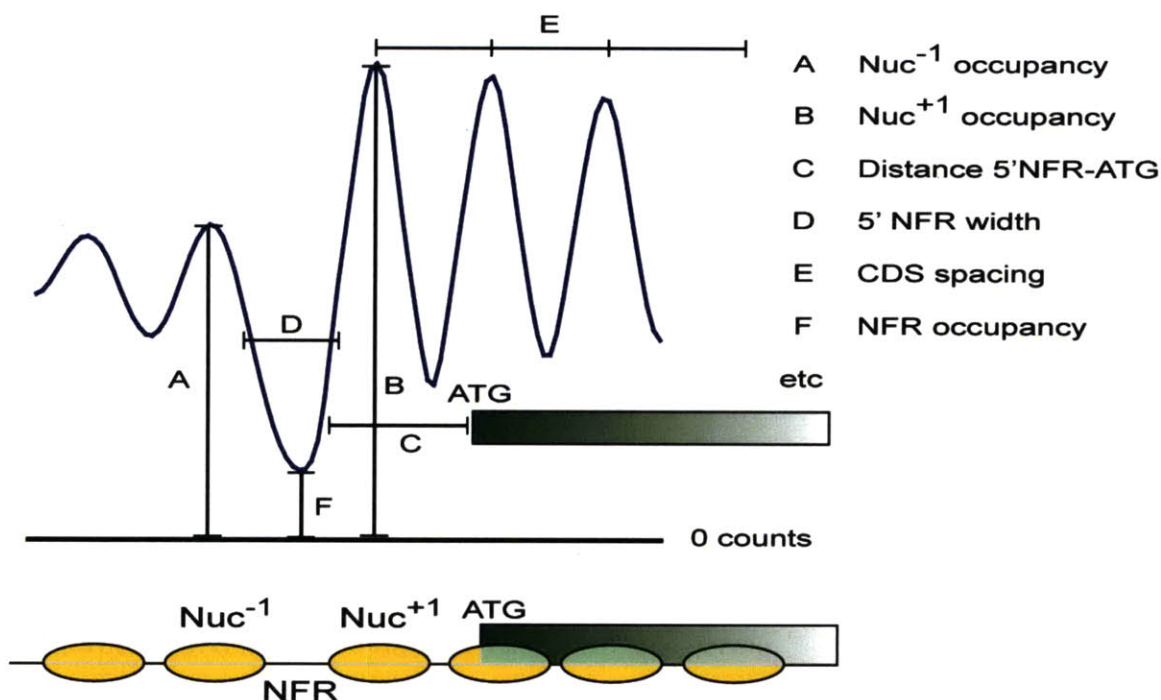


Figure 3-1: Chromatin organization at a typical gene. Shown is a schematic of a gene (green box), its promoter (black line) and associated nucleosomes (yellow), along with nucleosome sequencing data (dark blue curve), and several definitions of chromatin features.

3.1. Nucleosome Data Processing and Normalization

We used BLAT [39] to map single-end sequenced reads from each experiment to the corresponding reference genome, keeping only reads that mapped to a unique location and allowing for up to 4 mismatches. Each uniquely mapped read was then extended to a length of 100bp. To generate a genomic nucleosome occupancy landscape, we summed all extended reads covering each base pair. We then masked all repetitive regions along each track, defining repetitive regions as locations in the genome that cannot be uniquely defined by the length of a read (36 bp). We also masked all regions of nucleosome occupancy greater than 10 times the median occupancy, to remove outlier effects that occur in

places such as the rDNA locus. To normalize for sequencing depth for each genomic nucleosome track, we divided the occupancy at each location by the mean nucleosome occupancy per base pair. These normalized maps were used to generate the average nucleosome occupancy plots (Figure 3-1, Figure 3-4, and Figure 4-1).

3.2. Detection of Nucleosome Positions

3.2.1. Methodology

To infer the location of nucleosomes from the data, we used a Parzen window approach similar to that previously described [37, 38]. Our modified approach uses 3 parameters—the average DNA fragment length, the standard deviation of the Parzen window, and the maximum allowable overlap between nucleosomes. To estimate the mean DNA fragment length in each experiment, we shifted reads from one strand and then correlated them with the reads of the opposite strand. We summed all read occurrences per base pair on the forward strand to generate vector \mathbf{x} of length N and all read occurrences on the reverse strand to generate vector \mathbf{y} of length N and estimated their cross-correlation, $\hat{R}_{xy}(m)$, for positive shifts m as follows:

$$\hat{R}_{xy}(m) = \frac{1}{N-m} \sum_{n=0}^{N-m-1} x_{n+m} y_n. \quad (3.1)$$

For each species, we observed a peak in the cross-correlation at a shift between 127 and 153 bp, which we used to estimate the mean DNA fragment length $\bar{\ell}_{DNA}$ per experiment:

$$\bar{\ell}_{DNA} = \operatorname{argmax}_m [\hat{R}_{xy}(m)]. \quad (3.2)$$

We chose a standard deviation of the Parzen window of 30bp for all species, since it closely matched the observed standard deviation around the cross-correlation peak of each experiment. Finally, we set the maximum allowable overlap between nucleosomes to 20bp. We then shifted all read start locations by half of the mean DNA fragment length, $\bar{\ell}_{DNA}/2$, in the direction towards the dyad of the nucleosome they represent (ie. forward reads are shifted to the right and reverse strand reads to the left). For each read i , our approach places a Gaussian distribution with a standard deviation σ of 30bp at the read’s shifted location x_i . Summing all individual curves for all genomic positions x leads to a smoothed probability landscape $\hat{p}(x)$ of nucleosome occupancy

$$\hat{p}(x) = \frac{1}{N\sigma} \sum_{i=1}^N \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{(x-x_i)^2}{2\sigma^2}\right], \quad (3.3)$$

where N represents the total number of reads. We calculated each probability landscape per chromosome. We next identify all peaks along the landscape, which represent nucleosome centers. The method then places nucleosomes along the genome in the order of decreasing peak heights (greedy approach) and iteratively masks out these regions to prevent more than 20bp overlap between nucleosomes.

3.2.2. Computational Contribution

Our approach improves on previous methods [37, 38] based on Parzen likelihood estimation using a Gaussian Kernel. The distribution of forward and reverse read clusters closely approaches a Gaussian shape, justifying the Gaussian assumption. Previous methods depend on various parameters set by the user, such as the allowable window between corresponding forward and reverse read

clusters. Our modified approach removes these restrictions and depends only on 3 parameters, which we estimate directly from the data. Hence, our approach generalizes to experiments done by different labs for different species. One of the parameters is the mean DNA fragment length, which normalizes for different MNase digestion levels between experiments. Moreover, our method improves on previous methods by allowing for nucleosome detection using information from only one strand.

3.3. Inferring 5' and 3' NFRs

3.3.1. Methodology

We informally define 5' and 3' Nucleosome Free Regions (NFRs) as the linker DNA of “significant length” closest to the 5' and 3' end of each gene, respectively. It is difficult to automatically detect NFRs based on this informal definition because NFRs are rarely completely free of nucleosomal reads due to experimental noise and variability in nucleosome positions within a population of cells. As a result no such method exists today.

To automatically find NFRs, we first created a nucleosome call landscape for each genome, normalized for sequencing depth in the same manner as the nucleosome occupancy maps (above). NFR boundaries were often obscured by very low occupancy nucleosome calls. We therefore removed all nucleosome calls with occupancy less than 40% of the average nucleosome occupancy from the map. We searched for 5' or 3' NFRs within 1000 bases upstream/downstream of the 5' or 3' end of each gene, truncated when neighboring ORFs overlapped this region. We then defined an NFR as the linker DNA longer than 60bp closest to the 5' or 3' end of each gene. If no linker longer than 60bp was found in this search, we defined the NFR as the first linker from the 5' or 3' end.

3.3.2. Computational Contribution

To our knowledge, this is the first published method for finding 5' NFRs. As mentioned before, this is an important computational problem as the NFR region is very important for gene regulation. Besides its application in our work, our method could be useful for other biological problems, such as finding change in regulatory regions due to environmental stimuli. It can also be used in motif analysis for substantially reducing the search space either for learning new motifs or for scoring known ones.

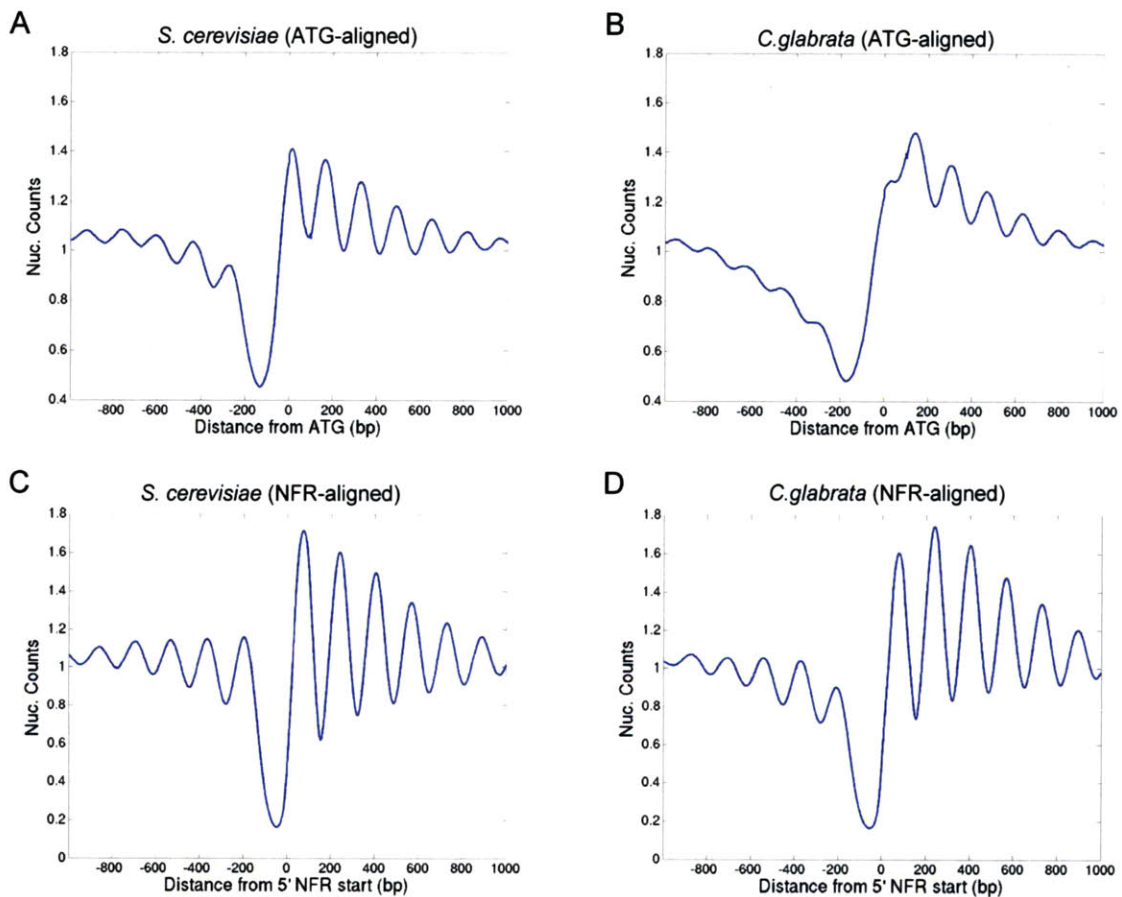


Figure 3-2: Alignment of nucleosome occupancy data by ATG and NFR. The normalized nucleosome occupancy at all *S. cerevisiae* (A,C) and *C. glabrata* (B,D) genes is averaged and displayed relative to the translational start site (ATG) and the 5'NFR and the +1 nucleosome boundary. (A-B) We observe a substantial difference in the ATG aligned profiles (blue curve) between *S.*

cerevisiae (A) and *C. glabrata* (B), a species that has more variable 5'NFR-ATG distances. (C-D) In contrast, alignment by the 5'NFR and the +1 nucleosome boundary produces very similar waveforms between the two species.

Moreover, identifying the 5'NFR is important when comparing between different species. Since 5'NFR-ATG distances vary substantially between species, an analysis of nucleosome organization that relies on alignment by ATG can be highly misleading. For example, the average nucleosome organization of *C. glabrata* and *S. castelli* look similar when aligned by the +1 nucleosome but very different when aligned by ATG (Figure 3-2). A previous study [34] defines a Promoter Nucleosome Depleted Region (PNDR) score as mean nucleosome occupancy of the most depleted 100-bp region within 200 bp upstream of the ATG. Since some species have longer 5'NFR-ATG distances we reasoned that the NFR of some genes might not be contained within a 200 bp window (*e.g.*, only a third of *C. glabrata* NFRs are contained within 200 bp, while 90% are contained within 500bp). To avoid such pitfalls and analyze nucleosome organization consistently in all species we aligned the data by the +1 nucleosome, which is consistent with alignment by transcription start site (TSS).

3.3.3. Performance Evaluation

Our method for finding 5'NFRs was highly predictive of transcription start sites (TSSs) in *S. cerevisiae* [40]. The NFR boundary closest to the 5' end of the gene was able to predict 84% of TSSs within 50 bp. This serves as strong biological validation for the accuracy of our approach. Moreover, 9% of TSSs could not be accurately predicted because they lie within long NFRs of highly expressed genes, but not near the +1 nucleosome and 5'NFR boundary. Since highly expressed genes evict their +1 nucleosome, we can no longer use the 5'NFR boundary to find the TSSs at these genes. Another 5% of TSSs lie inside nucleosomes and were enriched for genes that are known to require nucleosome remodeling to

initiate transcription; hence, these TSSs are also not indicative of the accuracy of our NFR calling method. In total, only 87% of TSSs can be predicted using 5'NFRs and we can accurately predict 84% of all TSSs, which corresponds to an error rate between 1-3%.

We also compared 5'NFR calls between biological replicates as an independent way of measuring the error rate of our method. We obtained sufficient sequencing reads for two biological replicates in only 2 species. We found that between two biological replicates in *S. cerevisiae*, the 5'NFR and +1 nucleosome boundary was within 50 bp for over 96% of genes. Moreover, for two replicates in *C. glabrata*, the 5'NFR and +1 nucleosome boundary was within 50 bp for about 98% of genes. This error rate of 2-4% between replicates was very similar to the error rate observed when comparing 5'NFRs to valid TSSs.

Our method was also robust to parameter changes. Varying the linker lengths between 50bp and 70bp and occupancy thresholds between 30% and 50% did not change the 5'NFR calls for over 90% of genes. The accuracy for predicting TSSs dropped by no more than 3% for any combination of these parameter settings. Moreover, the accuracy of 5'NFR calls and TSSs predications was also not affected by changes in the nucleosome detection parameters. Changes of the standard deviation $\sigma=30$ to 20bp or 40bp and of the maximum allowable overlap of 20bp between adjacent nucleosomes to 10bp or 30bp did not affect the accuracy of TSSs predictions by more than 2%.

Finally, our biological conclusions discussed in subsequent Chapters were very robust to different parameter settings of the 5'NFR or nucleosome position detection algorithms. Also, repetition of our analysis with biological replicates or sub-sampling of the data to control for sequencing depth did not affect our results. The trends in global chromatin organization differences (next section) remained the same and the correlation coefficient R between different samples

and parameter settings in the functional chromatin organization (Chapter 4) was around .95 for all combinations.

3.4. Defining of Global Chromatin Features

To quantitatively compare chromatin structure between species, we first called nucleosome positions, identified 5' and 3' NFRs, and then measured a number of nonredundant features that describe the chromatin organization at each gene. We exhaustively measured 56 chromatin features at each gene for each species, representing various potential aspects of chromatin organization. Since some of these may be highly dependent, we used Spearman rank correlation analysis to measure the redundancy between these features (Figure 3-3). Indeed, more than half of the features were very dependent. For example, the median spacing between the first 2, 4, or 6 adjacent nucleosomes in the coding region of genes are highly correlated. For economy of thought, the rest of the analysis will focus on a subset of nonredundant (distinct) features.

We focused on 22 features that quantify the chromatin organization at each gene (Table 3-1). We measured the *NFR occupancy* as the number of nucleosome reads per NFR base pair (NFRs with low occupancy are deeper/more prominent), and define the occupancy of the -1, +1, and +N nucleosome in the same way. To quantify how well-positioned a nucleosome is in a population of cells, we compute nucleosome *fuzziness* as the standard deviation of read distributions contributing to a given nucleosome. Finally, we measure the relative organization of the features. For example, we measure the *distance* between the border of the +1 nucleosome and 5' NFR to the start codon ($D_{5'NFR-ATG}$), the *width* of the -1 nucleosome, the +1 nucleosome, and the *5'NFR*, and the *spacing* of coding region nucleosomes, defined as the median distance between the centers of adjacent nucleosomes in a gene.

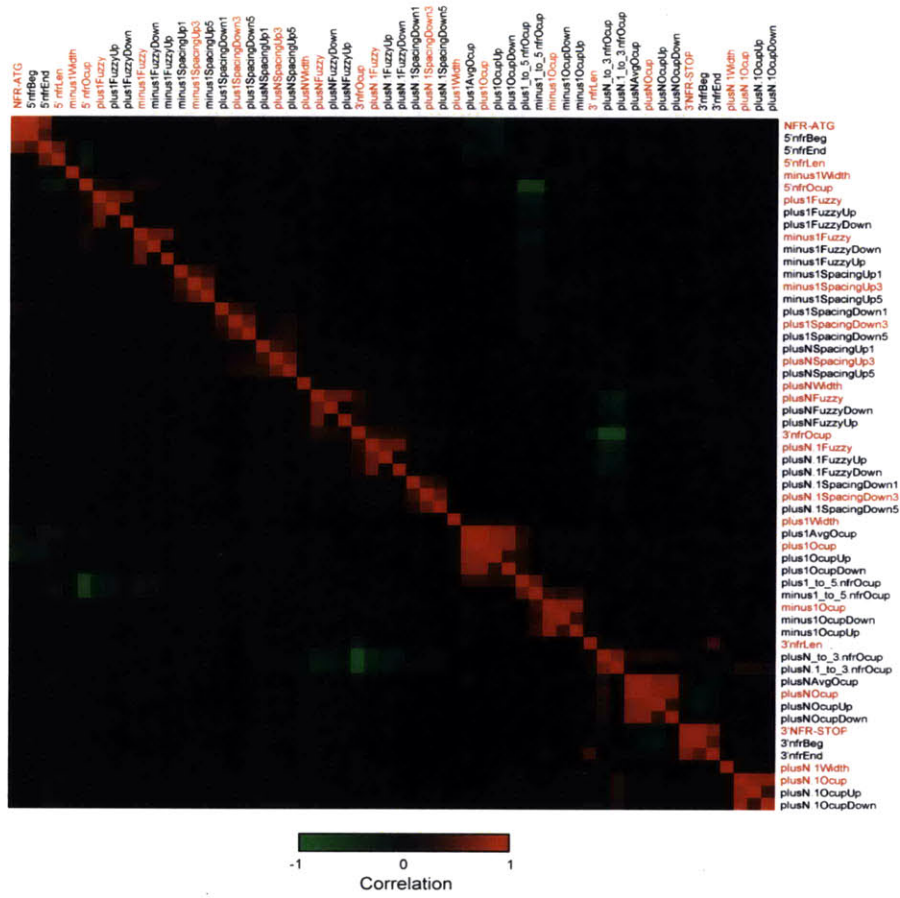


Figure 3-3: Spearman correlation matrix of all chromatin features. After calling nucleosomes from *S. cerevisiae* data, 56 chromatin features were measured at all gene promoters. Shown is the correlation matrix between all features in *S. cerevisiae*. The distinct features subsequently used in this study are highlighted in red.

Table 3-1: Definitions of Chromatin Organization Features.

Chromatin Feature	Definition
5'NFR-ATG distance	Distance between ATG and the NFR boundary closest to the ATG ($D_{5'NFR-ATG}$)
NFR length	Linker length between +1 and -1 nucleosomes
NFR occupancy	Mean normalized nucleosome occupancy over length of NFR
CDS nucleosome spacing	Median spacing between 4 adjacent nucleosomes (+1 through +4)
Nucleosome occupancy	Normalized number of forward and reverse reads
Nucleosome width	Forward read peak to reverse read peak distance
Nucleosome fuzziness	Weighted average of forward and reverse read cluster standard deviations

3.5. Evolution of Global Chromatin Organization

We first studied each feature *globally*, or averaged across all genes in a genome (this section), and will later study features *functionally*, or averaged across all genes that are functionally related (Chapter 4).

3.5.1. Conservation of Global Qualitative Features

Several qualitative chromatin features have previously been identified in all eukaryotes studied [2], and these were conserved across all 12 species (Figure 3-4). These included an abundant 5'NFR, a common 3'NFR, a well-positioned +1 nucleosome, and increasing nucleosome fuzziness over the body of genes (Figure 3-4). The similar nucleosome profiles of all 12 species are consistent with the theory of statistical positioning of nucleosomes [11, 41, 42], which proposes that NFRs act as nucleosome repelling boundaries that are bordered by a well-positioned the +1 nucleosome and increasingly more fuzzily (statistically) positioned nucleosomes over the coding region of the gene.

