value means that the user has not read the joke, but doesn't mean that the rating should be zero. A more reasonable choice is to minimize the MSE only on rated joke. Let's define a loss function:

$$L\Big(\{u_i\}, \{v_j\}\Big) := \sum_{(i,j)\in T} (\langle u_i, v_j\rangle - R_{i,j})^2 + \lambda \sum_{i=1}^{n} \|u_i\|_2^2 + \lambda \sum_{j=1}^{m} \|v_j\|_2^2,$$

where T and $R_{i,j}$ here are from the training set and $\lambda > 0$ is the regularization coefficient. Implement an algorithm to learn vector representations by minimizing the loss function $L(\{u_i\}, \{v_j\})$. Note that you may need to tune the hyper-parameter λ to optimize the performance.

- HW3 problem 4c

sparse data, replacing all missing values by zero is not a completely satisfying solution. A missing
e means that the user has not read the joke, but doesn't mean that the rating should be zero. A more
onable choice is to minimize the MSE only on rated joke. Let's define a loss function:

$$L\Big(\{u_i\}, \{v_j\}\Big) := \sum_{(i,j)\in T} (\langle u_i, v_j\rangle - R_{i,j})^2 + \lambda \sum_{i=1}^{n} \|u_i\|_2^2 + \lambda \sum_{j=1}^{m} \|v_j\|_2^2,$$

re T and $R_{i,j}$ here are from the training set and $\lambda > 0$ is the regularization coefficient. Implement
lgorithm to learn vector representations by minimizing the loss function $L(\{u_i\}, \{v_j\})$. Note that you

Compute $\nabla_{u_k} L = \sum_{(i,j)\in T} \nabla_{u_k} (\langle u_i, v_j \rangle - R_{i,j})^2 + \dots$

$$= \sum_{(i,j)\in T:\, i=k} 2 v_j (u_i^T v_j - R_{i,j}) + 2\lambda u_k$$

$$u_k = \Big(\sum_{(i,j)\in T:\, i=k} v_j v_j^T + \lambda I \Big)^{-1} \Big(\sum_{(i,j)\in T:\, i=k} R_{i,j} v_j \Big)$$

$$v_k = \Big(\sum_{(i,j)\in T:\, j=k} u_i u_i^T + \lambda I \Big)^{-1} \Big(\sum_{(i,j)\in T:\, j=k} R_{i,j} u_i \Big)$$

Announcements

- HW3 problem 4c

Given $\{(x_i, y_i)\}_{i=1}^n$ $\quad \ell(w) = \left(\sum_{i=1}^n (y_i - x_i^T w)^2\right) + \lambda \|w\|_2^2$

What is $\nabla_w \ell(w)$? What is $\arg\min_w \ell(w)$?

$$\nabla_w \ell(w) = \left(\sum_{i=1}^n 2(y_i - x_i^T w)(-x_i)\right) + 2\lambda w$$

$$= \sum_{i=1}^n 2x_i(x_i^T w - y_i) + 2\lambda w$$

$$\nabla_w \ell(w) = 0 \qquad \underbrace{\left(\sum x_i x_i^T + \lambda I\right)}\, w = \sum x_i y_i$$

$$\hat{w} = \left(\sum x_i x_i^T + \lambda I\right)^{-1} \left(\sum x_i y_i\right)$$

Announcements

- HW3 problem 4c

Sequences and Recurrent Neural Networks

Machine Learning – CSE4546

Kevin Jamieson

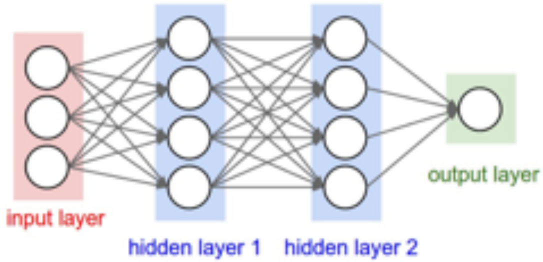
University of Washington

November 30, 2017

Variable length sequences

Images are usually standardized to be the same size (e.g., 256x256x3)

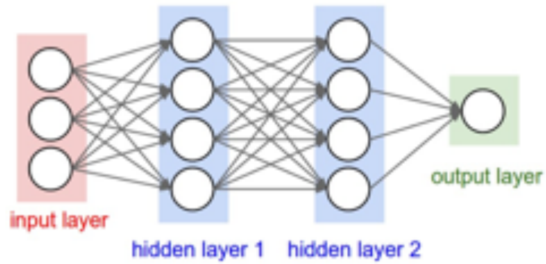
Neural Network



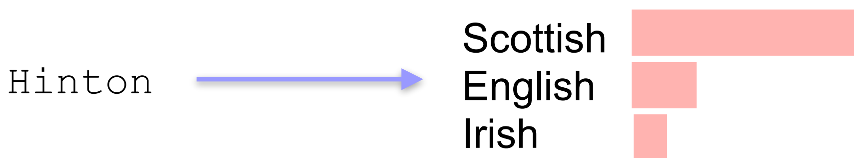
Variable length sequences

Images are usually standardized to be the same size (e.g., 256x256x3)

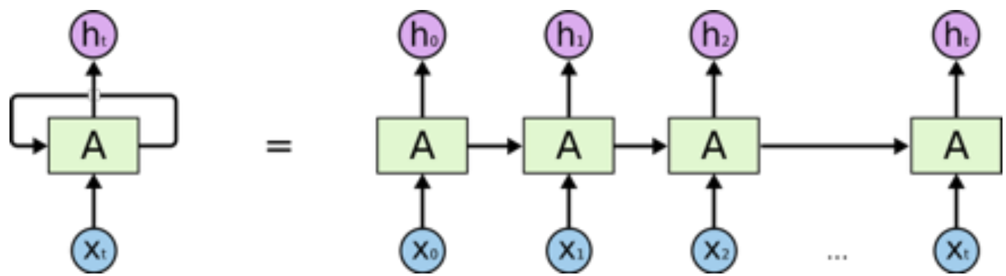
Neural Network



But what if we wanted to do classification on country-of-origin for names?

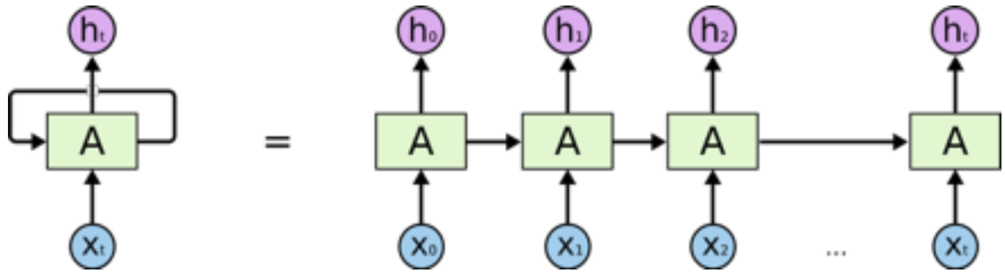


Recurrent Neural Network

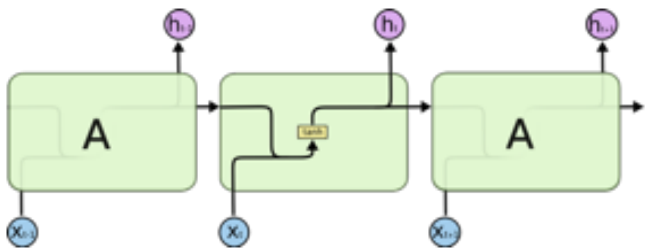


Variable length sequences

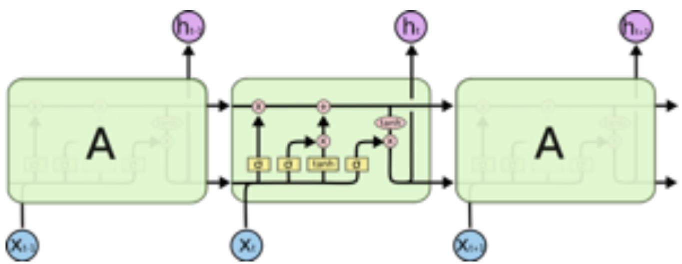
Recurrent Neural Network



Standard RNN



LSTM



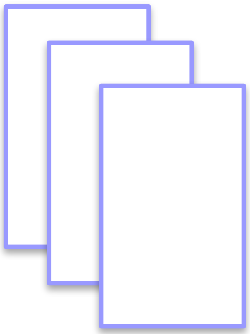
Slide: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Basic Text/Document Processing

Machine Learning – CSE4546
Kevin Jamieson
University of Washington

November 30, 2017

TF*IDF



n documents/articles with lots of text

How to get a feature representation of each article?

1. For each document *d* compute the proportion of times word *t* occurs out of all words in *d*, i.e. **term frequency**

$$TF_{d,t}$$

2. For each word *t* in your corpus, compute the proportion of documents out of *n* that the word *t* occurs, i.e., **document frequency**

$$DF_t$$

3. Compute score for word *t* in document *d* as $TF_{d,t} \log(\frac{1}{DF_t})$

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$

ratebeer

Two Hearted Ale - Input ~2500 natural language reviews

http://www.ratebeer.com/beer/two-hearted-ale/1502/2/1/

3.8 AROMA 8/10 APPEARANCE 4/5 TASTE 8/10 PALATE 3/5 OVERALL 15/20
fonefan (25678) - VestJylland, DENMARK - JAN 18, 2009

Bottle 355ml.
Clear light to medium yellow orange color with a average, frothy, good lacing, fully lasting, off-white head. Aroma is moderate to heavy malty, moderate to heavy hoppy, perfume, grapefruit, orange shell, soap. Flavor is moderate to heavy sweet and bitter with a average to long duration. Body is medium, texture is oily, carbonation is soft. [250908]

4 AROMA 8/10 APPEARANCE 4/5 TASTE 7/10 PALATE 4/5 OVERALL 17/20
Ungstrup (24358) - Oamaru, NEW ZEALAND - MAR 31, 2005

An orange beer with a huge off-white head. The aroma is sweet and very freshly hoppy with notes of hop oils - very powerful aroma. The flavor is sweet and quite hoppy, that gives flavors of oranges, flowers as well as hints of grapefruit. Very refreshing yet with a powerful body.

