Lecture 21:
Unlabeled data for NLP

Intro to NLP, CS585, Fall 2014

http://people.cs.umass.edu/~brenocon/inlp2014/

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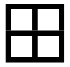
- Project scheduling
- Labeling

- What to do when we only have a little bit of labeled data? (Like in the final project!)
  - Get more labels
  - Different forms of supervision
    - Tag dictionaries: type-level supervision
    - More sophisticated features
  - Exploit unlabeled data
    - Semi-supervised learning
    - Active learning:
      intelligently choose which unlabeled data to annotate

Unlabeled data

- Labeled data: human element is costly
  - PTB or ImageNet: the largest labeled datasets and very successful -- but very expensive!
    - PTB = 1M tokens
    - ImageNet = 1M images
  - Small efforts and new problems: typically thousands of tokens
- But we have huge quantities of unlabeled, raw text. Can we use them somehow?

45k tokens
(our NER dataset)



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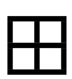
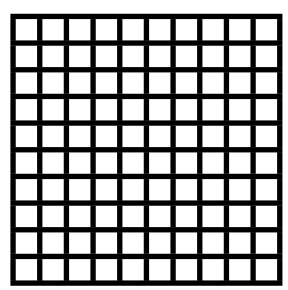
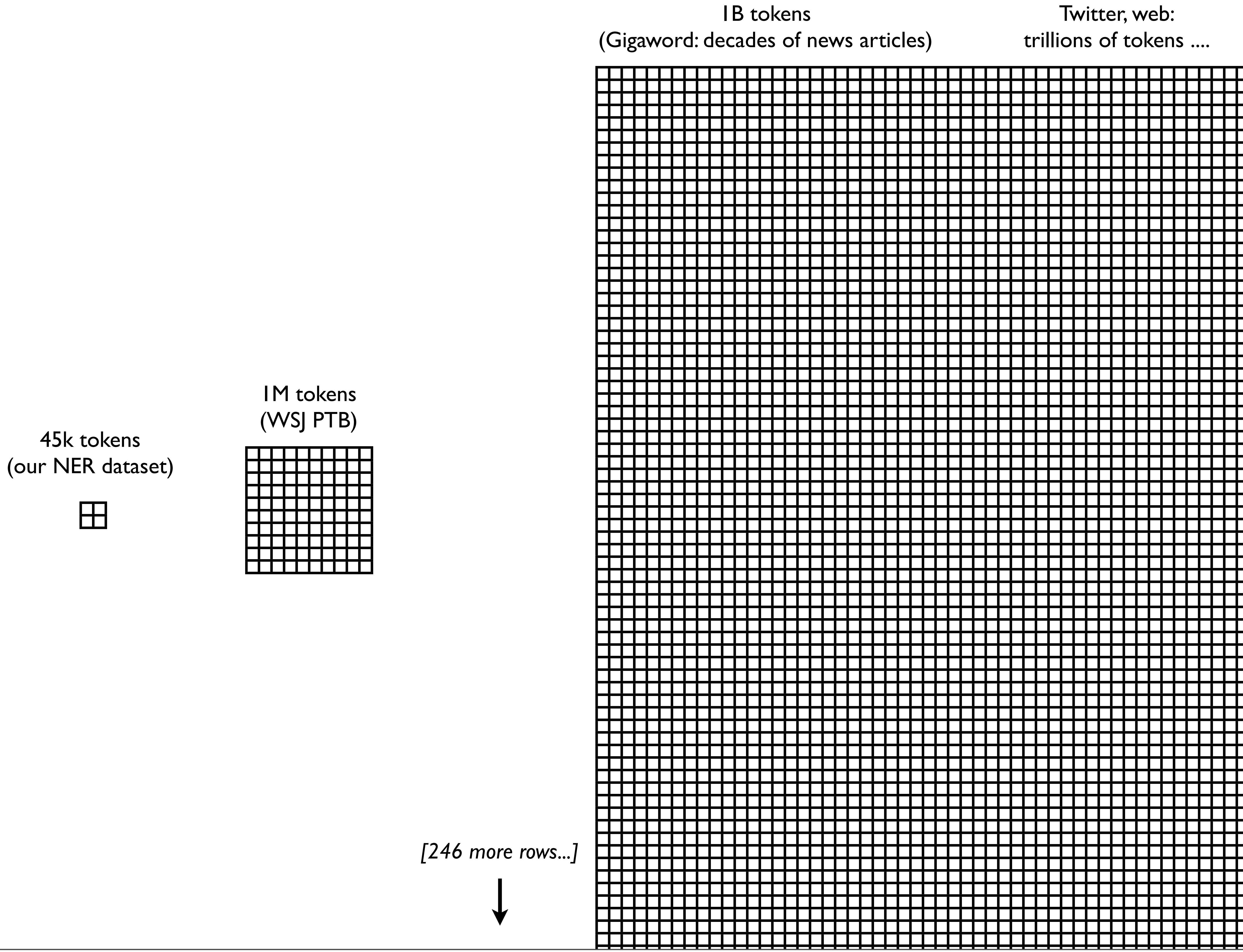


