

**Eigenplaces: Segmenting Space Through Digital Signatures**

The MIT Faculty has made this article openly available. Please share how this access benefits you. Your story matters.

<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>As Published</td>
<td><a href="http://doi.ieeecomputersociety.org/10.1109/MPRV.2009.62">http://doi.ieeecomputersociety.org/10.1109/MPRV.2009.62</a></td>
</tr>
<tr>
<td>Publisher</td>
<td>Institute of Electrical and Electronics Engineers</td>
</tr>
<tr>
<td>Version</td>
<td>Final published version</td>
</tr>
<tr>
<td>Accessed</td>
<td>Thu Oct 11 09:51:24 EDT 2018</td>
</tr>
<tr>
<td>Citable Link</td>
<td><a href="http://hdl.handle.net/1721.1/52542">http://hdl.handle.net/1721.1/52542</a></td>
</tr>
<tr>
<td>Terms of Use</td>
<td>Article is made available in accordance with the publisher’s policy and may be subject to US copyright law. Please refer to the publisher's site for terms of use.</td>
</tr>
<tr>
<td>Detailed Terms</td>
<td></td>
</tr>
</tbody>
</table>
Francesco Calabrese
Jonathan Reades
Carlo Ratti

Eigenplaces: Segmenting
Space through Digital Signatures
Eigenplaces:
Segmenting Space through Digital Signatures

Francesco Calabrese, Jonathan Reades, and Carlo Ratti

Vol. 9, No. 1
January–March 2010
**Eigenplaces: Segmenting Space through Digital Signatures**

Researchers use eigendecomposition to leverage MIT’s Wi-Fi network activity data and analyze its correlation to the physical environment.

In the past two decades, wireless networks have permeated our public and private spaces, their usage shaped by the built environment’s impact on user activity in the vicinity of transceivers. So, unlike unidirectional radio and television infrastructure, bidirectional wireless data networks can act as probes, propagating data about their users’ environment back to a network observer. This fundamental difference lets us use the volume, timing, and distribution of packets across networks to study the “bricks and mortar” of physical space.

In contrast to the mobile network, Wi-Fi (IEEE 802.11) systems are particularly accessible to researchers because they’re more modest in scale and are often operated by institutions with a vested interest in primary research. To date, most campus Wi-Fi deployment studies have focused on network performance and management or inferred user mobility. However, as Jong Hee Kang and his colleagues note, incorporating the concept of place allows a more sophisticated analysis and understanding of wireless environments. We propose a method to analyze and categorize wireless access points (APs) based on common usage characteristics that reflect real-world, place-based behaviors.

We use eigendecomposition to study the Wi-Fi network at the Massachusetts Institute of Technology (MIT), correlating data generated as a byproduct of network activity with the physical environment. Our approach provides an instant survey of building use across the entire campus at a surprisingly fine-grained level. The resulting eigenplaces have implications for research across a range of wireless technologies as well as potential applications in network planning, traffic and tourism management, and even marketing.

**The MIT Wireless Environment**

Like many universities, MIT has covered its campus with a unified Wi-Fi network; all APs share the MIT network name, enabling 20,000 users to establish more than 250,000 sessions a day. Filippo Dal Fiore and his colleagues found that 73 percent of MIT students bring their laptops to the campus either daily or on most days of the week. So, network activity is a reasonable proxy for many student activities, making it suitable for an aggregate spatial analysis.

During the 14-week 2006 spring semester, we polled each of the 3,053 APs in our data collection infrastructure at 15-minute intervals to determine the number of connected users. (For more information on the collection architecture, see “Mapping the MIT Campus in Real Time Using WiFi” and “Urban Activity Dynamics.”) Although we couldn’t tell what types of content the students, staff, and faculty were accessing, we hoped that the APs’ spatiotemporal access profiles would provide an interesting

---

**Francesco Calabrese**  
*Massachusetts Institute of Technology*

**Jonathan Reades**  
*University College London*

**Carlo Ratti**  
*Massachusetts Institute of Technology*
Figure 1. A Fourier transform of signals from all access points (APs). The transformation highlights the underlying data’s most important cycles—24 hours and one week—by representing the signal as the sum of a set of sinusoidal frequencies multiplied by coefficients.