Reviews for each beer	Bag of Words weighted by TF*IDF	Get 100 nearest neighbors using cosine distance	Non-metric multidimensional scaling	Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$

Two Hearted Ale - Weighted Bag of Words:

Reviews for each beer

Bag of Words weighted by TF*IDF

Get 100 nearest neighbors using cosine distance

Non-metric multidimensional scaling

Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$

Weighted count vector for the ith beer:

$$z_i \in \mathbb{R}^{400{,}000}$$

Cosine distance:

$$d(z_i, z_j) = 1 - \frac{z_i^T z_j}{||z_i|| \, ||z_j||}$$

Two Hearted Ale - Nearest Neighbors:

Bear Republic Racer 5
Avery IPA
Stone India Pale Ale (IPA)
Founders Centennial IPA
Smuttynose IPA
Anderson Valley Hop Ottin IPA
AleSmith IPA
BridgePort IPA
Boulder Beer Mojo IPA
Goose Island India Pale Ale
Great Divide Titan IPA
New Holland Mad Hatter Ale
Lagunitas India Pale Ale
Heavy Seas Loose Cannon Hop3
Sweetwater IPA

Reviews for each beer

Bag of Words weighted by TF*IDF

Get 100 nearest neighbors using cosine distance

Non-metric multidimensional scaling

Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$

Find an embedding $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$ such that

$||x_k - x_i|| < ||x_k - x_j||$ whenever $\underline{d(z_k, z_i)} < \underline{d(z_k, z_j)}$

for all 100-nearest neighbors.

(10^7 constraints, 10^5 variables)

distance in 400,000 dimensional "word space"

Solve with hinge loss and stochastic gradient descent.

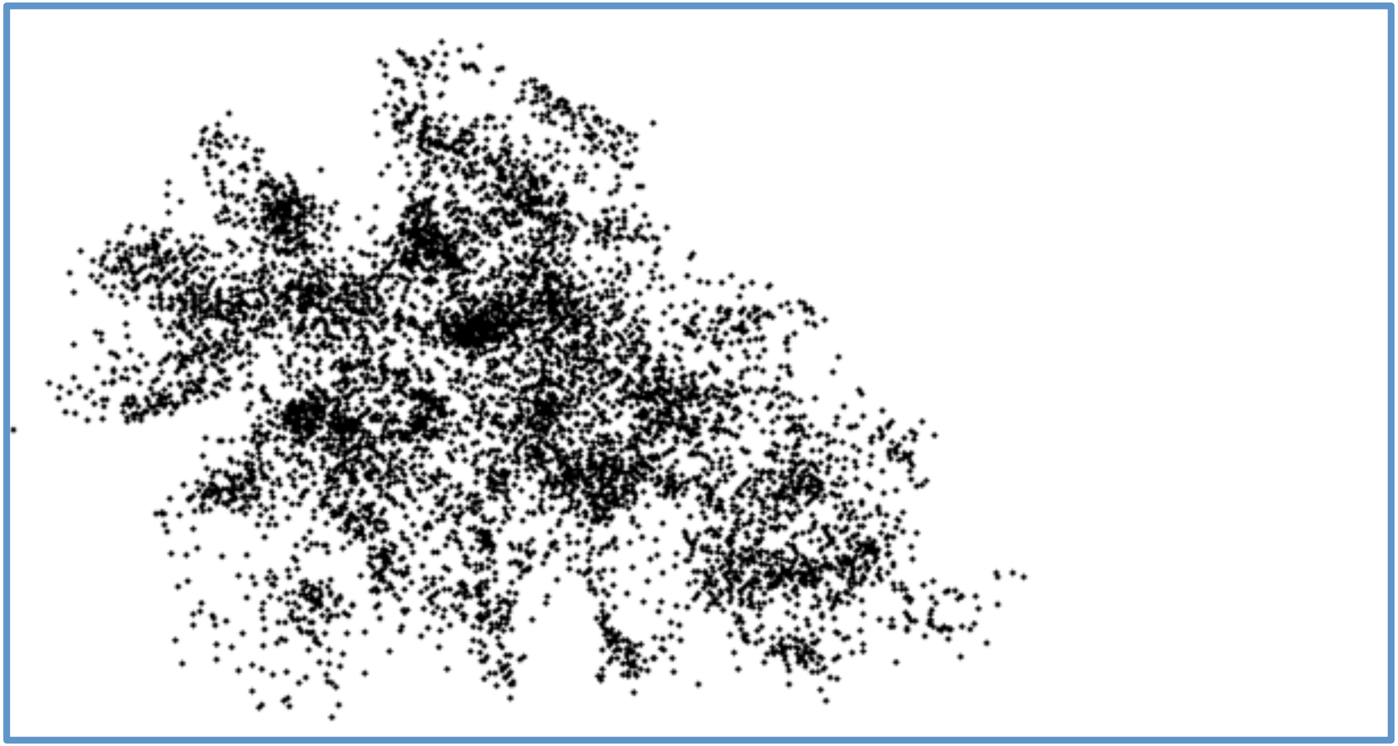
(20 minutes on my laptop) (d=2,err=6%) (d=3,err=4%)

Could have also used local-linear-embedding, max-volume-unfolding, kernel-PCA, etc.

Reviews for each beer	Bag of Words weighted by TF*IDF	Get 100 nearest neighbors using cosine distance	**Non-metric multidimensional scaling**	Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$



Reviews for each beer

Bag of Words weighted by TF*IDF

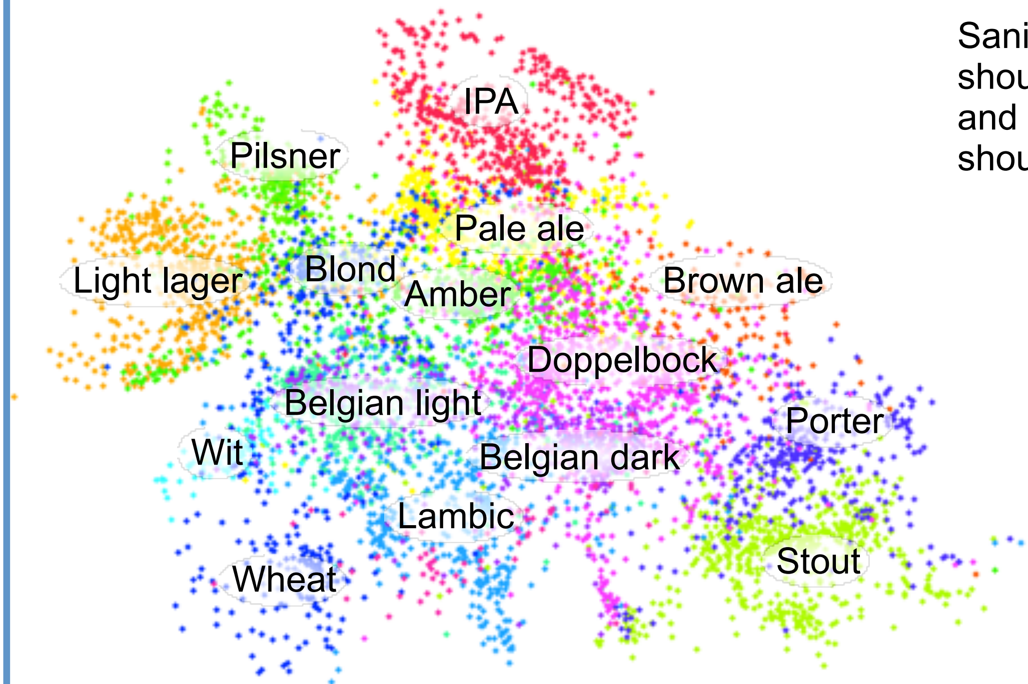
Get 100 nearest neighbors using cosine distance

Non-metric multidimensional scaling

Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$

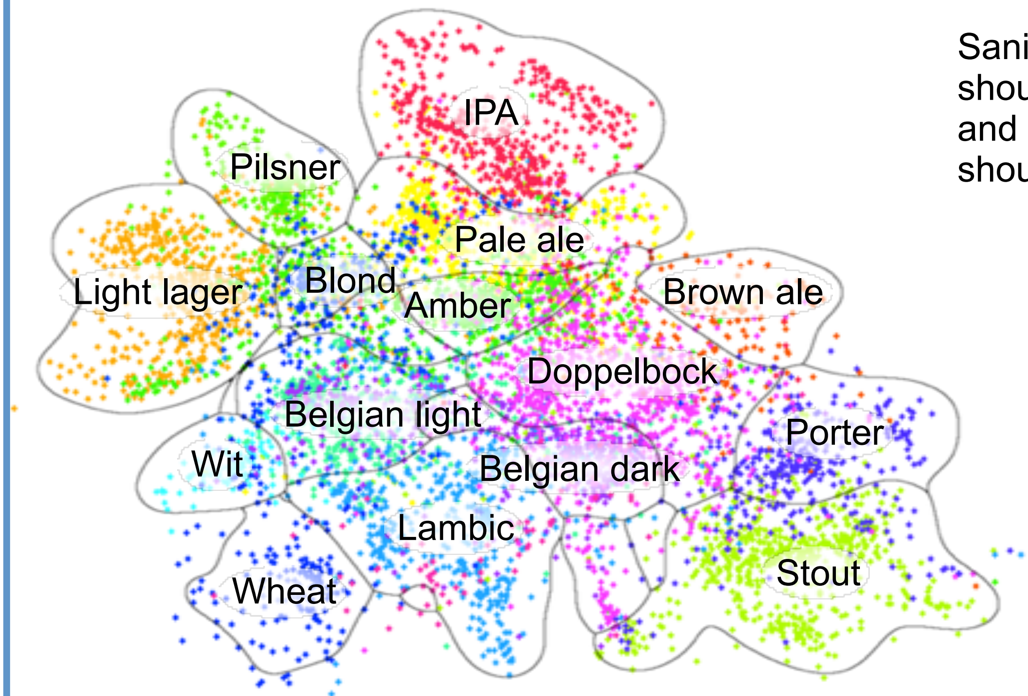


Sanity check: styles should cluster together and similar styles should be close.