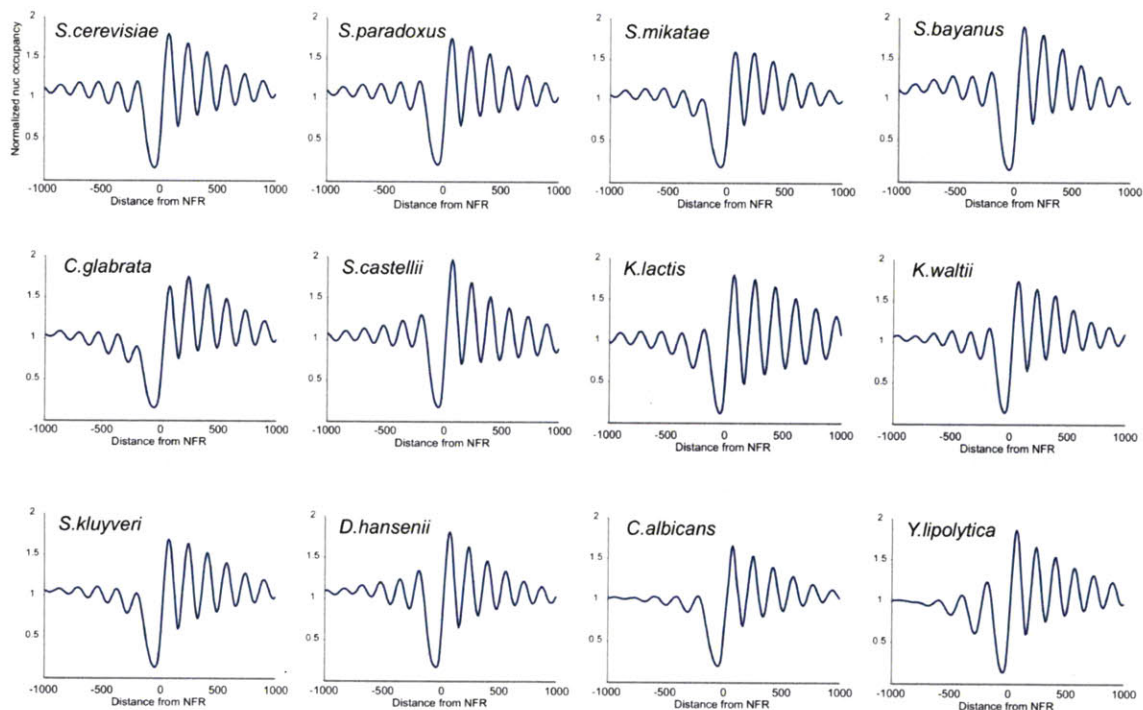
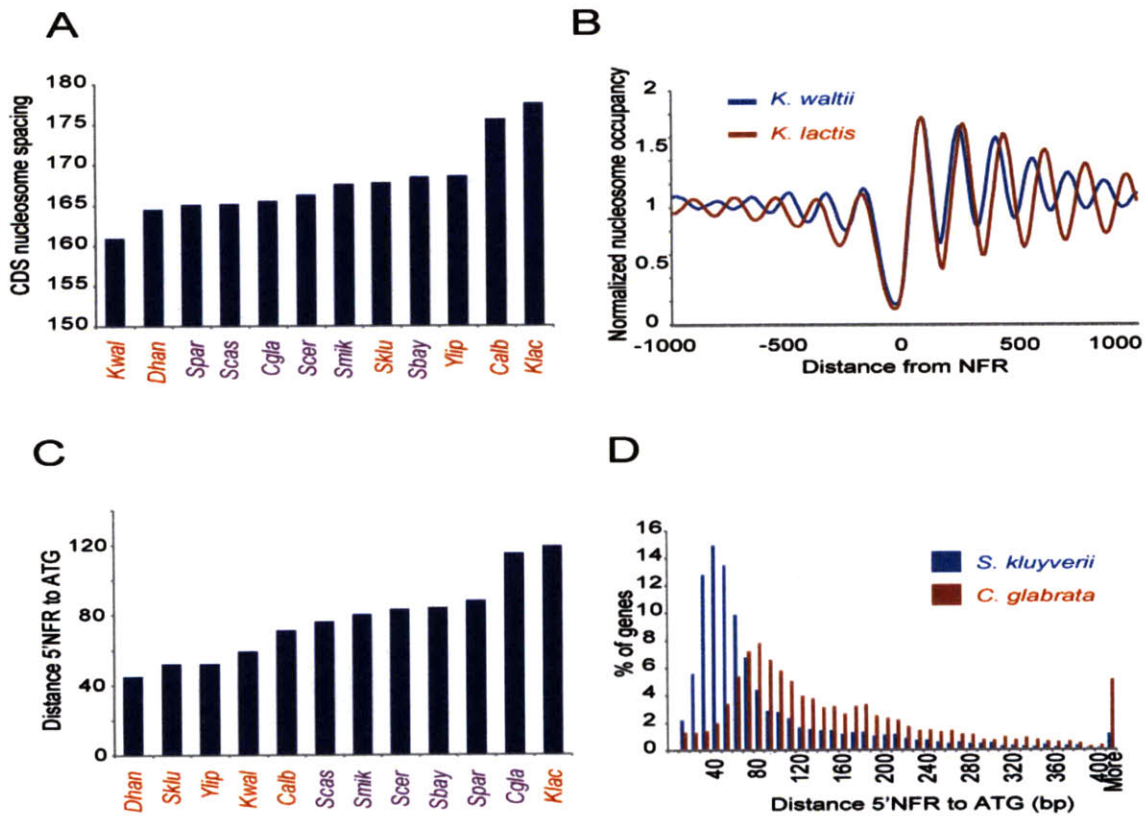


Figure 3-4: 5' promoter alignment of nucleosome data for 12 species. Sequencing reads were extended to a length of 100 bp. Data for all annotated genes was extracted and aligned by the +1 nucleosome, and average profiles over all genes are shown for each species. Similarly, we also aligned data by the +N nucleosome to study the chromatin organization at 3' NFR (data not shown).

3.5.2. Divergence of Global Quantitative Features

Quantitative global features were often variable between species (Figure 3-5 and Figure 3-6). Our measurements recapitulated previous predictions or bulk assays in the few cases where these were available, thus validating our dataset and analytical methods. For example, nucleosome spacing in coding regions was variable between species (Figure 3-5A,B), consistent with observed nucleosome laddering on gels [43, 44]. This leads to variation in the specific coding sequences exposed in linker DNA, and could affect patterns of sequence variation [45-47] and higher-order packaging into the 30nm fiber [48].



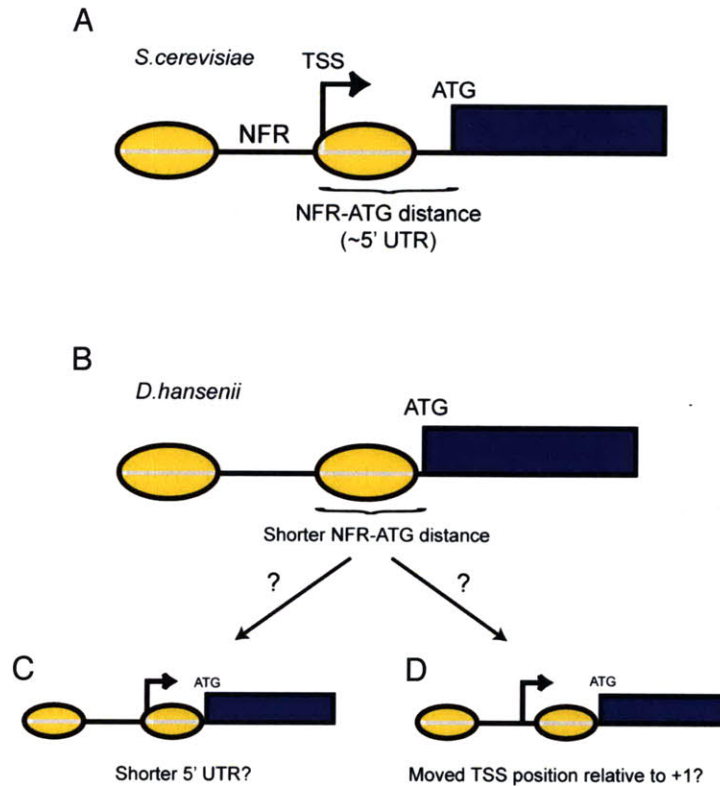


Figure 3-6: Two scenarios for changes in NFR-ATG distance. (A) Canonical promoter architecture in *S. cerevisiae* – transcriptional start site (TSS) is typically found at ~13bp 3' to the upstream border of the +1 nucleosome. (B) 5'NFR to ATG distance ($D_{5'NFR-ATG}$) varies in other species without annotated TSSs. For example, NFR-ATG distance is shorter in *D. hansenii* than in *S. cerevisiae* (Figure 3-5C). Depending on the location of the TSS, this result is consistent with two possibilities (or any admixture thereof): (C), TSSs are located 13 nt into the +1 nucleosome, and 5' UTRs are globally shorter, or (D), 5' UTRs are the same length and the TSS is situated within the NFR.

The distance between the NFR and a gene's start codon (Figure 3-5C,D and Figure 3-6) is also variable between species, consistent with prior computational predictions [49]. Depending on the location of the TSS, this result is consistent with two possibilities (or any admixture thereof): (1), TSSs are located 13 bp into the +1 nucleosome, and 5' UTRs are globally shorter, or (2), 5' UTRs are the same length and the TSS is situated within the NFR. Several lines of evidence support the latter possibility (Figure 3-6D), including the conservation of 5'UTR length distribution in a small number of measured cases in

S. cerevisiae and *C. albicans* [49], the known variation in TATA-TSS distances between *S. pombe* and *S. cerevisiae* [50], and the known variation between yeast, fly, and humans in TSS location relative to the +1 nucleosome [14, 38, 51, 52]. Thus, it is likely that TSS location relative to the +1 nucleosome varies substantially between *Ascomycota* species. This would affect TSS-exposure rates and pre-initiation complex geometry, and has unknown consequences for basic gene regulatory mechanisms [4, 53].

Moreover, the median NFR width was highly variable between species, ranging from 109 to 155 nucleotides. This is linked to the variation in the length of intrinsic anti-nucleosomal sequences between species (Section 5.2.3). Shorter NFRs may constrain regulatory information into more compact promoters.

Chapter 4. Statistical Framework for Functional Evolution

We next explored possible functional implications of chromatin organization in specific sets of genes with related function. Prior studies in *S. cerevisiae* and *C. albicans* have shown that in both species “growth” genes, defined by their co-expression with cytoplasmic ribosomal proteins (cRPs), have a more open chromatin organization on average [34]. Conversely, “stress” genes, whose expression is anti-correlated to that of growth genes, have a more closed chromatin organization in both species.

To assess the generality of this observation, we developed a general statistical framework for studying the functional evolution of gene regulation. For *S. cerevisiae* we gathered functional gene sets from several sources: KEGG [54], GO categories [55], MIPS [56], and BioCyc [57], as previously described [36]. For all other species, we projected these genes sets based on gene orthologies [36] using the ortholog mapping at www.broad.mit.edu/regev/orthogroups. For a given gene set in each species, we tested whether the constituent genes tended to have high or low values for each chromatin features relative to the background of that feature’s overall distribution in that species (Figure 4-1). This chapter discusses the methodology we used based on the Kolmogorov-Smirnov (K-S) statistic (Section 4.1), the advantages of this approach to previous methods (Section 4.2), and the biological insight gained from our analysis (Section 4.3).

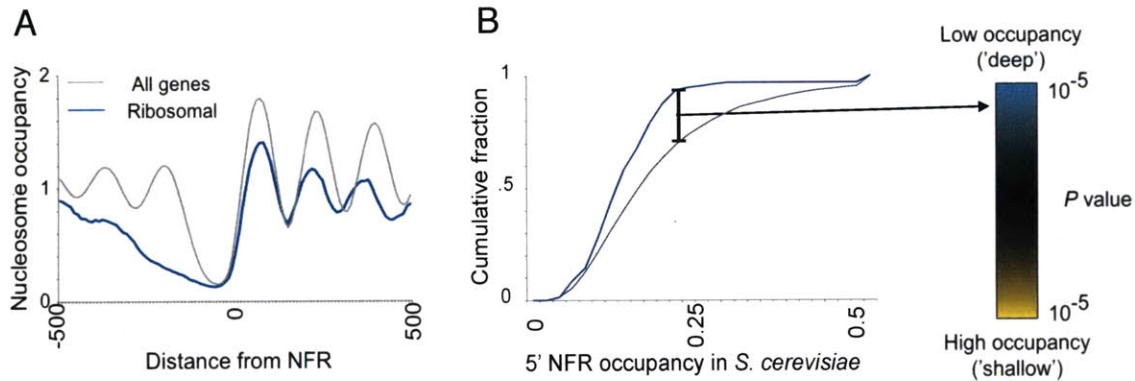


Figure 4-1: Strategy for associating chromatin features with gene sets. (A) Shown is the +1 nucleosome aligned nucleosome data for all genes (gray) and ribosomal protein genes (blue) in *S. cerevisiae*, demonstrating that ribosomal protein genes are associated with wider NFRs. (B) Cumulative distribution plot of NFR occupancy in all genes (gray) vs. ribosomal protein genes (blue). Y-axis shows fraction of promoters with NFR occupancy below a given value, with NFR occupancy values on the x-axis. Wide separation between curves (black vertical line) is captured by a significant K-S statistic, indicating that ribosomal genes have significantly low occupancy, or ‘deep’ NFRs. K-S P values are converted to color scale (right panel): blue – significantly low feature values; yellow – significantly high feature values.

4.1. Methodology and K-S Statistic

To quantify the enrichment for a given feature within a functional category we used the two-sample Kolmogorov-Smirnov (K-S) test. For each K-S test, we defined our two sample sets as genes within a given functional group and all other genes in the genome. For each chromatin feature, the K-S test quantifies the distance between the distributions of the two sets with n_1 and n_2 members. The K-S statistic K_{K-S} is defined as the maximum absolute difference between the cumulative distribution functions (CDFs) of the two samples. We estimated the P value, P_{K-S} , for the statistical significance of this difference as follows:

$$P_{K-S} = 2 \sum_{i=1}^{\infty} -1^{i-1} e^{-2i^2 \lambda^2}, \quad (4.1)$$

$$\lambda = \sqrt{\frac{n_1 n_2}{n_1 + n_2}} K_{K-S}. \quad (4.2)$$

For further analysis, we converted P values to K-S scores, S_{K-S} , where

$$S_{K-S} = \pm \log_{10}(P_{K-S}) \quad (4.3)$$

is positive or negative if the difference realizing the statistic K_{K-S} is positive or negative, respectively. To account for multiple hypotheses testing, we only considered P_{K-S} as significant if it was below the P value threshold for a False Discovery Rate of 5% [58]. In the following chapters, this functional enrichment analysis will also be applied to absolute expression levels, Poly(dA:dT) strength in NFRs, and *trans* factor motif affinity scores in NFRs. Moreover, the K-S test allowed for identification of TFs as activators and repressors across species, by comparing downstream expression of binding sites located in NFRs versus sites located in nucleosomes (Section 7.1.3).

4.2. Computational Contribution

Previous work on functional evolution introduced several methods for linking functional differences to divergent phenotypes. Man and Pilpel [59] measured translational efficiency for a number of *Ascomycota* species and found a number of links between divergence in phenotype and translational efficiency. They created a translational efficiency matrix of gene-orthologs versus species and used the Friedman test, which is a non-parametric extension of ANOVA, to look for a species-effect in translational efficiency. They found such an effect at mitochondrial ribosome and splicing genes, which matched the known phenotype.

Field et al. [34] linked divergence in gene expression in the mitochondrial ribosome genes to divergence in ‘openness’ of chromatin.

Our statistical framework for studying functional evolution presents several improvements over previous work. As discussed in Section 3.3.2, the analysis in [34] was done by comparing chromatin organization relative to the translation start site (ATG) and does not account for the differences in 5’NFR-ATG distances between species. Our method takes into account divergence in global chromatin organization, which allows for a more precise and thorough comparison. Moreover, our analysis is more general as it can test for the functional enrichment of any feature (chromatin property, gene expression, PolyA abundance) in the same manner.

Our approach also provides advantages to the Friedman test used by Man and Pilpel [59], because it does not base the analysis only on genes present in a gene-orthology matrix. Since many genes do not have clear orthology relations for all species, the matrix in [59] consists of less than half (2800) of the *S. cerevisiae* genes. As more species are included in an evolutionary study, the number of genes with orthology relationships for all species will further decrease. Moreover, genes that have clear orthology for the entire phylogeny are enriched for being housekeeping genes and depleted of stress response genes [36], which means that the sample of genes left in the gene-orthology matrix is likely functionally biased.

Our approach tests the functional enrichment for each gene set against the entire population of genes per species, which has three main advantages. First, it tests the tendency of each gene set against the background distribution of all genes, which precludes the functional bias introduced by gene-orthology matrices. Second, it normalizes for distribution differences between species. Since the K-S test is non-parametric, the background distribution can take on any shape. And third, our method scales with increasing number of species because it does not

exclude orthologs from a projected gene set in species A if species B lacks an orthology relationship with *S. cerevisiae*.

We also clustered genes for all chromatin features (both absolute and Z scores), and looked for GO enrichments within the resulting clusters. We found that fewer significant trends emerge, which include mostly nonspecific GO annotations such as “cellular process”. Hence, our supervised approach of using functional groups to guide the enrichment analysis uncovers more biological insights. This was also observed for translational efficiency in [59]. This is presumably because one does not need to find the right correspondence between number of clusters that partition the data and number of GO categories.

4.3. Regulatory Evolution of Functional Gene Sets

We applied this method in each species to thousands of functional gene sets to test for enrichment of each of 13 distinct chromatin parameters. This provides a comprehensive overview of promoter chromatin organization for each functional gene set across the 12 species (Figure 4-2, middle panels, Figure 4-3). In order to compare chromatin changes to gene expression levels, we also calculated the enrichment of the genes in each gene set for high or low mRNA expression in each species (Figure 4-2, left panels).

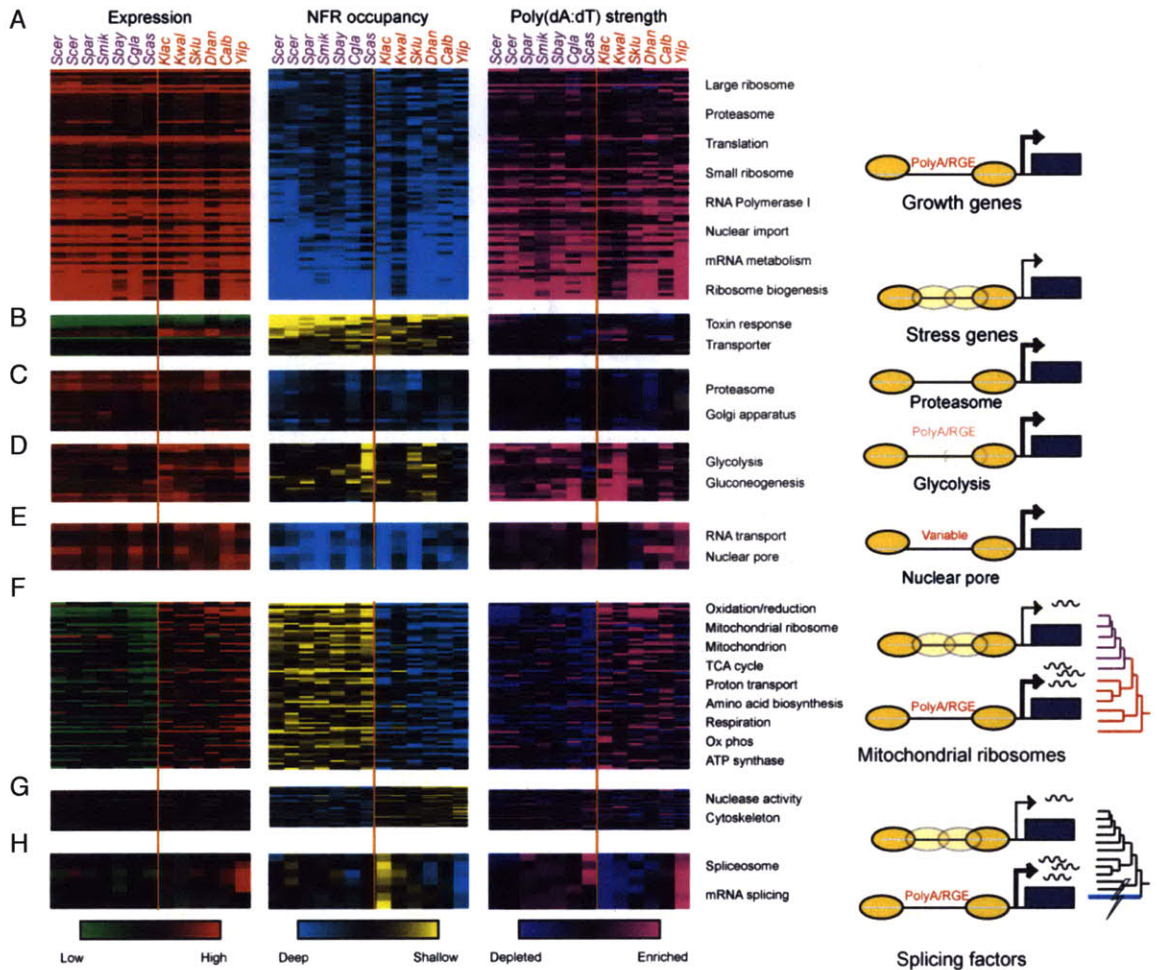


Figure 4-2: Functional conservation and divergence at gene sets. Shown are the K-S scores for expression level (red – high expression, green – low expression, left panel), NFR occupancy (yellow/blue, middle panel), and Poly(dA:dT) tracts in NFRs (purple – high Poly(dA:dT) strength enrichment; dark blue – low strength enrichment, right panel) for gene sets (rows) with distinct phylogenetic patterns across the 12 species (columns; species names are color coded by WGD). KS scores at saturation are 10^{-20} (Expression, A-C), 10^{-5} (occupancy and PolyA, A-C), 10^{-10} (Expression, D-E), $10^{-2.5}$ (occupancy and PolyA D-E). For F-H, all genesets are normalized to an average row value of zero (ie. centered to show relative changes), and p -value saturation values are 10^{-8} (expression) and 10^{-2} (occupancy, PolyA). Also shown are cartoons (right) reflecting the chromatin organization inferred from the test, and relevant phylogenetic events. (A) Conserved deep NFRs in growth genes, associated with high expression and strong Poly(dA:dT) tracts; (B) Conserved occupied NFRs in stress genes, associated with low expression and weak Poly(dA:dT) tracts; (C) Conserved deep NFRs in proteasome genes associated with high expression but not with Poly(dA:dT) tracts; (D) Conserved occupied NFRs in glycolysis genes despite high expression; (E) Deep NFRs and high expression at nuclear pore genes associated with Poly(dA:dT) tracts only in a subset of species; (F) Divergence

from deep to occupied NFRs following the WGD at mitochondrial protein genes, associated with reduction in expression and in Poly(dA:dT) tracts; (G) Divergence from occupied to deep NFRs following the WGD in cytoskeletal genes, despite little change in expression or Poly(dA:dT) tracts; (H) Divergence from deep to occupied NFRs in splicing after the divergence of *Y. lipolytica* associated with reduction in expression and in Poly(dA:dT) tracts.

4.3.1. Conserved Dichotomy of ‘Stress’ and ‘Growth’ Chromatin Organization

We confirm a strong dichotomy in the promoter chromatin architecture of most ‘stress’ and ‘growth’ genes in *S. cerevisiae* [7, 38, 60-62] and *C. albicans* [34], and find that it is conserved across all 12 species (Figure 4-2A,B and Figure 4-3). Promoters of ‘growth’ genes (*e.g.*, ribosomal, proteasomal and nuclear pore proteins, Figure 4-2A,C,E) exhibit long and deep (low occupancy) 5’NFRs. Conversely, those of ‘stress’ genes (*e.g.*, toxin-response genes, integral membrane proteins, Figure 4-2B) exhibit a more variable chromatin architecture, with shallower (higher occupancy) and narrower 5’NFRs. A host of additional chromatin features are also distinct between the two functional groups (Figure 4-3). Thus, the separation of the ‘growth’ and ‘stress’ axes is a hallmark of *Ascomycota* gene regulation [16, 17] and imposes strong constraints at various different levels of chromatin organization. There are, however, several exceptions to this rule. Most notably, several key ‘growth’ genes (including glycolysis genes and endoplasmic reticulum genes) are highly expressed yet do not exhibit deep NFRs in any species (Figure 4-2D).

