Caltech

Machine Learning & Data Mining

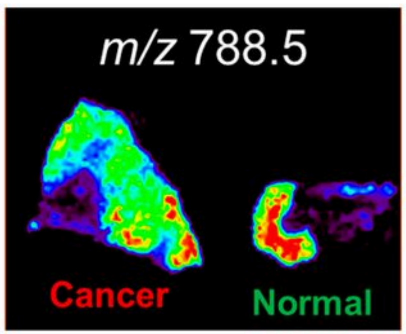
CS/CNS/EE 155

Lecture 4:

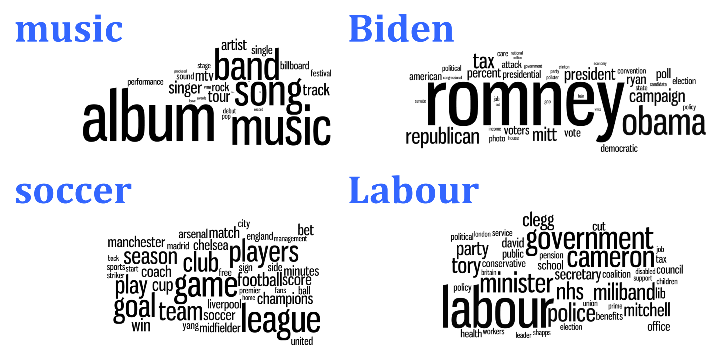
Recent Applications of Lasso

Today: Two Recent Applications

Cancer Detection



Personalization via twitter



- Applications of Lasso (and related methods)
- Think about the data & modeling goals
- Some new learning problems

Slide material borrowed from Rob Tibshirani and Khalid El-Arini

Image Sources: http://www.pnas.org/content/111/7/2436
https://dl.dropboxusercontent.com/u/16830382/papers/badgepaper-kdd2013.pdf

Aside: Convexity

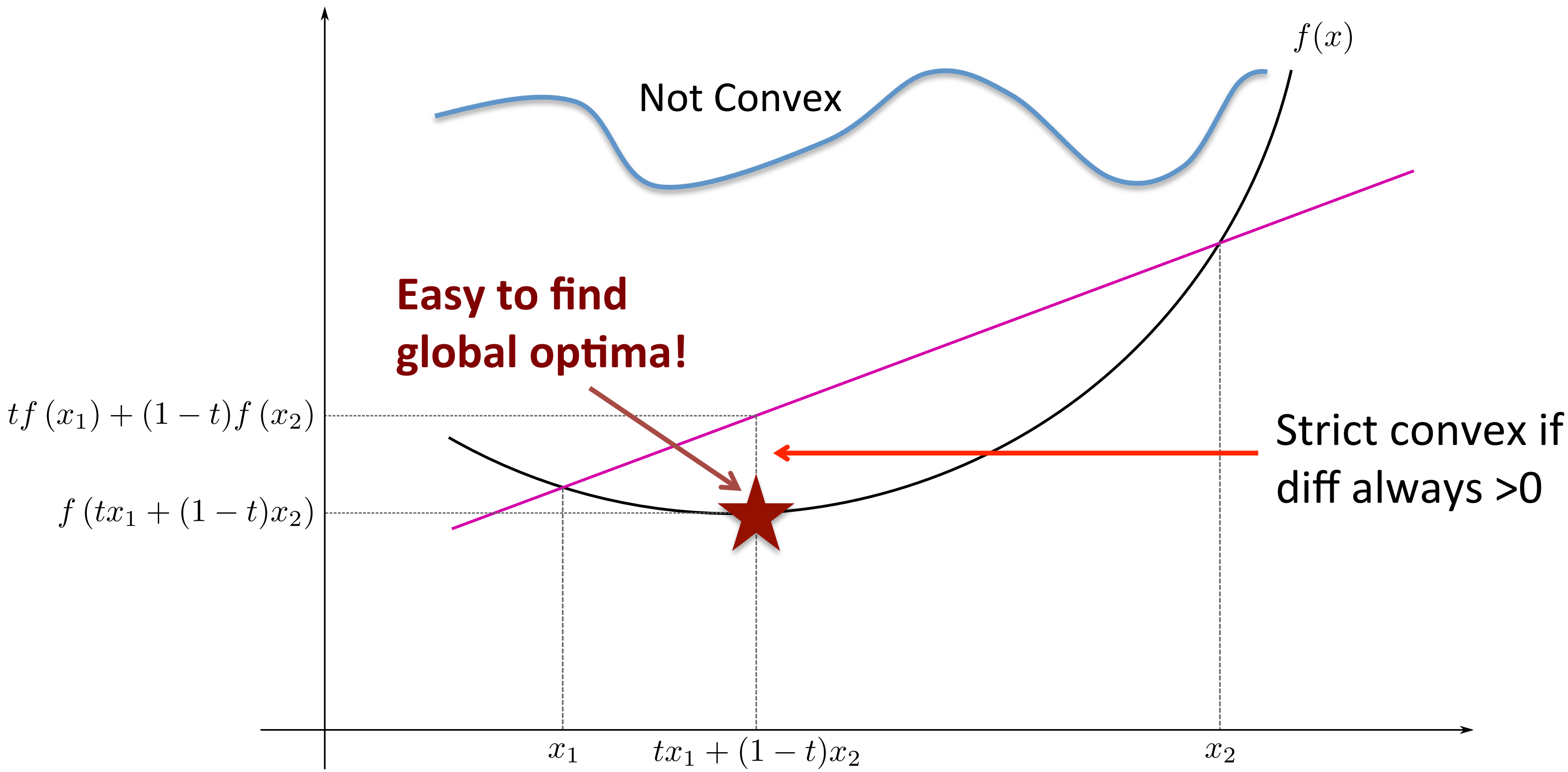
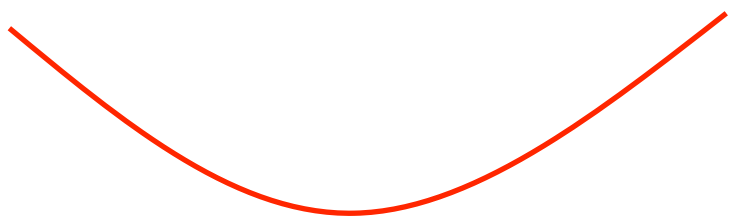


Image Source: http://en.wikipedia.org/wiki/Convex_function

Aside: Convexity

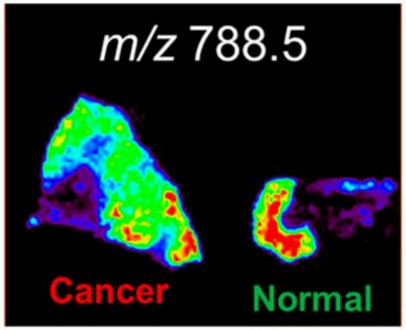
- All local optima are global optima:

- Strictly convex: unique global optimum:



- Almost all objectives discussed are (strictly) convex:
  - SVMs, LR, Ridge, Lasso… (except ANNs)

Cancer Detection

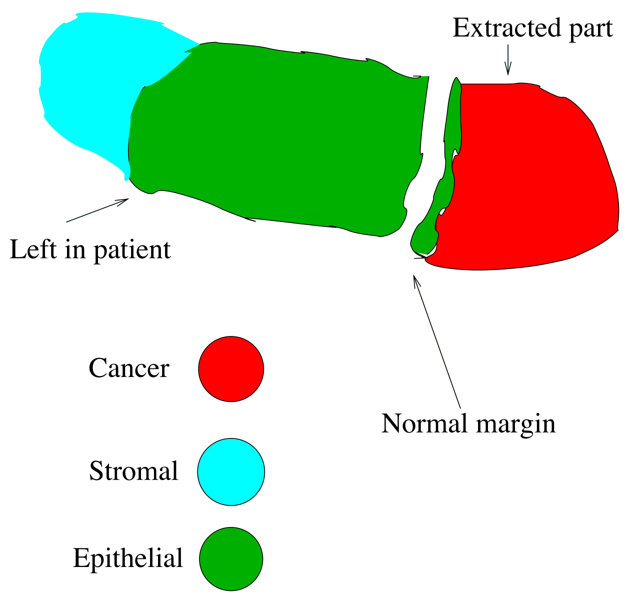


“Molecular assessment of surgical-resection margins of gastric cancer by mass-spectrometric imaging”

Proceedings of the National Academy of Sciences (2014)

Livia S. Eberlin, Robert Tibshirani, Jialing Zhang, Teri Longacre, Gerald Berry, David B. Bingham, Jeffrey Norton, Richard N. Zare, and George A. Poultsides

http://www.pnas.org/content/111/7/2436
http://statweb.stanford.edu/~tibs/ftp/canc.pdf