Reviews for each beer → Bag of Words weighted by TF*IDF → Get 100 nearest neighbors using cosine distance → Non-metric multidimensional scaling → Embedding in d dimensions

BeerMapper - Under the Hood

Algorithm requires feature representations of the beers $\{x_1, \ldots, x_n\} \subset \mathbb{R}^d$



Sanity check: styles should cluster together and similar styles should be close.

Reviews for each beer → Bag of Words weighted by TF*IDF → Get 100 nearest neighbors using cosine distance → Non-metric multidimensional scaling → Embedding in d dimensions

Other document modeling

Matrix factorization:

1. Construct word x document matrix of counts
2. Compute non-negative matrix factorization
3. Use factorization to represent documents
4. Cluster documents into topics

Also see latent Dirichlet factorization (LDA)

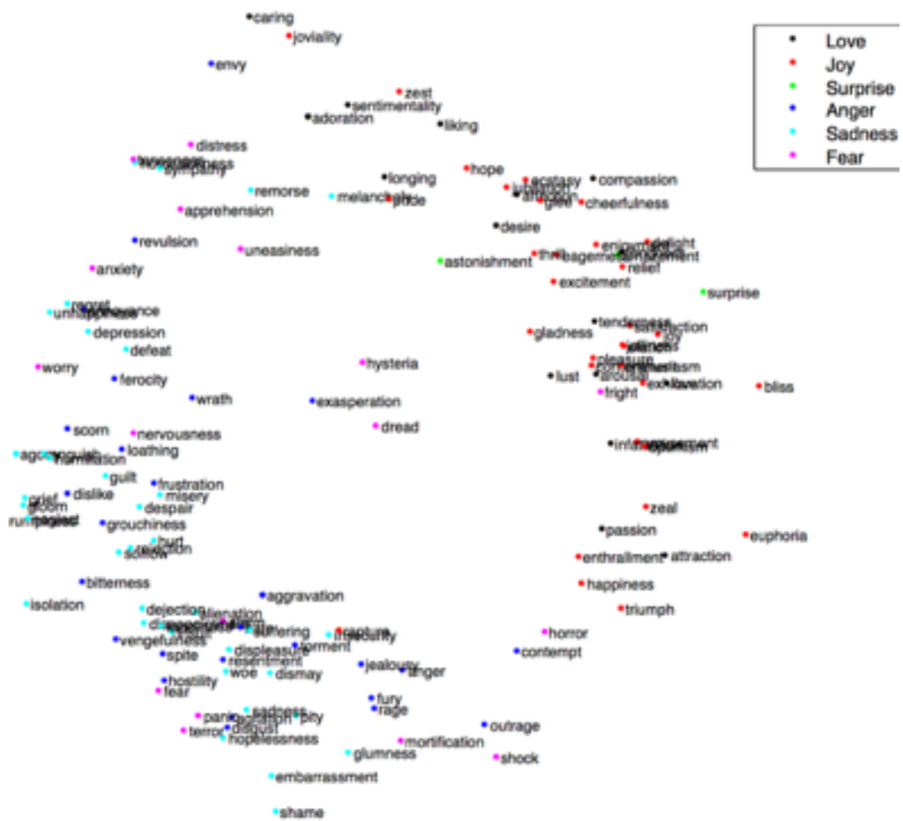
Word embeddings, word2vec

Previous section presented methods to **embed documents** into a latent space

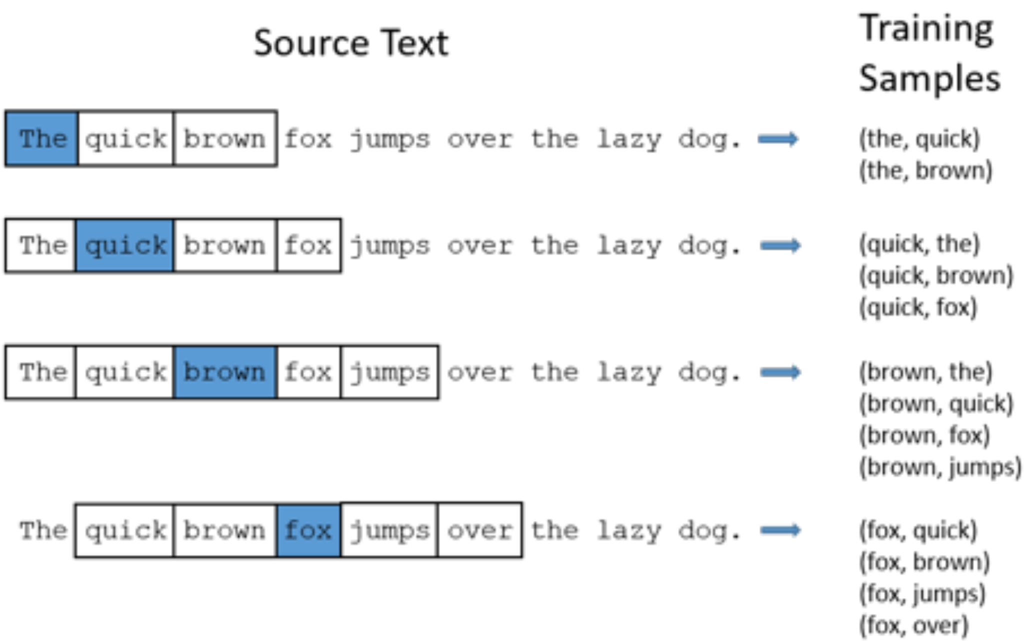
Alternatively, we can **embed words** into a latent space

This embedding came from directly querying for relationships.

word2vec is a popular unsupervised learning approach that just uses a text corpus (e.g. nytimes.com)

