Artificial Intelligence Impact on Occupations and Workforce

by

Hazal Mine Kansu

B.S. Quantitative Economics and International Relations, Tufts University (2014)

Submitted to the Institute of Data, Systems, and Society (IDSS) in partial fulfillment of the requirements for the degree of Master of Science in Technology and Policy at the MASSACHUSETTS INSTITUTE OF TECHNOLOGY September 2019

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Abstract

Recent developments in machine learning (ML) have persuaded researchers that automated technologies without human intervention may transform occupations across the economy. My research seeks to assess how and where ML will affect the workforce. I extend the ideas of Brynjolfsson, Mitchell, and Rock (2018), who assess each task in the economy for its Suitability for Machine Learning (SML). This paper builds on their summary statistics to provide a more detailed analysis of where ML is likely to have its greatest impact in the economy. Combining their technological suitability data with labor market data, this paper suggests a policy model for better planning labor mobility and allocation of human resources in the face of upcoming technological changes.

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Chapter 1

Introduction

The goal of this research is to explore the susceptibility of occupations in the US economy to near-term disruption from ML technologies, and how the policy makers can better plan for allocation of labor resources in the face of upcoming technological changes.

This work is motivated by the desire to better understand the relationship between skills, job tasks, and occupations and what they mean for the future human labor force. There have been many academic studies to better understand the potential impact of the new technological developments on the economy. On the policy side, many people are working on new policies and strategies to find ways to prepare the workers for potential upcoming changes. However, there seems to be a disconnect between data driven studies and policy makers. Informed policy making could allow better preparation of the current and the future workforce to meet the needs of our changing economy in response to the ever changing innovation landscape. As our understanding of how the new technologies will change occupations improves, the potential to utilize data driven insights in policy making will improve as well. This paper attempts to bridge the gap between academic studies and decision makers who work on future of work policies. Using currently
available data, the paper proposes a model that could improve job transition and training policies regarding future of work, and presents a road map for future analysis when better, more granular data becomes available.

1.1 Motivations

The recent developments and trends that motivated this research project can be presented under three categories: 1) recent employment trends in labor markets that led to income inequality, 2) technological improvements in artificial intelligence, 3) current policy options addressing the questions around future of work. This section will provide an overview of these trends.

1.1.1 Labor market trends

The fear of automation and its potential to displace labor have been around for a long time. In 1930, Keynes voiced his concerns over technological unemployment due to labor’s inability to catch up with increasing technical efficiency [Keynes, 2010]. While the automation impact on job creation has been positive in long term by leading to creation of more complementary jobs, the short term effects are more mixed, potentially displacing workers [Autor, 2015]. In the past, similar examples of various disruptive technologies replacing human labor in short term led to increased employment by creating more jobs that require similar skills in long term [Mandel, 2017]. Below is an overview of some of the employment trends from the past few decades, and how they may be affected from adoption of new technologies.
1.1.1.1 Changes in educational attainment in the U.S.

There have been vast changes in educational attainment of the US workforce in the last few decades. Both high school and college completion rates have increased: the high school completion rate increased from less than 65% for people born in 1930 up to about 90% in 1950s. For the same period, college graduation rates increased from less than 15% to more than 25% [Acemoglu et al., 2012; Autor, 2014]. On the contrary, the U.S. experienced a serious slow down of educational attainment in the 1970s, particularly for males [Gruber, 2000].

While there have been an increase in supply of highly educated workers, the wage dynamics have shown an unexpected trend. Basic economic principles would suggest that the lower relative demand would make the high school educated workforce a scarce resource, causing their wages to increase. On the other hand, increasing supply of college educated people would create competition for a limited number of jobs, lowering their wages. Contrary to expectations the wages for the college educated workers continued to increase, while the wages for the less educated workforce declined [Autor et al., 2019]. The wage gap between high school graduates and college graduates have continued to widen in the 1980s, which then saw a gradual decline and a flattening into the 2000s [Valletta, 2018]. In fact, returns to education fell in the first half of the twentieth century, but rose at the end of the second half [Goldin and Katz, 2007].

Researchers have been trying to identify the potential reasons for the patterns observed in wage trends. A prominent explanation has been the deployment of new technologies changing the need for skilled (college-educated) labor in the workplace.
1.1 Motivations

1.1.1.2 Changes in labor demand in the U.S.

There have been significant changes in industry mix over the past few decades as well. Sales, production, and administrative occupations, which are classified as "middle-skill" positions, have declined as percentage of the overall jobs in the U.S. Technician and manager positions, which are classified as "high-skill", have increased, as well as jobs in personal services, care and protection services and labor occupations, which are considered to be "low-skill" jobs [Autor et al., 2019]. College educated workers tend to fulfill the high-skill or middle-skill jobs in the economy, while people who completed high school or less tend to be placed in middle-skill or low-skill jobs.

There seems to be a decline in the available middle-skill jobs in the economy over the last few decades. During this period, people with college degrees in middle-skill positions seem to have moved into high-skill occupations, which implies higher wages as well. However, for people without a college degree who were in middle-skill jobs seem to have taken jobs in the low-skill job categories, which may pay significantly lower wages [Autor et al., 2019].

In addition to the changes in the characteristics of the labor force, the overall labor contribution to the economy has been declining [Autor et al., 2017]. While the causes for this phenomenon remain uncertain, there seems to be an impact from large monopolies leveraging more capital, which implies more resources being spent on implementing new machinery and solutions to leverage new technologies.

1.1.1.3 Effect of observed trends on the U.S. workforce

The trends explained above have real life implications for different groups in the society. For certain subgroups in the U.S. population, especially men with high school education, wage declines during this period have been dramatic [Autor et al., 2019]. In addition, the upward income mobility between generations has
1.1 Motivations

decreased dramatically due to increasing inequality in income distribution, with the rate of upward mobility down from 90% for 1940 birth cohort to 50% for the 1980 cohort [Chetty et al., 2017].

As the new technological developments are perceived to be a major driver in changes in labor dynamics, understanding what these new technologies are and how they will get incorporated into the workplaces is an important step for this paper.

1.1.2 Technological developments in AI

The idea of creating automated processes to combine knowledge and information to generate new knowledge has been around for a long time. Alan Turing presented this idea in 1950 to identify what we mean by intelligence in humans and how that may be replicated by machines [Turing, 1950]. However, the expensive-ness of the amount of computing power required was a big barrier until recently. In the last 25 years, available computing power per dollar spent has increased by a factor of ten in about every four years, which is the main reason why the scientists were able to start implementing the ideas they have started developing long before [Nordhaus, 2001]. Computers have become faster, cheaper, more accessible, and can store more information. Machine learning algorithms have also improved and people have gotten better at knowing which algorithm to apply to their problem. These improving cost advantages enabled significant successes in AI through the past few decades [Anyoha, 2017].

The increase in pace of AI innovation has been largely attributed to ML as it shifted from computers acting based on codes entered by programmers to methods that enable computers leveraging the potential for accumulated data [Brynjolfsson et al., 2018b]. Some of the ways in which AI technologies are implemented are not new. For example, the idea of using patterns in available data and identifying
correlations has been around for a long time. However, the increase in computational speed with declining costs and the availability of data from many new data sources (sensors, tools, online etc.) have improved ML prediction models and made them much more effective to complete everyday tasks [Agrawal et al., 2017].

Recently, we have seen computers beating humans in games and autonomous cars getting closer to becoming part of daily life [Buchanan, 2005; Moldrich, 2018]. Examples include Google’s AlphaGo application, AI systems capable of classifying diseases as successfully as doctors, and language translations at human-level accuracy. These examples also demonstrate that teaching machines could be more human-like, which means ML systems will be able to improve themselves over time towards unsupervised learning [McAfee and Brynjolfsson, 2017].