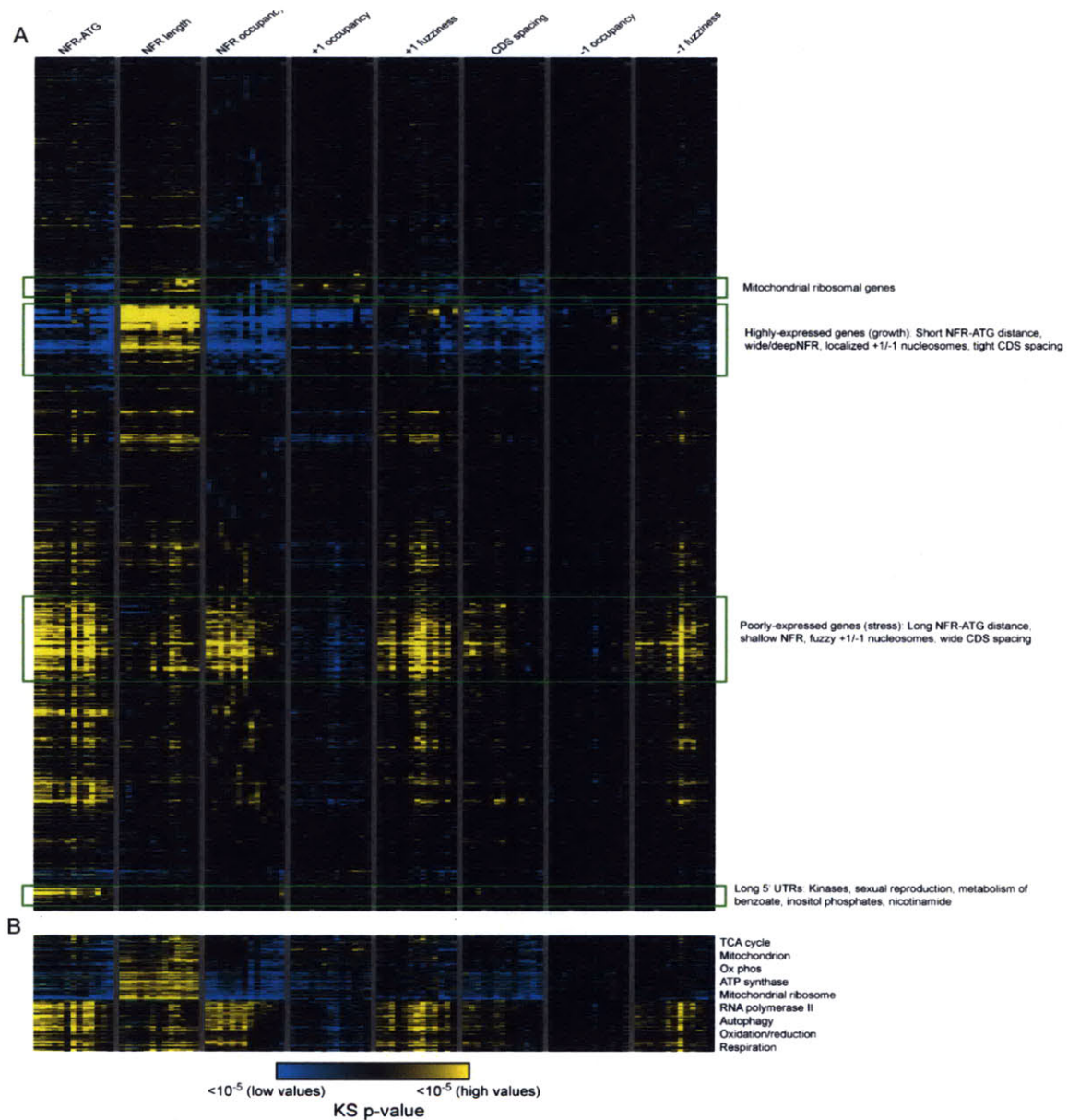


Figure 4-3: Functional conservation and variation in chromatin structure. (A) Global overview of chromatin behavior within functional gene sets. K-S scores were calculated for 8 parameters for 4774 gene sets in each species as in Figure 4-1. Only gene sets with over 10 members in 10 or more of species are shown (1159 genesets, including “transcriptional modules” and genes annotated based on expression changes in deletion strains [36], both excluded from Figure 4-2). Gene sets were clustered by their K-S scores and visualized as in Figure 4-2. Selected clusters of gene sets are marked on the right. Note that stress-related gene sets tend to become less enriched for various chromatin and expression features at increasing phylogenetic distance from *S. cerevisiae*, likely due to the rapid gain/loss of these genes over this phylogenetic distance [36]. Importantly, genes in distant species associated with orthogroups lacking an *S. cerevisiae* member

tend to be poorly expressed and exhibit stress-related chromatin characteristics (not shown), indicating that these genes likely play species-specific stress-related roles. (B) Gene sets associated with increase in NFR occupancy in post-WGD species were identified, and are shown as in panel A.

We identify a range of additional conserved patterns of chromatin architecture associated with other specific functions, which were not previously reported. For example, a number of gene sets (*e.g.* reproduction, cell wall, inositol phosphate, benzoate, and nicotinamide metabolism genes) have conserved long 5'NFR to ATG distances (Figure 4-3), but have few other hallmarks of stress genes, and are expressed at average levels. In *S. cerevisiae*, these genes have long 5' untranslated regions (5'UTRs) [40], suggesting that relatively long 5'UTRs are conserved at their orthologs in all 12 species. This may indicate a conserved role for translational control in the regulation of these functions [63].

4.3.2. Coordinated Divergence in Chromatin Structure and Gene Expression

On this backdrop of conservation, we find that coordinated changes have occurred in chromatin organization of specific functional gene sets, consistent with major phenotypic changes. Most notably, respiration and mitochondrial genes have switched from a 'growth'-like chromatin pattern in pre-WGD species (where they are highly expressed) to a more 'stress'-like pattern post-WGD (Figure 4-2F and Figure 4-3). We confirm the previously-reported change between *S. cerevisiae* and *C. albicans* for genes involved in respiratory metabolism [34]. We further extend these results across the full phylogenetic scope and to several other gene sets of related function (Figure 4-2F and Figure 4-3). This change corresponds to a major change in lifestyle from respiration to respiro-fermentation after the WGD [28, 33, 34, 64]. We also discover the converse evolutionary pattern (Figure 4-2G)—a number of gene sets involved in

cytoskeletal organization are packaged into deeper NFRs in post-WGD species than in pre-WGD species. Surprisingly, the expression level of these genes has not substantially changed with this transition.

Changes in chromatin organization have also occurred at other phylogenetic points of phenotypic evolution, suggesting a general evolutionary mechanism. For example, we discovered that in *Yarrowia lipolytica* spliceosome genes are associated with long and deep NFRs, but in all other species they are enriched for short and shallow NFRs (Figure 4-2H, middle panel). This switch from deep to shallow NFRs is accompanied by a decrease in expression of these genes (Figure 4-2H, left panel), and is consistent with the much larger number of introns in *Yarrowia lipolytica* genes [65], and with the loss of introns and reduction of splicing in the subsequently diverged species.

Chapter 5. Discovery of Novel Nucleosome Positioning Sequences

Understanding the underlying rules that govern nucleosome positioning in living cells presents a great challenge. Nucleosome positions are partially encoded by the intrinsic DNA sequences [8-12], primarily those that repel nucleosome formation such as Poly(dA:dT) tracts. In addition, *trans*-acting proteins can remodel (“move”) nucleosomes at different loci [13, 14]. Our current understanding of nucleosome positioning sequences is largely based on observations in the model organism *S. cerevisiae*. We hypothesized that the inherent sequence variation and divergence in protein composition between different species can give us a deeper, more complete insight into how nucleosomes are positioned *in vivo*.

Looking across evolution allowed us to uncover new intrinsic and *trans*-regulated sequences that organize chromatin, which we validate experimentally. We first quantified the nucleosome positioning potential of all possible 5-mer, 6-mer, and 7-mer DNA sequences. Section 5.1 discusses the method and initial biological discoveries that resulted from this analysis. Our findings motivated us to develop more elaborate algorithms for characterizing intrinsic anti-nucleosomal sequences (Section 5.2) and for discovering DNA-binding motifs for *trans*-acting chromatin regulators (Section 5.3). In these two sections, we discuss the methodology, our computational contribution, and the biological findings and

experimental validation of the analysis. We find that Poly(dC:dG) elements act as intrinsic anti-nucleosomal sequences globally, in a manner similar to the well-studied Poly(dA:dT) tracts (Section 5.2.3). We also mechanistically show that the transcription factor Cbf1 can globally reposition nucleosomes in *C. albicans*, but not in *S. cerevisiae* (Section 5.3.3.1). These and other novel nucleosome positioning sequences play an important and evolvable role across a number of yeast species (Section 5.3.3).

5.1. 7-mer analysis of Nucleosome Positioning Sequences

In order to investigate the sequence characteristics underlying nucleosome depletion at various promoters, we first calculated the extent of nucleosome depletion over all possible 7-mer sequences in the genome of each species (Figure 5-1A). We estimated the nucleosome depletion of each 7-mer using both our *in vivo* nucleosome maps for all species and *in vitro* nucleosome maps for *S. cerevisiae* and *C. albicans*, as measured by an *in vitro* assembly method that uses only purified nucleosomes and genomic DNA [9, 34]. If sequences repelled nucleosomes both *in vitro* and *in vivo*, we hypothesized they would act globally as intrinsic anti-nucleosomal sequence. Moreover, if sequences were significantly more (or less) depleted *in vivo* than *in vitro*, this would provide evidence for remodeling of nucleosomes by a *trans*-acting protein.

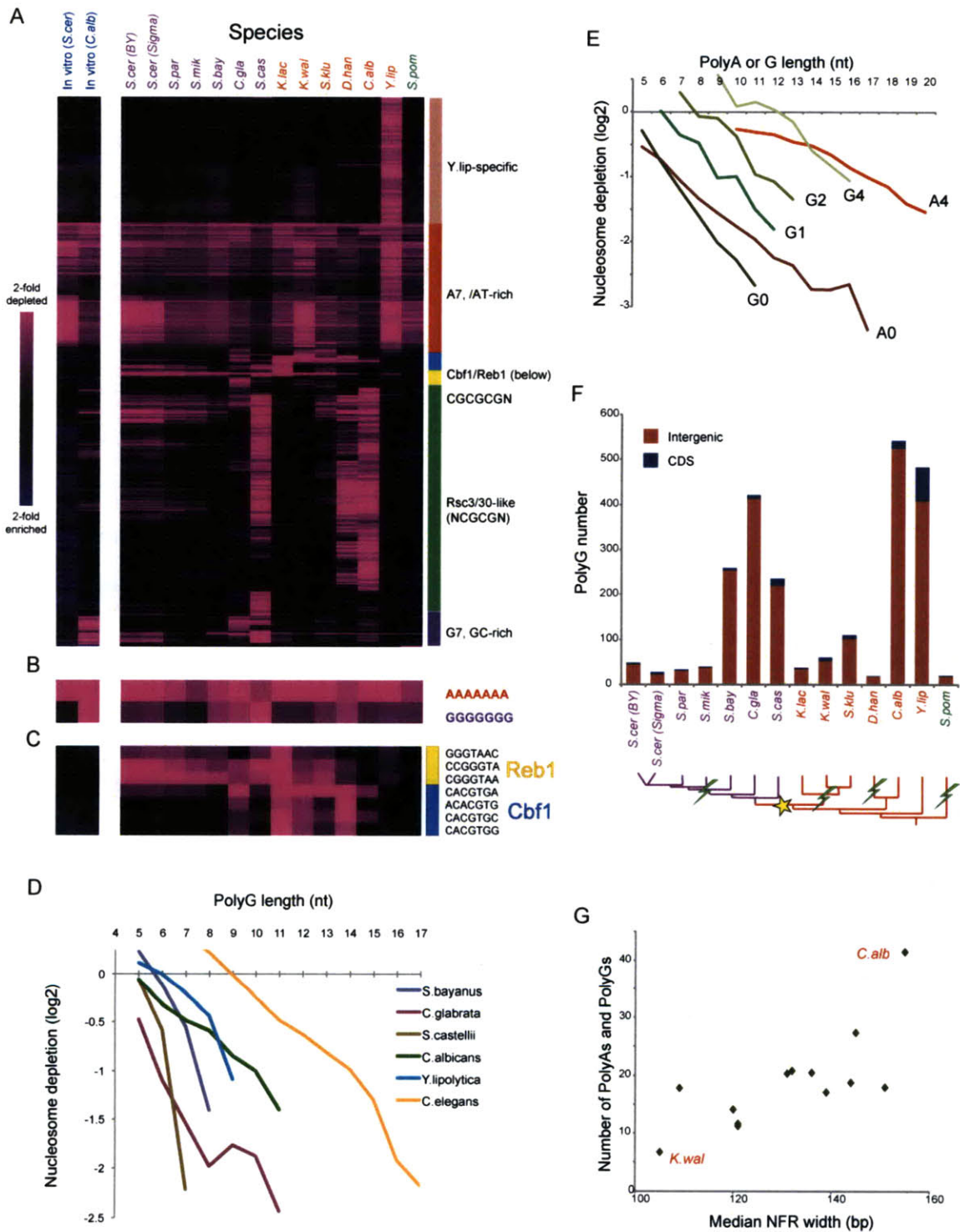


Figure 5-1: Nucleosome positioning sequences are highly evolvable. (A) The matrix illustrates the depletion score for all nucleosome depleted 7-mer sequences (rows) across all species in this study (rows), where purple represents strong nucleosome depletion (legend on left). (B) Zoom in from panel A showing the

nucleosome depletion of intrinsic anti-nucleosomal A7 and G7 sequences. (C) Zoom in from panel A on the evolutionary handoff between Reb1 and Cbf1 *trans*-regulated nucleosome positioning sequences. (D) PolyG elements (no mismatches) are nucleosome depleted *in vivo* in a number of yeast species and nematode *C. elegans*. Depletion increases with length. (E) PolyG elements with 0 (G0), 1 (G1), 2 (G2), and 4 (G4) mismatches are also nucleosome depleted *in vitro*, as shown by assembly of nucleosomes and *C. albicans* genomic DNA. Moreover, PolyGs depletion increases with length at a steeper slope than PolyA elements with 0 (A0), or 4 (A4) mismatches. (F) Abundance of PolyG tracts of strength ≥ 4 (x-axis) is highest in intergenic regions, and in species where G7 nucleosome depletion is strongest. (G) Abundance of intrinsic anti-nucleosomal sequences of strength ≥ 2 (y-axis in thousands) correlates with global chromatin organization of NFR width (x-axis measures the median NFR width over all gene promoters).

We performed the N-mer analysis for N=5, 6, 7, and 8. We first log2-transformed the normalized nucleosome occupancy data (Section 3.1), subtracted the mean and divided by the standard deviation. The distribution of the transformed nucleosome occupancy data for each species is approximately normal with zero mean and unit variance. We also repeated the same procedure for processing published *in vitro* data [9]. This ensured that each species' chromatin map is normalized for differences in sequencing depth and MNase digestion level.

For each N-mer, we define the *in vivo depletion score* as the mean $-\log_2$ normalized nucleosome occupancy across all instances of that N-mer and all instances of its reverse complement. We also defined the *depletion score relative to in vitro* as power 2 of the difference between the *in vivo* depletion scores in each species and the *in vitro* depletion scores in *S. cerevisiae* DNA (also repeated for *in vitro* data from *C. albicans* DNA [34]). We repeated the analyses for N-mers found only in coding regions and only in upstream promoter regions. Here we focus on the analysis of 7-mers over the entire genome, as it proved to be most insightful.

We found that most 7-mer sequences were similarly depleted of nucleosomes between all species. As expected, 7-mers that are AT rich were highly depleted of nucleosomes *in vivo* in all species, although the level of

depletion varied between species (Figure 5-1A, red bar). Such intrinsic anti-nucleosomal sequences were also highly depleted of nucleosomes *in vitro* in *S. cerevisiae* and *C. albicans* [9, 34].

We also identified a number of 7-mers that were nucleosome-depleted in a subset of these species but were not particularly nucleosome-depleted in *S. cerevisiae*, both *in vivo* and *in vitro*. For example, GC-rich sequences such as GGGGGGG (G7) were significantly depleted of nucleosomes *in vivo* in only a subset of species, but not in *S. cerevisiae* (Figure 5-1A,B). Interestingly, classic studies on the *HIS3* promoter showed that Poly(dC:dG) can substitute for Poly(dA:dT) as an anti-nucleosomal sequence [8, 66], suggesting that PolyGs may play a global role as novel *intrinsic* anti-nucleosomal sequence in some species. Supporting this hypothesis, we found that G7 is nucleosome-depleted in the *in vitro* nucleosome reconstitutions reported using genomic DNA from *C. albicans*, demonstrating that nucleosome depletion over G7 can occur in the absence of any *trans*-acting binding proteins (Figure 5-1B).

5.2. Evolution of Intrinsic Anti-Nucleosomal Sequences

To further characterize the intrinsic effects of PolyGs and PolyAs on a global scale, we estimated the average extent of nucleosome depletion over Poly(dC:dG) and Poly(dA:dT) elements of different length and homopolymeric mismatches using the *in vitro* nucleosome map in *C. albicans*. Our method is similar to the approach in [48] with several modifications and improvements. The next two sections describe the methodology and then highlight the computational contributions and improvements made to previous work.

5.2.1. Methodology

For each species' genome, we annotated all PolyA or PolyT tracts of length L of 5bp or more. We define the depletion score for a tract of length L as the mean of the $-\log_2$ normalized nucleosome occupancy across all instances of that length. This was calculated both using *in vitro* data from *S. cerevisiae* [9] and the *in vivo* data from each species. For long Poly(dA:dT) tracts with very few occurrences in a given genome we noticed a larger variation in the depletion score, likely due to small sample size. To mitigate this problem, we fit a line for depletion scores versus L using a weighted linear least squares fit with weights proportional to the number of occurrences for tracts of length L . We then used the line as an estimate for long tracts with fewer than 100 occurrences in a given genome. We iterated this procedure for all maximal Poly(dA:dT) tracts with k allowed mismatches, $k = 1, \dots, 20$. The depletion score increases linearly with L for tracts with different k , confirming that a linear fit is appropriate (Figure 5-2A).

To aggregate all non-overlapping Poly(dA:dT) tracts within a given genome, we first discretized the strengths for each L . We define the fold depletion score of all tracts of length L as power 2 of the depletion score. We then quantized all Poly(dA:dT) tract fold depletion scores to the highest fold depletion level exceeding 2, 4, 8, 16, and 32. For example, a tract with a depletion score of 3.5 is $2^{3.5}=11.3$ -fold depleted in nucleosomes relative to average, and would be assigned a fold depletion score of 8. We next iterated over all Poly(dA:dT) tracts with mismatches $k = 0, \dots, 20$, replacing overlapping tracts only if the tract with more mismatches had a higher quantized fold depletion score. To annotate Poly(dC:dG) tracts, we used the same approach as above but now treating consecutive sequences of Cs and Gs as homopolymeric tracts and other, interrupting nucleotides as mismatches.

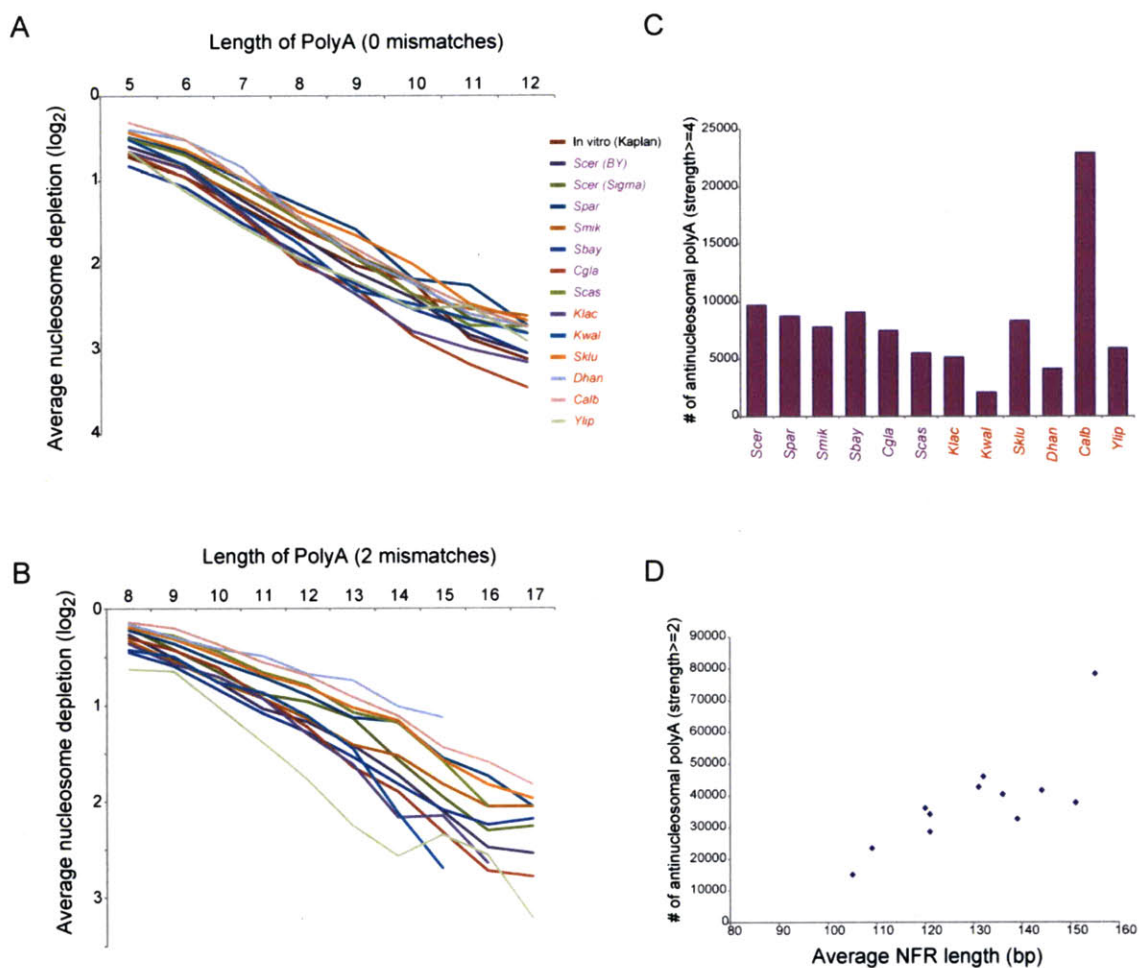


Figure 5-2: Evolution of anti-nucleosomal Poly(dA:dT) tracts. (A,B) Shown are plots of nucleosome depletion (\log_2 , y axis) vs length of Poly(dA:dT) tract (x axis) for Poly(dA:dT) tracts with no mismatches (A) or 2 mismatches (B). (C) Species differ in the number of antinucleosomal Poly(dA:dT) tracts. Shown are the number of anti-nucleosomal Poly(dA:dT) tracts with a strength score ≥ 4 in each species. (D) Median NFR width (per species) is correlated ($r = 0.77$) with number of anti-nucleosomal Poly(dA:dT) tracts in each genome. Shown are the number of anti-nucleosomal Poly(dA:dT) tracts with a strength score ≥ 2 in each species' genome vs. that species average NFR length.

5.2.2. Computational Contributions

Our method was similar to the approach in [61], except for the following modifications. First, we used *in vitro* data from *C. albicans* [34], instead of *in vivo* data from *S. cerevisiae*. The *in vitro* data allows us to more accurately

estimate the intrinsic nucleosome repelling strength of PolyA elements. Also, using data from *C. albicans* allows us to discover the intrinsic anti-nucleosomal properties of Poly(dC:dG) tracts. Such tracts are very rare in the *S. cerevisiae* genome and have escaped attention in the literature. Second, we calculated nucleosome depletion in the log domain. This is advantageous because depletion scales linearly with length L of Poly(dA:dT) tract in the log domain, which was not previously observed. Third, the log-linear scaling allows us to estimate the *in vitro* depletion of rare homopolymers, which have too few instances in the genome to estimate accurately. To do this, we fit a line for depletion scores versus L using a weighted linear least squares fit with weights proportional to the number of occurrences for tracts of length L .

5.2.3. Divergence in Use of Intrinsic Anti-nucleosomal Sequences

Our modified methodology enabled us to study the intrinsic anti-nucleosomal properties of PolyGs on a global level, which was not previously possible. As is known for PolyAs, we found that PolyGs reside predominantly in intergenic regions and become more depleted of nucleosomes *in vitro* as they increased in length (Figure 5-1F,E). This is true for both homopolymeric tracts and PolyG elements with mismatches. Interestingly, PolyG elements decreased in nucleosome occupancy at a steeper slope than PolyAs (Figure 5-1E), suggesting that they repel nucleosomes more efficiently *in vitro*.

PolyG elements were also highly depleted of nucleosomes *in vivo* in a number of species in addition to *C. albicans*. Using the same method, we identified Poly(dC:dG) elements in other species and measured their *in vivo* nucleosome depletion. We observed that PolyGs of various lengths were significantly depleted of nucleosomes in both human pathogens *C. albicans* and

C. glabrata (Figure 5-1D), as well as in the yeasts *S. castelli*, *S. bayanus*, and *Y. lipolytica*. Moreover, Poly(dC:dG) tracts became more depleted of nucleosomes with increasing length in the nematode *C. elegans*, showing that PolyGs acts as a global anti-nucleosomal sequence in metazoans as well as fungi.