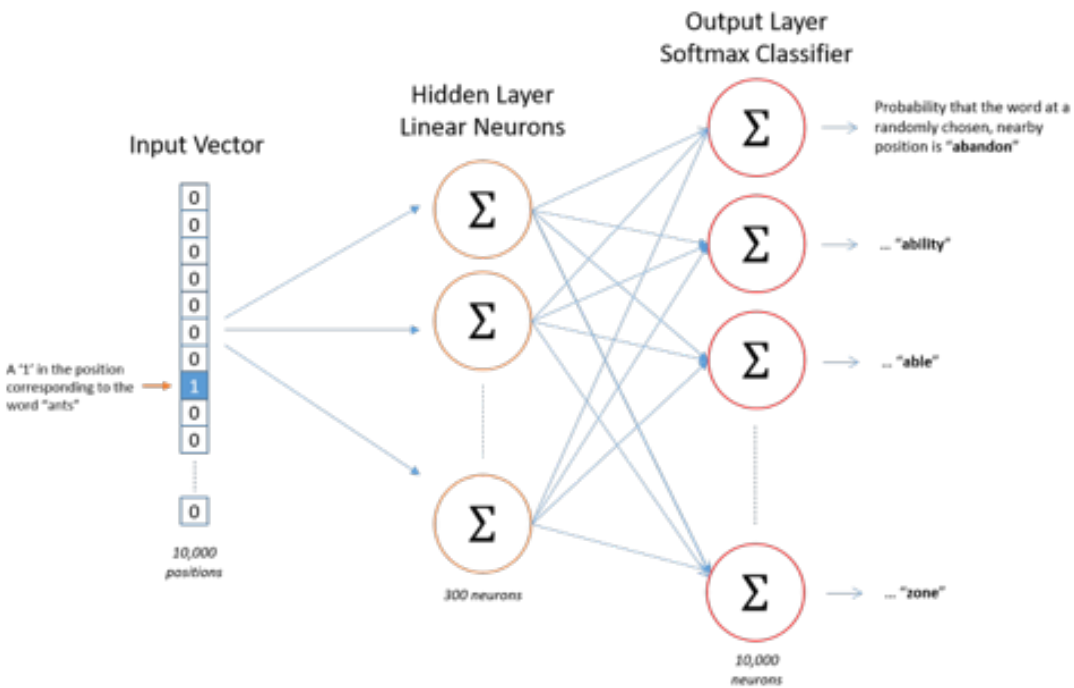


Word embeddings, word2vec



slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

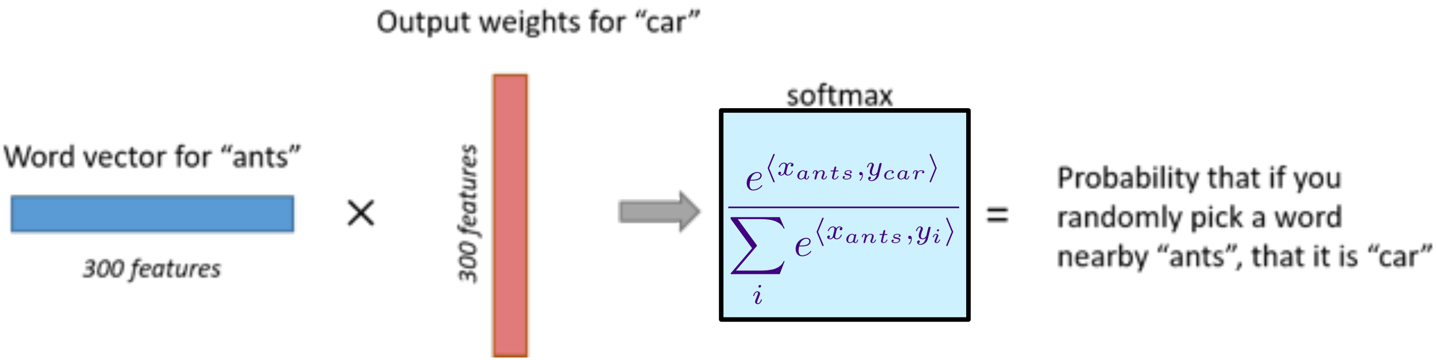
Word embeddings, word2vec



Training neural network to predict co-occuring words. Use first layer weights as embedding, throw out output layer

slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

Word embeddings, word2vec

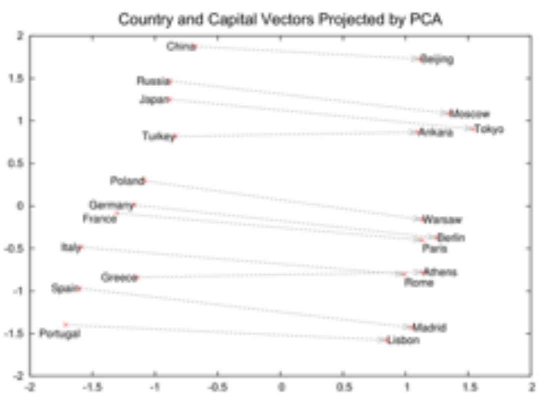


Training neural network to predict co-occuring words. Use first layer weights as embedding, throw out output layer

slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

word2vec outputs

king - man + woman = queen



country - capital

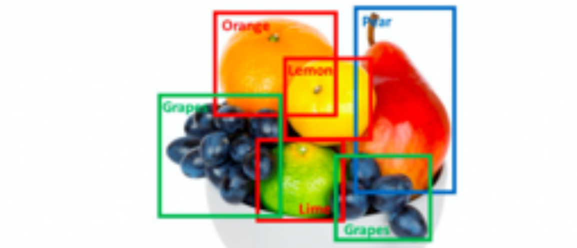
slide: https://blog.acolyer.org/2016/04/21/the-amazing-power-of-word-vectors/

Active Learning, classification

Machine Learning – CSE4546
Kevin Jamieson
University of Washington

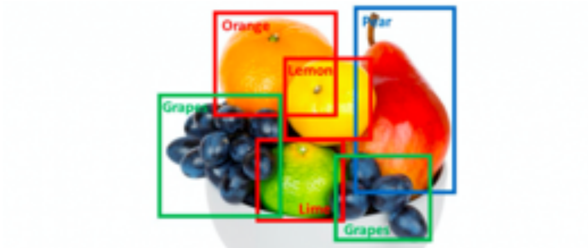
November 30, 2017

Impressive recent advances in image recognition and translation…

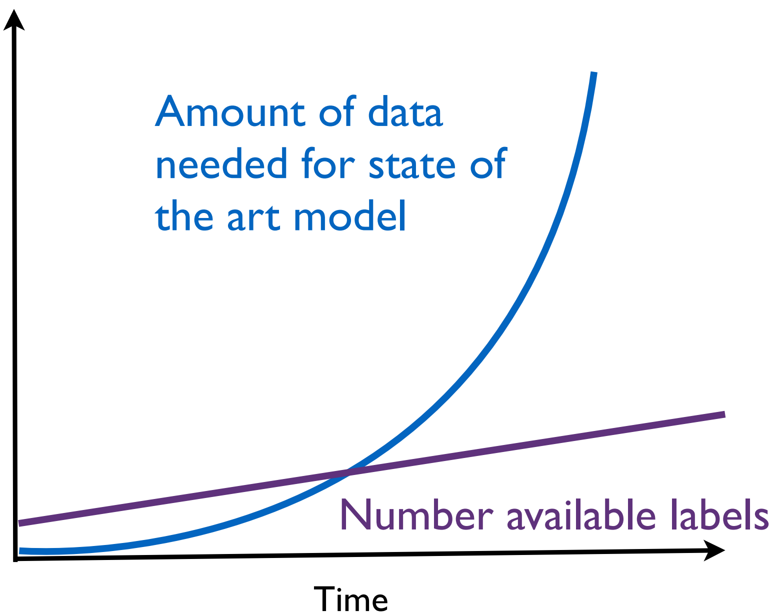


Google Translate
Break through language barriers.

Impressive recent advances in image recognition and translation…



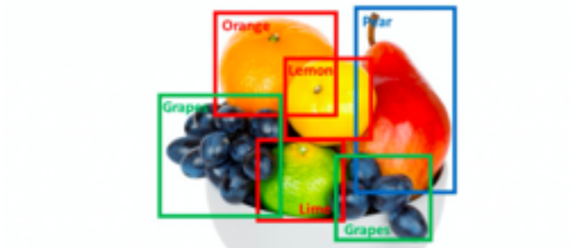
Google
Translate
Break through language barriers.

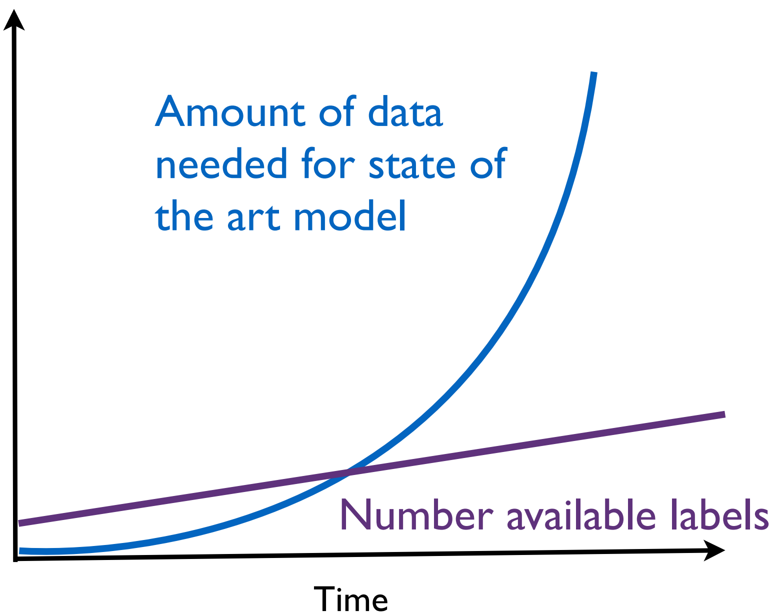


Challenges for large models:

1) An enormous amount of ***labeled data*** is necessary for training

Impressive recent advances in image recognition and translation…

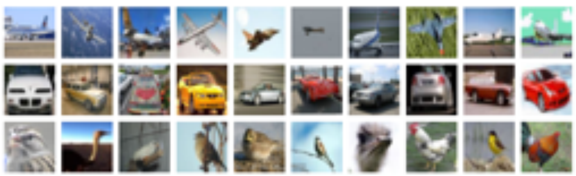




Challenges for large models:

1) An enormous amount of ***labeled data*** is necessary for training
2) An enormous amount of ***wall-clock time*** is necessary for training

