CS4705

Supervised Machine Learning

Some of the slides in this class were adapted from The Oxford slides and from slides from Dragomir Radev

Announcements and Questions

- Reading for today: 2.1-2.6,2.8 NLP
- Reading for next class: 4.4, 4.5 NLP
- Questions?

Outline for Today's Class

- Smoothing
- Text Classification: definition
- Bag of words and feature vectors
- Generative vs discriminative classifiers
- Discriminative classifiers
- Optimization
- Loss
- Regularization
- HW1

Some Useful Empirical Observations

- A small number of events occur with high frequency
- A large number of events occur with low frequency
- You can quickly collect statistics on the high frequency events
- You might have to wait an arbitrarily long time to get valid statistics on low frequency events
- Some of the zeroes in the table are really zeros But others are simply low frequency events you haven't seen yet. How to address?

Smoothing

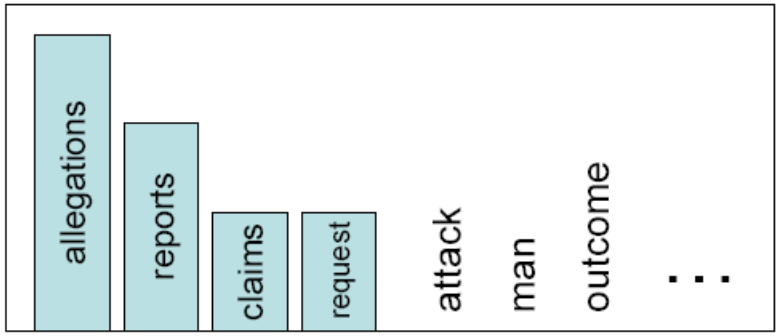
- Words follow a Zipfian distribution
  - Small number of words occur very frequently
  - A large number are seen only once
  - Zipf's law: a word's frequency is approximately inversely proportional to its rank in the word distribution list

- Zero probabilities on one bigram cause a zero probability on the entire sentence

Smoothing is like Robin Hood:
Steal from the rich and give to the poor (in probability mass)

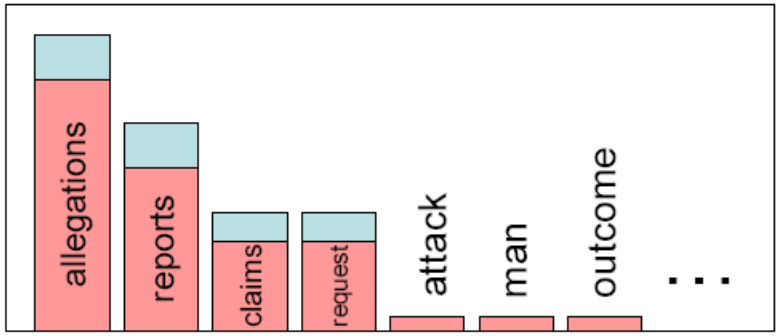
- We often want to make predictions from sparse statistics:

P(w | denied the)
3 allegations
2 reports
1 claims
1 request
7 total



- Smoothing flattens spiky distributions so they generalize better

P(w | denied the)
2.5 allegations
1.5 reports
0.5 claims
0.5 request
2 other
7 total



- Very important all over NLP, but easy to do badly!

Slide from Dan Klein

Smoothing Techniques

- Every n-gram training matrix is sparse, even for very large corpora
- Solution: estimate the likelihood of unseen n-grams
- Problems: how do you adjust the rest of the corpus to accommodate these ‘phantom’ n-grams?