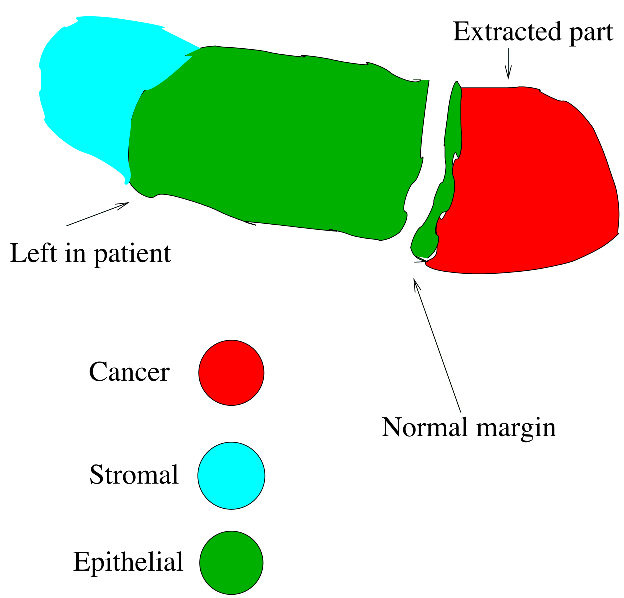
Gastric (Stomach) Cancer

1. Surgeon removes tissue
2. Pathologist examines tissue
   – Under microscope
3. If no margin, GOTO Step 1.

Image Source: http://statweb.stanford.edu/~tibs/ftp/canc.pdf

Drawbacks

- **Expensive:** requires a pathologist
- **Slow:** examination can take up to an hour
- **Unreliable:** 20%-30% can't predict on the spot



Gastric (Stomach) Cancer

1. Surgeon removes tissue
2. Pathologist examines tissue
   – Under microscope
3. If no margin, GOTO Step 1.

Image Source: http://statweb.stanford.edu/~tibs/ftp/canc.pdf

Machine Learning to the Rescue!

(actually just statistics)

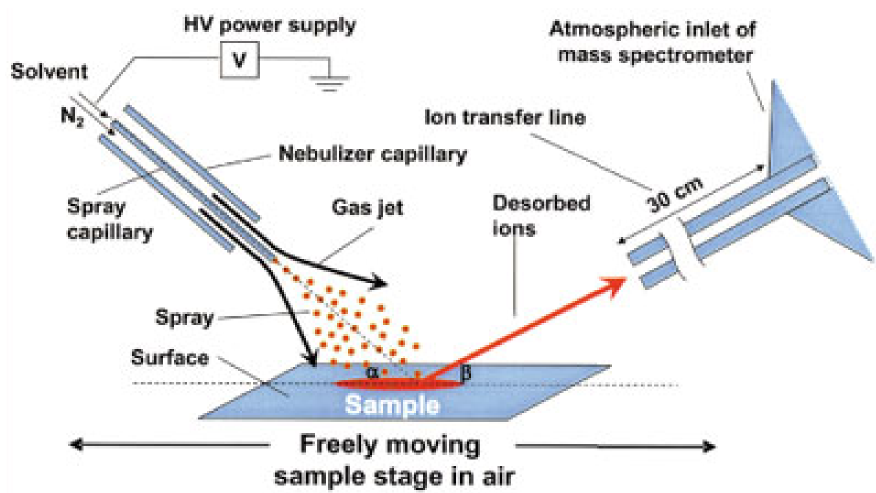
- Lasso originated from statistics community.
  - **But we machine learners love it!**

Basic Lasso: $$\underset{w,b}{\operatorname{argmin}}\, \lambda|w| + \sum_{i=1}^{N} L\left(y_i, w^T x_i - b\right)^2$$

- Train a model to predict cancerous regions!
  - Y = {C,E,S} (How to predict 3 possible labels?)
  - What is X?
  - What is loss function?

Mass Spectrometry Imaging

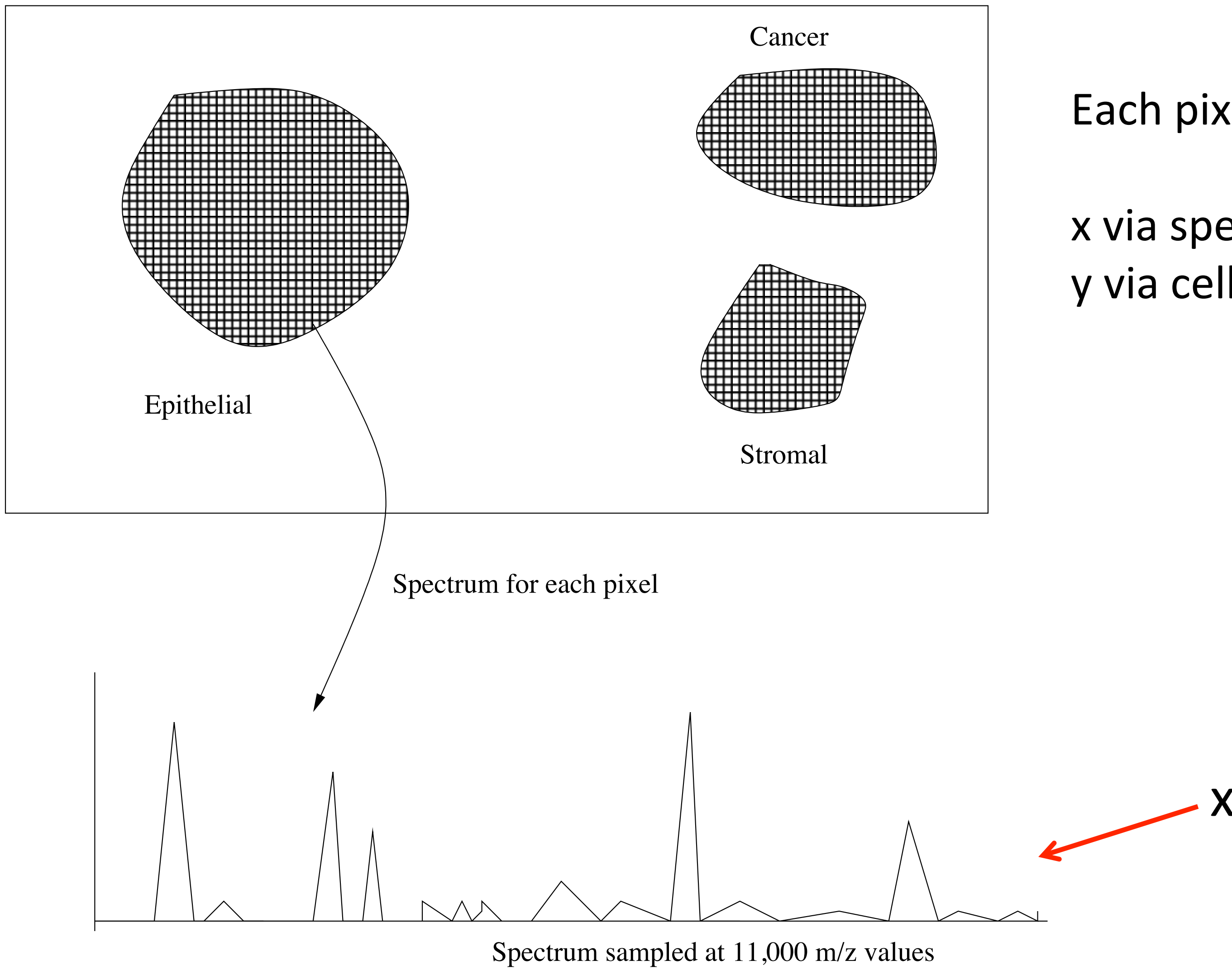
- DESI-MSI (Desorption Electrospray Ionization)



- Effectively runs in real-time (used to generate x)

