

# Visualizing Instagram: Tracing Cultural Visual Rhythms

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## Abstract

Picture-taking has never been easier. We now use our phones to snap photos and instantly share them with friends, family and strangers all around the world. Consequently, we seek ways to visualize, analyze and discover concealed socio-cultural characteristics and trends in this ever-growing flow of visual information. How do we then trace global and local patterns from the analysis of visual planetary-scale data? What types of insights can we draw from the study of these massive visual materials? In this study we use Cultural Analytics visualization techniques for the study of approximately 550,000 images taken by users of the location-based social photo sharing application Instagram. By analyzing images from New York City and Tokyo, we offer a comparative visualization research that indicates differences in local color usage, cultural production rate, and varied hue's intensities—all form a unique, local, 'Visual Rhythm': a framework for the analysis of location-based visual information flows.

## Introduction

Every moment counts. Or at least so it seems through the eyes of social media users who take countless pictures of everything imaginable, instantly sharing them over the Internet. Instagram, the recent fad in mobile photo sharing applications, provides exactly that: a way to snap photos, tweak their appearance, and share them on various social networks with friends, family and complete strangers. Although only launched in October 2010, its 15 million users have already taken more than 400 million pictures from all over the globe (Instagram 2011).

How are we then to gain insights from this type of massive collective visual production? Can we identify within it different patterns or trends, both on a local and global scale? Differently put, which new forms of knowledge can we extract from the analysis of large-scale visual data? In this paper we visualize and analyze samples from a data set of about 550,000 Instagram photos from New York City and Tokyo, by applying visualization and Cultural Analytics techniques. We discern global and local patterns of repetitive visual information flows that collectively form a 'Visual Rhythm'—spatio-temporal deviations of tone, cultural productivity rates, and cultural color affinities.

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## Background and Related Work

Released exclusively for the iPhone on October 6, 2010, Instagram is a mobile location-based social network application that offers its users a way to take pictures, apply different manipulation tools ('filters') to transform the appearance of an image (for example: fade the image, adjust its contrast and tint, over or under-saturate colors, blur areas to exaggerate a shallow depth of field, add simulated film grain, etc.), and share it instantly with the user's friends on the application itself or through other social networking sites such as Facebook, Foursquare, Twitter, etc.

Our research offers a first glance into potential possibilities in the examination of Instagram photos. It is situated within the recently developed field of Digital Humanities where humanists work with computer sciences to apply data analysis techniques to large sets of cultural artifacts. Specifically, we adopt the methodology and techniques of Cultural Analytics,<sup>1</sup> a paradigm developed within Digital Humanities for working with massive image and video collections. By exploring large image sets in relation to multiple visual dimensions (brightness, saturation, color, texture, etc.) using high resolution visualizations, Cultural Analytics approach allows us to detect patterns which are not visible with standard interfaces for media viewing.

In contrast to standard visualizations which represent data as points, lines, and other graphical primitives, Cultural Analytics visualizations show all images in a collection. This paper uses three such visualization techniques. Similar to a scatter plot, an ImagePlot positions images according to their visual features. Montage is a 2D grid of images arranged according to their metadata (such as upload dates). Slice is a sequence of parts of the images (such as a vertical column of pixels in the center of an image) also arranged according to metadata.

Prominent similar research examples include the visualizations of one million Manga pages (Manovich, Douglass, and Huber 2011), Time magazine covers from 1923 to 2009 (Manovich 2011a), and the comparison of various artworks such as Piet Mondrian vs. Mark Rothko (Manovich 2011b).

Several studies have also examined geo-tagged images collected from users and web services like Flickr. These

<sup>1</sup><http://lab.softwarestudies.com/2008/09/cultural-analytics.html>

projects mostly used content analysis methods based on text tags and geo-spatial data, with limited visual analysis to offer enhanced search, representation and behavioral patterns mapping for different locations around the world (Crandall et al. 2009; Kisilevich et al. 2010; Kennedy and Naaman 2008).

### Methodology

Our study relies on Cultural Analytics tools and techniques developed by the Software Studies Initiative at the University of California, San Diego.<sup>2</sup> Using Instagram’s API, we downloaded approximately 550,000 photos from New York City and Tokyo over a two months time frame (January 1st, 2012 - February 27th, 2012), based on latitude and longitude criteria. The images were downloaded together with their meta data: user ID, location (latitude/longitude), comments, number of ‘likes’, date of creation, type of filter and tags.

