The Science of Culture?

Theory and examples of computational analysis of visual culture

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03/2016

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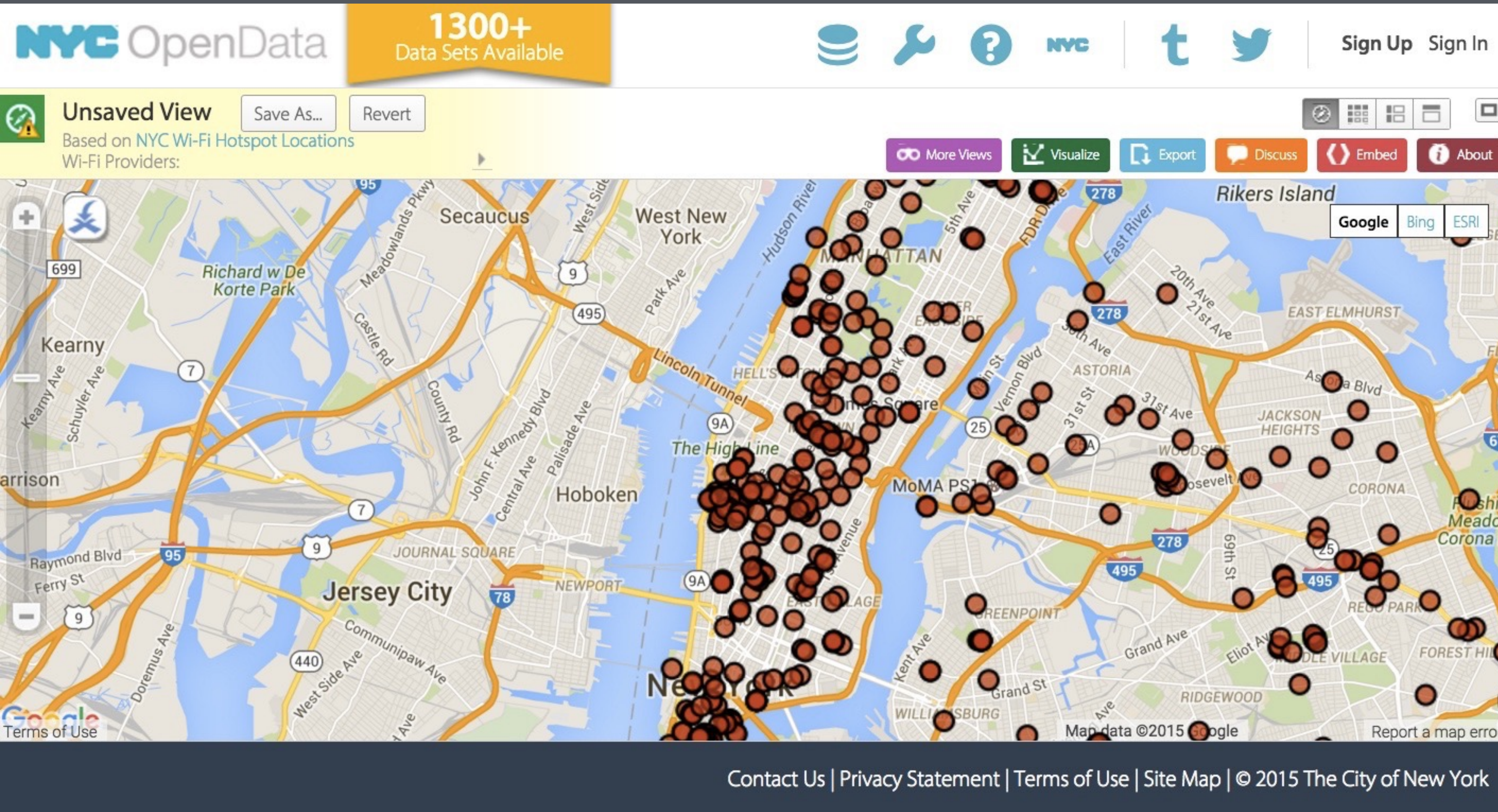
www.softwarestudies.com

2004 - present:
new types / cheaper **urban sensors;** new ways to **capture human behavior / new forms of digital culture**

- social media + user generated content
- higher resolution satellite photography
- location + movement data (phones)
- Arduino for interfacing with sensors
- data from city bike programs
- open data movement
- etc.


NYC OpenData
1300+
Data Sets Available
Sign Up
Sign In
Unsaved View
Save As...
Revert
Based on NYC Wi-Fi Hotspot Locations
Wi-Fi Providers:
More Views
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Bing
ESRI
Secaucus
West New York
Rikers Island
MANHATTAN
Richard w De Korte Park
Kearny
EAST ELMHURST
ASTORIA
JACKSON HEIGHTS
The High Line
Hoboken
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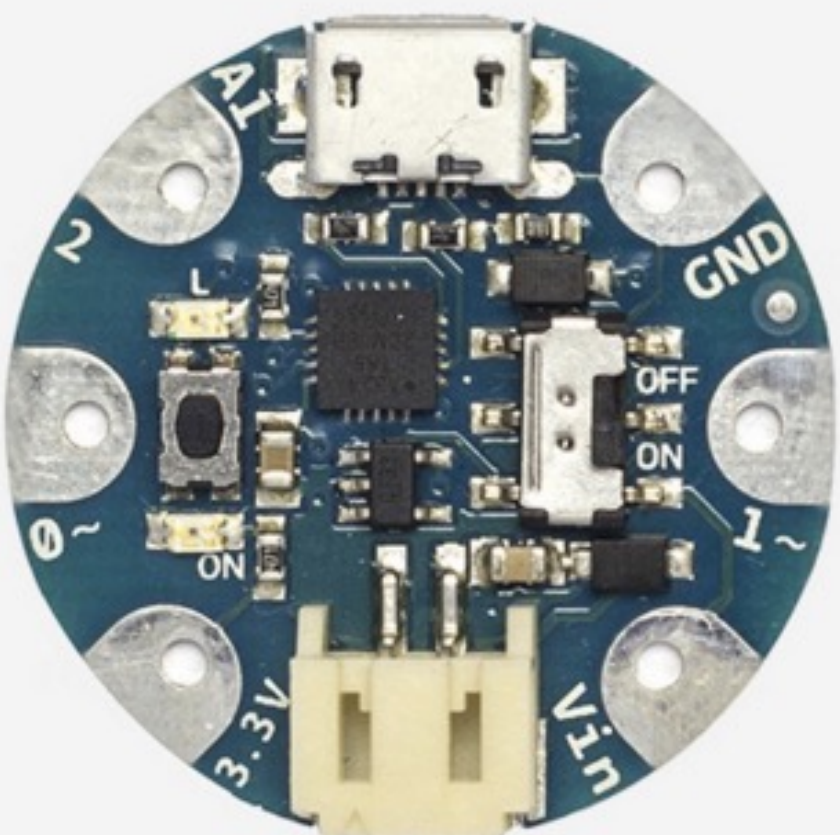
ARDUINO PRODUCTS > Arduino Gemma



Arduino Gemma

Arduino Gemma is a miniature wearable microcontroller board based on the ATtiny85. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a battery to get started on your wearable projects!

GETTING STARTED | SHOP NOW

Overview

Technical Specs

Overview

3.3V | 8-bit | 8 MHz | ATtiny85

Hall Element Hall Switch sensor Magnetic for Detect

$1.59 ~~$4.59~~

1pcs HC-SR04 Ultrasonic Module Distance

$1.59 ~~$2.45~~

5pcs KY008 Laser Transmitter Module for

$4.29 ~~$7.29~~

ICSG010A PIR Motton Sensor Infrared module

$2.12 ~~$5.12~~

3-axis ADXL335 Analog Output Accelerometer

$2.84 ~~$5.84~~

2pcs KY-008 Laser Transmitter Module for

$2.09 ~~$5.09~~

10pcs TCRT5000 Infrared Reflective Photoelectric

$7.56 ~~$10.56~~

DHT22 AM2302 Digital Temperature and Humidity

$6.29 ~~$9.29~~

HX711 Weight Sensor 2.6-5.5V 10HZ/80Hz 1mA

$2.00 ~~$5.00~~

5PCS Soil Humidity Sensor Module Hygrometer

$3.79 ~~$6.79~~

Correlation Photoelectric Switch Infrared Sensor

$3.91 ~~$6.91~~

Capacitive Touch Dimmer LED Dimmer Precise PWM

$2.24 ~~$5.24~~

2006 - present:

new research fields that use **big cultural data** (including social media, user generated content and digitized cultural heritage) to study social and cultural patterns and cultural histories

-social computing

-computational social science

-other CS fields: computer vision, media computing, web science, NLP

-science of cities, urban analytics

-digital humanities, digital history, digital art history

Web Images More... manovich.lev@gm

Google twitter dataset

Scholar About 329,000 results (**0.04** sec) My Citations 20

Articles
Case law
My library

Any time
Since 2015
Since 2014
Since 2011
Custom range...

Sort by relevance
Sort by date

include patents
include citations

Create alert

Enhanced sentiment learning using **twitter** hashtags and smileys [PDF] from aclweb.org
D Davidov, O Tsur, A Rappoport - Proceedings of the 23rd International …, 2010 - dl.acm.org
... If there are no matching vectors found for v, we assigned the default "no sentiment" label since there is significantly more non-sentiment sentences than sentiment sentences in **Twitter**. 4 **Twitter dataset** and sentiment tags ... 4.1 **Twitter dataset** ...
Cited by 363 Related articles All 17 versions Cite Save

Semi-supervised recognition of sarcastic sentences in **twitter** and amazon [PDF] from aclweb.org
D Davidov, O Tsur, A Rappoport - Proceedings of the Fourteenth …, 2010 - dl.acm.org
... Using the Mechani- cal Turk we created a gold standard sam- ple in which each sentence was tagged by 3 annotators, obtaining F-scores of 0.78 on the product reviews **dataset** and 0.83 on the **Twitter dataset**. ... **Twitter Dataset**. ...
Cited by 148 Related articles All 23 versions Cite Save

Predicting flu trends using **twitter** data [PDF] from psu.edu
H Achrekar, A Gandhe, R Lazarus… - … WKSHPS), 2011 IEEE …, 2011 - ieeexplore.ieee.org
... Until October 23, 2010 we have collected 4.7 million tweets from 1.5 million unique users from **Twitter**. Since CDC does not provide weekly ILI activity data for the period from May 23, 2010 to October 9, 2010, we have 31 weeks of CDC data for the **Twitter dataset**. ...
Cited by 141 Related articles All 13 versions Cite Save

Why we **twitter**: understanding microblogging usage and communities [PDF] from umbc.edu
A Java, X Song, T Finin, B Tseng - Proceedings of the 9th WebKDD and …, 2007 - dl.acm.org
... Based on our study of the communities in **Twitter dataset**, we observed that this is a representative community in **Twitter** network: people in one community have certain common interests and they also share with each other about their personal feeling and daily experience. ...
Cited by 2403 Related articles All 24 versions Cite Save

[PDF] Measuring User Influence in **Twitter**: The Million Follower Fallacy. [PDF] from aaai.org
M Cha, H Haddadi, F Benevenuto, PK Gummadi - ICWSM, 2010 - aaai.org
... Page 2. The **Twitter dataset** used in this paper consists of 2 billion follow links among 54 million users who produced a total of 1.7 billion tweets. ... **Dataset** We asked **Twitter** administrators to allow us to gather data from their site at scale. ...
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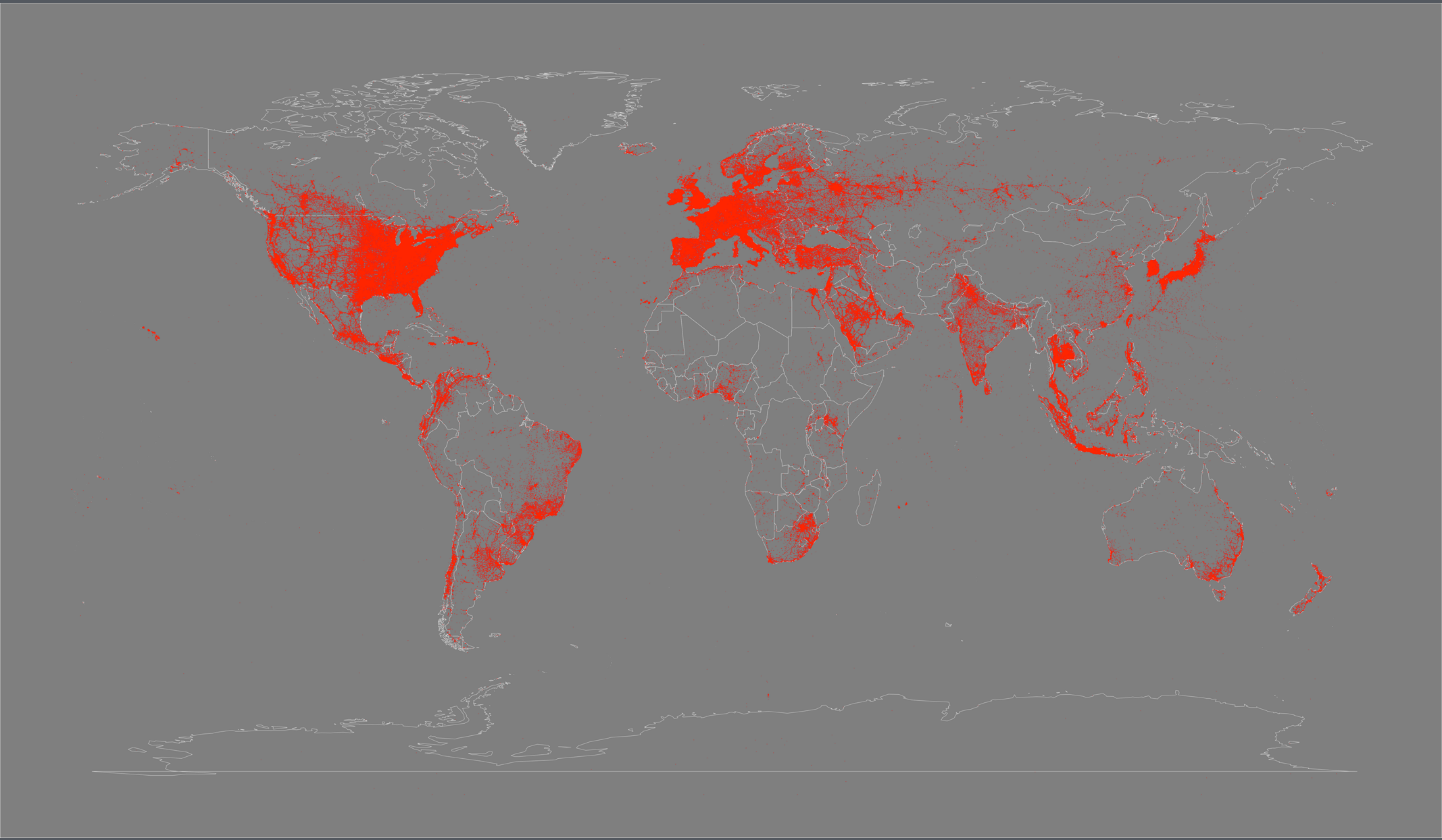


We have to always remember that not everybody is using social media.
Example: our map of 100 million tweets with images (sampled from 265 million tweets, 2011-2014)

Key characteristics of social media relevant for the study of cultural and social patterns:

1
very high spatial and temporal resolution in cities (time and location metadata)

2
automatic detection of subjects + styles + sentiment

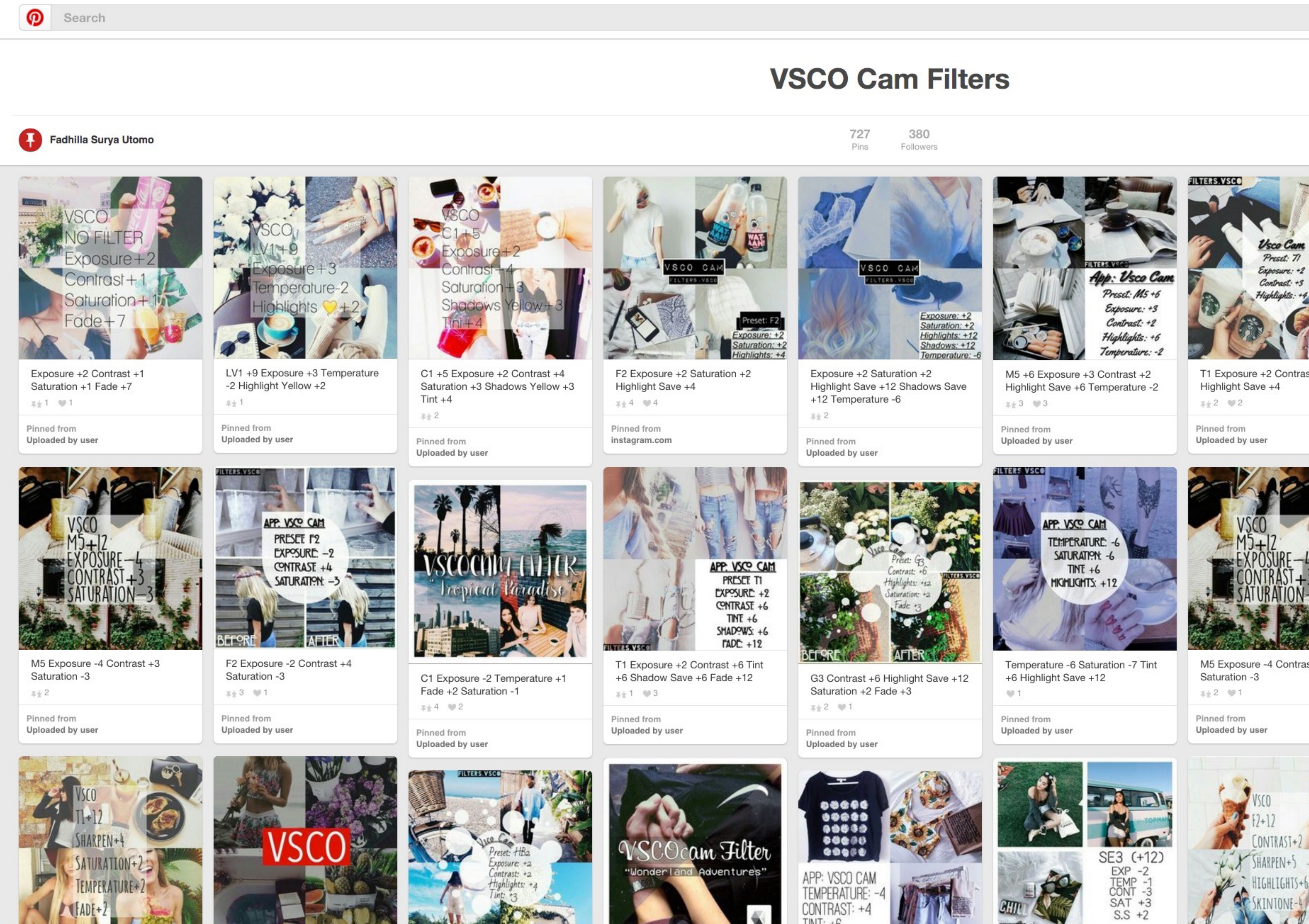
3
connectivity (content propagation, influences, groups, structure of networks)

4

engagement: likes, comments, shares, web navigation, gameplay, etc. -

for the first time, we can study **cultural reception** on mass scale data allows us to qualitatively study interactions between -

a) people (online and physically)
b) people and spaces
c) people and cultural software tools
d) people and cultural artifacts (“reception,” “engagement”)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VSCO Cam Filters
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380 Followers
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C1 +5 Exposure +2 Contrast +4 Saturation +3 Shadows Yellow +3 Tint +4
F2 Exposure +2 Saturation +2 Highlight Save +4
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M5 +6 Exposure +3 Contrast +2 Highlight Save +6 Temperature -2
T1 Exposure +2 Contrast Highlight Save +4
M5 Exposure -4 Contrast +3 Saturation -3
F2 Exposure -2 Contrast +4 Saturation -3
C1 Exposure -2 Temperature +1 Fade +2 Saturation -1
T1 Exposure +2 Contrast +6 Tint +6 Shadow Save +6 Fade +12
G3 Contrast +6 Highlight Save +12 Saturation +2 Fade +3
Temperature -6 Saturation -7 Tint +6 Highlight Save +12
M5 Exposure -4 Contra Saturation -3
Pinned from Uploaded by user
Pinned from instagram.com
VSCO
VSCOcam Filter
"Wonderland Adventures"

Google aesthetic computing prediction

Scholar

About 32,600 results (**0.06** sec)

Articles

Case law

My library

Any time

Since 2015

Since 2014

Since 2011

Custom range...