Smoothing Methods

- Add-one smoothing (easy, but inaccurate)
  - Add 1 to every word count
  - Increment normalization factor by Vocabulary size: N (tokens) + *V (types)* :

$$p_i^* = \frac{c_i + 1}{N + V}$$

- Backoff models
  - When a count for an n-gram is 0, back off to the count for the (n-1)-gram
  - These can be weighted

$$c^*(i,j) = c(i,j) - d \qquad [6.15]$$

$$p_{\text{Katz}}(i \mid j) = \begin{cases} \frac{c^*(i,j)}{c(j)} & \text{if } c(i,j) > 0 \\ \alpha(j) \times \frac{p_{\text{unigram}}(i)}{\sum_{i':c(i',j)=0} p_{\text{unigram}}(i')} & \text{if } c(i,j) = 0. \end{cases} \qquad [6.16]$$

- Class-based smoothing
  - For certain types of n-grams, back off to the count of its syntactic class
  - E.g., Count ProperNouns in place of names (e.g., Obama)
- Good-Turing
  - Re-estimate amount of probability mass for zero (or low count) ngrams by looking at ngrams with higher counts
  - Estimate

$$c^* = (c+1)\frac{N_{c+1}}{N_c}$$

Text Classification

- Authorship
- German vs English
- Genre
- Positive vs negative reviews

Genre

- Devastating, but yet amazing storm. IMBY just some branches, ton of leaves, …This surpasses any Big daddy storm, should be called Big Mama. (Computer Guy)
- Produced by a team of 26 scientists led by the University of New South Wales Climate Research Centre, the Diagnosis convincingly proves that the effects of global warming have gotten worse in the last three years. (Somerville et al 2011)
- Hurricane Sandy churned about 290 miles off the Mid-Atlantic coast Sunday night, with the National Hurricane Center reporting that the monster storm was expected to come ashore with near-hurricane-force winds and potentially "life-threatening" storm surge flooding.
- *It was broad day—eight or nine o'clock; the storm raging, in lieu of the batteries; and someone knocking and calling at my door. 'What is the matter?' I cried. 'A wreck! Close by!' I sprung out of bed, and asked, what wreck? 'A schooner, from Spain or Portugal, laden with fruit and wine. Make haste, sir, if you want to see her! …'*

Features

- *What words give a clue about genre?*
- *What other information could we use?*

What words give a clue about genre?

What other information could we use?

Positive or Negative Review

- **I hate** the **iphone** headphones they hurt **my** ears
- Well I absolutely **love my iPhone** 6+. Battery life is just awesome. Having 40% left at the end of the day is great.

- Received email from Voldemort this morning & he has demanded that 10pgs of this grant be finished my Monday.
- Do you love what you do for life? I do and have fun:-)

Features

- *What words give a clue about sentiment?*
- *What other information could we use?*

What words give a clue about sentiment?

What other information could we use?

Other Classification Tasks in NLP

- POS tagging
- Parsing
- Word sense disambiguation
- Demographics in social media (e.g., gender)
- Named entity detection

Slide from Dragomir Radev

Types of Classification

- Binary (e.g., adult? T,F)
- Multi-class (e.g., age: child, teen, adult)
- Multi-label (e.g., child, American)
- Result of clustering (no labels)

Generative vs Discriminative Classifiers

- Generative
  - Probabilistic
  - Specify a joint probability distribution over observations and targets: $P(c,d)$
  - Bayes rule enables a conditional distribution
- Discriminative
  - Provide a model for the target variable
  - Use analysis of observed variables
  - Learn boundaries between classes
  - Infer outputs based on inputs: $P(c|d)$

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Bag of Words Classifier

- Vector to represent all possible words
  - Value = number of times word appears in the document
  - Unigrams
- Vector or matrix to represent all possible pairs of words
  - Value = number of times bigram appears in the document
  - Bigrams
- Bag because we've thrown out information about order, syntax, sentence boundaries, paragraphs

Feature Vector Representation

- Unigrams
- Bigrams
- Adding meta-level features
  - Document length, sentence length, sentence position, word position, author name

How big would the unigram vector be?

How big would the bigram vector be?

