computational social media

lecture 4: shooting

part 1

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24.04.2020
announcements

course until end of semester will be online

project day (presentation + report): Fri 05.06.2020

reading #5 will be presented today
A. G. Reece and C. M. Danforth, Instagram photos reveal predictive markers of depression, EPJ Data Science, 2017

assignment #3 will be given today

next week: project progress presentations by 6 teams
5-minute talks
update the 5 project slides you sent me earlier
one designated presenter per team
this lecture

1. a snapshot of the present
   flickr, instagram, snapchat

2. a look into the past
   20th century image sharing practices

3. understanding research on social image systems
   flickr: tags & communities
   computer vision as an enabler
   instagram: selfies & engagement
   snapchat: ephemeral social media
1.

a snapshot of the present
reminder: participation in social media

% of U.S. adults who use...

http://www.pewinternet.org/fact-sheet/social-media/
1. “help people make their photos available to the people who matter to them
2. enable new ways of organizing photos and video”

02.2004 launched
03.2005 bought by Yahoo
08.2011 hosting over 6 billion images
03.2013 87 million users
04.2018 3.5 million images per day
04.2018 bought by SmugMug

https://www.flickr.com/about/
http://en.wikipedia.org/wiki/Flickr
# Instagram

“capture and share the world’s moment”

<table>
<thead>
<tr>
<th>Year</th>
<th>Monthly Active Users</th>
<th>Users Outside US</th>
<th>Shared Photos</th>
<th>Uploaded Photos Per Day</th>
<th>Daily Stories</th>
<th>Likes Per Day</th>
</tr>
</thead>
<tbody>
<tr>
<td>2015</td>
<td>300M</td>
<td>70%</td>
<td>30B</td>
<td>70M</td>
<td>n/a</td>
<td>2.5B</td>
</tr>
<tr>
<td>2016</td>
<td>400M</td>
<td>75%</td>
<td>40B</td>
<td>80M</td>
<td>n/a</td>
<td>3.5B</td>
</tr>
<tr>
<td>2018</td>
<td>800M</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>300M</td>
<td>n/a</td>
</tr>
<tr>
<td>2019</td>
<td>1B</td>
<td>n/a</td>
<td>n/a</td>
<td>n/a</td>
<td>500M</td>
<td>n/a</td>
</tr>
</tbody>
</table>

10.2010 launched
04.2012 bought by Facebook

“We are not the sum of everything we have said or done or experienced or published – we are the result. We are who we are today, right now.”

09.2011 launched
04.2013 80% of users are in US
11.2013 70% users are women
400 million “snaps” received per day
declined offers from facebook & google
08.2014 100 million monthly active users

http://en.wikipedia.org/wiki/Snapchat
2.
a look into the past
“Everything exists to end up in a book”
Stéphane Mallarmé, 1842-1898

“Everything exists to end up in a photograph”
Susan Sontag, On Photography, 1977
social uses of personal photos (Nancy Van House)

1. memory & identity
2. maintaining relationships
3. self-representation
4. self-expression


credit (cc): Prince Gladson @ flickr
https://www.flickr.com/photos/princegladson
kodak moments (before digital):

few people take few pictures

share photos with family & close friends as single pics or albums

kodak moments (after digital):

more people take more pictures

...but share photos in the same way as before
Ofoto (1999) bought by Kodak in 2001

Kodak EasyShare Gallery (2005)

2012: Kodak goes bankrupt
Shutterfly buys Kodak Gallery

Kodak Gallery is closing and your photos will be moved to Shutterfly.