Sort by relevance

Sort by date

include patents

include citations

Create alert

High level describable attributes for **predicting aesthetics** and interestingness
S Dhar, V Ordonez, TL Berg - Computer Vision and Pattern ..., 2011 - ieeexplore.ieee.org
... Some of these pictures are extremely beautiful and **aesthetically** pleasing, but the vast majority are uninterest- ing ... Next we demonstrate that these high level attribute pre- dictors are useful for estimating **aesthetic** quality (DPChal ... Results on **aesthetics** for DPChallenge are in Sec ...
Cited by 137 Related articles All 25 versions Cite Save

Studying **aesthetics** in photographic images using a **computational** approach
R Datta, D Joshi, J Li, JZ Wang - Computer Vision–ECCV 2006, 2006 - Springer
... paper that there exist certain visual properties which make photographs, in general, more **aesthetically** beautiful ... for choosing classes with a gap is that pictures with close lying **aesthetic** scores, eg ... the features values to see if it is possible to directly **predict** the **aesthetics** scores in ...
Cited by 454 Related articles All 7 versions Cite Save

[PDF] **Prediction**-driven **computational** auditory scene analysis
DPW Ellis - 1996 - sound.media.mit.edu
... Would that it were not so; elegance is surely the ultimate **aesthetic** good in science as in art, but my chosen goal dictates otherwise. ... **prediction** error ... Figure 1.2: Overview of the goal, a **computational** auditory scene analysis system (described in detail in chapters 3 and 4). ...
Cited by 406 Related articles All 16 versions Cite Save More

Asymptotic behaviors of support vector machines with Gaussian kernel
SS Keerthi, CJ Lin - Neural computation, 2003 - MIT Press
... Soft **Computing**. Online publication date: 24-Jul-2014. ... (2014) **Prediction** of shear wave velocity using empirical correlations and artificial intelligence methods. NRIAG Journal of Astronomy and Geophysics 370-81. ... **Computers** & Operations Research 43328-334. ...
Cited by 1194 Related articles All 19 versions Cite Save

Predicting users' first impressions of website **aesthetics** with a quantification of percei
visual complexity and colorfulness
K Reinecke, T Yeh, L Miratrix, R Mardiko... - ... Factors in **Computing** ..., 2013 - dl.acm.org

___cvpr2014_final (1).pdf (page 1 of 8)

6 Seconds of Sound and Vision: Creativity in Micro-Videos

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[2]Universitat Pompeu Fabra, Barcelona, Spain {trevisiol}@acm.org
[3]Università degli Studi di Torino, Torino, Italy {schifane}@di.unito.it

Abstract

The notion of creativity, as opposed to related concepts such as beauty or interestingness, has not been studied from the perspective of automatic analysis of multimedia content. Meanwhile, short online videos shared on social media platforms, or micro-videos, have arisen as a new medium for creative expression. In this paper we study creative micro-videos in an effort to understand the features that make a video creative, and to address the problem of automatic detection of creative content. Defining creative videos as those that are novel and have aesthetic value, we conduct a crowdsourcing experiment to create a dataset of over 3,800 micro-videos labelled as creative and non-creative. We propose a set of computational features that we map to the components of our definition of creativity, and conduct an analysis to determine which of these features correlate most with creative video. Finally, we evaluate a supervised approach to automatically detect creative video, with promising results, showing that it is necessary to model both aesthetic value and novelty to achieve optimal classification accuracy.

the Tribeca Film Festival in New York.

Not all micro-videos uploaded on social media platforms are creative in nature (1.9% of randomly sampled videos were annotated as creative in our study), and quality can vary widely. This motivates the need for automatic approaches to detect and rank the best, and in particular the most *creative*, micro-video content on social media platforms. Such applications can increase the visibility of video authors, and replace or augment current features of social-media platforms such as "Editors Picks", which showcases the best content on Vine.

Micro-videos provide a unique opportunity to address the study of audio-visual creativity using computer vision and audio analysis techniques. The very short nature of these videos means that we can analyze them at a micro-level. Unlike short video sequences within longer videos, the information required to understand a micro-video is contained within the video itself. This allows us to study audio-visual creativity at a fine-grained level, helping us to understand what, exactly, constitutes creativity in micro-videos.

In this paper we study the audio-visual features of *cre-*

Group	Feature	Dim	Description
			AESTHETIC VALUE
			Sensory Features
Scene Content	*Saliency Moments* [26]	462	Frame content is represented by summarizing the shape of the salient region
Filmmaking Technique	*General Video Properties*	2	*Number of Shots*, *Number of Frames*
	Stop Motion	1	Number of non-equal adjacent frames
	Loop	1	Distance between last and first frame
	Movement	1	Avg. distance between spectral residual [9] saliency maps of adjacent frames
	Camera Shake	1	Avg. amount of camera shake [1] per frame
Composition and Photographic Technique	*Rule of Thirds* [5]	3	HSV average value of the inner quadrant of the frame (*H(RoT),S(RoT),V(RoT)*)
	Low Depth of Field [5]	9	LDOF indicators computed using wavelet coefficients
	Contrast [6]	1	Ratio between the sum of max and min luminance values and their difference
	Symmetry [27]	1	Difference between edge histograms of left and right halves of the image
	Uniqueness [27]	1	Distance between the frame spectrum and the average image spectrum
	Image Order [28]	2	Order values obtained through Kologomorov *Complexity* and Shannon's Entropy
			Emotional Affect Features
Visual Affect	*Color Names* [17]	9	Amount of color clusters such as red, blue, green, ...
	Graylevel Contrast Matrix Properties [17]	10	*Entropy, Dissimilarity, Energy, Homogeneity* and *Contrast* of the GLCM matrix
	HSV statistics [17]	3	Average *Hue, Saturation and Brightness* in the frame
	Pleasure, Arousal, Dominance [30]	3	Affective dimensions computed by mapping HSV values
Audio Affect	*Loudness* [15]	2	Overall *Energy* of signal and avg *Short-Time Energy* in a 2-seconds window
	Mode [15]	1	Sums of key strength differences between major keys and their relative minor key
	Roughness [15]	1	Avg of the dissonance values between all pairs of peak in the sound track spectru
	Rythmical Features [15]	2	*Onset Rate* and *Zero-Crossing Rate*
			NOVELTY
Novelty	*Audio Novelty*	10	Distance between the audio features and the audio space
	Visual Novelty	40	Distance between the visual features and each visual feature space

Table 4. Audiovisual features for creativity modeling

Preview File Edit View Go Tools Window Help 2.81 GB 49% Sat Nov 14 8:45 AM

____cvpr2014_final (1).pdf (page 7 of 8)

Feature	**Accuracy**		
	D-60	**D-80**	**D-100**
Aesthetic Value			
Sensory Features			
Scene Content	0.67	0.69	0.74
Filmmaking Techniques	0.65	0.69	0.73
Composition & Photographic Technique	0.67	0.74	**0.77**
All Sensory Features	0.69	**0.75**	0.77
Emotional Affect Features			
Audio Affect	0.59	0.53	0.67
Visual Affect	0.65	0.66	0.66
All Emotional Affect Features	0.62	0.56	**0.71**
All Aesthetic Value Features	0.68	0.72	**0.79**
Novelty			
Audio	0.58	0.58	0.63
Visual	0.63	0.67	**0.74**
Audio + Visual Novelty	0.59	0.63	0.69
Novelty + Aesthetic Value	0.69	0.73	**0.80**

Table 5. Prediction results for value and novelty features

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emotions, and don
emotions. Loop a
designed for model
high correlation wi
associated with bea
tions with creative
between creativity
color, symmetry a
modeling beauty ar
creative *micro-vide*
Finally, we eval
cation of creative *n*
overall, with a high
The best results are

social networks as medium and message

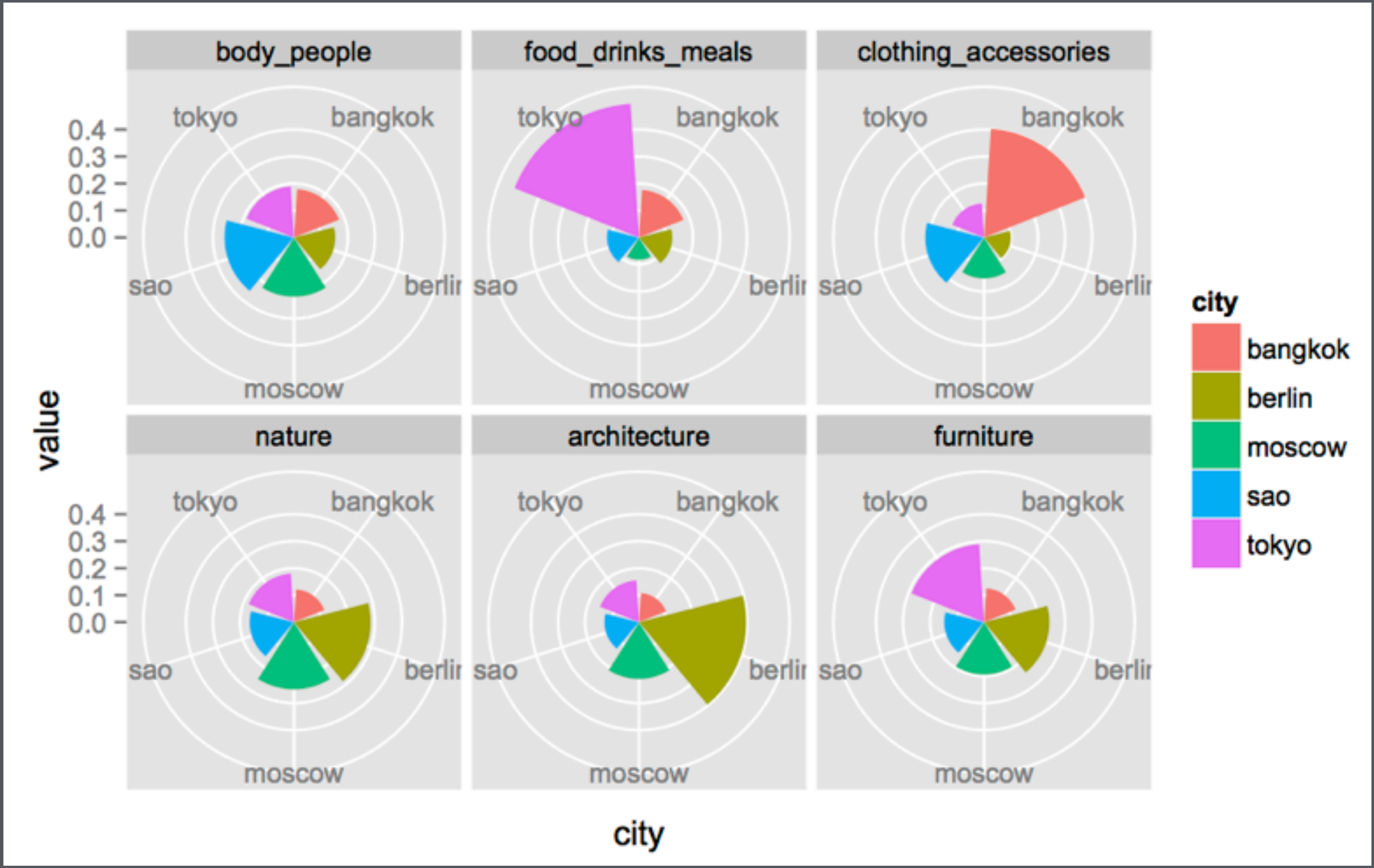
(using Instagram as the example)

message 1 (“surface”): what people who use social networks say, do, capture

message 2 (“depth”): what they “really” say, do, and how they live

medium 1: digital vernacular photography as it exists on Instagram

medium 2: Instagram as its own visual, narrative and networked media platform


body_people
food_drinks_meals
clothing_accessories
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furniture
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Журналист

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Вместе с 4 книгами „Библиотеки журналиста" в год — 10 руб., 6 м.—5 руб. 50 коп.,
ПЕРЕВОДЫ АДРЕСОВАТЬ: Москва, 6, Страстной бульв., д. 11 Акц. Изд. О-ву „Огонек".
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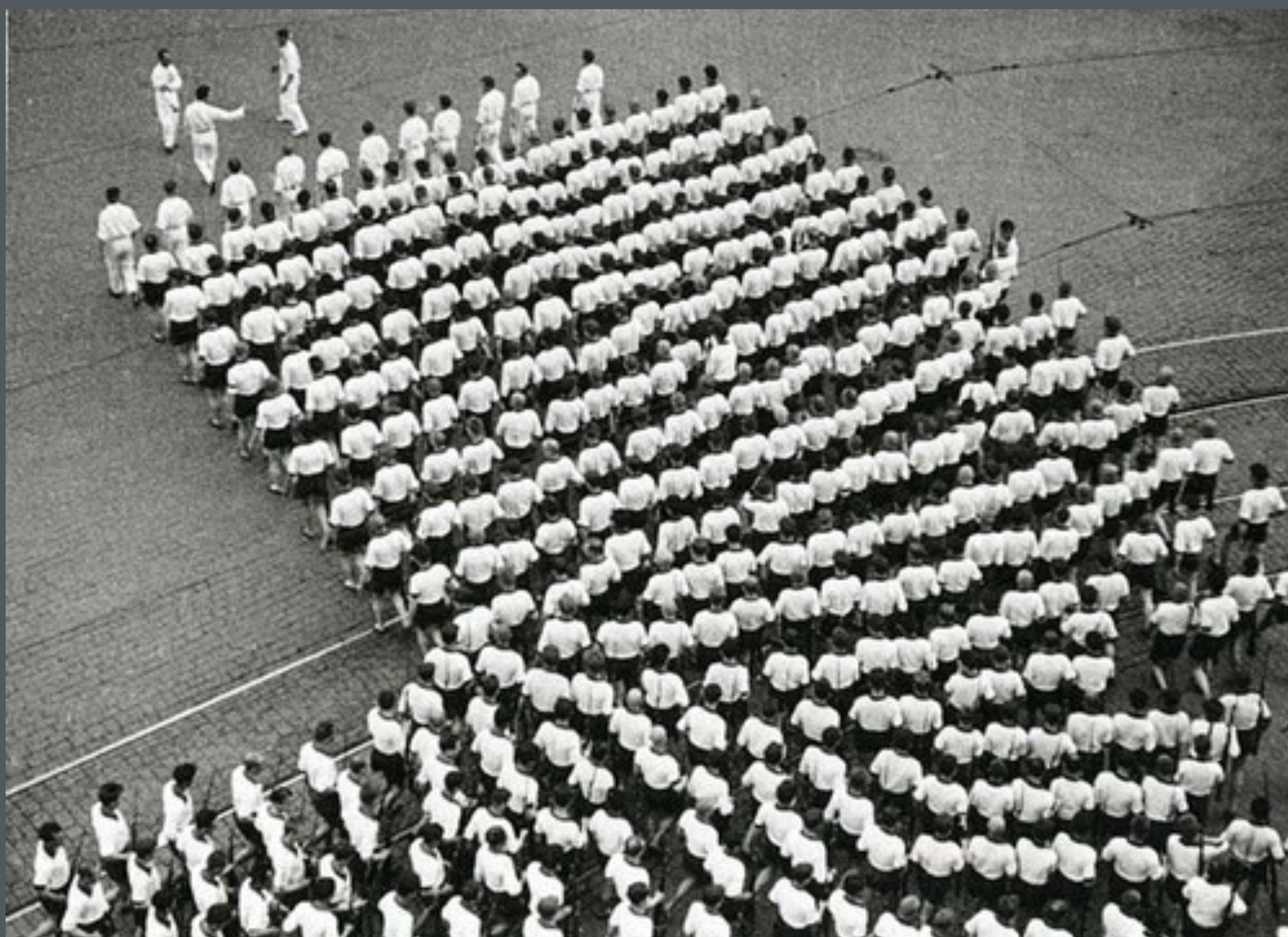
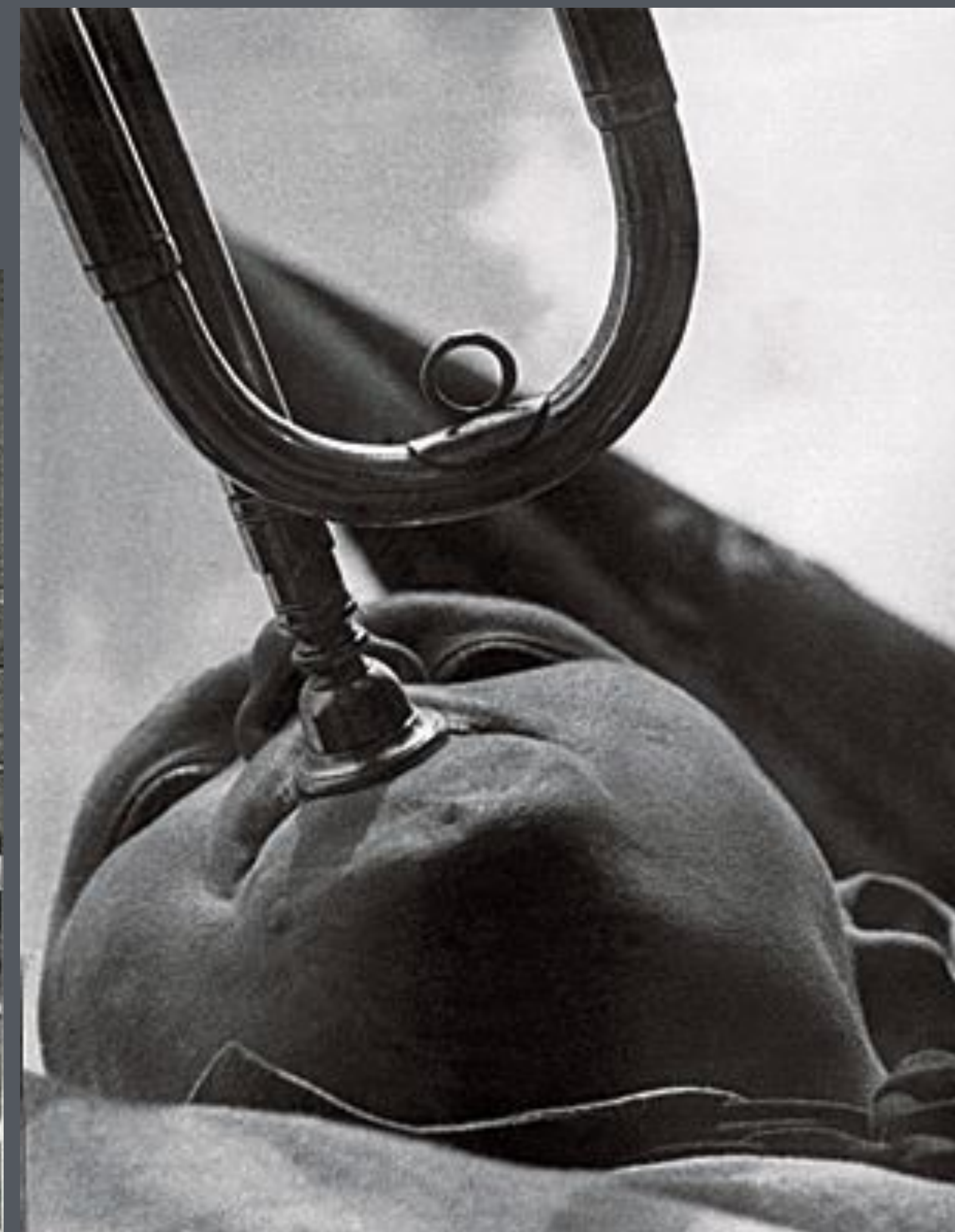
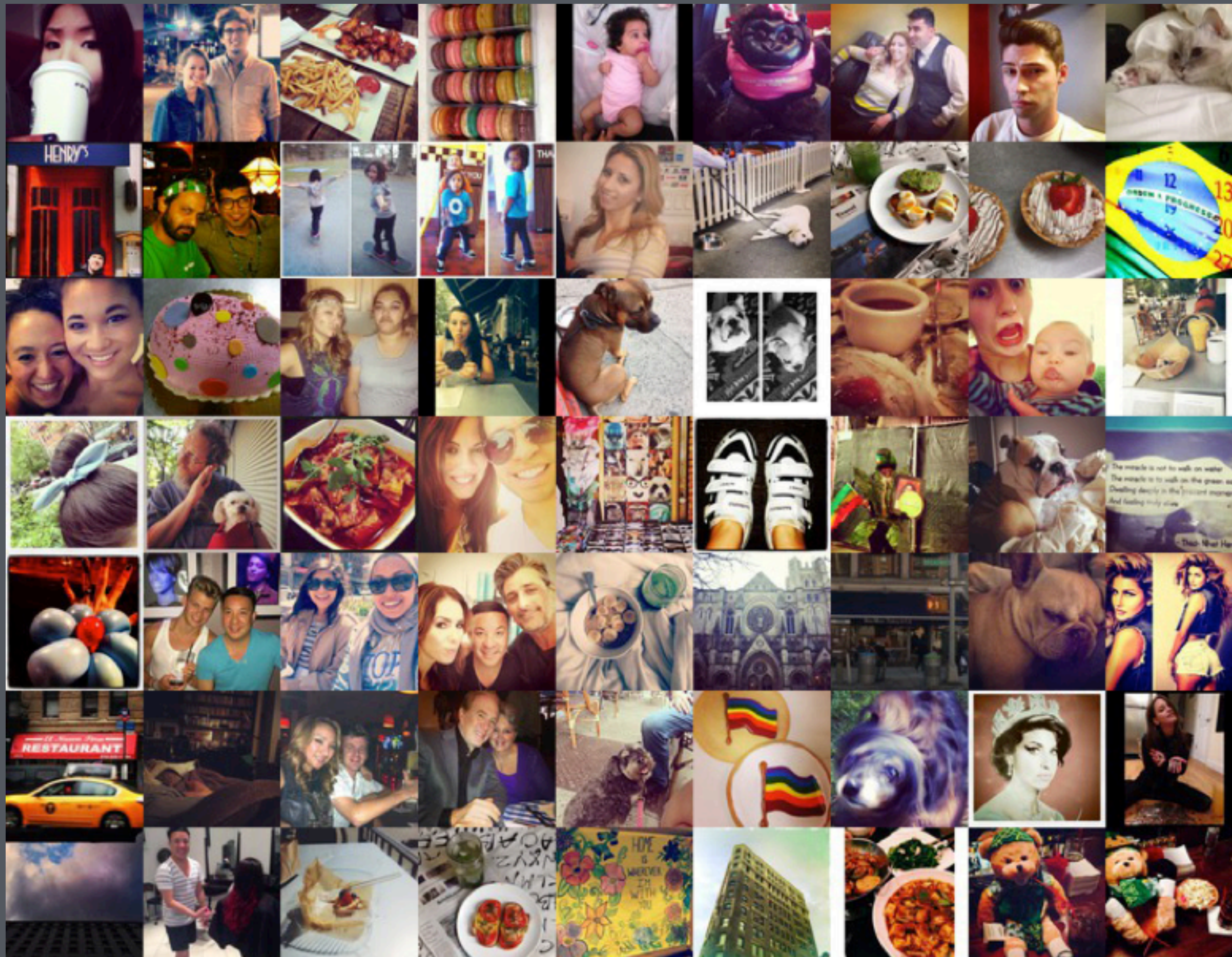
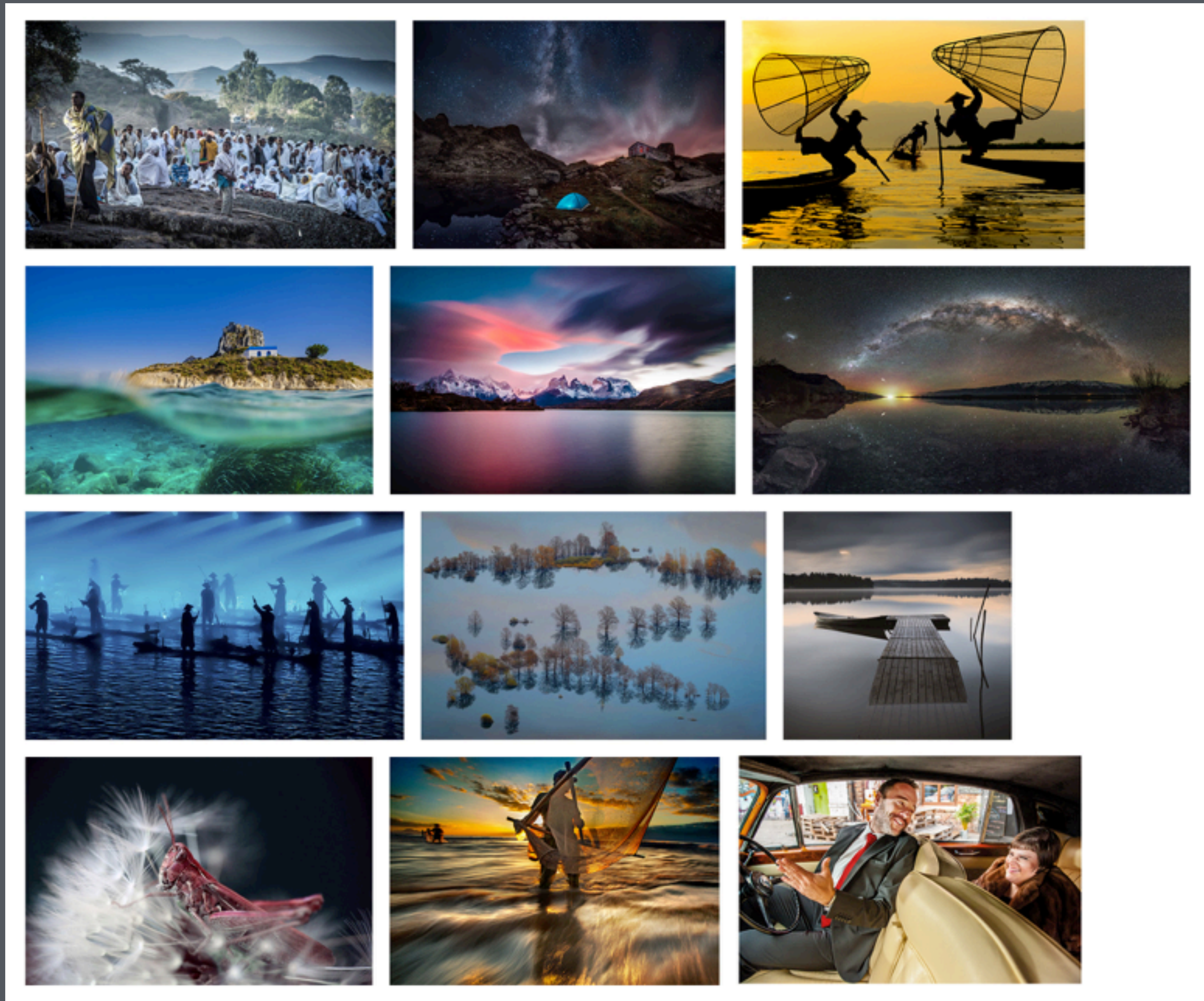
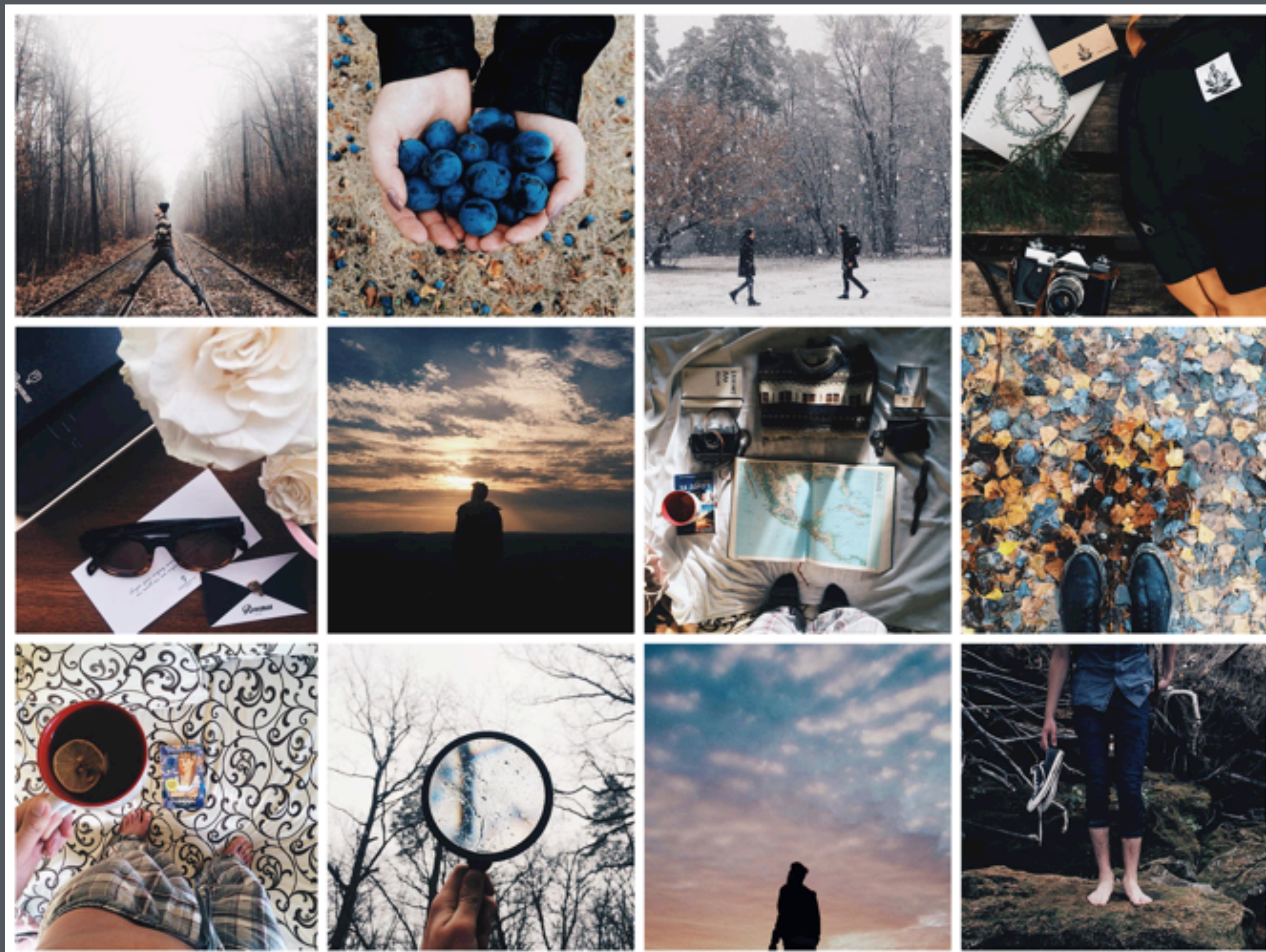