To explain the variability in nucleosome depletion of PolyG elements between different species, we tested whether the genomic abundance of Poly(dC:dG) tracts can provide further insight. For each species' genome, we counted all non-overlapping PolyG elements that had an *in vitro* strength of 4 or more, as measured using *in vitro* data from *C. albicans* DNA (Section 5.2.1). We found that species with significant *in vivo* depletion at 7-mer GGGGGGG were also the species with the most occurrences of strong PolyG elements in their genomes (Figure 5-1F). For example, *S. cerevisiae* has 10 fold fewer PolyG elements than *C. albicans*, which explains why the global role of PolyGs as an intrinsic anti-nucleosomal sequence has not been previously reported. Similarly, we observed larger *in vivo* depletion of A7 elements in genomes that contain more Poly(dA:dT) tracts (Figure 5-2B).

The abundance of Poly(dA:dT) tracts can affect the global chromatin properties of a species' genome, such as NFR width. As studied in *S. cerevisiae*, anti-nucleosomal sequences such as PolyAs play a major role in establishing NFRs. We find that the abundance of PolyA and PolyG sequences at promoters is correlated with the median NFR widths in the species (Figure 5-1G), where species with fewer intrinsic anti-nucleosomal sequences, such as *Debaryomyces hansenii*, are characterized by shorter NFRs. In the case of *D. hansenii*, a halophile typically found in high-salt environments, the loss of PolyAs might be related to the increased flexibility of DNA in high salt and resulting loss of effectiveness of intrinsic "stiff" sequences such as PolyAs in excluding nucleosomes. Thus, major aspects of chromatin architecture can be plastic over evolutionary timescales.

5.3. Evolution of *Trans*-acting Chromatin Regulators

We next wanted to use evolution to gain further insight into *trans*-regulated sequences that can reposition nucleosomes. We hypothesized that the chromatin maps in different species can reveal variation in the *cis*-regulatory elements bound by ‘General Regulatory Factors’ (GRFs) that recruit chromatin remodelers [13, 67, 68]. To identify such *cis*-elements, we searched for 7-mer sequences that are depleted of nucleosomes *in vivo* but not *in vitro* [9]. Such sequences lie below the diagonal of *in vivo* versus *in vitro* depletion scores (Figure 5-4A).

We devised a method (Section 5.3.1) that integrates 7-mers in order to find the consensus DNA-binding motifs for GRFs (Figure 5-3). To our knowledge, there is no other technique for GRF motif discovery in the literature (Section 5.3.2). We then use this methodology to study the evolution of GRFs (Section 5.3.3).

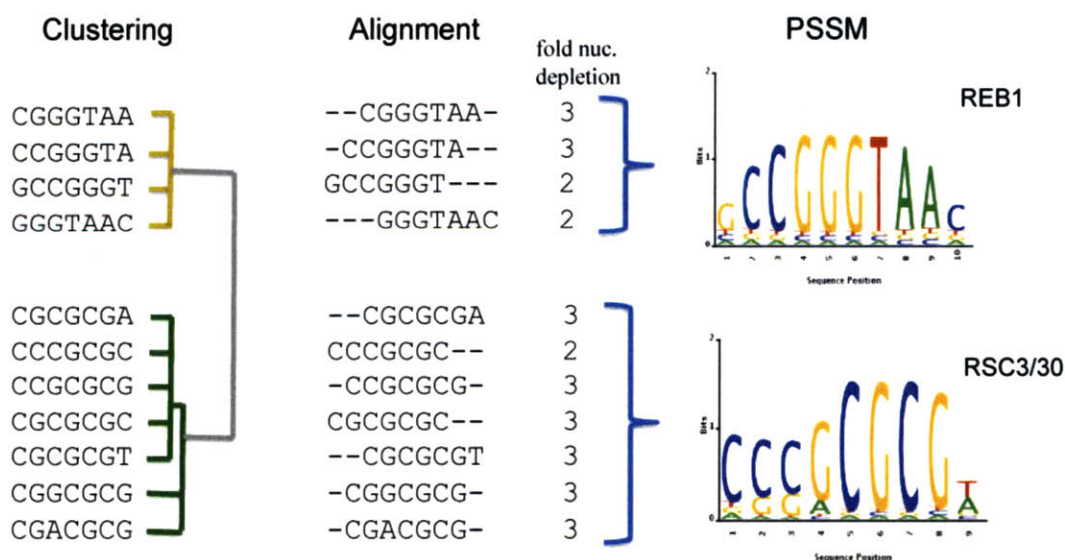


Figure 5-3: Overview of GRF motif finding algorithm. *In vivo* depleted sequences in each genome are clustered based on similarity, aligned, and combined into a

PSSM. Shown are the results for *S. cerevisiae*, where the algorithm outputs the known PSSMs of chromatin regulators Reb1 and Rsc3/30.

5.3.1. Methodology

To discover motifs, we ranked all 7-mers by their mean *in vivo* depletion score relative to *in vitro*. We then used the top 15 7-mers in each species as input to our algorithm. To construct PSSMs, we first calculated a similarity matrix between all possible pairs of these 7-mers. The similarity was measured using the dot product of the best possible ungapped alignment between two 7-mers, allowing for reverse complements. We defined the similarity between two 7-mers \bar{x} and \bar{y} as:

$$S(\bar{x}, \bar{y}) = M - \frac{1}{4}L, \quad (5.1)$$

where L is the length of the alignment and M is the number of matches. To group similar 7-mers, the similarity was then converted to a distance by subtracting $S(\bar{x}, \bar{y})$ from the self-similarity, $S(\bar{x}, \bar{x})$, as follows:

$$d(\bar{x}, \bar{y}) = S(\bar{x}, \bar{x}) - S(\bar{x}, \bar{y}). \quad (5.2)$$

The distances between all 7-mers were then clustered using single-linkage hierarchical clustering. Single-linkage allows for grouping of 7-mers with the same number of alignment mismatches without increasing the cluster similarity distance. For all species, we grouped subtrees of 7-mers into clusters by allowing for at most 1 alignment error or mismatch between the two most similar 7-mers in a cluster. Clusters of less than 3 elements were removed from consideration.

We then performed progressive multiple alignment for all 7-mers within each cluster. We used the NUC44 scoring matrix and computed the average score for two matched residues (S_m). Opening gaps within 7-mers was not allowed. Gaps flanking the 7-mers were penalized as $S_m/3$, as it produced a good

tradeoff for penalizing mismatches between 2 residues versus 1 residue and a terminal gap.

To form PSSMs, letters in each position of the alignment were summed, weighted by their depletion score relative to *in vitro*. Therefore, 7-mers with a higher depletion score contributed more to the PSSM. To prevent overfitting, we inserted pseudocounts of .5 for each entry in the PSSM, equivalent to adding an extra, non-informational 7-mer with a depletion score relative to *in vitro* of 2.

5.3.2. Computational Contribution

Previous methods for finding motifs of transcription factors used co-expression, conservation or binding (ChIP-chip, ChIP-seq, protein binding arrays) information [69, 70]. This is the first method for specifically finding motifs of GRFs, and requires genomic sequence and genome-wide nucleosome data. Moreover, finding motifs using this approach implies the sites' function as a binding site for a *trans*-acting chromatin factor, even when the chromatin factor is unknown. This biological insight cannot be gained by conservation or binding data alone. The limitation of this approach is that it does not directly link the *cis*-regulatory sequence to a specific protein. Nonetheless, in the next section we show that in many cases the specific protein can be inferred by searching the literature and follow-up experiments.

5.3.3. In-trans Chromatin Regulators have Diverged

Our methodology identified *in vivo*-specific depletion over 7-mers consistent with the binding sites for known *S. cerevisiae* GRFs such as Reb1 [71, 72] (Figure 5-4A, orange) and the Rsc3/30 components of the RSC ATP-dependent chromatin remodeling complex [13, 71, 72] (Figure 5-4A, green), validating our approach. We also found a number of sequence motifs that were nucleosome-

depleted *in vivo* in some species, but not in *S. cerevisiae*, such as the CACGTGA motif that serves as the binding site for Cbf1 in *S. cerevisiae* and *C. albicans* [69, 71-73] (Figure 5-4A, blue). This suggests that Cbf1 functions as a GRF in some species, but may have lost this function in *S. cerevisiae*.

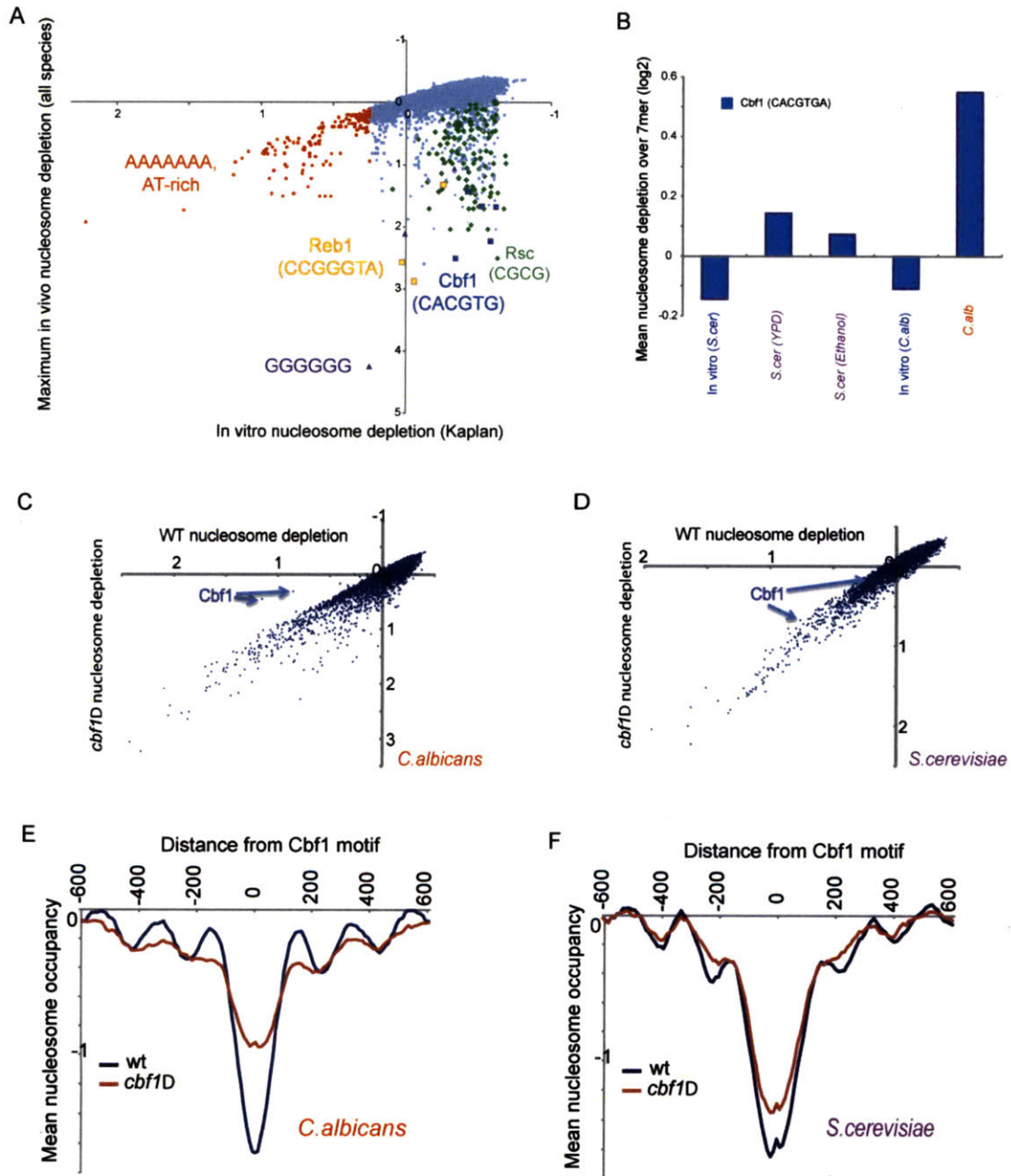


Figure 5-4: Evolution of GRF motifs associated with nucleosome depletion. (A) Identification of putative GRF sites. Nucleosome depletion scores were calculated

over all 7-mers from *in vitro* reconstitution data [9], and from our *in vivo* data for all species. Scatter plot shows the *in vitro* depletion score (x axis) vs. the maximal 7-mer nucleosome depletion score observed *in vivo* in any of the 12 species (y axis). Motifs corresponding to select known binding sites are indicated. (B-F) Cbf1 acts as a GRF in *C. albicans* but not in *S. cerevisiae*. (B) Cbf1 known binding site CACGTGA is nucleosome depleted *in vivo* in *C. albicans*, but not *in vitro*. Moreover, Cbf1 site is not significantly nucleosome depleted in *S. cerevisiae in vitro*, or *in vivo* in rich and ethanol medium. (C) Cbf1 sites CACGTGA and ACGTGAC are the only 7-mers that are significantly more nucleosome occupied upon deletion of Cbf1 in *C. albicans*. (D) This is not the case for these 2 and any other 7-mers upon deletion of Cbf1 in control species *S. cerevisiae*. (E-F) Moreover, average nucleosome data centered at all CACGTGA Cbf1 motif instances (located at position 0 on the x-axis) is significantly more nucleosome occupied upon deletion of Cbf1 versus wildtype in *C. albicans* (E), but not in *S. cerevisiae* (F).

5.3.3.1. Cbf1 acts as a GRF in *C. albicans* but not *S. cerevisiae*

To test this hypothesis, we first checked if the depletion score of the Cbf1 binding site depends on the sensory state of the cell and the activity of the transcription factor. In *S. cerevisiae*, we found that the binding site CACGTGA is similarly depleted of nucleosomes in ethanol medium, where Cbf1 activates respiration genes, and in glucose medium (Figure 5-4B). Moreover, the higher than average nucleosome occupancy of Cbf1 sites in the *in vitro C. albicans* data shows that the *in vivo* depletion of Cbf1 is not due to coincident positioning of Cbf1 sites near intrinsic anti-nucleosomal sequences (Figure 5-4B).

To experimentally validate that Cbf1 serves as a GRF in *C. albicans* but not in *S. cerevisiae*, we measured nucleosome positions (as described in Section 2.2) using strains that lack the transcription factor Cbf1 in the two species. Following deletion of Cbf1 in *C. albicans*, only two 7-mers become significantly occluded by nucleosomes—CACGTGA and ACGTGAC, which both correspond to Cbf1’s experimentally validated binding site (Figure 5-4C). In the control species *S. cerevisiae*, no 7-mers (including the two above) are significantly affected upon deletion of Cbf1 (Figure 5-4D). Moreover, averaging the nucleosome occupancy at all 766 intergenic CACGTGA occurrences shows that

deletion of Cbf1 significantly increased the nearby nucleosome occupancy and reduces the phasing between adjacent nucleosome peaks (Figure 5-4E) in *C. albicans*, but not in *S. cerevisiae* (Figure 5-4F). This shows that Cbf1 functions as a GRF on a global level in *C. albicans* through its binding site CACGTGA but has lost this global function in *S. cerevisiae*.

In *C. albicans*, the *in vivo* role of Cbf1 in recruiting nucleosome remodelers counteracts the effect of intrinsic anti-nucleosomal sequences such as PolyGs. We observed that GC-rich 7-mers become significantly depleted of nucleosomes when Cbf1 is removed (Figure 5-4C). Furthermore, on average, nucleosome occupancy at 1343 intergenic PolyGs of strength ≥ 2 is remarkably lower in the strain lacking Cbf1 (Figure 5-5A) than in WT strains. Moreover, the nucleosome occupancy at PolyGs decreases as the length of the tracts increases in the mutant strain, and it is stronger than both the *in vivo* and *in vitro* nucleosome depletion measured at the same Poly(dC:dG) elements in the WT strains (Figure 5-5B). Deletion of Cbf1 also makes PolyA elements more nucleosome depleted than their wildtype *in vivo* and *in vitro* estimates in *C. albicans* (Figure 5-5C). However, this is not the case in *S. cerevisiae* (Figure 5-5E).

To assess the transcriptional response of the strains lacking Cbf1, we used species-specific microarrays to measure the relative abundance of RNA collected from the same mutant and wildtype cultures as used for the nucleosome mapping. In *C. albicans*, we found that deletion of Cbf1 represses most processes related to cell growth, including mitochondrion, ribosome, and TCA cycle related proteins (p-value $< 10^{-10}$). This is consistent with the slow growth phenotype of the Cbf1 mutant strain and with Cbf1's established role in regulation of ribosomal genes. The proteasome and mRNA processing protein complexes were the only significantly upregulated functional groups of genes, which may be

needed for precluding errant transcription and translation due to improper formation of NFRs.

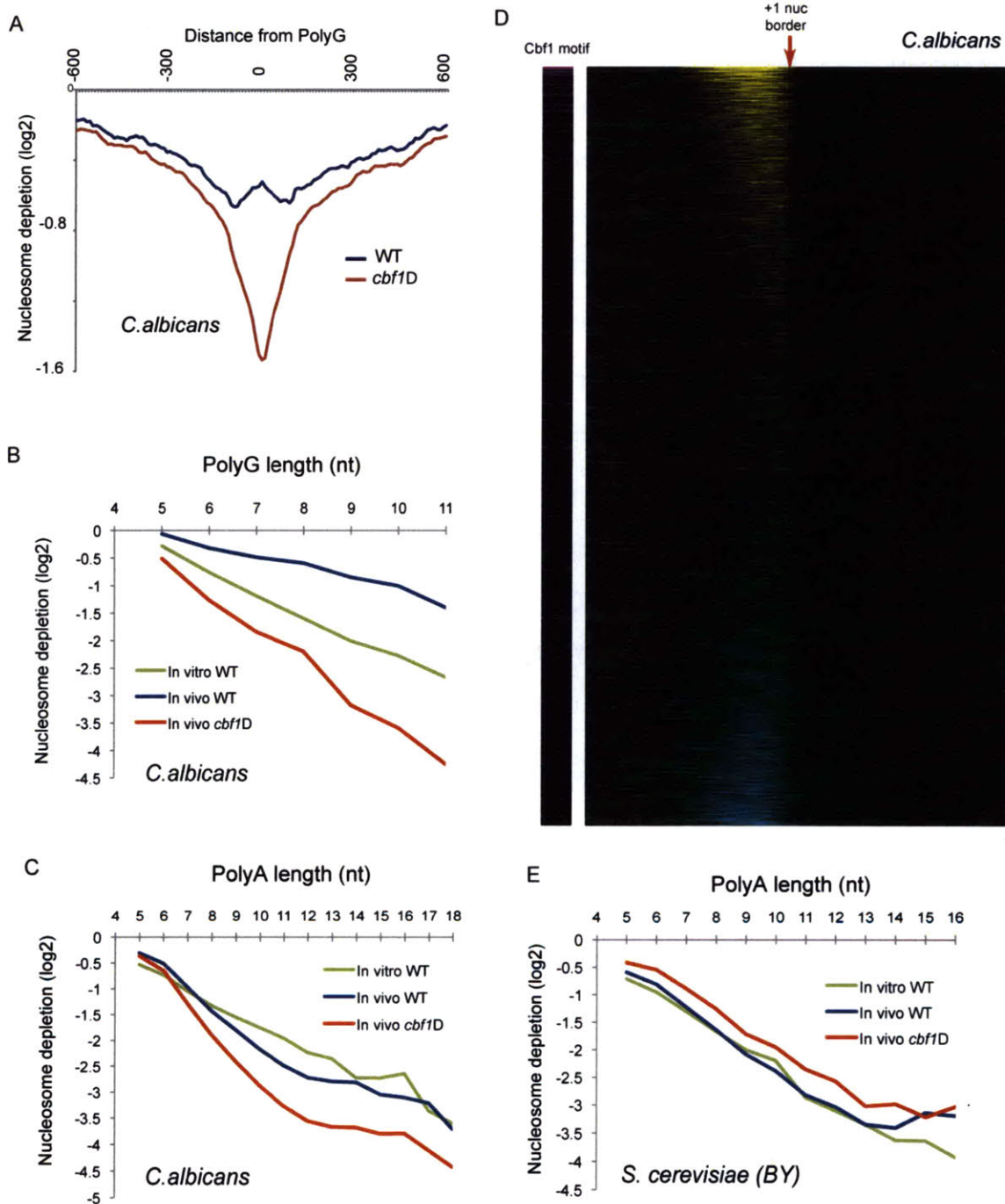


Figure 5-5: Effect of deleting Cbf1 on intrinsic anti-nucleosomal sequences. (A) Average nucleosome data centered on all PolyG elements of strength of 2 or

greater (located at position 0 on the x-axis) is more nucleosome depleted in Cbf1-delete versus wildtype strains in *C. albicans*. (B) PolyGs of different lengths in *C. albicans* are least nucleosome depleted *in vivo*, more so *in vitro*, and even more so *in vivo* upon deletion of Cbf1. (C,E) Moreover, PolyAs of different length are more depleted of nucleosomes in Cbf1-delete versus wildtype strain in *C. albicans* (C), but in *S. cerevisiae* (E). (D) Left image shows the NFR affinity score for Cbf1 motifs at all *C. albicans* genes (rows), where purple represents a strong affinity score. Matrix on the right shows the difference in nucleosome occupancy between Cbf1-delete and wildtype *C. albicans* strains (yellow--more occupied in Cbf1-delete, blue—more occupied in WT) relative to the NFR/+1 nucleosome boundary (at center of x-axis). Rows are all genes, ranked by amount of nucleosome occupancy difference.

We next wanted to study the effect of deleting Cbf1 in *C. albicans* at the level of individual genes. Ranking all genes by the difference in nucleosome occupancy between mutant and wildtype strains, we observed that NFRs with Cbf1 sites were amongst the most occluded with nucleosomes (K-S p-value $< 10^{-21}$, Figure 5-5D). Genes with Cbf1 sites in their promoters have a slightly lower expression level than those without Cbf1 sites (K-S p-value = .0202). Moreover, genes that contained strong Poly(dC:dG) tracts in their NFRs were amongst the most depleted with nucleosomes (K-S p-value $< 10^{-18}$, Figure 5-5D) and were also more up-regulated than genes without strong PolyG elements in their promoters (K-S p-value $< 10^{-4}$).

Deletion of Cbf1 in the two species has drastically different effects on global chromatin organization. In both species, we found that approximately 20% of NFRs were significantly repositioned between the wildtype and mutant strains (Experimental Procedure). However in *C. albicans*, NFRs that changed in position between mutant and wildtype were on average 47% longer and 28% more nucleosome depleted in the mutant strain. In contrast, in *S. cerevisiae* NFRs that changed position between mutant and wildtype were 31% shorter and 11% less depleted upon Cbf1 deletion. These global effects highlight the possibility for different global functions of Cbf1 in the two species; in *S. cerevisiae*, Cbf1 acts as a transcription factor that enhances NFR formation,

whereas in *C. albicans* Cbf1 recruits nucleosome remodelers that use energy to occlude anti-nucleosomal sequences such as PolyAs and PolyGs.

5.3.3.2. Sap1 acts as a ‘GRF’ in *Schizosaccharomyces pombe*

In addition to uncovering the role of the CACGTG Cbf1 motif as a GRF site for pre-WGD species, we also identified numerous 7-mers, which did not obviously correspond to known TF binding sites (Figure 5-1A). For instance, a large group of related 7-mers were nucleosome-depleted specifically in *Y. lipolytica* but not in other species (Figure 5-1A). Using these 7-mers as inputs, our GRF finding algorithm found two distinct PSSMs for anti-nucleosomal motifs in *Y. lipolytica* (Figure 5-6A,B). Moreover, when looking at the position of these factors’ DNA binding sites relative to chromatin organization, we found a significant enrichment for presence in NFRs (Figure 5-6C,D). When we compared these two PSSMs to known TF binding motifs in *S. cerevisiae*, we found a correspondence to the motifs for TFs Phd1 and Tbf1 (Figure 5-6A,B). Thus, we propose that TFs Phd1 and Tbf1 act as GRFs in *Y. lipolytica*, although we cannot rule out the possibility that another unknown protein has evolved to bind this motif. Using our GRF motif discovery algorithm, we also found a handful of other species-specific PSSMs. These motifs appear to capture sites for currently uncharacterized factors, as we have not been able to determine the relevant TF that binds to the *C. albicans* specific CACGAC motif.