Thank you for your business and support. Kodak Gallery is closing on July 2, 2012. We're pleased to share that your Kodak Gallery photos will be moved, for free, to Shutterfly.com.
participatory culture and photo communities
(Henry Jenkins)

a culture in which “fans and other consumers are invited to actively participate in the creation and circulation of new content”

photo communities have existed for as long as photos and cameras have been available

fan clubs, sport fans, birdwatchers, amateur photographers

web 2.0 empowered communities

credit (cc): Bradley Stemke @ flickr
https://www.flickr.com/photos/detroitsunrise

stock photography

Corel Gallery (1st ed. 1994)

PhotoDisc (2000), now gettyimages

https://openlibrary.org/works/OL16047006W/Corel_gallery

http://en.wikipedia.org/wiki/Getty_images
3. understanding research on social image systems
tags, communities, geo-tagged media

selfies & followers

ephemeral social media
tags, communities, geo-tags

Find your inspiration.

Join the Flickr community, home to tens of billions of photos and 2 million groups.

Sign Up
tagging on flickr
flickr tags

https://www.flickr.com/photos/rypscl26/44036709975/in/pool-damndada/
a basic tagging model
why do people tag?

M. Ames and M. Naaman, Why we tag: motivations for annotation in mobile and online media, in Proc. ACM CHI, 2007
flickr communities
group photo pool

https://www.flickr.com/groups/damndada/pool/
flickr groups: aggregates of images, tags, users

- self-organized users with common interests:
  - photographic techniques
  - specific content
  - geographical locations
  - social events
  - “just” social interaction

- sharing photos with groups creates pools of **photos & tags**

how to discover groups in flickr?

**topic-model** group representation

probabilistic unsupervised learning

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R. Negoescu and D. Gatica-Perez, Analyzing Flickr Groups, in Proc. ACM CIVR 2008
quick detour: introduction to probabilistic graphical models

representing joint distributions with graphs

- **nodes**
  - subsets of random variables (RVs)
  - discrete or continuous

- **vertices**
  - relations between RVs
  - directed or undirected

- **resulting graphs**
  - acyclic (no loops)
  - cyclic

\[ p(x_1, \ldots, x_K) = ? \]
probability theory

- **sum rule**
  (marginalization)

\[ p(x) = \sum_y p(x, y) \]

- **product rule**
  (conditional probability)

\[ p(x, y) = p(x|y)p(y) \]

- **Bayes’ theorem**
  (posterior \(\propto\) likelihood \(\times\) prior)

\[ p(y|x) = \frac{p(x|y)p(y)}{p(x)} \]

\[ p(x) = \sum_y p(x|y)p(y) \]
bayesian networks (BNs): directed graphical models

- **directed acyclic graphs**
  - no closed paths in the graph
  - we cannot go from node to node along vertices on the direction of the arrows and end up at the original node
  - nodes have ‘parents’ and ‘children’
  - $x_4$ is a child of $x_1, x_2, x_3$ and is a parent of $x_6$ and $x_7$
  - $x_1$ has no parents

no directed cycles
BNs: the basic equation

- joint distribution for $\mathbf{x} = \{x_1, \ldots, x_K\}$

$$p(\mathbf{x}) = \prod_{k=1}^{K} p(x_k | \text{pa}_k)$$

$\text{pa}_k$: set of parents of $x_k$

$$p(\mathbf{x}) = p(x_1)p(x_2)p(x_3)p(x_4 | x_1, x_2, x_3) \cdot$$

$$p(x_5 | x_1, x_3)p(x_6 | x_4)p(x_7 | x_4, x_5)$$
BNs: the plate notation

\[ p(t, w) = p(w) \prod_{n=1}^{N} p(t_n | w). \]
BNs: types of variables

- variables may be **hidden** (latent) or **visible** (observed)

  - visible variables
    - physical measurements (text, audio, image)
  - latent variables
    - define richer models
    - often have a clear interpretation
BNs: two key problems

- given a parametric form for

\[ p(x) = \prod_{k=1}^{K} p(x_k | pa_k) \]

- **learning**: given training data, estimate the model parameters

- **inference**: given a learned model, compute probabilities of hidden nodes
probabilistic topic models
probabilistic topic models: unsupervised learning for text collections