1M tokens
(WSJ PTB)




45k tokens
(our NER dataset)
1M tokens
(WSJ PTB)
1B tokens
(Gigaword: decades of news articles)
Twitter, web:
trillions of tokens ....
[246 more rows...]

Semi-supervised learning

- Formally: given
  - (1) small labeled dataset of (x,y) pairs,
  - (2) large unlabeled dataset of (x, _) pairs,
  - ... learn a better f(x)->y function than from just labeled data alone.
- Two major approaches
  - 1. Learn an unsupervised model on the x's. Use its clusters/vectors as features for labeled training.
  - 2. Learn a single model on both labeled and unlabeled data together

Unsupervised NLP

- Can we learn lexical or grammatical structures from unlabeled text?
  - Maybe lexical/structural information is a latent variable ... like alignments in IBM Model 1
  - (Different use: exploratory data analysis)
- Intuition for lexical semantics: the distributional hypothesis.
  - *You shall know a word by the company it keeps* (Firth, J. R. 1957:11)
- Very useful technique: learn word clusters (or other word representations) on unlabeled data, then use as features in a supervised system.

Distributional example:
What types of words can go into these positions?

the ___
that ___
of ___
by ___

he __
she __
Mary __
John __

red ___
green ___

__ it
__ him
__ her

happy ___
angry ___
sad ___

__ lol
__ haha

Distributional semantics is based on the idea that: Words with similar context statistics have similar meaning.

Assemble sets of words with similar context frequencies.

Many ways to capture this... including HMMs.

Brown HMM word clustering

- HMM for the unlabeled dataset
  - With a one-class-per-word restriction!
    - (Remember: real-world POS data kinda has this property)
  - Thus each HMM class is described by a hard clustering of words (a set of words)
- Heuristically search for word clusters that maximize likelihood

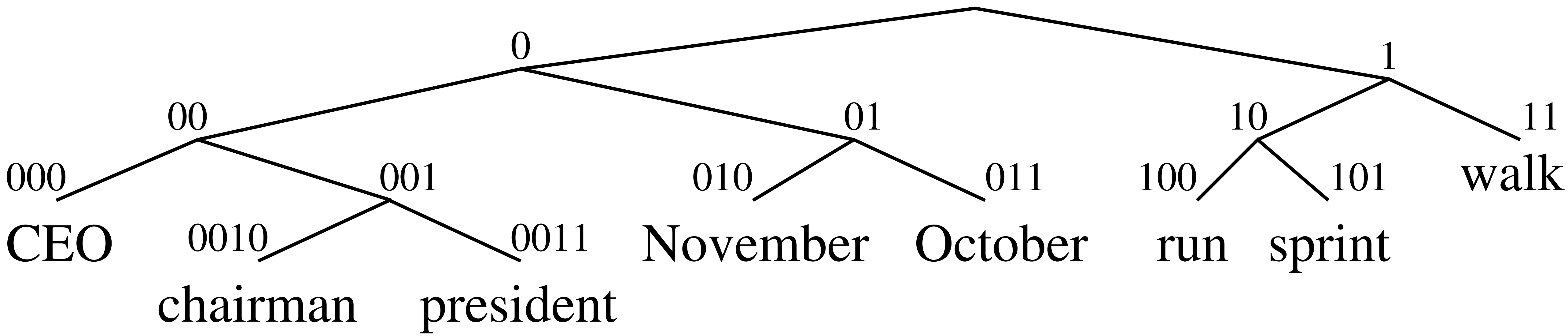
Notation:
c is a clustering of wordtypes. *c(w)* is w's cluster ID.

$$c^* = \arg\max_{c \in C} \prod_i p_{\text{MLE}}(c(w_i) \mid c(w_{i-1})) \times p_{\text{MLE}}(w_i \mid c(w_i))$$