Bag of words representation

- Devastating, but yet amazing storm. IMBY just some branches, ton of leaves, …This surpasses any Big daddy storm, should be called Big Mama. (Computer Guy)

be	**1**
big	2
branches	1
batteries	0
convincingly	0
computer	1
daddy	1
day	0
devastating	1
fruit	0

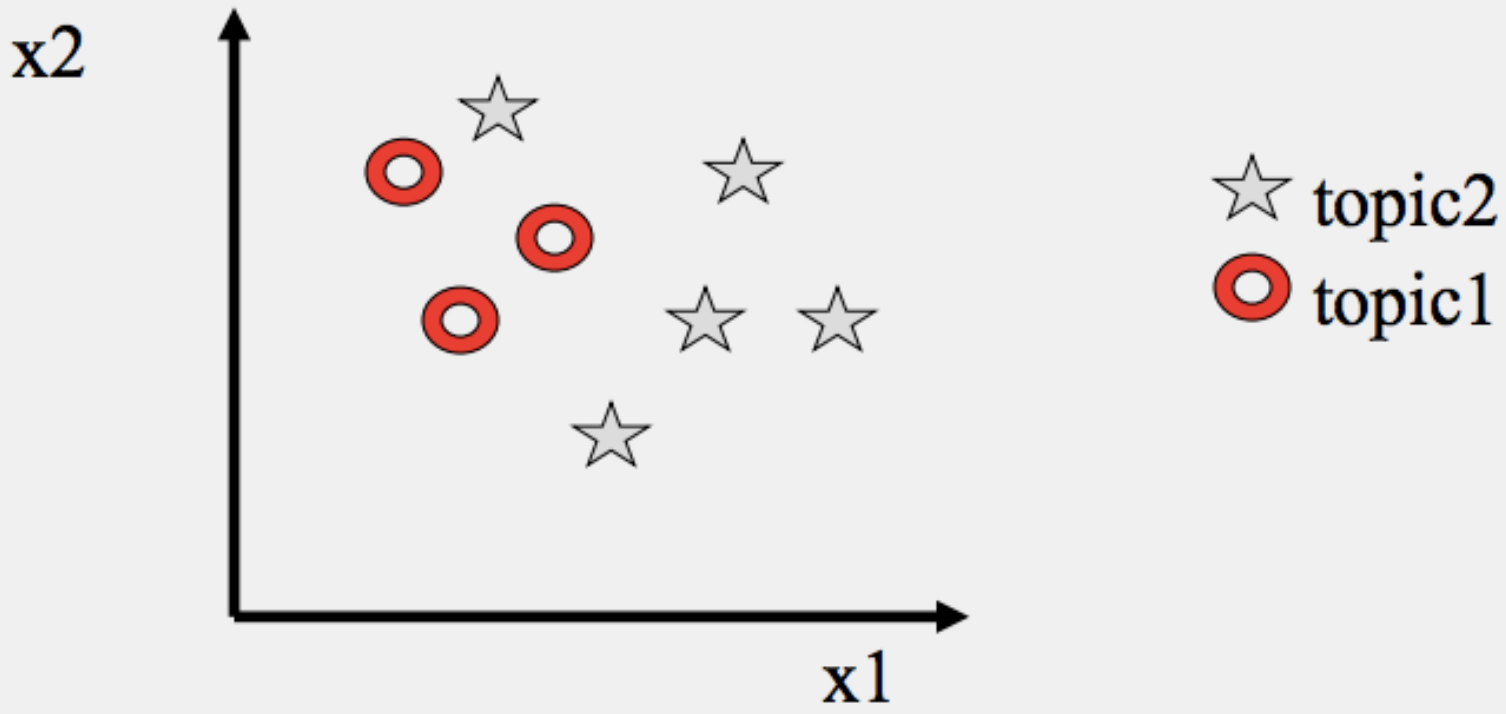
Weights

- Positive vs negative reviews
  - Surprising vs wonderful vs awful
- Genre: twitter vs novels vs scientific journal articles
  - Exclaimed vs neuro-transmitter vs LOL