The technological improvements in some fields such as image recognition are more rapid than in other fields (e.g. achieving humanlike general intelligence) [McAfee and Brynjolfsson, 2017]. Faster development signal that business applications of these new technologies are on the horizon. Today, the commercial use of these new AI applications is limited. However, frontier companies such as Google are starting to use deep learning in many projects across the firm [McAfee and Brynjolfsson, 2017]. While we have not seen the impact of these new technologies in the workplace yet, industry players are starting adopt some of these technological developments, with many companies testing and incorporating machine learning, robotics, and natural language processing technologies into their business [Shoham et al., 2018]. The yearly report by AI Index shows a steep increase in academic papers published on AI, as well as jobs requiring AI skills.

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1https://deepmind.com/blog/alphago-zero-learning-scratch/

2Yoav Shoham, Raymond Perrault, Erik Brynjolfsson, Jack Clark, James Manyika, Juan Carlos Niebles, Terah Lyons, John Etchemendy, Barbara Grosz and Zoe Bauer, "The AI Index 2018 Annual Report, AI Index Steering Committee, Human-Centered AI Initiative, Stanford University, Stanford, CA, December 2018."
1.1 Motivations

The graph below shows the mentions of AI and ML in earnings calls through the past 10 years. While the increase in mentions does not indicate adoption of the technologies by these companies, it shows that the companies have these new technologies as part of their agenda, potentially signaling adoption in the near-term.

![Technology mentions in earnings calls have increased in recent years](image)

Figure 1.1: Technology mentions in earnings calls have increased in recent years

Source: Prattle, data shared as part of AI Index Annual Report 2018

It is also important to note that AI may be a general purpose technology (GPT), which is the type of innovation that generates significant spill over affects and has a broader impact on the economy than just in its direct application areas [Brynjolfsson et al., 2017]. Thus we would expect these breakthroughs to stimulate innovation in areas that are not measurable at the moment, increasing the potential productivity gains to the levels higher than what would be predicted based only on the current technological developments.
1.2 The Role for Policy

1.1.3 Connecting data to policy

Rising wage inequality and increasing automation in the workplace will likely affect many workers in the near future. The spread of technology is uneven \(^1\), which could disadvantage certain groups in the short term while advantaging others, hence further contributing to inequality. Thus, there is a certain need for policy makers to address these concerns in a timely manner.

There are multiple challenges on the research side that present obstacles to accurately analyzing impact of AI on labor, including lack of high-quality granular data on occupational descriptions and job requirements, lack of modeling to better understand substitutive vs. complementary effect of new technologies, and the need for better understanding of how technological change is linked to other market dynamics such as migration and trade \([\text{Frank et al., 2019}]\). However, there seems to be many more opportunities to leverage existing data resources and research in policy making \(^2\) \(^3\).

The next section discusses more broadly the role of policy in the AI impact on labor. Chapter 4 presents a model which could help policy makers plan their AI policy and worker retraining strategies.

1.2 The Role for Policy

The rapid developments in AI technology have the potential to drastically change employment opportunities. What this change may look like in real life has been difficult to predict due to unknowns about how the new technologies may get implemented in the work place and varying job market dynamics.

\(^1\)https://www.mckinsey.com/featured-insights/artificial-intelligence/ai-adoption-advances-but-foundational-barriers-remain
1.2 The Role for Policy

The expectations for how AI technologies will impact the economy vary significantly. Some think that automation will replace many of the existing jobs and limit new job creation, while others expect a big productivity boost that will lead to extensive amount of free time for people working fewer hours [Autor, 2015; Muro et al., 2019; Stevenson, 2018]. It is unclear at this point whether the optimists or pessimists have a better sense of what the job market will look like in the next few years.

The concerns around new technologies and how they may affect jobs and employment are not new to AI [Jones, 2013; Keynes, 2010; Leontief, 1952]. Observing the full impact of the new AI technologies will take time, similar to how other new technologies affected the workforce in the past [Brynjolfsson et al., 2018b]. Also, whether the impact of AI will be the same as other impactful technologies of the past remains as an open question.

Despite the unknowns, there is a role for policy makers to shape how these technologies may affect societies in the near future. There are two broad categories regarding AI that require policy input: the rate of diffusion of AI technologies, and the effects of the diffusion [Agrawal et al., 2019]. How policy makers address these issues will have a significant impact on employment and wage inequality issues due to technological improvements.

The way new technologies will be adopted in the workplace depends on many factors other than technological feasibility. Based on which application areas emerge earlier and the needs of different job markets, we would expect to see regional and across-industry differences in adoption. Workers in the first adopter industries would be affected sooner, and certain job categories/industries may get affected differently. Even though we expect to see these differences evening out in the longer term, an uneven spread of new technologies in the short term may affect employees across jobs in different ways and magnitude. Adoption will also
be influenced by local labor demand and supply, taxation, and offshoring trends among other factors.

Another unknown is whether the productivity effect from new technologies will propagate growth for a specific job line/industry or whether the substitution effect will be dominant, replacing human labor [Acemoglu and Restrepo, 2018]. The same technology could have different net effects on different job categories due to other factors affecting the labor market.

By weighing in on education policies and business cycles, policy makers may be able to make appropriate adjustments to minimize inequalities [Agrawal et al., 2017]. In the face of upcoming technological changes policy makers will need to address a number of questions including 1) how to deal with the potential unemployment in case the productivity gains from AI prove to be significant and spread fast? 2) how to prevent an increase in income distribution if the a new technology benefits groups of society unevenly 3) if automation does replace human labor, how will people re-purpose their time and energy?

Leveraging available data sources and studies in policy making would lead to better future of work policies. Improvements in data collection would help to eliminate some of the unknowns about the impact of new technologies [Mitchell and Brynjolfsson, 2017]. Governments can use methods that are already utilized by the private sector to better understand the changing job market and the skill landscape across different regions. By combining the ability to collect real time digital information with the traditional data sources such as national surveys, local governments can deliver a clear and comprehensive picture of the job landscape, taking a big step to understand the job market issues and identify potential solutions. In the meantime, available data can be used differently to improve decision making, which this paper discusses in Chapter 4.
1.3 Labor Economics Perspectives on Technology and Labor

1.3.1 The canonical model

The economic modeling on wage and skills distribution has been based on the idea that the college/high school wage ratio serving as a summary index of the education premium. College educated workers tend to get higher wages relative to non-college educated workers, supposedly as compensation for spending longer time in school gaining advanced skills. The wage difference is determined by the relative supply and demand for these skills [Katz and Murphy, 1992; Tinbergen, 1974].

The basic model to think about returns to schooling or other skill differentials was pioneered by Katz and Murphy [Katz and Murphy, 1992]. The model utilizes a competitive supply-demand model in a closed economy which produces only one good. In this model, the workers are paid based on their respective marginal contribution. This model assumes two types of workers: skilled and unskilled. These two groups are imperfect substitutes, meaning changes in wages do not depend on the relative supply of workers in different groups but on the factor of skills [Autor, 2019]. The production function can be written as follows:

\[ Y(t) = [(A_l(t)L(t))^\rho + (A_h(t)H(t))^\rho]^{1/\rho} \]  \hspace{1cm} (1.1)

L(t) stands for unskilled workers, H(t) for skilled workers, and A for changes in technology, with an inelastic supply of workers at time t. Note that this equation ignores the capital factor for now. This function assumes that technologies only augment the productivity of workers and do not substitute them in the
production process. The model suggests that skilled and unskilled workers are q-complements, meaning the greater supply of one category of workers should increase the wages for the workers in the other category [Autor, 2019]. The intuition behind this idea is as follows: a certain, fixed fraction of input from both high skilled and low skilled labor groups is required to generate output. If there is an increased number of workers in one group, there will be room to employ more workers from the other group since the two groups are not perfect substitutes, and skills from both groups are required to generate output. This increase in demand would create scarcity on the supply side, pushing wages higher. However, as discussed earlier, the opposite of this trend has been observed in empirical data on wages in the 20th century.