http://en.wikipedia.org/wiki/Desorption_electrospray_ionization

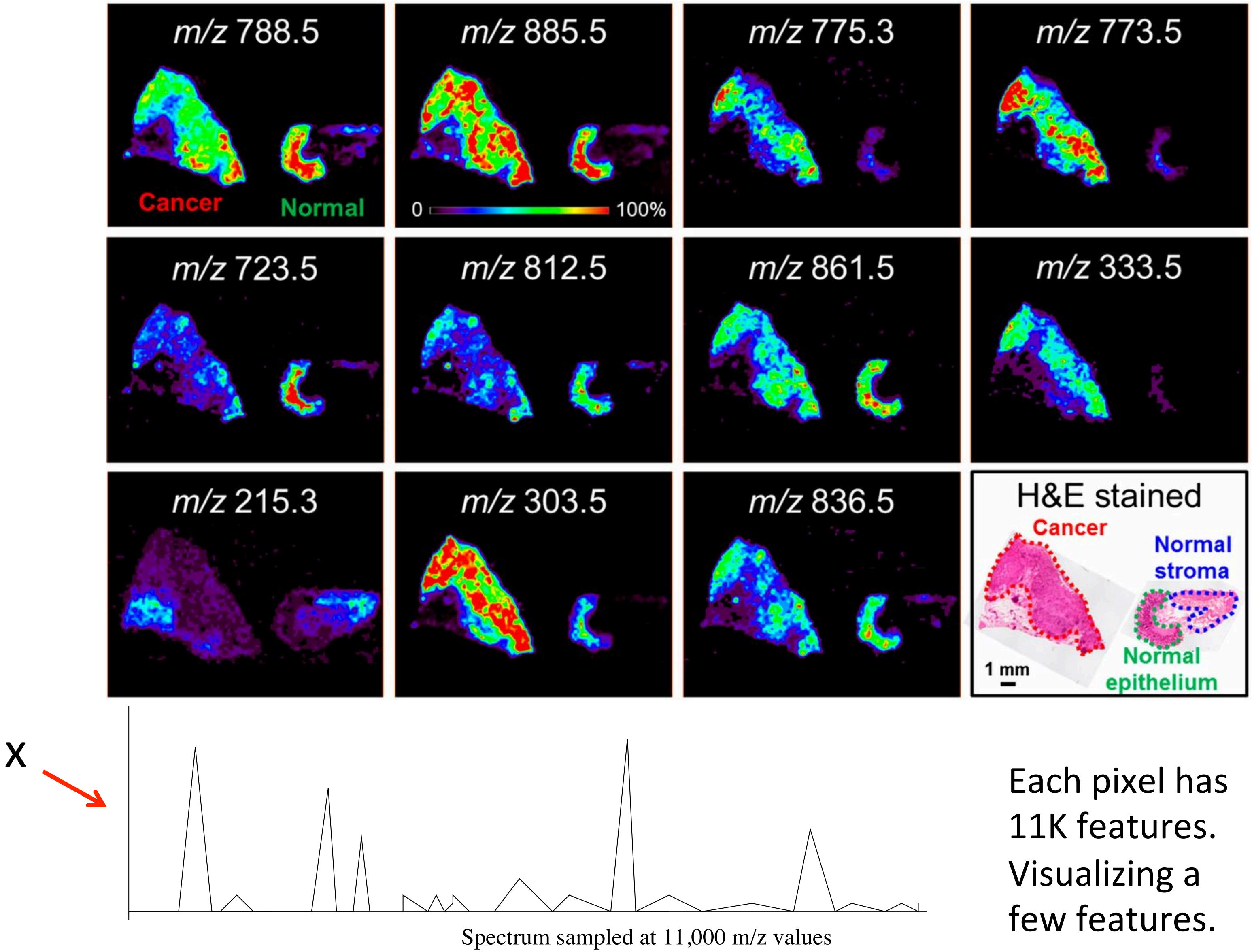
Image Source: http://statweb.stanford.edu/~tibs/ftp/canc.pdf



Each pixel is data point

x via spectroscopy
y via cell-type label

Image Source: http://statweb.stanford.edu/~tibs/ftp/canc.pdf



Each pixel has 11K features. Visualizing a few features.

Image Source: http://statweb.stanford.edu/~tibs/ftp/canc.pdf

Multiclass Prediction

- Multiclass y:

$$S = \left\{(x_i, y_i)\right\}_{i=1}^{N} \qquad x \in R^D \qquad y \in \{1, 2, \ldots, K\}$$

- Most common model:

Replicate Weights:

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_K \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix}$$

Score All Classes:

$$f(x \mid w, b) = \begin{bmatrix} w_1^T x - b_1 \\ w_2^T x - b_2 \\ \vdots \\ w_K^T x - b_K \end{bmatrix}$$

Predict via Largest Score:

$$\operatorname*{argmax}_k \begin{bmatrix} w_1^T x - b_1 \\ w_2^T x - b_2 \\ \vdots \\ w_K^T x - b_K \end{bmatrix}$$

- **Loss function?**

Multiclass Logistic Regression

Binary LR: $$P(y \mid x, w, b) = \frac{e^{y\left(w^T x - b\right)}}{e^{y\left(w^T x - b\right)} + e^{-y\left(w^T x - b\right)}} \qquad y \in \{-1, +1\}$$

"Log Linear" Property: $$P(y \mid x, w, b) \propto e^{y\left(w^T x - b\right)}$$ $(w_1,b_1) = (-w_{-1},-b_{-1})$

Extension to Multiclass: $$P(y = k \mid x, w, b) \propto e^{w_k^T x - b_k}$$ Keep a (w_k,b_k) for each class

Multiclass LR: $$P(y = k \mid x, w, b) = \frac{e^{w_k^T x - b_k}}{\sum_m e^{w_m^T x - b_m}}$$

Referred to as Multinomial Log-Likelihood by Tibshirani

http://statweb.stanford.edu/~tibs/ftp/canc.pdf

Multiclass Log Loss

$$\underset{w,b}{\operatorname{argmin}} \sum_i -\ln P(y_i \mid x_i, w, b)$$

$$x \in R^D$$

$$y \in \{1, 2, \dots, K\}$$

$$P(y \mid x, w, b) = \frac{e^{w_y^T x - b_y}}{\sum_m e^{w_m^T x - b_m}}$$

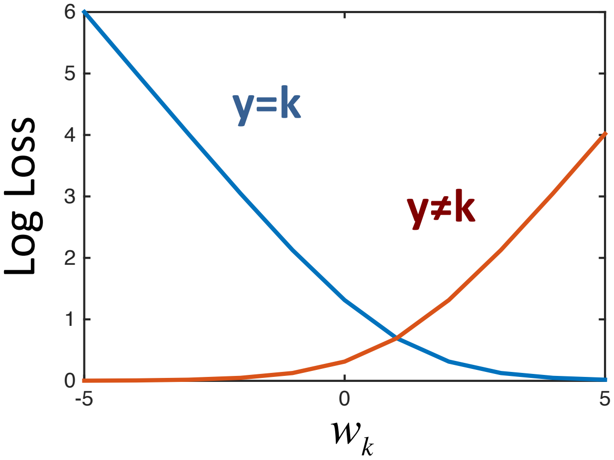
$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_K \end{bmatrix} \qquad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix}$$

$$-\ln P(y \mid x, w, b) = -w_y^T x + b_y + \ln\left(\sum_m e^{w_m^T x - b_m}\right)$$

$$\partial_{w_k} - \ln P(y \mid x, w, b) = \begin{cases} \left(-1 + P(y \mid x, w, b)\right) x & \text{if} \quad y = k \\ P(y \mid x, w, b) x & \text{if} \quad y \neq k \end{cases}$$

Multiclass Log Loss

- Suppose x=1 & ignore b
  - Model score is just w_k
  - Vary one weight, others = 1



$$-\ln P(y \mid x, w, b) = -w_y^T x + b_y + \ln\left(\sum_m e^{w_m^T x - b_m}\right)$$

$$\partial_{w_k} - \ln P(y \mid x, w, b) = \begin{cases} \left(-1 + P(y \mid x, w, b)\right) x & \text{if} \quad y = k \\ P(y \mid x, w, b) x & \text{if} \quad y \neq k \end{cases}$$

Lasso Multiclass Logistic Regression

$$\underset{w,b}{\operatorname{argmin}}\, \lambda |w| + \sum_i -\ln P(y_i \mid x_i, w, b)$$

$$x \in R^D$$
$$y \in \{1, 2, \ldots, K\}$$

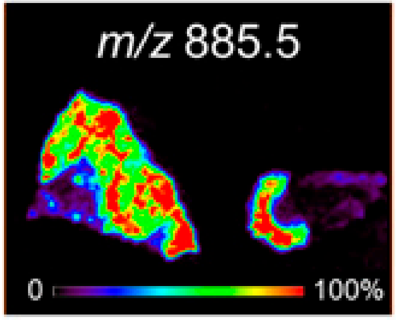
$$|w| = \sum_k |w_k| = \sum_k \sum_d |w_{kd}|$$

$$w = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_K \end{bmatrix} \quad b = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_K \end{bmatrix}$$

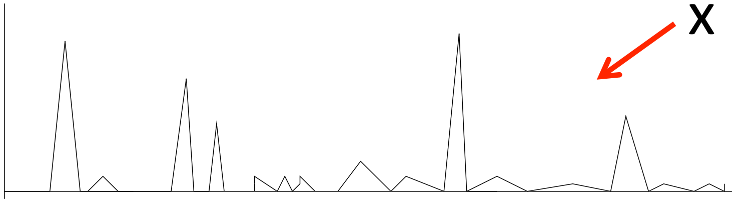
- Probabilistic model
- Sparse weights

Back to the Problem

- Image Tissue Samples
- Each pixel is an x
  - 11K features via Mass Spec
  - Computable in real time
  - 1 prediction per pixel
- y via lab results
  - ~2 weeks turn-around



