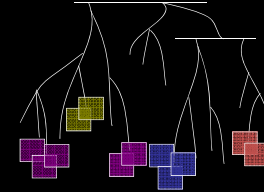




+



Exploring Image, Video and Multimedia in Large Data Applications

Prof. Shih-Fu Chang

<http://www.ee.columbia.edu/dvmm>

January 29th, 2016



COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

First Digital Camera in 1975

- film-less photography



by Steve Sassan of Kodak

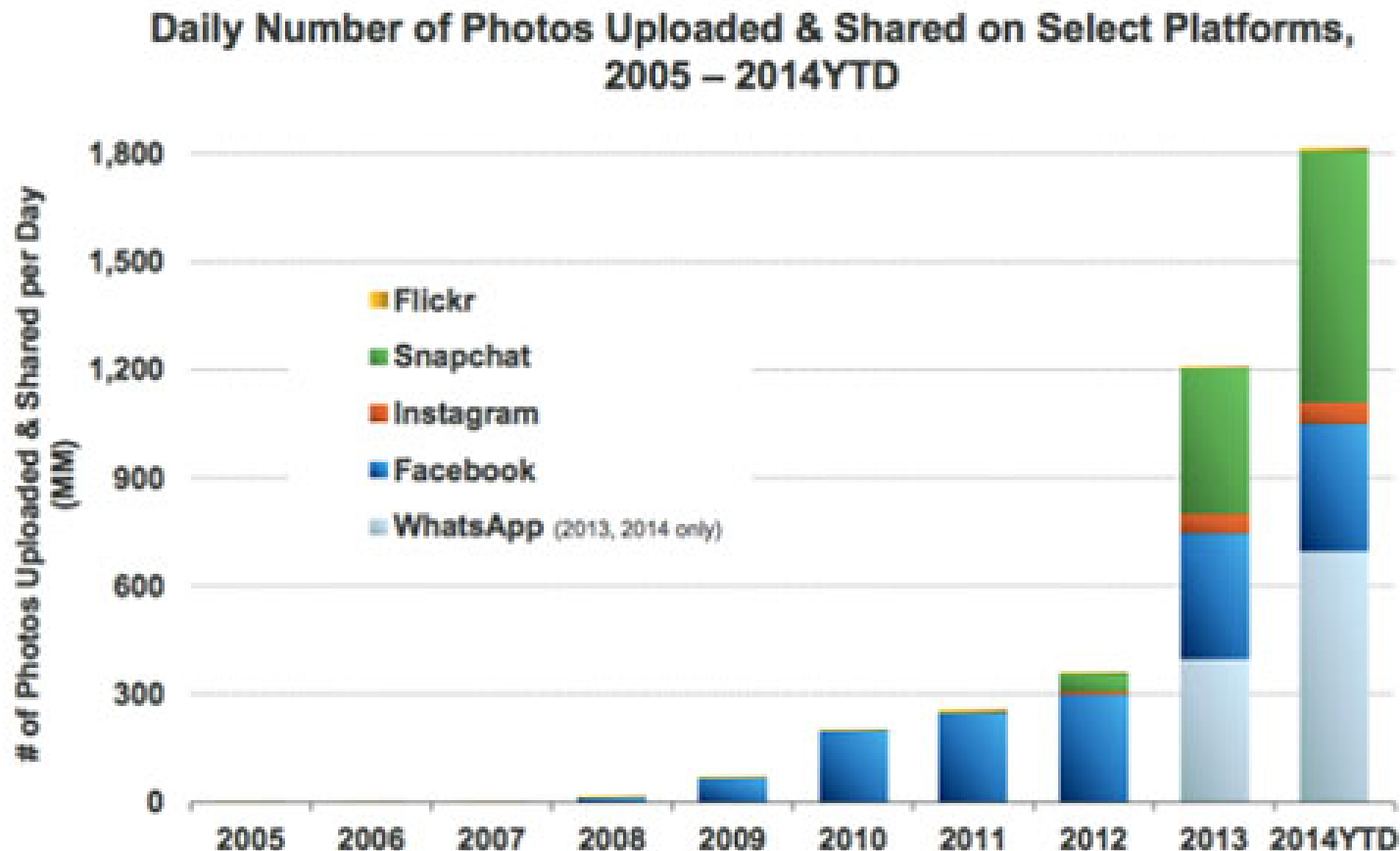


- CCD array, A/D converter, 16 batteries
- 23 seconds to record a photo to cassette
- customized reader on a B/W TV for viewing

Q: quality, size, cost, store, share?

Today ...

Photos Alone = 1.8B+ Uploaded & Shared Per Day...
Growth Remains Robust as New Real-Time Platforms Emerge



Source: KPCB estimates based on publicly disclosed company data, 2014 YTD data per latest as of 5/14
S.-F. Chang

The New York Times

Researchers Announce Advance in Image-Recognition Software

By JOHN MARKOFF NOV. 17, 2014

How Facebook is teaching computers to see

by Stacey Higginbotham @gigastacey JUNE 15, 2015, 1:15 PM EST

FORTUNE

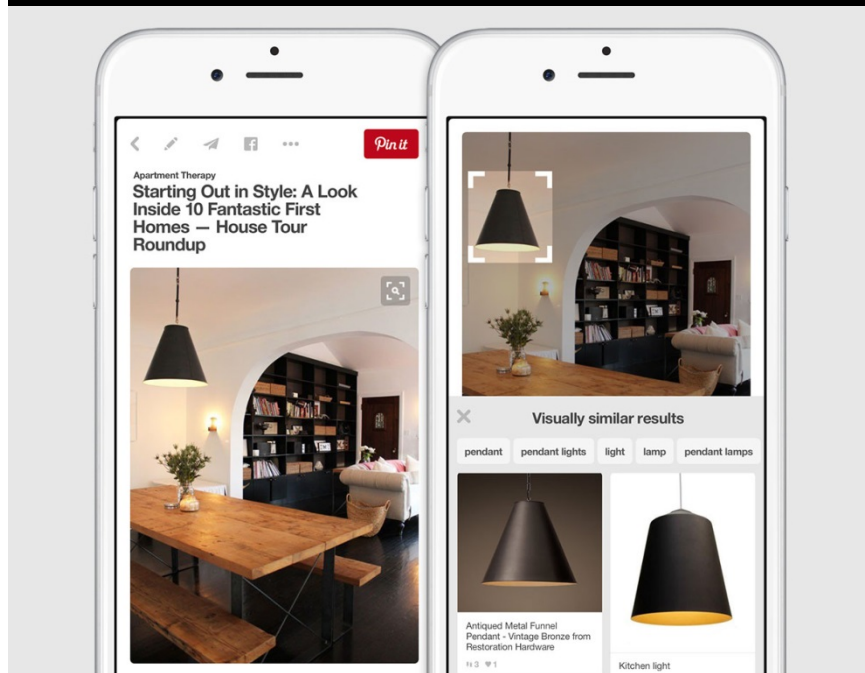
**MIT
Technology
Review**

AI Advances Make It Possible to Search, Shop with Images

Deep learning software has dramatically improved image recognition tools. Pinterest and Shoes.com are testing it out on shoppers.

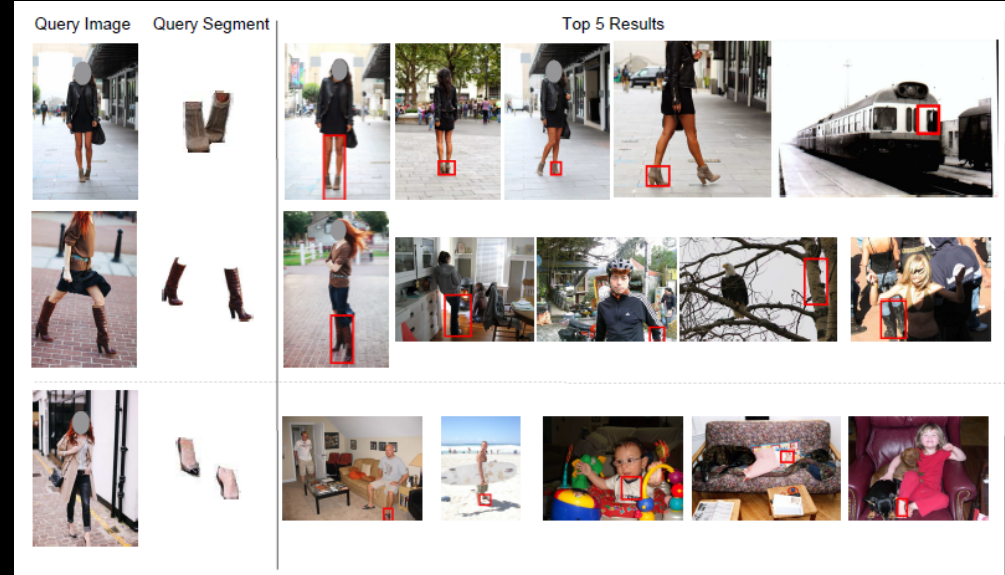
By Tom Simonite on November 17, 2015

Pinterest Visual Search



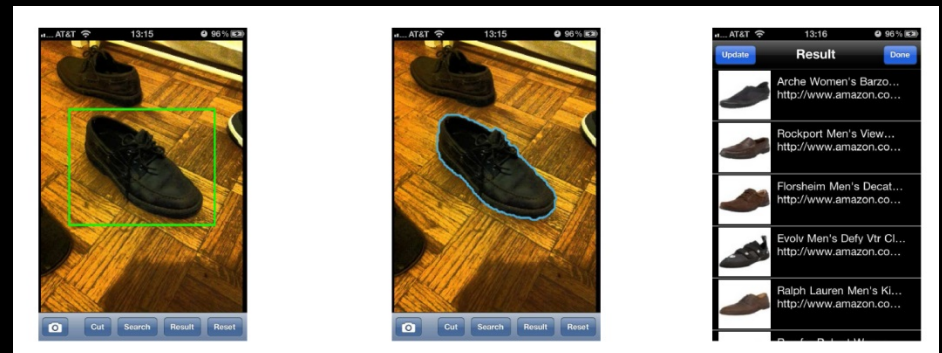
Instance Search

(R. Tao, A. Smeulder and S.F. Chang, CVPR 15)



Columbia Mobile Visual Search

(MM'11, 1KB compact hash code over 0.5M products)



[video demo](#)



ImageNet Large Scale Visual Recognition Challenges



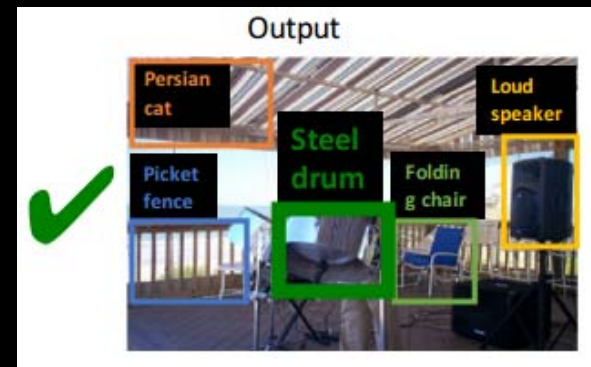
ImageNet:
Recognize > 1,000
object categories

Variety of object classes in ILSVRC

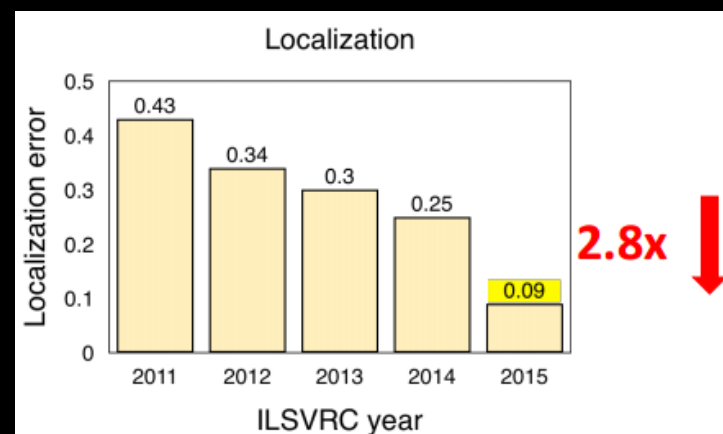
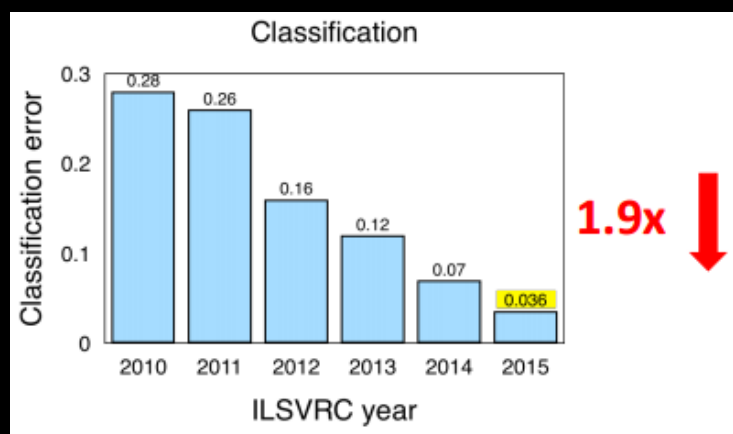


Rapid Progress in Recent Years:

Classification/ Detection Task

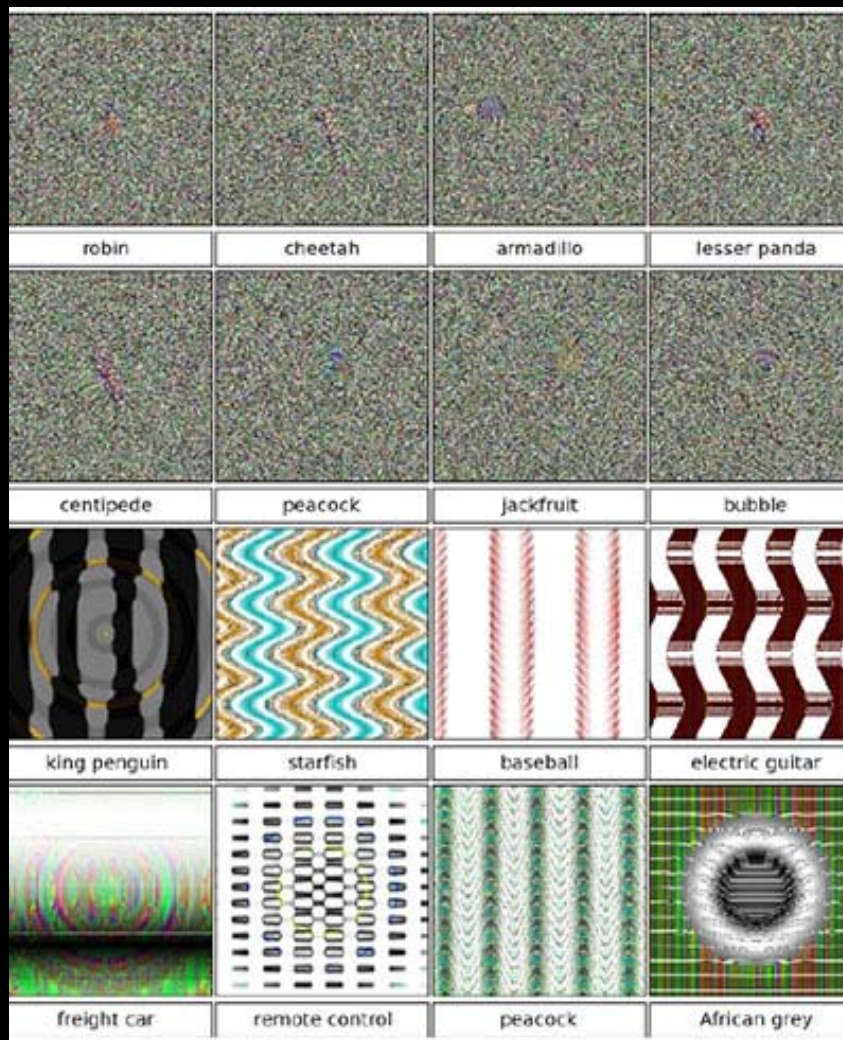


$$\text{Error} = \frac{1}{100,000} \sum 1[\text{incorrect on image } i]$$



But Use with Caution!