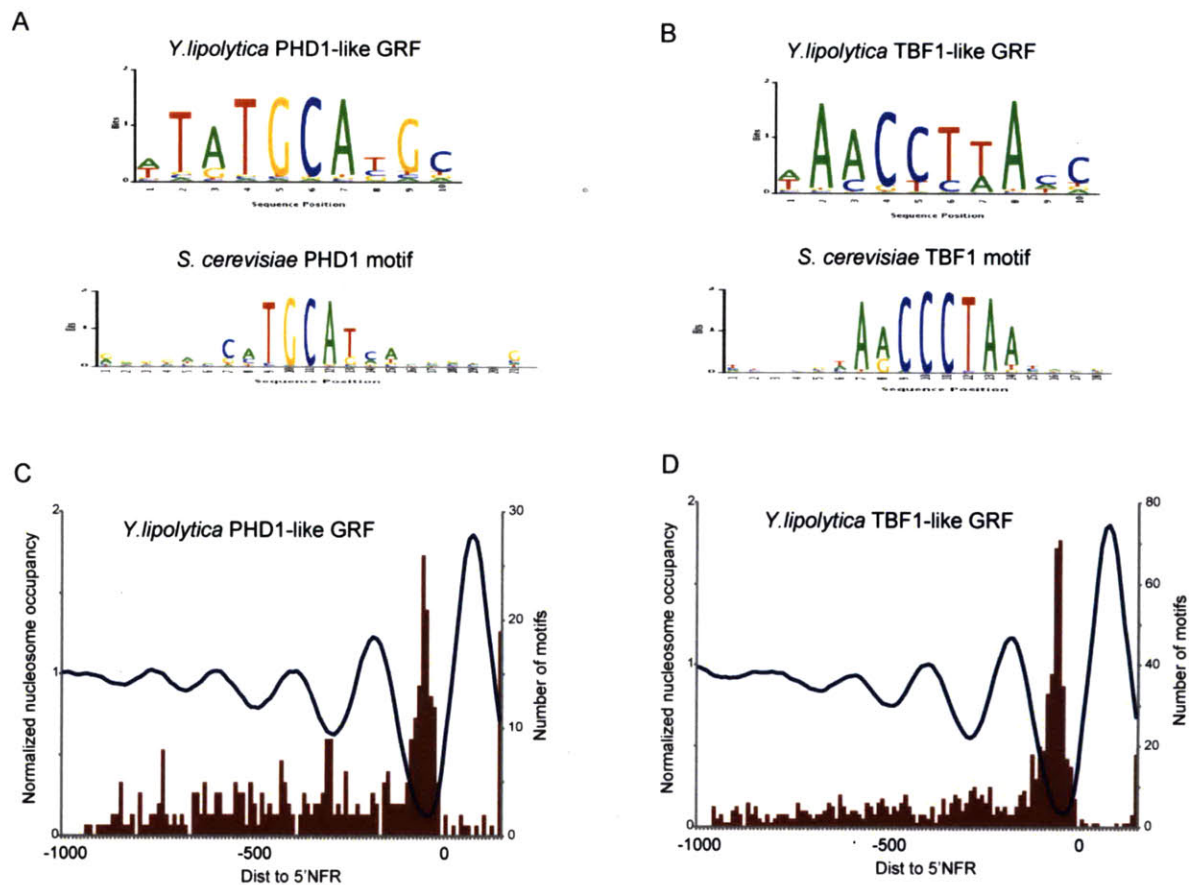


Figure 5-6: Two putative GRF motifs in *Y. lipolytica*. (A-B) The GRF motif finding algorithm predicts two motifs are similar to know *S. cerevisiae* motifs for transcription factors (A) PHD1 and (B) TBF1. (C-D) Identifying the location of the newly discovered motifs shows that they are positioned preferentially in NFRs. Red—abundance of GRF motifs relative to NFR/+1 nucleosome boundary (position 0 on the x-axis). Blue—average nucleosome occupancy data (aligned by NFRs) at promoters of all genes with relevant motif sites.

Most interestingly, we noted that the anti-nucleosomal sequences identified from *S. pombe* strongly resemble the motif for the essential factor Sap1, which is involved in mating type switching and chromosome stability. We also found that Sap1 binding sites are significantly enriched within NFRs (Figure 5-7A). Moreover, the Sap1 motif contains the 5-mer CGTTA, which was recently identified as the most discriminative feature in an N-score algorithm for predicting nucleosome occupancy in *S. pombe in vivo* [35]. Since the GRF Abf1 in *S. cerevisiae* is linked to mating type silencing and genomic replication, we

hypothesized that Sap1 plays an analogous role in nucleosome eviction in *S. pombe*.

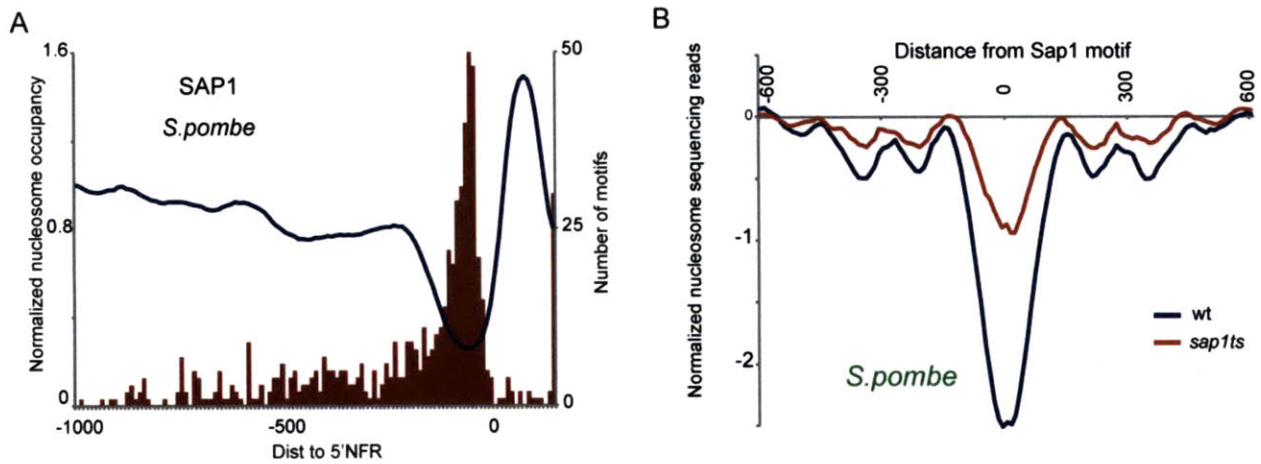


Figure 5-7: Sap1 acts as GRF in *S. pombe*. (A) Sap1 motif instances are located primarily in NFR of genes (see Figure 5-6C,D caption). (B) In *S. pombe*, average nucleosome data centered at all Sap1 motif instances (located at position 0 on the x-axis) is significantly more nucleosome occupied in Sap1ts mutant strain under restrictive temperatures (red) than in wildtype strain (blue).

To confirm Sap1's role as a GRF in *S. pombe*, temperature sensitive strains of Sap1 (Sap1ts) were created and shifted to the restrictive temperature. Genome-wide nucleosome mapping was performed in both WT and restrictive temperature conditions as previously described. Confirming our predictions, Sap1 binding sites were extensively nucleosome-depleted in wild-type *S. pombe*, but gained nucleosome occupancy in the absence of Sap1 function (Figure 5-7B). This was not an artifact of overall nuclease digestion, as promoters without Sap1 sites were unchanged. We thus conclude that Sap1 acts to evict or exclude nucleosomes, and is a GRF in *S. pombe*. This gives a mechanistic explanation for the species-specific nucleosome positioning sequence reported in *S. pombe* [35]. Moreover, the Sap1 and Cbf1 validation experiments confirm that our motif discovery algorithm can find novel, biologically meaningful GRF motifs.

5.3.3.3. Evolutionary Transition in Anti-nucleosomal Sequence Usage

Comparing the repertoires of anti-nucleosomal sequences across all species reveals several evolutionary insights. First, the divergence of anti-nucleosomal sequences generally increases with phylogenetic distance (Figure 5-1A). The extent of nucleosome depletion for all 7-mers is well conserved between closely related species, such as *S. cerevisiae* and *S. mikatae* (~2-5 Mya, Figure 5-8A). In contrast, a subset of *trans*-regulated sequences exhibited dramatically different nucleosome occupancy when comparing *S. cerevisiae* to the more distant *K. lactis* or *K. waltii* (Figure 5-8B and Figure 5-1A) – Rsc3/30-like motifs were much less depleted of nucleosomes in *K. lactis* and *K. waltii*, where the Rsc3/30 ortholog appears to be lost [74], whereas the Cbf1-like motif was dramatically nucleosome-depleted in these species but not *S. cerevisiae*.

Second, the Rsc3/30-like binding sites were highly variable across species, suggesting evolution of Rsc3/30 proteins and their binding site specificity. In most species, certain 7-mers (CGCGCGC, CGCGAAA) had strong nucleosome depletion scores (Figure 5-8C and Figure 5-1A). However, in *S. castellii* and the *Candida* clade, there was a large expansion of CGCG-containing 7-mers that were widely depleted (Figure 5-1A). The gradual changes in the specific Rsc3/30 CGCG-containing motifs suggest co-evolution of this GRF and its binding site, as previously observed for transcription factors [17, 21].

Third, we observe changes in the relative balance between nucleosome-depletion via GRFs and constitutively programmed depletion via Poly(dA:dT) sequences, suggesting a global mode of compensatory evolution. Most notably, A7/T7 is less nucleosome-depleted at *D. hansenii* promoters than at promoters of any other species, whereas Cbf1-like and Rsc3/30-like sites are strongly nucleosome-depleted in *D. hansenii* (Figure 5-8C and Figure 5-1B). As previously noted, the fewer, less depleted Poly(dA:dT) stretches in *D. hansenii*

(Figure 5-2) may be an adaptation to the high salt concentrations of this species' ecological niche. We hypothesize that the expansion in use of the Cbf1 and Rsc3/30 GRFs may have arisen through evolution to compensate for the lower abundance of PolyAs in this species' genome.

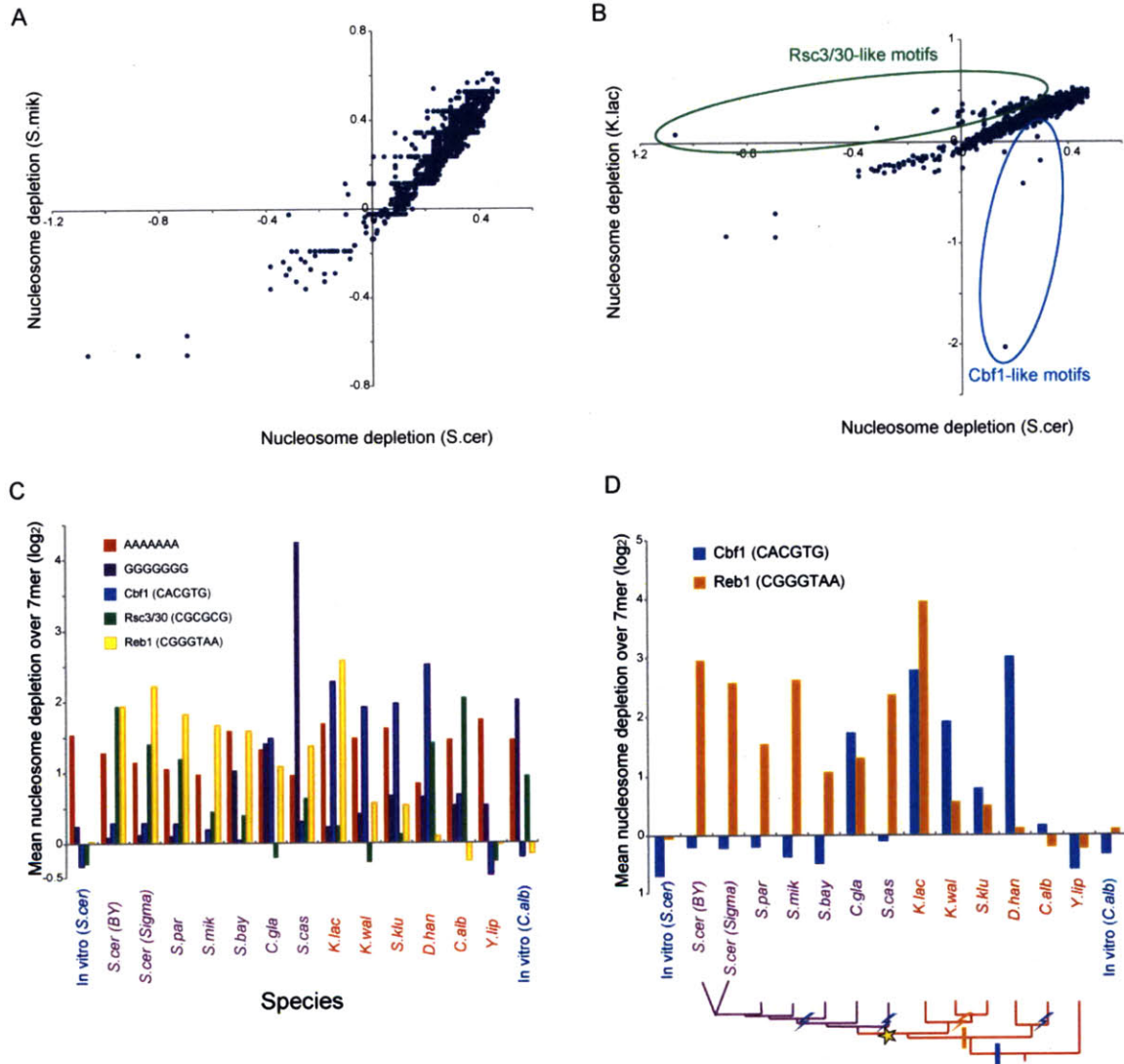


Figure 5-8: GRF usage has diverged. (A) *In vivo* nucleosome depletion of each 6-mer in *S. cerevisiae* is plotted against that in *S. mikatae*. Few differences are observed as points largely lie along the diagonal. (B) As in A, but for *S. cerevisiae* vs. *K. lactis*. CGCG-containing Rsc3/30-like motifs (green) are more nucleosome-depleted in *S. cerevisiae* than in *K. lactis*, whereas the Cbf1 motif CACGTG and related motifs (blue) are more nucleosome-depleted in *K. lactis*

than in *S. cerevisiae*. (C) Nucleosome depletion score for five major anti-nucleosomal 7mers across 13 *in vivo* datasets and 2 *in vitro* datasets [9, 34]. (D) Evolutionary transition from the GRF Cbf1 to the GRF Reb1 through a redundant intermediate. Shown are the nucleosome depletion scores for the Cbf1 (blue) and Reb1 (orange) sites for the *in vivo* data from the 12 species (purple species—pre-WGD, red species—post-WGD), and for two published *in vitro* reconstitution datasets (blue) in *S. cerevisiae* (left) [9] and *C. albicans* [34] (right). Bottom – phylogenetic tree marked with inferred events including the ancestral role of Cbf1 (blue bar), the gain of Reb1 (orange bar) and the loss of Cbf1’s and Reb1’s role as GRFs (lightning bolts).

Finally, the dominant use of different GRF sites often transitions gradually within the phylogeny. Most notably, we find that use of Reb1 and Cbf1 sequences is anti-correlated (Figure 5-8D and Figure 5-1C) across species: most post-WGD species are characterized by nucleosome depletion over Reb1 sites, whereas most pre-WGD species are characterized by nucleosome depletion over Cbf1 sites (Figure 5-8D and Figure 5-1C). This complementary phylogenetic pattern suggests an evolutionary scenario where Cbf1 was a major ancestral GRF, Reb1 and Abf1 emerged as a GRF before the WGD, and gradually ‘took over’ Cbf1’s global functionality. We observe some overlap in usage of Reb1 and Cbf1 as GRFs in *C. glabrata* and *K. lactis*, suggesting the presence of an ancestor around the WGD event that acted as a ‘redundant’ intermediate, where both GRF systems were functional. Similar evolutionary patterns were previously observed for transcription factors [17, 23, 73, 75], and this is the first demonstration of such a ‘mediated replacement’ for GRFs.

Together, our results show that the existence of essential transcription factors that play widespread roles in nucleosome eviction is conserved across 1 billion years of evolution, but that the identity of these general regulatory factors is highly plastic over evolution. These results help explain recent reports of apparent evolution of “sequence rules” for chromatin structure [35], as some of the most important sequence rules learned from *in vivo* data from *S. pombe* correspond to partial Sap1 binding sites, which we show here acts as a GRF. The

changes in GRF identity raise questions regarding the evolutionary pressures (or lack thereof) that affect GRF identity. Our results point towards extensive plasticity in chromatin regulation by sequence-specific factors, and should help guide future work on the interplay between genomic sequence and chromatin structure.

Chapter 6. Contributions of Main Determinants to Chromatin Organization

Although several established mechanisms affect chromatin organization at the promoter of a gene, the relative contribution of each is still unknown. Three main determinants have been implicated in establishing NFRs in *S. cerevisiae* [2]: (1) the expression level of the gene, as RNA polymerase recruitment affects NFR width; (2) the presence of intrinsic anti-nucleosomal sequences such as Poly(dA:dT) tracts in the gene's promoter; and (3) the binding of chromatin remodelers that actively evict or move nucleosomes.

In this chapter, we first develop a computational method for assessing the relative contribution of these three major determinants and then discuss the method's computational novelty (Section 6.1). We then apply the method to quantify the global effect of the three major determinants on nucleosome depletion at NFRs and to study how this has evolved across our phylogeny (Section 6.2). Finally, we study the preference for either intrinsic or *trans*-regulated nucleosome positioning signals at promoters of functionally related genes (Section 6.3), and find that these preferences are often functionally conserved, but can also gradually change through evolution.

6.1. Methodology

To quantify the global contribution of the three major determinants on NFR occupancy, we used robust Lowess smoothing, as described next in Section 6.1.2. We assess the contribution of transcriptional activity by absolute RNA expression (Section 2.3.2). We estimate the contribution of intrinsic anti-nucleosomal sequence by summing the strengths of all Poly(dA:dT) elements in NFRs (Section 5.2.1), since it explains the vast majority of the intrinsic sequence information and generalizes to all species in an unbiased manner. Other models of intrinsic sequence contribution [9, 61] yielded very similar results (data not shown). We quantify the contribution of chromatin modifiers based on the Abf1 and Reb1 motif affinity scores in NFRs. This is a conservative estimate, since we only considered the two most established GRFs. In the next section (Section 6.1.1), we introduce motif affinity scoring in NFRs.

6.1.1. Motif Affinity Scores in NFRs

We represent each motif of length L by a position specific scoring matrix (PSSM) P , or the probability distribution $P(S_1, \dots, S_L)$ of that motif occurring over any sequence $S_1 \dots S_L$. This is a standard approximation to a factors binding energy for sequence $S_1 \dots S_L$. We also learned the 0th-order Markov background probability distribution $B(S_1, \dots, S_L)$ for each sequence $S_1 \dots S_L$, set to the frequency of the four nucleotides in the promoter regions of a given species. We calculate $A(P, S)$, a motif's affinity score for an NFR sequence S , by summing the contributions of $P(S_1, \dots, S_L)/B(S_1, \dots, S_L)$ over all allowable positions k in S as follows:

$$A(P,S) = \sum_k \frac{P(S_k, \dots, S_{k+L-1})}{B(S_k, \dots, S_{k+L-1})} = \sum_k \prod_{j=1}^L \frac{p(S_{k+j-1}, j)}{b(S_{k+j-1})}. \quad (6.1)$$

Here, $b(S_{k+j-1})$ is the background probability of the nucleotide S_{k+j-1} of sequence S , and $p(S_{k+j-1}, j)$ is the probability for nucleotide S_{k+j-1} in position j of the motif's PSSM. For the results in this study, we combined the contributions of both forward and reverse strands of each NFR. Also, normalizing the affinity by the length of each NFR sequence did not affect our results significantly.

6.1.2. Robust Lowess Smoothing

To quantify the global contribution of the three determinants to NFR occupancy, we use robust Lowess smoothing. We smoothed the scatter data of the strength of each determinant versus NFR occupancy at all promoters using a Lowess linear fit and a smoothing window set to 10% of the span of expression level values (Figure 6-1A-D). We assigned zero weight to outliers, defined as data more than six standard deviations from the mean.

To compute the percent of variance explained by the robust Lowess fit, the nucleosome occupancy of each NFR was assigned a “fitted” value F_i from the robust Lowess fitting line based on each of the 3 determinants. Then the variance of the residuals, $\sigma_R^2 = \text{Var}(F_i - Z_i)$, is compared to the variance of the original data, $\sigma_D^2 = \text{Var}(Z_i)$. The percent of variance explained is defined as:

$$100 \left(1 - \frac{\sigma_R^2}{\sigma_D^2} \right). \quad (6.2)$$

To find the percent variance explained by all determinants we first fit NFR occupancy versus one determinant, then iteratively take the residual, and fit it against the next determinant. In Figure 6-1E, we first fit expression, then fit the successive residual versus Poly(dA:dT) tracts, and then fit the residual versus

Abf1 and Reb1 motif affinity scores. Changing the order of the successive fits did not significantly reduce the total percent variance explained. We also used robust Lowess smoothing to subtract the effect of expression on observed chromatin features. K-S functional enrichments for the Lowess subtracted chromatin features were calculated as described in Section 4.1.

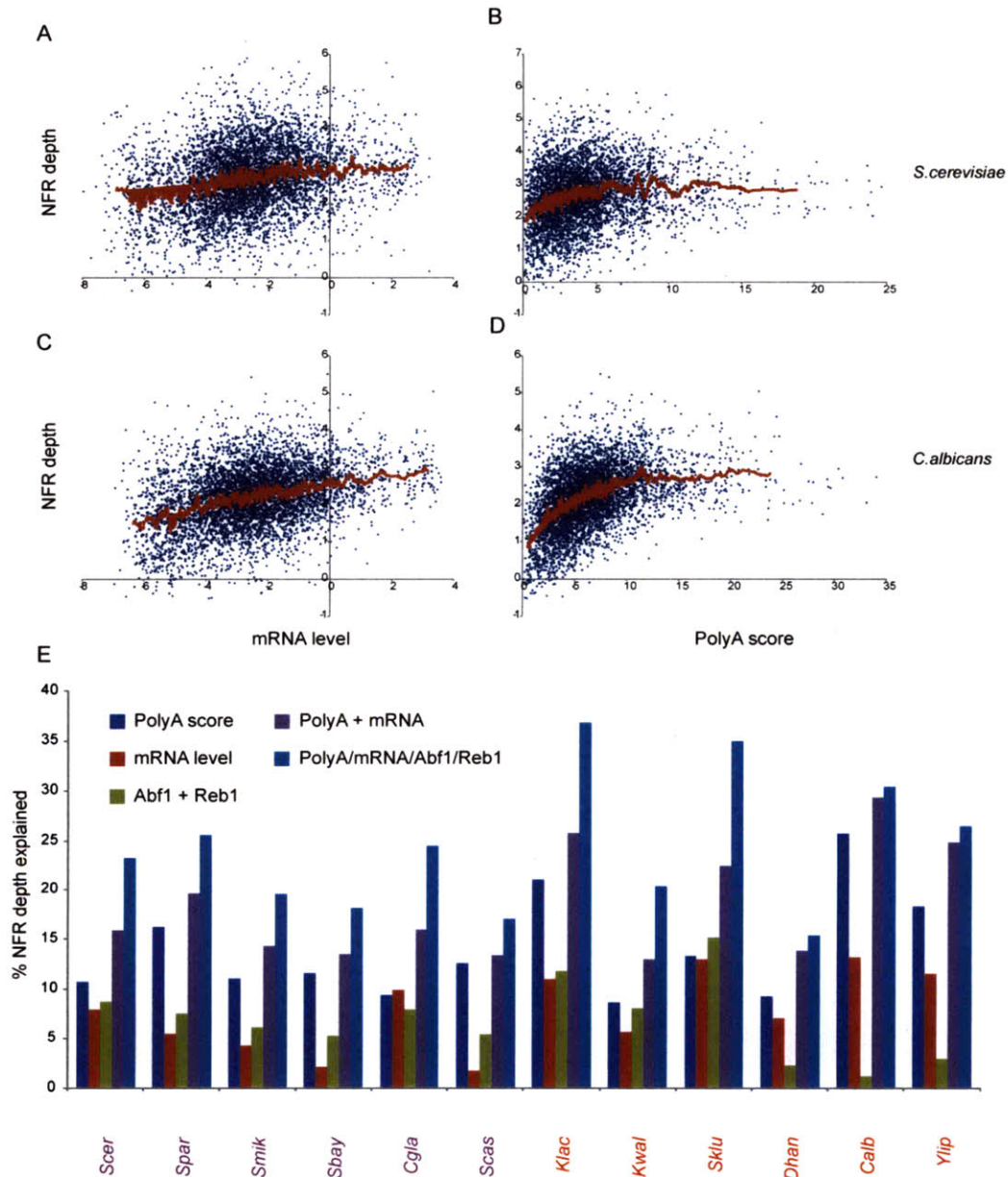


Figure 6-1: Global contributions of 3 determinants to NFR depth. (A-D) Gene-by-gene comparisons of NFR depth to mRNA levels or Poly(dA:dT) signal.