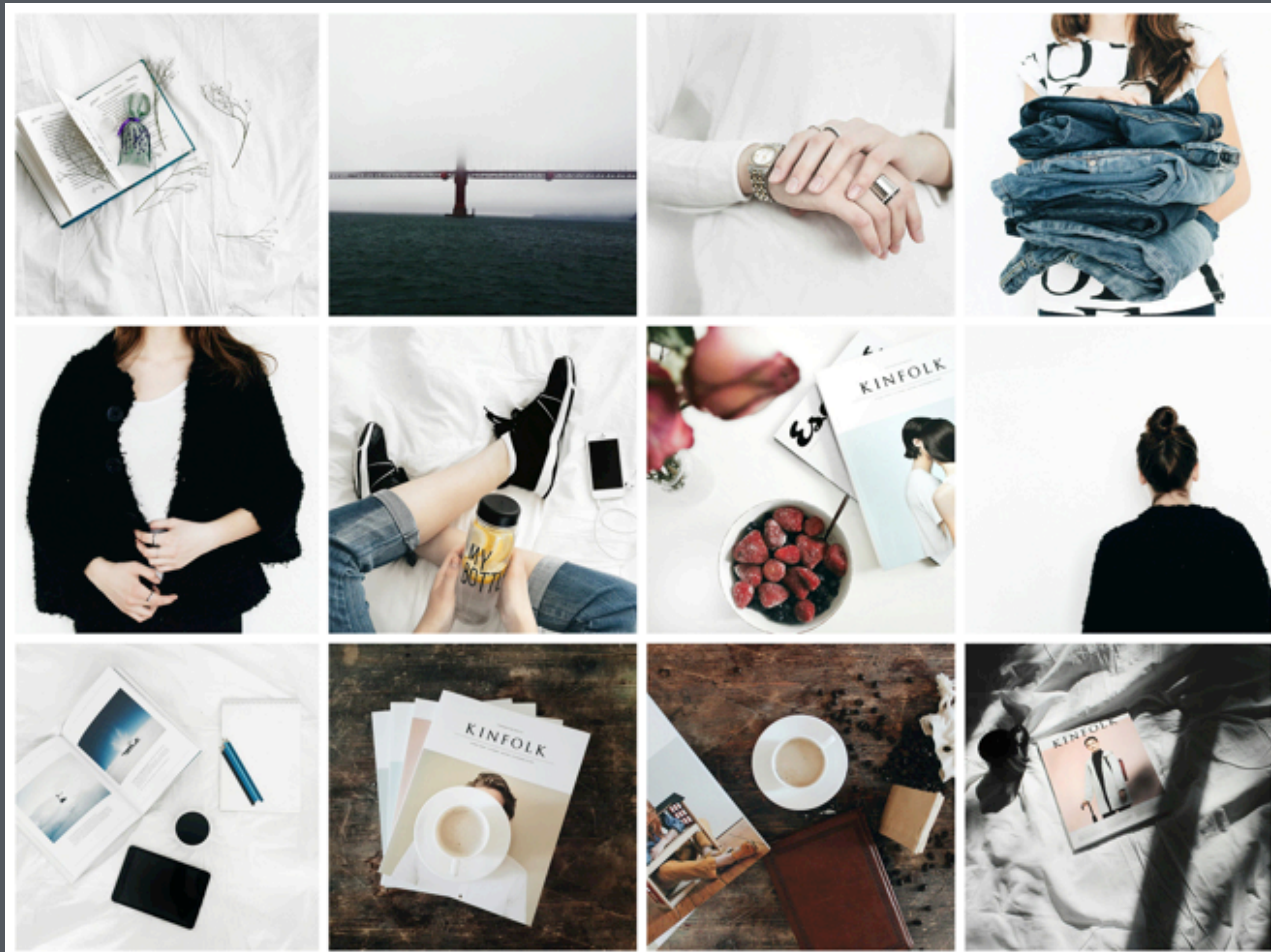



HENRY'S
RESTAURANT


Mother's Day - 1959
ME! Mama Lee






KINFOLK
KINFOLK

data analysis and visualization as "medium"

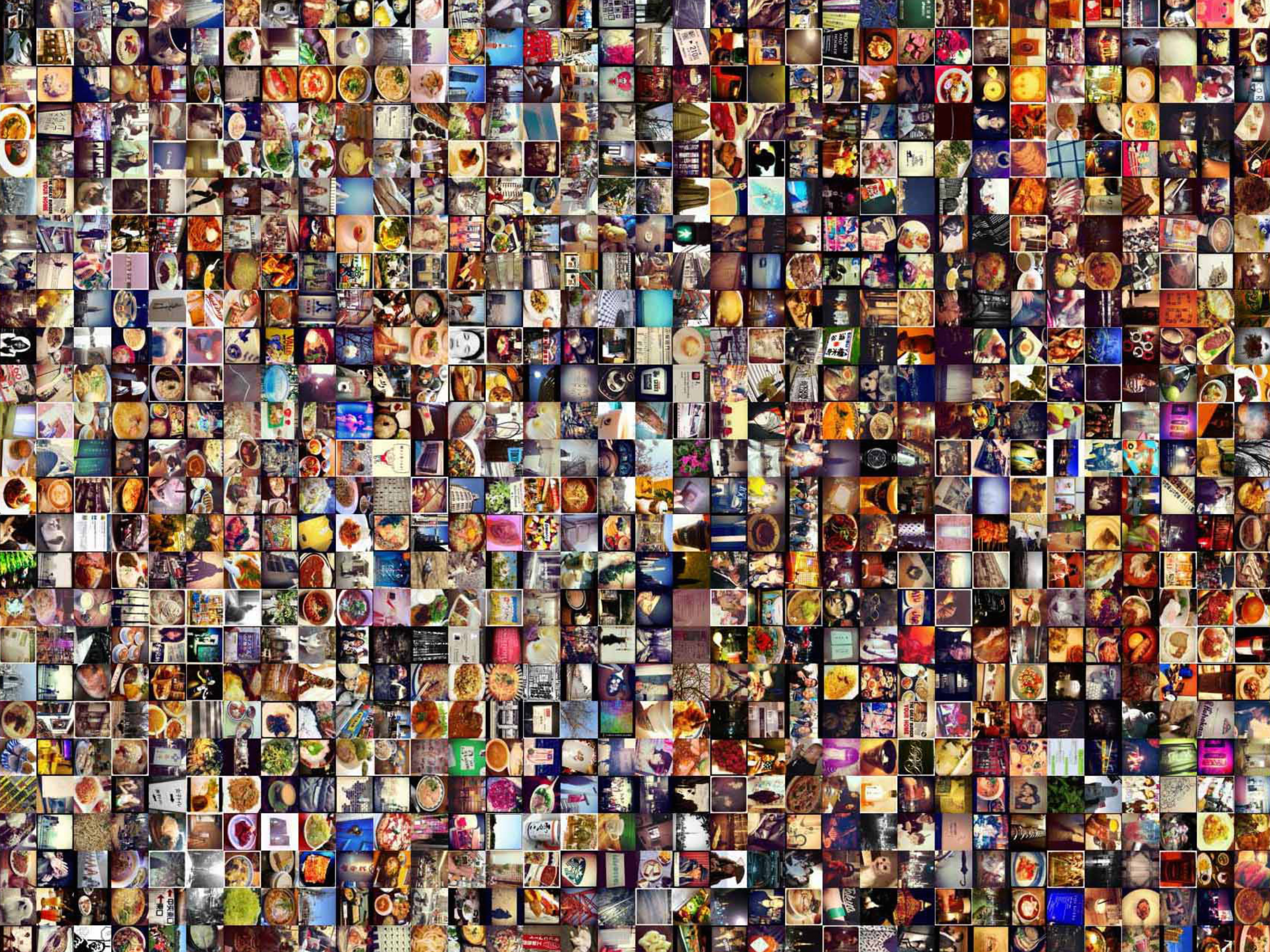
Features extracted from content, the available metadata, and data mining **techniques** determine what we can learn from social media

Visualization layouts and options further influences what patterns we can see, the meanings, and interpretations

the general and the particular:

18th-20th centuries:
social statistics, social science and data visualization - aggregation, summarization, reduction; focusing on the regular (that can be modeled and predicted)

21st century: from summarization to individualization; from general to focusing on variability and individual



examples of cultural analysis using large visual data

all examples in the following slides are from
- projects created in our lab,
- collaborative projects with external collaborators
- student work from Manovich's classes
2009 - 2015

Visual evolution of news media

(front covers of a single newspapers)

Treasury regu-
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nd books will be
station, for the

direction of President Jared Smith, United States commissioner in charge of the Hawaiian Agricultural Experiment Station. It contains the addresses delivered at meetings held heretofore and is distributed with circulars announcing the next meeting, to take place next Saturday. President Smith says that the Institute sessions have been successful beyond the expectations of those who organized the movement, and that the publication of proceedings will do much to distribute information about Hawaii. His introduction contains the following:

"There is a general demand for information in regard to Hawaiian agriculture both among residents of this Territory who are not themselves professional small farmers, and in an equal degree among the people of the Mainland. The proceedings of these Farmers' Institute meetings, if distributed among the public libraries and to Farmers' Institute workers in the United States, will be of great educa- advertised than by distributing literature of this character. Men who want to come here to make their homes will be glad to know that there is already in operation an organization which is actively interested in the advancement of the interests of the farmers of Hawaii.

"A recent visitor from the Mainland stated that he sought, and failed to find, information relating to Hawaii in the public library of the second largest city on the Pacific Coast. Besides some articles in encyclopedias and a few relating to the political history of Hawaii, there was absolutely nothing available in this library to help a man who wanted to come here to settle, to learn something of the prevailing agricultural conditions. These are all good reasons why the proceedings of this body should be published and widely distributed. An edition of 3,000 copies should be distributed in this Territory and throughout the balance of the United States."

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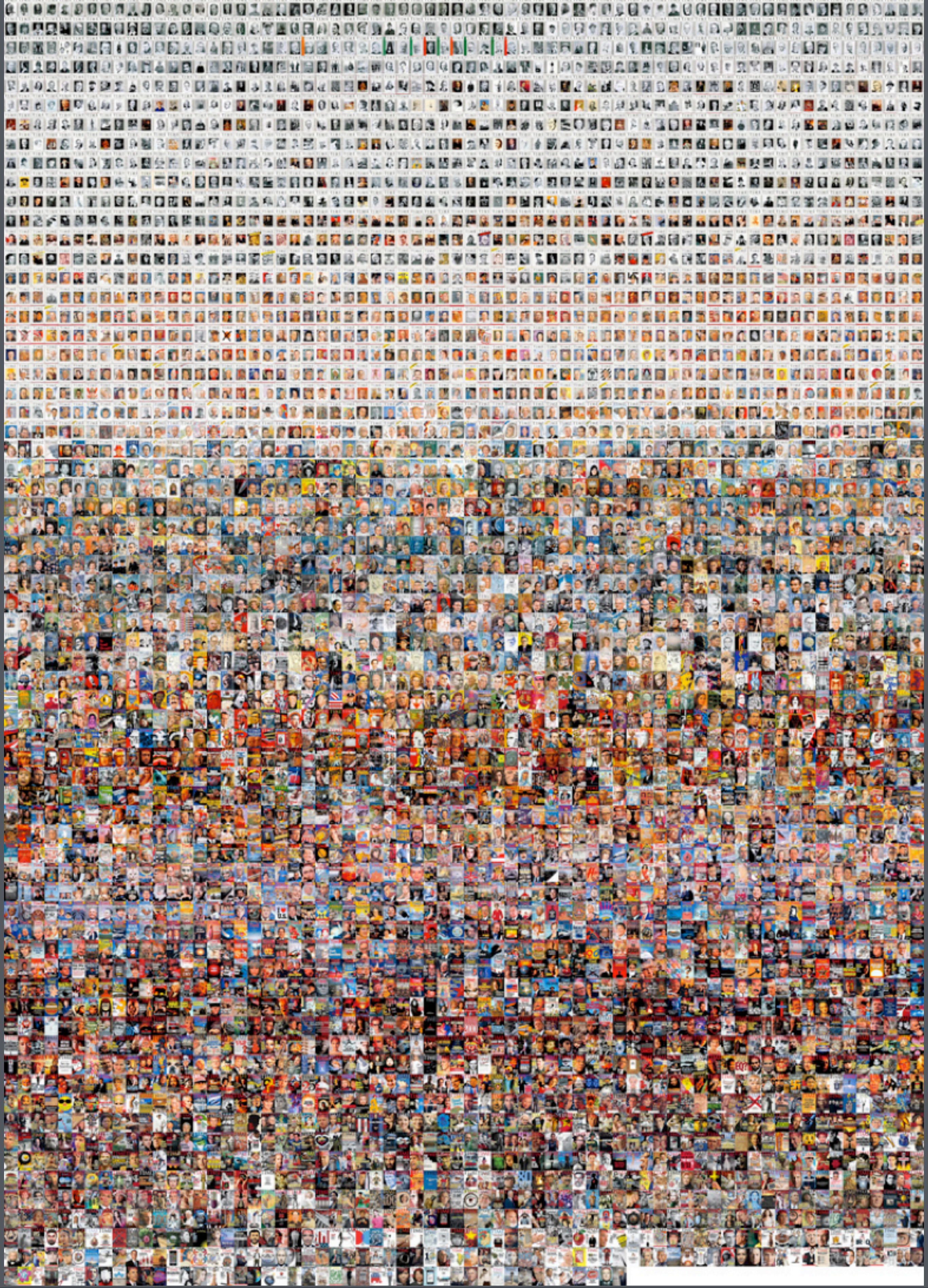
Visual evolution of news media - longer period

(4535 Time magazine covers, 1923-2009)



4535 Time covers 1923-2009.

Organized by date, left to right, top to bottom.