Learning weights from data

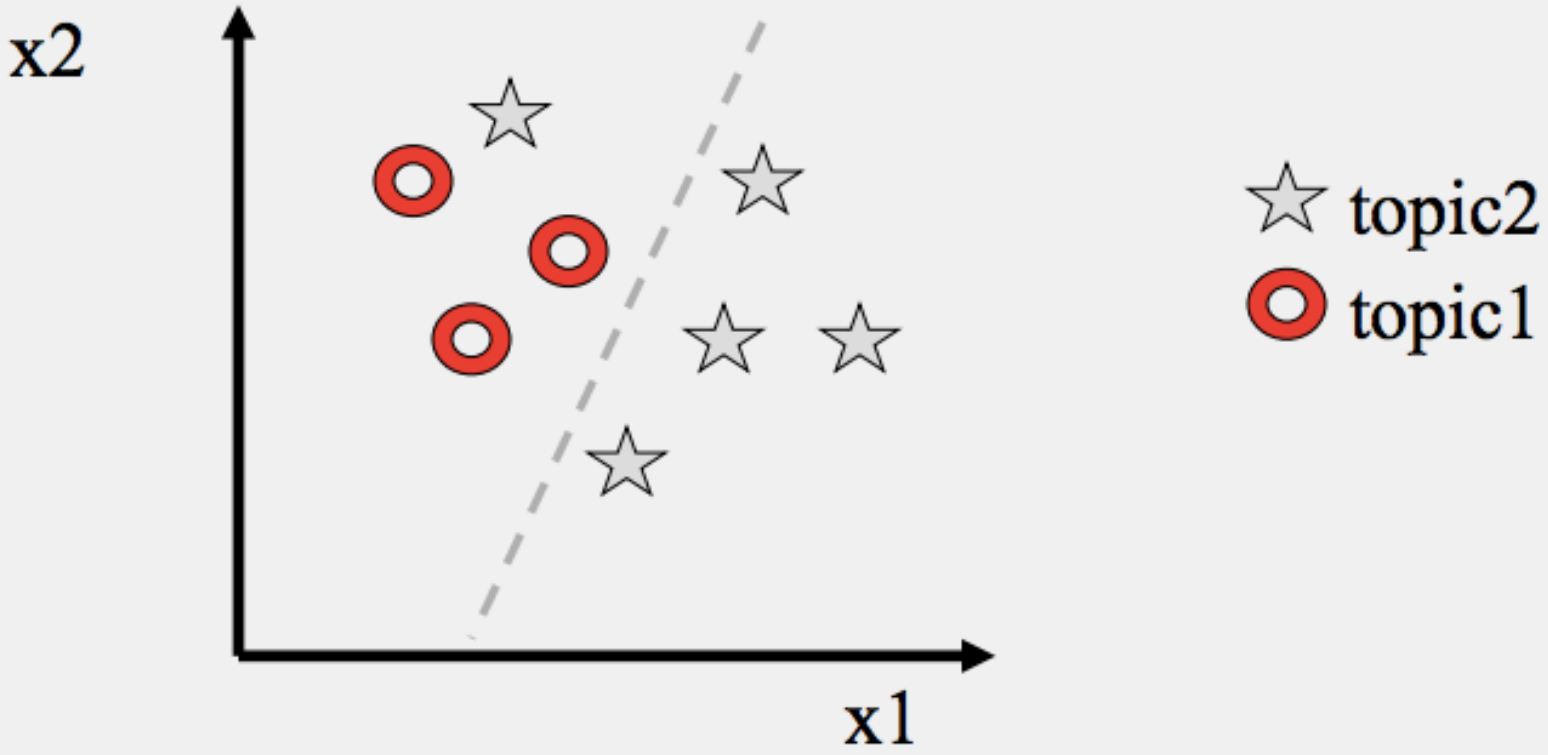
- Training data
  - Labeled text
  - Sentences or paragraphs drawn from online sources
    - Reddit
    - Novels
    - Journals
    - News
  - Feature vector: bag of words plus output prediction

Vector Space Classification



Slide from Dragomir Radev

Linear boundary



Slide from Dragomir Radev

Feature Vector Representation

x_1	**be**	**1**
x_2	big	2
x_3	branches	1
x_4	batteries	0
x_5	convincingly	0
x_6	computer	1
x_7	daddy	1
x_8	day	0
x_9	devastating	1
x_{10}	fruit	0
Y_1	**Social media**	**1**
Y_2	**Novel**	**0**
Y_3	**Scientific journal**	**0**
Y_4	**News**	**0**

- Devastating, but yet amazing storm. IMBY just some branches, ton of leaves, … This surpasses any Big daddy storm, should be called Big Mama. (Computer Guy)