Shown are plots of NFR depth (Y axis) vs mRNA level (A,C) or Poly(dA:dT) score at the NFR (B,D) for each gene (blue dot) in the *S. cerevisiae* (A,B) or *C. albicans* (C,D) genome. Also shown is a 50-gene running window average for each panel (red). (E) Variation in NFR depth explained by each determinant and their combination. Shown are the % variation in NFR depth (bars, y axis) explained in each species by each determinant alone (dark blue – polyA, red – mRNA expression; green – binding sites for Abf1 and Reb1 in the NFR) and two combinations (purple – polyA and mRNA expression; light blue – polyA, mRNA, and the GRF sites).

6.1.3. Computational Contribution

The relative contribution of these 3 determinants on nucleosome organization is a subject of debate. Some studies argue that intrinsic sequences play a dominant role in positioning nucleosomes ('nucleosome code'), showing that sequence predictions of nucleosome occupancy correlate with *in vivo* measurements at $R=0.75$ [9]. Other works argue against a nucleosome code by pointing out that the *in vivo* pattern of statistical positioning (the well positioned +1 nucleosome and downstream nucleosome phasing) is not observed in *in vitro* nucleosome reconstitutions on genomic DNA [12]. They also show that the *in vivo* pattern is linked to transcriptional initiation. Our approach was to focus on NFRs, which act as nucleosome-excluding barriers and lead to statistical positioning of nucleosomes on both sides. By focusing on nucleosome depletion at NFR barriers, this is the first analysis that has quantified the relative contribution of all three major proposed determinants. Moreover, it allows us to observe this relationship in 12 other yeasts. The use of robust Lowess fitting was appropriate due to the nonlinear relationships between these 3 determinants and NFR occupancy, and allows for measuring the percent variance explained individually and successively.

6.2. Contribution of each Determinant to NFR Occupancy

We applied our methodology to study the evolution of chromatin organization due to each of the three determinants. We first study the contribution of each determinant to global NFR occupancy and then explore the functional role of each determinant through evolution and its effect on species divergence.

6.2.1. Gene Expression Level

Globally, expression level alone explains between 1.7% and 13.1% of the variation in NFR occupancy in each of the 12 species (Figure 6-1A,C,E). In some cases, variation in chromatin organization in a gene set, both within and between species, correlates with gene expression level. Within each species, many highly expressed ‘growth’ genes (*e.g.*, RP genes) are packaged with wide and deep NFRs, while many poorly-expressed stress genes have shorter, occupied NFRs (Figure 4-2A,B, Figure 4-3). Between species, evolutionary shifts from high to low expression levels were sometimes accompanied by corresponding changes in chromatin organization (*e.g.* mitochondrial RP and splicing genes, Figure 4-2G,H).

Transcription levels alone, however, are insufficient to solely explain the NFR occupancy measured across the 12 species. When we use Lowess subtraction to correct for the relationship between mRNA level and each chromatin feature, the enrichments of most gene sets for high or low values of chromatin features were maintained (Figure 6-2). Within species, the discrepancy is prominent in some of the gene sets, (*e.g.* glycolysis, gluconeogenesis) that are highly expressed in all species but do not exhibit the expected deep NFRs (Figure 4-2D). Between species, cytoskeleton and nuclease-related gene sets have shifted

from shallow to deep NFRs at the WGD, often without a concomitant change in expression levels (Figure 4-2G). The failure of transcript levels to fully explain NFR width and depth is consistent with recent experimental results in *S. cerevisiae*, where the distinctive chromatin organization of growth and stress genes was largely maintained even after genetically-inactivating RNA Pol II [7].

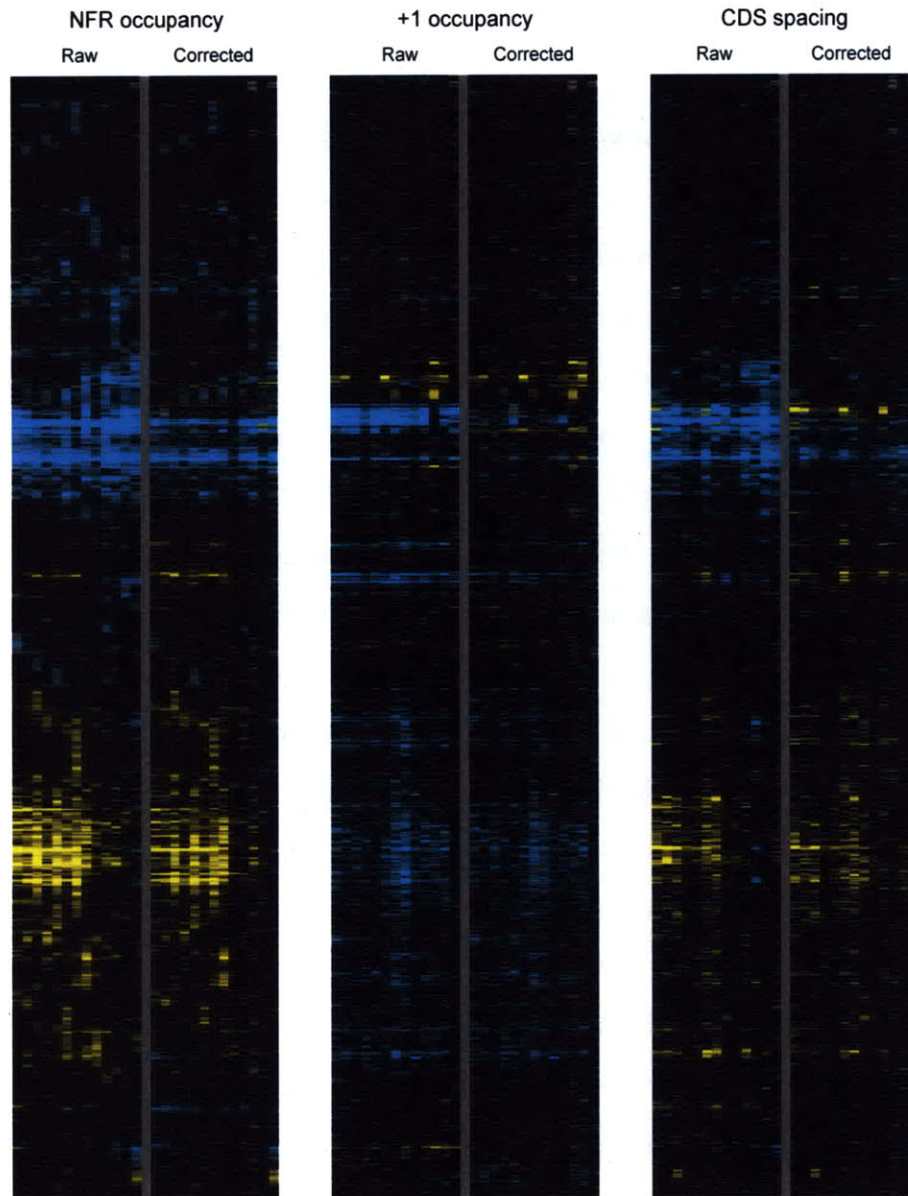


Figure 6-2: Relationship between RNA level and chromatin structure. For all projected gene sets (rows, y-axis) in all species (columns, x-axis), the extent of variation in a given chromatin parameter which is explained by RNA abundance

was calculated. The fitted LOWESS curve was then used to correct for the effect of transcription on chromatin packaging, and KS enrichments were recalculated as before. Shown are KS enrichments, as in Figure 4-3, for gene sets calculated before ('Raw') and after ('Corrected') LOWESS-correction. NFR occupancy enrichments are not strongly influenced by RNA levels, whereas the +1 nucleosome occupancy and CDS nucleosome spacing enrichments were more substantially explained by RNA abundance measures.

6.2.2. Intrinsic Anti-nucleosomal Sequences

We next tested an alternative hypothesis that chromatin organization at the NFR is determined by intrinsic anti-nucleosomal sequences with low affinity for the histone octamer, such as Poly(dA:dT) tracts [8-10, 12, 66, 76]. We estimated the average extent of nucleosome depletion over a variety of Poly(dA:dT) elements for each species (Figure 5-2). We then tested if functional gene sets in each species were enriched or depleted for strongly anti-nucleosomal sequences in their NFRs. Finally, we compared this pattern to their chromatin organization (Figure 4-2, right vs. middle panels).

Globally, intrinsic anti-nucleosomal sequences explain 8.6-25.7% of the variation in NFR occupancy within a given species (Figure 6-1). When combining expression levels and sequence information together, these can explain 13-29% of the global variation in nucleosome organization in the 12 species (Figure 6-1E). Similar results are obtained when considering other measures of intrinsic anti-nucleosomal sequences, such as those based on computational models [9, 61] derived from *in vitro* data (data not shown).

In some cases, the variation in chromatin organization within and between species is associated with variation in intrinsic 'anti-nucleosomal' Poly(dA:dT) tracts. Within each species, Poly(dA:dT) sequences are enriched upstream of many highly-expressed, nucleosome-depleted, 'growth' gene sets, consistent with previous observations in *S. cerevisiae* [61, 62]. Between species, we found that gain and loss of polyA sequences is associated with changes in chromatin

organization at several gene sets and phylogenetic points, suggesting that this is a common evolutionary mechanism used more than once in this phylogeny. We confirmed a prior observation [34] that the change in chromatin organization at mitochondrial ribosomal protein (mRP) genes in post-WGD respiro-fermentative species is accompanied by the loss of PolyA-like sequences from these promoters (Figure 4-2F). In addition, we found that the deeper and wider NFRs at splicing genes in *Y. lipolytica* are associated with greater length and number of PolyA sequences at these genes (Figure 4-2H). Conversely, the relatively shallow NFRs of gluconeogenesis genes observed in *S. castellii* are associated with concomitant depletion of polyA sequences in this species (Figure 4-2D).

Anti-nucleosomal sequences and expression patterns, however, are insufficient to fully explain either conservation or divergence in chromatin organization across species. This is the case globally, as previously stated, and also within functional groups of genes. For example, proteasomal genes are highly expressed and have deep NFRs conserved in all species, but are not associated with intrinsic anti-nucleosomal sequences (Figure 4-2C). Furthermore, RNA Polymerase II subunits, RNA export, and nuclear pore genes are highly expressed with deep NFRs conserved in most species, but are only enriched for intrinsically anti-nucleosomal sequences in a subset of species (Figure 4-2E). Conversely, peroxisome genes are highly-expressed in *D. hansenii*, *C. albicans*, and *Y. lipolytica*, where they are packaged with long (but not deep) NFRs, despite no enrichment for Poly(dA:dT) tracts (Section 6.3.3). In these and other cases, even when we consider expression levels, much of the depletion in NFRs remained unexplained (Figure 6-1, Figure 6-2).

6.2.3. *Trans*-acting Chromatin Regulators

We therefore wished to explore the role that the third mechanism – nucleosome eviction by chromatin remodelers – plays across the 12 species. We first assessed the potential contribution of chromatin remodelers to chromatin organization based on the presence in NFRs of the known binding sites for the two best-studied *S. cerevisiae* GRFs: Abf1 and Reb1 (Figure 6-1E). Together, the two motifs explain 1.2-15.1% of the observed variation in nucleosome organization in the 12 species. Furthermore, Abf1 and Reb1 can explain up to 12.6% of the residual variation after accounting for the contribution of expression levels and intrinsic sequences (Successive Lowess, Figure 6-1E, difference between last 2 bars). Thus, GRFs can play an important role in explaining global chromatin organization.

Notably, the Abf1 and Reb1 sites explain little of the variation in *D. hansenii*, *C. albicans*, and *Y. lipolytica* – the species from the two clades most distant from *S. cerevisiae*. In particular, the Abf1 binding site explains less than 1% of the variation in each of these species, consistent with the absence of the Abf1 ortholog from their genome, and validating the specificity of our approach. Furthermore, although the Reb1 ortholog is present in each of these species, its contribution is substantially reduced (compared to *e.g.* *S. kluyveri*). In species *D. hansenii*, *C. albicans*, and *Y. lipolytica*, we found a number of putative binding sites for GRFs (Section 5.3.3.2). These factors likely have replaced the role of Reb1 and Abf1 and can better explain the contribution of *trans*-acting chromatin regulators on NFR occupancy in these species.

6.3. Functional Preference for Different Determinants

We next explored if intrinsic or *trans*-regulated nucleosome positioning sequences are important for the observed chromatin organization in functional gene sets across species. To test this hypothesis, we assessed the enrichments of intrinsic sequences and GRF motifs in the NFRs of each gene set across the 13 species. We find that functional groups of genes often have a preference for either intrinsic or *trans*-regulated nucleosome positioning sequences at promoters. This preference is conserved in proteasome genes and other functional groups, but can also gradually shift from one mode to another, as with RNA polymerase genes.

6.3.1. Divergent GRFs Maintain Conserved Chromatin Organization

In some cases, GRF motifs (but not Poly(dA:dT) tracts) were enriched in a gene set across multiple species, strongly indicating a conserved mechanism. For example, the Abf1 site is enriched in RNA polymerase genes across the clade spanning *S. cerevisiae* and *S. kluyverii* (Figure 6-3D). However, since the spectrum of GRFs is species-specific (Figure 5-8), we found no gene set associated with the same GRF site across the entire phylogeny.

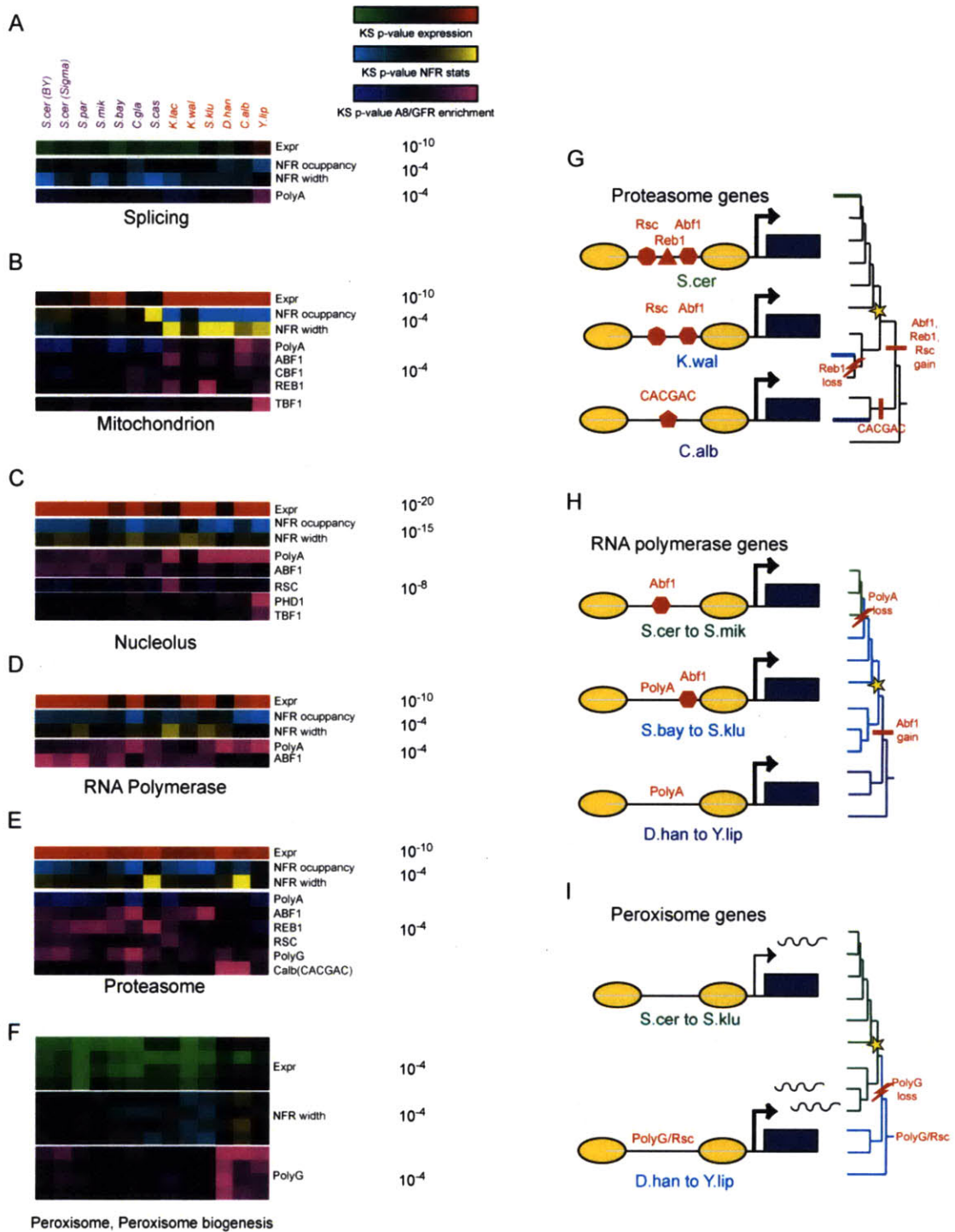


Figure 6-3: Evolution of anti-nucleosomal programming at gene sets. (A-F) Enrichment of Poly(dA:dT) tracts (A8) or motifs for various GRFs was calculated for the indicated gene sets. Enrichments are shown for high (red) or low (green) expression levels, high (yellow) or low (blue) 5'NFR occupancy or length, and enrichment (pink) or depletion (blue) of PolyA or GRF motifs for

each gene set. KS P value saturation levels are indicated to the right of each panel. (G-I) Schematics of the evolution of usage of GRF and intrinsic anti-nucleosomal sites in proteasome genes (G), RNA polymerase genes (H), and peroxisome genes (I). Yellow ovals – nucleosomes, blue box – coding sequence; arrow – promoter, polyA – intrinsic anti-nucleosomal sequences; Abf1, Rsc, Reb1, CACGAC (*C.albicans*-specific GRF site) – enriched GRF motifs. The phylogenetic tree is shown on the right, with the relevant clades in colors matching to the highlighted species. Bar – gain of functional site; lightning bolt – loss of functional site.

Instead, we found a number of cases where gene sets have conserved chromatin architectures, but are associated with distinct GRF sites in different species, consistent with changes in the global GRF repertoire. This is most notable in proteasome genes, which are uniformly associated with wide/deep NFRs but are depleted of Poly(dA:dT) tracts (Figure 4-2C). The establishment of NFRs in these genes has likely transitioned from a mechanism dependent on the CACGAC sequence in the *Candida* clade to an Abf1-dependent mechanism in later lineages, with additional contribution from Reb1, Rsc3/30, and PolyG sites, as these GRFs gained dominance in specific species and clades (Figure 6-3D,G). Although the specific GRF mechanism underlying NFRs in proteasome genes has diverged, the establishment of NFRs by a GRF-regulated (rather than polyA/constitutive) mechanism is conserved in all species. The utility of regulated NFRs at proteasome genes may be related to their unusual transcriptional regulation: these are among the few highly expressed “growth” genes that are also upregulated (rather than down regulated) during stress responses [77].

6.3.2. Shift from Programmed to *Trans*-regulated NFRs

Could promoters evolve from having constitutively programmed NFRs to regulated ones? To test this, we searched for gene sets where chromatin organization is conserved, while the underlying anti-nucleosomal sequences have diverged in a phylogenetically coherent pattern. We found that genes encoding

RNA polymerase subunits exhibit deep NFRs across most of the phylogeny (Figure 6-3D). These genes' promoters are associated with Poly(dA:dT) tracts in *Y. lipolytica* and the species of the *Candida* clade, with both Poly(dA:dT) and the site for the Abf1 GRF in species from *S. kluyveri* to *S. bayanus*, and only with Abf1 in the clade spanning *S. mikatae*, *S. paradoxus* and *S. cerevisiae* (Figure 6-3D,H). Similar behavior is seen at a number of other genesets, such as those encoding nuclear pore components (data not shown). This profile suggests an evolutionary scenario where the ancestral mechanism relied on Poly(dA:dT). With the emergence of Abf1 in the last common ancestor of the pre- and post-WGD species [36], it gained additional control of the NFRs in this gene set, alongside Poly(dA:dT) tracts. Then, after the divergence of *S. bayanus*, Poly(dA:dT) tracts were lost from the genes' promoters, leading to a complete switch from a constitutively programmed to a regulated NFRs. This compensatory evolution is consistent with patterns observed for TF binding sites in functional regulons [17, 75] and with the global transitions in GRFs and polyAs as described above.

6.3.3. Changes in GRFs Contribute to Divergence in Chromatin Organization

In some cases, the gain or loss of binding sites for GRFs can contribute to divergence in chromatin organization, coupled to phenotypic changes. Most notably, peroxisomal genes are associated with wider NFRs in *Y. lipolytica*, *C. albicans*, and *D. hansenii*, and shorter NFRs in subsequently divergent species (Figure 6-3F,I), but are not associated with intrinsic anti-nucleosomal Poly(dA:dT) tracts in any of the species. Instead, we find that these genes' promoters are enriched for Poly(dC:dG) elements and Rsc3/30-like sites in *Y. lipolytica*, *C. albicans*, and *D. hansenii*, but not in other species. This suggests

an evolutionary scenario where either a Rsc-like motif or PolyG-based nucleosome depletion was the ancestral mechanism controlling peroxisomal genes, and was subsequently lost in the last common ancestor of the clade spanning *S. kluyverii* and *S. cerevisiae*. This scenario is consistent with the higher expression of peroxisomal genes in *Y. lipolytica* (where peroxisomes are particularly central for carbon metabolism) and *C. albicans* (where peroxisomes play a key role in virulence).

Chapter 7. TF Binding Sites, NFRs, and Gene Expression

In this Chapter, we study the interplay between transcription factor (TF) binding sites, nucleosome free regions (NFRs), and gene expression. For all 13 species, we developed a computational method for identifying the genomic locations of TF sites (Section 7.1.1), testing their functional enrichment in promoters of related genes (Section 7.1.2), their position relative to NFRs (Section 7.1.3), and their role as activators or repressors (Section 7.1.3). Using our approach, we find that repositioning of TF binding sites relative to chromatin can accompany phenotypic changes, for example at mating genes in *C. glabrata* (Section 7.2). We also found that a number of motifs that act as activators in pre-WGD species have evolved to have a dual activator and repressor role in post-WGD species (Section 7.3) through gene duplication and divergence of paralogs.

7.1. Methodology

7.1.1. Promoter TF Motif Scanning

Promoter sequences for each gene were defined as 1000 bases upstream, truncated when neighboring ORFs overlapped with this region. We collected a library of Position Weight Matrices (PWMs) for several hundred *S. cerevisiae* DNA-binding proteins as previously defined [69, 71, 72, 78]. Motif targets were identified via

the TestMOTIF software program [79] using a 3rd-order Markov background model estimated from the entire set of promoters per genome.