Every pattern we observe is continuous, with changes taking places over years or decades.

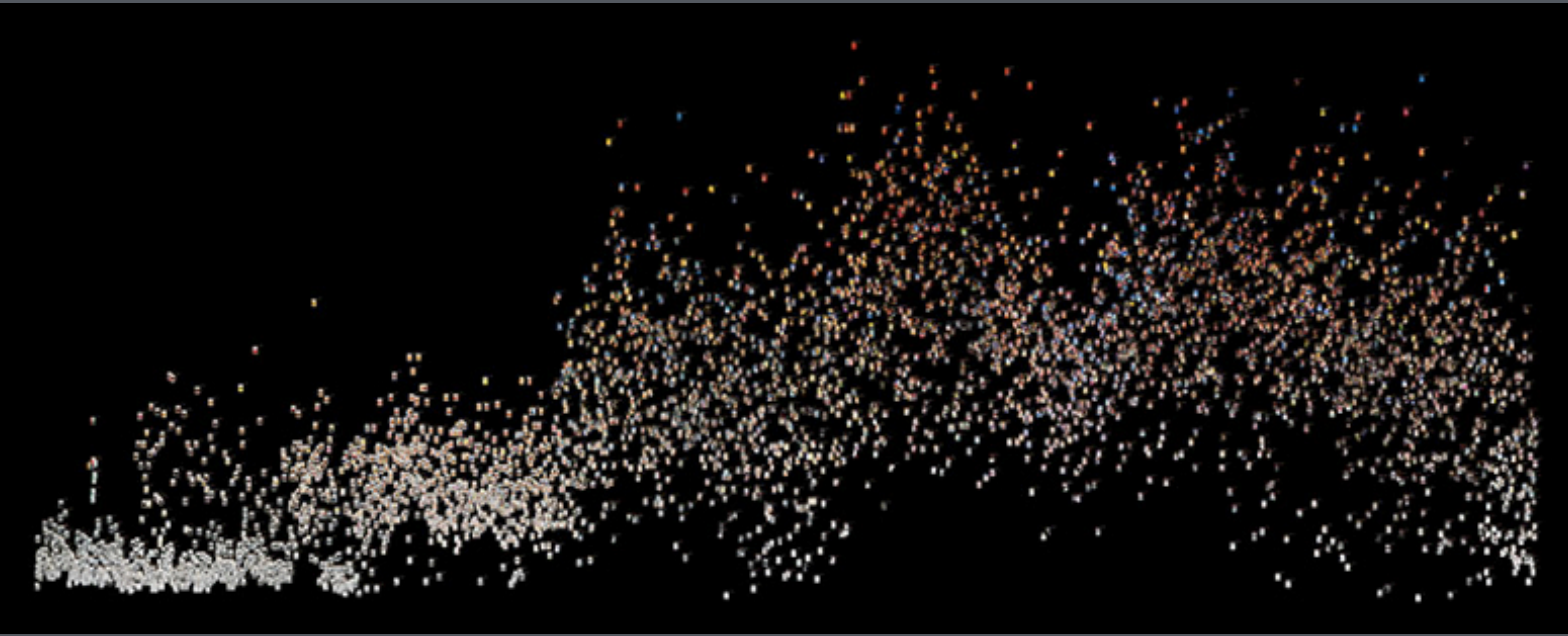
4535 Time covers
1923-2009.

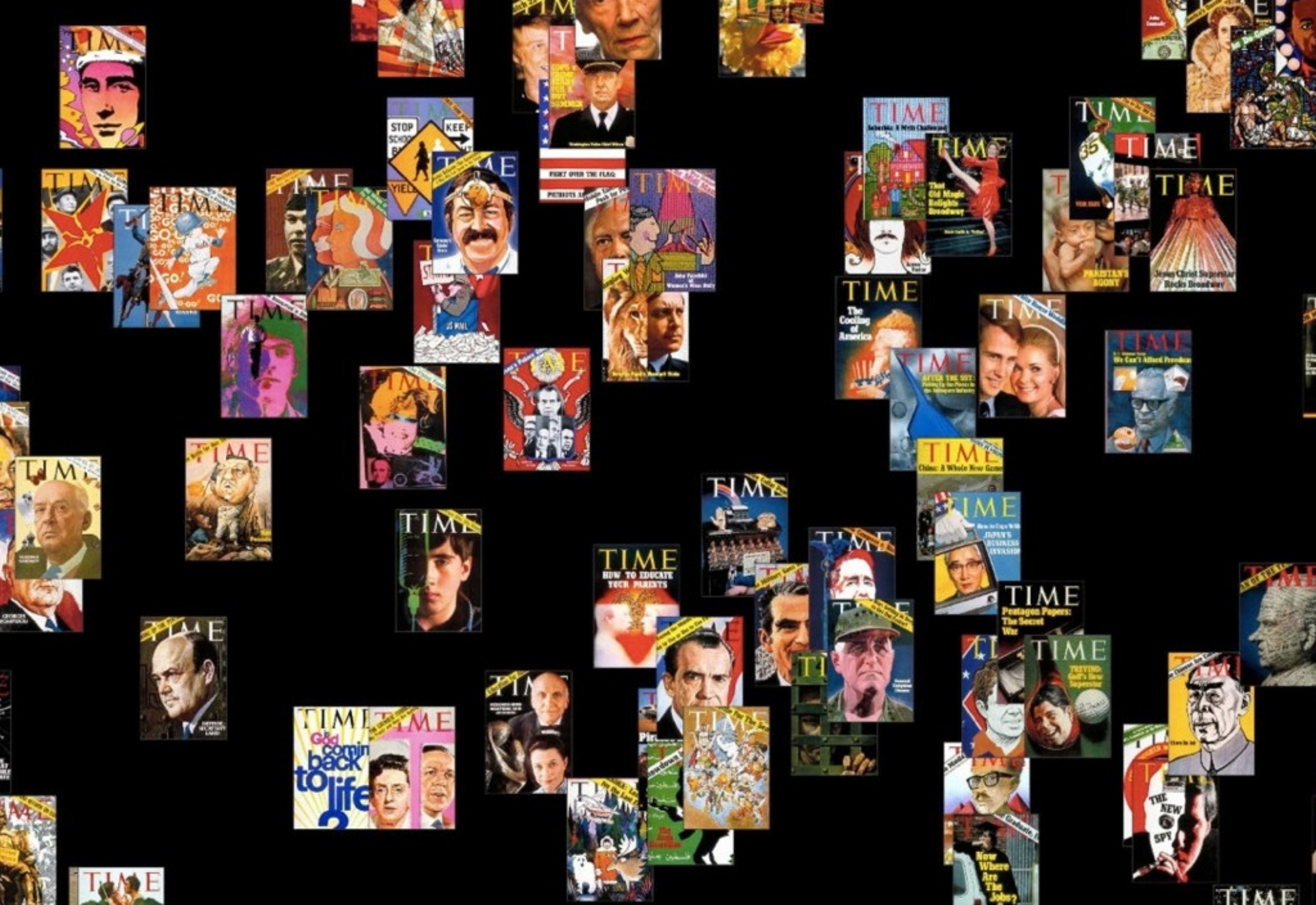
closeup: 1920s

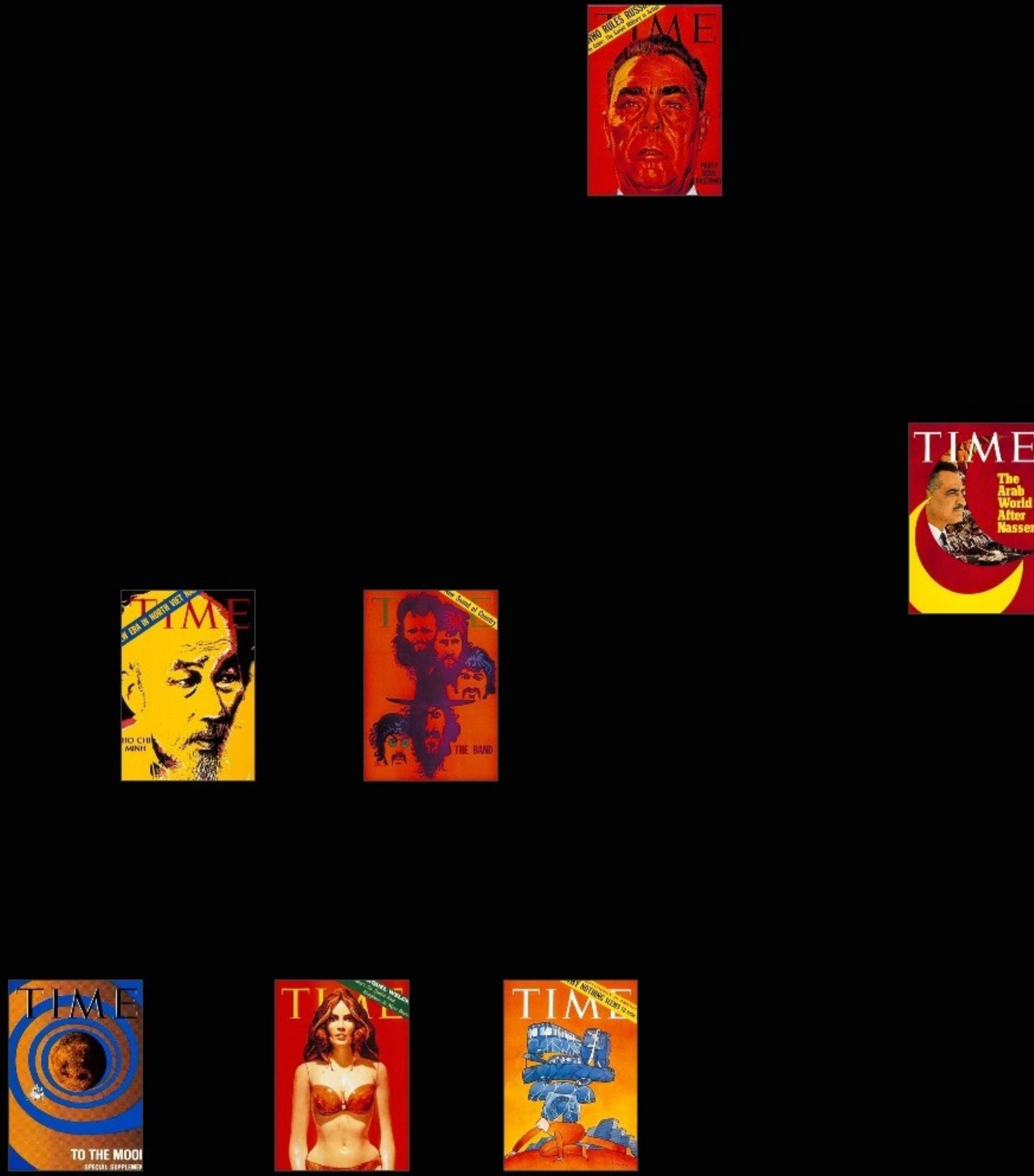
closeup: 1990s-2000s

4535 Time covers 1923-2009 (left to right). Each cover is represented by a single vertical line.

Image plots of 4535 Time covers, 1923-2009. X-axis = date; Y-axis = saturation mean.




TIME
The Cooling of America
HOW TO EDUCATE YOUR PARENTS
Pentagon Papers: The Secret War
That Old Magic Relights Broadway
Jesus Christ Superstar Rocks Broadway
China: A Whole New Game
THE NEW SPY
Now Where Are The Jobs?
FIGHT OVER THE FLAG
STOP
KEEP
YIELD
US MAIL



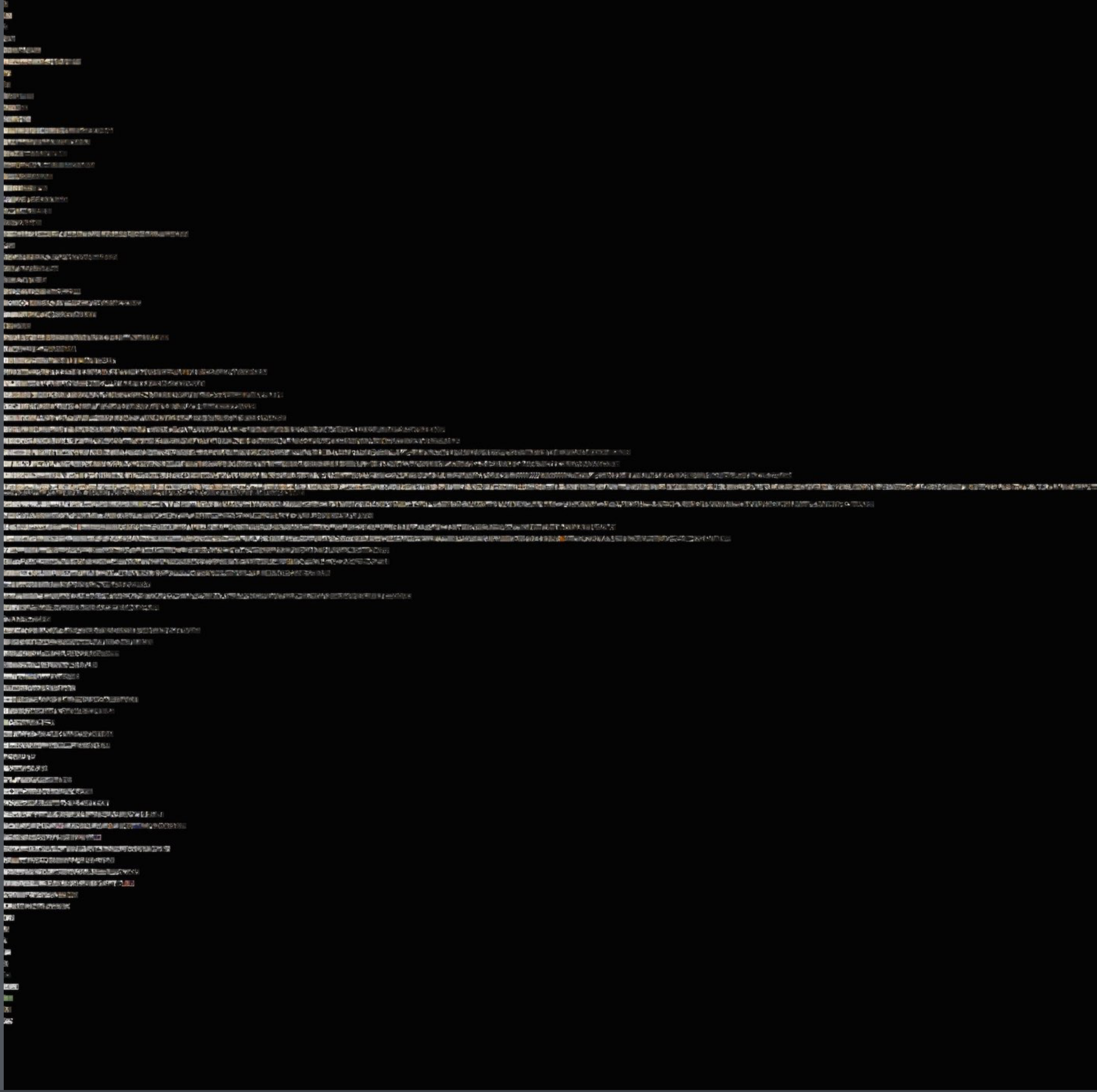
covers that have highest saturation (1960s)

History of a cultural medium (photography) as represented by a single institution (MoMA)

In 2013 we were invited by MoMA to analyze their whole photo collection and contribute to the OBJECT : PHOTO exhibition website

Seeing the museum collection: 20,000 photographs from MoMA,1844-1989.

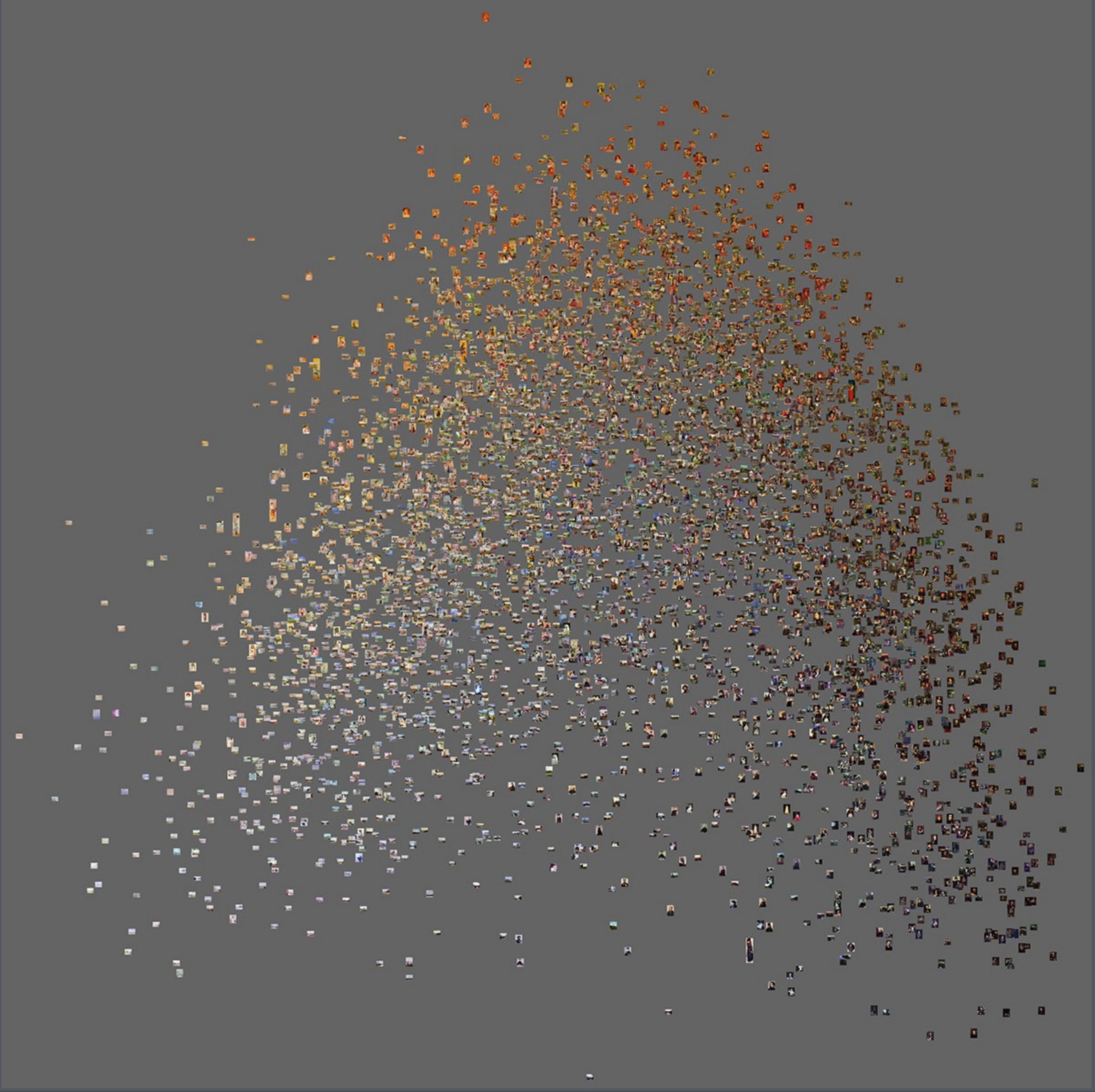
Organized by year (top to bottom). Each bar shows photographs from a particular year.



closeup, 1925-1929

Mapping an artistic movement

(French Impressionists)



Visualization of 5000 paintings of French Impressionist artists

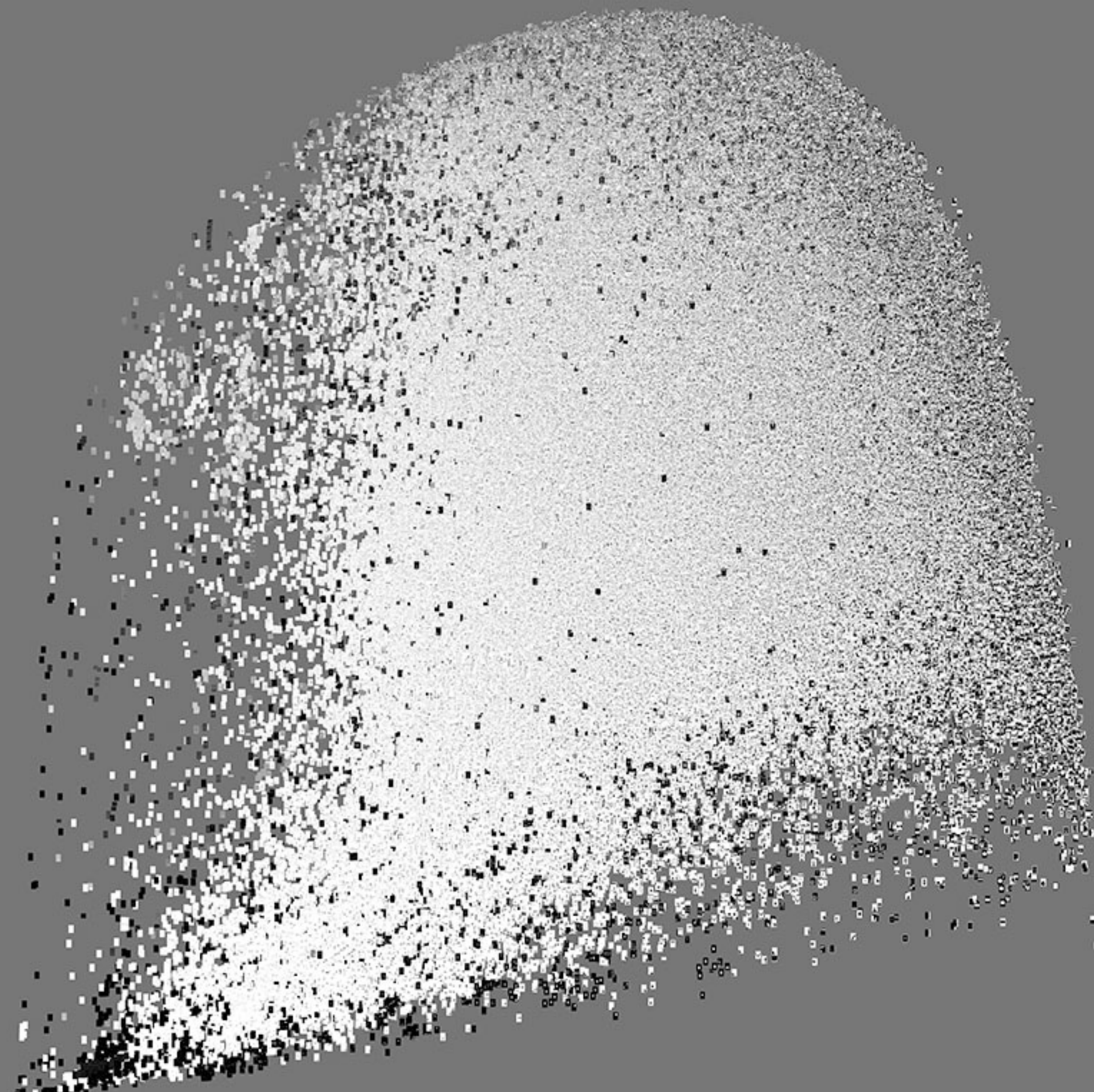
x and y - first two dimensions of PCA using 200 features