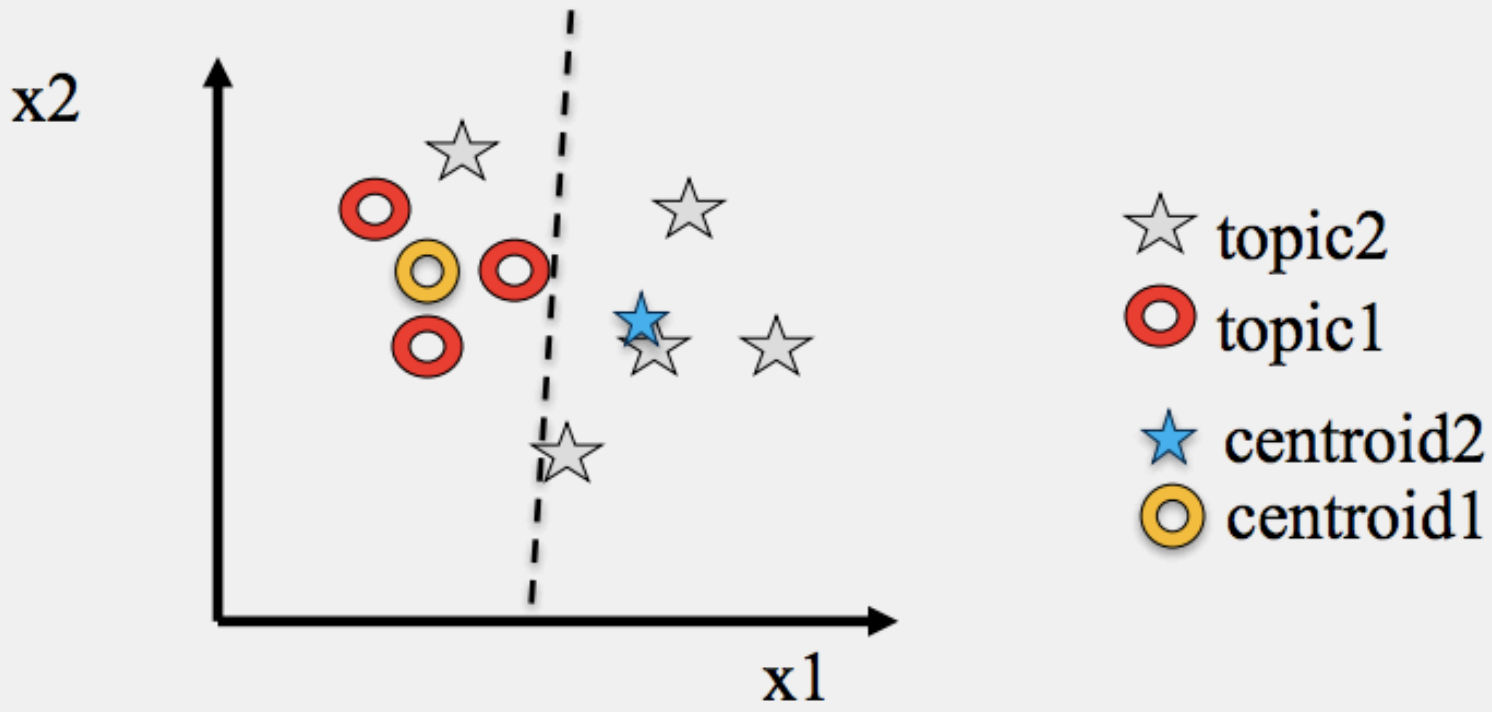
One hot vector for output class

Classification using centroids

- Centroid
  - The point most representative of a class
- Compute centroid by finding vector average of known class members
- Decision boundary is a line that is equi-distant from the two centroids
- New document on one side of the line goes in class 1 and on other side goes in class2