JANUARY–MARCH 2010

From Eigenvectors to Eigenplaces

Adapting a technique drawn from signal analysis and remote sensing, we applied eigendecomposition to extract the discriminant features from our time-series data (the AP signatures in Figure 2). We represented the number of connections to an AP over time as a vector and assembled the observations from all APs into a single covariance matrix. Following eigendecomposition, we expressed each AP’s original signal as a sum of the matrix’s eigenvectors \( \mathbf{V}_i \), \( i = 1, \ldots, n \) each modified by a coefficient \( C_{ij} \), \( i = 1, \ldots, n \) particular to that AP. So, we describe a signature \( S_i \) observed at a randomly selected access point \( j \) by the equation \( S_i = C_{i1}\mathbf{V}_1 + C_{i2}\mathbf{V}_2 + \cdots + C_{in}\mathbf{V}_n \). We would describe a second AP signature \( S_j \) using the same vector set \( \mathbf{V}_1 \) through \( \mathbf{V}_n \), but with differing coefficients \( C_{j1} \) through \( C_{jn} \).

Applying eigendecomposition to MIT’s network data yields many eigenvector and coefficient pairs; the latter’s magnitude establishes the vectors’ ranking according to their value in reconstituting the original data. Using the mean-square-error test, we determined that only the first four pairs were required to lower this error below a reasonable threshold of 0.1, letting us disregard the remaining eigenvectors and coefficients. Figure 3 shows the four eigenvectors that capture the decomposed signals’ most significant aspects. Negative values on the y-axis are an unavoidable effect of eigendecomposition but aren’t significant for this analysis.

The daily cycle in Figure 1—rapidly rising usage in the early morning followed by a steady decline in the afternoon and evening—is also evident in Figure 3’s first eigenvector. The second vector shows an evening activity pattern that’s sustained on weekends, suggesting residential usage. As we might expect, by the third vector, the plot becomes more difficult to interpret holographically because these vectors express the observed signals’ lesser aspects. So, we were surprised to find that the fourth vector mapped quite clearly onto the usage pattern in building 10, room 250—the large auditorium.

Generating a single set of eigenvectors common to all APs has an important analytical benefit: compression. Because all spaces on campus share the same eigenvectors, we can capture the differences between APs entirely in the coefficients.
So, we can accurately represent thousands of different, noisy, complex, time-varying signals with just four scalar values per hotspot. Figure 4 illustrates how this approach captures the usage variation: the distinctive plot of the auditorium’s four coefficients reflects its equally distinctive usage pattern. The second coefficient is positive for the AP in building 62, room 302 only, reinforcing the residential inference we drew from the raw-signal study.

We term the combination of coefficients describing each AP an eigenplace because it encapsulates the principal components of a space’s telecommunications profile. The eigenplace’s key analytical benefit is that it’s quantitatively comparable to any other place described with the same characteristic vector set. Because the coefficients are simple scalars, we can cluster APs solely on the basis of the similarities and differences between the coefficients, then examine the groups’ distributions across campus.

Although many clustering methods exist, we wanted a bottom-up mapping to avoid imposing our own expectations about campus life on the usage data, so we chose an unsupervised k-means clustering. This approach partitions data such that each observation is as much like its own group’s members, and unlike other groups’ members, as possible. However, the k-means method requires researchers to specify the desired number of clusters, which can allow other preconceptions to intrude. In “Urban Activity Dynamics,” the authors imposed a constraint of three clusters, reflecting MIT’s own tripartite categorization of buildings into academic, residential, and service categories, and found that they could perfectly recreate this classification.

Fortunately, we can gauge clusters’ appropriateness both mathematically and visually using the silhouette plot. Each AP’s silhouette value (s-value) measures how suited it is to its assigned cluster and how far—by whatever measure is appropriate—it is from any other cluster. We calculated the s-value using the squared Euclidean distance across the four dimensions abstracted from the eigen-decomposition process using the following formulation in Matlab: 

\[ S(i) = \frac{(\min(b(i,:),2))}{\max(a(i),\min(b(i,:),2))} \]

where \( a(i) \) is the average distance from the \( i \)th point to all other points in the cluster, and each \( b(i,k) \) is the average distance from the \( i \)th point to all points in another cluster \( k \).