The key result from the canonical model is that when the supply of one labor group increases, the skill premium for that group would fall. However, in developed countries we have seen a steady increase in wages of skilled workers while the supply of skilled (educated) workers continued to increase [Broecke et al., 2018]. While the canonical model seems to explain long term trends relatively well, there are certain periods (1940s and 1970s) where the trends remain unexplained by this model [Autor, 2019].

1.3.2 Skill Biased Technological Change

One prominent assumption to explain labor market trends in recent decades is an increase in relative demand for the high skilled labor. An explanation for this increase is the sense that new technologies demand more high skilled workers in the workplace. This complementarity between technological developments and the increase in demand for high skilled labor is called skill-biased technological change (SBTC) [Deming, 2017; Katz and Murphy, 1992]. The skill-biased characteristic of new technologies, coupled with significant investments to encourage
more schooling, led to the so-called "race" between technology and supply of skilled labor [Acemoglu and Autor, 2011; Goldin and Katz, 2007].

This framework assumes new technologies introduced to the production system are factor-augmenting, meaning any technological change has a positive effect on the productivity of at least one skill group [Acemoglu and Autor, 2011]. The assumption ignores the possibility that a new technology may instead substitute some skills attributed to workers, or have a skill-unbiased impact on the workforce, which is one of the missing elements in understanding how employment has been historically affected from technological changes [Goldin and Katz, 1998].

### 1.3.3 The task based approach

Despite its success in predicting longer term patterns, increasing wage inequality, falling real wages for certain subgroups, employment polarization, and declines in labor share, cannot be fully explained by the canonical model. The task based model helps to improve our understanding of relationships between skills, job tasks, and how new technologies affect workers and their wages.

An understanding of the difference between skills and tasks is crucial to appreciate this model. Skills can be defined as a collection of capabilities that a worker gains through schooling or other means of training. Tasks can be defined as building blocks of an occupation; each occupation encompasses a number of tasks that are executed by workers who fall under the respective job title. Tasks are not unique; many tasks are required in multiple occupations. A skill is an ability that a worker can utilize effectively to complete multiple tasks.

In the canonical model, there is a one-to-one mapping assumption between skills and tasks, meaning a worker utilizes one skill to complete one task in the production process. In real life, a worker usually utilizes a combination of her different skills to complete a number of required tasks depending on the job.
New technologies may automate some tasks currently performed by a worker, but automation of a subset of requirements per job does not replace the worker entirely. A task-based approach provides flexibility in thinking about how new technologies may affect labor.

Steps in a production process can be thought of as different tasks that use both capital input (think of machines that are utilized in completing the task) and human labor input. When a new technology is used to automate a task or part of a task, the share of each task per unit production assigned to labor vs. capital changes. The task model enables variability to study these changes. The units of production are identified as tasks that collectively represent what each occupation entails. These tasks can be completed by human labor, capital, trade, or off-shoring [Autor, 2013]. Tasks can also be grouped into categories to better identify which ones could be accomplished by new technologies [Autor et al., 2003]. Enabling regrouping of tasks is a powerful concept as it is in line with the malleable nature of occupations and how they emerge/change/disappear over time [Autor et al., 2019]. This approach will be useful in this paper when discussing job and task adjacencies and potential labor movements from one position to another.

1.4 Data

This paper uses the following datasets in analysis:

- Suitability for machine learning (SML) data collected using the AI rubric developed by Brynjolfsson, Mitchell, and Rock (2018).
- Data from the Occupational Information Network (O*NET) database
- Job growth data from the Bureau of Labor Statistics (BLS)
1.4 Data

- Local labor market data for various U.S. cities

A brief description of how different data sources have been used is included below.

1.4.0.1 SML data

The unique dataset used in this paper is the second iteration of the dataset measuring suitability for machine learning (SML) using the rubric developed by Brynjolfsson, Mitchell, and Rock (2018). The questions were answered for each work activity corresponding to each occupation in the U.S. economy. The goal of the survey is to understand whether each task identified in the U.S. job market today can be completed by a machine learning application.

The first version of the rubric, containing 23 questions, was used in their earlier paper [Brynjolfsson et al., 2018a]. The updated rubric with 21 questions was applied to 2,069 detailed work activities (DWAs) in the Bureau of Labor Statistics O*NET content model for all of the occupations in the U.S. Each DWA was rated on each of the 21 questions on a 5-point scale varying from Strongly Disagree (1) to Strongly Agree (5). The SML rubric questions are included in Appendix A [Rock, 2019]. The respondents were found via Amazon Mechanical Turk. Each DWA was rated minimum at least 10 times in randomized batches [Rock, 2019]. These DWA scores are mapped to 18,112 specific occupation-level tasks defined by O*NET (with equal weighting of each rubric question within a task). These tasks are then weighed by the occupational importance scores provided in the O*NET database to calculate occupational-level SML scores.

The results of a PCA analysis on the scores at the task level are shown below in Figure 1.2. As seen in the correlation circle, the survey questions vary on one axis, with the first principal component explaining around one third of the variation in the data, with second component down to 12%. This decline is
expected as we would like the survey questions to measure the job’s exposure to ML impact, with all questions collectively supporting the suitability aspect.

Figure 1.2: PCA correlation for SML task scores

The clusters below in Figure 1.3 are obtained by dimension reduction on survey answers grouped for each occupation, and colored by O*NET job families. The job families are occupations that are grouped based on the required work activities, skills, education, training, and credentials by each occupation. As expected, jobs with similar training and skill requirements tended to cluster together based on their SML scores. Further information on score calculation methods are provided in Chapter 2.

It is important to note the limitations of survey data in measuring the routine-ness of tasks. There may be mispresentation and human error baked into the collected survey responses. In addition, it is a challenge to ask responders to distinguish what is routine from a human’s perspective vs. the complexity of automation from the technological perspective. A mundane cleaning task done by a janitor would be distinctly repetitive from the janitor’s perspective, but the level of visual recognition and motor skills to be performed by a machine to complete the same task is much more complicated [Autor, 2013]. This survey
tries to avoid such friction through specific questions at work activity level.

1.4.0.2 Government data (O*NET and BLS)

Other data used in this study include data from the O*NET database. Occupational Information Network (O*NET) is a government database that uses standardized surveys to conduct interviews to understand and explain the occupations in the U.S. market. The database was mainly established as a guide to assist people who are looking for jobs in their search. Through the website users can search for jobs, skills, tasks, better understand the needs and expectations of different jobs. O*NET database has also been used by many researchers as a comprehensive standardized index of the U.S. workforce and occupations. The detailed data includes importance and frequency scores for tasks, skills, and work activities, as well as insights into similarities between different jobs.

Historical and projection job growth data from Bureau of Labor Statistics (BLS) was used to identify any trends between job growth and SML scores. The exploratory analysis done with this data is further described in Chapter 2.
In Chapter 4, data from all the data sources listed above are used in combination. The SML survey data was used in combination with the O*NET automation data and labor market data from three U.S. cities: Boston, St. Louis, and Houston. Various data on regional labor demand, wages, and job requirements were used to account for regional differences that need to be taken into account when using ML suitability metrics in policy making. My model that uses these data sets is explained in detail in Chapter 4.
Chapter 2

Analysis of Tasks

Summary

This section includes an exploratory analysis using the SML scores. The SML scores were combined with job growth projections to identify trends and understand which skills/tasks will be on demand given expected technological changes.

2.1 SML score calculations

As explained in the previous chapter, the crowd sourced SML data by Brynjolfsson, Mitchell, and Rock (2018) provides very granular machine learning suitability ratings for all work activities identified in the U.S. economy.