Hierarchical clustering

- One form of Brown clustering is also hierarchical, through agglomerative clustering: iteratively merge clusters, and track the merge history
    - Initialize: Greedily assign words to K clusters
    - Iterate: Merge the two clusters that causes the least-worst hit to likelihood
- (There are many other approaches to this type of HMM; see http://statmt.blogspot.com/2014/07/understanding-mkcls.html)

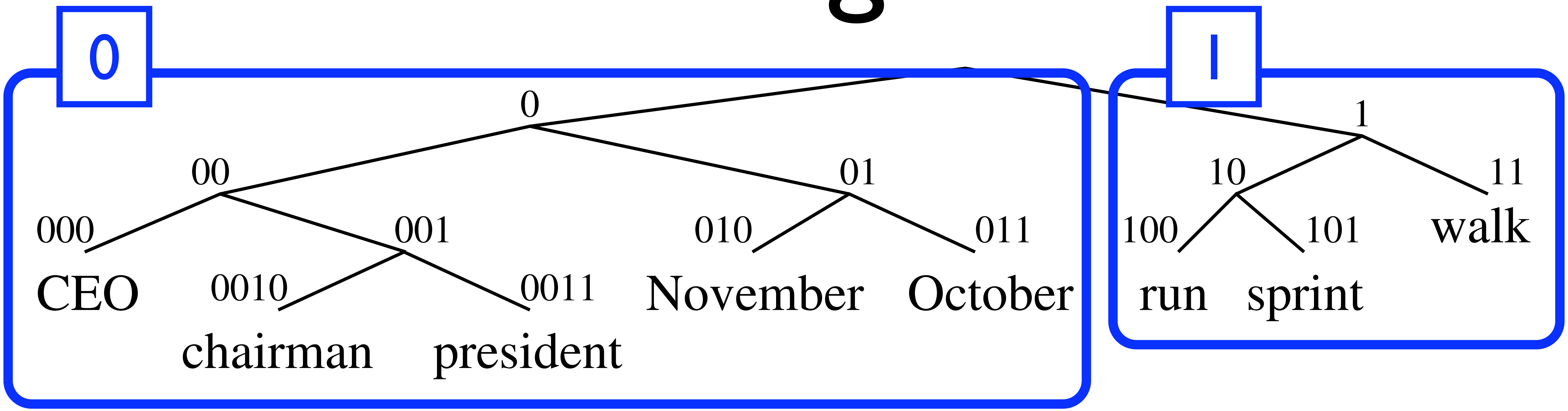
Brown Algorithm



- Words merged according to contextual similarity
- Clusters are equivalent to bit-string prefixes
- Prefix length determines the granularity of the clustering

[Slide credit: Terry Koo]

Brown Algorithm



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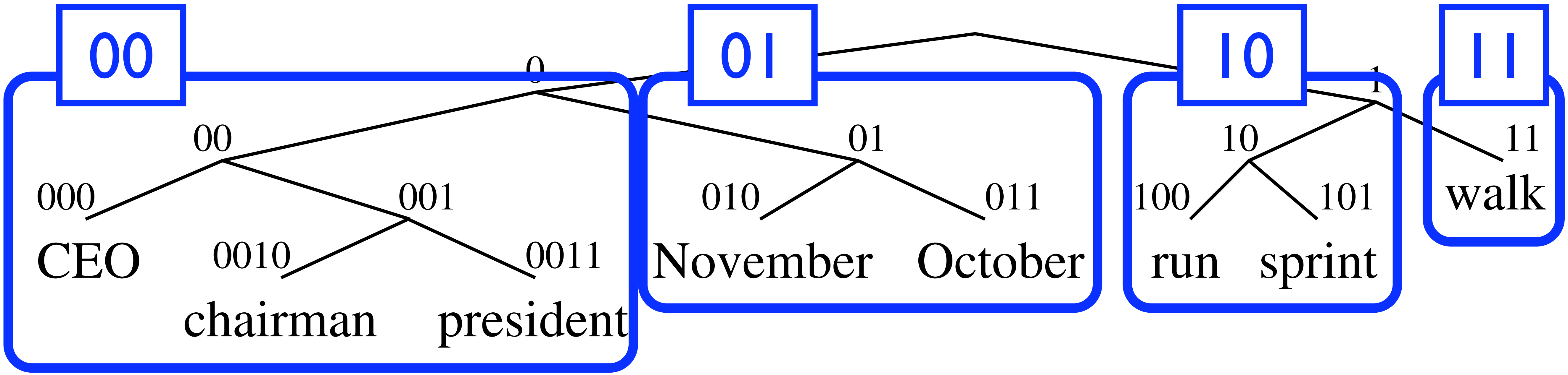