We considered all motif instances with P value < 0.05 as significant. Since a few motifs had thousands of instances for this cutoff, we also limited the number of promoters with significant sites to the top 1000. The upper bound was chosen to exceed the maximal number of promoters bound (866, P value < 0.05) by any transcription factor in *S. cerevisiae*, as measured by ChIP-chip [69]. For all subsequent motif analysis, we used the above criterion to define two sets of sites: (1) all significant sites within allowed promoters; and (2) the best sites per allowed promoters.

7.1.2. Motif GO Enrichments

To estimate the probability that k or more elements intersect subsets of n and m members at random in a superset of size N (or the P value for overlap of k , P_{HG}) we summed over the right tail of a hypergeometric distribution:

$$P_{HG} = \sum_{l=k}^{\min(n,m)} \frac{\binom{N-m}{n-l} \binom{m}{l}}{\binom{N}{n}}. \quad (7.1)$$

Using the hypergeometric P values, we estimated the significance of k overlaps between n genes with sites in their upstream promoter and m genes within a GO category, for a species with N genes.

7.1.3. Global Motif Analysis

All motif instances were binned into five regions (+1 nucleosome, 5'NFR, -1 nucleosome, -2 nucleosome, and NFR2 (the linker between -1 and -2 nucleosomes) if their centers overlapped with the defined regions. In addition,

sites were also split into two categories: *Linkers* (5'NFR and NFR2) and *Nucs* (+1, -1, and -2 nucleosomes). We assigned the expression level of each gene to each site in the upstream promoter of that gene. We used a two-sample K-S test (as described in Section 4.1) to quantify the difference in expression levels between sites in *Linkers* versus *Nucs* bins.

To quantify the preference of a motif's binding sites for NFRs, we compared the mean log₂ normalized nucleosome occupancy at all sites (\mathbf{x}) against the mean log₂ normalized nucleosome occupancy over the corresponding promoters (\mathbf{y}). To estimate the significance of the difference of the two vectors ($\mathbf{x}-\mathbf{y}$), we used the paired Wilcoxon signed rank test that assigns a P value for rejecting the null hypothesis that $\mathbf{x}-\mathbf{y}$ comes from a continuous, symmetric distribution with a zero median.

7.2. Repositioning of TF Sites Relative to NFRs Links to Phenotypic Change

The interplay between chromatin organization and TF binding sites can play an important role in regulatory divergence. Nucleosomes are generally inhibitory to transcription factor (TF) binding [1], and in *S. cerevisiae* most functional TF binding motifs are found in NFRs [11]. Precise positioning of TF binding sites relative to nucleosomes has regulatory consequences such as changing signaling thresholds [80] or logic gating [81]. We therefore hypothesized that an evolutionary change in the location of TF-binding motifs relative to the nucleosomes in a gene's promoter can lead to regulatory divergence between species.

To test this hypothesis, we examined the location of known TF binding motifs (from *S. cerevisiae* – [69, 71, 72, 78]) relative to nucleosome positions in all

species (Section 7.1.3). As expected in *S. cerevisiae* (Figure 7-1A,B), up to 90% of the binding sites for growth-related TFs are localized to NFRs (*e.g.* REB1, ABF1, RAP1, and FHL1), whereas as few as 25% of sites for stress-related TFs are at NFRs (*e.g.*, HSF1, YAP6, HAP2/3/5, GZF3, and CRZ1). Thus, sequences that are mostly occluded by nucleosomes tend to be the binding sites for inactive TFs, and we can use chromatin information to infer TF activity under our growth conditions in each species. We therefore calculated for each motif the fraction of its instances located in NFRs in all species (Figure 7-1C).

The NFR positioning of many key motifs is strongly conserved. For example, sites for growth-related factors such as SWI4/6 and GCN4 were similarly NFR-exposed in all species in this phylogeny. Notably, this conservation is observed despite the fact that many motifs, which were experimentally defined for *S. cerevisiae* proteins, were globally less NFR-localized in distantly related species (Figure 7-1C). This can be attributed in some cases to divergence of binding site preferences of the cognate TFs, and in other cases to the absence of the TF's ortholog from the genome (Figure 7-1C, white). Nevertheless, many motifs showed robust positioning in NFRs.

Conversely, the motifs for key TFs associated with regulation of respiration and carbohydrate metabolism have repositioned relative to NFRs at the WGD, consistent with regulatory divergence in these functions (Figure 7-1D). For example, the sites for the HAP2/3/4/5 complex (a regulator of respiration genes) and for YAP6 (a regulator of oxidative functions) have re-positioned from NFRs to nucleosome-occluded positions post-WGD, consistent with the reduction in expression of respirative genes. In contrast, the sites for the carbon catabolite repressor MIG2 and for the glucose-responsive transcription factor RGT1 have repositioned from nucleosomes into NFRs in post-WGD species, consistent with these factors' role in establishing a fermentative strategy through gene repression.

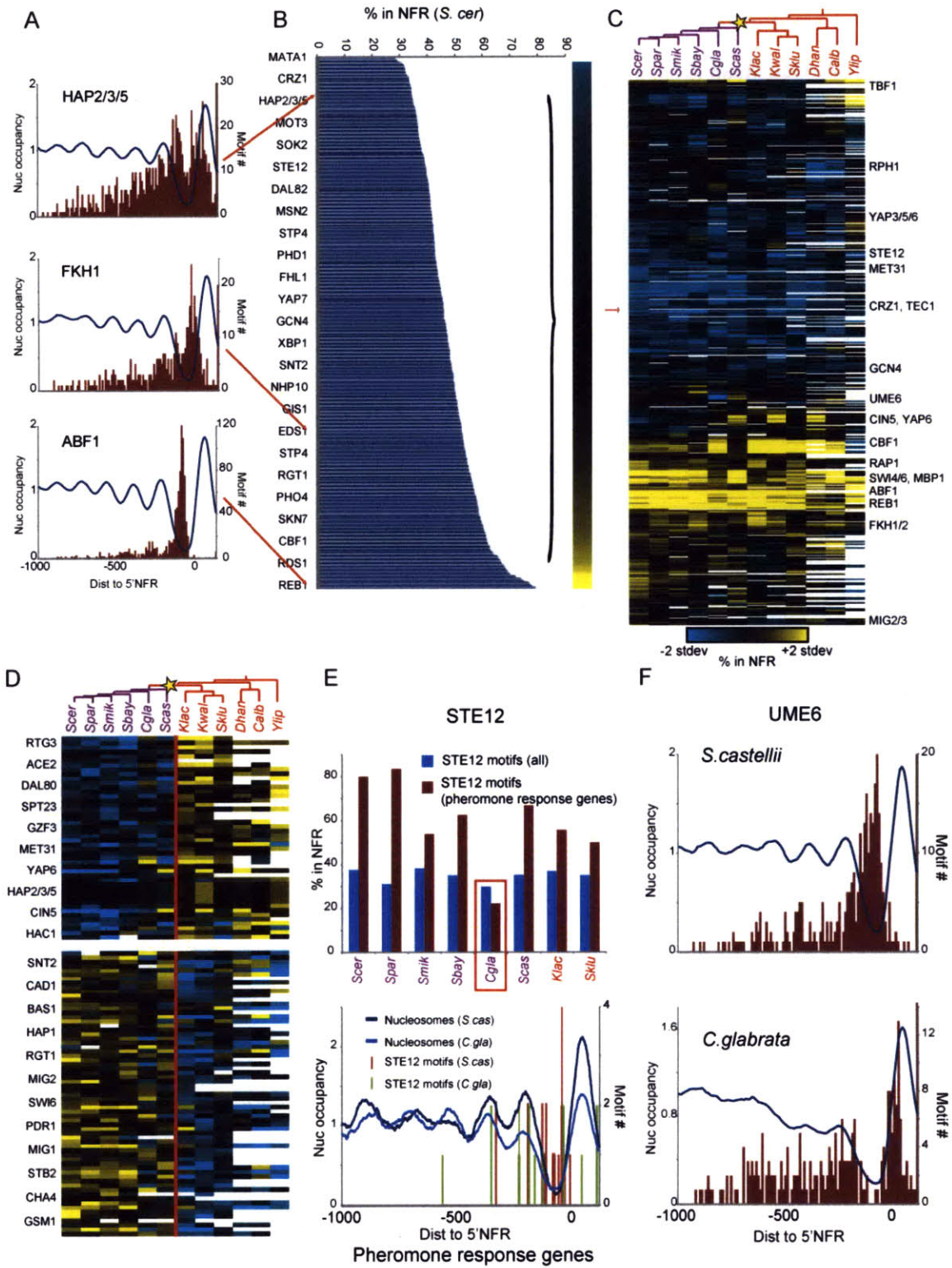


Figure 7-1: Evolutionary re-positioning of TF motif sites relative to NFRs. (A) Motif site location relative to chromatin features in *S. cerevisiae*. Shown are

distributions of locations of the indicated TF binding sites (red), relative to the averaged chromatin profile for genes bearing instances of these sites (blue) in *S. cerevisiae*. (B) Fraction of TF binding sites located in the NFR in *S. cerevisiae* was calculated for 435 motifs, and TFs are arranged from NFR-depleted (top) to NFR-enriched (bottom). Red arrows point to TFs displayed in (A). (C) Location of TF binding sites relative to NFRs in all 12 species. Blue, NFR depleted; yellow, NFR enriched. Since the fraction of sites in NFRs varies with average NFR width and phylogenetic distance from *S. cerevisiae*, the fraction of motif instances located in NFR for each species was normalized by each species' mean and standard deviation. White is used for *S. cerevisiae* motifs for TFs whose orthologs are absent from a given species. (D) Motif repositioning at the WGD. Shown are the most significantly repositioned motifs between pre- and post-WGD species (*t*-test) from NFRs to nucleosomes (top) and vice versa (bottom). Star-WGD. Blue, NFR depleted; yellow, NFR enriched; values were first normalized as in panel A, and then each row was mean-normalized for visual emphasis. (E,F) Repositioning of TF binding sites relative to NFRs in *C. glabrata* meiosis and mating genes. (E) Top panel: Fraction of STE12 sites in NFRs genome-wide (blue) or at pheromone-response genes (red) for species where STE12 motif instances are enriched upstream of this gene set ($P < 10^{-3}$, Hypergeometric test). Bottom panel: Nucleosome data and STE12 sites location shown as in (A) for pheromone response genes in *S. castellii* and *C. glabrata*. (F) Distributions of locations of the UME6 binding site (red), relative to the averaged chromatin profile for genes bearing instances of these sites (blue) in *S. castellii* and *C. glabrata*.

Motif re-positioning has also occurred at other phylogenetic points and gene sets, suggesting that this is a general regulatory and evolutionary mechanism (Figure 7-1E,F). For example, the mating-related STE12 motif is significantly enriched upstream of reproduction and mating-related genes in species from *S. cerevisiae* to *S. kluyverii*, including *C. glabrata*. Although STE12 sites are found in NFRs at mating genes for most of these species, they are largely nucleosome-occluded in *C. glabrata* (Figure 7-1E), an organism which has never been observed to mate [82]. We speculate that occlusion of STE12 sites under nucleosomes may contribute to this species' reluctance to mate, but the continued enrichment of STE12 upstream of mating genes and the retention of many meiosis-related genes [36] in *C. glabrata* suggests that it may still be capable of mating under special conditions. We therefore predict that conditions (environmental or perhaps genetic) that either mobilize or destabilize the nucleosomes covering STE12 sites at pheromone-response genes might enable

mating in this species. Similarly, motifs for UME6, a major regulator of meiosis genes in *S. cerevisiae* [83] are globally NFR-positioned in all species except *C. glabrata* (Figure 7-1F), despite the fact that UME6 sites are enriched upstream of orthologs of meiosis-related genes in *C. glabrata*. Thus, the relative repositioning of NFRs and TF binding sites may help explain the molecular underpinnings of dramatic changes in regulatory and phenotypic evolution.

7.3. Duplication of TF Genes Increases Regulatory Capacity of Sites in NFRs

We next asked whether chromatin information could be used to infer the regulatory effect of exposed transcription factor binding sites from the expression level of their target genes. Exposed TF binding sites are expected to have very different regulatory consequences depending on whether or not the TF is active, and whether it acts as an activator or a repressor. To this end, we calculated the expression level of all downstream genes where a given TF motif was located within nucleosomes vs. those in which the motif was located within promoter linkers (largely the NFR, Figure 7-2A). We reasoned that an NFR-positioned site for an active positive regulator would be associated with a higher expression of the target genes. Conversely, an NFR-positioned site for an active negative regulator will be associated with a lower expression of the target genes. Consistent with our expectation, in *S. cerevisiae*, transcriptional activators known to be active in mid-log phase, such as RPN4 or PBF1, were associated with higher expression levels at genes carrying an accessible, linker-positioned motif. In contrast, NFR-positioned motifs for transcriptional repressors known to be active in mid-log (*e.g.*, MIG1, SUM1, NRG1, DIG1, STB1/2, or RIM101, Figure 7-2A) were associated with lower downstream gene expression. Thus, we devised

a novel approach to predict whether a given motif is associated with an activator or repressor *in vivo* in the growth condition tested.

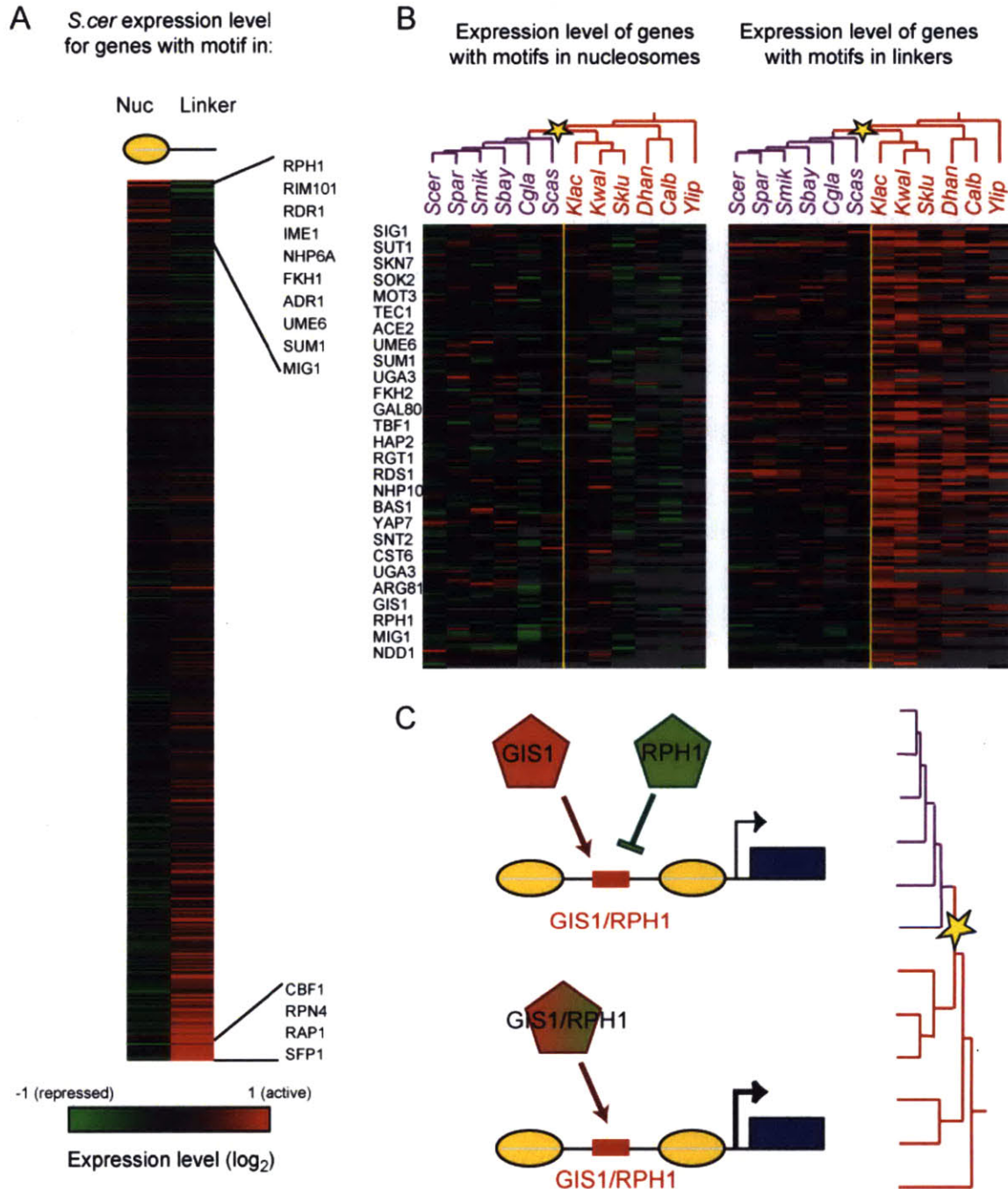


Figure 7-2: Evolution of TF activity at NFR-localized binding sites. (A) Nucleosome positions can be used to infer the positive or negative role of TFs in transcriptional control in *S. cerevisiae*. Average expression (mRNA abundance) of

all genes with a given motif instance located in promoter nucleosomes (left) or NFRs (right). TFs are ordered by expression difference between NFR and nucleosomal binding sites, revealing transcriptional activators (bottom) and repressors (top) known to be active in these growth conditions. (B) Chromatin information reveals repressors associated with post-WGD nutrient control. For each species (columns) and each motif (rows), shown are mean expression levels of genes with the motif in nucleosomes (left matrix) or in linkers (right matrix). Shown are only the 138 motifs with increased activity in pre-WGD species [a correlation of over 0.5 to the vector (0,0,0,0,0,0,1,1,1,1,1,1)]. A small number of motifs were associated with higher activity in post-WGD species (unpublished data). Yellow star, WGD. (C) A model of increased regulatory capacity. Pre-WGD, only a single (activator-like) TF was present (GIS1/ RPH1, bottom). Post-WGD (star), two paralogous TFs with the same sequence specificity are present in the genome (GIS1, RPH1, top), one is an activator (red), and the other a repressor (green).

When we extended this analysis to all 12 species, we found substantial divergence in the regulatory logic of the same NFR-positioned motif, most notably at the WGD (Figure 7-2B). We found a host of motifs which, when present in NFRs, were associated with differences in RNA expression levels between pre- and post-WGD species. Many of those (~100) appeared to shift from activator-like behavior in pre-WGD species (higher target expression when in NFR) to repressor-like behavior in post-WGD species (lower target expression when in NFR). These included sites for a surprisingly large number of TFs involved in repression of metabolic genes in *S. cerevisiae*, including MIG1, GIS1, RGT1, and GAL80. Interestingly, several of these genes are found in a single copy in pre-WGD species but were retained as duplicates [36] with similar DNA-binding specificity following the WGD (*e.g.* GIS1/RPH1, RGT1/EDS1, Figure 7-2B,C). This suggests that widespread usage of competing activator/repressor pairs in *S. cerevisiae* may have been facilitated by the generation of such TF pairs at the WGD. Such duplication of *trans*-factors can serve as an alternative evolutionary mode to expand and evolve regulatory capacity [84] even when NFRs and motif positioning may be conserved.

Chapter 8. Conclusions

In this study we used a comparative functional genomics approach to study the evolutionary interplay between chromatin organization, gene expression, and regulatory sequence elements. We aimed to achieve two main goals: **(A)** to use evolution and comparative genomics in order to understand the determinants of chromatin organization (Section 8.1); and **(B)** to use chromatin information to gain insight into the evolution of gene regulation (Section 8.2). In the process, we improved on existing methods and developed new computational techniques for studying chromatin organization and evolution of gene regulation (Section 8.3).

8.1. Studying Evolution to Understand Chromatin Organization

What establishes the nucleosomal organization of a genome? While it has been argued that intrinsic DNA sequence can almost fully explain nucleosome organization [9], recent analysis of *in vitro* reconstitution data showed that the major intrinsic contributor to nucleosome positioning in budding yeast is the antinucleosomal behavior of Poly(dA:dT) and related sequences [9, 12, 85]. Conversely, recent reports indicate that in *S. pombe* Poly(dA:dT) plays only a minor role in nucleosome exclusion *in vivo* [35], indicating that even the best-understood sequence contributor to chromatin organization plays variable roles in chromatin structure in different species.

Our analysis provides several lines of evidence that expression levels, intrinsic anti-nucleosomal sequences, and binding sites for GRFs that may recruit chromatin modifiers all play a role in establishing promoter chromatin architecture, and that the balance between these three contributors changes in evolution and between functional groups of genes. (1) We show that a sequence-based model based on *in vitro* depletion alone [9] can only account for 8.6-25.7% of variance in NFR depth within any of the 12 species, including *S. cerevisiae* (10.6%). Similarly, expression levels alone can only account for 1.7-13.1% of the variation in each species. Even when combining both the expression and intrinsic models we can only explain 13-29% of the variation within any single species. (2) Although changes in intrinsic sequences and expression levels can explain changes in chromatin across species for some gene sets (*e.g.* mRPs or splicing genes – Figure 8-1A,B), they are insufficient to explain conserved chromatin behavior across the phylogeny (*e.g.* RNA Polymerase subunit genes, Figure 8-1D), nor do they explain changes in chromatin organization across species in other groups of genes (*e.g.* peroxisome genes, Figure 6-3I,F). Thus, these two determinants (alone or in combination) are insufficient to explain both intra- and inter-species variation. (3) In contrast, by comparing our *in vivo* data in each species to two *in vitro* datasets [9, 34], we find in each species a host of sequences that exhibit significantly greater nucleosome depletion *in vivo* than *in vitro*. Many of these correspond to binding sites for known GRFs that play an active role in nucleosome eviction in *S. cerevisiae* [2, 13, 67, 71], whereas others represent novel candidate GRF sequences (Figure 5-1A and Figure 8-1C). (4) The relative contribution to nucleosome organization from GRFs, intrinsic sequences and expression levels varies between different genes sets (in all species). For example, we show that intrinsic anti-nucleosomal sequences are enriched at NFRs in cytoplasmic RPs (in all species – Figure 4-2A), whereas GRFs fulfill this role in proteasome genes (in all species – Figure 6-3G,D). (5) We also show that the

relative contribution of one mechanism *vs.* another can change in evolution (across species), both globally (as in the halophile *D. hansenii*, that relies more on GRFs) and in specific gene sets (as in the RNA polymerase gene module that shifted from intrinsic to regulated NFRs – Figure 8-1D). (6) Globally, even when we consider only the binding sites for the two best-characterized GRFs from *S. cerevisiae* (Abf1 and Reb1), GRFs alone can explain 5.2-15.1% of the variation in nucleosome organization (in species where their orthologs are present), and 3.7-12.6% of the residual variation after considering the contribution from expression and Poly(dA:dT). Taken together, this analysis points to a complex interplay between the different factors that control nucleosome positions, allows us to assess their contributions, and recognizes the plastic and evolvable nature of all the determinants.

8.2. Studying Chromatin to Understand the Evolution of Gene Regulation

Our study also discovers an intricate and intimate relationship between conservation and divergence of chromatin organization and evolution of gene regulation. At one extreme, we found a broad functional dichotomy in chromatin organization between ‘growth’ and ‘stress’ genes, which is largely conserved. At the other extreme, we found that chromatin organization has diverged at a major evolutionary scale, as has happened for the evolution of respiration-fermentation, and at other points of phylogenetic and phenotypic divergence.