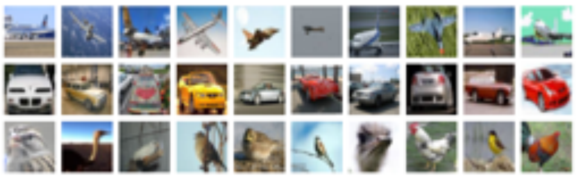
Example: Image recognition

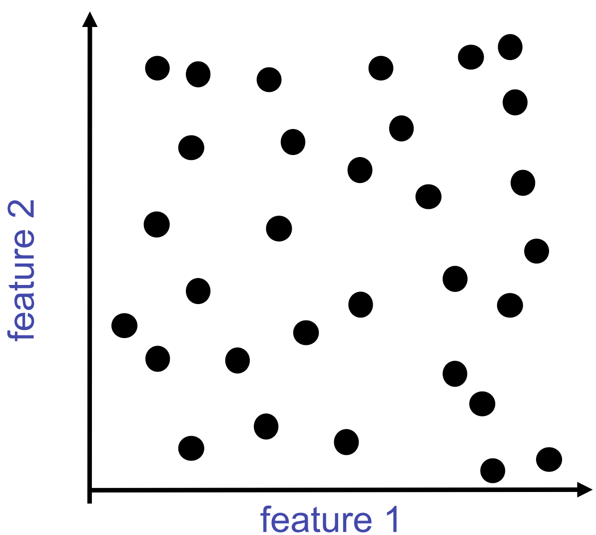


airplane
automobile
bird

Example: Image recognition

airplane
automobile
bird

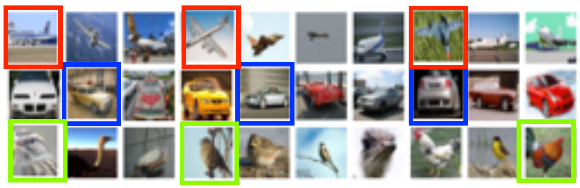


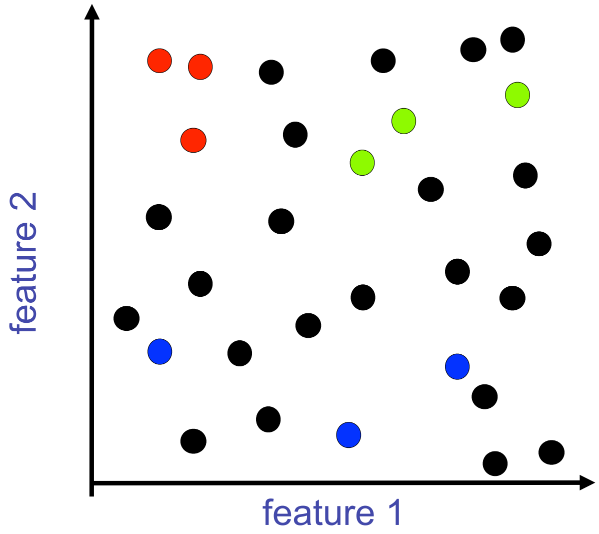


Example: Image recognition

airplane
automobile
bird

Nonadaptive label assignment

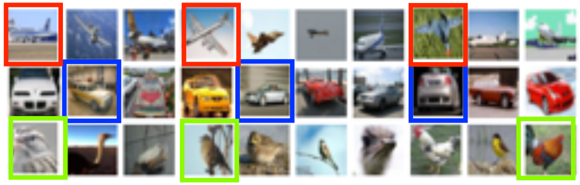


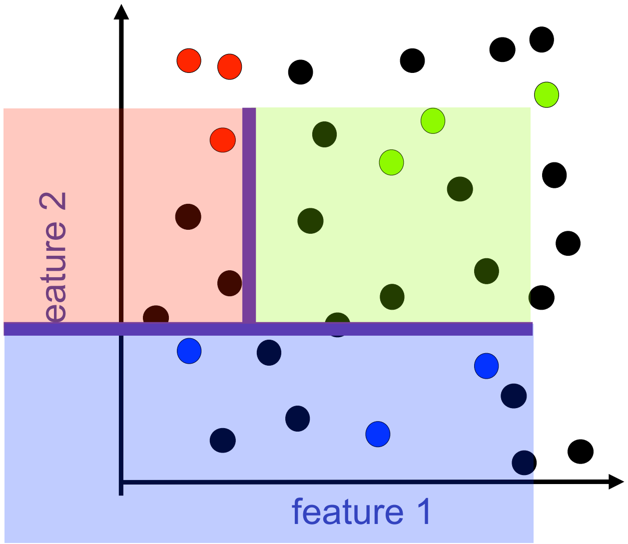


Example: Image recognition

airplane
automobile
bird

Nonadaptive label assignment

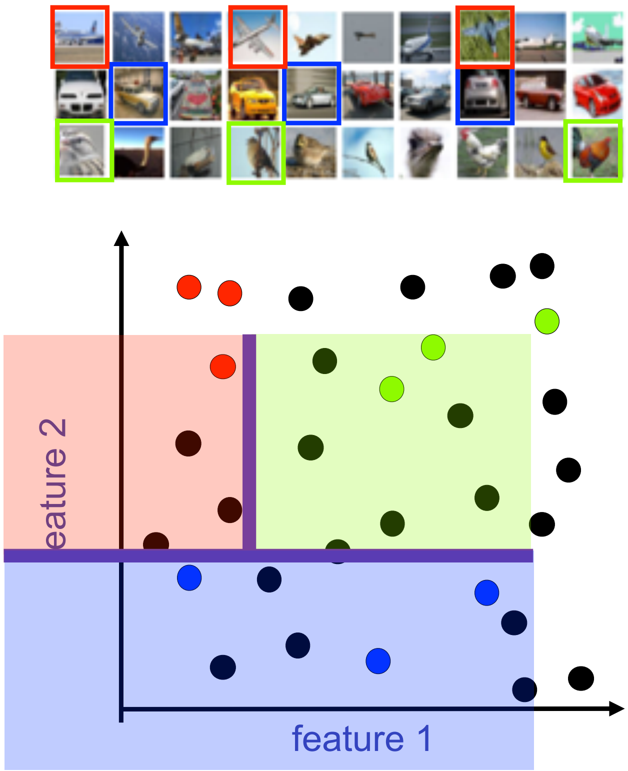




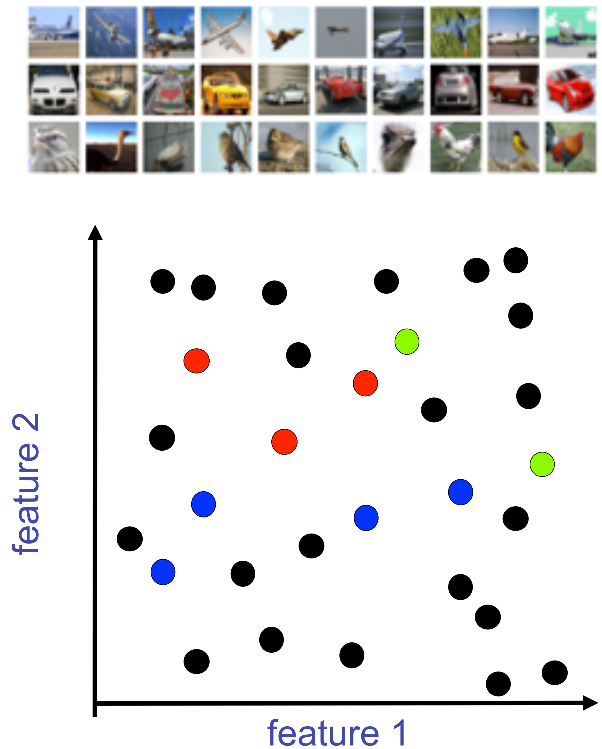
Example: Image recognition

airplane
automobile
bird

Nonadaptive label assignment



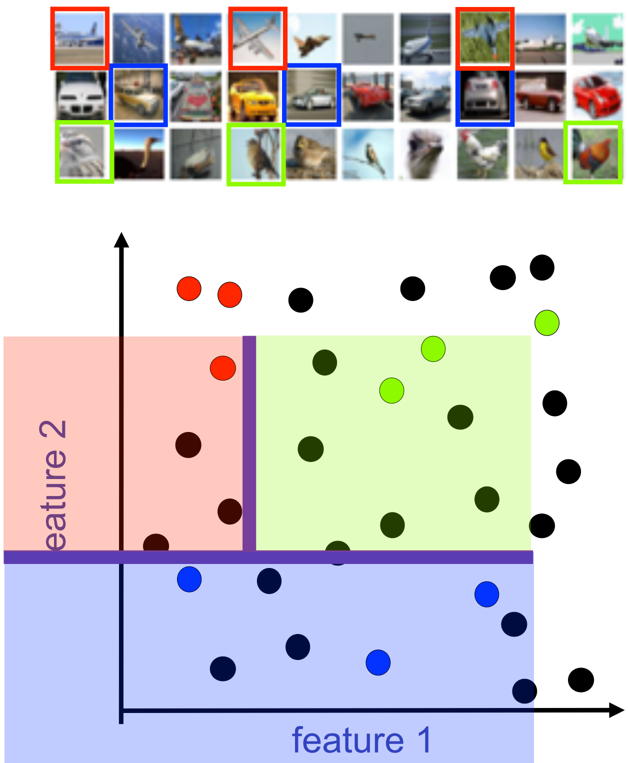
Adaptive label assignment



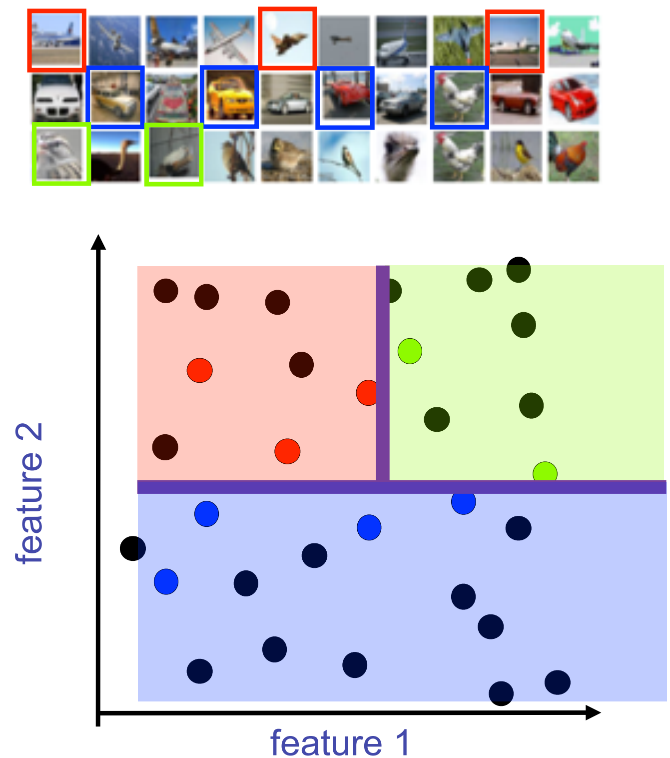
Example: Image recognition

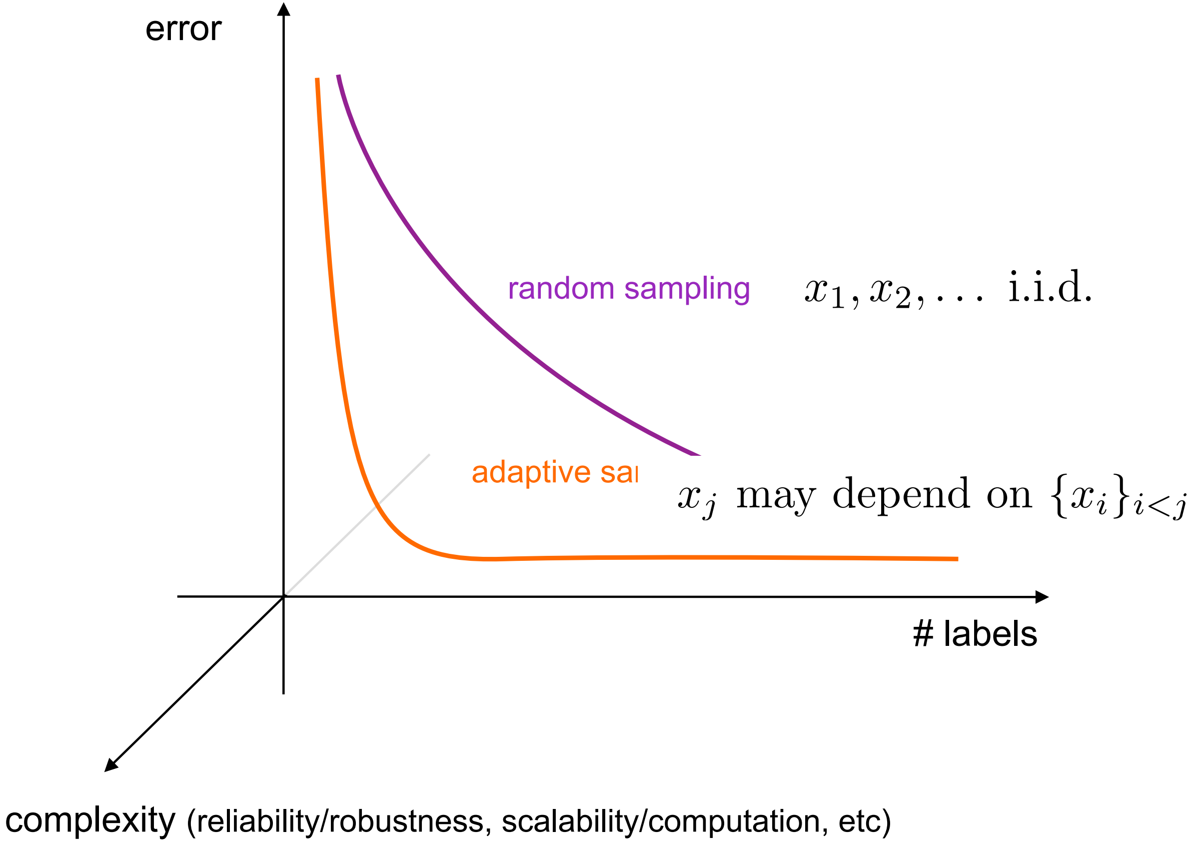
airplane
automobile
bird

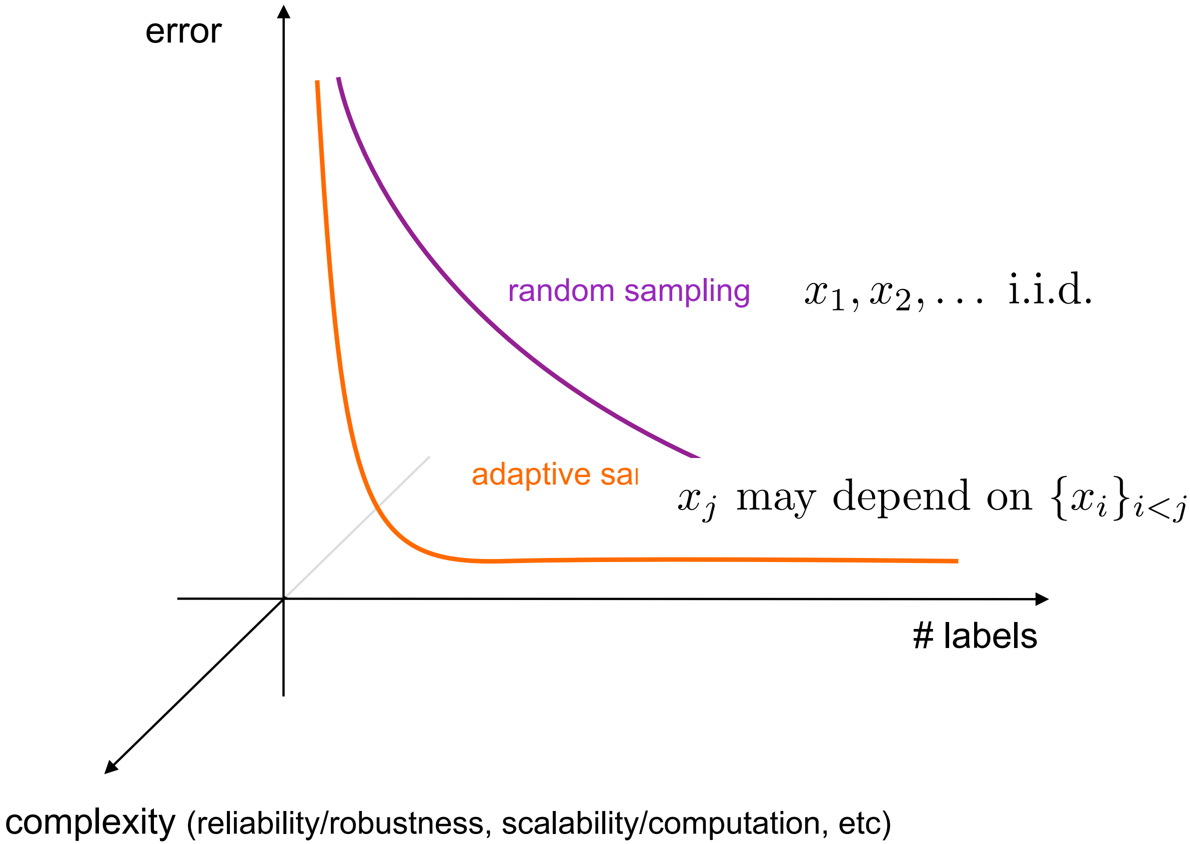
Nonadaptive label assignment



Adaptive label assignment




error
random sampling
$x_1, x_2, \ldots$ i.i.d.
adaptive sa
x_j may depend on $\{x_i\}_{i<j}$
labels
complexity (reliability/robustness, scalability/computation, etc)



Being convinced that data-collection ***should be adaptive*** is not the same thing as knowing ***how to be adaptive***.

THE NEW YORKER
CARTOON CAPTION CONTEST

Caption Contest #553
January 20, 2017

Third *“Maybe his second week will go better”*

Second *“I’d like to see other people”*

First *“The corrupt media will blow this way out of proportion”*

THE NEW YORKER
CARTOON CAPTION CONTEST

Bob Mankoff
Cartoon Editor, The New Yorker

- $n \approx 5000$ captions submitted each week
- crowdsource contest to volunteers who rate captions
- goal: identify funniest caption

newyorker.com/cartoons/vote

Vote - The New Yorker

Kevin

www.newyorker.com/cartoons/vote

THE NEW YORKER

“It's amazing to think he started out in the lobby.”