The familiar paintings of French impressionists (see closeup on next slide) turn to be only %20-%30 of their whole creative output

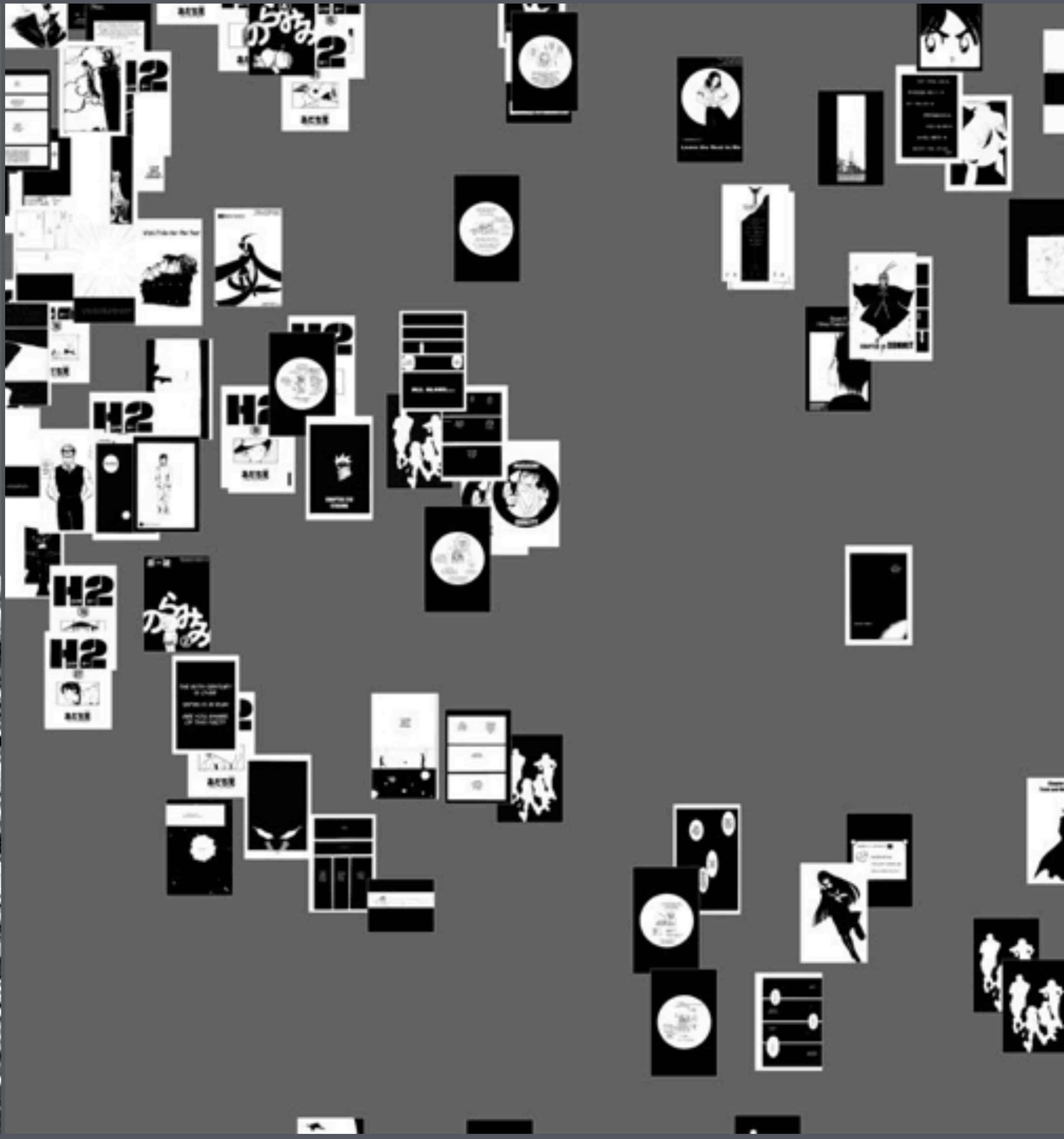
Mapping a cultural field using a large sample

(883 manga publications containing 1,074,790 pages)

1 million manga pages
x - standard deviation
y - entropy

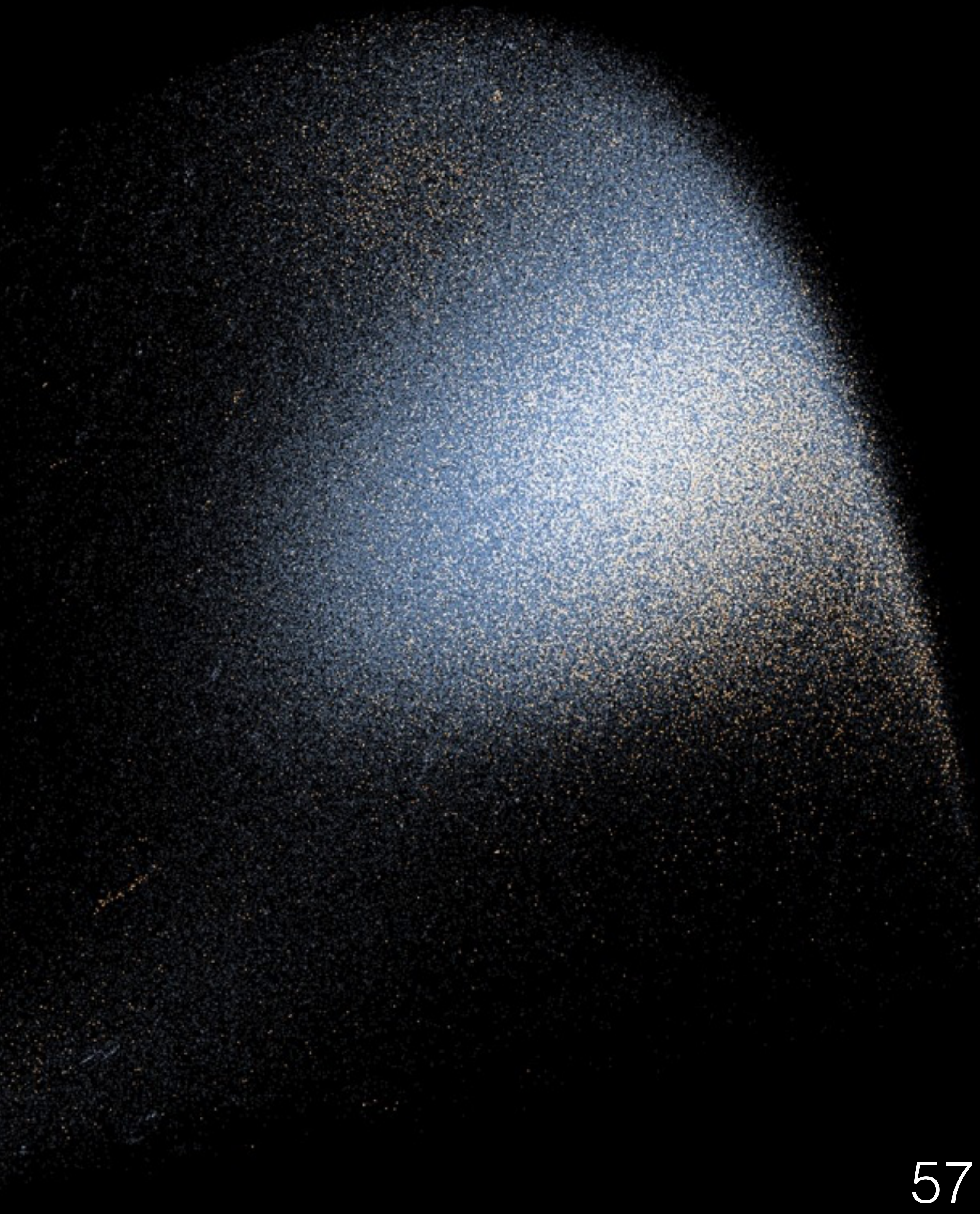


Closeups of the bottom left corner and top corner (previous slide). Entropy feature sorts all pages according to low detail/no texture/flat - high detail/texture/3D dimension. Visualization reveals continuos variation on this dimension. This example suggests that our standard concept of "style" may not be appropriate when looking at particular characteristics of big cultural samples (because "style assumes presence of distinct characteristics, not continuos variation across a whole dimension).

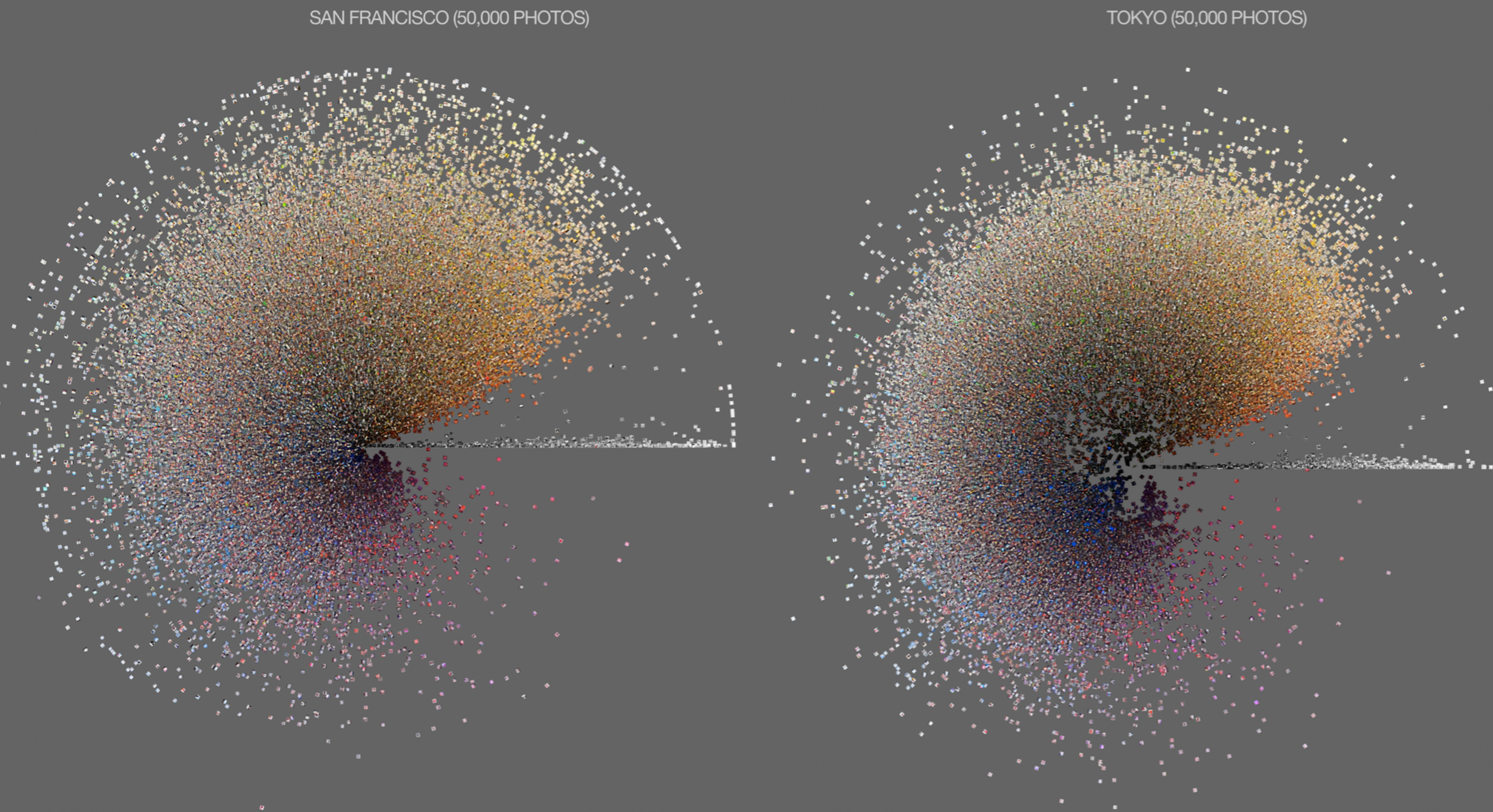


1 million manga pages plotted as points
x - standard deviation
y - entropy

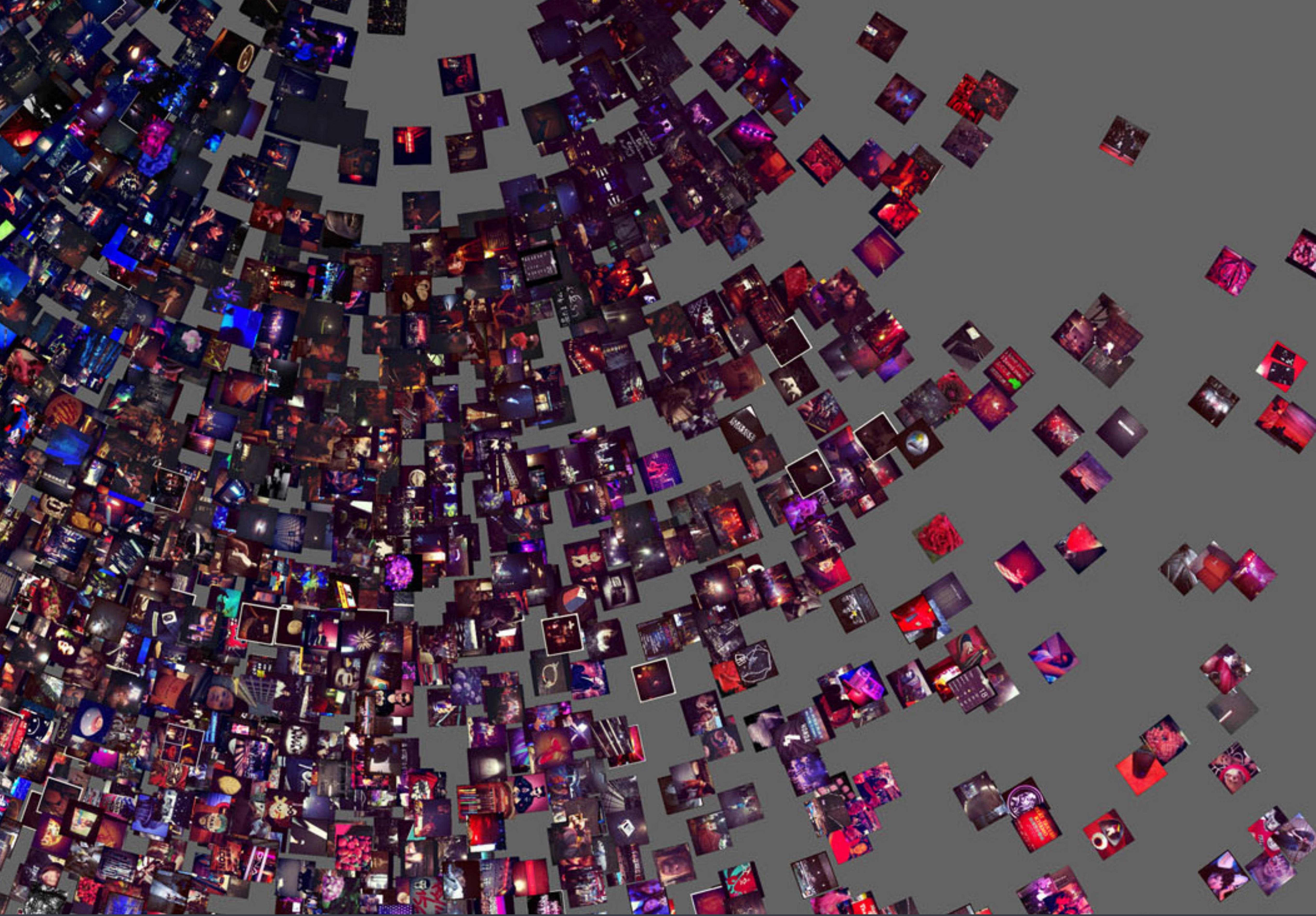
Some plot areas are densely filled in, while others are almost empty. Why manga visual language developed in this way? Visualization of a large number of samples allows us to map a cultural fields to see what is typical and what is rare, and what kind of clusters (if they exist) are present in this field.



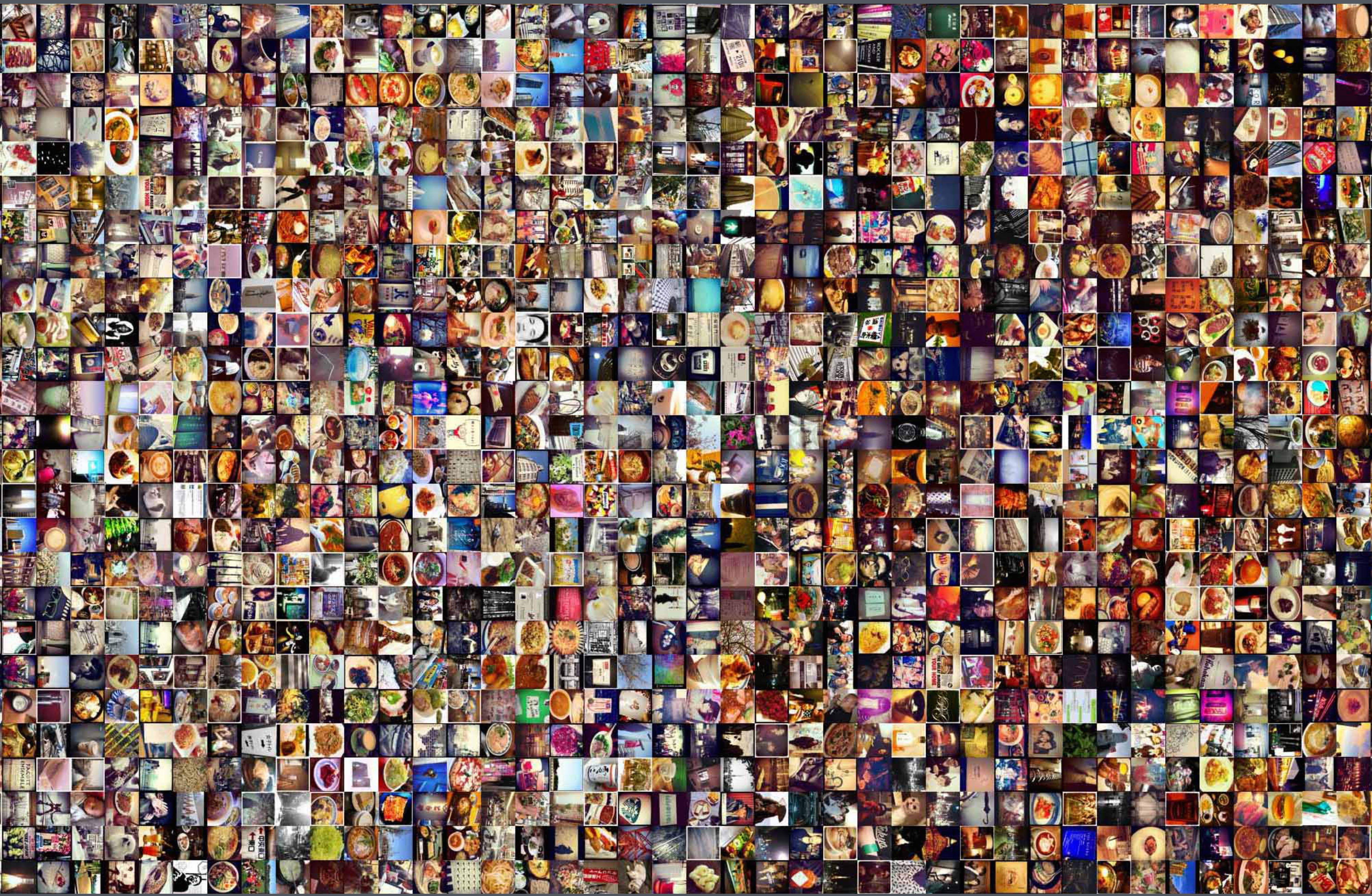
Visual signatures of cities: sampling and aggregating images from a social media platform (Instagram)