These work activity scores are used to calculate task level scores for each task identified in the O*NET database. The task level scores are then used to calculate job-level scores for each occupation. Multiple methods to calculate the consolidated scores have been tested to account for the varying importance, sophistication, and frequency of each task in different occupations. Occupational average scores were calculated using 1) equal weights for each task, 2) only im-
2.2 Identifying potential complementarities using SML scores

portant tasks, 3) all tasks weighted by their O*NET importance scores.

These three score types were matched with job growth projections to identify any trends. The expectation was that the jobs that are more susceptible to ML may have lower future growth. We tested whether one of the calculation methods had a stronger explanation power assuming technological change will be a major driver of future job opportunities. Figure 2.1 below shows the scores based on different calculations. Each data point represents the standardized SML score for an occupation, colored by whether it is projected to be a high growth (top 5%) or low growth (bottom 5%) job. The first column only uses important tasks to calculate the job score, the second column is non-weighted, and the third column includes all tasks weighted by their O*NET importance scores.

There were no identifiable trends distinguishing the different calculation methods. No clustering of high growth vs low growth jobs on the y-axis was observed. I chose to use importance weighted scores for my analyses to account for all identified components of an occupation.

2.2 Identifying potential complementarities using SML scores

While there are some studies on how likely the specific tasks, occupations and industries will be impacted from new technologies, there have not been many attempts in clarifying the kind of impact we would expect to see. A new technology can 1) complement existing work, 2) substitute workers, or 3) have no impact at all. What type of effect we will observe in the workplace depends on many variables including economic incentives, labor market dynamics as well as technological feasibility. This section presents the exploratory work on the path to identify complementing or substituting effects of new technologies.
2.2 Identifying potential complementarities using SML scores

Figure 2.1: SML scores for highest vs. lowest growth occupations (2016-2026)

Figure 2.2 shows the task score distribution for each occupation in the finance and insurance industry (industry chosen for visual simplicity). Frequency peaks are visible at different score points for each occupation. The dispersion of scores within a job may suggest complementarity. The score spread may suggest that part of the tasks in a given occupation may be very suitable for ML while the remaining tasks will continue to be carried out by human labor, signaling potential reorganization and regrouping of tasks within or between occupations.

Any patterns we expect to observe in SML data should be easiest to observe for the highest scoring vs. the lowest scoring occupations. Thus the following figures show the highest 5% and lowest 5% scoring occupations for visual simplicity.

At the task level, Figure 2.3 shows the standard deviation of SML scores for all tasks identified for the highest and lowest scoring occupations. The graph suggests that the tasks in lowest scoring jobs had higher variation in the survey answers. For example, of the 21 questions answered per task, for a given task in
2.2 Identifying potential complementarities using SML scores

Figure 2.2: Density graph for occupation task scores in finance and insurance.

A low growth job, some questions may have received 5s (fully automatable) and other questions may have received 1s (not automatable). Ideally, a task that is fully automatable should have the highest score (5s) for all survey questions, and vice versa. The dispersion in lowest scoring jobs suggests that the answers to the survey were not as strongly supportive of the automation prospects of the task.

Figure 2.4 shows standard deviation vs. SML score for each occupation, taking each answer to survey questions per task as a separate data point. There is significant dispersion in results with an obvious distinction between the high and low scoring jobs.

High scoring jobs with high standard deviation may signal some complementary impact of ML technologies. We would also expect for a perfectly replaceable task to receive same high marks on all questions, with low standard deviation and a higher mean, placed on the upper left corner of the graph. However further analysis and higher quality data is needed to make any inferences as the variance could be due to a number of reasons. The dispersion could also be a reflection of
lower quality data from surveys.

Figure 2.3: Standard deviation for tasks in highest and lowest scoring jobs

2.3 Occupation growth and SML scores

Assuming technological change will be a major driver in employment trends in the future, next we examined SML scores by growth projections. Occupations with higher employment growth projection are expected to hire more workers to meet the market need in completing the tasks of an occupation. Such growth could occur due to an increase in 1) product/service demand, or 2) new emerging tasks increasing labor demand. Higher growth may suggest that any negative impact from technology that could have slowed down employment is outweighed by the need for higher labor input, or that most of the important and relevant
2.3 Occupation growth and SML scores

Figure 2.4: Task score dispersion for highest and lowest scoring jobs

Tasks of the job cannot be automated in the next ten years. On the other hand, lower occupational growth could indicate higher chance of deployment of new technologies as opposed to utilizing labor for completing tasks.

The boxplots below show the dispersion seen in task level scores for both high and low growth jobs, suggesting there may be potential for identifying certain types of task groups within these occupations.

Figure 2.5: Task score dispersion for highest growth jobs

An initial text analysis on the task descriptions of jobs that grew the most in the last 10 years vs. those that are projected to grow the most in the next 10 years showed interesting results. As seen in the word clouds built for the tasks of occupations that grew the most in the past 10 years (between 2006-
2.3 Occupation growth and SML scores

Task scores for lowest growth occupations

Figure 2.6: task score dispersion for lowest growth jobs

2016), the most frequent word was "equipment", while the same analysis for the jobs that are expected to grow the most in the next 10 years revealed that the word "patient" is the most frequently used word in the task descriptions. This is consistent with other studies that identify growing opportunities in care services as opposed to the more prevalent jobs requiring the ability to use certain tools in the past Fujisawa and Colombo [2009].

Figure 2.7: Task descriptions for highest growing jobs (2006-2016)

Figure 2.8: Task descriptions for highest growing jobs (2016-2026)

Next, we used k-means clustering for the tasks in jobs with highest potential growth to identify any distinct task groups based on their SML scores. The visual representations of these clusters for the growth projections between 2016-
2.3 Occupation growth and SML scores

2026 are included below. The same clustering methods were used for the highest and lowest growing jobs between 2006-2016 (graphs included in Appendix B).
Figure 2.9: task clusters for highest growth jobs (2016-2026)
2.3 Occupation growth and SML scores

Grouping clustered tasks into broader categories of work activities was helpful in identifying some trends in high and low growth occupations over different time periods. Figures 2.11-2.14 show these clusters for high growth vs low growth jobs over two periods: 2006-2016 and 2016-2026.

Below in Figure 2.10 is a graph showing task clusters for jobs that have seen the highest changes in 10-year growth. In this graph we see all task clusters dominated by activities that require physical and manual effort, which is consistent with the previously observed trends reducing reliance on manual effort by workers due to automation along with other trends (e.g. offshoring).

![Figure 2.10: task clusters for jobs with highest difference in growth (2006-2016 vs 2016-2026)](image)

Comparing work activities for the lowest growth jobs in 2006-2016 vs 2016-2026 (Figure 2.11 vs. 2.12), it can be seen that the tasks in the 2006-2016 period are dominated by the physical and manual labor tasks, consistent with the lower growth expectation for physical labor intensive tasks. For 2016-2026, while manual tasks are still present, there is an increased number of tasks that involve communication and coordination in the jobs that are expected to grow.
2.3 Occupation growth and SML scores

While the clusters do not exhibit very distinct groups of tasks, they still provide some insight in comparison to one another. In the highest growing jobs (2006-2016) there is only one cluster with manual tasks. For jobs that are expected to grow the most in the next 10 years, there seems to be less information communication and data processing related tasks, which may be due to the use of new technologies in the workplace already streamlining these activities.

While some preliminary patterns are identifiable from these visuals that are consistent with the broader literature discussed earlier, further analysis is necessary to identify any meaningful clusters within the task data set and better understand why the pattern changes may be happening in work activity distributions. NLP analysis with larger data sets from companies like Burning Glass could provide more valuable insights, building on the preliminary results here based on the O*NET descriptions.
Figure 2.11: Work activity groups for lowest growing jobs (2006-2016)

Figure 2.12: Work activity groups for lowest growing jobs (2016-2026)

Figure 2.13: Work activity groups for highest growing jobs (2006-2016)

Figure 2.14: Work activity groups for highest growing jobs (2016-2026)
Chapter 3

Industry Level Analysis: Finance and Insurance

Summary

This chapter provides an exploratory susceptibility analysis of the Finance and Insurance industry. It covers limitations of the analysis done with the current available data, and includes suggestions for further analysis to better understand industry dynamics of ML susceptibility going forward.