Slide from Dragomir Radev

Classification Using Centroids



Slide from Dragomir Radev

Linear Separators

$f(x) = \Theta X + b$

where

Θ is a vector of weights: $w_1 \ldots . w_n$

X is the input vector

b is a constant

Two dimensional space:

$$w_1 x_1 + w_2 x_2 = b$$

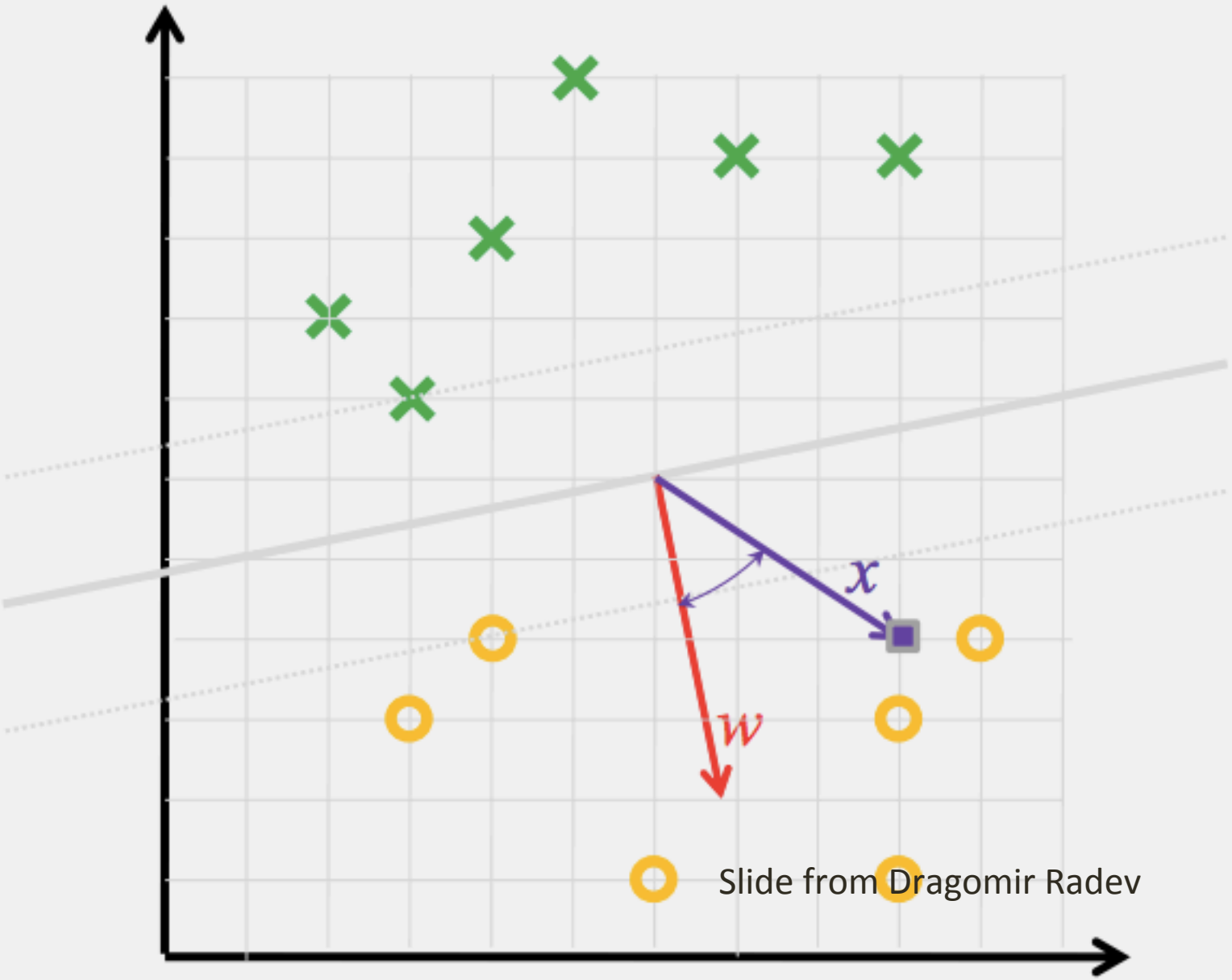
In n-dimensional spaces:

$$\Theta X = \Sigma_{i=1}^{n} = w_1 x_1 + w_2 x_2 + \ldots . + w_n x_n$$

One can also add $w_{0=} 1$, $x_0 = b$ to account for bias

Pass output of f(x) to the sign function, mapping negative values to -1 and positive values to 1