The silhouette plot simply shows the s-value for each cluster element, and the average silhouette measures how appropriately we clustered the data. An s-value close to +1 means that the element is appropriately clustered, whereas an s-value close to −1 suggests the element is quite different from the other elements in the cluster as measured by its distance from the centroid.

When we subjected our results to fitness tests, we were surprised to find that three clusters wasn’t the optimal solution suggested by the data. We now wanted to investigate why evidence existed of more than three distinct Wi-Fi usage types, and determine whether these additional usage types had real-world behavioral correlates.

### Cluster Training on a Partial Data Set

The APs’ complex physical environment makes our clustering algorithm quite sensitive to initial conditions. To manage this risk, we employed a training process to create and calibrate pro-
otype clusters using a subset of the data. Selecting APs from three representative buildings—10 (auditorium, classroom, and administrative), 62 (residential), and the Stata Center (auditorium, food/café, and administrative)—we found that five clusters maximized the average silhouette value; only the fourth cluster showed significant within-cluster distances (see Figure 5a).

The centroid signals in Figure 5b show the clusters’ average signal, which we calculated for each cluster centroid eigenplace and then recombined with the original vectors to generate a composite signal. The cluster 1 centroid suggests residential origins because it maintains relatively heavy weekend usage; cluster 2 demonstrates the large auditoriums’ impact. Clusters 3, 4, and 5 are more difficult to interpret solely on the basis of the centroid. Cluster 3 suggests public spaces because of a low-intensity pattern during both weekends and weekdays. The silhouette plot suggests that cluster 4 will be problematic regardless of our approach. Finally, cluster 5 appears to serve classroom and administrative functions because of the much lower average number of weekend users.

The Department of Facilities-supplied usage type classifications in Figure 5c reinforce our understanding of Figures 5a and 5b. The public spaces in cluster 1 are from the second floor and higher in building 62. The public spaces in cluster 3 are from the ground floors and basements of buildings 10 (academic) and 62 (residential). Cluster 5 is exclusively academic, incorporating classroom and administrative functions. Interestingly, all APs in cluster 4 come from just one building—the mixed-use Stata Center. We aren’t sure why this building shows up in our training data this way, but we speculate that the complex floor plan and mix of uses create difficulties in our clustering approach.

**Cluster Analysis of the Full Data Set**

Using the centroids we obtained from the testing data to populate a second k-means clustering of the entire campus reduces the risk of nonoptimal solutions by ensuring that the test results respect the intercluster differences we identified in Figure 5. The issue arises because of the probability that usage at some outlying APs deviates so far from the norm that it skews the clustering process toward solutions in which most clusters contain just a few extreme APs. Figure 6 suggests that although the data fit is slightly weaker, the overall grouping remains remarkably coherent and the centroids are still quite distinct.

Because we added the rest of the campus, the average s-value of 0.58 in Figure 6a is lower than the training data’s s-value. The centroids for clusters 1 and 3 in Figure 6b demonstrate sustained weekend loads, suggesting important residential components. Cluster 2 has significant peaks every day of the week, indicating that it contains a variety of large-group spaces, which likely caused the large in-group variation in Figure 6a. We expected different departments to use their classroom spaces differently, leading to a lower in-cluster consistency for those APs, and this is the case for cluster 4.

Because public spaces are an important component of each cluster, we analyzed this use category in more detail and found that the spaces varied by cluster in specific ways. Cluster 1 contains public APs with very high traffic levels from buildings 62, 64, and 79 (Simmons Hall), all of which are undergraduate dormitories. Cluster 2 incorporates a small number of high-traffic public spaces, including some from the Sloan School of Management. Cluster 3’s public APs come primarily from residential blocks, but almost exclusively from the second floor and higher, indicating that these aren’t areas open to the general public.
public or nonresident student body. Cluster 4 public APs are principally from the first through fifth floors of the core research, administrative, and classroom buildings. Finally, public spaces from cluster 5 incorporate activity from the most accessible ground and first floors of academic buildings.

Our analysis of Figure 6c implies that researchers need a priori knowledge of each cluster’s constituent APs to extract meaningful information from the data set. However, Figure 7 makes it clear that our approach can impart important information about activity distribution across campus without recourse to any reference data. In effect, Figure 7 is a user-generated campus map, created entirely from anonymous, aggregate wireless data. The features that emerge—the graduate towers and highly connected undergraduate dorms, the academic core, and the lecture halls—are entirely the product of the clustering.