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Hier. clusters as POS features

- 1000 leaves, cluster prefixes as features for Twitter POS
  Using the Liang 2005 version of Brown clustering:
  https://github.com/percyliang/brown-cluster

Highest Weighted Clusters

Cluster prefix	Tag	Types	Most common word in each cluster with prefix
11101010*	!	8160	lol lmao haha yes yea oh omg aww ah btw wow thanks sorry congrats welcome yay ha hey goodnight hi dear please huh wtf exactly idk bless whatever well ok
11000*	L	428	i'm im you're we're he's there's its it's
1110101100*	E	2798	x <3 :d :p :) :o :/
111110*	A	6510	young sexy hot slow dark low interesting easy important safe perfect special different random short quick bad crazy serious stupid weird lucky sad
1101*	D	378	the da my your ur our their his
01*	V	29267	do did kno know care mean hurts hurt say realize believe worry understand forget agree remember love miss hate think thought knew hope wish guess bet have
11101*	O	899	you yall u it mine everything nothing something anyone someone everyone nobody
100110*	&	103	or n & and

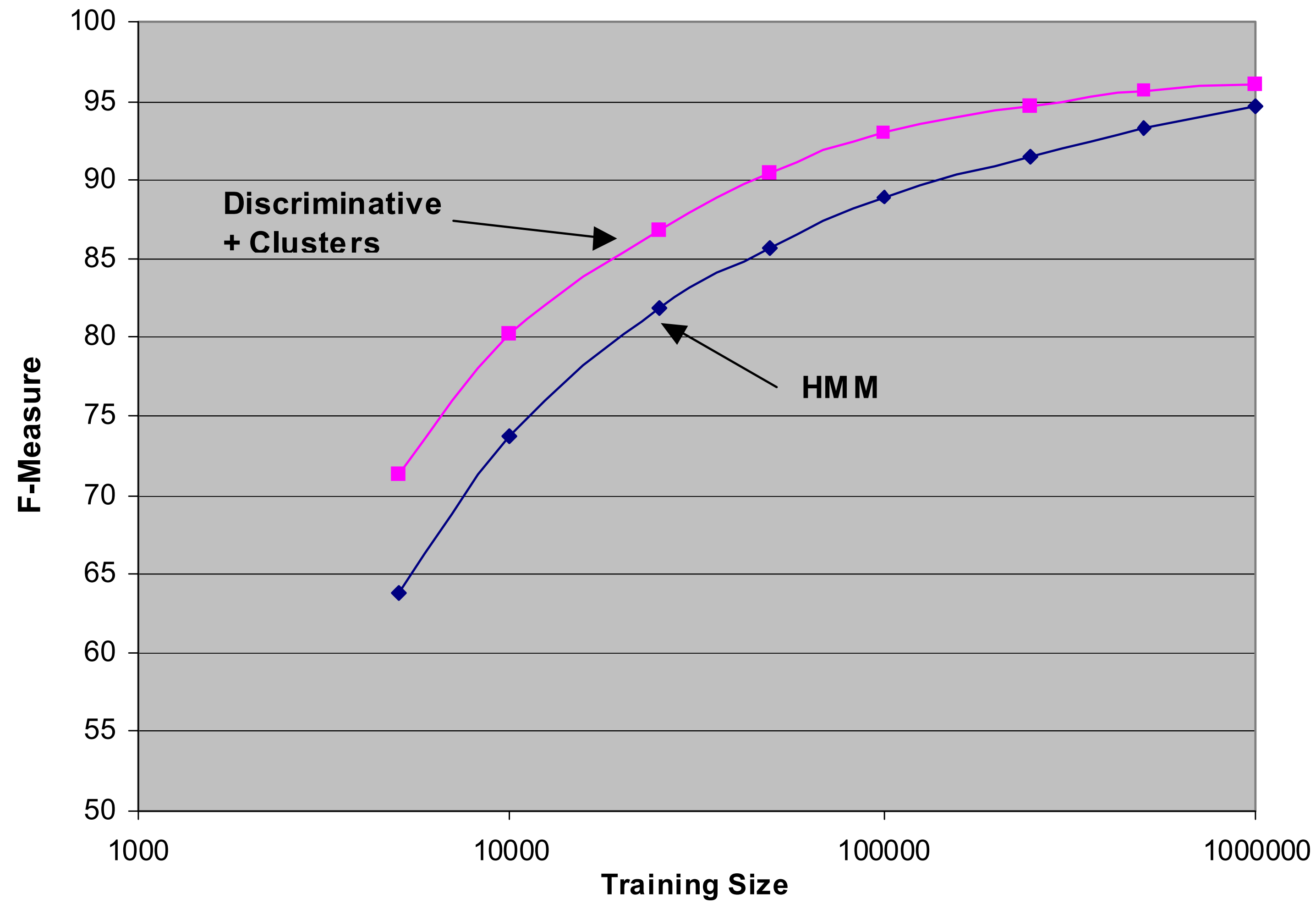
http://www.ark.cs.cmu.edu/TweetNLP/cluster_viewer.html