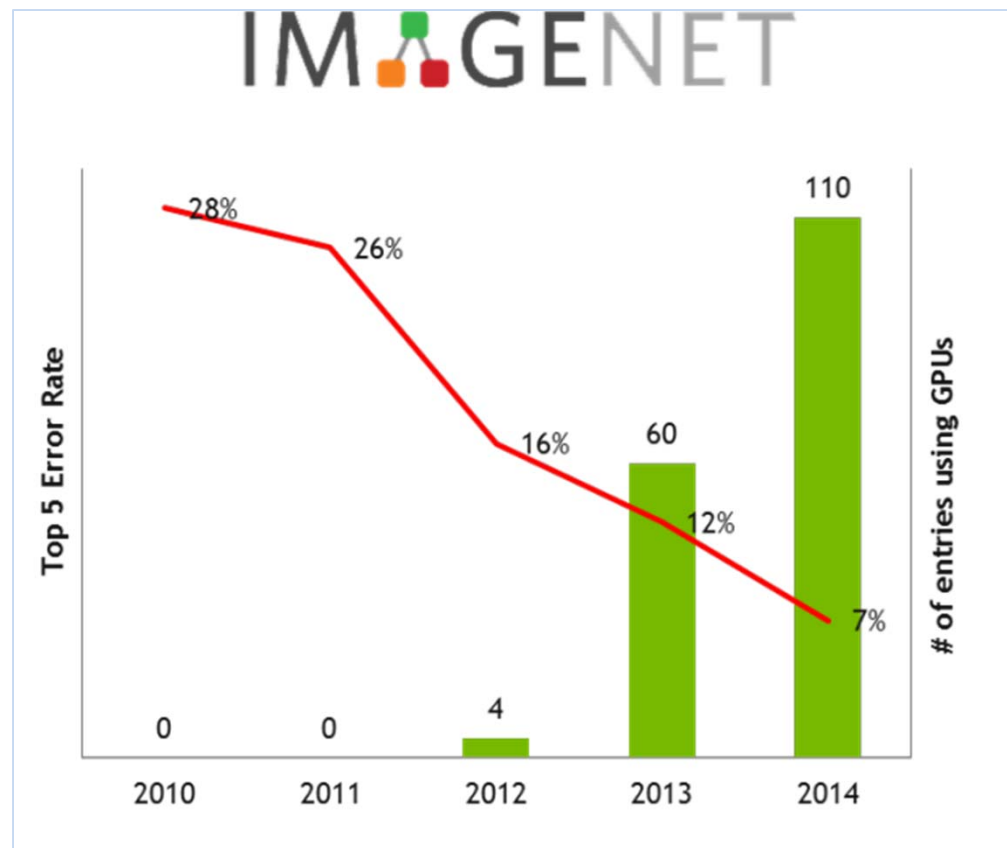
“Smart” Software Can Be
Tricked into Seeing What Isn’t
There



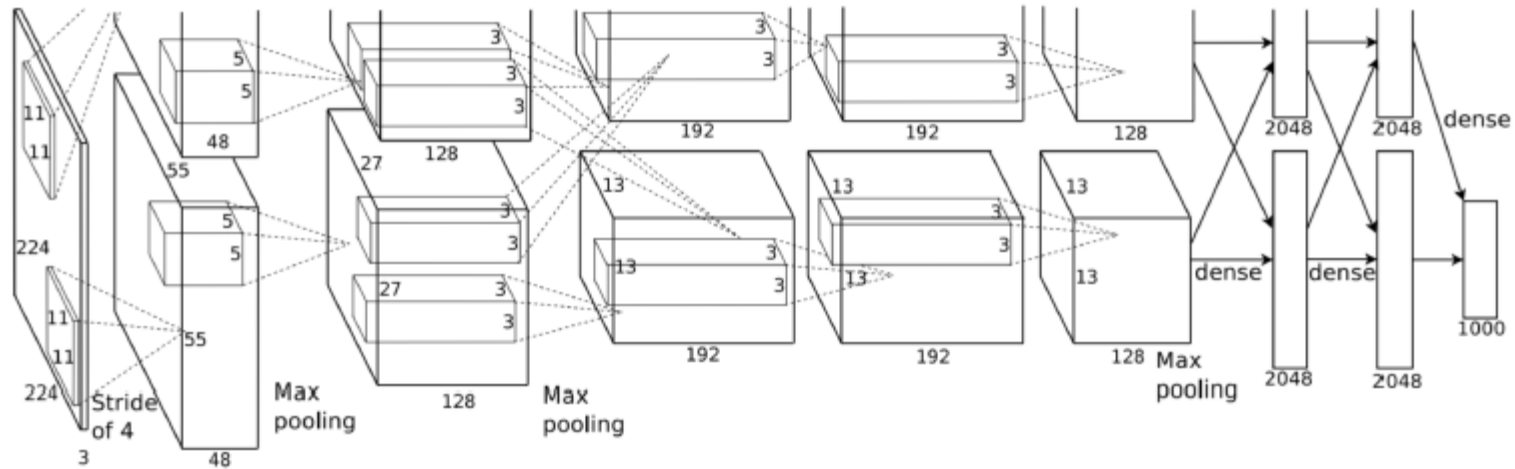
Nguyen, et al, CVPR 2015

Research Issue: Complexity

- How to handle huge data and computational cost?



Circulant Neural Networks



- ▶ Captures global information.
- ▶ 90 - 95% of the memory in AlexNet.
- ▶ 20 - 30% of the computational time.

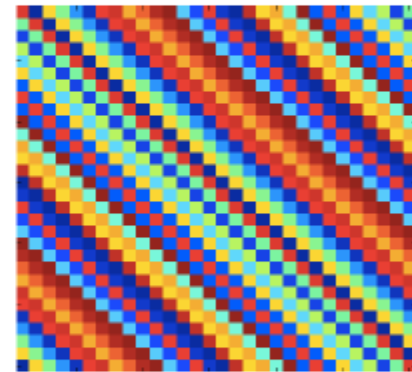
Circulant Binary Embedding (CBE)

Replace fully connected layer with structured component:

$$h(\mathbf{x}) = \phi(\mathbf{R}\mathbf{D}\mathbf{x}), \phi(\cdot): \text{a nonlinear activation function}$$

- $\mathbf{R}$ is a **circulant matrix**, defined by $\mathbf{r} = (r_0, r_1, \dots, r_{d-1})^T$

$$\mathbf{R} = \text{circ}(\mathbf{r}) := \begin{bmatrix} r_0 & r_{d-1} & \cdots & r_2 & r_1 \\ r_1 & r_0 & r_{d-1} & & r_2 \\ \vdots & r_1 & r_0 & \ddots & \vdots \\ r_{d-2} & & \ddots & \ddots & r_{d-1} \\ r_{d-1} & r_{d-2} & \cdots & r_1 & r_0 \end{bmatrix}$$



- $\mathbf{D}$ is a diagonal matrix, each entry ± 1 with probability $1/2$ (random sign flipping, dropped to simplify notation)
- Gradient computation in back-propagation can be done using FFT.

Circulant Neural Networks (cont'd)

Method	Time	Space	Time (Learning)
Conventional	$\mathcal{O}(d^2)$	$\mathcal{O}(d^2)$	$\mathcal{O}(ntd^2)$
Ours	$\mathcal{O}(d \log d)$	$\mathcal{O}(d)$	$\mathcal{O}(ntd \log d)$

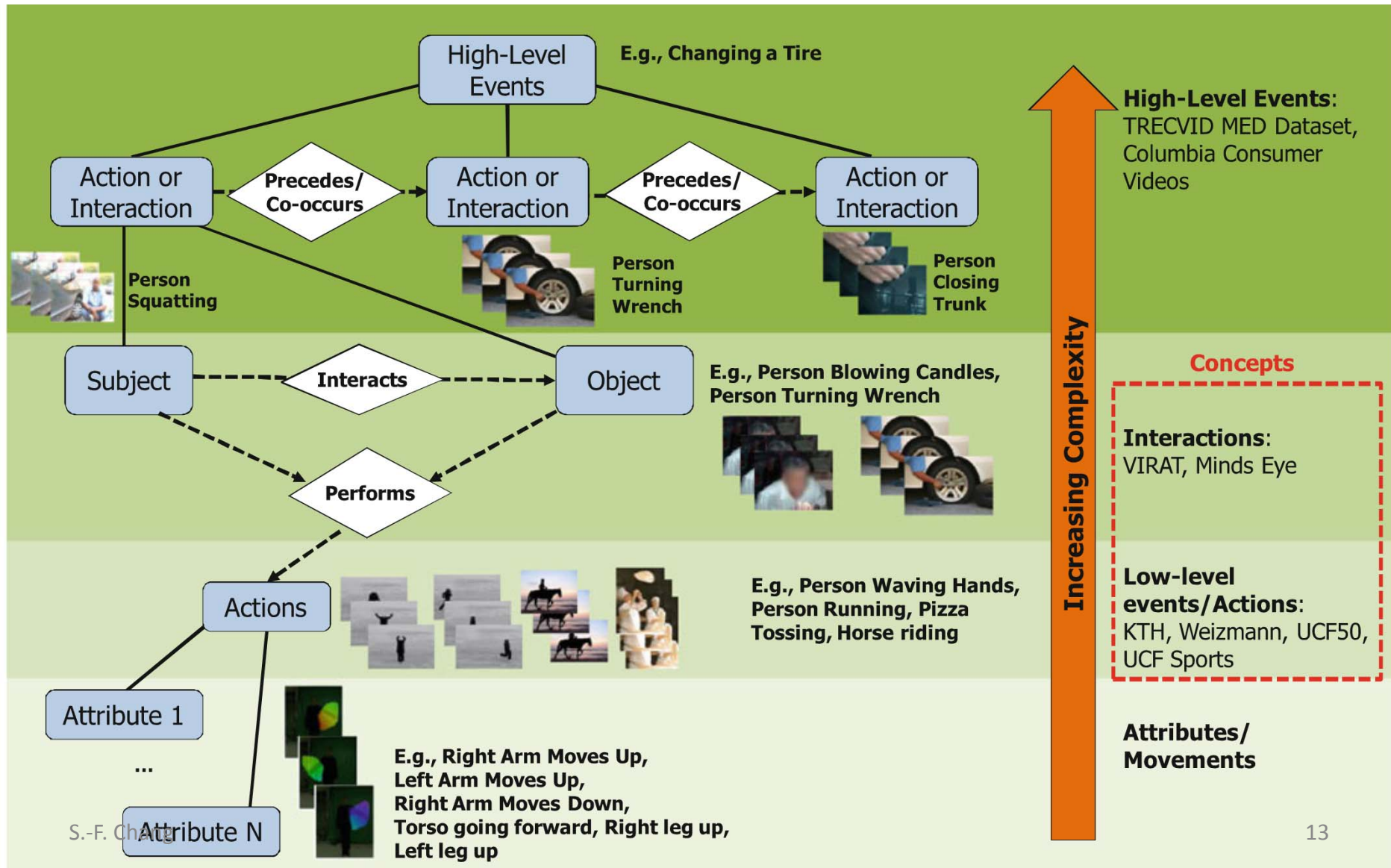
1000x less parameters in fc

- $4K \times 4K$ layer: 64MB $\rightarrow$ 16KB

Method	Top-5 Err	Top-1 Err	Memory
AlexNet (rand)	33.5%	61.7%	233.2MB
C-AlexNet (rand)	35.2%	62.8%	20.5MB
AlexNet	17.1 %	42.8%	233.2MB
C-AlexNet	19.4 %	44.1%	20.5MB
More parameters	17.8 %	43.2%	20.7MB
Reduced AlexNet	37.2 %	65.3%	20.7MB

Open Issue: How to Describe Complex Events in Video?

- Y. Jiang et al., high level events recognition in unconstrained videos, IJMIR, 2012 (survey)