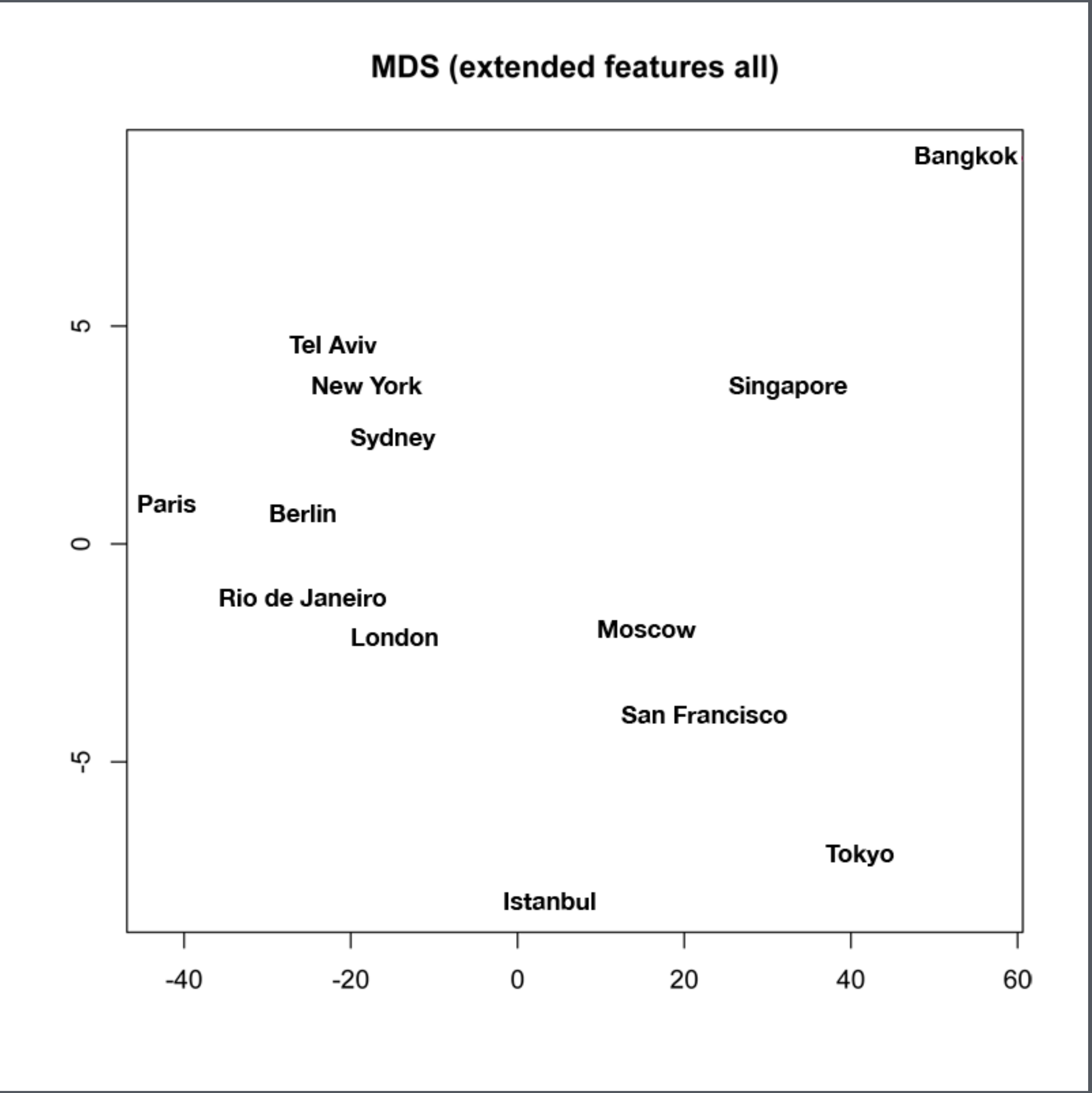
Comparing San Francisco and Tokyo using 50K image samples.
Photos are organized by average brightness (distance to plot center) and average hue (angle).



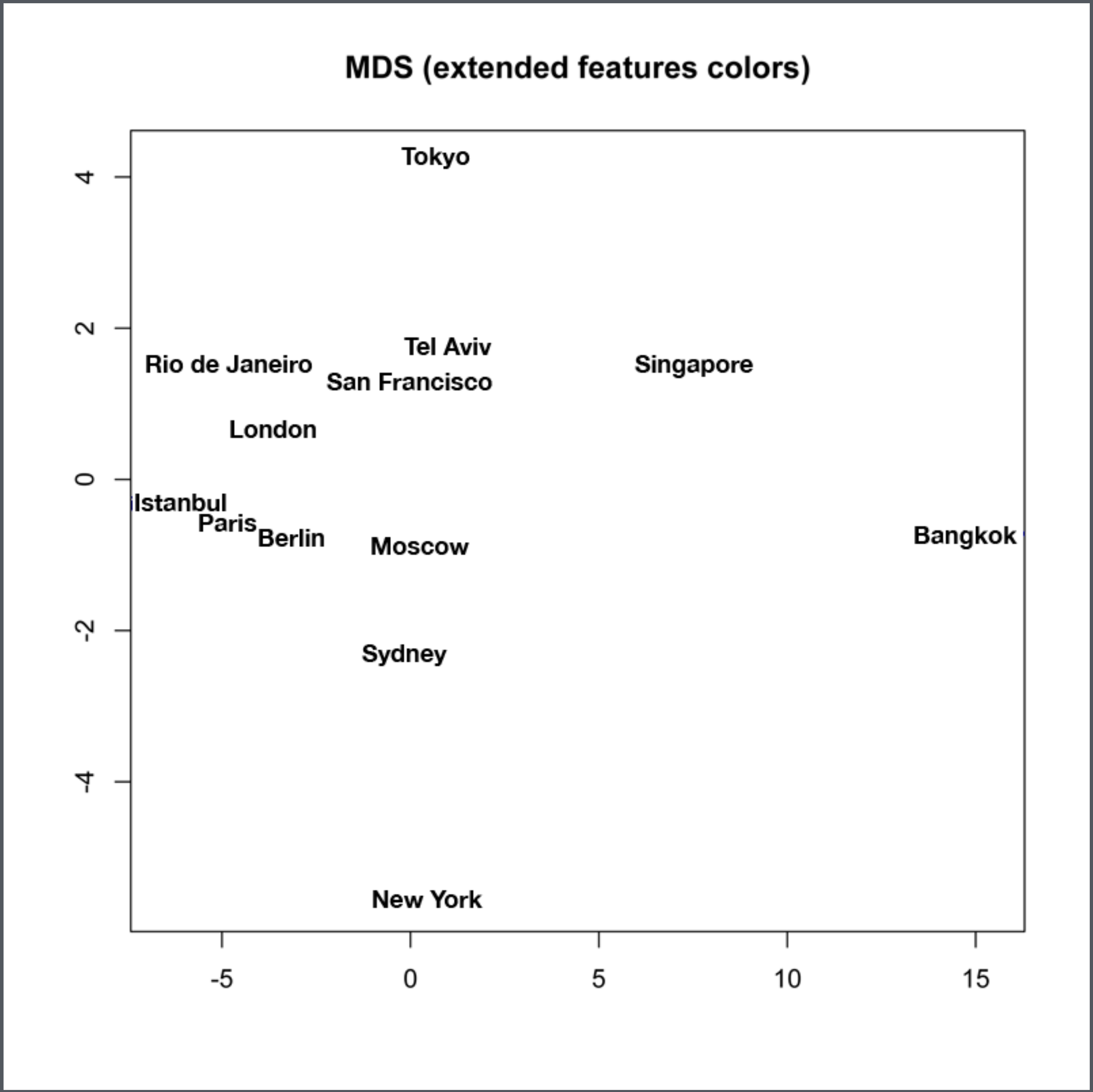
Comparing NYC and Tokyo using 50K image samples shared over few days (organized by upload date/time.)



closeup of the visualization from previous slide

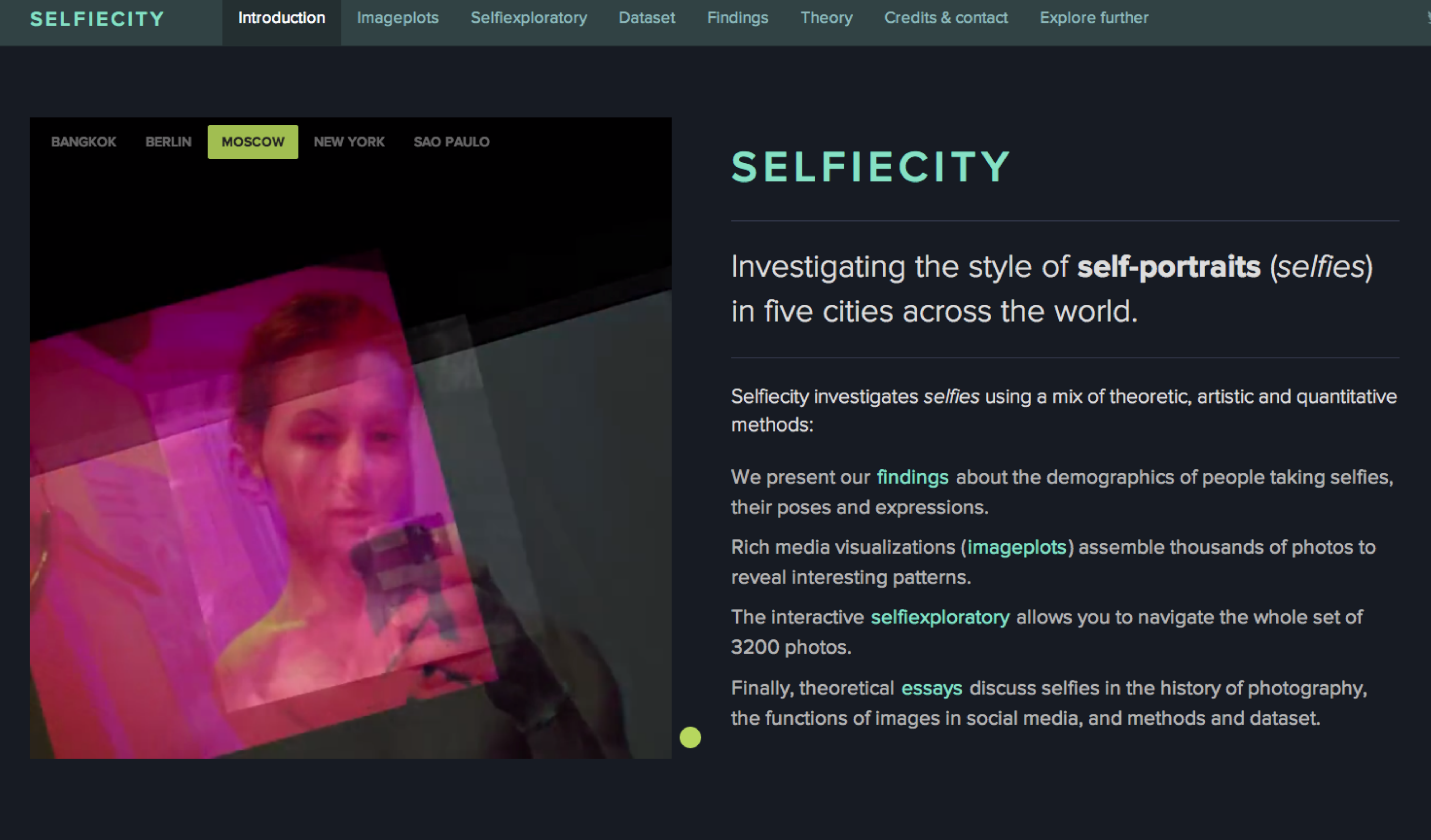


Example of data aggregation - reducing 2.3M photos to 13 data points (one point per city)

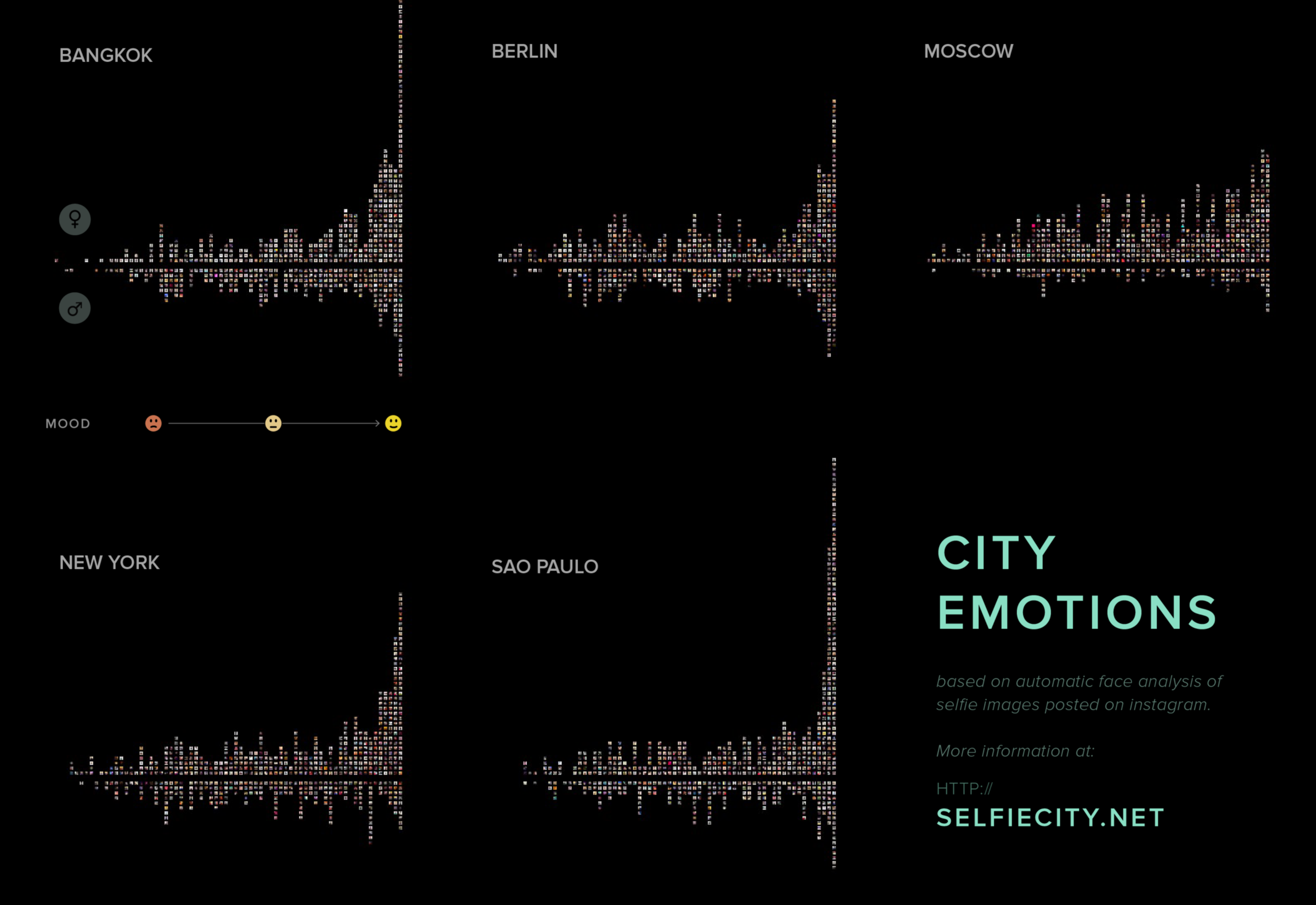


Another plot of cities differences (using only color features)

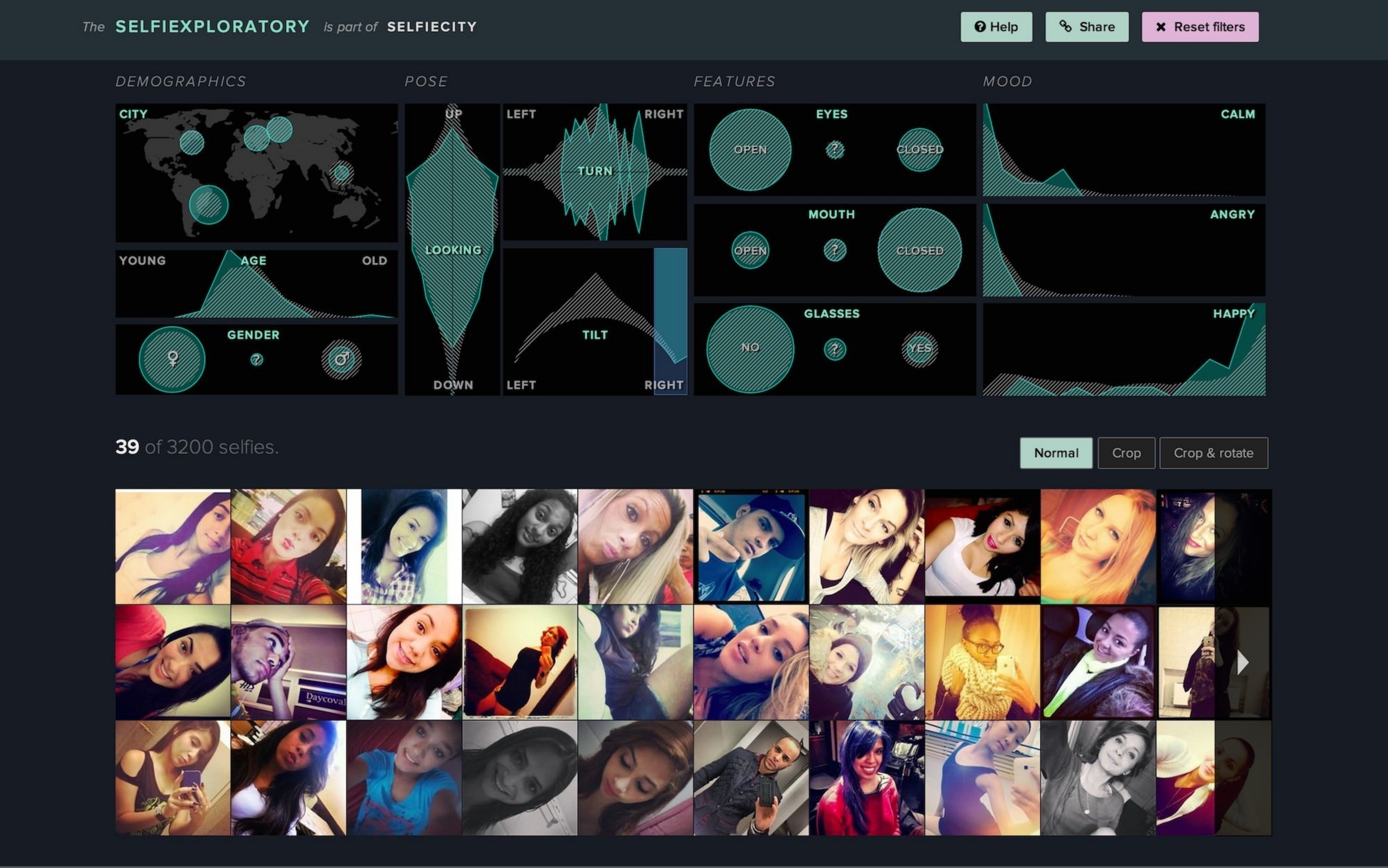
How people represent themselves? How they construct themselves in social media?