Visualization of all pixels for one feature



Spectrum sampled at 11,000 m/z values

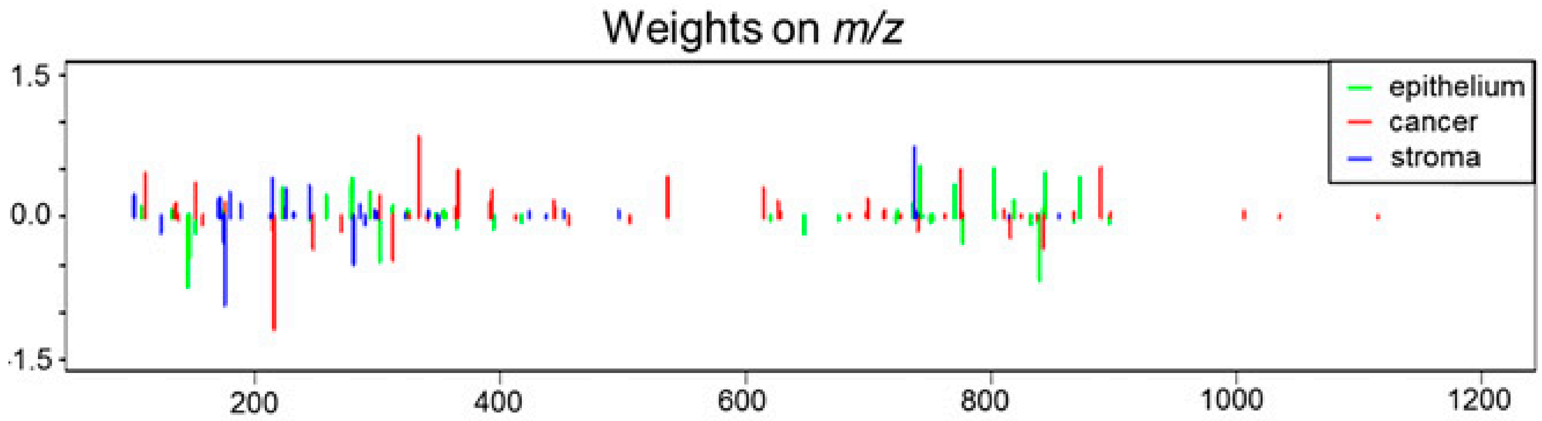
Learn a Predictive Model

- Training set: 28 tissue samples from 14 patients
  - Cross validation to select λ
- Test set: 21 tissue samples from 9 patients
- Test Performance:

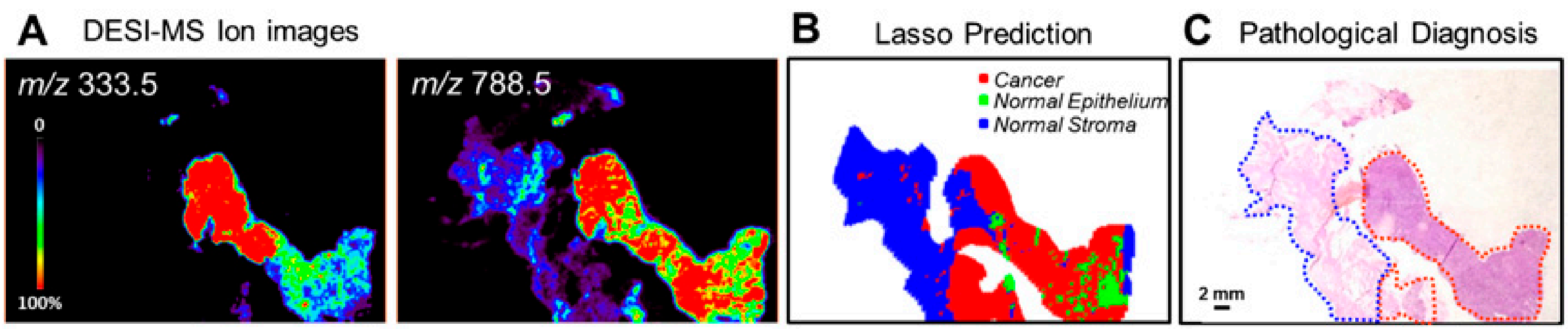
≥0.2 margin in probability

	Predicted					
Pathology	Cancer	Epithelium	Stroma	Don't know	Agreement, %	Overall agreement, %
Cancer	5,809	114	2	230	97.0	97.2
Epithelium	134	3,566	118	122	96.8	
Stroma	25	82	2,630	143	96.1	

	Cancer	Normal		Agreement, %	Overall agreement, %
Cancer	5,809	116	230	97.0	98.4
Normal	159	6,396	265	99.7	



- **Lasso yields sparse weights!** **(Manual Inspection Feasible!)**
- Many correlated features
  - Lasso tends to focus on one



http://cshprotocols.cshlp.org/content/2008/5/pdb.prot4986

Extension: Local Linearity

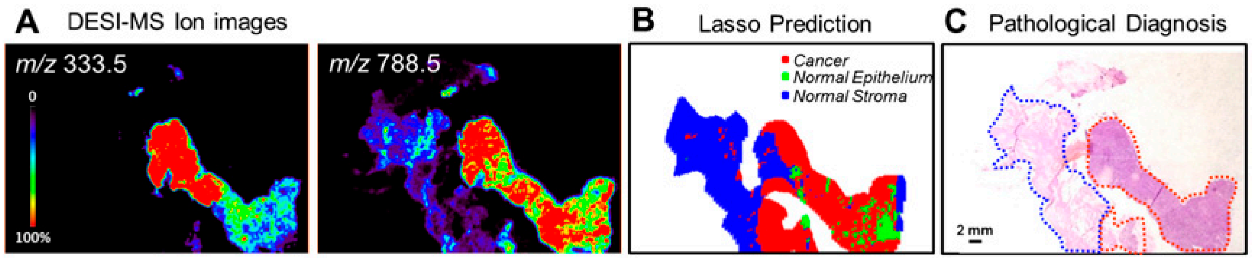
$$P(y \mid x, w, b) = \frac{e^{w_y^T x - b_y}}{\sum_m e^{w_m^T x - b_m}}$$

- Assumes probability shifts along straight line
  – Often not true
- **Approach:** cluster based on x
  – Train customized model for each cluster

Patient	1	2	3	4	5	6	Overall
Standard training	0.29%	4.56%	6.78%	0.00%	13.76%	2.77%	3.58%
Customized training	0.71%	1.89%	0.82%	0.40%	9.43%	0.92%	1.89%

http://statweb.stanford.edu/~tibs/ftp/canc.pdf

Recap: Cancer Detection

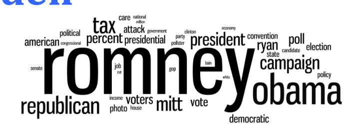


- Seems Awesome! What's the catch?
  - Small sample size
    - Tested on 9 patients
  - Machine Learning only part of the solution
    - Need infrastructure investment, etc.
    - Analyze the scientific legitimacy
  - Social/Political/Legal
    - If there is mis-prediction, who is at fault?

Personalization via twitter

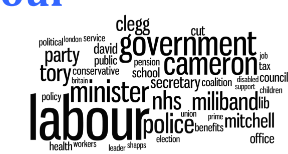
music

Biden



soccer

Labour



“Representing Documents Through Their Readers”

Proceedings of the ACM Conference on Knowledge Discovery and Data Mining (2013)