UNFUNNY

FUNNY

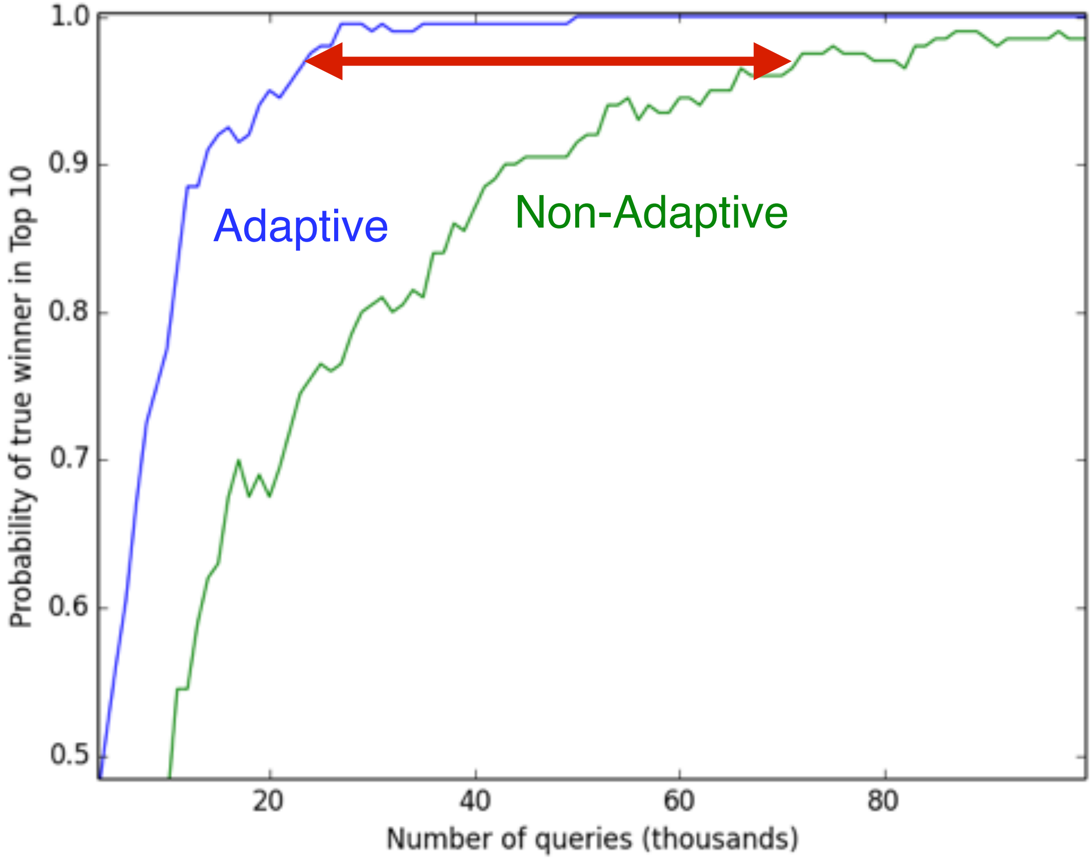
DONE


Vote - The New Yorker
Kevin
www.newyorker.com/cartoons/vote
THE NEW YORKER
“I thought all our plants moved to Mexico.”
UNFUNNY
FUNNY
DONE

Which caption do we show next?

1) Non-adaptive uniform distribution over captions
2) Adaptive: stop showing captions that will not win

4-5 times fewer ratings needed

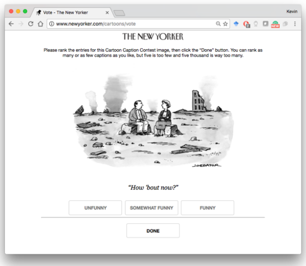


Which caption do we show next?

1) Non-adaptive uniform distribution over captions
2) Adaptive: stop showing captions that will not win

Best-action identification problem

Stopping rule



While algorithm does not exit:

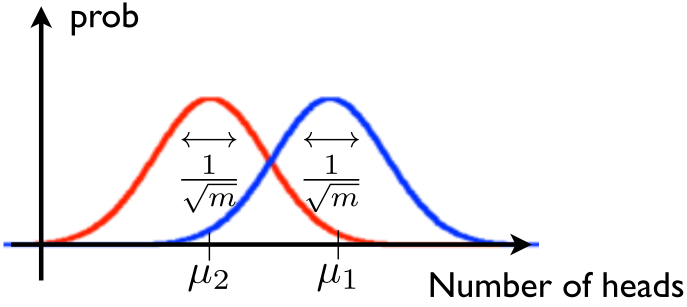
- algorithm shows caption $i \in \{1, \ldots, n\}$
- Observe iid Bernoulli with $\mathbb{P}(\text{“funny”}) = \mu_i$

Sampling rule

Objective: with probability .99, identify $\arg\max_{i=1,\ldots,n} \mu_i$ using as few total samples as possible

Best-arm Identification n=2

Consider $n = 2$ and flip coins $i = 1, 2$ to get $X_{i,1}, X_{i,2}, \ldots, X_{i,m}$



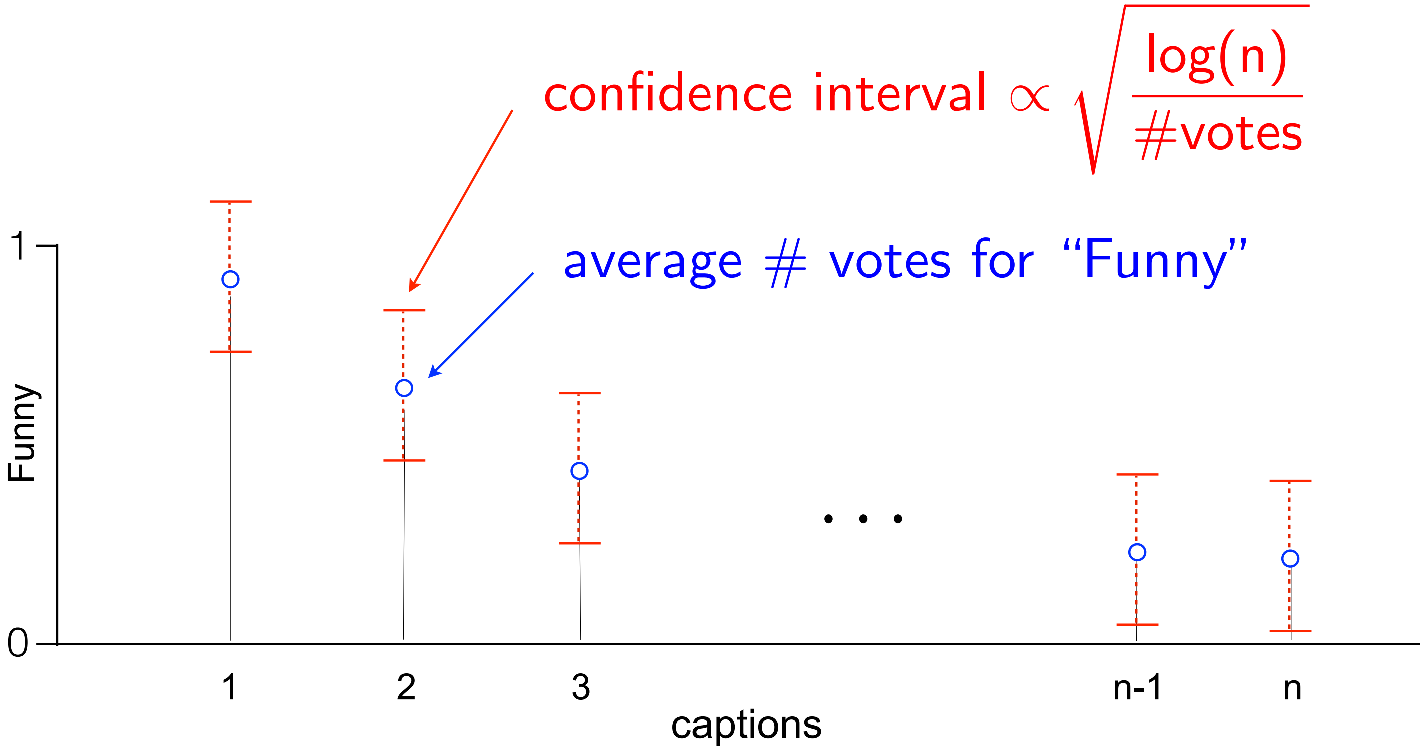
$$\widehat{\mu}_{i,m} = \frac{1}{m} \sum_{j=1}^{m} X_{i,j}$$

Test: $\widehat{\mu}_{1,m} - \widehat{\mu}_{2,m} \geq 0$

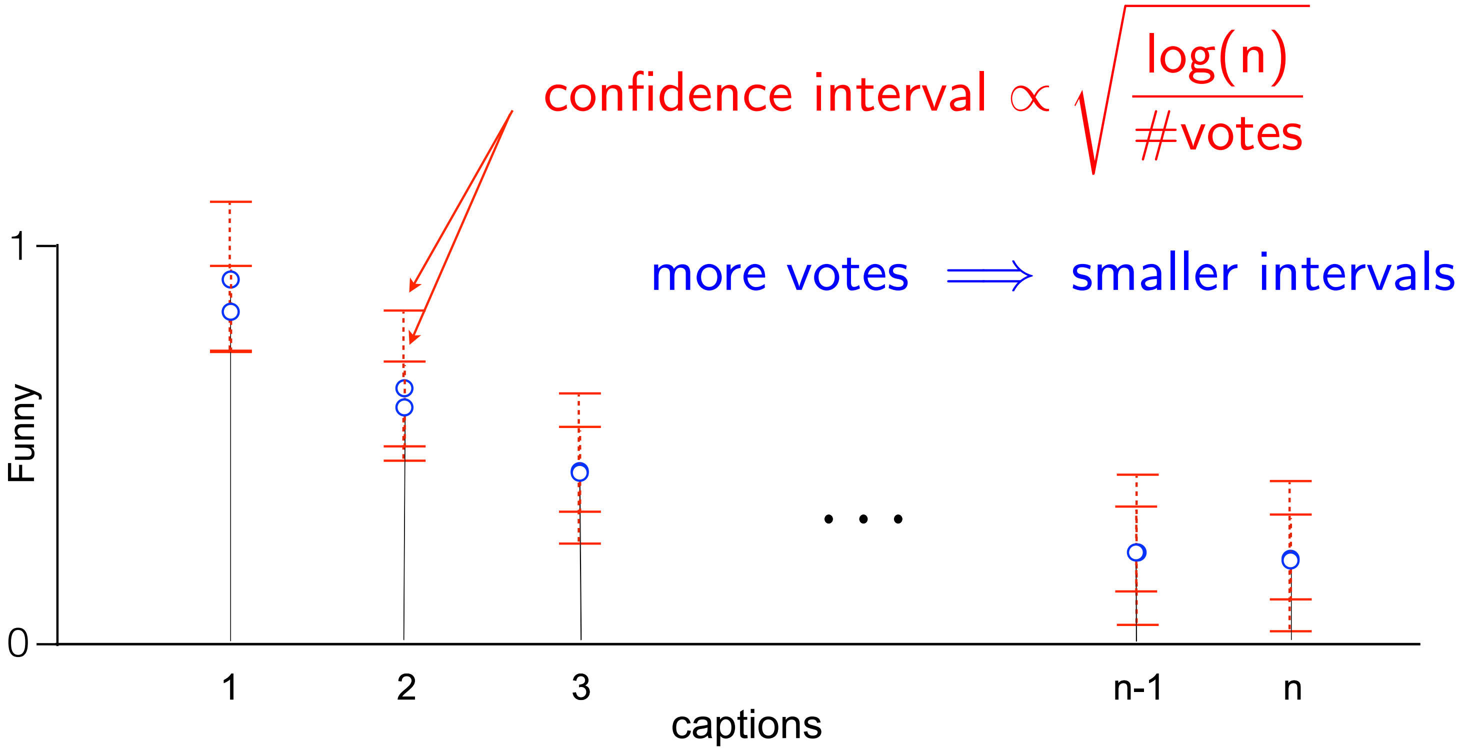
By a Chernoff Bound, if $\Delta = \mu_1 - \mu_2$ then