Research: Complex Video Event Recognition

K.-T. Lai; F. X. Yu; M.-S. Chen; S.-F. Chang. CVPR 2014

- Detecting complex events in $\sim 100,000$ videos

**MED
2011
devel.
events**



Attempting a board trick



Feeding an animal



Landing a fish



Wedding ceremony



Working on a
woodworking project

**MED
2011
testing
events**



Birthday party



Changing a vehicle tire



Flash mob gathering



Getting a vehicle unstuck



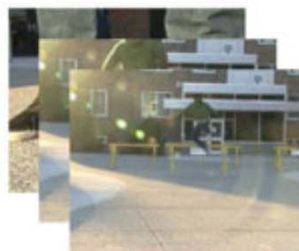
Grooming an animal



Making a sandwich



Parade



Parkour

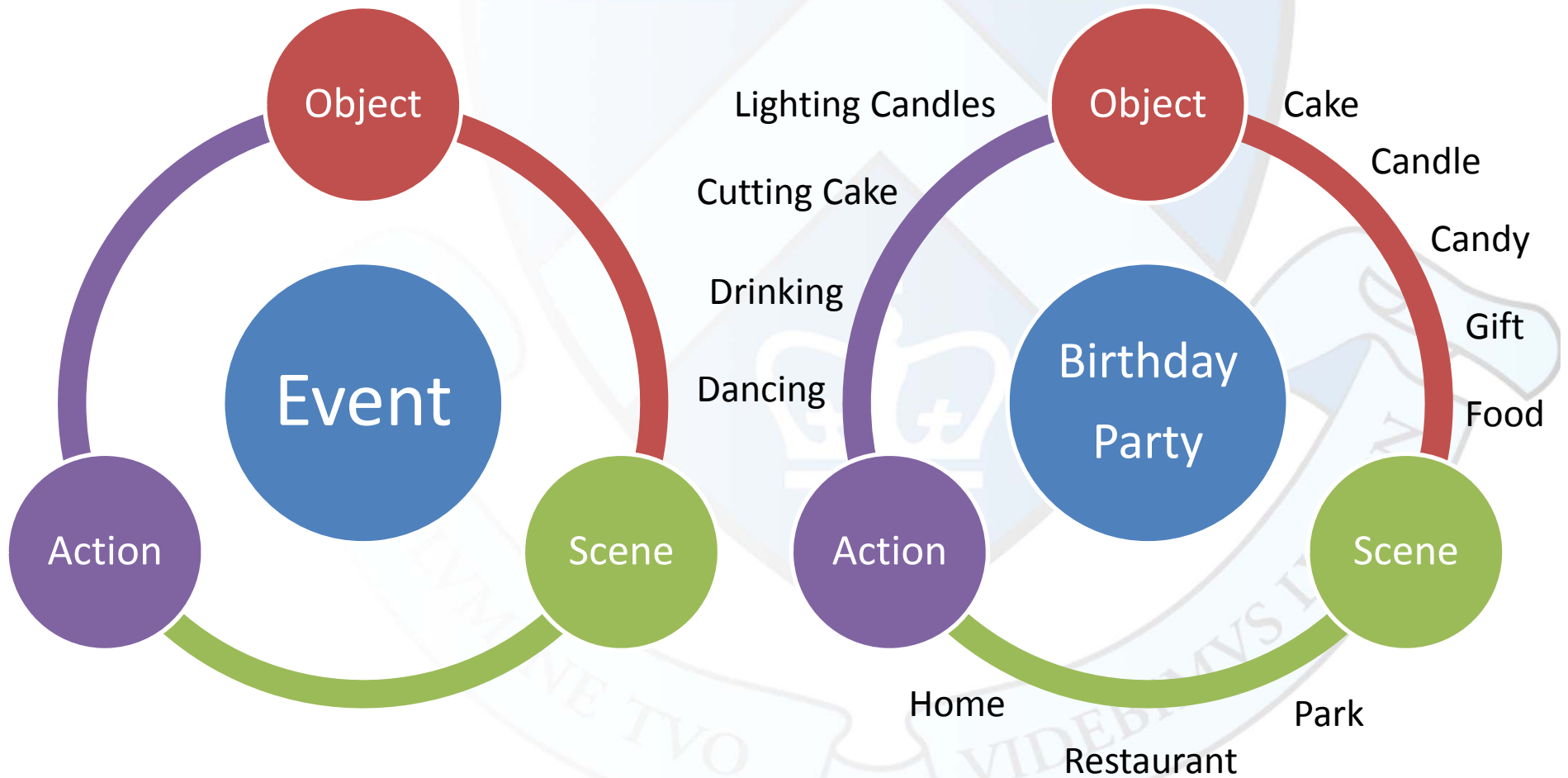


Repairing an appliance



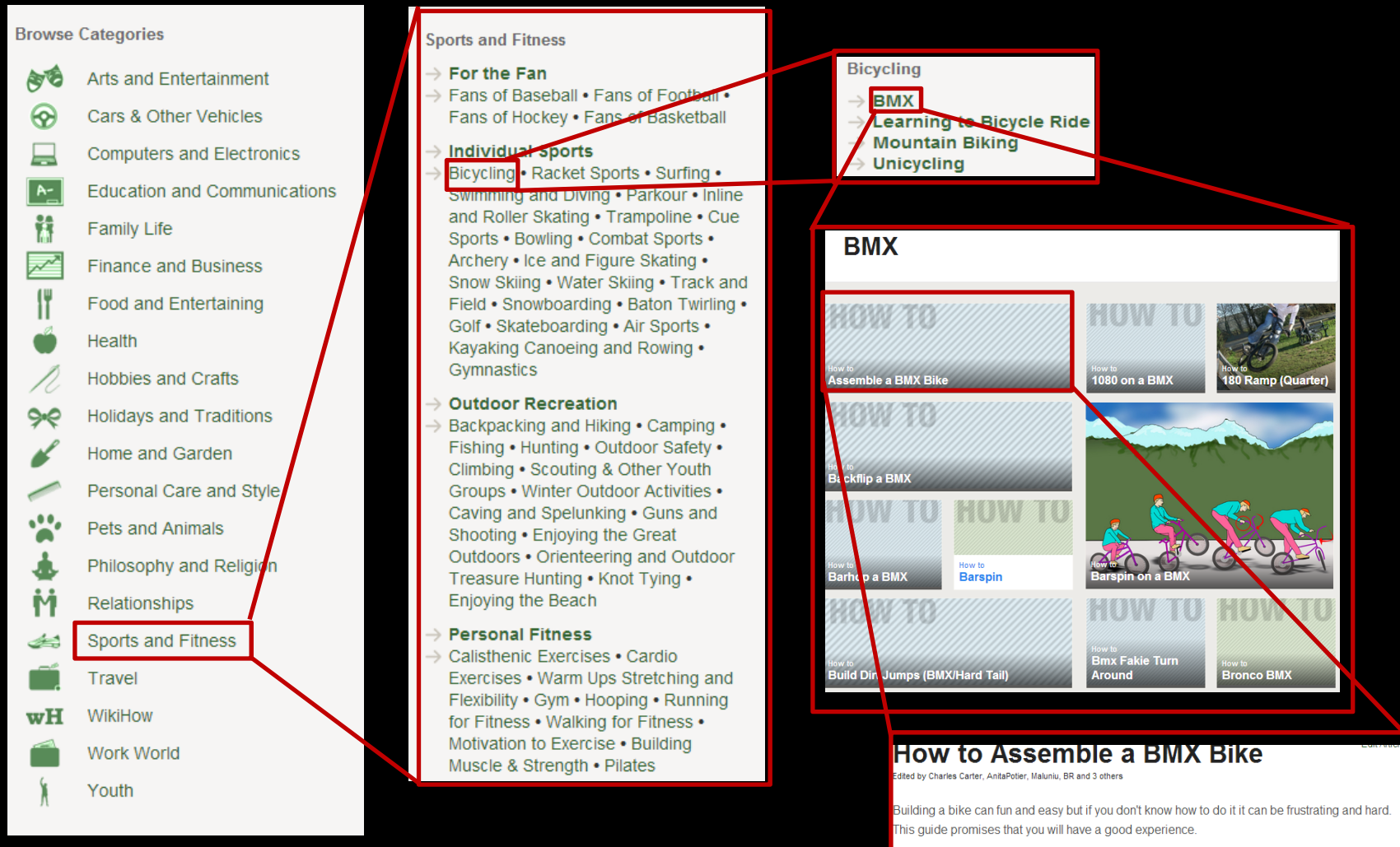
Working on a sewing project

What Salient Concepts Are Associated with Each Video Event?



Inspiration from Crowd – WikiHow

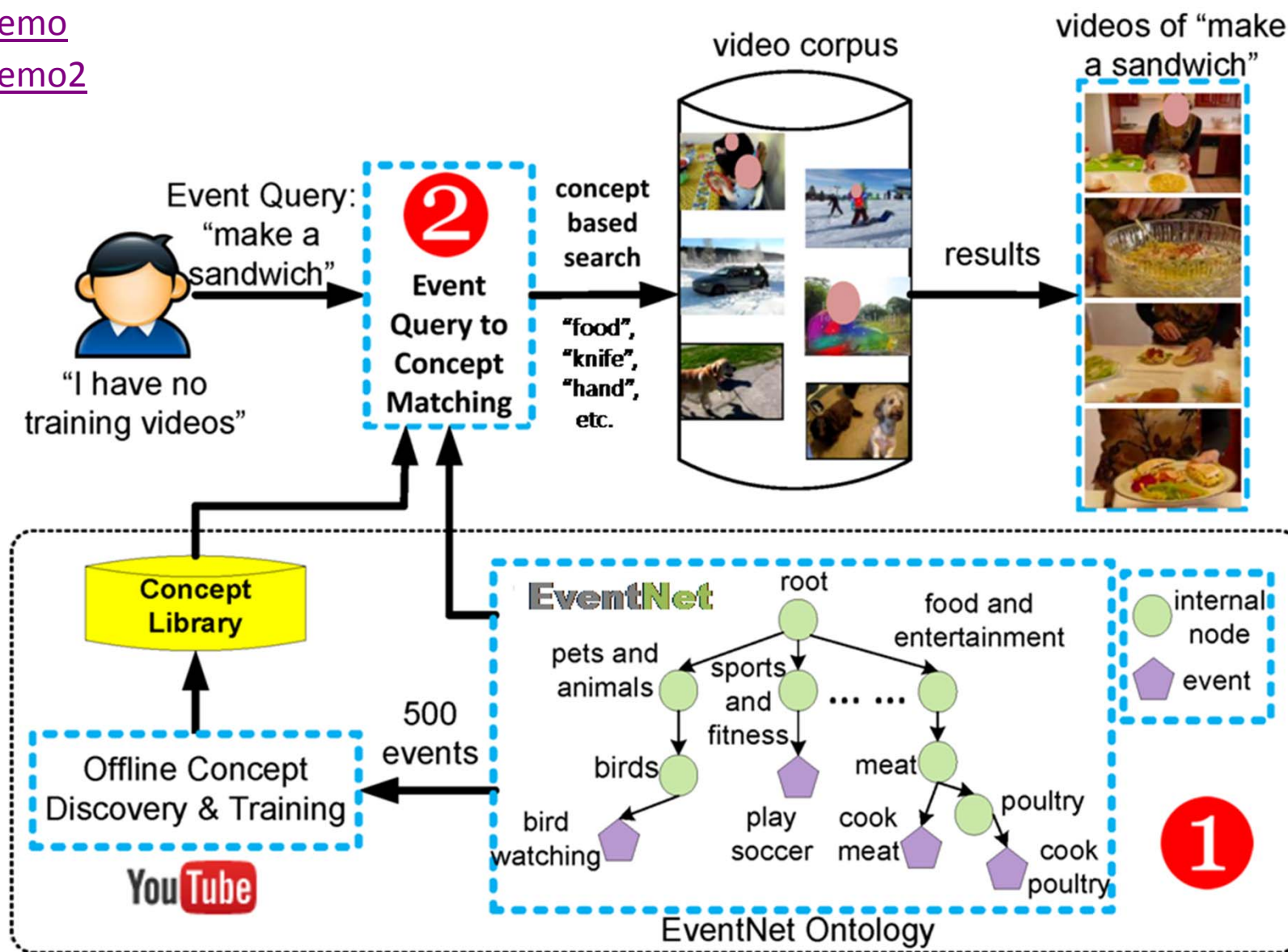
- A wiki contains ~300,000 articles on 2,803 “how to” category.
- All articles are organized into a hierarchical structure.

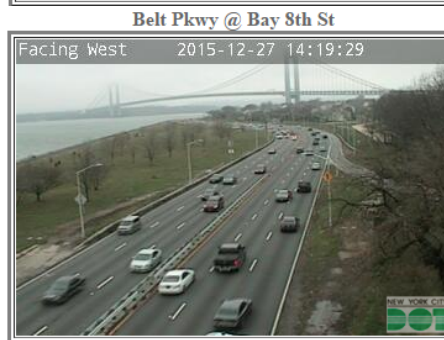


Columbia Video EventNet Ontology (500 events, 4,800 concepts)

[Demo](#)

[Demo2](#)





Urban Sensing: City webcam and social media

- 400+ traffic webcams in NYC: <http://nyctmc.org/>
- Resolution 352x240. Framerate between 1fps and 1 frame every 3s.
- Data-agreement: <http://www.nyc.gov/html/dot/downloads/pdf/video-partnership-agreement.pdf>
- No ground truth. Event calendars from OpenData and DOT API
 - <https://developer.cityofnewyork.us/api/dot-data-feeds-beta>
 - <https://developer.cityofnewyork.us/api/events-calendar>
 - <http://www.nyc.gov/html/dot/html/motorist/wkndtraf.shtml>

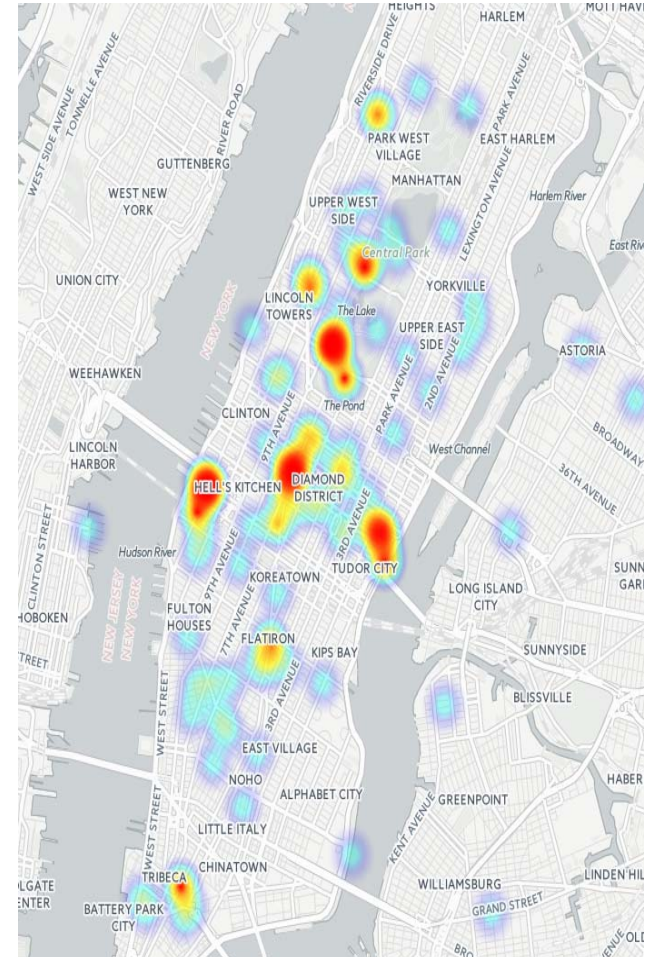
<i>event</i>	<i>date</i>	<i>time</i>	<i>location</i>
CBGB Music Festival	12 Oct	10am-7pm	Broadway 51 Street
Hispanic Parade	12 Oct	12pm-5pm	5th Avenue
Columbus Day Parade	13 Oct	11am-5pm	5th Avenue
Saint Patrick's Day Parade	17 Mar	12pm-5pm	5th Avenue
Million March NYC Protest	13 Dec	2pm-5pm	Washington Square Park, 5th Avenue, Foley Square

Example Tweets (Wu & Kankanhalli, WWW'15)