3.1 SML scores by industry

Figure 3.1 shows the SML scores by industry. The highest scoring industry seems to be the Finance and Insurance industry. A potential reason could be the high number of assistants and phone agents in this industry that emerge as a highly ML susceptible occupation group.

Figure 3.2 shows the dispersion of task scores for each occupation in the finance and insurance category. Each red dot shows the SML score for a specific task,
3.1 SML scores by industry

Figure 3.1: SML scores by industry

and each box-plot shows the dispersion of task scores within each occupation.

The dispersion of scores Figure 3.2 suggests that within a sector different positions may get effected from new technologies in different ways, at different times. The highest median scoring job is Brokerage Clerks (43-4011). Operations Research Analysts (15-2031) seem to have very little dispersion in their task scores, with most tasks seeming equally susceptible to ML. In contrast, task scores for Compensation Managers (11-3111) show a very large spread as the job seems to combine highly automatable tasks with others that require human input.

Figure 3.3 depicts the analysis of the same data in a slightly different way. The density plot has the added benefit of showing task score distributions with multiple peaks. For instance, Securities, Commodities, and Financial Services Sales Agents (41-3031), and Credit Authorizers, Checkers, and Clerks (43-4041) show multiple peaks in their density graphs. This could mean that a significant portion of tasks belonging to these occupations have high/low SML scores, which may
3.1 SML scores by industry

Figure 3.2: Task score dispersion - finance and insurance provide further insight that is not readily accessible from only the occupational mean and standard deviation.

Figure 3.3: Density graphs - finance and insurance

Such plots can be a starting point for industry deep-dives. Similar dispersion graphs could serve as visual tools to identify particularly susceptible-appearing occupations and groups of tasks preemptively. However, further information is needed to deduce actionable results based on these analyses. Further data on task frequency, importance, and level of sophistication for each task would give a much
better sense of which jobs with a significant portion of their crucial tasks getting automated. Task similarity data could be incorporated to understand which jobs show similar susceptibility characteristics. Job pairing data (complementary positions that tend to work together) may help in identifying the jobs that could get combined as a result of automation, with fewer people being required to fulfill merged positions.
Chapter 4

Connecting data to policy

Summary

Technical feasibility of new ML implementations is important, but not sufficient in understanding its potential affect on workers. The speed of adoption and the way new technologies are used by employers depend on many other local labor market conditions. The proposed model in this chapter attempts to incorporate such effects into decision making for worker movements and retraining due to technological changes.

4.1 Missing links

As demonstrated earlier in this paper, it is very hard to predict the kind of impact a new technology might have on jobs. Certain technologies may increase productivity and have a net positive impact on employment while others may substitute the need for human labor and cause unemployment.

In addition, the same technology may have different impacts on different societies depending on labor force demographics, taxation, or cost of adoption. These
4.2 Proposed model

dynamics are not easy to measure as the data sources available today are not tai-
lored for our purposes, which creates challenges in linking data to actionable
policies.

There are many existing options to implement future of work policies and
programs depending on the needs of different job markets \(^1\) \(^2\) \(^3\) \(^4\) \(^5\). The proposed
model is intended to help identify jobs and industries in need for policy interven-
tion. This analysis can help with identifying the right policy options, connecting
the results from data analysis to actionable policies in funding and retraining the
workforce preparing for future changes.

4.2 Proposed model

The model’s goal is to combine the ML susceptibility and automation data with
local dynamics to identify opportunities in local markets where people may move
between jobs as a result of technological changes. This model was influenced by
Morgan Frank’s analysis of skill adjacencies [Alabdulkareem et al., 2018] as well
as the works presented at the MIT Technology and Policy Hackathon 2019 Future
of Work challenge.

The model takes into account the following factors:

- SML data
- O*NET automation score
- Job vacancies

\(^1\)https://www.QUESTSA.org
\(^3\)https://www.irs.gov/credits-deductions/individuals/earned-income-tax-credit
\(^5\)state-run individual retirement accounts - https://www.paychex.com/articles/employee-
benefits/8-states-state-sponsored-ira
4.2 Proposed model

- Occupational wages
- Education requirements

Note that the model uses both SML scores as well as the O*NET automation scores, which is a more comprehensive impact measure for new technologies. As discussed earlier, the current version of the SML rubric is designed to capture only the potential impact of ML on occupations, while the new technological developments include many others such as robots as well as improvements in traditional IT that impact occupations.

4.2.1 SML scores vs. O*NET automation scores

Figures 4.1 and 4.2 show the correlation between the expected job growth rates from the BLS and the scores that measure impact of new technologies. The first figure shows the correlation between the SML score and expected growth rate of occupations, which is very low. The latter shows a stronger correlation between the O*NET automation score and the same growth projections, which is expected as automation is a broader concept that includes all other technological developments. ML is only one part of overall workplace automation, which is why we may see some correlation between these scores. Accordingly, in Figure 4.3 below SML scores only corresponds to explaining roughly 1/3 of the variation in the O*NET automation data.

Note that the O*NET score measures the level of current automation in the job and does not account for new technological changes that will have an impact in the future. For example, we have not really seen the impact from ML applications since we are still in the early stages of transformation. While surveys similar to the SML survey on other aspects of the automation in workplace can give a more complete picture of the impact of technological developments on the
4.2 Proposed model

Figure 4.1: SML job scores vs. expected job growth (2006-2016)

Figure 4.2: O*NET job automation scores vs. expected job growth (2016-2026)

Figure 4.3: Comparing SML scores to O*NET automation scores
job market, for the policy recommendation part we use the currently available O*NET automation scores for a more complete representation of overall technology impact on work.

The impact of new technologies is significant in shaping what the future of work looks like, but it is not the only determinant of how employment trends change. For all stakeholders involved in the economy there are many other factors, including changes in population, off-shoring, and trade, that affect how workers chose and change jobs. These factors affect job opportunities differently depending on the location (e.g. city vs. rural, geography). Thus, it is important to take as many factors as available data allows into consideration.

4.2.2 Skill adjacencies

Multiple skills are required to complete the tasks for different occupations, with some skills being more important for certain jobs. For example, speaking is an important skill for judges as well as machine operators, but the frequency of utilizing this skill as well as the level of sophistication expected in completing daily tasks using this skill differ drastically between these jobs.

The skills data was used in this analysis as a way of identifying abilities and expertise of a worker to determine areas where the worker have some exposure and the potential to improve themselves given sufficient training. As data availability and granularity improves over time, more accurate analysis could be done by incorporating additional data on skills, as well as complexity, importance, and frequency of various tasks.

Using annual data from the O*NET database, we used the importance score of each skill listed for an occupation indicating how essential a skill s is for occupation k; onet(k,s) ∈ [0, 1], where onet(k, s) = 1 indicates that s is a crucial skill for job k, and onet(k, s) = 0 indicates that the skill s is not necessary to complete
4.2 Proposed model

the requirements of occupation k.

The skill importance score was calculated based on Morgan Frank's calculation to identify the skills that are relatively more important for each job, called revealed comparative advantage (RCA) [Alabdulkareem et al., 2018]: the relative importance of a skill to an occupation (the numerator in Eq. 4.1) to the expected relative importance of a skill on aggregate (the denominator in Eq. 4.1).

\[
RCA = \frac{onet(k, s)/\sum_{s\in S} onet(k, s')}{\sum_{k\in K} onet(k', s)/\sum_{k\in K, s\in S} onet(k', s')} 
\]  

(4.1)

The heatmap below demonstrates the relative importance of the skills identified in the O*NET database for each occupation. As demonstrated, same skills exist in many different jobs but with different importance levels as some skills could be crucial for one job and only a nice-to-have for another. While the red areas show skills that are relatively less critical for an occupation, green skills are crucial and heavily relied on in their respective occupations.