$$m = 2\log(1/\delta)\Delta^{-2} \implies \underline{\widehat{\mu}_{1,m} > \widehat{\mu}_{2,m} + 2\sqrt{\frac{\log(1/\delta)}{2m}}} \implies \underset{\text{with probability } \geq 1-2\delta}{\mu_1 > \mu_2}$$

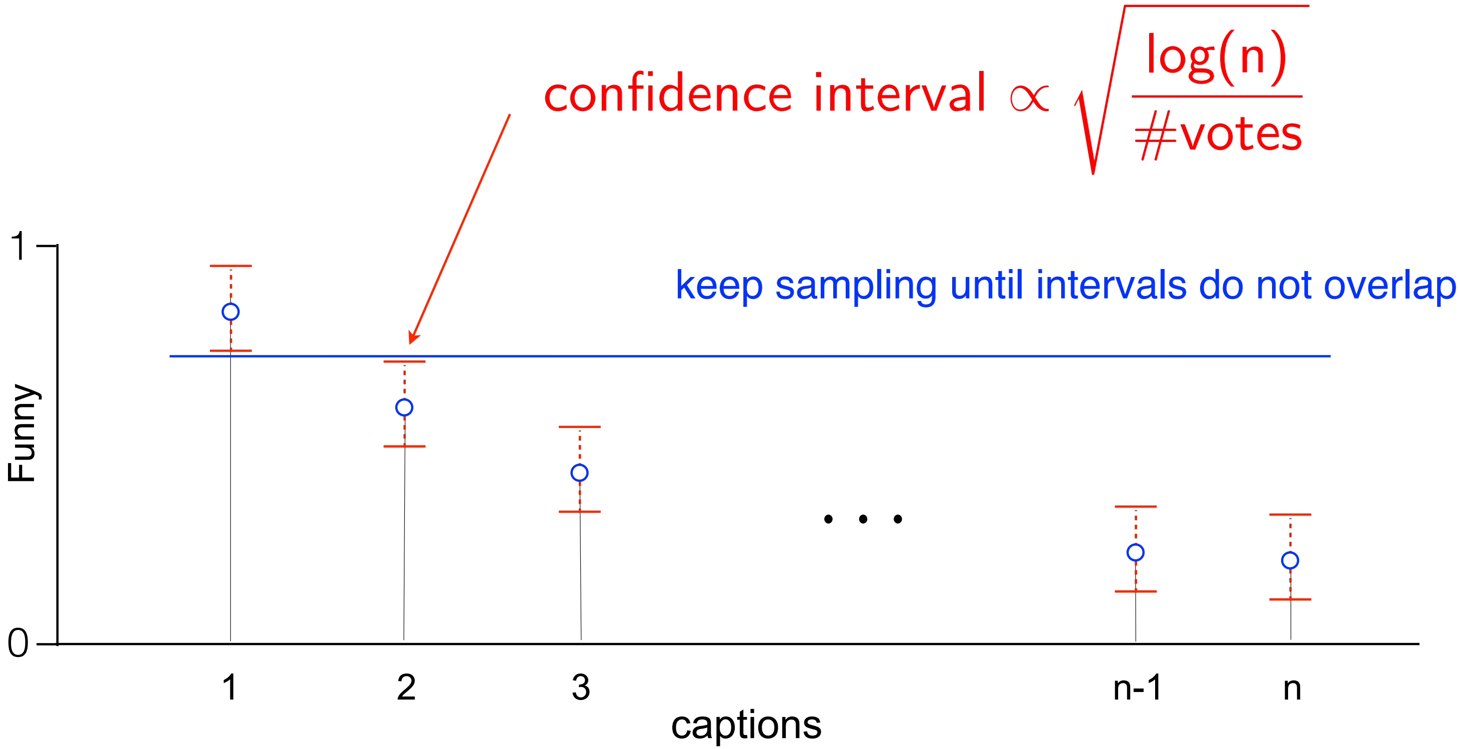
Arm 1 lower confidence bound > Arm 2 upper confidence bound



confidence interval $\propto \sqrt{\frac{\log(n)}{\#\text{votes}}}$
average # votes for “Funny”
Funny
1
0
1
2
3
n-1
n
captions

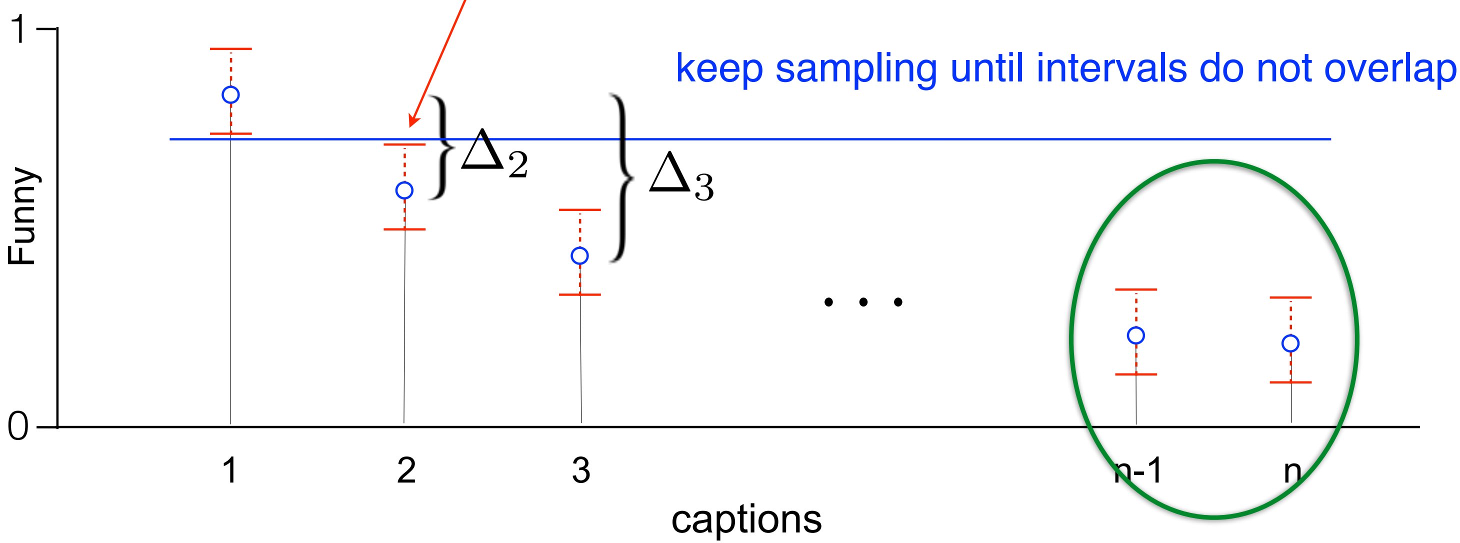


confidence interval $\propto \sqrt{\frac{\log(n)}{\#\text{votes}}}$
more votes $\Longrightarrow$ smaller intervals
1
0
Funny
1
2
3
. . .
n-1
n
captions



confidence interval $\propto \sqrt{\frac{\log(n)}{\#\text{votes}}}$
keep sampling until intervals do not overlap
1
0
Funny
1
2
3
. . .
n-1
n
captions

confidence interval $\propto \sqrt{\frac{\log(n)}{\#\text{votes}}}$

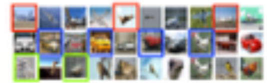


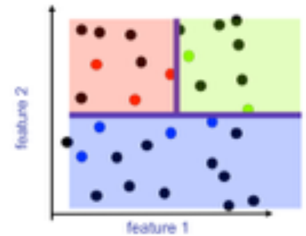
votes Non-adaptive: $n \max_{i=1,\ldots,n} \Delta_i^{-2} \log(n)$

Successive Elimination [Even-dar…'06]: $\sum_{i=1}^{n} \Delta_i^{-2} \log(n)$

Stop sampling caption *i* as soon as no overlap

Learn an accurate classifier using a small number of labels





Find the winner of a competition using a small number of judgements

Very related to adaptive A/B testing

Pure Exploration

Find the ad that results in highest click-through-rate and keep showing it

Balance of **exploration versus exploitation**