“Professional football leagues are impacted economically by the coronavirus. Players see their salaries reduced as the leagues are interrupted and clubs lose money. Fans are afraid of getting sick and spreading the disease”

Topics: Sports Economics Health

assumptions:
+ observed documents: bags of words (vectors of word counts)
+ documents are mixtures of topics
+ latent topics: “soft clusters” of words
+ generative models: documents are generated by sampling words from the topics


latent Dirichlet allocation (LDA)

Figure 1. The intuitions behind latent Dirichlet allocation. We assume that some number of “topics,” which are distributions over words, exist for the whole collection (far left). Each document is assumed to be generated as follows. First choose a distribution over the topics (the histogram at right); then, for each word, choose a topic assignment (the colored coins) and choose the word from the corresponding topic. The topics and topic assignments in this figure are illustrative—they are not fit from real data.

latent Dirichlet allocation (2)

\[
p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left( \prod_{n=1}^{N} p(z_{d,n} | \theta_d) p(w_{d,n} | \beta_{1:K}, z_{d,n}) \right)
\]

Assume D documents, N words per document, and K latent topics
Topics are \( \beta_{1:K} \), where each \( \beta_k \) is a distribution over the vocabulary
For each document \( d \) in the collection \( D \)
- Sample topic proportion \( \theta_d \sim \text{Dirichlet}(\alpha) \)
- For each of the N words \( w_{d,n} \)
  - Sample topic assignment \( z_{d,n} \sim \text{Multinomial}(\theta_d) \)
  - Sample word \( w_{d,n} \sim p(w_{d,n} | \beta_{1:K}, z_{d,n}) \), a multinomial conditioned on the topic specified by \( z_{d,n} \) (out of all possible topics)

topic modeling for Flickr groups
50k groups, 6.9M photos

+ groups are **documents (bags of tags)**
+ groups described by the **topics** they are about
+ inference using Markov Chain Monte Carlo (MCMC)

\[
p(t \mid z) = p(w \mid z)
\]

| P(t | z) | Tag       |
|--------|-----------|
| 0.0766 | flower    |
| 0.0555 | flowers   |
| 0.0555 | nature    |
| 0.0431 | ilovenature |
| 0.0323 | spring    |
| 0.0295 | garden    |
| 0.0243 | green     |
| 0.0221 | yellow    |
| 0.0212 | macro     |
| 0.0204 | pink      |
### learned topics: top words and top groups (using PLSA, precursor to LDA)

#### Topic 1 top tags

| P(t | z) | Tag       |
|-------|-----------|
| 0.0766| flower    |
| 0.0555| flowers   |
| 0.055 | nature    |
| 0.0431| ilovenaure|
| 0.0323| spring    |
| 0.0295| garden    |
| 0.0243| green     |
| 0.0221| yellow    |
| 0.0212| macro     |
| 0.0204| pink      |

#### Topic 1 top groups

| P(z | G) | Group                          |
|------|--------------------------------|
| 0.9715| 1-Plants World                |
| 0.9456| Flickr Gardens                 |
| 0.8783| In my garden                   |
| 0.8718| My Garden                      |
| 0.8347| Daffodil World                 |
| 0.8337| What plant is that?            |
| 0.8214| Gardening for Fun              |
| 0.8102| Garden Flowers                 |
| 0.7993| grow                           |
| 0.7377| Backyard Nature                |
visualizing the top groups for topic 1