![Jobs vs Skills heatmap](image)

Figure 4.4: Jobs vs Skills heatmap
4.2 Proposed model

Note that a certain skill enables a worker to complete many different tasks in different occupations. Skills serve like a toolkit that can be used when necessary. We might see an employee communicating with investors also communicating with customers; the speaking skills utilized in both settings have similarities in explaining the value proposition of the firm.

Similarly, for an individual who is looking to move between careers, it would be much easier to move to a job that has requires a similar set of skills, to minimize the cost of retraining and adjustment period. Below is the formula used to calculate a distance measure between occupations using O*NET importance scores. The shorter the distance between skills required between two jobs, the easier it would be to transition from one job to the other.

\[
J_{ij} = \sqrt{\sum_{i=1}^{k} (s_{jk} - s_{ik})^2}
\]  \hspace{1cm} (4.2)

\(J_{ij}\) is the distance between jobs \(i\) and \(j\), calculated using the sum of differences in importance of each of the \(k\) skills in the job market. The larger differences between skill scores for different jobs imply harder transition from one job to the other for a worker. The job score is calculated by summing the differences for all skills between the two jobs. The job matrix shown on the next page demonstrates the results of the distance calculations.

As expected, the diagonals have 0 score indicating no move from one job to other. Red colored areas indicate many overlaps in skills between the jobs which should presumably make the transition easier from one position to the other. Green colored areas indicate that there is very little skill overlap between the two jobs in question, suggesting higher transition friction which would require more effort and training for the individual to move from one job to the other.
4.2 Proposed model

4.2.3 Local dynamics

The automation score and the skill distance data enable a complete look on the feasibility of a job change between different occupations from technology and abilities perspectives, while in real life the local labor market dynamics (and non-local ones which are not addressed in this paper) affect how the workforce is allocated. These factors include wages, both the difference between occupations and for the same job at different locations (average wage of a software developer in San Francisco is different than that of one in St. Louis) and the net job openings within commuting distance. As these factors are just as important in determining the feasibility of job transfers for workers, our model incorporates such data into assessment. Due to lack of granular data we used the mean annual wage statistics in this analysis.

From an organizational perspective, related industries tend to cluster in the same geographic area to optimize for productivity [Florida and Kenney, 1988; Neffke and Henning, 2013; Porter, 2000]. Related industries may employ people
with similar skill sets. This skill concentration can increase the vulnerability of a city or a region to automation if a group of tasks pertaining to a skill that is considered crucial by most jobs in the region gets automated. However, the chances of automating all tasks as quickly at the same time across all businesses is unlikely.

On the other hand, such business concentration may imply more opportunities for job transfer between related fields as we would expect to see some overlap in required skills between related industries. If one business in the value chain starts to adopt a new technology, there may be more jobs options in the vicinity that require similar skill set and training. This could enable easier job transitions and allow more time for the labor force to adjust to technological changes.

4.2.4 Other factors

There are many other factors that may influence the moves from one job to another including education requirements, commuting distance, additional perks from the current job and/or social security. We include the educational requirements into our model, but do not have the granular data to adjust and fine tune for other factors that may create friction or encourage job changes locally.

4.3 Sample analysis

Below are a few examples of what the proposed model suggests for different cities and how these results could be interpreted in policy making. The goal was to identify viable transfer options for people who are currently employed in jobs that are susceptible to automation. Ideally, such transfers should happen in a commutable distance, without a pay cut, into jobs that have maximum overlap in skills and work activities required. Identifying these potential transfer paths
can also help to shape policy as governments have been allocating more money into worker retraining programs.

For the purposes of this analysis, employment data was used from three U.S. cities: Houston, TX, Boston, MA and St. Louis, MO. The jobs that have the highest automation score based on the SML rubric results were identified, and analyzed for workers in these three different cities to identify the best course of action for these workers. Out of the 30 jobs with the highest SML scores, the results for 10 jobs that have sizable employment in all three cities are included for demonstrative purposes. Below are the results for two of these occupations to demonstrate the differences based on location. Graphs for the other occupations are included in Appendix B.

The figures demonstrate the potential transfer options for those who are currently employed in jobs that are highly susceptible to automation based on skill similarity and wage potential.

Figure 4.6 shows that there are plenty of job opportunities for police, fire, and ambulance dispatchers in all three cities that offer better pay than their current position. The labeled occupations pay 1.3x of the current occupation, with more job openings available and the same minimum education requirements. The job distance of the labeled occupations are on the lower end of the spectrum, implying plenty of transferable skills and possibly less required training for transitioning into a new job.

Conversely, in Figure 4.7 we see very few job transfer options in St. Louis for postal service mail carriers. In Boston and Houston, the available jobs — particularly the better paying options — have higher job distance values, meaning there is fewer opportunities for transfer of skills and more training would be necessary for the job transfer to happen.

This type of analysis could be useful for local governments to better under-
4.3 Sample analysis

stand the characteristics of their work force and opportunities for better alignment in job transfers. Such understanding would lead to better resource allocation for various training programs funded by governments, ensuring that the financial and other resources are spent in the most effective way for the community.
Potential job transfers - police, fire, and ambulance dispatchers

Solar Energy Installation Managers

Figure 4.6: A number of viable job transfer options for Police, Fire, and Ambulance Dispatchers with better pay and similar skill requirements
Figure 4.7: Limited job transfer options for Postal Service Mail Carriers suggests more retraining efforts will be needed.
4.4 Future steps in modeling

While the proposed model could serve as a good start for local governments, individuals, and other stakeholders who are interested in preparing the workforce for potential upcoming changes, it is important to take note of its limitations. A few improvements include but are not limited to:

- dynamic modeling with more up to date data from sources such as LinkedIn
- incorporating trade/offshoring impact into the model
- utilizing more elaborate and complete measures of automation in place of the O*NET automation metric or the SML score
- including more flexible options for subgroups to identify pockets of opportunity for certain demographics (e.g. younger people, single people may be more open to commuting and/or relocation)
- using more sophisticated education and training requirements data
- utilizing more granular, job level data as opposed to occupational generalizations as jobs at different organizations tend to vary even under the same occupational title
- examining city vs. suburban locations

4.5 Public policy recommendations for local governments on their future of work efforts

Local government officials have the opportunity to prepare their citizens for the ways that work is changing in their districts. Bridging the gap between data analysis and policy should start with improvements in data collection, and utilizing
available data in decision making. The recommendations below would serve to build a skilled and resilient workforce by prioritizing future of work policies and aligning employment strategies accordingly.

4.5.1 Collect high-quality data about work and workforce

The existing government data on the skills requirements of jobs is limited. Currently, there are two widely used proxies used in research to identify high level vs. low level skills: 1) occupational education requirements and 2) wages [Autor et al., 2010, 2003; Beaudry et al., 2016; David and Dorn, 2013; Kerckhoff, 2001]. While these measures could reflect the complexity of skills required to a certain extent, the results are highly generalized and not very insightful in determining actionable policy agendas.

The publicly available O*NET data set provides some insights into skills required and tasks attributed to occupations, but it is a static database with not much granularity. The lack of detailed information prevents high accuracy predictions on impact of technological change and how jobs and tasks will be reshaped by these technologies.