Decision Boundary



Slide from Dragomir Radev

Example

ΘX = b

Assume b = 0

Social mediaany	.2	any	-.2
be	.2	be	-.2
Big	1	Big	-.5
surpasses	.5	surpasses	-.7
computer	.3	batteries	-.8
daddy	1	convincingly	-.1
day	.7	day	-.8
fruit	.5	fruit	-.5
Storm	.5	Storm	-.5
this	.3	this	-.3

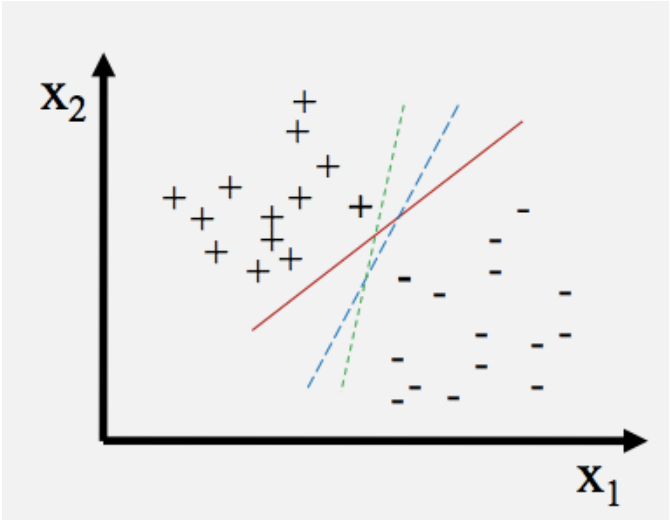
"This surpasses any Big daddy storm"

ΘX = .3*1+.5*1+.2*1+1*2+1*1+.5*1=4.5 > 0

How to find the linear boundary?

- How to find the vector of weights Θ ?

- Many methods
  - Perceptron
  - Linear least squares
  - Logistic regression



- Problem
  - There are infinite number of linear boundaries if the classes are linearly separated
  - Maximum margin: support vector machines

Slide from Dragomir Radev

Training using optimization

- Select values for w
- Compute f(x)
- Compare f(x) output to gold labels and compute *loss*
- Adjust w

Slide from Dragomir Radev

Using a loss function

- Training data
  - x_1 x_2 …. x_n (input)
  - $y_1 y_2$ …. y_n (labels)
- Algorithm that returns f(x) with predictions $\hat{y}$
- Loss function $L(\hat{y},y)$
- Parameters of the learned function (Θ,b) set to minimize L

Loss

- Given: labeled training set, L, parameterized function f(x,Θ) where Θ = $w_1 \ldots w_n$, b
- Corpus wide loss = average loss over all training examples:

$$\mathcal{L}(\Theta) = \frac{1}{n}\sum_{i=1}^{n} L(f(\mathbf{x}_i;\Theta), \mathbf{y}_i)$$

- Training algorithm sets Θ to minimize L:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}}\, \mathcal{L}(\Theta) = \underset{\Theta}{\operatorname{argmin}}\, \frac{1}{n}\sum_{i=1}^{n} L(f(\mathbf{x}_i;\Theta), \mathbf{y}_i)$$

- To prevent overfitting, a regularization parameter R(Θ) is added:

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}} \left(\overbrace{\frac{1}{n}\sum_{i=1}^{n} L(f(\mathbf{x}_i;\Theta), \mathbf{y}_i)}^{loss} + \overbrace{\lambda R(\Theta)}^{regularization} \right)$$

Loss Functions

- Can be an arbitrary function mapping two vectors to a scalar
- Hinge Loss (binary)
  - Classifier output: ŷ, gold output: y (-1,1)
  - Ŷ correct if ŷ*y>1 (Classification rule is sign (ŷ)

$$L_{\text{hinge(binary)}}(\hat{y}, y) = \max(0, 1 - y \cdot \hat{y})$$

Loss is 0 when ŷ, y share the same sign and |ŷ| >= 1, linear otherwise

  - Attempts to achieve correct classification with a margin of <= 1

Hinge Loss (multi-class)