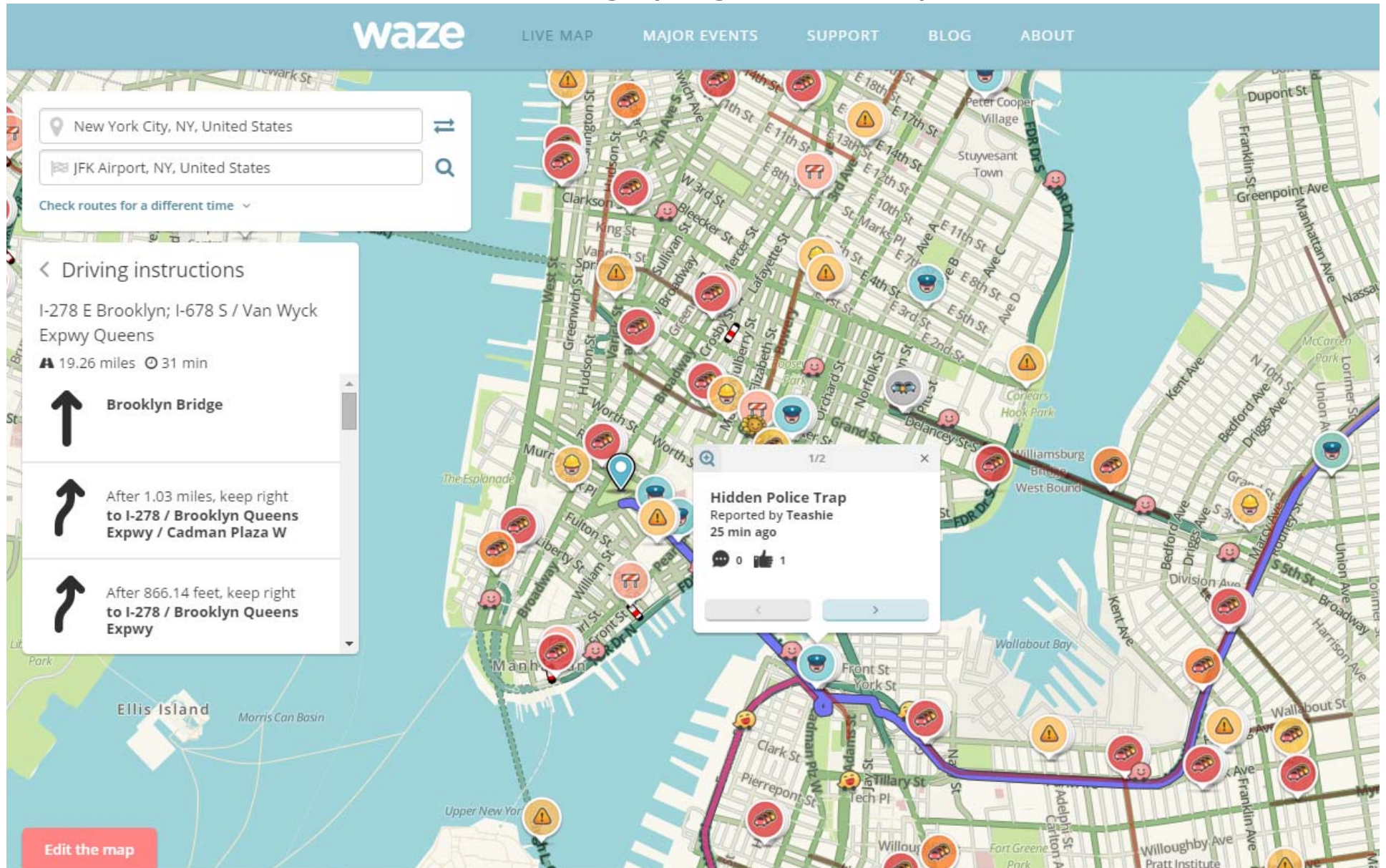
2011 2015-10-31 05:45:21 Binnen... Incl honered guest
bandje ? 1 day 2 #tcsnycmarathon @ Times Square, New York
City <https://t.co/ew4buSUhDR> 40.758895 -73.985131

2074 2015-10-31 06:07:34 The honey and I got new
running shoes at the NYC marathon expo!! I have never been in a
morej <https://t.co/UleMSZhZdy> 40.75759585 -
74.00118993

2226 2015-10-31 06:55:00 Not a bad view from my hotel
room watching the sun come up!! Off to the marathon expo to
collect myj <https://t.co/HWr9OH88Ht> 40.75807569
-73.9753008

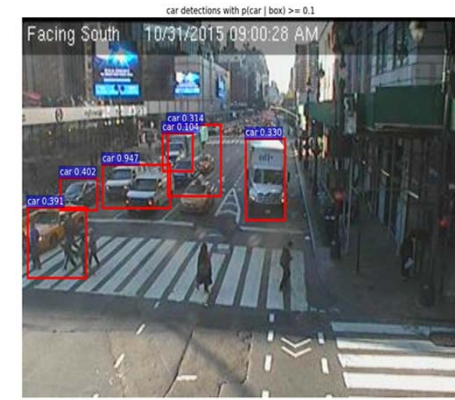
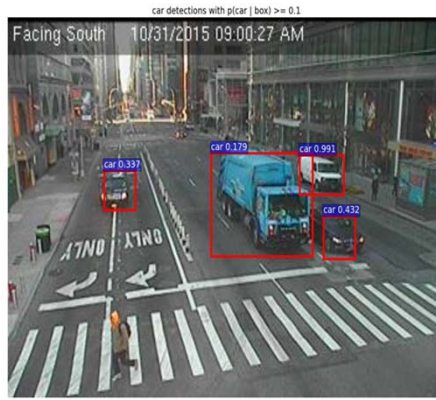


Social Crowd Reporting (e.g., Waze)

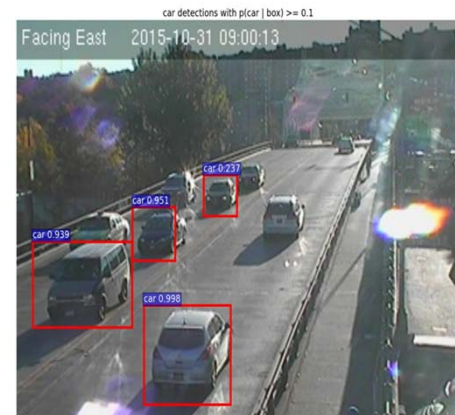
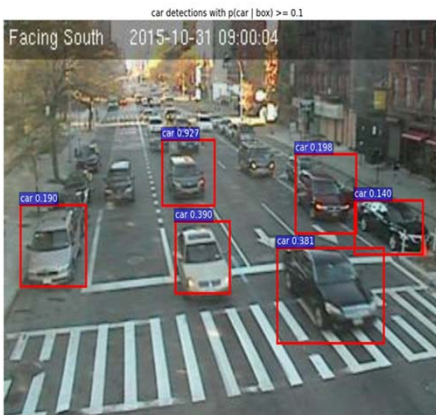


Computer Vision Tools

car detection - success in most cases:



car detection - some missing detections:



Potential Applications and on-going research:

- Traffic patterns
- Accidents
- Individual vehicle condition:
aggressive driving, abnormal driving, car breakdown
- Vehicle tracking across cameras

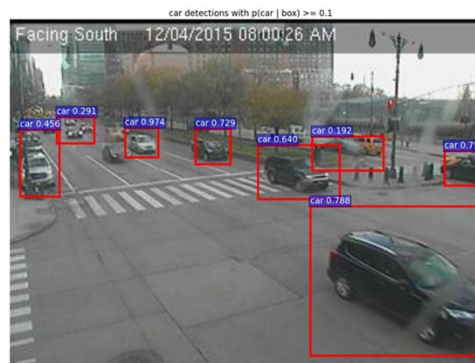
observations

Three nearby cameras:

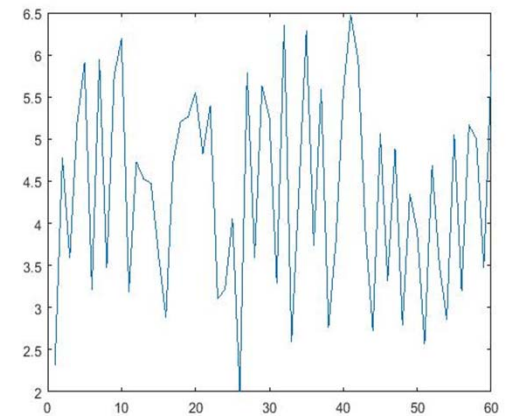
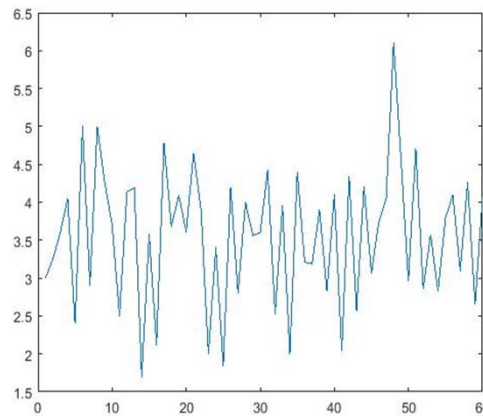
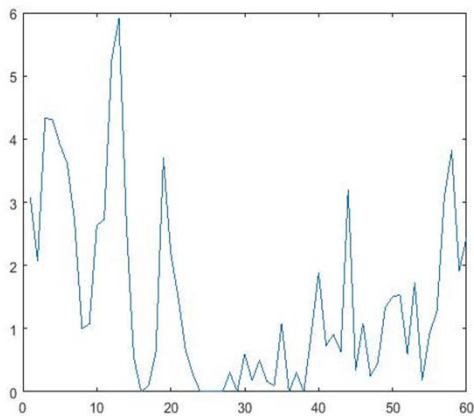
157-92_Holland_Tunnel

430-320_RT_9A_@_N._Moore_St

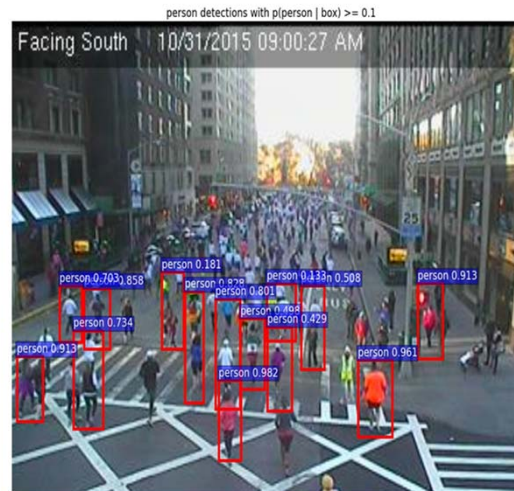
715-664_West_St_@_West_Houston_St



Number of cars detected on each image. 8am~9am. Dec 3rd. y: #car, x: minute.



Person Detection

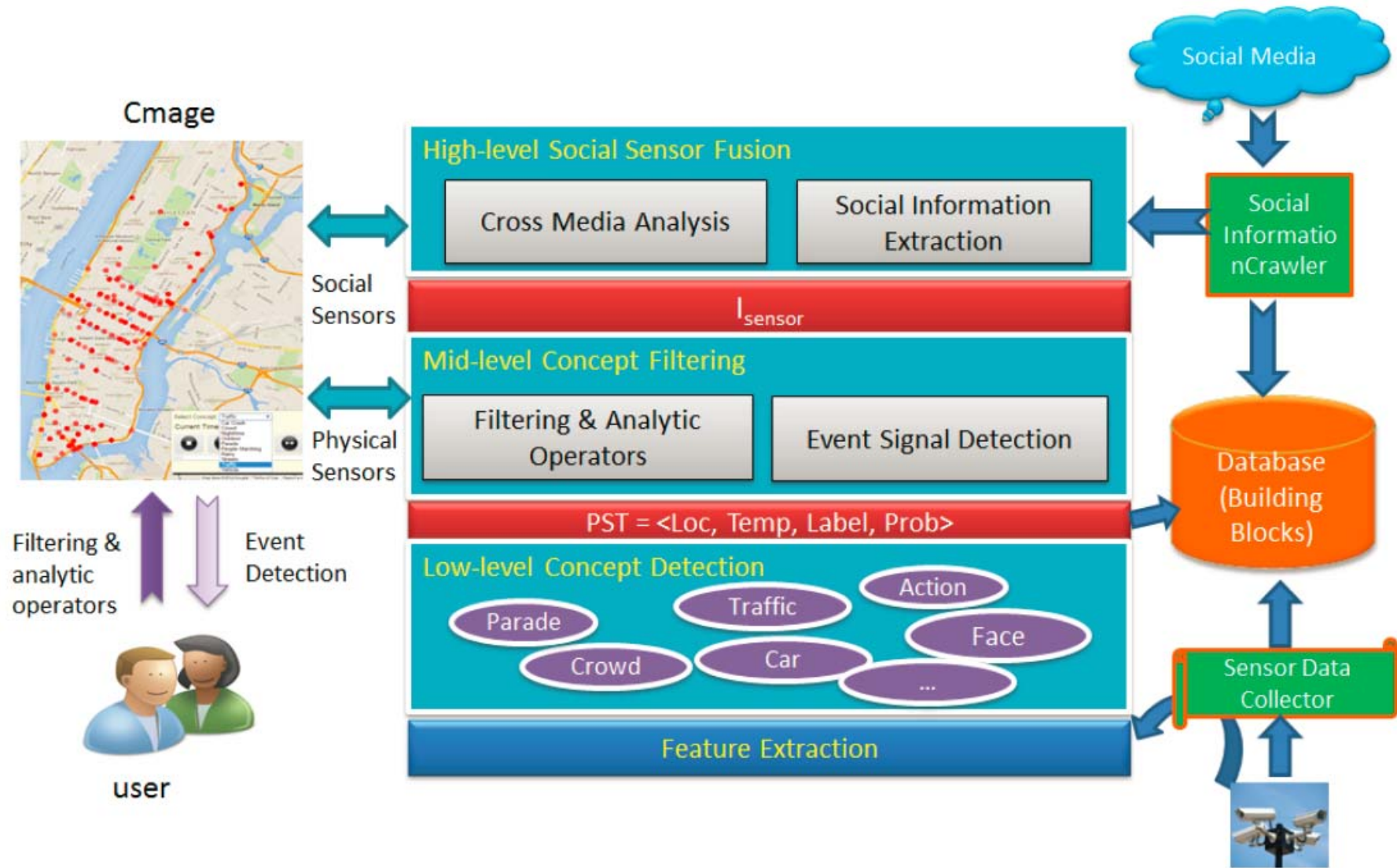


Possible Applications:

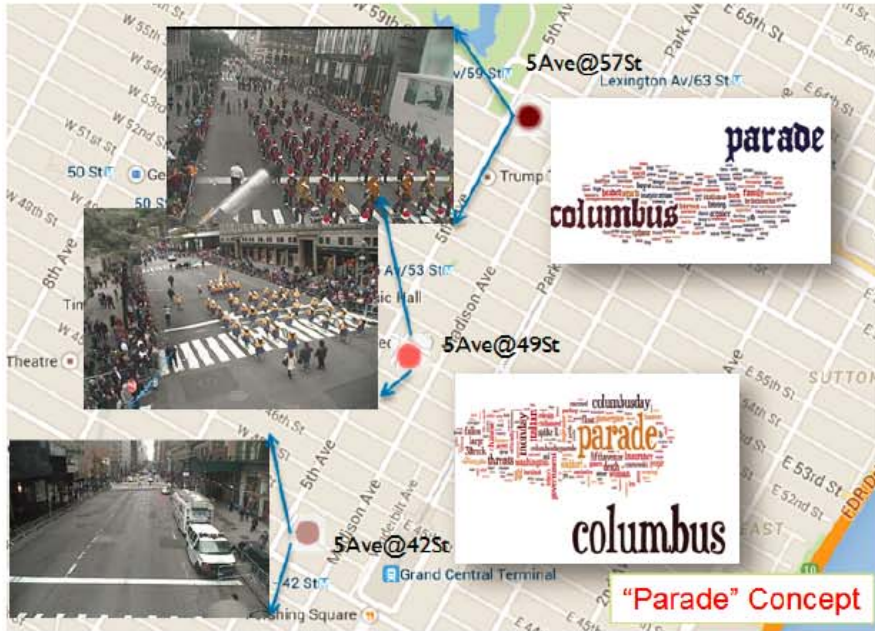
- People density: few people, crowd, crowd motion
- Categorize events: parade, marathon
- Social Behavior: random crowd vs. affiliated groups

DEMO

Social Tweeting Camera, (Wang & Kankanhalli, WWW'15)



Combining Camera Sensors and Social Signals



(a) Social Sensor Fusion for “Columbus Day Parade”



(b) Social Sensor Fusion for
“Hispanic Parade” Event

Ongoing research Issues

Deeper Analysis

- Vision: people, object, setting, events
- NLP: entity, topic, events, sentiments

Joint Analysis

- Naming events seen in video
- Illustrating entities mentioned in text
- Disambiguate concepts (e.g., “truck”, “sign”)

Social Sharing -> Opinion Expression



The Power of Social (Visual) Multimedia

2012 Tweets of the Year

@BarackObama: Four more years.