More granular data on skills and tasks in the economy would be beneficial to understand the short term impact of new AI technologies. Job postings data, data from training programs at large employers, information on popular college courses, syllabi from successful retraining programs could be alternative methods to collect more granular information on the changing needs of the job market. Governments could benefit from data partnerships with companies such as LinkedIn or Burning Glass Technologies to go beyond the static survey based data collection methods and utilize the active, up-to-date databases, that are currently available to the private sector, in policy making.
4.5 Public policy recommendations for local governments on their future of work efforts

4.5.2 Utilize empirical models in funding decisions for job transfer and training programs

High quality data on jobs is fundamental in better data analysis, but not sufficient to make informed policy decisions impacting the overall labor market. Considering local labor market dynamics, the needs of the workforce, and how the local markets are affected from global labor markets is needed for optimizing resource allocation.

Further data collection would enable much better modeling to predict changes to the workforce. However, the currently existing data sets could still be used more effectively when planning/budgeting for retraining programs. Local governments could utilize models that are similar to what was presented earlier in this chapter as they lay out policies based on the constraints and opportunities in their local labor markets. By partnering with local companies and organizations, they can prioritize training efforts to meet the most pressing needs of the local economy and build specialized training programs to develop skills that are less likely to be automated in the near future.

It is important not to rely entirely on historical data to understand trends when using such data models. While previous shocks to labor market caused by technological changes could show some common patterns, the AI technologies could affect different worker groups in different ways. Various technological applications get adopted first by different industries, replacing or complementing different tasks and job positions. Thus it is important not to overextend the historical results into future predictions.

Ethical concerns should also be taken into consideration while using data models in policy making. Any algorithmic bias in modeling or biased datasets could affect the results and propagate mistakes from the past or any long-embedded biases of the society. Data modeling should serve as a solid starting point, which
4.5 Public policy recommendations for local governments on their future of work efforts

then is accompanied with rigorous qualitative analysis and partnerships with community organizations to identify the best strategies in workforce efforts.

4.5.3 Build tools to empower employees to make better use of job market information

There already exists some mismatch between available job opportunities and people who are looking for new jobs [Patterson et al., 2016; Sahin et al., 2014]. The unknowns around how new technologies will affect jobs over time could exacerbate this issue. An analysis by the World Economic Forum states that most workers whose jobs may be affected from automation will need to find opportunities outside of their current work area, but due to information disconnect, most will not be aware of other opportunities even when they highly match their skill profile [Forum, 2019]. To fix this problem the data used in policy making could be made available for public.

Via an online tool that allows job seekers to find the best transfer options available, workers can seek jobs that match their skill sets under the existing market conditions and expected technological changes. While many workers are interested in getting jobs that can improve their wage and career prospects significantly, they may not have access to the market information to identify the best openings that are suitable for their skill set. A similar tool was developed by Belot et al. for research purposes [Belot et al., 2018]. Such a tool could be empowering for job seekers by enabling them to understand where they stand in the job market relative to others, how technology trends may influence their job prospects, and what opportunities exist in their region, creating an equal ground by informing employees on existing market trends and enabling more fluidity in job markets to increase efficiency.
4.5.4 Incentivize companies to increase in-house training efforts

There seems to be declining investment in employee training programs by employers [Waddoups, 2016]. According to a Harvard Business Review report, many companies cut their HR spending first in case of a financial downturn, which directly impacts the in-house training efforts. Investments in internal training programs seem to have shrunk, and the number of apprenticeship programs are down 36% since 1998 1.

The private sector can be incentivized to join in the efforts to retrain the workforce [Maxim and Muro, 2019]. Companies have significant amount of information on their employees and the requirements of the jobs in their company, and they can meet their changing needs through offering their own training programs, providing tuition support or other benefits that could help with skill-development. Companies can also be encouraged to develop apprenticeship programs to ensure that the training programs meet their changing needs [Institute, 2019]. Data analysis tools can be helpful here in identifying industries that will be affected from technological change the most and partnering with the private companies in these industries whose interests in the changing job markets would be aligned with those of the local governments.

4.5.5 Build support networks and career pathway systems for transitioning workers

Displaced workers may need financial support until they figure out their next career move. For lower income members of the workforce there may be higher need for supportive services as they try to balance the demands of retraining programs

1https://hbr.org/2012/12/who-can-fix-the-middle-skills-gap
4.5 Public policy recommendations for local governments on their future of work efforts

while attending to their daily responsibilities. In the shorter term period, it is likely to see many people taking multiple part time jobs, participating in the gig economy which deprives them from the perks and benefits of a stable full time job. The additional financial burden would make the transition process more challenging for those workers who need time and resources to get retrained.

In addition to funding the identified training and retraining programs to prepare people for job transfers, the local government should also plan supportive services such as child care, mentorship opportunities, post-training follow ups, transportation stipends, and tuition. Under-threat or displaced workers can get enrolled in career counseling programs to identify next steps, and local governments can provide financial support for workers in retraining programs ¹. Providing such services would open up new opportunities to a broader base of workers and enable them to invest in themselves in the most efficient ways possible.

Chapter 5

Conclusions

AI implementations have the potential to impact the nature of occupations, demand for human labor, and career paths across industries in the U.S. and the rest of the world. While no occupation can be fully automated using artificial intelligence technologies in the near term, many occupations have certain tasks that are suitable for AI automation. These results suggest that many jobs may change in terms of their task composition in the future.

The changes in requirements from workers will require restructuring and retraining efforts to prepare today's workers for future job opportunities. Better quality, highly granular data collection can significantly improve our ability to predict the types of changes the modern labor market will face in the near term due to progress in AI technologies. There is room to utilize more data modeling capabilities using existing data sets to improve current policy making processes, showcasing which has been a goal of this paper.

Informed, data driven policy making by local governments regarding future of work would help better prepare their workforce for the upcoming changes. In addition to a top-down approach where available data could be used in policy making, such information can help employees identify the best job options in the market based on their skill sets, broader trends in local labor markets, and new
technologies.
Appendix A

The Suitability for Machine Learning Rubric

1. Task information is recorded or recordable by computer
   1: It is very difficult or impossible to save particular inputs and outputs in a computerized form (e.g. completely recording ideas and strategies, evaluating relationships with coworkers)
   3: It is possible to partially represent inputs and outputs in a digital format (e.g. ranking a series of possible sales leads, recording security footage to evaluate possible dangers)
   5: It is easy to store inputs and results on a machine/computer (e.g. calculation of an account balance, generating a record of a transaction, taking a picture or video recording)

2. Task feedback is immediate
   1: Feedback is never received or takes a very long time (e.g. making art of different kinds, working for world peace)
   3: Feedback is received but response time is inconsistent/unclear and/or unclear on if it is beneficial to progress (e.g. measuring teacher performance using standardized tests)
   5: Feedback and results are instantly received when task is completed (e.g. sending a text message, scheduling a meeting, making a reservation)

3. It is okay to make mistakes when completing this task
   1: A mistake could lead to serious harm, injury, or death to those involved, or could lead to lasting negative consequences (e.g. mistake during surgery, mistake at a nuclear facility)
   3: A mistake will have negative consequences, but can be fixed with some work (e.g. making a clerical error that can be corrected, accidentally writing a
bug in software code)
5: A mistake can be easily fixed, and holds few, if any negative consequences (e.g. delivering packages, scheduling a meeting, walking a dog)

4. It is not important that the task is done by a human
1: Task fundamentally requires human connection (e.g. providing psychological therapy services, making a speech)
3: Task could be done by a non-human, but might cause frustration or inefficiency (e.g. customer service)
5: Task requires little human connection, empathy, or emotional intelligence (e.g. preparing taxes, performing calculations, lifting boxes)

5. Task does not require complex reasoning
1: Task requires intuition or highly involved reasoning (e.g. determining hiring needs, coming up with a research proposal/plan, teaching)
3: Task requires some reasoning, but can mostly be broken into well-defined rules (e.g. playing chess, sorting mail)
5: Task is mainly perception and does not require complex reasoning skills (e.g. catching a ball, recognizing an animal)