- 1-Plants World
- Flickr Gardens
- In my garden
- My Garden
- Daffodil World
- What plant is that?
- Gardening for Fun
- Garden Flowers
- grow
- Backyard Nature
learned topics (2)

| Topic 18 top tags | P(t | z) | Tag   |
|-------------------|--------|-------|
|                   | 0.0478 | music |
|                   | 0.0175 | rock  |
|                   | 0.0171 | concert |
|                   | 0.0156 | live  |
|                   | 0.0131 | band  |
|                   | 0.0127 | party |
|                   | 0.0124 | florida |
|                   | 0.0123 | guitar |
|                   | 0.0104 | friends |
|                   | 0.0088 | label |

| Topic 18 top groups | P(z | G) | Group                                         |
|---------------------|------|-----------------------------------------------|
|                     | 0.9917 | **LIVE in CONCERT**                         |
|                     | 0.9783 | Vinyl Junkie                                 |
|                     | 0.973  | BUSH-IT Artist                               |
|                     | 0.9512 | REHNQUIST RETIRES THE WAR BEGINS             |
|                     | 0.9386 | Rock and Roll : live shows only please       |
|                     | 0.9307 | Concerts                                     |
|                     | 0.9234 | Rock in Paris                                |
|                     | 0.9171 | Live Music Photography                      |
|                     | 0.9135 | SINGERS SING! (4 pics at any one time)       |
|                     | 0.9088 | Concerts!!                                  |
learned topics (2)

Topic 18 top tags

| P(t | z) | Tag |
|-------|-----|

Topic 18 top groups

| P(z | G) | Group |
|------|-------|
| 0.9917 | **LIVE in CONCERT** |

Flickr

Concerts

Group Pool (58,836 items) | Only members can add to the pool. Join?

Group Pool

From Biayo
From t.i.m.e
From kanoto
From Karsten W. Rohrbach
From Karsten W. Rohrbach
From Turgodson
From lart-scenes
From lart-scenes
From lart-scenes
From lart-scenes
From lart-scenes
From lart-scenes
### Learned Topics (3)

#### Topic 2 Top Tags

| P(t | z)  | Tag       |
|--------|-----------|
| 0.0957 | canada    |
| 0.0397 | bc        |
| 0.0343 | snow      |
| 0.0334 | vancouver |
| 0.024  | britishcolumbia |
| 0.0213 | ontario   |
| 0.021  | winter    |
| 0.0129 | water     |
| 0.0128 | mountain  |
| 0.0127 | ice       |

#### Topic 2 Top Groups

<table>
<thead>
<tr>
<th>P(z</th>
<th>G)</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9978</td>
<td>BC Peaks &amp; Mountains</td>
<td></td>
</tr>
<tr>
<td>0.9971</td>
<td>ASCENT - (how you get to the top)</td>
<td></td>
</tr>
<tr>
<td>0.9937</td>
<td>British Columbia Provincial Parks</td>
<td></td>
</tr>
<tr>
<td>0.9922</td>
<td>Climbing Photography</td>
<td></td>
</tr>
<tr>
<td>0.9809</td>
<td>Rock Climbing</td>
<td></td>
</tr>
<tr>
<td>0.9667</td>
<td>Climbing lifestyle</td>
<td></td>
</tr>
<tr>
<td>0.965</td>
<td>Climbing</td>
<td></td>
</tr>
<tr>
<td>0.9632</td>
<td>Where am I in BC</td>
<td></td>
</tr>
<tr>
<td>0.951</td>
<td>ROCKCLIMBING</td>
<td></td>
</tr>
<tr>
<td>0.9421</td>
<td>Alpinism</td>
<td></td>
</tr>
</tbody>
</table>
### learned topics (4)

#### Topic 13 top tags

| P(t | z) | Tag     |
|-------|---------|
| 0.0846 | holland |
| 0.0613 | netherlands |
| 0.0458 | nederland |
| 0.0255 | thenetherlands |
| 0.021  | amsterdam |
| 0.0182 | denhaag |
| 0.0148 | bike |
| 0.0141 | dutch |
| 0.0136 | bw |
| 0.0119 | rotterdam |

#### Topic 13 top groups

| P(z | G) | Group                                                |
|------|-------|
| 0.9599 | Den Haag (The Hague) |
| 0.9591 | Den Haag / The Hague, The Netherlands |
| 0.8626 | goingdutch |
| 0.8202 | 1-2-3 Nederland |
| 0.7831 | Nederland/The Netherlands |
| 0.7679 | Made in Holland |
| 0.7671 | Dutch |
| 0.7665 | horses |
| 0.7639 | Dutch Skylines |
| 0.7566 | Amsterdam today |
how many topics are flickr groups about?