Selfiecity project, 2014: analysis of 3200 Instagram single selfie photos from 5 global cities.
http://selfiecity.net



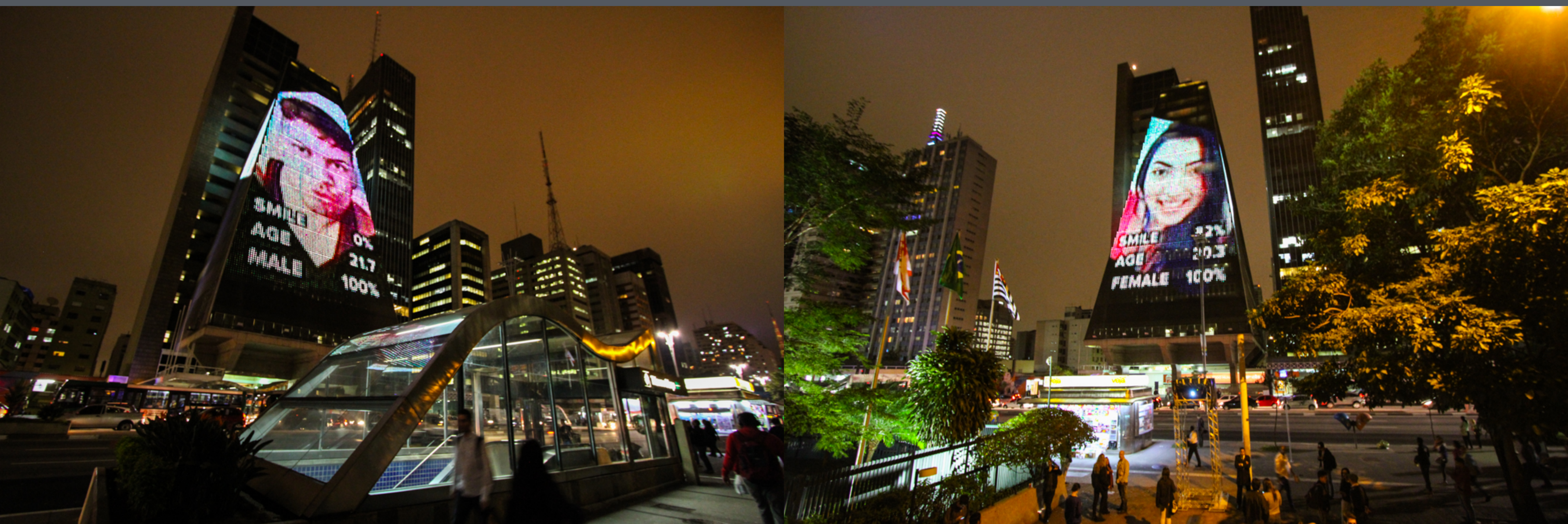
One of the visualizations from Selfiecity



Screenshot from interactive app selfiexploratory:
http://selfiecity.net/selfiexploratory/

SELFIECITY

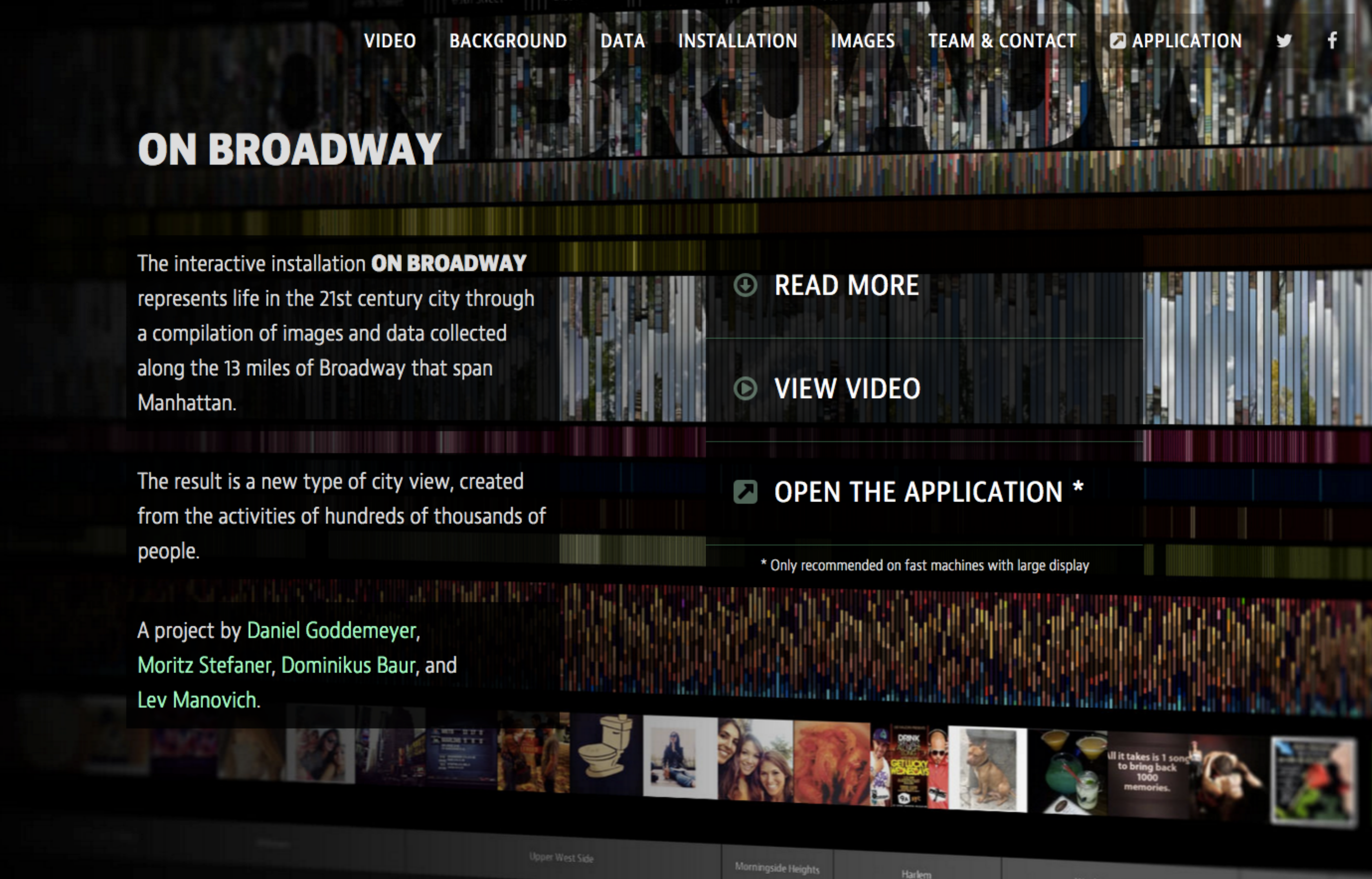
Exploring the cultural meaning of the selfie



SelfieSaoPaolo project, 2014. Views of the animated projection.

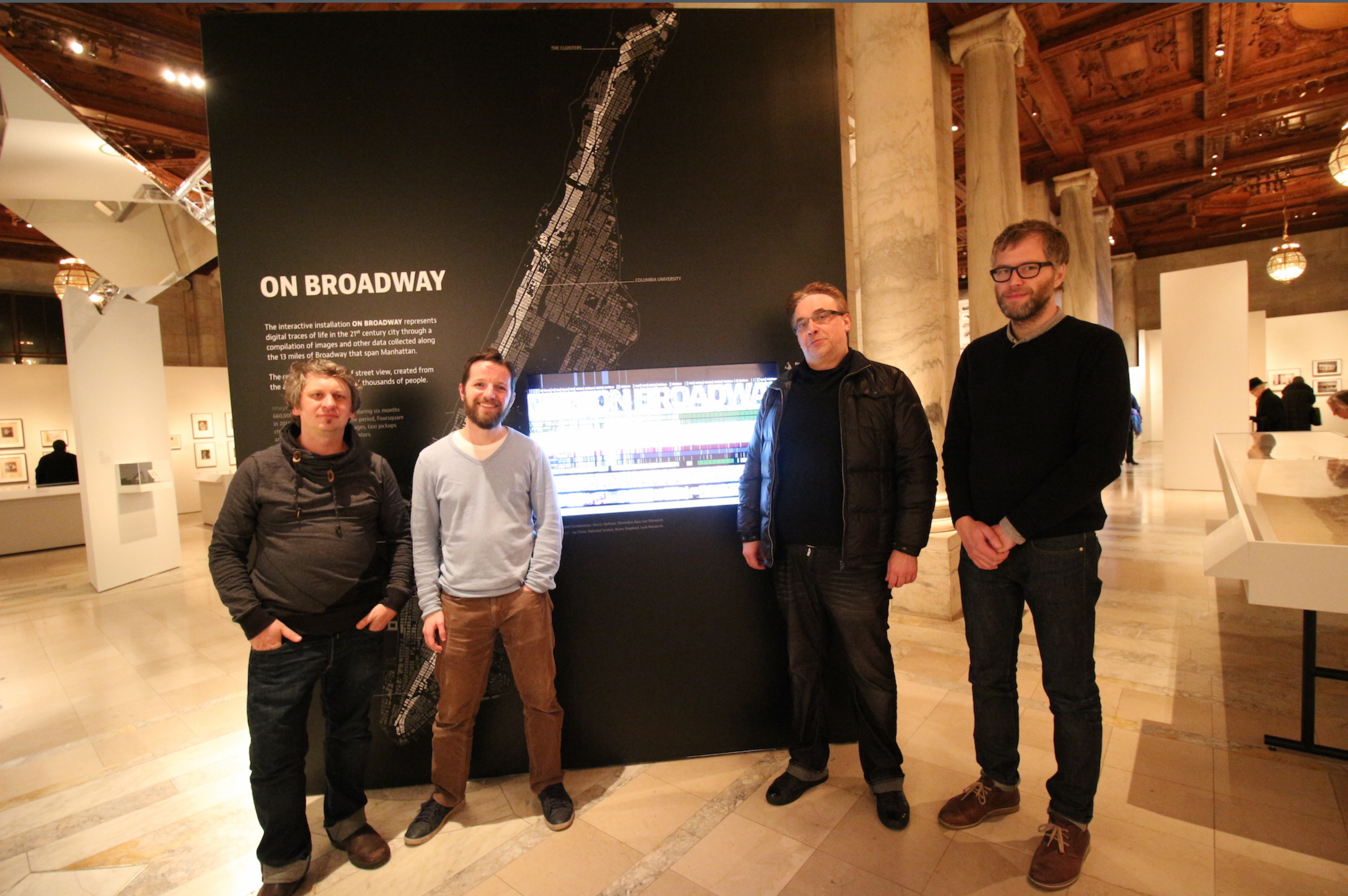
Interfaces for people to interact with urban social media data + census and government data;

Combining multiple types + resolution of data

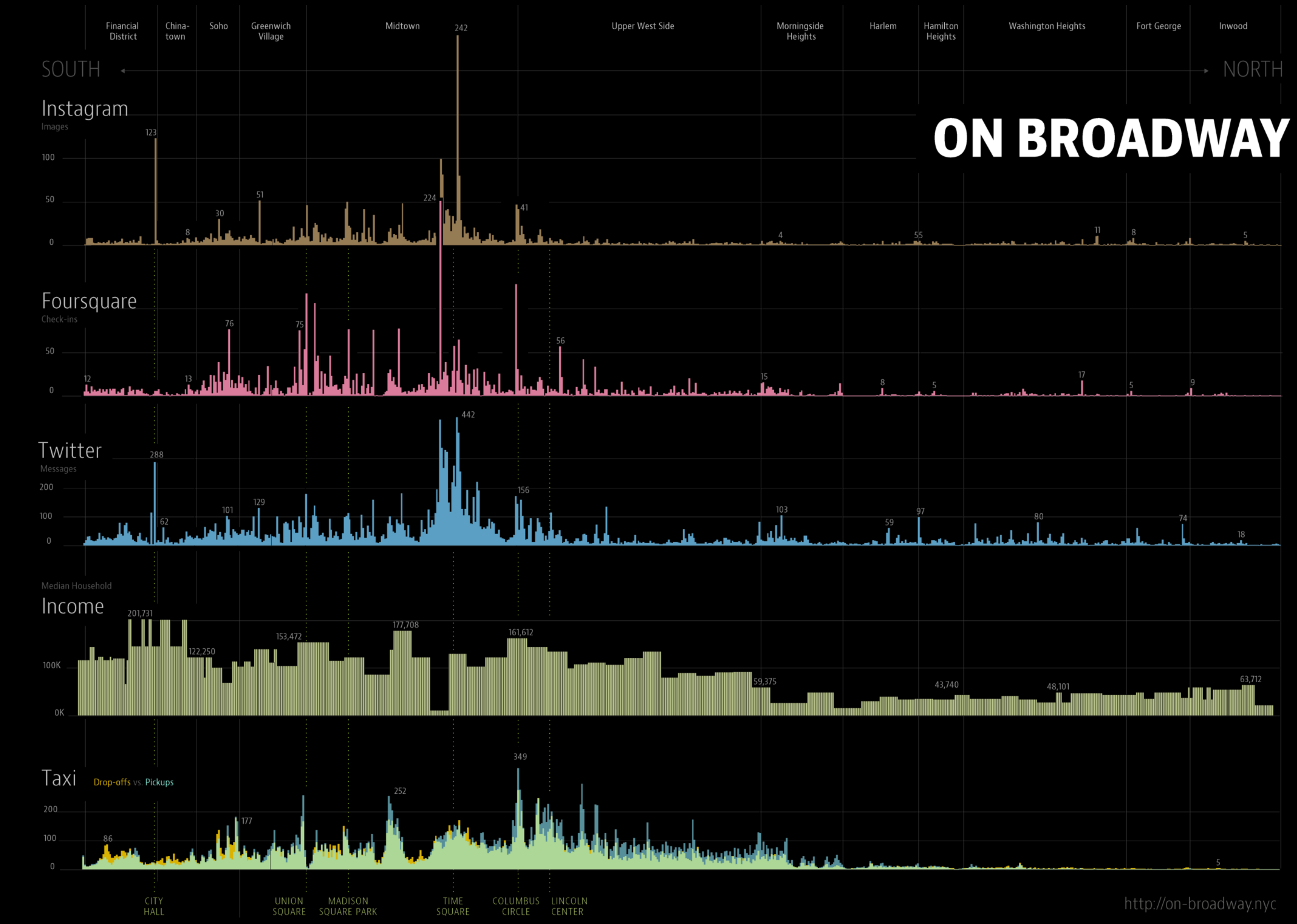


On Broadway project, 2014. http://http://on-broadway.nyc/

On Broadway is an interactive installation shown at New York Public Library, 12/2004-1/2016



Artists team in front of On Broadway installation


ON BROADWAY
SOUTH
NORTH
Financial District
China-town
Soho
Greenwich Village
Midtown
Upper West Side
Morningside Heights
Harlem
Hamilton Heights
Washington Heights
Fort George
Inwood
Instagram
Images
Foursquare
Check-ins
Twitter
Messages
Median Household
Income
Taxi
Drop-offs vs. Pickups
CITY HALL
UNION SQUARE
MADISON SQUARE PARK
TIME SQUARE
COLUMBUS CIRCLE
LINCOLN CENTER
http://on-broadway.nyc

ON BROADWAY
DATA LAYERS

Landmarks & anecdotes

Google Street View facades

Facade colors

Taxi statistics

Google Street View: sky view

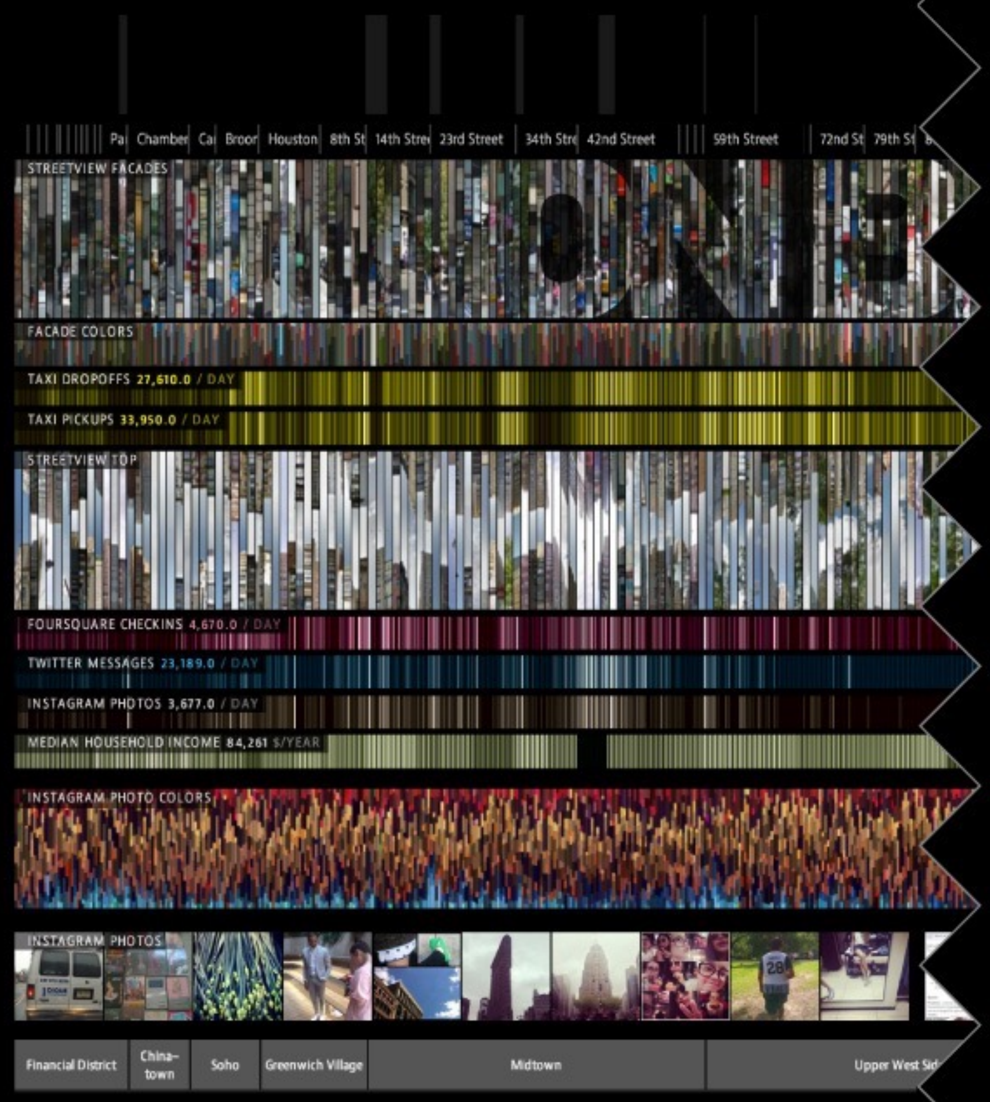
Social media statistics

Median income

Colors in Instagram photos

Instagram photos

Neighborhoods



Interface uses familiar multi-touch gestures to navigate Broadway street in Manhattan (21 km, 30M data points)

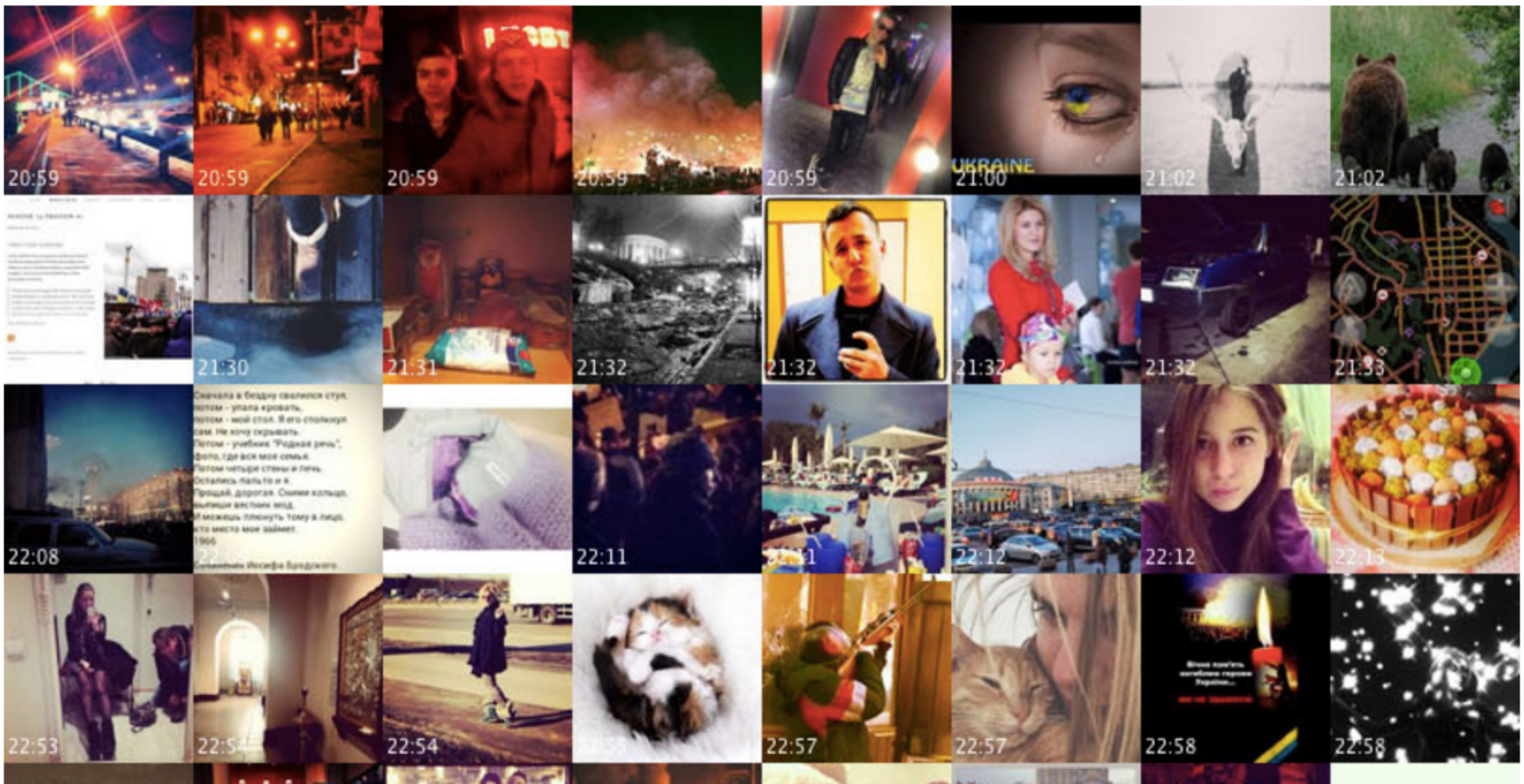
Video showing interaction with On Broadway interactive application on a 46-inch touch screen