Khalid El-Arini, Min Xu, Emily Fox, Carlos Guestrin

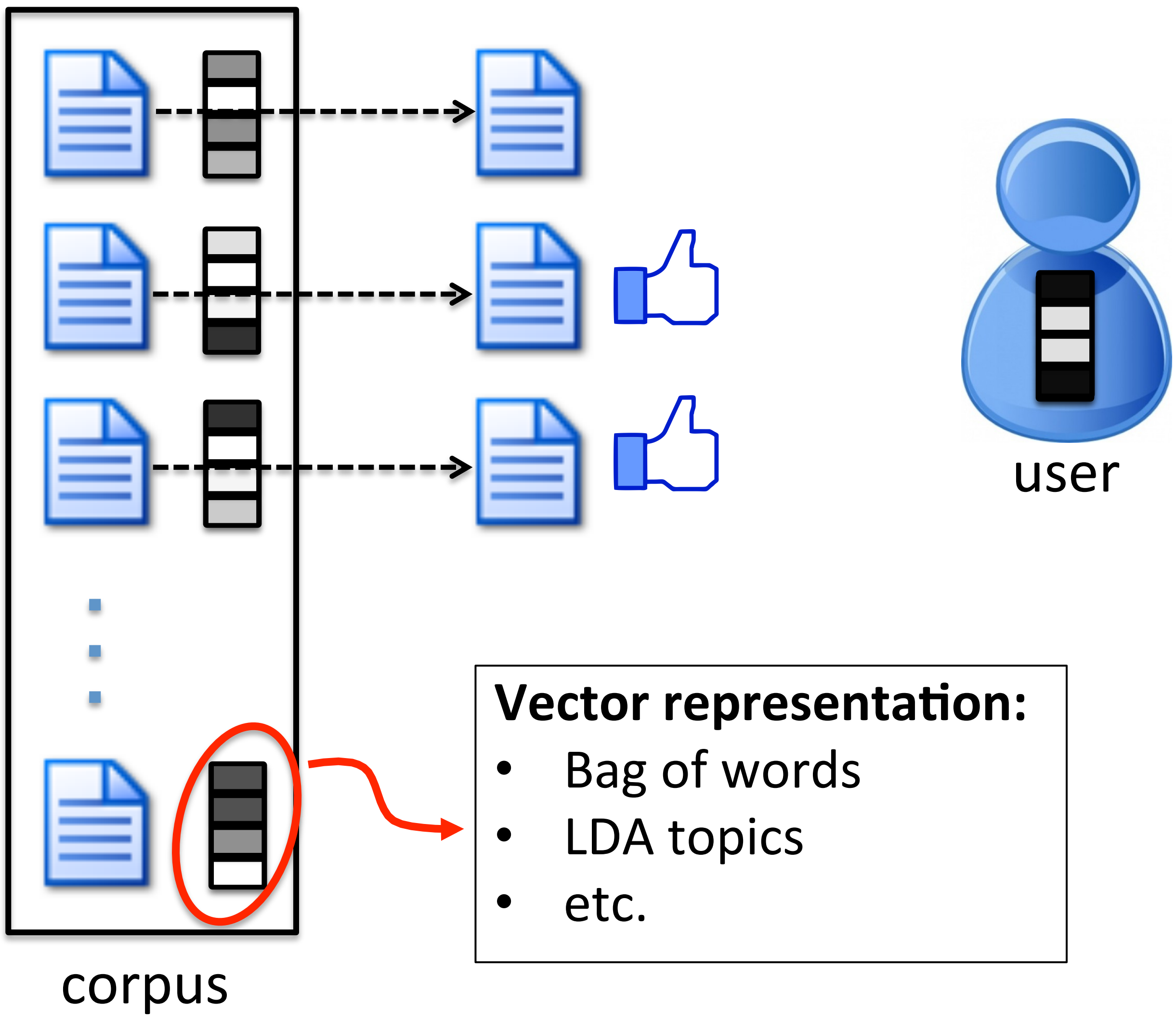
https://dl.dropboxusercontent.com/u/16830382/papers/badgepaper-kdd2013.pdf

overloaded by news

≥ 1 million news articles & blog posts generated every hour*

* [www.spinn3r.com]

News Recommendation Engine

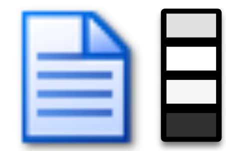


Vector representation:

- Bag of words
- LDA topics
- etc.

Challenge

Most common representations don't naturally line up with user interests



Fine-grained representations (bag of words) too specific

Haqqani network is considered most ruthless branch of Afghan insurgency

Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion

High-level topics (e.g., from a topic model)

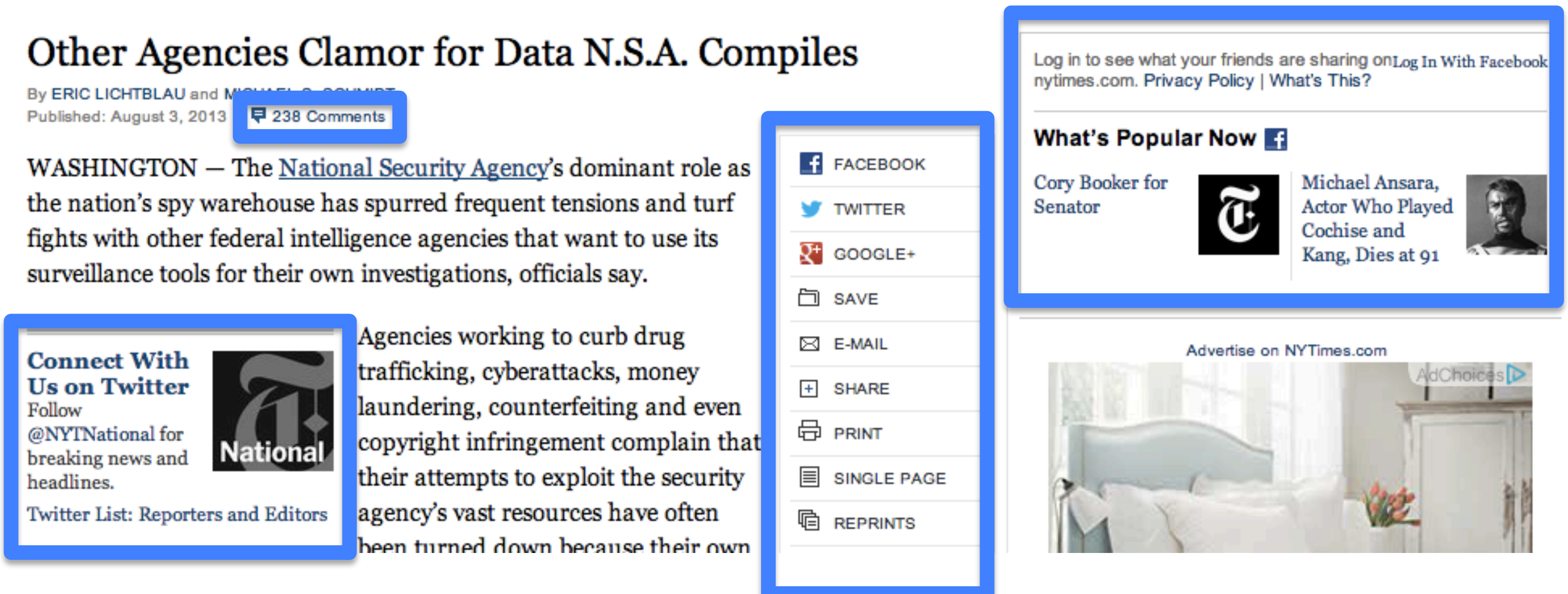
- **too fuzzy and/or vague**
- **can be inconsistent over time**

Goal

Improve recommendation performance through a more natural document representation

An Opportunity: News is Now Social

- In 2012, Guardian announced more readers visit site via Facebook than via Google search



Substandard Nerd

@substandardnerd

Gig Going, Festival Attending, Music Loving, Linux Fettling, Perl Hacking, Cycling, Vegan

badges

The Gdansk of Oxfordshire ·

https://www.youtube.com/user/apusskidu/featured

Substandard Nerd @substandardnerd 13 Jan

Stevie Nicks: the return of Fleetwood Mac

guardian.co.uk/music/2013/jan…

View summary

Approach

Learn a document representation based on how readers publicly describe themselves

Substandard Nerd

@substandardnerd

Gig Going, Festival Attending, Music Loving, Linux Fettling, Perl Hacking, Cycling, Vegan

The Gdansk of Oxfordshire ·

https://www.youtube.com/user/apusskidu/featured

Substandard Nerd @substandardnerd 13 Jan

Stevie Nicks: the return of Fleetwood Mac

guardian.co.uk

View summary

Culture › Music › Stevie Nicks

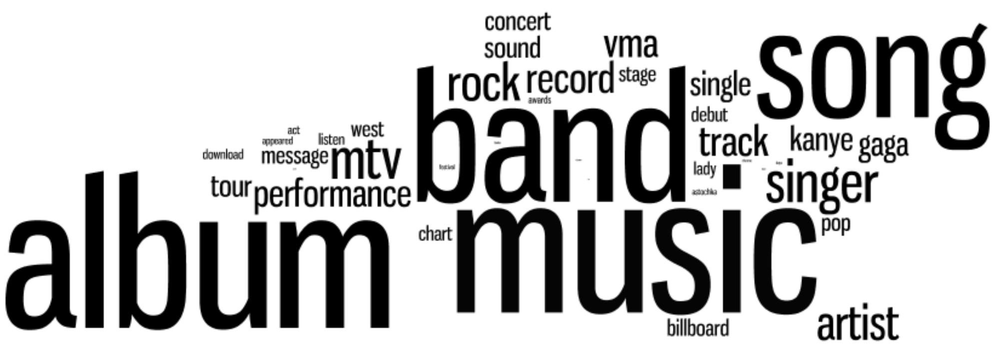
Stevie Nicks: the return of Fleetwood Mac

Stevie Nicks's tumultuous life as a rock queen led her to addiction, heartbreak and "insanity". As Fleetwood Mac reunite, she tells Caspar Llewellyn Smith why she's going back for more

Using **many** tweets, can we learn that someone who identifies with

via profile badges → **music**

reads articles with these words:

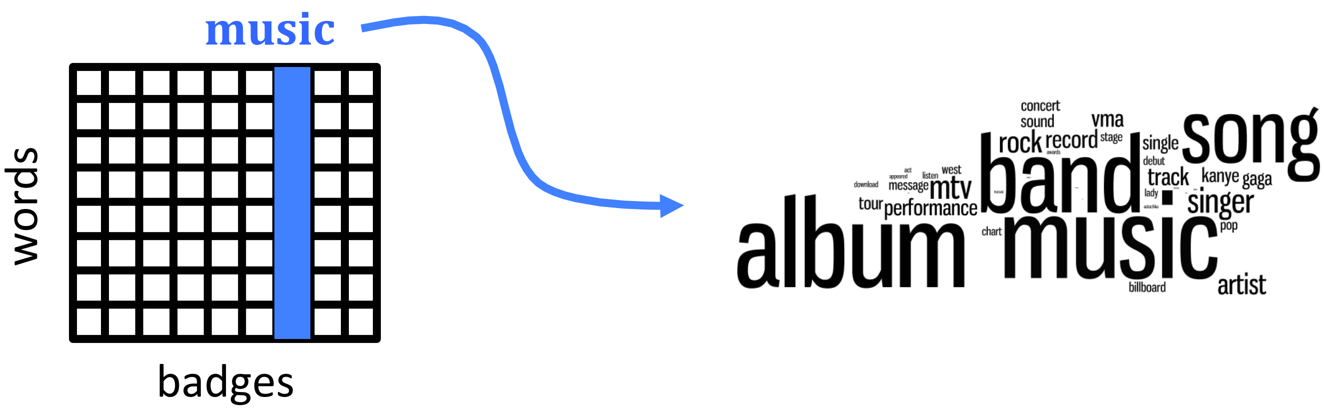


?