- **topic-expert groups** have spiky topic distributions, with one dominant topic.

- Approximately 35% of groups with 3-5 topics: focused interests (content-oriented groups).

- Less semantic coherence in large **social-oriented groups** (20+ topics).
topic decomposition for group *Portrait*
topic decomposition for group *Flickr Central*

![Topic distribution for group Flickr Central](image)

**Topic 49**
- canon
- portrait
- model
- sexy
- beautiful
- female
- rebel

**Topic 30**
- night
- reflection
- lights
- sky
- long exposure
- winter
- city

**Topic 24**
- me
- selfportrait
- portrait
- woman
- face
- girl
- eyes
- female
- hair

**Topic 12**
- sky
- sunset
- ocean
- sea
- beach
- clouds
- sand
- sun
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This publicly available curated dataset of almost 100 million photos and videos is free and legal for all.

BY BART THOMEE, DAVID A. SHAMMA, GERALD FRIEDLAND, BENJAMIN ELIZALDE, KARL NI, DOUGLAS POLAND, DAMIAN BORTH, AND LI-JIA LI

YFCC100M: The New Data in Multimedia Research

comparing image sharing practices
two image sharing practices

**kodak culture:** take photos to share with a small existing social group & to archive

**snaprs:** take photos with the primary objective of sharing them with the world

credit (cc): john ragai @ flickr: https://www.flickr.com/photos/johnragai/

two datasets

**flickr**: images with tags
**kodak gallery**: images with free text

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Flickr</th>
<th>Kodak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total photos</td>
<td>4.6M</td>
<td>413,000</td>
</tr>
<tr>
<td>Total tag occurrences</td>
<td>13M</td>
<td>900,000</td>
</tr>
<tr>
<td>Total users</td>
<td>25,800</td>
<td>5400</td>
</tr>
<tr>
<td>Photos / user</td>
<td>157</td>
<td>76</td>
</tr>
<tr>
<td>Unique tags / user</td>
<td>81</td>
<td>34</td>
</tr>
</tbody>
</table>

10,000 most popular words (in terms of number of users) for each source

credit (cc): Klearchos Kapoutsis @flickr: https://www.flickr.com/photos/klearchos

R. Negoeascu, A. Loui, & D. Gatica-Perez, Kodak Moments and Flickr Diamonds: How Users Shape Large-Scale Media, in Proc. ACM Multimedia, 2010
comparing kodak & flickr language

Distribution of 10-category tag taxonomy (top 200 tags)

+ **flickr but not kodak**
  - macro, selfportrait, blackandwhite, photoshop, flickr, abigfave, geotagged

+ **kodak but not flickr**
  - enjoying, showing, giving, checking, loved, visiting, dressed, wearing
using topic models to study topic specificity for kodak & flickr

+ 5400 users for each source
+ learn LDA on **joint vocabulary**
+ determine relevant topics for each user based on topic distribution

+ topic specificity

  **“flickr”** topic: abigfave, flickrdiamond, anawesomeshot

  **“flickr”** topic: nature, landscape, flora, ilovенature, plant, animal

  **“kodak”** topic: i, time, daddy, ready, mommy, love, big, happy, playing

  **“kodak”** topic: picture, pictures, edited, png

Figure 3: Topic specificity among the two communities. Specificity is computed as the ratio of the difference between Kodak and Flickr users for which that topic is relevant, and the total number of users for which the topic is relevant.
what to remember

sharing images with family & friends is an old practice, transformed by digital, online, social

professional producers & consumer of images also saw their work transformed

flickr as an early social image system
  convergence of amateur & professional photographers
  photos, tags & communities as key features

probabilistic topic models
  tool to mine text collections & tagged image collections
questions?

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