We measured the properties of each image by using the QTIP digital image processing application that provided us with measurement files listing the means values of brightness and red, green and blue use in each image.<sup>3</sup> We then used the ImageJ software to perform the visualization of the data.<sup>4</sup> More specifically, we processed and applied the ImagePlot macro to create high resolution visualizations which scatter plot graphs of images over X and Y axis.<sup>5</sup> In addition, we used the ImageMontage macro to produce a large canvas populated by thumbnails of the examined collection of images.<sup>6</sup> Finally, we used the ImageSlice macro to create a high resolution ‘slice’ view of an image collection over specific time periods.<sup>7</sup>

### Results

Using ImageJ’s Montage function we produced a visualization of a sample of images from Tokyo (53,498 files) and NYC (57,983 files) representing a week long period between the 18th and the 25th of February 2012. The montage algorithm re-sized the images and placed them in a chronological order from earlier to later that resulted in a large canvas populated by small thumbnails. (Figure 1)

As seen from the truncated montage results, both cities display ‘waves’ of brighter and darker images according to the time of day, depicting the recurrent shifts of day and night. In both visualizations we can see four nights and four days displayed from top to bottom from Wednesday until Saturday. We can notice that towards the weekends there are more darker images during night time. (Figure 2)

In addition, we can see that the amount of images during weekend days is larger than during weekdays and also darker during the nights. In this way, Friday, Saturday and Sunday nights display darker colors than weekday nights.

We also noticed a perceptible hue difference between the two cities. To examine this finding, we calculated the mean

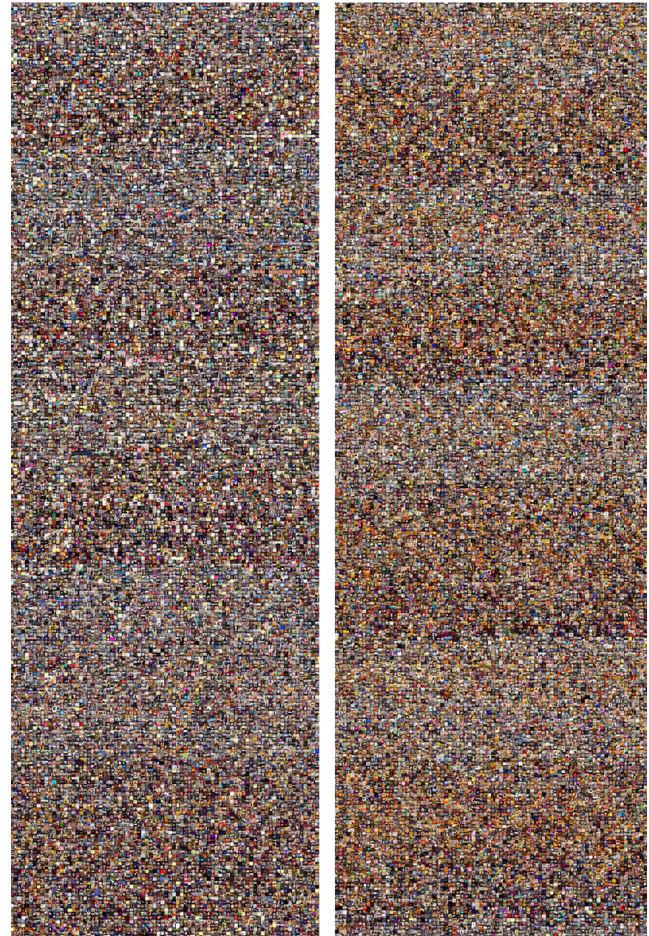


Figure 1: Sample of Four Days from the Montage Visualization: 57,983 images from NYC (left), 53,498 images from Tokyo (right)

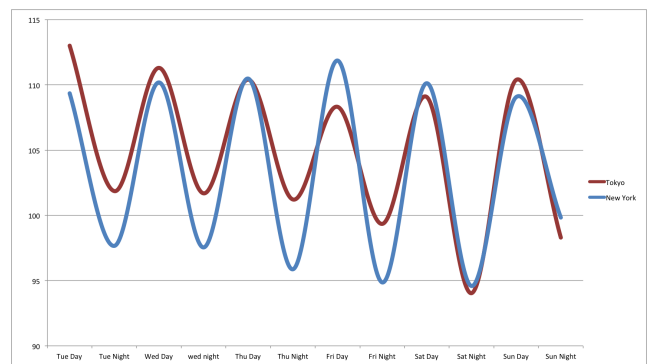


Figure 2: Daily Brightness Shifts: NYC (blue), Tokyo (red)