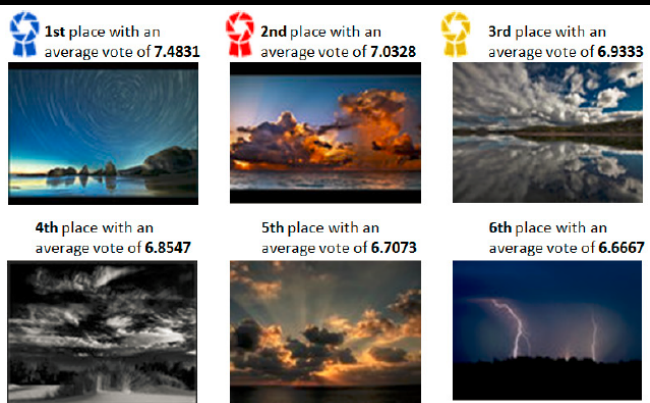


@Brynn4NY: Rollercoaster at sea.



@Fang-Ru: Queen of the far far away land.





(CVPR 2014 Tutorial)



Aesthetics

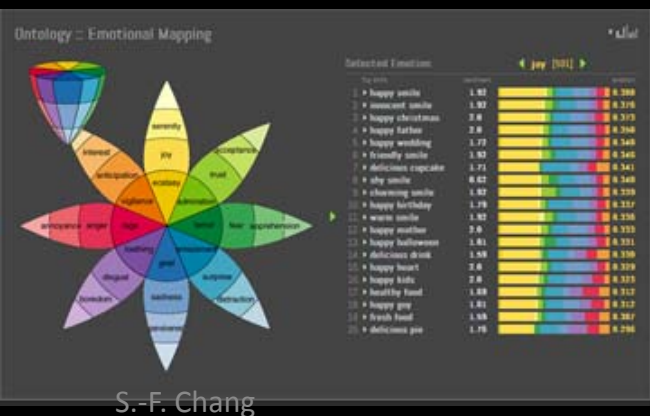
Interestingness

Beyond Semantics

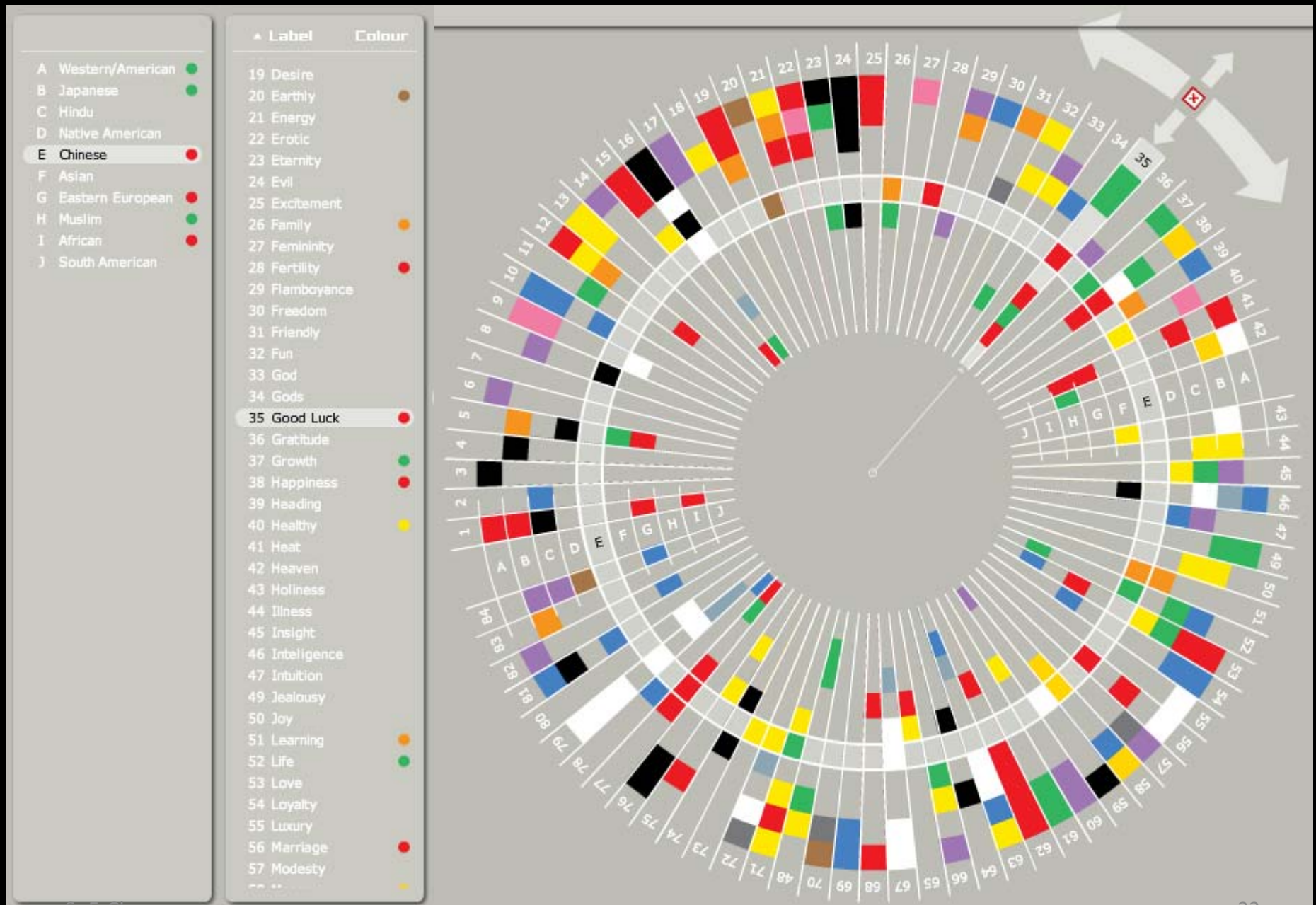
Emotion

Style

Others:
Creativity,
Intent,
Memorable ...



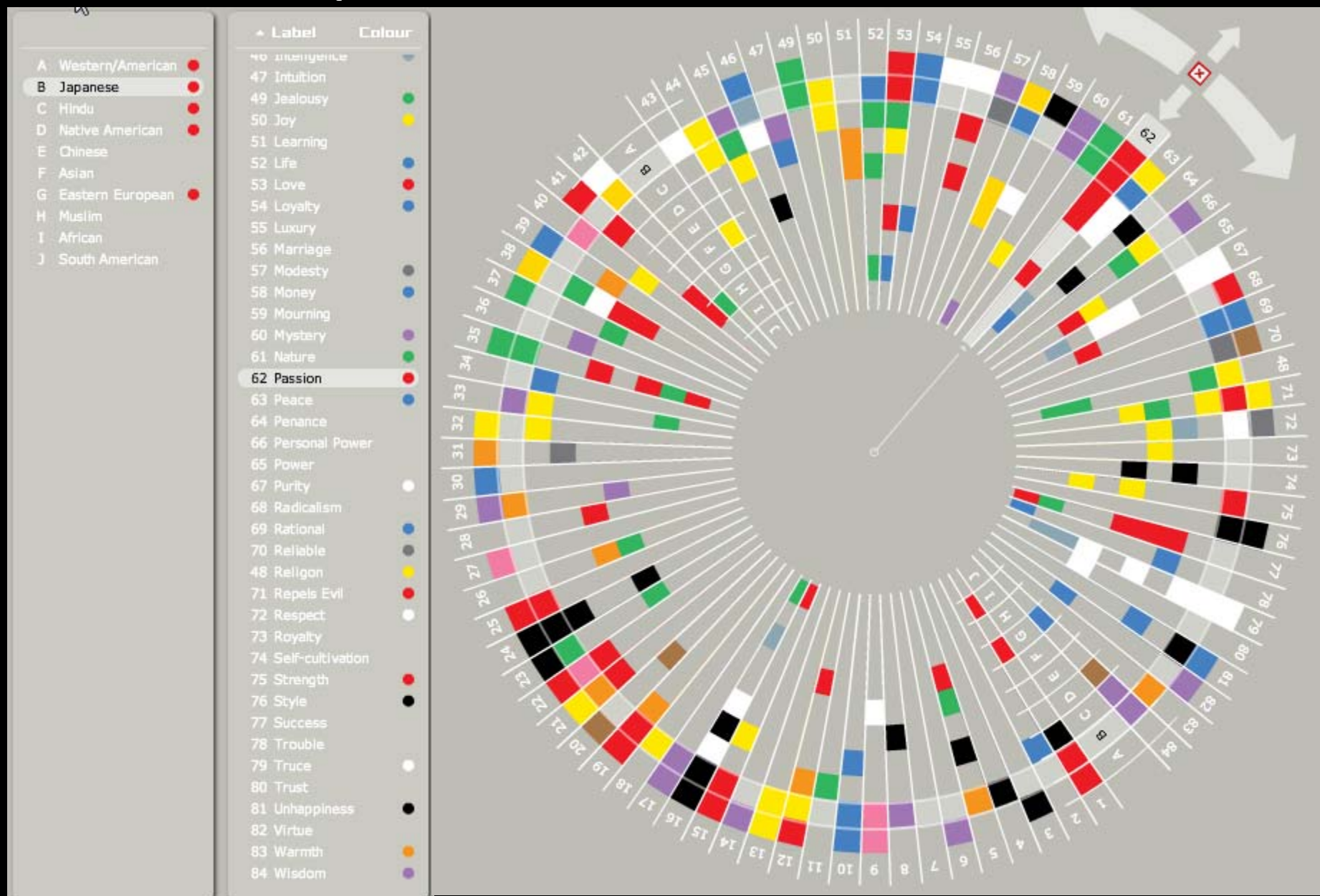
Culture plays an important role in visual presentation



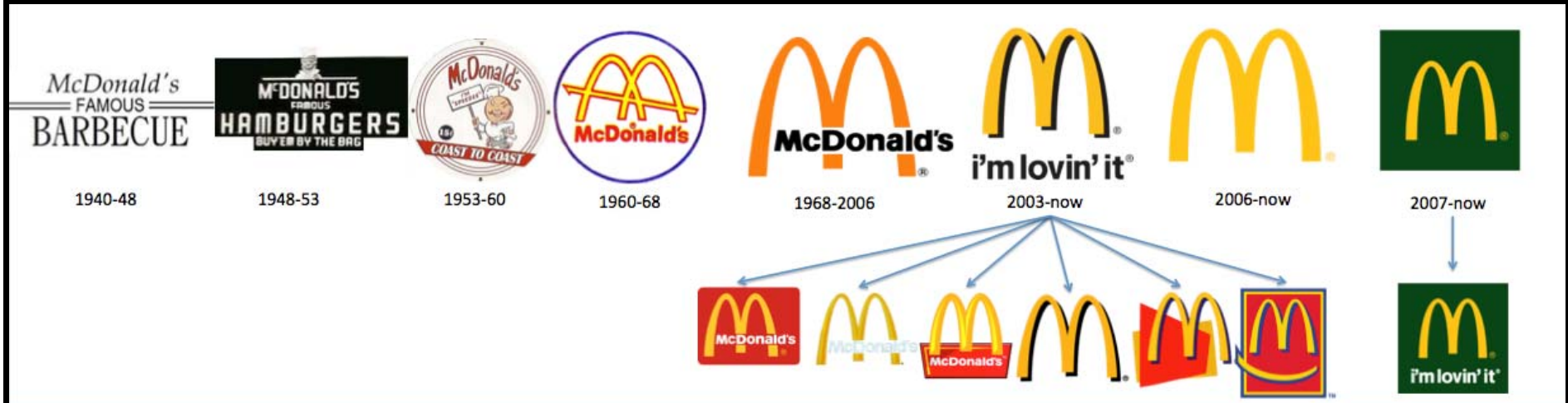
S. F. Chang

David McCandless, Information is Beautiful, Interactive tools by Lab Zoho

Some colors are pan-cultural

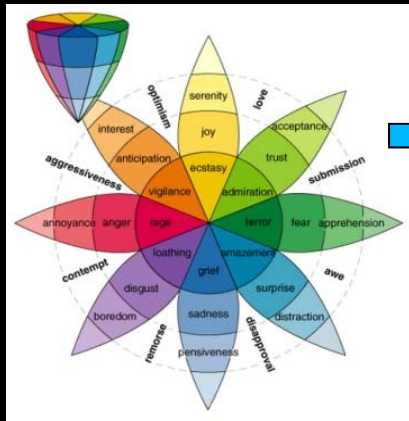


Color Logos in the World

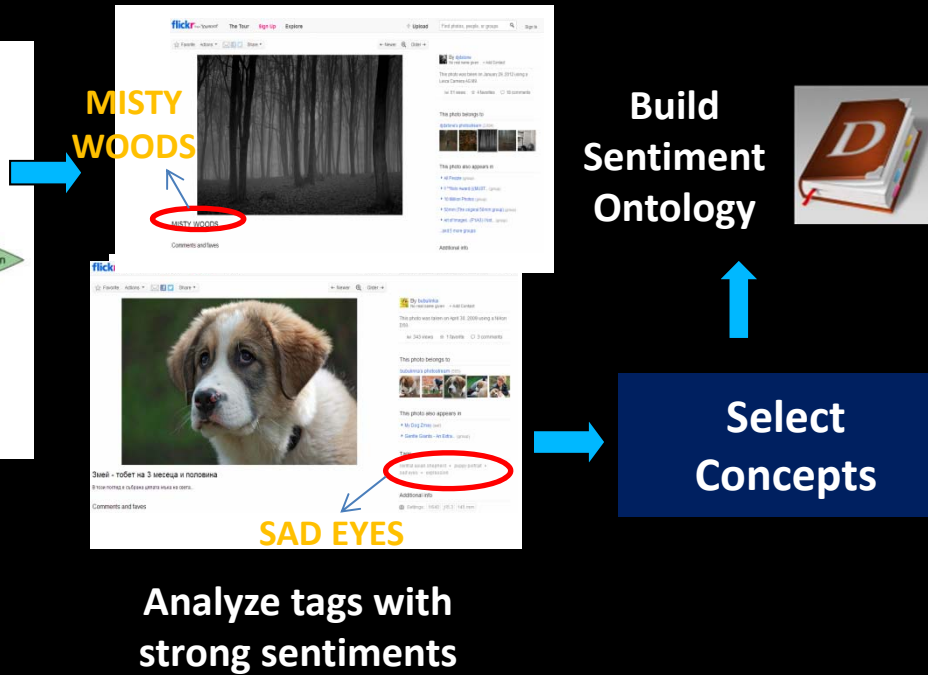


Columbia Visual Sentiment Ontology:

- Discover popular visual concepts used to express emotions



Psychology emotion wheel (8 emotions)
Robert Plutchik, '91

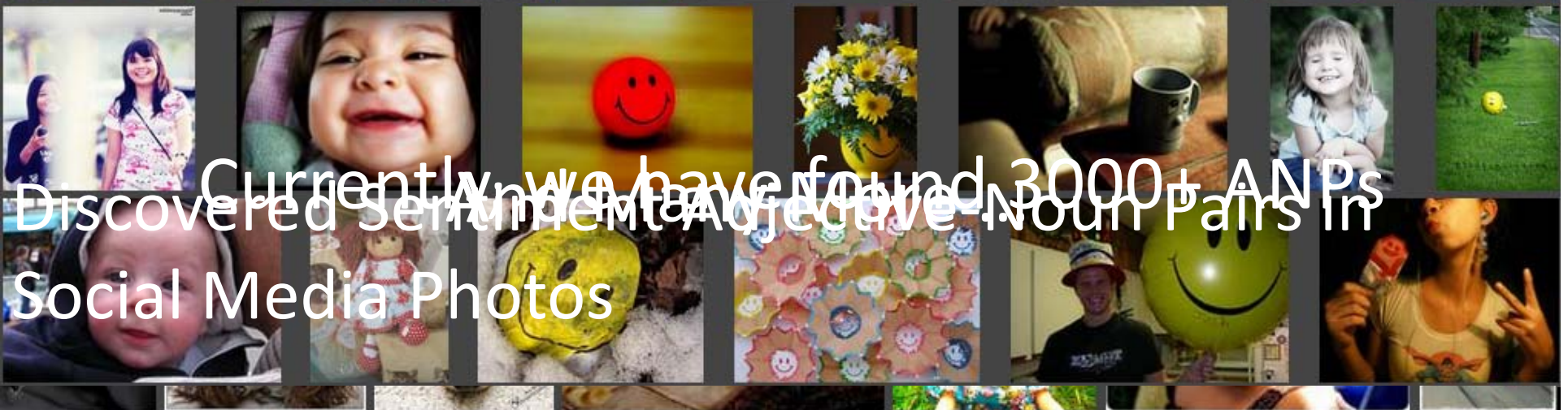


Borth, Ji, Chen, Breuel, Chang, *Large-Scale Visual Sentiment Ontology*, ACM Multimedia 2013

Frequent Photo Tags Related to Emotions



Slippery Slope
Slippery Slope



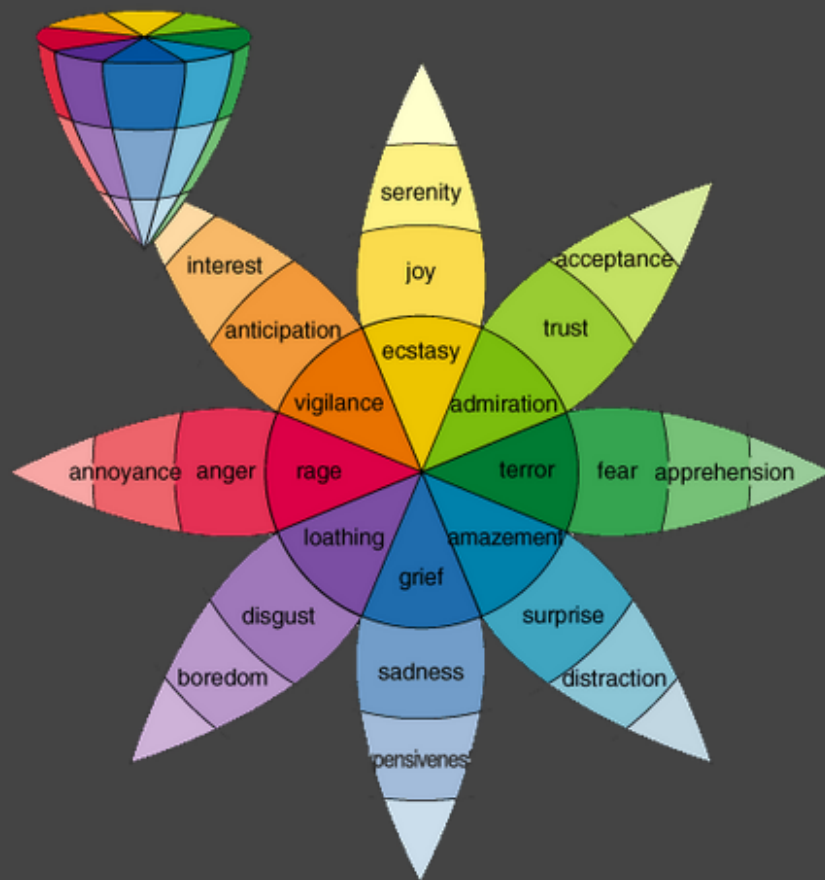
Discovered Sentiment-Adjective-Noun Pairs In
Social Media Photos

Visual Sentiment Ontology (Browser)

Home :: Ontology :: Adjective Noun Pairs :: Downloads :: About

Visual Sentiment Ontology 

Ontology :: Emotional Mapping



Selected Emotion:

◀ joy [591] ▶

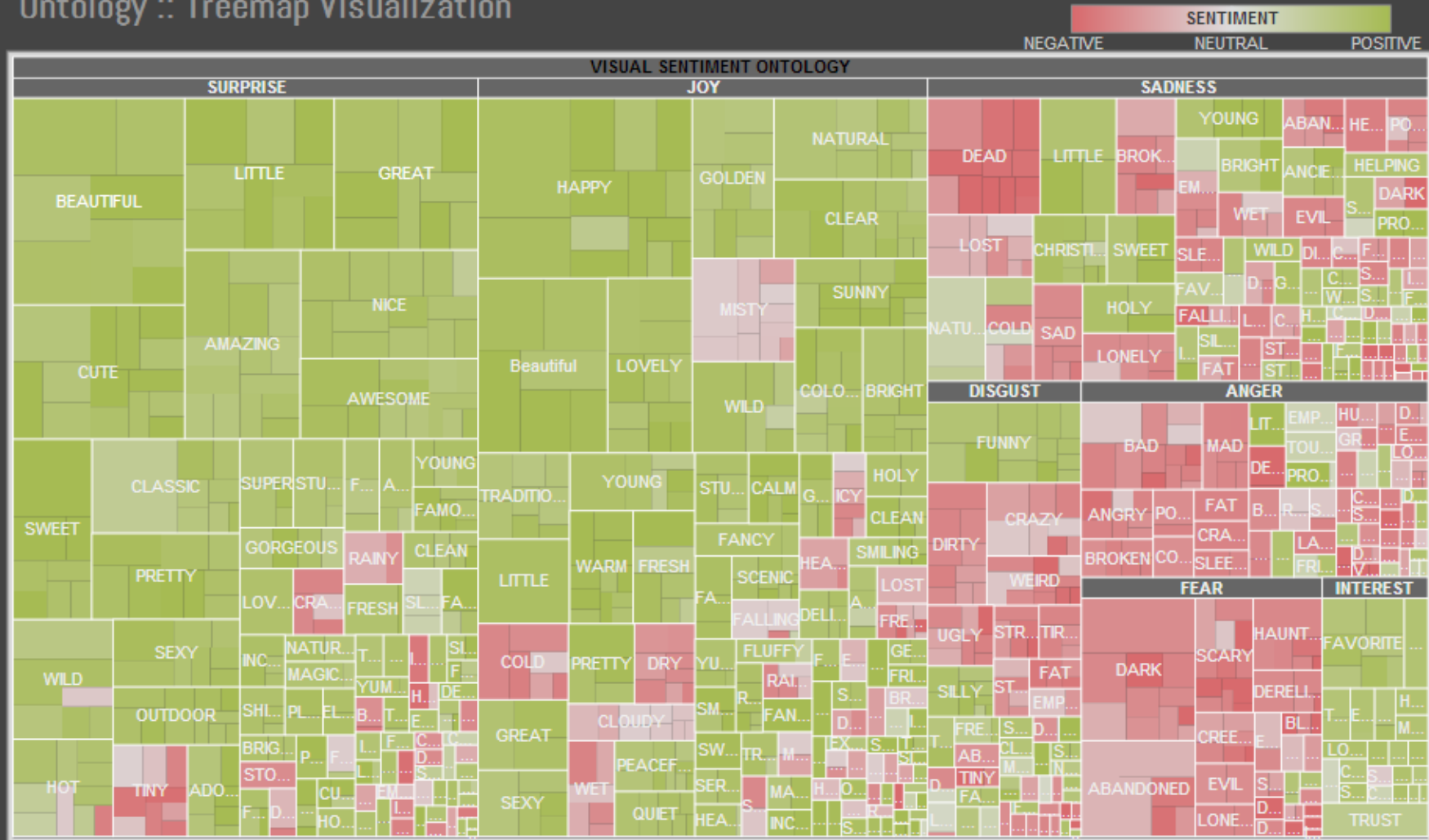
Top ANPs	sentiment	emotion
1. ▶ happy smile	1.92	0.388
2. ▶ innocent smile	1.92	0.376
3. ▶ happy christmas	2.0	0.373
4. ▶ happy father	2.0	0.358
5. ▶ happy wedding	1.72	0.348
6. ▶ friendly smile	1.92	0.346
7. ▶ delicious cupcake	1.71	0.341
8. ▶ shy smile	0.62	0.340
9. ▶ charming smile	1.92	0.339
10. ▶ happy birthday	1.79	0.337
11. ▶ warm smile	1.92	0.336
12. ▶ happy mother	2.0	0.333
13. ▶ happy halloween	1.81	0.331
14. ▶ delicious drink	1.59	0.330
15. ▶ happy heart	2.0	0.329
16. ▶ happy kids	2.0	0.323
17. ▶ healthy food	1.69	0.312
18. ▶ happy guy	1.61	0.312
19. ▶ fresh food	1.59	0.307
20. ▶ delicious pie	1.76	0.296

Visual Sentiment Ontology (Browser)

Home :: Ontology :: Adjective Noun Pairs :: Downloads :: About

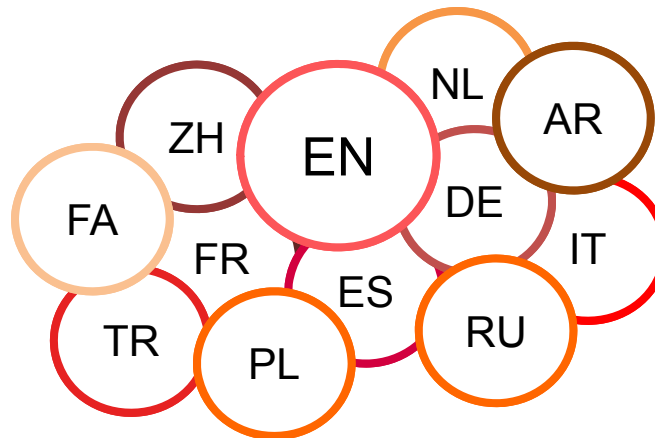
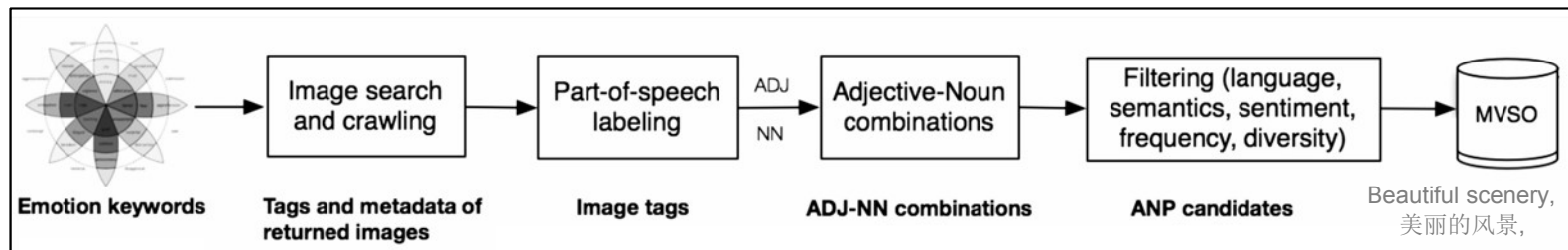
Visual Sentiment Ontology 

Ontology :: Treemap Visualization



THE MULTILINGUAL VISUAL SENTIMENT ONTOLOGY

MVSO Pipeline



16,000 visual concepts, 7 million images, 12 languages

Brendan Jou, Tao Chen, Nikolaos Pappas, Miriam Redi, Mercan Topkara, Shih-Fu Chang.
"Visual Affect Around the World: A Large-scale Multilingual Visual Sentiment Ontology," ACM Multimedia 2015.

Images + Emotions in Different Languages

trust
interest joy
fear surprise



(i) **english** (top: interest, joy, trust)

interés dolor miedo
alegría sorpresa
tristeza confianza



(ii) **spanish** (top: alegría, dolor, sorpresa)

joie
surprise



(iii) **french** (top: surprise, joie, intérêt)

興趣 憤怒
無聊 歡樂 悲
寧靜 恐怖 沉思
信任 驚 煩惱



(iv) **chinese** (top: 恐怖, 歡樂, 无聊)

Vertrauen
Freude Angst
Überraschung Trauer
Interesse Wut



(v) **german** (top: Angst, Freude, Interesse)

الفرح
الحزن
الحزن
الحزن



(vi) **arabic** (top: الفرح, الحزن, الحزن)

Emotion keyword clouds (in English)

- emotion queries performed in Flickr after translating 24 emotions words from English to 15 other languages
- kept languages which have at least 100k results (search on full metadata: title, description and tags)
- word size is proportional to the number of flickr results



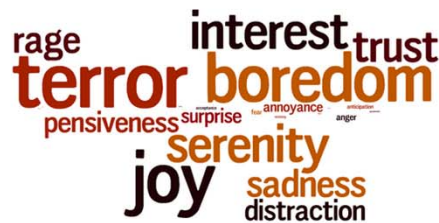
(i) **english** (top: interest, joy, trust)



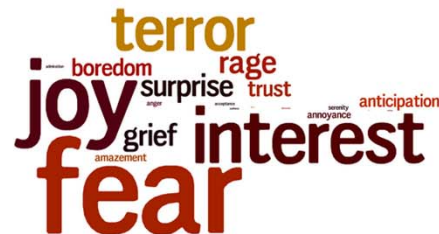
(ii) **spanish** (top: joy, grief, surprise)



(iii) **french** (top: surprise, joy, interest)



(iv) **chinese** (top: terror, joy, boredom)



(v) **german** (top: fear, joy, interest)

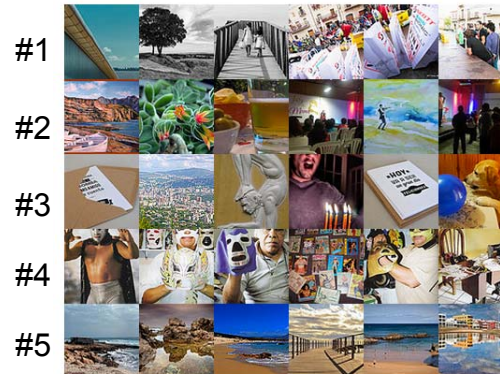
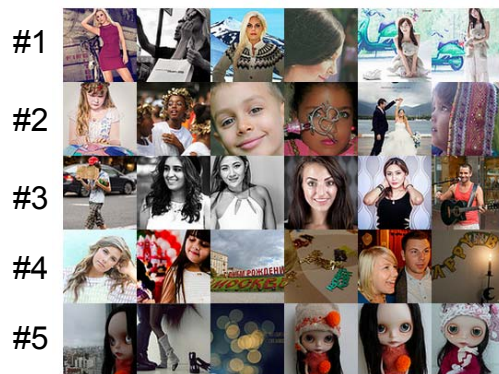


(vi) **arabic** (top: sadness, grief, joy)

Multilingual Emotion-Related Concepts for 'joy'

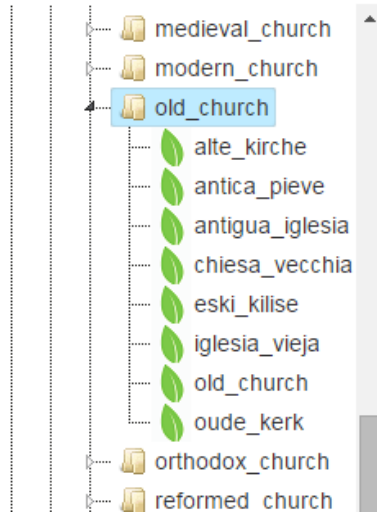
- filtering rules: non-neutral sentiment, 100 exact matches on Flickr, sorted by co-occurrence with 'joy'

	English (joy)	Spanish (alegría)	French (joie)
# 1	beautiful girl	aire libre (open air)	bonne humeur (good mood)
# 2	happy child	feliz día (happy day)	plein air (open air)
#3	beautiful smile	feliz cumpleaños (happy birthday)	belle plage (beautiful beach)
#4	happy birthday	<i>libre lucha</i> (free fight/wrestling)	bonne année (happy new year)
#5	cute love	buen tiempo (good time)	belle femme (beautiful woman)
#6	beautiful game	natural belleza (natural beauty)	belle fille (beautiful girl)
#7	happy smile	grande agua (great water)	<i>parcours ludique</i> (fun trail)
#8	happy living	simple vida (simple life)	quotidienne vie (everyday life)
#9	beautiful portrait	libre mundo (free world)	grand soleil (great sun)
#10	beautiful man	mejores amigas (best friends)	belle fleur (beautiful flower)



How do images of the same concept vary in different languages?