Given: training set of tweeted news articles from a specific period of time

3 million articles

1. Learn a **badge dictionary** from training set



2. Use badge dictionary to **encode new articles**


Haqqani network is considered most ruthless branch of Afghan insurgency

Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion

Advantages

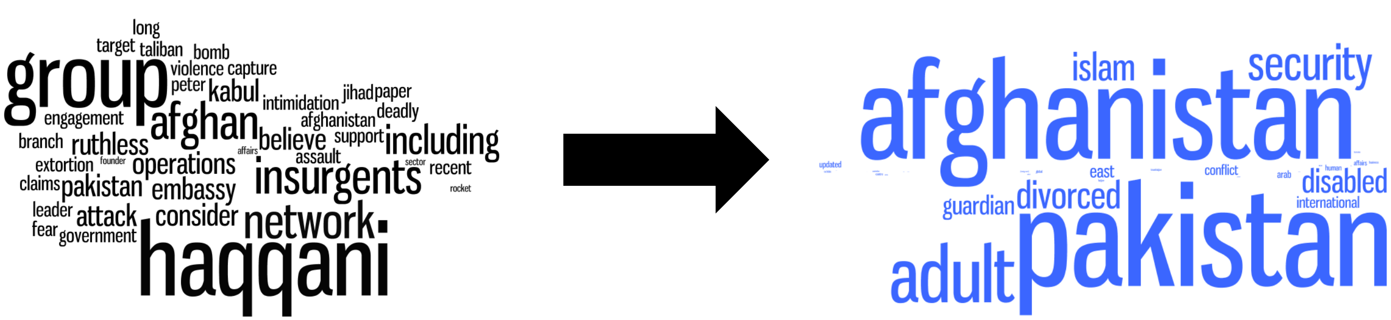
- Interpretable
  - Clear labels
  - Correspond to user interests
- Higher-level than words

Advantages

- Interpretable
  - Clear labels
  - Correspond to user interests

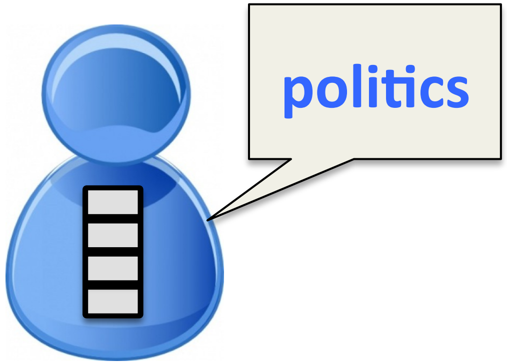
Haqqani network is considered most ruthless branch of Afghan insurgency

Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion



Advantages

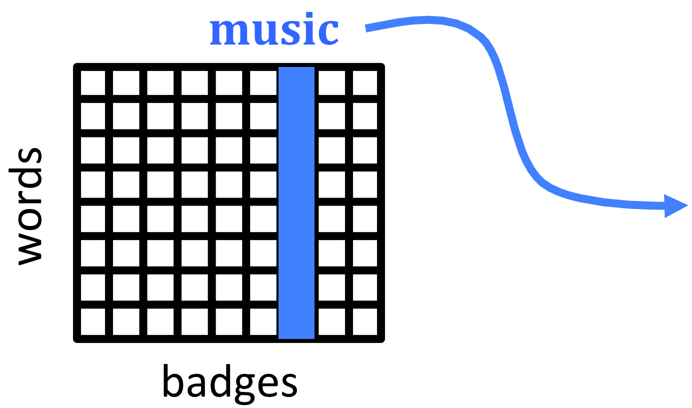
- Interpretable
  - Clear labels
  - Correspond to user interests
- Higher-level than words
- Semantically consistent over time

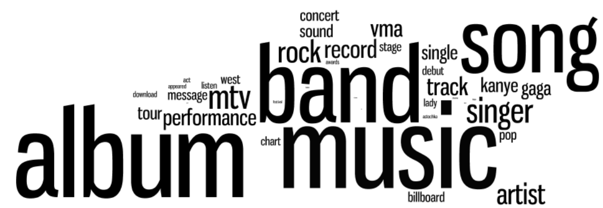


Given: training set of tweeted news articles from a specific period of time

3 million articles

1. Learn a **badge dictionary** from training set





2. Use badge dictionary to **encode new articles**


Haqqani network is considered most ruthless branch of Afghan insurgency

Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion

Dictionary Learning

- Training data : $S = \{(z_i, y_i)\}_{i=1}^{N}$

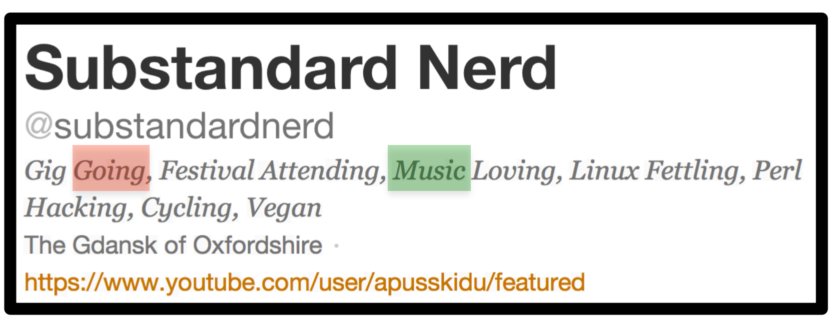
Identifies badges in Twitter profile of tweeter

Bag-of-words representation of document

Culture Music Stevie Nicks

Stevie Nicks: the return of Fleetwood Mac

Stevie Nicks's tumultuous life as a rock queen led her to addiction, heartbreak and "insanity". As Fleetwood Mac reunite, she tells Caspar Llewellyn Smith why she's going back for more



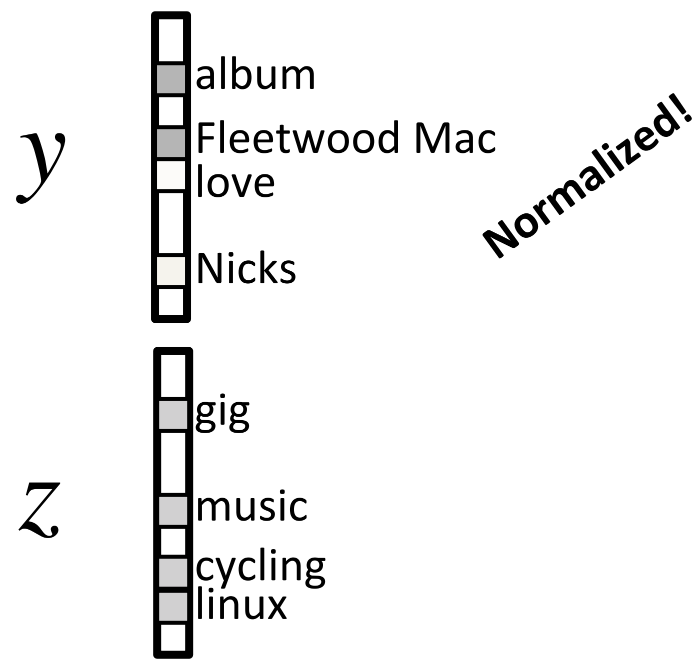
Substandard Nerd

@substandardnerd

Gig Going, Festival Attending, Music Loving, Linux Fettling, Perl Hacking, Cycling, Vegan

The Gdansk of Oxfordshire ·

https://www.youtube.com/user/apusskidu/featured



Dictionary Learning

$$S = \left\{ \left(z_i , y_i \right) \right\}_{i=1}^{N}$$

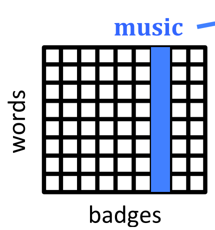
Identifies badges in Twitter profile of tweeter

Bag-of-words representation of document

- Training Objective:

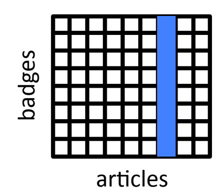
$$\underset{B,W}{\operatorname{argmin}} \lambda_B \left| B \right| + \lambda_W \left| W \right| + \sum_{i=1}^{N} \left\| y_i - BW_i \right\|^2$$

"Dictionary"



Haqqani network is considered most ruthless branch of Afghan insurgency

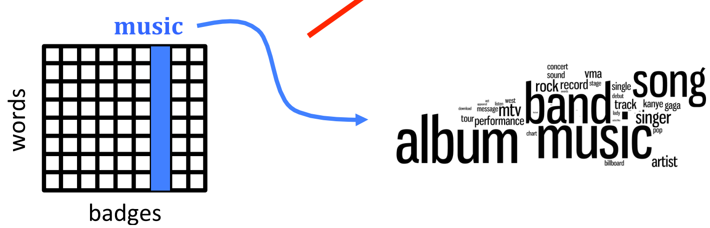
Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion

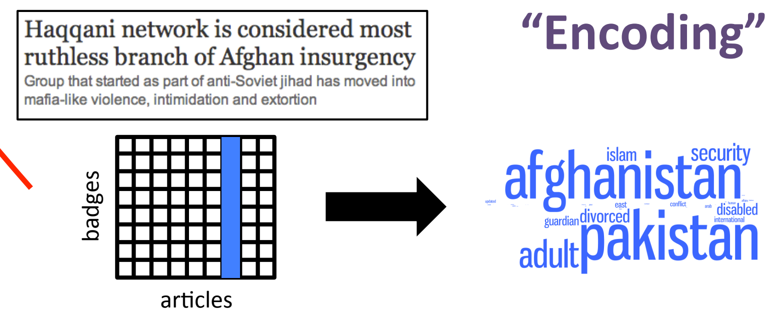


"Encoding"

$$\underset{B,W}{\operatorname{argmin}}\ \lambda_B |B| + \lambda_W |W| + \sum_{i=1}^{N} \left\| y_i - BW_i \right\|^2$$

“Dictionary”



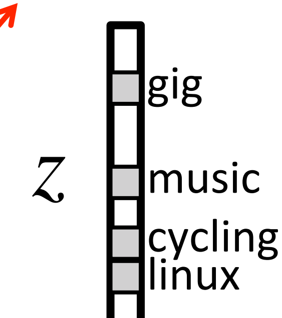


- Not convex! (because of BW term)
- Convex if only optimize B or W (but not both)
- Alternating Optimization (between B and W)
- How to initialize?

Initialize:

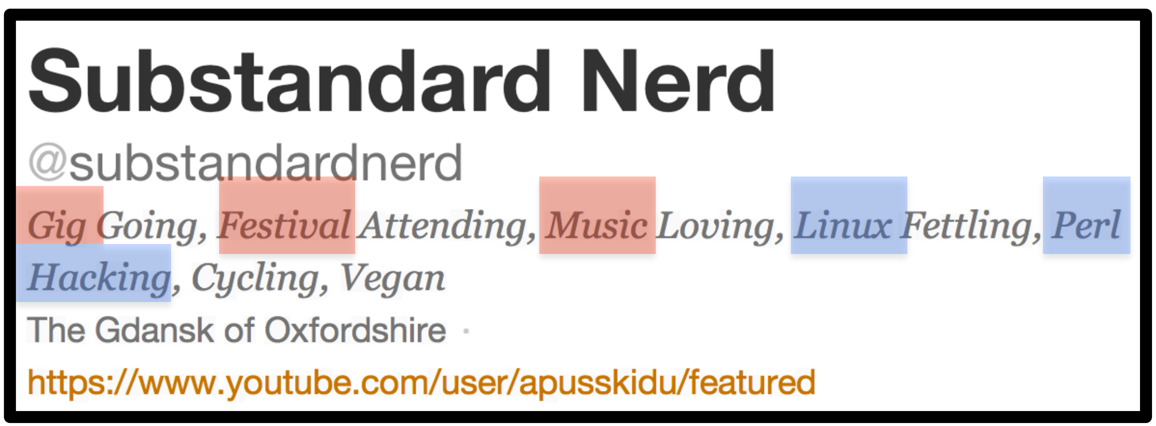
$$W_i = z_i / |z_i|$$

Use: $S = \left\{ (z_i, y_i) \right\}_{i=}^{N}$



$$\underset{B,W}{\operatorname{argmin}}\, \lambda_B |B| + \lambda_W |W| + \sum_{i=1}^{N} \| y_i - B W_i \|^2$$

- Suppose Badge s often co-occurs with Badge t
  - B_s & B_t are correlated
- From perspective of W, B's are features.
  - Lasso tends to focus on one correlated feature



Many articles might be about Gig, Festival & Music simultaneously.

$$\underset{B,W}{\operatorname{argmin}} \lambda_B |B| + \lambda_W |W| + \sum_{i=1}^{N} \| y_i - BW_i \|^2$$

- Suppose Badge s often co-occurs with Badge t
  - B_s & B_t are correlated
- From perspective of W, B's are features.
  - Lasso tends to focus on one correlated feature
- Graph Guided Fused Lasso:

$$\underset{B,W}{\operatorname{argmin}} \lambda_B |B| + \lambda_W |W| + \lambda_G \sum_{i=1}^{N} \underbrace{\sum_{(s,t) \in E(G)}}_{\text{Graph G of related Badges}} \omega_{st} |W_{is} - W_{it}| + \sum_{i=1}^{N} \| y_i - BW_i \|^2$$

Co-occurance Rate
On Twitter Profiles

Encoding New Articles

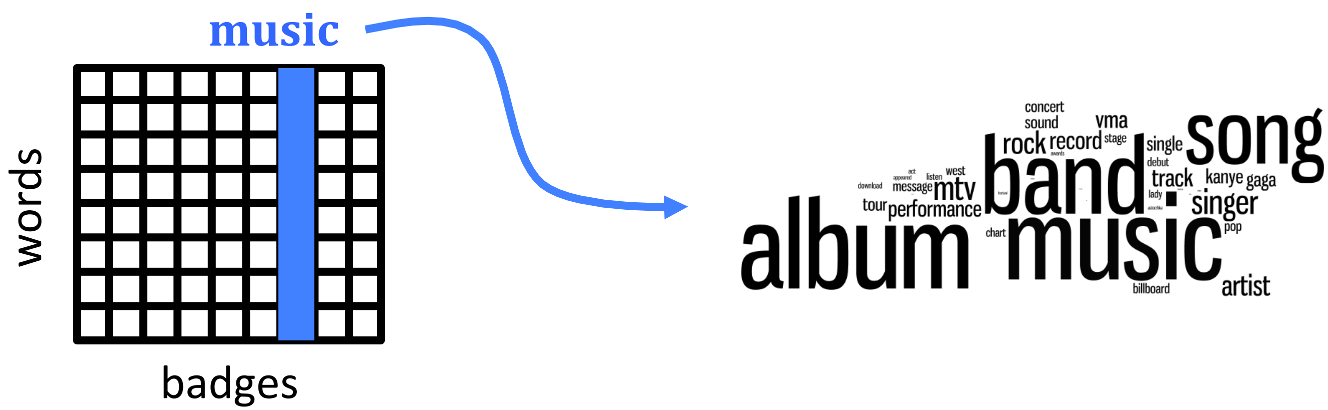
- Badge Dictionary B is already learned

- Given a new document j with word vector y_j
  - Learn Badge Encoding W_j:

$$\underset{W_j}{\operatorname{argmin}} \lambda_W \left|W_j\right| + \lambda_G \sum_{(s,t)\in G} \left|W_{js} - W_{jt}\right| + \left\|y_j - BW_j\right\|^2$$

Recap: Badge Dictionary Learning

1. Learn a **badge dictionary** from training set



2. Use badge dictionary to **encode new articles**


Haqqani network is considered most ruthless branch of Afghan insurgency

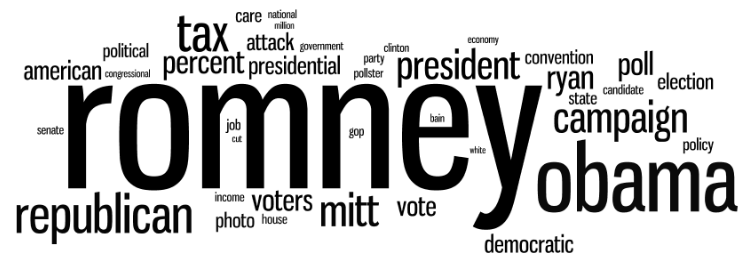
Group that started as part of anti-Soviet jihad has moved into mafia-like violence, intimidation and extortion