<sup>2</sup><http://lab.softwarestudies.com/>

<sup>3</sup><http://culturemaps.net/software/qtip-qtimageextractor/>

<sup>4</sup><http://rsbweb.nih.gov/ij/>

<sup>5</sup><http://lab.softwarestudies.com/p/imageplot.html>

<sup>6</sup><http://rsbweb.nih.gov/ij/plugins/image-montage/index.html>

<sup>7</sup><http://rsbweb.nih.gov/ij/plugins/image-slice/index.html>



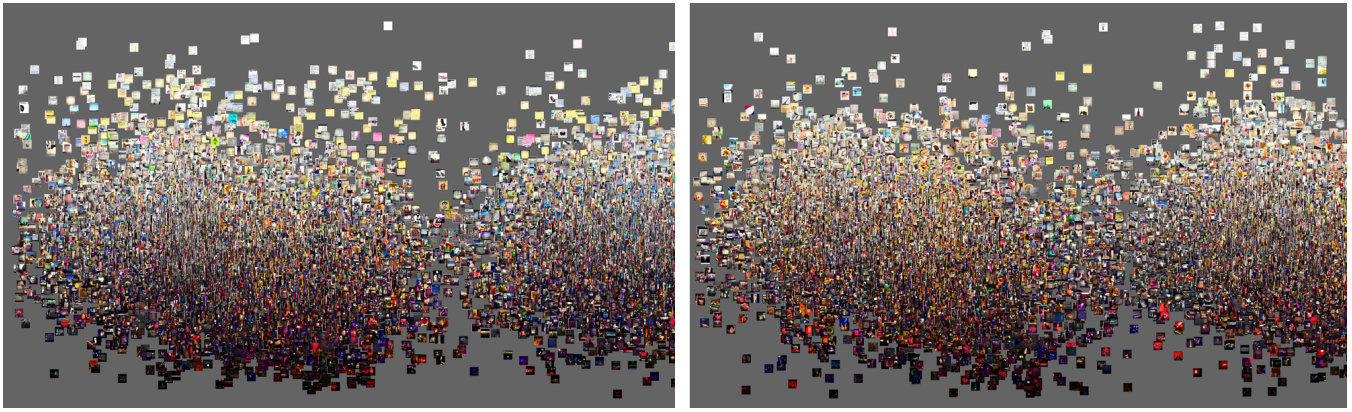


Figure 5: 36 Hours of Brightness: 12,023 images from NYC (left), 10,611 images from Tokyo (right)

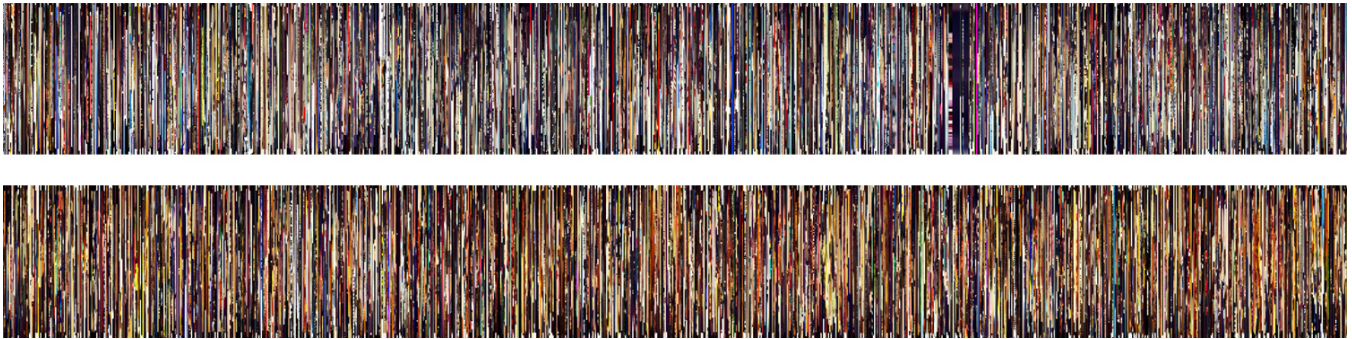


Figure 6: Slice Visualization of February 23rd, 2012: 7,621 images from NYC (top), 7,034 images from Tokyo (bottom)

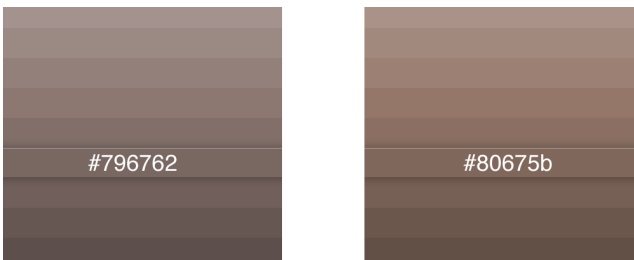


Figure 3: Local Color Scales: NYC (left): #796762, Tokyo (right): #80675b

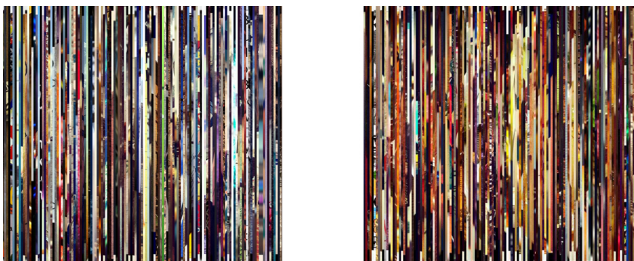


Figure 4: 91 Images Sample from Slice Visualization: NYC (left), Tokyo (right)

of the red, green and blue values of each image in our data set and then an average mean of the entire data. In this way, the results showed that the average values of New York City are: R 121, G 103, B 98 and for Tokyo are: R 128, G 103, B 91. (Figure 3)