Other examples

- Dependency parsing (Koo et al. 2008)

Training Sentences	Baseline	Cluster-based
1000	82.0	85.3 (+3.3)
2000	85.0	87.5 (+2.5)
4000	87.9	89.7 (+1.8)
8000	89.7	91.4 (+1.7)
16000	91.1	92.2 (+1.1)
32000	92.1	93.2 (+1.1)
39832	92.4	93.3 (+0.9)

- NER (Miller et al. 2004)



This is a **<u>learning curve</u>** analysis:
performance as a function of training set size

Brown clusters as features

- Have been seen useful for
  - POS
  - NER
  - Dependency parsing
  - (others?)

- More generally: use automatically learned *word representations*. Next week: vector-valued reprs.
- I think word reprs are the most established use of unlabeled data for NLP systems
  See also: http://metaoptimize.com/projects/wordreprs/

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EM for semi-sup learning

- we have
  - (1) small labeled dataset of (x,y) pairs,
  - (2) large unlabeled dataset of (x, _) pairs,
- Treat missing labels as latent variables. Learn with EM!
  - Init: train model on labeled data
  - E-step: soft predictions on unlabeled
  - M-step: maximize labeled loglik, PLUS weighted loglik according to our new soft predictions. So the entire unlabeled dataset is part of the training set

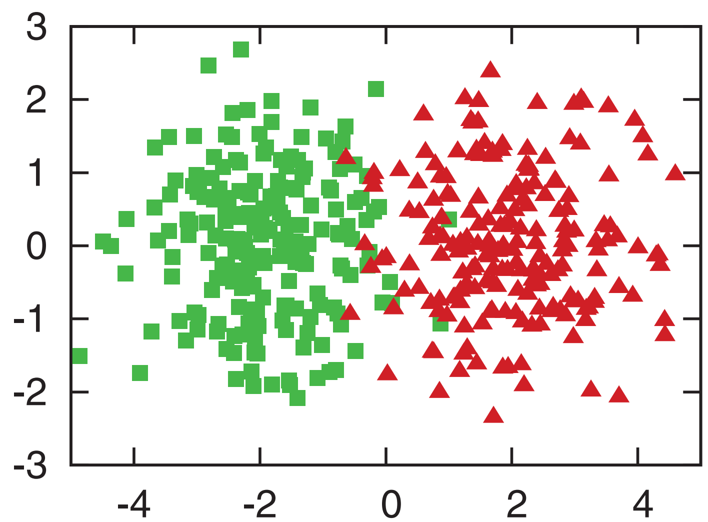
- Issues:
  - Have to re-weight the M-step (what if unlabeled data is 1 million times bigger?)
  - Can go off the rails

Self-training

- Same setup, but only add in a small number of highly-confident examples
  - Label all unlabeled x's. Choose the top-10 most confident (and/or higher than 99% confidence...).
  - Add those 10 to the labeled dataset
  - Re-train and iterate
- Many examples of this being useful -- may have to limit the number of iterations and/or play with thresholds
  - E.g. best parsers use self-training

Active learning

- You want to label more data. Use your current classifier to help choose the most useful examples to annotate.
  - **<u>Uncertainty sampling</u>**: Choose the example where the model is most uncertain. (If binary: closest to 50% predicted prob. If multiclass: highest entropy)