- Classifier output: $\hat{Y}=\hat{y}_1 \ldots \hat{y}_n$
- Y is one-hot vector for correct class
- Prediction = $\text{argmax}_i \hat{y}_i$

$$L_{\text{hinge(multiclass)}}(\hat{\mathbf{y}}, \mathbf{y}) = \max(0, 1 - (\hat{\mathbf{y}}_{[t]} - \hat{\mathbf{y}}_{[k]}))$$

- where t is the correct class and k is the highest scoring class where $k \neq t$
- Scores the correct class above all other classes with a margin of at least 1

Many other loss functions

- Log loss
- Binary cross entropy
- Categorical cross entropy
- Ranking losses

Regularization

- Consider the case where one or more documents are mis-labeled
  - Text from a novel may be mis-labeled as social media if posted as a quote
- The classifier will attempt to learn weights that promote words characteristic of novels as predictors of social media
- Overfitting can also occur when the social media documents in the training set are not representative

Two Common regularizers

- L_2 regularization
  - Keeps sum of squares of parameter values low

$$R_{L_2}(\mathbf{W}) = ||\mathbf{W}||_2^2 = \sum_{i,j}(\mathbf{W}_{[i,j]})^2$$

  - Gaussian prior or weight decay (Here W is weights not including b)
  - Prefers to decrease parameter with high weight by 1 than 10 parameters with low weights
- L_1 regularization
  - Keeps sum of absolute value of parameters low

$$R_{L_1}(\mathbf{W}) = ||\mathbf{W}||_1 = \sum_{i,j}|\mathbf{W}_{[i,j]}|$$

    Punished uniformly for high and low values

Gradient based optimization

- Repeat until L < margin
  - Compute L over the training set
  - Compute gradients of Θ with respect to L
  - Move the parameters in the opposite direction of the gradient

Stochastic Gradient Descent

Algorithm 1 Online Stochastic Gradient Descent Training

Input:

- Function $f(\mathbf{x}; \Theta)$ parameterized with parameters Θ.
- Training set of inputs $\mathbf{x_1}, \ldots, \mathbf{x_n}$ and desired outputs $\mathbf{y_1}, \ldots, \mathbf{y_n}$.
- Loss function L.

1: **while** stopping criteria not met **do**
2: Sample a training example $\mathbf{x_i}, \mathbf{y_i}$
3: Compute the loss $L(f(\mathbf{x_i}; \Theta), \mathbf{y_i})$
4: $\hat{\mathbf{g}} \leftarrow$ gradients of $L(f(\mathbf{x_i}; \Theta), \mathbf{y_i})$ w.r.t θ
5: $\Theta \leftarrow \Theta - \eta_t \hat{\mathbf{g}}$
6: **return** Θ

Problem

- Error is calculated based on just one training sample
- May not be representative of corpus wide loss
- Instead calculate the error based on a set of training examples: *minibatch*
- -> Minibatch stochastic gradient descent

Computing Gradients

$$\frac{\partial L}{\partial \mathbf{b}_{[i]}} = \begin{cases} -1 & i = t \\ 1 & i = k \\ 0 & \text{otherwise} \end{cases}$$

$$\frac{\partial L}{\partial \mathbf{W}_{[i,j]}} = \begin{cases} \frac{\partial(-\mathbf{x}_{[i]} \cdot \mathbf{W}_{[i,t]})}{\partial \mathbf{W}_{[i,t]}} = -\mathbf{x}_{[i]} & j = t \\ \frac{\partial(\mathbf{x}_{[i]} \cdot \mathbf{W}_{[i,k]})}{\partial \mathbf{W}_{[i,k]}} = \mathbf{x}_{[i]} & j = k \\ 0 & \text{otherwise} \end{cases}$$

Summary

- Smoothing helps to account for zero valued n-grams
- Text classification using feature vectors representing n-grams and other properties
- Discriminative learning
- Methods for optimization, loss functions and regularization

Questions?