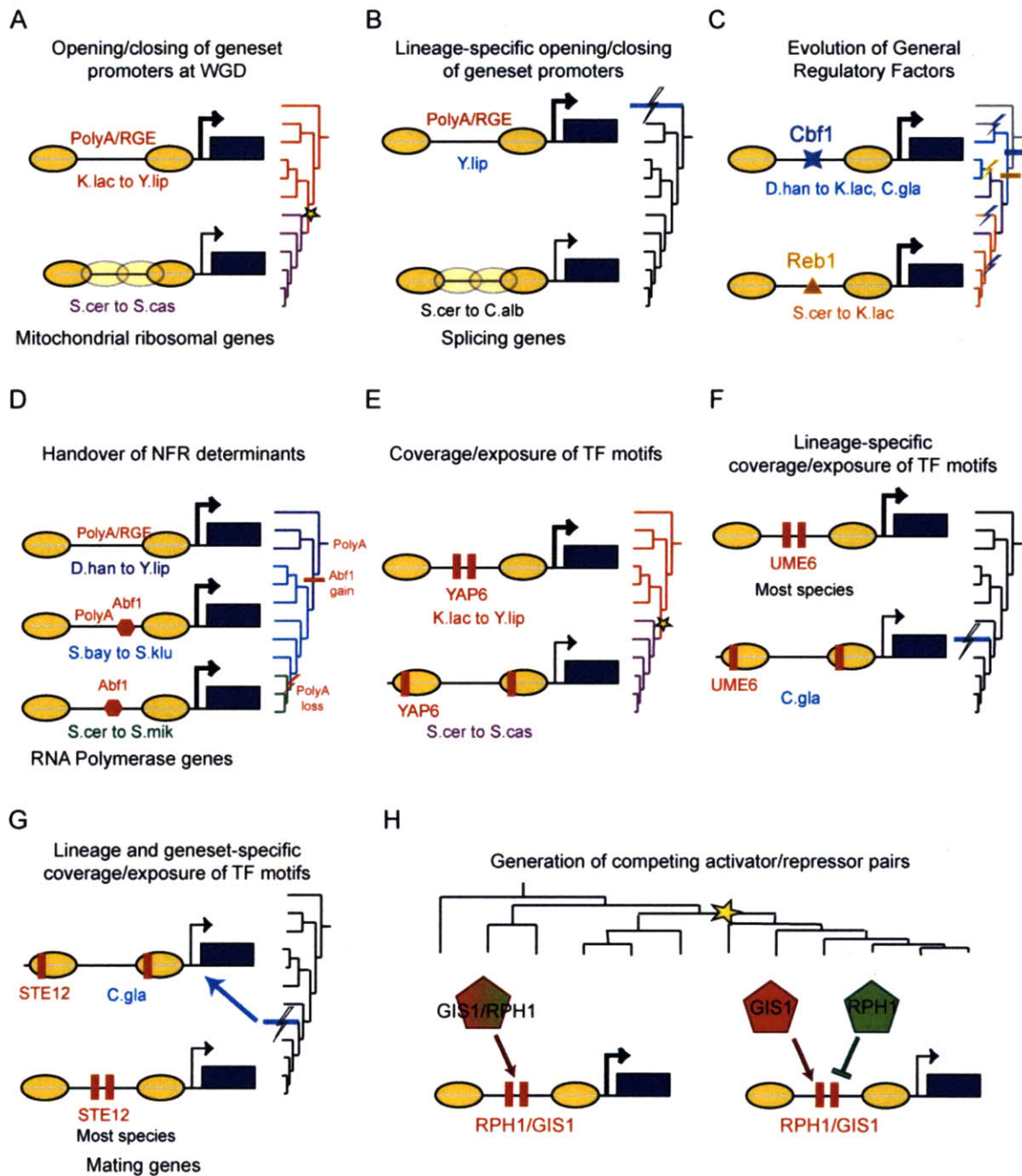


Figure 8-1: Overview of role of chromatin on regulatory evolution. Examples for the five key evolutionary modes discovered in the study. (A,B) Transition from “open” to “closed” NFRs associated with reduction in expression and loss of intrinsic anti-nucleosomal Poly(dA:dT) tracts in mitochondrial protein genes (at WGD) and splicing genes (after divergence of *Y. lipolytica*). (C) Global shift in usage of GRFs, resulting in a gradual transition from a Cbf1-dominated mechanism to a Reb1-dominated mechanism, through a redundant intermediate. (D) Compensatory evolution results in switch from constitutively programmed

NFRs to GRF-regulated NFRs in RNA polymerase genes. (E–G) Re-positioning of motifs from NFRs to nucleosomes in oxidative functions following the WGD (E), and in meiosis and mating functions in *C. glabrata* (F,G). (H) Increased regulatory capacity at conserved NFRs and binding sites, through the duplication of *trans*-factors at the WGD.

We found five major mechanisms by which chromatin organization can be associated with divergence of gene expression. Each of these was ‘used’ more than once in the phylogeny, and is associated with more than one phenotypic or regulatory change, including the changes described in carbon metabolism, mating, meiosis, and splicing genes. These include (1) gain or loss of intrinsic (PolyA) sequences can open or close NFRs (Figure 8-1A,B) [34]; (2) conserved NFRs can be controlled by different GRF determinants, through compensatory evolution (Figure 6-3G); (3) NFRs can shift between constitutive and regulated determinants by compensatory (‘balanced’) gain/loss of intrinsic anti-nucleosomal sequences and GRF binding sites (Figure 8-1D); (4) motifs can re-position relative to NFRs to change transcriptional output (Figure 8-1E-G); and (5) duplication and divergence of *trans*-factors can expand the regulatory behavior of conserved NFRs and binding sites (Figure 8-1H).

8.2.1. Evolution of Gene Regulation: the Case of Respiratory Fermentation

The evolution of the respiro-fermentative lifestyle following the WGD required a major reprogramming of the yeast transcriptional network and involved all of the mechanisms we describe. The shift thus included loss of intrinsic Poly(dA:dT) anti-nucleosomal sequences in some functional modules (*e.g.* mitochondrial RP genes), and the loss or switch of putative GRF sequences in others (*e.g.* oxidation-reduction genes). Furthermore, sites for certain respiratory TFs (*e.g.* HAP2/3/5, YAP1/3/6) have re-positioned out of NFRs, and those for glucose repression TFs have re-positioned into NFRs (*e.g.* RGT1, MIG1). In yet other

cases, the WGD has resulted in the retention of paralogous activator-repressor pairs that control several modules in carbohydrate metabolism. Notably, each of these mechanisms has acted also at other phylogenetic points, suggesting that they point to general principles, and emphasizing the utility of the WGD as a model to study regulatory evolution.

8.3. Computational Framework for Studying Evolution and Chromatin

Our work provides a general computational framework for the study of chromatin organization, function and evolution. We developed a modified method for detecting nucleosome positions by reducing the number of parameters in a previous algorithm to three and by using the data to estimate these parameters (Section 3.2.1). This improvement normalizes for differences in MNase digestion level that can arise between experiments done by different labs for different species. After inferring nucleosome positions, we developed a new method for identifying 5'NFRs (Section 3.3.1). This allowed us to identify the most critical regions for gene regulation across our phylogeny, and has broad applicability in studying how chromatin organization changes with time, in evolution and in response to environmental stimuli.

Detecting nucleosomes and NFRs allowed us to characterize a number of features that describe the chromatin organization at each gene's promoter. We first explored how these features have evolved on a global manner and then developed a method to study the evolution of gene regulation functionally (Section 4.1). Our approach relies on sets of functionally related genes to guide the analysis in a supervised manner, and uses the K-S statistic to identify significant trends.

We also developed new methods for characterizing sequences that position nucleosomes. We improved on previous approaches for annotating Poly(dA:dT) sequences, and extended these techniques to study the global role of Poly(dC:dG) as intrinsic nucleosome repelling sequences (Section 5.2.1). Moreover, we developed a new method for discovering DNA-binding motifs of *trans*-regulated factors that affect chromatin organization (Section 5.3.1). Follow-up experiments validated the biological accuracy of our approach. Furthermore, we introduced a method for quantifying the relative contribution of the 3 major determinants on nucleosome depletion at NFRs, using robust Lowess smoothing (Section 6.1).

And finally, we developed a quantitative framework for studying the interplay between transcription factor binding sites, chromatin organization, and gene expression (Section 7.1). Across our phylogeny, we identified TF binding sites, their role in regulation of functional groups of genes, their position relative to NFRs, and their role as activator or repressor. We identified a number of significant biological trends using the two-sample K-S test and paired Wilcoxon signed rank test.

8.4. Future Prospects

Future experimental studies can shed light on the mechanisms that underlie many of our evolutionary observations. For example, we propose that increased instability of *C. glabrata* nucleosomes can provide access to Ste12 sites and allow for this species to mate. Moreover, expanding this work to other species can provide useful insight. For example, *K. polysporus* is a species that rapidly diverged from other post-WGD species following the WGD event. It would be interesting to explore how its regulatory programs compare with pre- and post-WGD species, as it provides an intermediary sample point.

In addition to introducing a host of analytical approaches for studying chromatin structure and evolution, our work includes a comprehensive genomics resource, <http://www.broadinstitute.org/regev/evolfungi/>. Future studies can use our published data and methods to develop more detailed models of the relationship between sequence elements, *trans*-factors, and gene expression, as well as on the evolution of regulatory systems. Finally, our comprehensive study in the emerging field of comparative functional genomics demonstrates how to combine the power of functional assays with extensive phylogenetic scope, to shed light both on mechanistic and evolutionary principles.

Bibliography

1. Kornberg, R.D. and Y. Lorch, *Twenty-five years of the nucleosome, fundamental particle of the eukaryote chromosome*. Cell, 1999. 98(3): p. 285-94.
2. Radman-Livaja, M. and O.J. Rando, *Nucleosome positioning: How is it established, and why does it matter?* Dev Biol, 2009.
3. Rando, O.J. and H.Y. Chang, *Genome-wide views of chromatin structure*. Annu Rev Biochem, 2009. 78: p. 245-71.
4. Jiang, C. and B.F. Pugh, *Nucleosome positioning and gene regulation: advances through genomics*. Nat Rev Genet, 2009. 10(3): p. 161-72.
5. Li, B., M. Carey, and J.L. Workman, *The role of chromatin during transcription*. Cell, 2007. 128(4): p. 707-19.
6. Venters, B.J. and B.F. Pugh, *A canonical promoter organization of the transcription machinery and its regulators in the Saccharomyces genome*. Genome Res, 2009. 19(3): p. 360-71.
7. Weiner, A., et al., *High-resolution nucleosome mapping reveals transcription-dependent promoter packaging*. Genome Res, 2009.
8. Drew, H.R. and A.A. Travers, *DNA bending and its relation to nucleosome positioning*. J Mol Biol, 1985. 186(4): p. 773-90.
9. Kaplan, N., et al., *The DNA-encoded nucleosome organization of a eukaryotic genome*. Nature, 2008.
10. Sekinger, E.A., Z. Moqtaderi, and K. Struhl, *Intrinsic histone-DNA interactions and low nucleosome density are important for preferential accessibility of promoter regions in yeast*. Mol Cell, 2005. 18(6): p. 735-48.
11. Yuan, G.C., et al., *Genome-scale identification of nucleosome positions in S. cerevisiae*. Science, 2005. 309(5734): p. 626-30.
12. Zhang, Y., et al., *Intrinsic histone-DNA interactions are not the major determinant of nucleosome positions in vivo*. Nat Struct Mol Biol, 2009. 16(8): p. 847-52.
13. Clapier, C.R. and B.R. Cairns, *The biology of chromatin remodeling complexes*. Annu Rev Biochem, 2009. 78: p. 273-304.
14. Whitehouse, I., et al., *Chromatin remodelling at promoters suppresses antisense transcription*. Nature, 2007. 450(7172): p. 1031-5.
15. King, M.C. and A.C. Wilson, *Evolution at two levels in humans and chimpanzees*. Science, 1975. 188(4184): p. 107-16.

16. Thompson, D.A. and A. Regev, *Fungal regulatory evolution: cis and trans in the balance*. FEBS Lett, 2009.
17. Wohlbach, D.J., et al., *From elements to modules: regulatory evolution in Ascomycota fungi*. Curr Opin Genet Dev, 2009. 19(6): p. 571-8.
18. Jeong, S., A. Rokas, and S.B. Carroll, *Regulation of body pigmentation by the Abdominal-B Hox protein and its gain and loss in Drosophila evolution*. Cell, 2006. 125(7): p. 1387-99.
19. Gompel, N., et al., *Chance caught on the wing: cis-regulatory evolution and the origin of pigment patterns in Drosophila*. Nature, 2005. 433(7025): p. 481-7.
20. McAdams, H.H., B. Srinivasan, and A.P. Arkin, *The evolution of genetic regulatory systems in bacteria*. Nat Rev Genet, 2004. 5(3): p. 169-78.
21. Gasch, A.P., et al., *Conservation and evolution of cis-regulatory systems in ascomycete fungi*. PLoS Biol, 2004. 2(12): p. e398.
22. Tirosh, I., et al., *A genetic signature of interspecies variations in gene expression*. Nat Genet, 2006. 38(7): p. 830-4.
23. Tuch, B.B., et al., *The evolution of combinatorial gene regulation in fungi*. PLoS Biol, 2008. 6(2): p. e38.
24. Lavoie, H., et al., *Evolutionary tinkering with conserved components of a transcriptional regulatory network*. PLoS Biol, 2010. 8(3): p. e1000329.
25. Prud'homme, B., N. Gompel, and S.B. Carroll, *Emerging principles of regulatory evolution*. Proc Natl Acad Sci U S A, 2007. 104 Suppl 1: p. 8605-12.
26. Khaitovich, P., et al., *Evolution of primate gene expression*. Nat Rev Genet, 2006. 7(9): p. 693-702.
27. Kellis, M., B.W. Birren, and E.S. Lander, *Proof and evolutionary analysis of ancient genome duplication in the yeast Saccharomyces cerevisiae*. Nature, 2004. 428(6983): p. 617-24.
28. Conant, G.C. and K.H. Wolfe, *Increased glycolytic flux as an outcome of whole-genome duplication in yeast*. Mol Syst Biol, 2007. 3: p. 129.
29. Brem, R.B., et al., *Genetic dissection of transcriptional regulation in budding yeast*. Science, 2002. 296(5568): p. 752-5.
30. Lee, S.I., et al., *Identifying regulatory mechanisms using individual variation reveals key role for chromatin modification*. Proc Natl Acad Sci U S A, 2006. 103(38): p. 14062-7.
31. Tirosh, I., et al., *A yeast hybrid provides insight into the evolution of gene expression regulation*. Science, 2009. 324(5927): p. 659-62.
32. Tirosh, I., et al., *On the relation between promoter divergence and gene expression evolution*. Mol Syst Biol, 2008. 4: p. 159.
33. Ihmels, J., et al., *Rewiring of the yeast transcriptional network through the evolution of motif usage*. Science, 2005. 309(5736): p. 938-40.
34. Field, Y., et al., *Gene expression divergence in yeast is coupled to evolution of DNA-encoded nucleosome organization*. Nat Genet, 2009. 41(4): p. 438-45.

35. Lantermann, A.B., et al., *Schizosaccharomyces pombe* genome-wide nucleosome mapping reveals positioning mechanisms distinct from those of *Saccharomyces cerevisiae*. *Nat Struct Mol Biol*, 2010. 17(2): p. 251-7.
36. Wapinski, I., et al., *Natural history and evolutionary principles of gene duplication in fungi*. *Nature*, 2007. 449(7158): p. 54-61.
37. Shivaswamy, S., et al., *Dynamic remodeling of individual nucleosomes across a eukaryotic genome in response to transcriptional perturbation*. *PLoS Biol*, 2008. 6(3): p. e65.
38. Albert, I., et al., *Translational and rotational settings of H2A.Z nucleosomes across the *Saccharomyces cerevisiae* genome*. *Nature*, 2007. 446(7135): p. 572-6.
39. Kent, W.J., *BLAT--the BLAST-like alignment tool*. *Genome Res*, 2002. 12(4): p. 656-64.
40. Xu, Z., et al., *Bidirectional promoters generate pervasive transcription in yeast*. *Nature*, 2009. 457(7232): p. 1033-7.
41. Kornberg, R.D. and L. Stryer, *Statistical distributions of nucleosomes: nonrandom locations by a stochastic mechanism*. *Nucleic Acids Res*, 1988. 16(14A): p. 6677-90.
42. Mavrich, T.N., et al., *A barrier nucleosome model for statistical positioning of nucleosomes throughout the yeast genome*. *Genome Res*, 2008. 18(7): p. 1073-83.
43. Heus, J.J., et al., *The nucleosome repeat length of *Kluyveromyces lactis* is 16 bp longer than that of *Saccharomyces cerevisiae**. *Nucleic Acids Res*, 1993. 21(9): p. 2247-8.
44. Van Holde, K.E., *Chromatin*. Springer series in molecular biology. 1989, New York: Springer-Verlag. xii, 497 p.
45. Sasaki, S., et al., *Chromatin-associated periodicity in genetic variation downstream of transcriptional start sites*. *Science*, 2009. 323(5912): p. 401-4.
46. Warnecke, T., N.N. Batada, and L.D. Hurst, *The impact of the nucleosome code on protein-coding sequence evolution in yeast*. *PLoS Genet*, 2008. 4(11): p. e1000250.
47. Washietl, S., R. Machne, and N. Goldman, *Evolutionary footprints of nucleosome positions in yeast*. *Trends Genet*, 2008. 24(12): p. 583-7.
48. Routh, A., S. Sandin, and D. Rhodes, *Nucleosome repeat length and linker histone stoichiometry determine chromatin fiber structure*. *Proc Natl Acad Sci U S A*, 2008. 105(26): p. 8872-7.
49. Tirosh, I., J. Berman, and N. Barkai, *The pattern and evolution of yeast promoter bendability*. *Trends Genet*, 2007. 23(7): p. 318-21.
50. Li, Y., et al., *RNA polymerase II initiation factor interactions and transcription start site selection*. *Science*, 1994. 263(5148): p. 805-7.
51. Mavrich, T.N., et al., *Nucleosome organization in the *Drosophila* genome*. *Nature*, 2008. 453(7193): p. 358-62.
52. Schones, D.E., et al., *Dynamic regulation of nucleosome positioning in the human genome*. *Cell*, 2008. 132(5): p. 887-98.

53. Fuda, N.J., M.B. Ardehali, and J.T. Lis, *Defining mechanisms that regulate RNA polymerase II transcription in vivo*. *Nature*, 2009. 461(7261): p. 186-92.
54. Ogata, H., et al., *KEGG: Kyoto Encyclopedia of Genes and Genomes*. *Nucleic Acids Res*, 1999. 27(1): p. 29-34.
55. Harris, M.A., et al., *The Gene Ontology (GO) database and informatics resource*. *Nucleic Acids Res*, 2004. 32(Database issue): p. D258-61.
56. Mewes, H.W., et al., *MIPS: a database for genomes and protein sequences*. *Nucleic Acids Res*, 2002. 30(1): p. 31-4.
57. Karp, P.D., et al., *Expansion of the BioCyc collection of pathway/genome databases to 160 genomes*. *Nucleic Acids Res*, 2005. 33(19): p. 6083-9.
58. Benjamini, Y. and Y. Hochberg, *Controlling the false discovery rate: a practical and powerful approach to multiple testing*. *J. Royal Stat. Soc. B*, 1995. 57: p. 289-300.
59. Man, O. and Y. Pilpel, *Differential translation efficiency of orthologous genes is involved in phenotypic divergence of yeast species*. *Nat Genet*, 2007. 39(3): p. 415-21.
60. Choi, J.K. and Y.J. Kim, *Intrinsic variability of gene expression encoded in nucleosome positioning sequences*. *Nat Genet*, 2009. 41(4): p. 498-503.
61. Field, Y., et al., *Distinct modes of regulation by chromatin encoded through nucleosome positioning signals*. *PLoS Comput Biol*, 2008. 4(11): p. e1000216.
62. Tirosh, I. and N. Barkai, *Two strategies for gene regulation by promoter nucleosomes*. *Genome Res*, 2008. 18(7): p. 1084-91.
63. MacKay, V.L., et al., *Gene expression analyzed by high-resolution state array analysis and quantitative proteomics: response of yeast to mating pheromone*. *Mol Cell Proteomics*, 2004. 3(5): p. 478-89.
64. Kurtzman, C.P. and J.W. Fell, *The yeasts : a taxonomic study*. 4th ed. 2000, Amsterdam ; New York: Elsevier. xviii, 1055 p.
65. Marck, C., et al., *The RNA polymerase III-dependent family of genes in hemiascomycetes: comparative RNomics, decoding strategies, transcription and evolutionary implications*. *Nucleic Acids Res*, 2006. 34(6): p. 1816-35.
66. Iyer, V. and K. Struhl, *Poly(dA:dT), a ubiquitous promoter element that stimulates transcription via its intrinsic DNA structure*. *Embo J*, 1995. 14(11): p. 2570-9.
67. Hartley, P.D. and H.D. Madhani, *Mechanisms that specify promoter nucleosome location and identity*. *Cell*, 2009. 137(3): p. 445-58.
68. Yarragudi, A., L.W. Parfrey, and R.H. Morse, *Genome-wide analysis of transcriptional dependence and probable target sites for Abf1 and Rap1 in Saccharomyces cerevisiae*. *Nucleic Acids Res*, 2007. 35(1): p. 193-202.
69. Harbison, C.T., et al., *Transcriptional regulatory code of a eukaryotic genome*. *Nature*, 2004. 431(7004): p. 99-104.
70. Kellis, M., et al., *Sequencing and comparison of yeast species to identify genes and regulatory elements*. *Nature*, 2003. 423(6937): p. 241-54.

71. Badis, G., et al., *A library of yeast transcription factor motifs reveals a widespread function for Rsc3 in targeting nucleosome exclusion at promoters.* Mol Cell, 2008. 32(6): p. 878-87.
72. Zhu, C., et al., *High-resolution DNA-binding specificity analysis of yeast transcription factors.* Genome Res, 2009. 19(4): p. 556-66.
73. Hogues, H., et al., *Transcription factor substitution during the evolution of fungal ribosome regulation.* Mol Cell, 2008. 29(5): p. 552-62.
74. Byrne, K.P. and K.H. Wolfe, *Visualizing syntenic relationships among the hemiascomycetes with the Yeast Gene Order Browser.* Nucleic Acids Res, 2006. 34(Database issue): p. D452-5.
75. Tanay, A., A. Regev, and R. Shamir, *Conservation and evolvability in regulatory networks: the evolution of ribosomal regulation in yeast.* Proc Natl Acad Sci U S A, 2005. 102(20): p. 7203-8.
76. Kunkel, G.R. and H.G. Martinson, *Nucleosomes will not form on double-stranded RNA or over poly(dA).poly(dT) tracts in recombinant DNA.* Nucleic Acids Res, 1981. 9(24): p. 6869-88.
77. Gasch, A.P., et al., *Genomic expression programs in the response of yeast cells to environmental changes.* Mol Biol Cell, 2000. 11(12): p. 4241-57.
78. MacIsaac, K.D., et al., *An improved map of conserved regulatory sites for Saccharomyces cerevisiae.* BMC Bioinformatics, 2006. 7: p. 113.
79. Barash, Y., et al., *CIS: compound importance sampling method for protein-DNA binding site p-value estimation.* Bioinformatics, 2005. 21(5): p. 596-600.
80. Lam, F.H., D.J. Steger, and E.K. O'Shea, *Chromatin decouples promoter threshold from dynamic range.* Nature, 2008. 453(7192): p. 246-50.
81. Lomvardas, S. and D. Thanos, *Modifying gene expression programs by altering core promoter chromatin architecture.* Cell, 2002. 110(2): p. 261-71.
82. Muller, H., et al., *The asexual yeast Candida glabrata maintains distinct alpha and alpha haploid mating types.* Eukaryot Cell, 2008. 7(5): p. 848-58.
83. Williams, R.M., et al., *The Ume6 regulon coordinates metabolic and meiotic gene expression in yeast.* Proc Natl Acad Sci U S A, 2002. 99(21): p. 13431-6.
84. Wapinski, I., et al., *Gene duplication and the evolution of ribosomal protein gene regulation in yeast.* Proc Natl Acad Sci U S A, 2010. 107(12): p. 5505-10.
85. Tillo, D. and T.R. Hughes, *G+C content dominates intrinsic nucleosome occupancy.* BMC Bioinformatics, 2009. 10: p. 442.