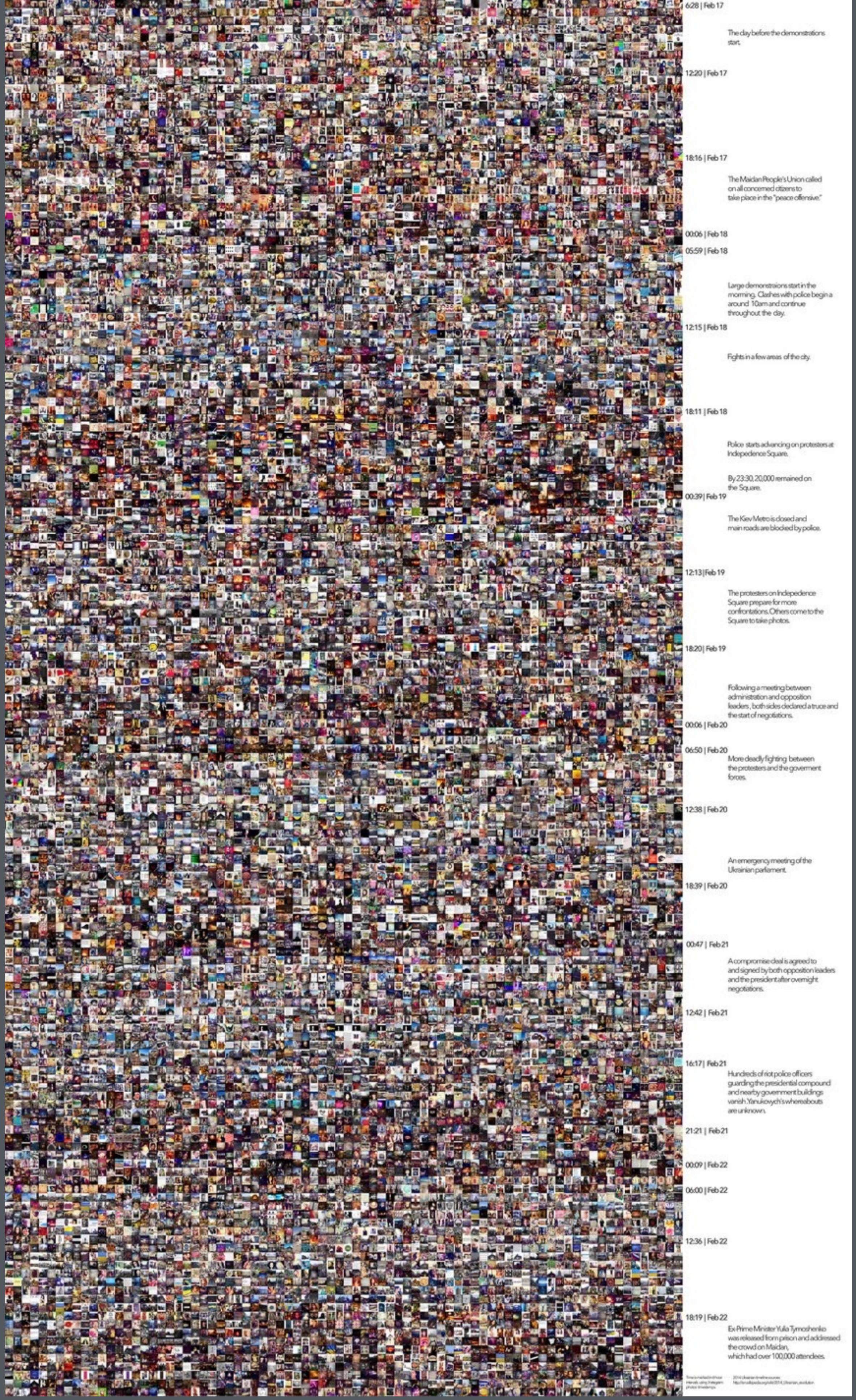
How exceptional events are represented in visual social media? The exceptional vs the everyday

Social media sensors vs. pop media coverage

The Exceptional & The Everyday: 144 Hours in Kiev

Visualizations | Intro | Data | Infra-ordinary | Iconography | Matviyenko essay | Losh essay | Bibliography | Team



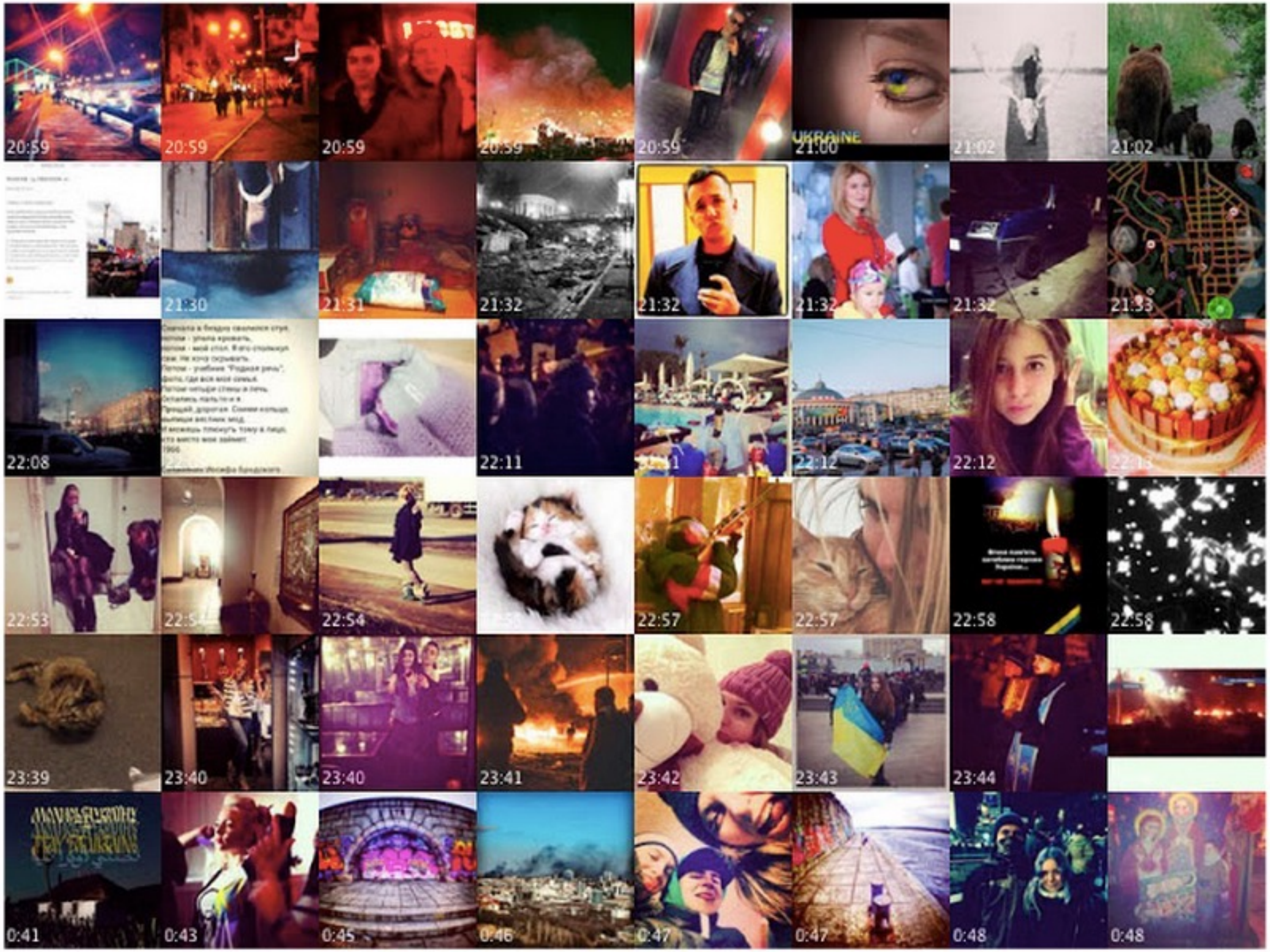


The Exceptional & The Everyday project, 2014
http://www.the-everyday.net/

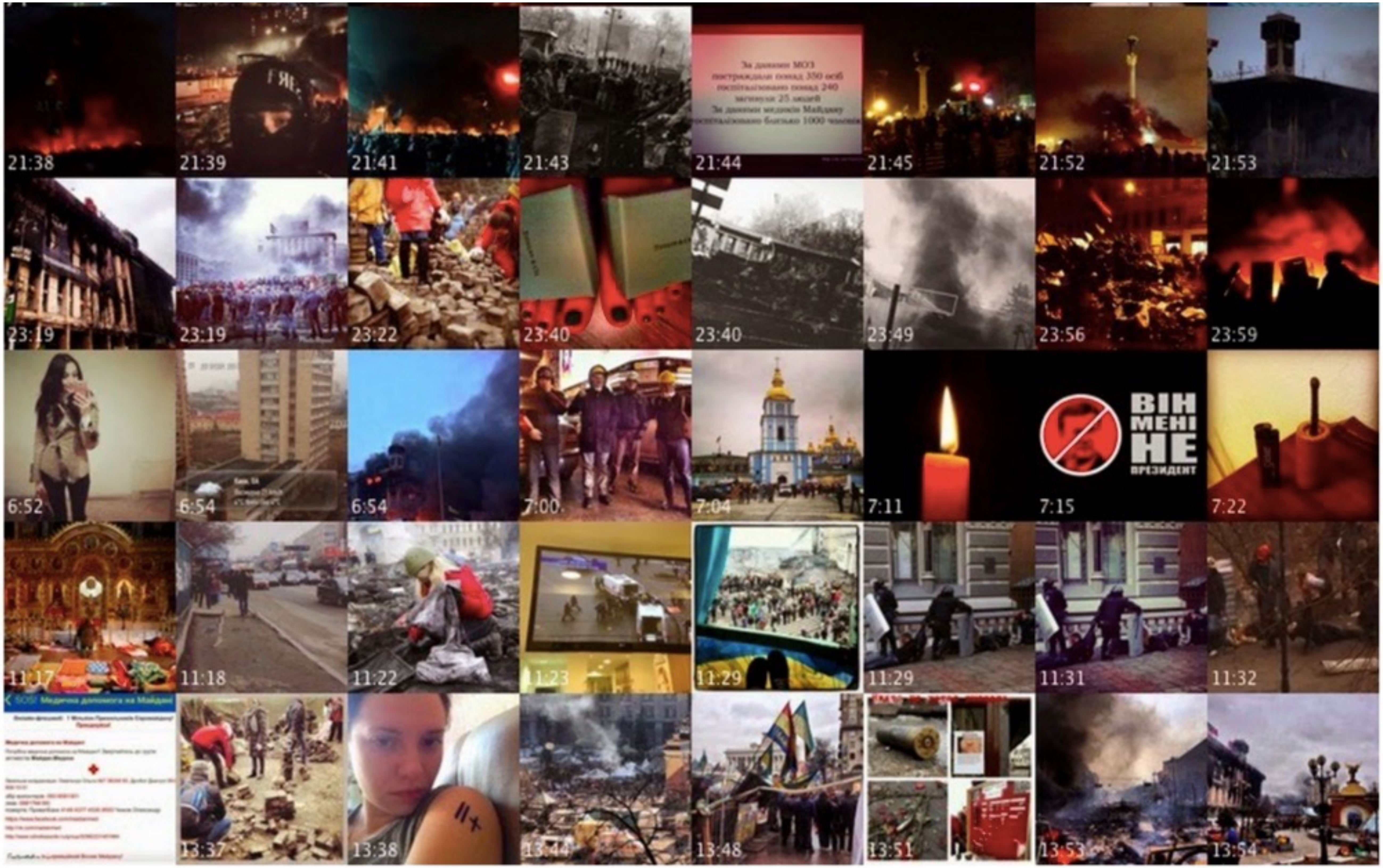
The visualization shows 13,208 Instagram images shared by 6,165 people in the center of Kiev during 2014 Ukrainian revolution (February 17 - February 22, 2014). The photos are organized chronologically (left to right, top to bottom). The right column shows summary of the events from Wikipedia page about the revolution.

A single condensed narrative history (Wikipedia text) vs. visual experiences of thousands of people (Instagram)? The second is potentially richer - but also more difficult to interpet.

Can we narrate history without aggregation and summarization? History as timelines of million of people?



From The Everyday Project



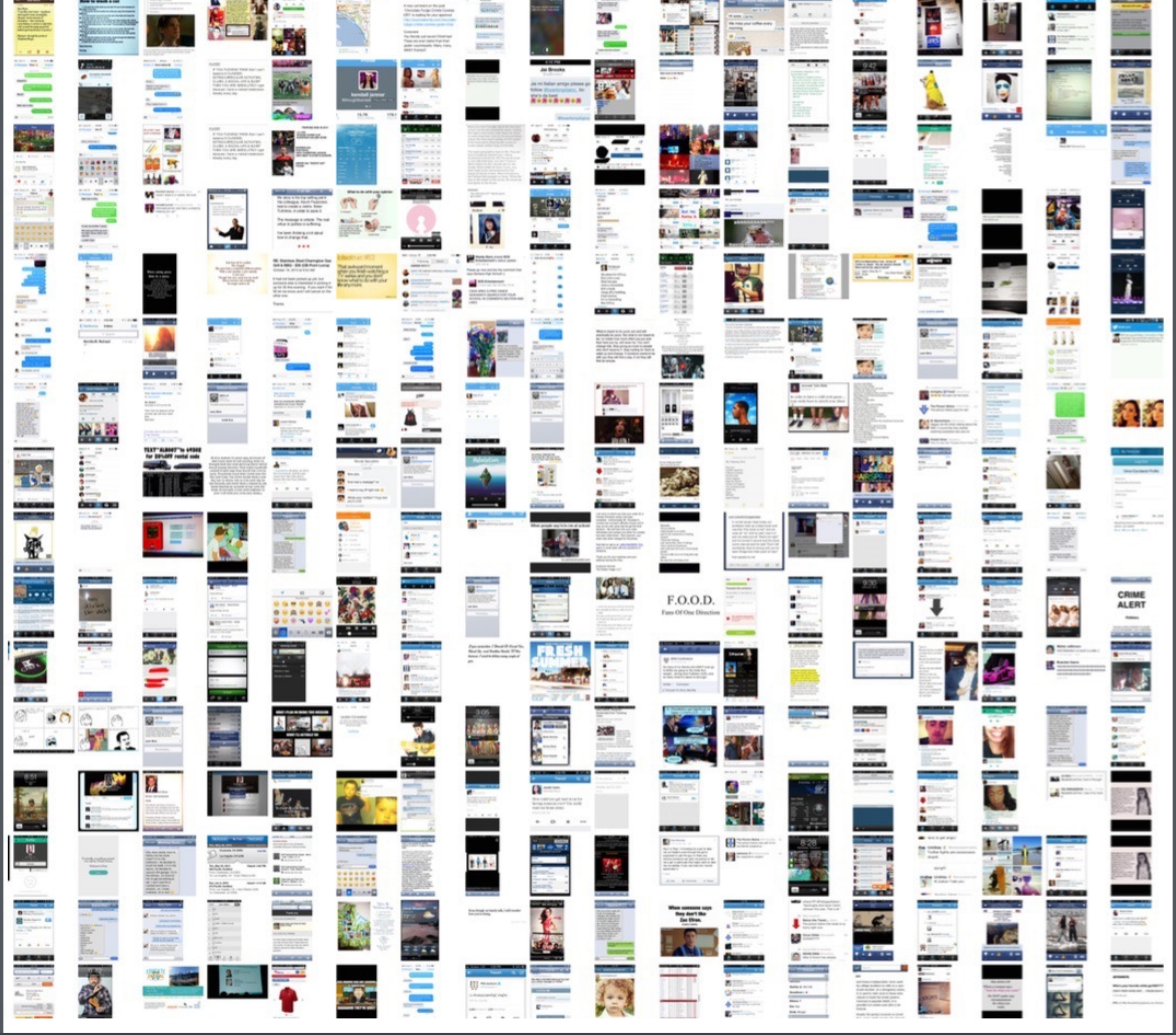
From The Everyday Project

2/17	2/18	2/19	2/20	2/21	2/22
kiev	kiev	kiev	kiev	kiev	kiev
ukraine	ukraine	euromaidan	ukraine	euromaidan	euromaidan
love	киев	ukraine	euromaidan	ukraine	ukraine
follow	euromaidan	євромайдан	євромайдан	євромайдан	евромайдан
followme	євромайдан	евромайдан	евромайдан	евромайдан	євромайдан
instagood	евромайдан	kyiv	revolution	kyiv	киев
me	kyiv	киев	киев	revolution	revolution
киев	revolution	revolution	kyiv	киев	kyiv
like	love	майдан	майдан	Ukraine	followme
photooftheday	followme	Ukraine	love	love	instagood

using visual social media to predict socio-economic indicators

Mehrdad Yazdani and Lev Manovich. "Predicting Social Trends from Non-photographic Images on Twitter." *Big Data and the Humanities* workshop, *IEEE 2015 Big Data* conference.

We classified 1 million twitter images shared in 20 US cities in 2013 using Google free Deep Learning Model available to all researchers



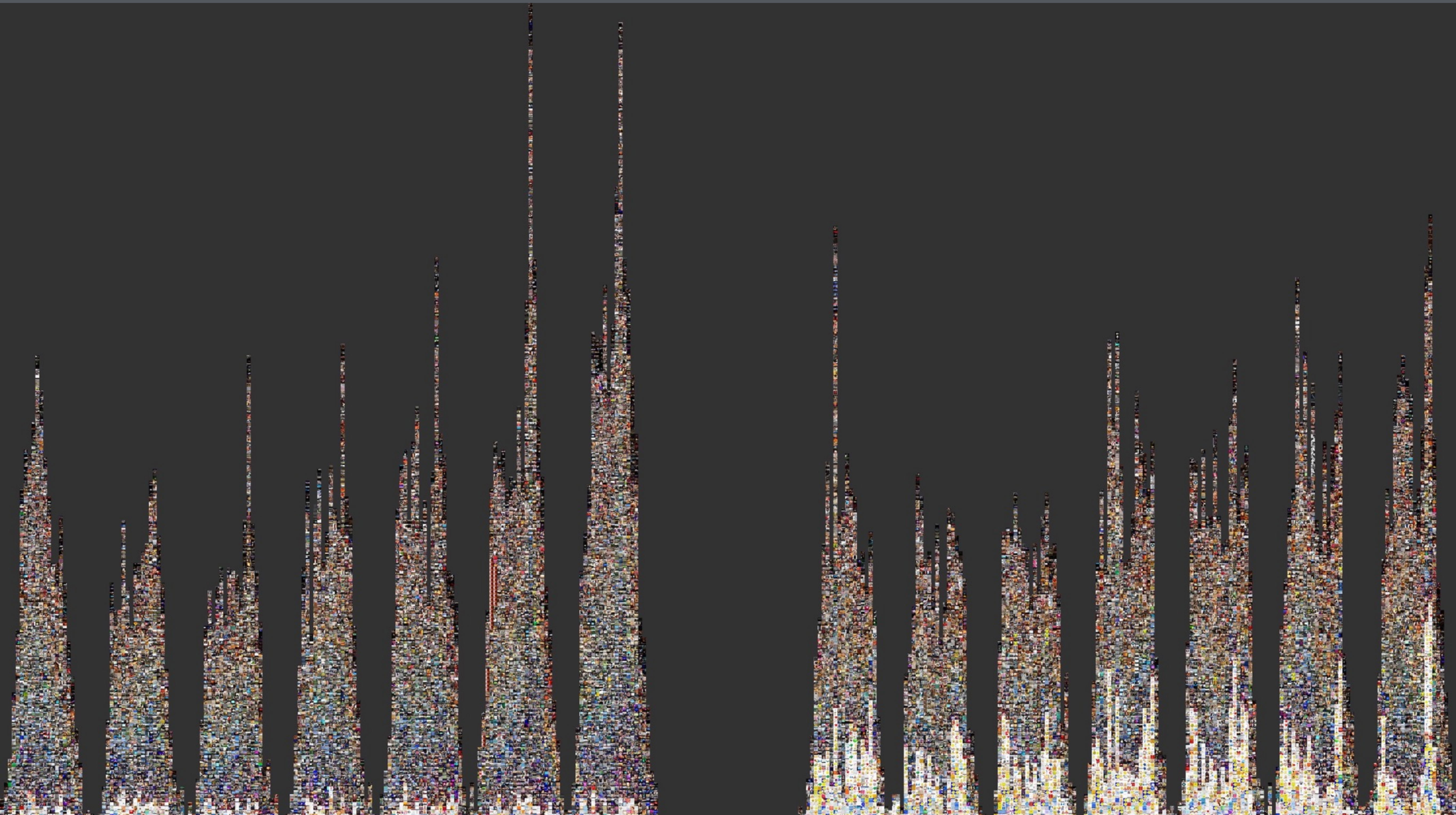


Fig. 3. The proportion of images in each city classified as "web site, website, internet site, site."

IV. Results and Discussion

We have classified one million images from 20 U.S. cities using the GoogLeNet Convolutional Neural Network. The most frequent category is "web site, website, internet site, site." We call these images "image-texts." Figure 2 shows a sample of these images. Figure 3 shows the proportion of this category for all 20 cities among all other images. This proportion varies from about 5% to over 10%. As Figure 2 shows, image-texts are memes, screenshots, and other images that are not directly representative of the real world. However, note that many of them are screenshots of text message conversations on smart phones. So while they do not show real life social interactions or natural environments, they are records of new forms of sociality enabled by networks and mobile phones.

We can see from Figure 3 that the rates of image-texts are different for each city. Furthermore, as Figures 4 and 5 demonstrate, each city also has a unique diurnal pattern of such images. Therefore, both characteristics can be used as features. The first feature is the overall rate of image-texts per city. The second feature is the entropy of the diurnal distribution of the image-text rates for 24-hour cycle per city.

To see if these two features have some connection to the socio-economic indicators, we calculate Pearson correlations between the values of the features and the indicators. Tables II and III show the correlation values. The absolute values of correlations range from 0.47 to 0.64. The values are significant with $p < 0.01$, except for income which has $p < 0.05$. The correlation with "objective" measures (i.e., housing prices, education levels and incomes) are negative, whereas the correlation with "subjective" measure of "social well-being" as reported by Gallup are positive.

These negative correlations suggest that people in cities that are more affluent as measured by objective measures such as housing prices share text-images less frequently. In contrast, people in less affluent cities share text-images more often.

Indicator	Correlation	P-value
Median Housing Price	-0.5638	0.007735
Rate of Bachelor's Degree	-0.6413	0.001623
Average Income	-0.4772	0.01805
Social well-being	0.56100	0.001623

TABLE II. PEARSON CORRELATIONS BETWEEN THE PROPORTION OF IMAGES CLASSIFIED AS IMAGE-TEXTS AND FOUR SOCIO-ECONOMIC VARIABLES (FIGURE 2).

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