(a) a 2D toy data set

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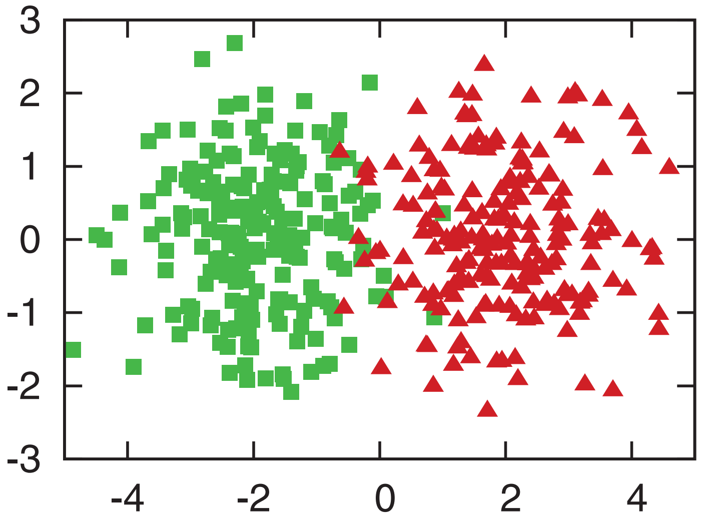

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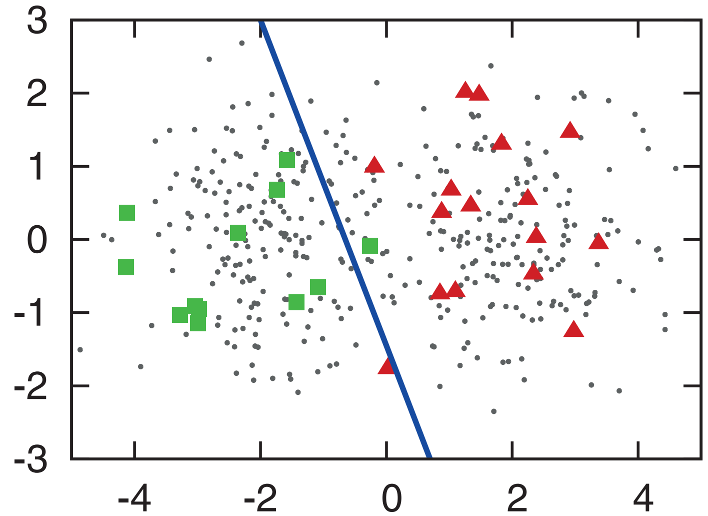

(b) random sampling

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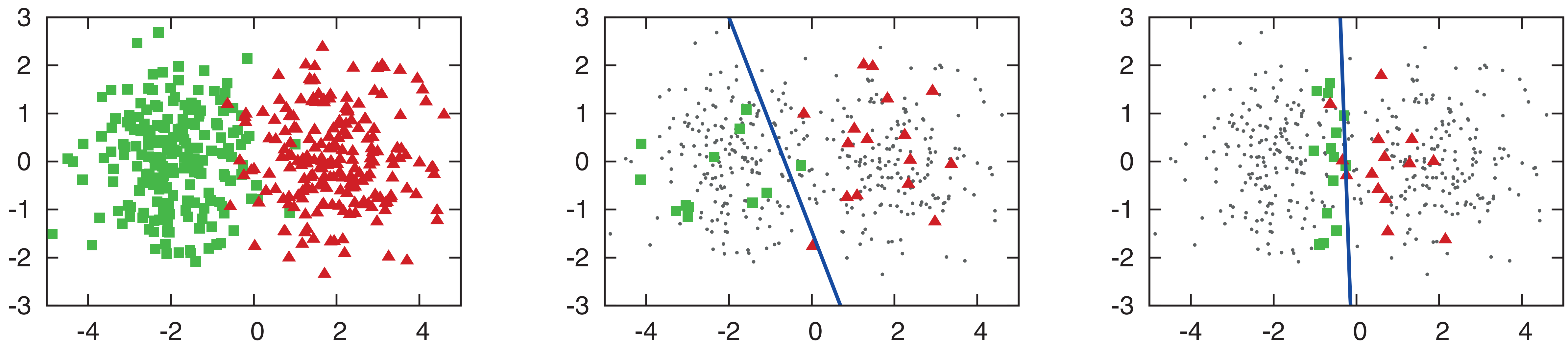

(a) a 2D toy data set (b) random sampling (c) uncertainty sampling

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