Ontology Structure



MVSO / C / church / old_church

“Old Church”

antigua_iglesia oude_kerk
eski_kilise alte_kirche chiesa_vecchia
antica_pieve iglesia_vieja
old_church

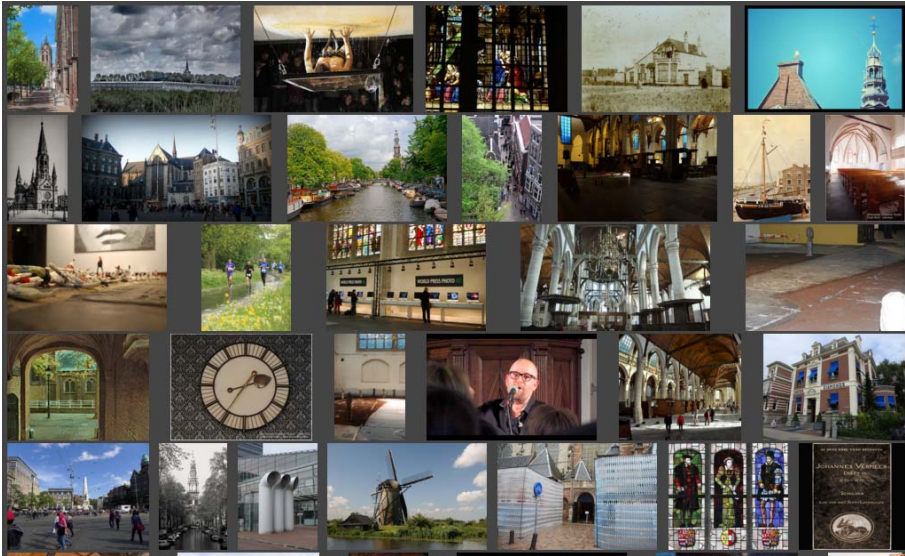
ANP Color Representation

ENGLISH
TURKISH
GERMAN
DUTCH
SPANISH
ITALIAN

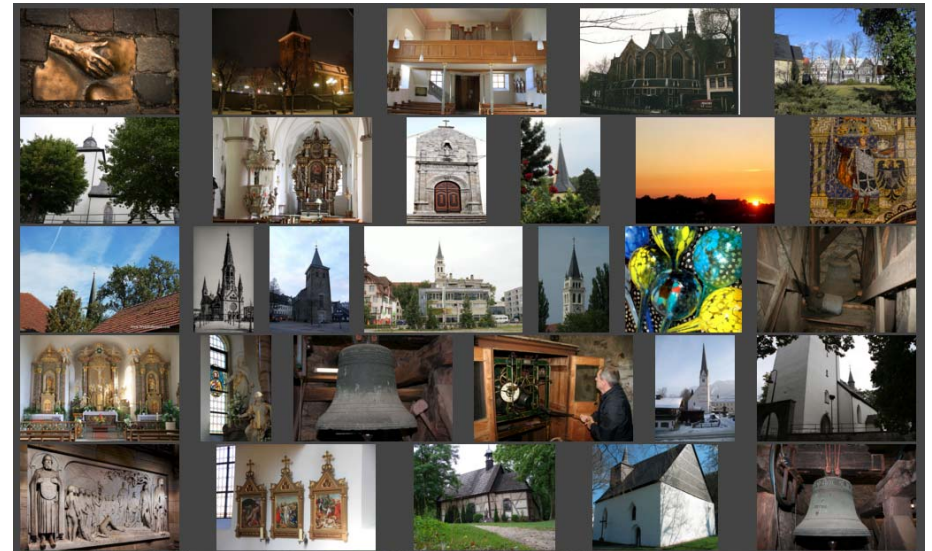


“Old Church” Images: Cultural Influences?

Dutch



German

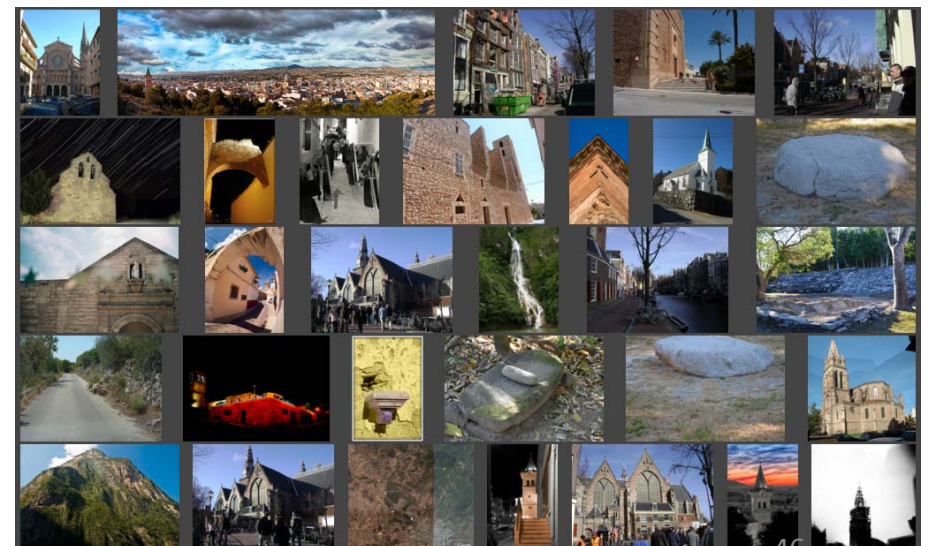


Italian

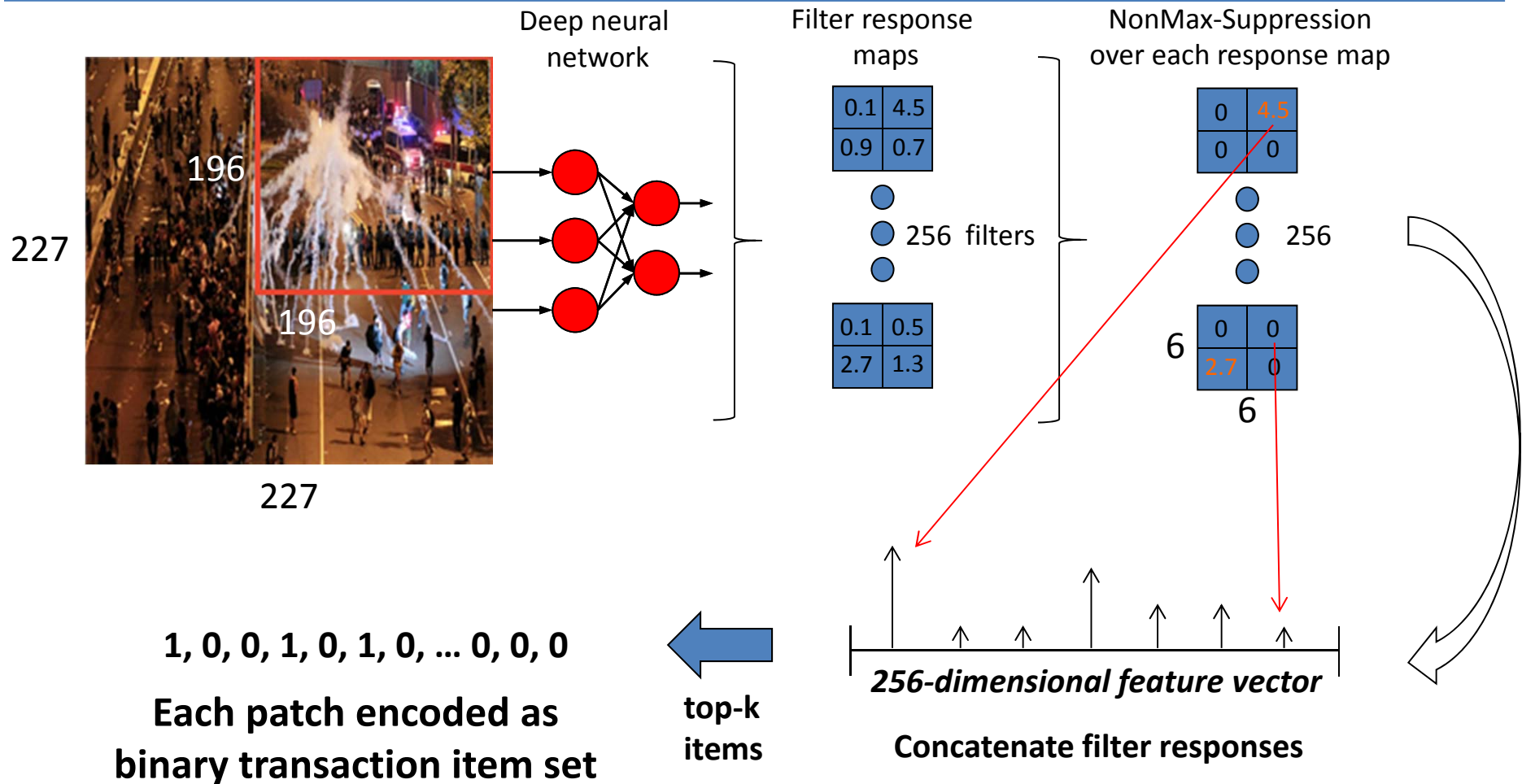


S. F. Chang

Spanish



Research: Find unique visual patterns for each language



Li, Ellis, Chang, arXiv, 2016

Unique Visual Patterns for Dutch Old Churches

Pattern # 1:



Pattern # 2:



Pattern # 3:



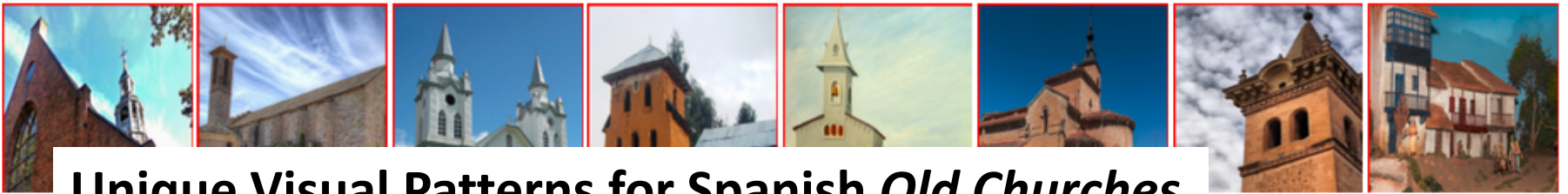
Pattern # 4:



Pattern # 5:



Pattern # 1:



Unique Visual Patterns for Spanish *Old Churches*

Pattern # 2:



Pattern # 3:



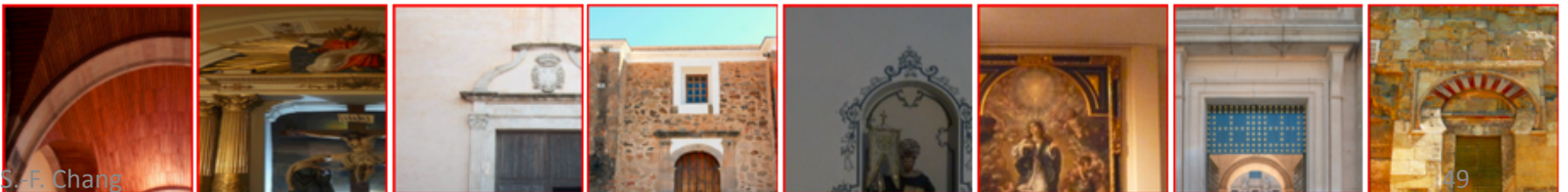
Pattern # 4:



Pattern # 5:



Pattern # 6:



How do images of the same concept vary in different languages?

Ontology Structure



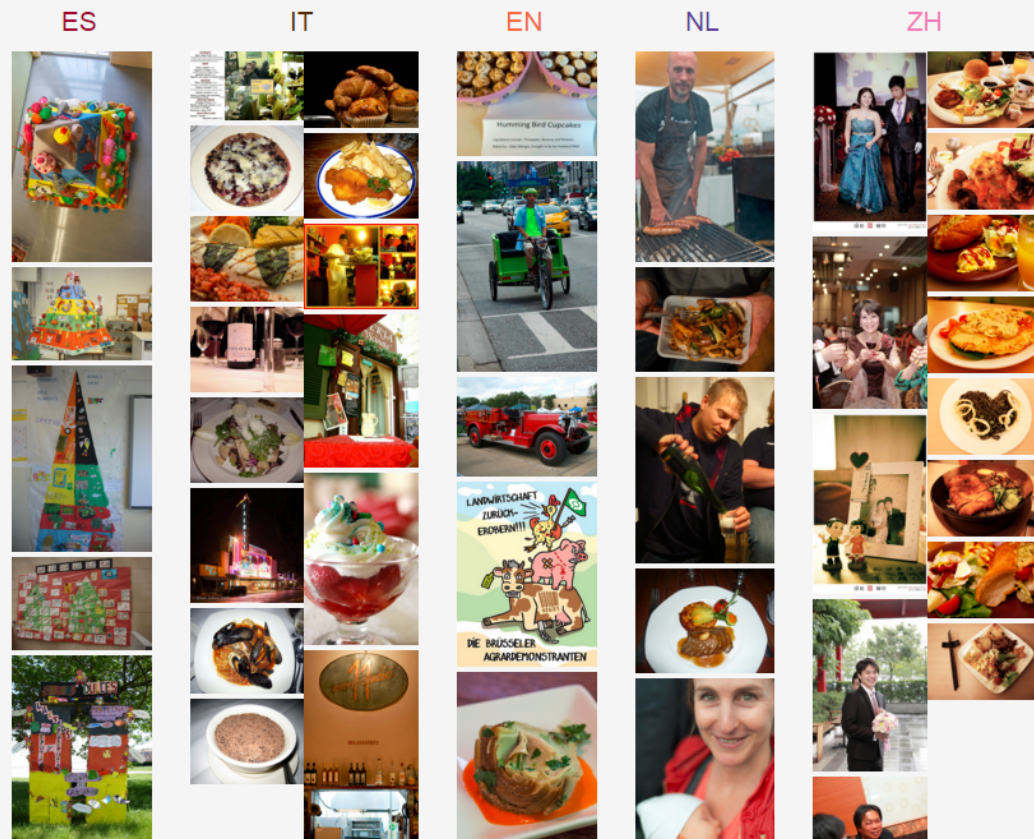
MVSO / F / food / good_food

Children of Cluster

cibo_buono **good_food**
alimentos_buenos 好_料理
lekker_eten **buona_tavola** 好_食物

ANP Color Representation

- ENGLISH
- CHINESE
- DUTCH
- SPANISH
- ITALIAN



Unique Visual Patterns for Chinese Good Food

Pattern #
1:



Pattern #
2:



Pattern #
3:



Pattern #
4:



Unique Visual Patterns for Italian Good Food

Pattern # 2:



Pattern # 3:



Pattern # 4:



Pattern # 5:



NEWS ROVER

New frontier of *multi-source*, *multi-modal*, *personalized*
news exploration



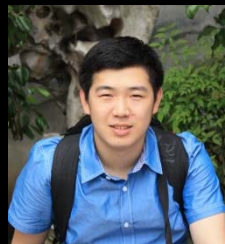
Shih-Fu Chang



Joe Ellis



Brendan Jou



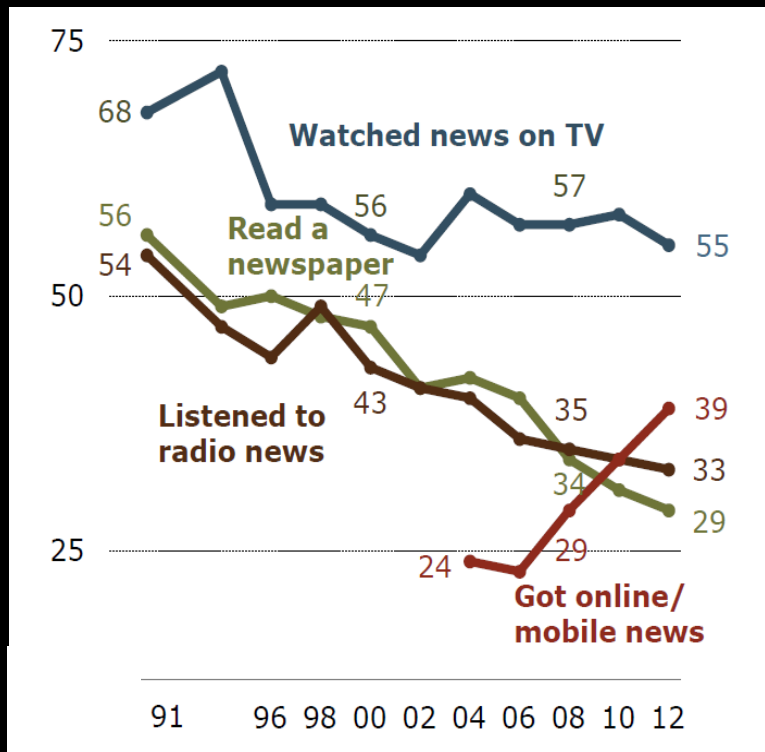
Hongzhi Li



Dan Morozoff-Abezgauz

User trend in news consumption

Where did you get your news yesterday?



Changing

- Towards mobile and social
- User interest guided by topic not by channel
- Mix any source (article, video, tweet)
- Access on any device, time, place

Source: PEW RESEARCH CENTER 2012 News Consumption Survey

NEWS ROVER

New frontier of *multi-source, multi-modal, personalized* news exploration

How will we watch news in the future?



NBA finals



tech



elections



elections



olympics



Greek riots



Topical + Personal



Organized by personal interest and trendy topics

Mix across multiple sources



Anywhere anytime

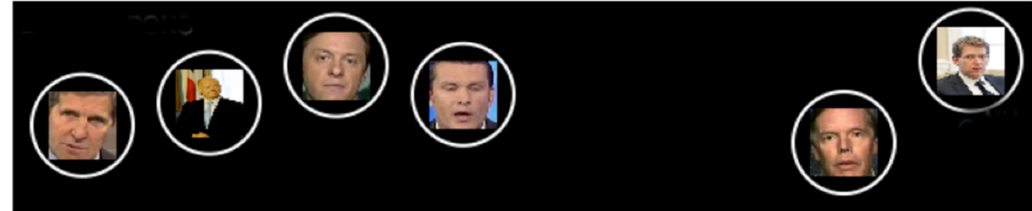


Videos analyzed and processed in the cloud, then consumed anywhere

Navigating the News

Who?

Name Extraction
& Normalization



What?

Topical
Organization



'Debt Limit'



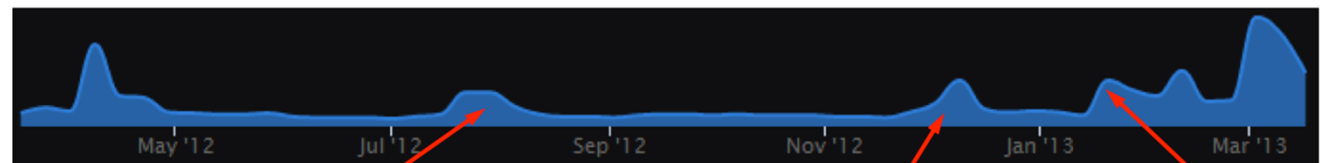
'Cong. Budget Office'



'Consumer Debt'

When?

Coverage
Trendline



Where?

Event Geo-
visualization

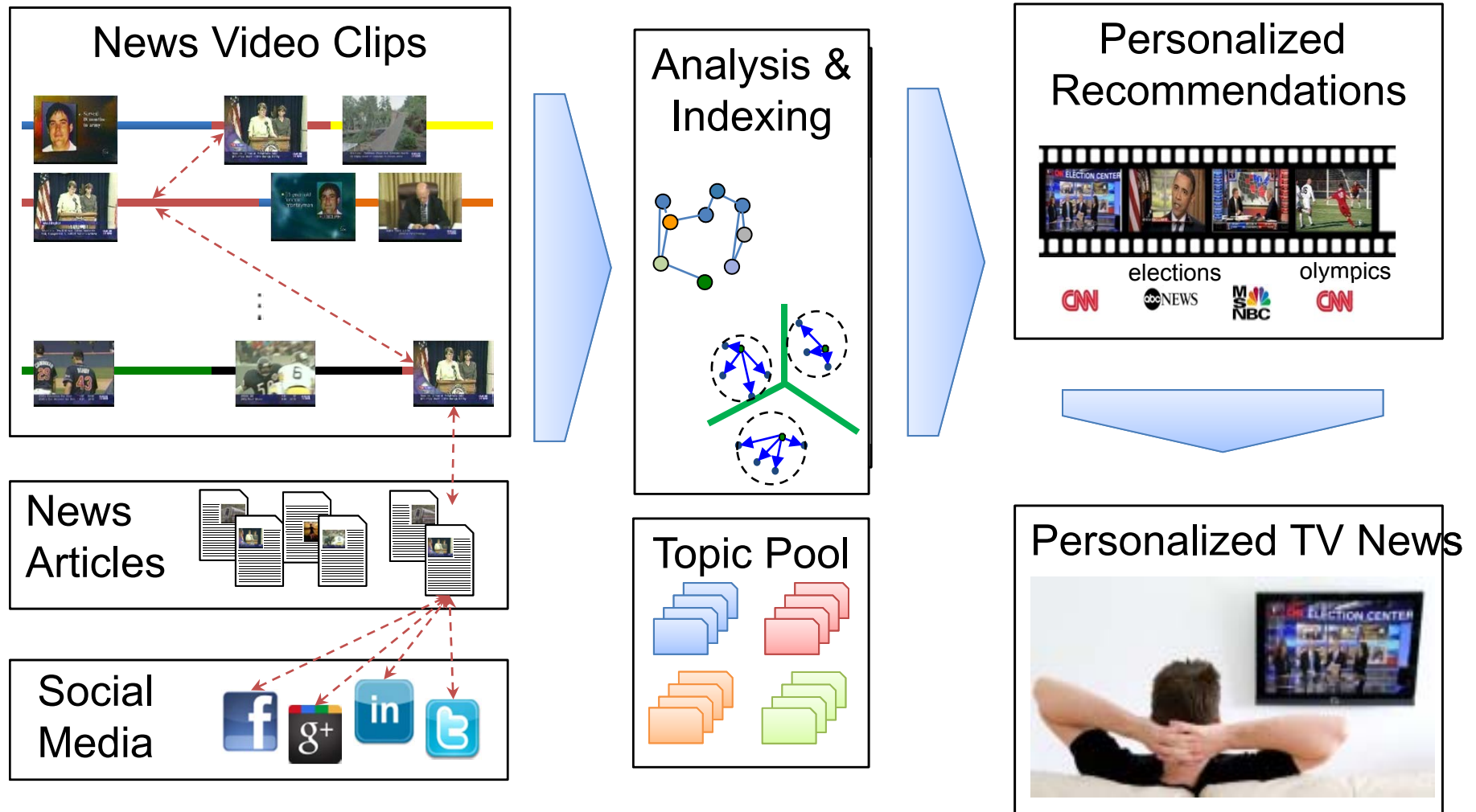


'Same-sex Marriage'



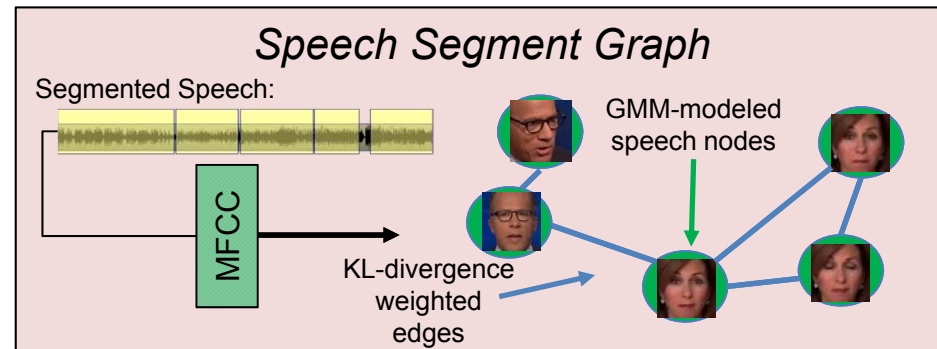
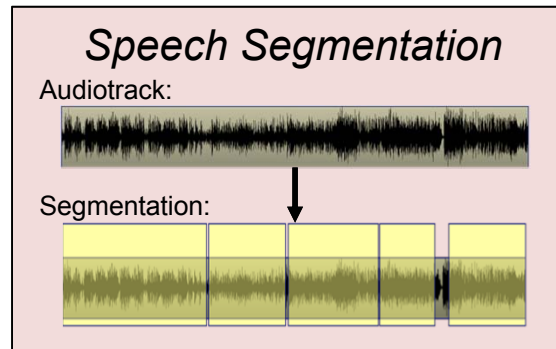
'France/Mali' conflict

Multi-Source Aggregation

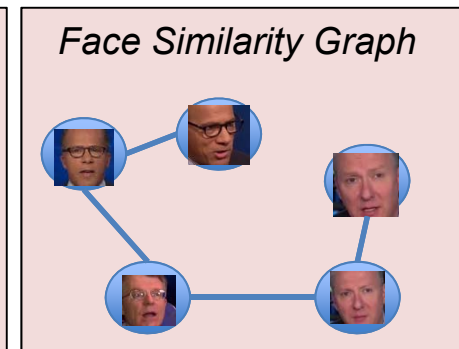
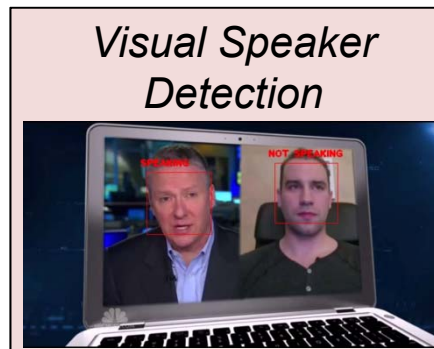


Research: Multimodal Analysis “Who Said What”

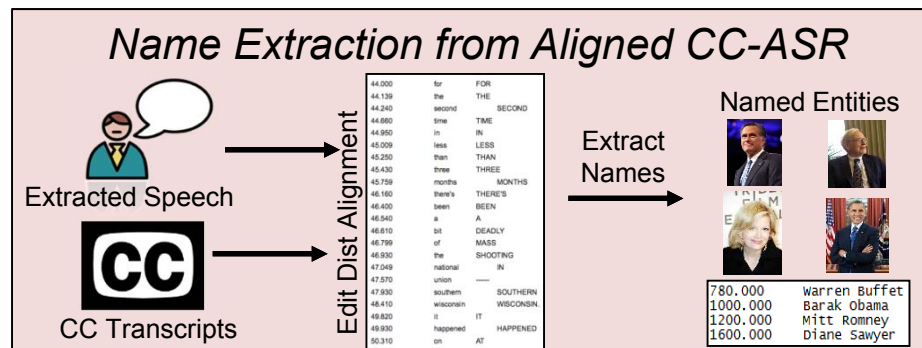
Audio



Visual



Text



Video-Based News Events

Find Candidate Events

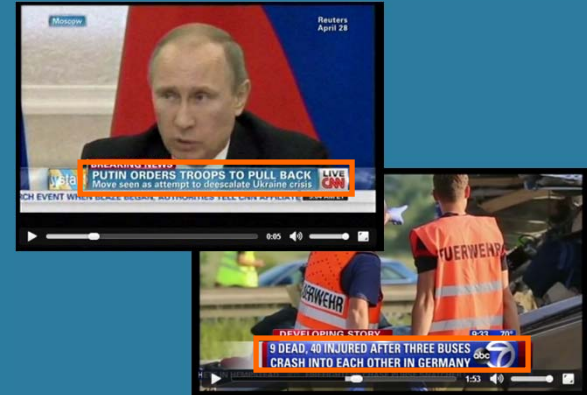


Detect key phrases on-screen

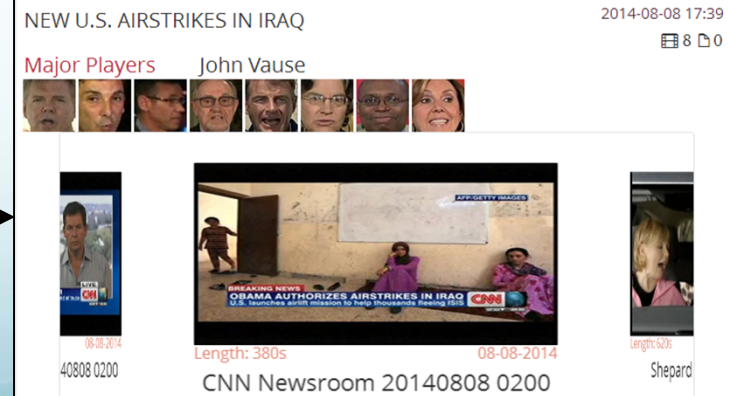
Cluster News Videos Based on Temporal and Text Similarity



Extract OCR Text as Video Feature



Generate News Rover Video Event



NewsRover Live Recording System

100 TV channels recorded continuously
Linked to Online News and Twitter topics

- Per day:
 - 110 hours video recorded
 - 1,380 video stories indexed
 - 460 Google News topics crawled
 - 550 Twitter topics crawled
- Total size:
 - 28,000 hours video recorded
 - 464,000 video stories
 - 24,500 News topics
 - 80,000 Twitter topics