Examining **B**

September 2012

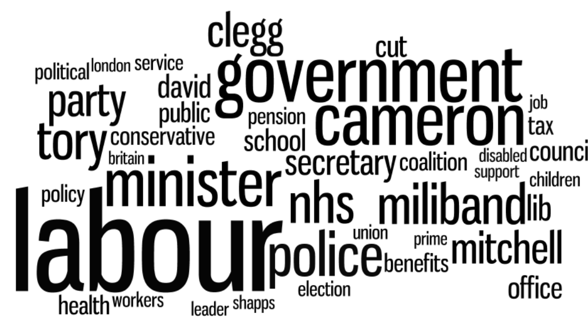
music

Biden



soccer

Labour

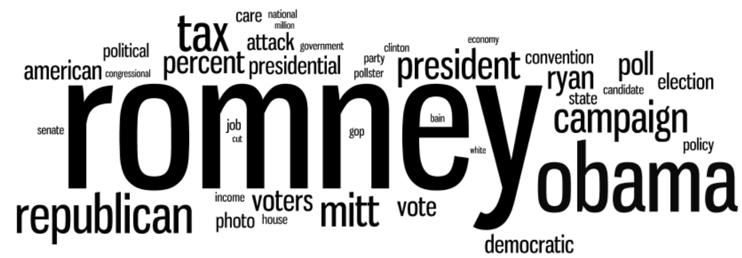


Badges Over Time

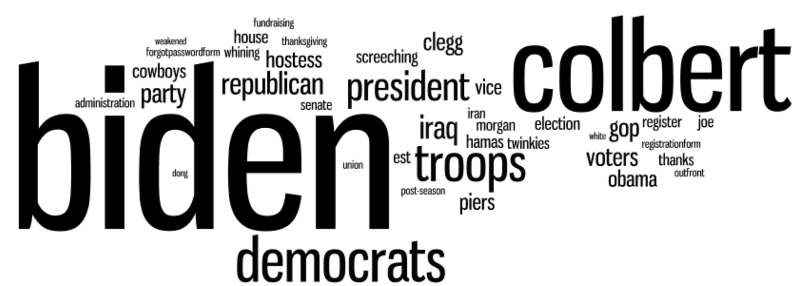
September 2012

music

Biden



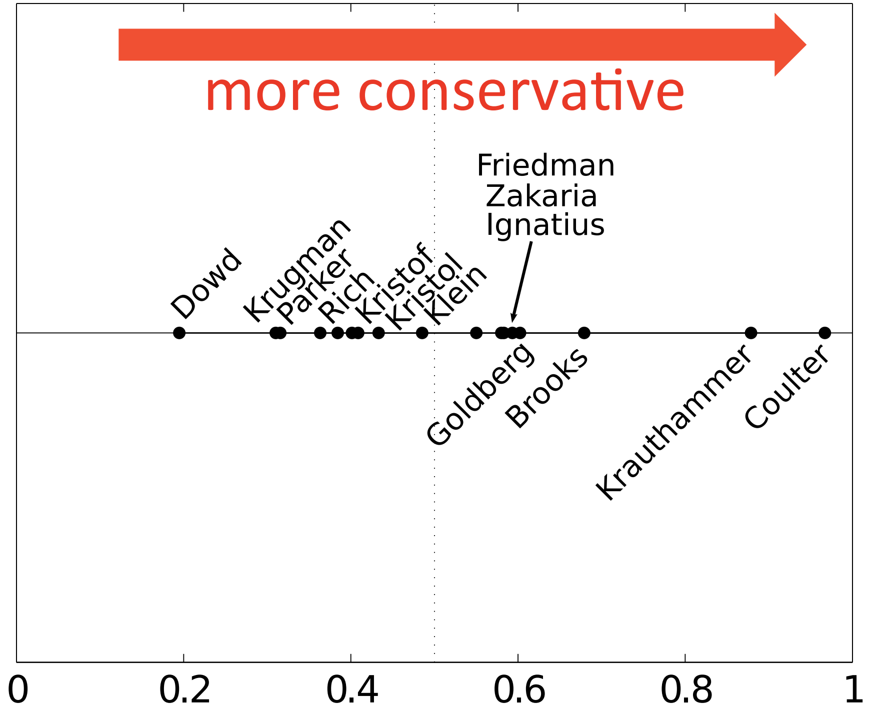
September 2010



A Spectrum of Pundits

"top conservatives on Twitter"

- Limit badges to **progressive** and **TCOT**
- Predict political alignments of likely readers?

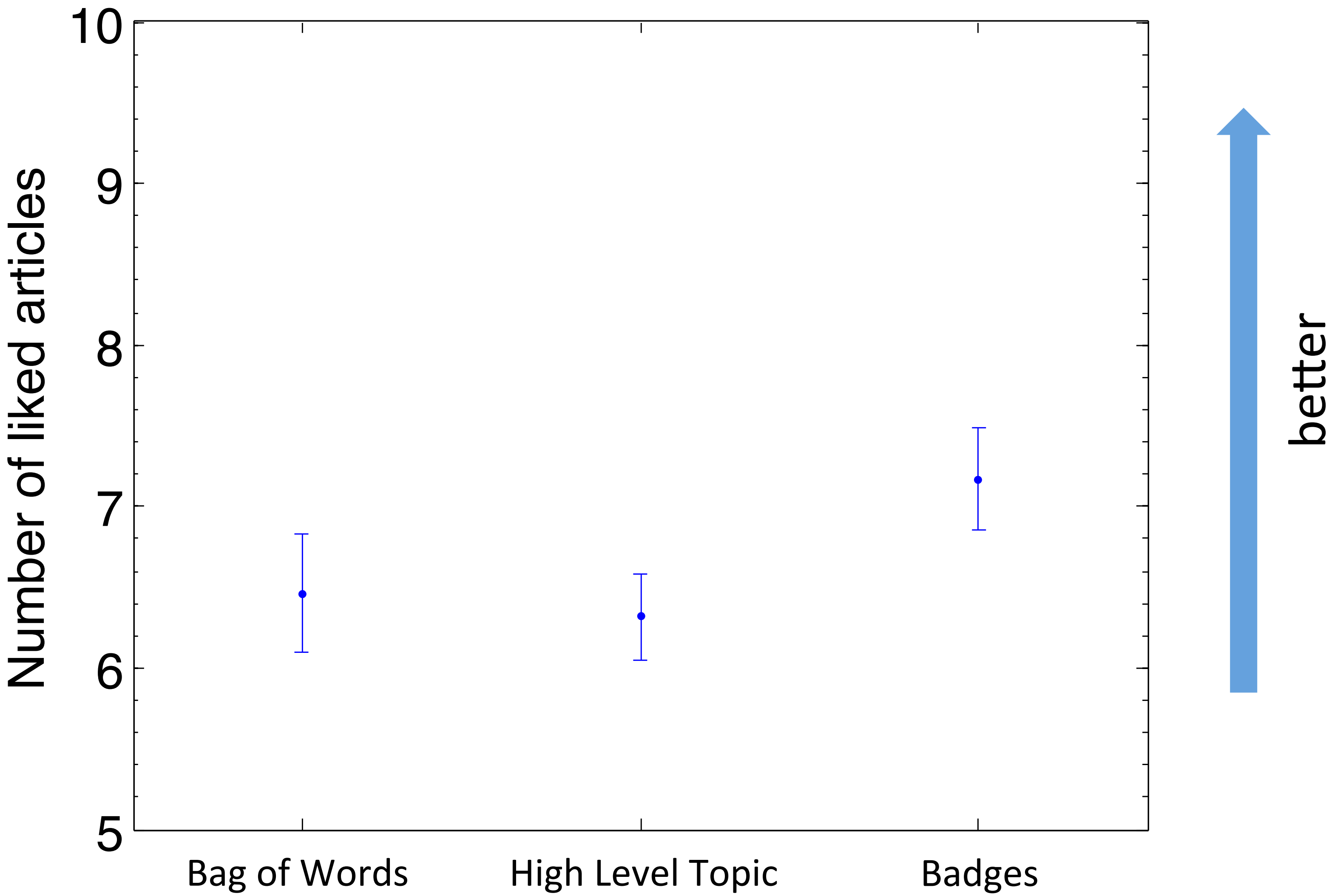


- Took all articles by columnist
- Looked at encoding score
  - progressive vs TCOT
- Average

User Study

- Which representation best captures user preferences over time?
- Study on Amazon Mechanical Turk with 112 users
  1. Show users random 20 articles from Guardian, from time period 1, and obtain ratings
  2. Pick random representation
     - bag of words, high level topic, Badges
  3. Represent user preferences as mean of liked articles
  4. GOTO next time period
     - Recommend according to preferences
     - GOTO STEP 2

User Study



10
9
8
7
6
5
Number of liked articles
Bag of Words
High Level Topic
Badges
better

Recap: Personalization via twitter

- Sparse Dictionary Learning
  - Learn a new representation of articles
  - Encode articles using dictionary
  - Better than Bag of Words
  - Better than High Level Topics
- Based on social data
  - Badges on twitter profile & tweeting
  - Semantics not directly evident from text alone

Next Week

- Sequence Prediction
- Hidden Markov Models
- Conditional Random Fields
- Homework 1 due Tues 1/20 @5pm
  - via Moodle