To measure the significance of the results we performed an unpaired two-tailed T-Test on each of the colors' data, comparing the average red, green and blue mean values of all images from New York City to those of Tokyo. The output confirmed the significance of the results portraying a difference in the use of red and blues in each of the cities. New York's montage therefore can be characterized with dominant blue-gray hues while Tokyo's montage is characterized by dominant red-yellow tones. These results can be practically perceived through the visualizations.

The second visualization technique uses ImagePlot to map changes in the brightness mean of images over time. In this study we chose to visualize a time span of a day and a half (36 hours). The selected dates were Feb 25th from 12pm until Feb 26th at 11:59pm EST. (Figure 5) The visualizations are made out of an X axis representing time and Y axis displaying the brightness mean of an image. In this way, images are ordered by their brightness on a time line.

The results show the changes in the amount of bright and dark images throughout the day. Starting with a bright batch of images in the morning until noon to darker group of im-

ages during night time. This visualization also shows the spread of images throughout the day and thus we can discern daily changes in the rate of image-taking.

In addition, similarly to the results of the montage, we can also notice a significant color difference between the two cities. In the New York City visualization there is a color tendency towards the blue shades whereas the Tokyo image shows high dominance of red-yellow hues.

To reinforce our results we also used ImageJ Slice visualization macro with a 24 hour data set from the 23rd of February 2012 from both cities. The macro created a strip of truncated 5px wide stripes from every image (with an X-axis offset of 50%) and placed them in a chronological order from left to right. (Figure 6) By comparing the two cities we discern significant color use differences. (Figure 4)

## Discussion

### Visual Rhythm

As shown in our results, we can identify reoccurring spatio-temporal visual deviations in a specific time period and a set place. We offer to typologize these deviations by a time-space-patterned approach, to capture differences as they unfurl over time and place. By measuring the geo-tagged images' timestamps, intensity and dominant colors, we conceptualize a spatio-temporal 'Visual Rhythm': a way of understanding geo-tagged visual information flows on a large scale. In this way, our visualizations present repeating 'beats' formed by three congruent characteristics: Local Color; Visual Weight; and Day Intensity. We suggest this typology as a way to read ongoing flows of large scale visual data that carry similar location and time characteristics.

**Local Color** Our results show the interplay between specific visual attributes such as color and their corresponding geo-spatial location. As shown above, we located dominant tones which correlate with specific cultural territories. As known from traditional color theory (Albers 2006), we borrow the term 'local color'—the depiction of the natural color of an object—to identify the local or intrinsic color of a culture within a specific territorial range. In this way, we show that we can potentially color-map various local and global areas, identify dominant tones, discern differences and similarities and verify or question traditional color-identifications in regard to specific cultural locations.

**Visual Weight** Visual Weight represents the amount of images generated by users during a specific time period. For example, in our results we can see the different number of images produced in each day and how this changes over time. (Figure 1) The visual weight of weekends (Friday, Saturday and Sunday) is heavier than weekdays, suggesting users are more active during these times. Visual Weight can point to deviations in daily usage, measure the rate of cultural productivity and trace unique events (such as holidays, catastrophes, etc.) on a planetary scale.

**Day Intensity** Day Intensity refers to the amount of hue, brightness, saturation and other image attributes used during a certain day. In this way, a day that will include very bright or dark hues can imply to different cultural productions and

activities. In both of the montage visualizations we noticed darker hues during later hours of weekend nights implying specific spatio-temporal social cultural activities. (Figure 2)

**Limitations** It should be noted that the data in our study is based on a limited survey of only two cities during a specific time period. Moreover, the use of Instagram can be attributed to a specific demographic that is limited to iPhone owners that downloaded and registered for the service.

## Conclusion

This preliminary study offers a first glance into the visualization and investigation of visual social location-based media data. By applying Cultural Analytics techniques, we identify reoccurring 'Visual Rhythms' that provide insights into the study of different cultural practices on a local and global scale. Future research should examine the ways these patterns apply to a broader array of locations over long durations, and may also address other intrinsic features of Instagram's metadata (such as its filter usage, tags, etc).

As our study concludes, every Visual Rhythm indeed beats differently, portraying the way a culture manifests itself through its collective visual production.

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