We’ve classified more than 3,000 APs for an entire campus without having to inspect each one in person, and we’ve done so using a method that can provide continuously updated results over time at minimal cost. In combination with observations at a small, stratified sample of hotspots, a large network operator could use an eigenplace analysis to understand the drivers of resource usage across an urban- or national-scale network.

**Limitations**

One challenge when working with wireless network analysis is signal propagation through walls and across floors. We had hoped that the Wi-Fi base stations’ modest footprints would mean that they spanned fewer distinct uses and had correspondingly higher correlation between signature and function. However, abundant evidence indicates that APs in a café might also serve adjacent classrooms or labs. And as the mixed results from the Stata Center suggest, coverage also varies with configuration because signals can propagate in unexpected ways. Nonetheless, correlating against only the use class of the room in which the AP is mounted still yields remarkable results using nothing more than aggregate wireless activity.

As Andres Sevtsuk and his colleagues detailed, there are important constraints on the activities that we can understand solely through network usage. At some places and times, such as during examinations or sporting events, network access is either banned outright or simply uncommon. We also can’t account for Wi-Fi usage demographics, although evidence suggests that staff, graduates, and undergraduates use the network differently. However, this approach’s power is that none of these issues is strictly relevant—we can search for similarities in network node usage without worrying about this difference’s underlying drivers.

![Figure 4. The eigenvectors’ coefficients by location: (a) auditorium, (b) research lab, (c) residential, and (d) library. The first seven eigenvalues highlight the way that lesser values contribute almost nothing to the observed signal. However, the auditorium’s extreme signal is much more difficult to fully capture with just four eigenvalues.](image-url)

W hat’s particularly interesting to us as built-environment researchers is that our method is a user-generated classification of space. Until recently, researchers have had difficulty investigating these aspects of human activity without extensive—and expensive—in-person studies, and this approach enables us to move toward a more nuanced vision of the environment as a
dynamic system, not as a set of static, discrete spaces. Our approach has potentially valuable applications beyond the campus. For example, large advertising-supported systems, whether public or private, have had to balance targeted advertising’s benefits against the privacy risks of snooping on individual users. Our approach offers an alternative that could be both anonymous and sensitive to activity context, including location, time of day, week, and year.

ACKNOWLEDGMENTS

Jonathan Reades’ research was supported by the International Balzan Prize Foundation.

REFERENCES


Figure 7. A 3D plot of campus clusters. Note the similarities between MIT’s official building classification and the eigenplace analysis clusters. The Wi-Fi probes also pick up differences at a finer spatial scale in terms of usage, highlighting within-building usage differences.

the AUTHORS

Francesco Calabrese is a postdoctoral associate at the Massachusetts Institute of Technology’s SENSEable City Laboratory. His research interests include ubiquitous computing; analysis of urban dynamics through sensor networks; and analysis and design of distributed, hybrid, embedded control systems and computer-numerically-controlled machines. Calabrese has a PhD in computer and system engineering from the University of Naples Federico II. He’s a member of the IEEE and the IEEE Control Systems Society. Contact him at fcalabre@mit.edu.

Jonathan Reades is a PhD candidate at University College London, where he is affiliated with the Centre for Advanced Spatial Analysis, part of the Bartlett School of Planning. His research interests include location theory and applying telecommunications data to the analysis of urban form and function. Reades holds a BA in comparative literature from Princeton University, and spent nearly 10 years working for a database mining and marketing firm that offered consultancy services to mobile network operators. He’s a student member of the Royal Town Planning Institute and the Town and Country Planning Association. Contact him at j.reades@ucl.ac.uk.

Carlo Ratti is the director of the MIT SENSEable City Laboratory and an adjunct professor at Queensland University of Technology. He’s also a founding partner (with Walter Nicolinio) and director of the architectural firm carloratti-associati—Walter Nicolinio & Carlo Ratti. Ratti has a PhD from the University of Cambridge. He’s a member of the Ordine degli Ingegneri di Torino and the Association des Anciens Élèves de l’École Nationale des Ponts et Chaussées. Contact him at ratti@media.mit.edu.