6. Task matches labels to concepts, predictions, or actions
1: The task does not have clear, consistent categories or labels (e.g. telling a story)
3: The task potentially has well-defined categories or labels, but does not require mapping of the two (e.g. assigning work to direct reports, deciding which products to sell)
5: The task has clear, consistent categories or labels (e.g. translating one language to another, matching an image to words describing the image)

7. Task involves a brief, simple, highly-structured conversation with a customer or someone else
1: Task does not require any form of communication/conversation with another person (e.g. solving equations, lifting objects, observing)
3: Task involves conversation with others, but it might not be simple or highly-structured (e.g. providing fashion advice, having a meeting in an office)
5: The task involves simple conversations with people with similar structure (e.g. taking orders and reservations at a restaurant, providing directions to locations of interest)

8. Task is repeated frequently
1: The task is not performed often (e.g. fighting a fire, treating rare and specific issues)

3: Task is performed often, but might be done differently each time (e.g. waiting tables, operating a multi-purpose machine, teaching a class)

5: Task is very repetitive, and is done in the same way each time (e.g. working in an assembly line, delivering things along a route, being a cashier)

9. There is no need to explain decisions when doing the task

1: Decisions highly impact the lives of others and require justification (e.g. persuasion, long term planning, lawmaking, courtroom decisions)

3: There is some need to explain decisions, particularly when people ask questions (e.g. doctors performing checkups, operating machinery)

5: There is no need to explain decisions. The task is only concerned with having the correct output, and does not depend on the process through which the output is determined. (e.g. correctly predicting the weather, performing the correct calculation, optimizing allocation of resources, determining quickest route)

10. Task is about choosing between multiple predetermined options.

1: Task output does not have to do with choosing one of a few options (e.g. lifting objects, collecting things, making things)

3: Task output typically isn't presented as choosing between one of a handful of preset options, but might be converted into that format (e.g. recommending a plan, choosing a supply company, setting a price on an item for sale)

5: Task is focused on picking between one of multiple options (e.g. grading food quality, diagnosing common conditions, sorting mail)

11. Long term planning is not required to successfully complete the task

1: The task is concerned with planning around a timeline of months or years (e.g. supervising research projects, constructing complex buildings, entrepreneurship, crafting long term cancer treatment plans)

3: The task is concerned with a timeline in the range of weeks or days or an indeterminate amount of time (e.g. managing others workloads, teaching students a specific set of lessons)

5: The task involves an immediate response and isn't concerned with a future impact (e.g. answer questions in a call center, lifting objects, performing calculations)

12. The task requires working with text data

1: Task does not include working with any text (e.g. making a hamburger, operating machinery)
3. Task may include some light reading and writing (e.g. reading labels, occasionally reading directions)
5. Task includes heavy text processing, reading, or writing (e.g. reading documents, writing a letter)

13. The task requires working with image or video data:
1. Task does not require looking at images or videos, or otherwise using your eyes (e.g. having a phone conversation)
3. Task may occasionally require looking at images and video (e.g. greeting customers, booking a hotel room)
5. Task requires analyzing images and videos (e.g. finding defects in products, looking at surveillance footage, classifying objects in pictures, face recognition)

14. The task requires working with speech data:
1. Task does not require listening to or communicating with speech (e.g. independent tasks such as lifting objects, repetitive assembly work)
3. Task may require occasional listening, talking, or communicating (e.g. construction work, being a cashier, financial analyst)
5. Task requires heavy speech processing, or communicating with speech (e.g. telemarketing, translating between languages, giving a speech, having a conversation)

15. The task requires working with other types of data (other than text, image, video, and speech):
1. Task does not require working with data in any form (e.g. making handmade art)
3. Task requires working with some types of data at a low frequency (e.g. performing restocking tasks at a grocery store, testing machines for maintenance needs)
5. Task requires constant interaction with digital records, sensor data, or other types of data. (e.g. monitoring temperature/weather, analyzing pricing data, pulling and reading medical records)

16. The task can be completed in one second or less
1. Task takes a long time to complete (e.g. making a plan, writing a book)
3. Task cannot be done instantly, but also does not involve much long-term planning (e.g. performing a surgery, delivering food)
5. Task can be done instantly, or can be broken up into smaller choices that can be done instantly (e.g. Identifying a picture)

17. Each instance, completion, or execution of the task is similar to
the other instances in how it is done

1: Task primarily involves rare or unique situations that cannot be summarized easily with machine-readable data (e.g. making strategic decisions for a company)

3: Data can be collected but the data output structure is highly varied (e.g. performing different types of surgery will generate different kinds of feedback)

5: Data are already available or can be easily collected (e.g. customer service transcripts, text translation, image classification, stock price movements)

18. Practicing the task to get better is easy

1: Task involves many rare-occurring or unique situations that make the task hard to practice (e.g. disaster relief, police detective casework)

3: Some parts of the task are possible to practice or learn by repeating (e.g. shipping/receiving in a warehouse, architectural design)

5: Sequences can be repeated and tested over and over again, and there are right moves that can be used to generate rewards (e.g. video games, learning a language)

19. The task is primarily about predicting something

1: The task has little to do with prediction (e.g. writing a novel, washing dishes, installing a solar panel, painting)

3: The task has some components which require predicting something or classifying (e.g. driving a vehicle requires guessing what people might do, forecasting financial results as part of business plan)

5: The task is entirely about prediction or classification (e.g. predicting the weather, identifying pictures with cats in them)

20. This task is part of this occupation (check 1) (this question is also included in reversed form, i.e. this task is not part of this occupation). 1: The occupation will almost certainly never do this task as part of their job (e.g. a teacher devising a business plan, a medical doctor underwriting corporate debt, a lawyer walking a dog).

3: It is unclear if this occupation will have to perform this task (e.g. a retail employee performing customer base analysis, an athlete preparing office documentation).

5: This occupation will have to do this as part of their work (e.g. an accountant has to balance ledgers, a restaurant server will have to wait tables)

21. The task output is not error tolerant (check 2)

1: A mistake can be easily fixed, and holds few, if any negative consequences (e.g. a slip up in factory work or mail sorting mistakes could go potentially
3: A mistake will have negative consequences, but can be fixed with some work (e.g. a construction mistake, or human resources slip-up will be noticed and reprimanded, but would not result in termination of employment or injury)

5: A mistake could lead to serious harm, injury, or death to those involved, or could lead to lasting negative consequences (e.g. mistake during surgery, mistake at a nuclear facility)
Appendix B

Additional plots
Figure B.1: task clusters for lowest growth jobs (2016-2026)
Figure B.2: task clusters for highest growth jobs (2016-2026)
Figure B.3: task clusters for lowest growth jobs (2006-2016)
Figure B.4: task clusters for highest growth jobs (2006-2016)
Figure B.5: Job transfer options for postal service clerks, with better pay and similar skill requirements
Potential job transfers - dispatchers, except police, fire, and ambulance

First-Line Supervisors of Non-Retail Sales Workers
Property, Real Estate, and Community Association Managers
Electricians
Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
Sheriffs and Deputy Sheriffs
First-Line Supervisors of Retail Sales Workers
Sales Representatives, Wholesale and Manufacturing, Except Technical and Scientific Products
Advertising Sales Agents
Rough Carpenters

Figure B.6: Job transfer options for dispatchers, except police, fire, and ambulance, with better pay and similar skill requirements
Figure B.7: Job transfer options for data entry keyers, with better pay and similar skill requirements
Figure B.8: Job transfer options for travel agents, with better pay and similar skill requirements
Potential job transfers - reservation and transportation ticket agents and travel clerks

Figure B.9: Job transfer options for reservation and transportation ticket agents and travel clerks, with better pay and similar skill requirements.
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REFERENCES


REFERENCES


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