Feature-based Discriminative Classifiers

Making features from text for discriminative NLP models

Christopher Manning

Classifiers

- A classifier is a function *f* which assigns an input datum *d* to one of |*C*| classes, $c \in C$
- The classes might be:
  - {spam, notspam} for an email message
  - {politics, sports, finance, technology, arts, leisure, …} for news
  - {we-are-coreferent, we-are-not-coreference}
    for a coreference candidate mention pair

Example problem

- Classify a capitalized proper noun as a class:
  - LOCATION, DRUG, PERSON
- For a data example *d*
  - *taking Zantac*
- We work by considering each class *c* for the word:
  - (LOCATION, *taking Zantac*,)
  - (DRUG, *taking Zantac*,)
  - (PERSON, *taking Zantac*,)
- and using features to score each candidate classification

Features for a classifier

- *Features f* are elementary pieces of evidence that link aspects of what we observe *d* with a category *c* that we want to predict
- A feature is a function with a bounded real value: $f\colon C \times D \rightarrow \mathbb{R}$
  - Common special case:
    - binary features $f\colon C \times D \rightarrow \{0, 1\}$

Example features

- $f_1(c, d) \equiv [c = \text{LOCATION} \wedge w_{-1} = \text{“in”} \wedge \text{isCapitalized}(w)]$
- $f_2(c, d) \equiv [c = \text{LOCATION} \wedge \text{hasAccentedLatinChar}(w)]$
- $f_3(c, d) \equiv [c = \text{DRUG} \wedge \text{ends}(w, \text{“c”})]$

1.8 LOCATION *in Arcadia*

-0.6 LOCATION *in Québec*

0.3 DRUG *taking Zantac*

PERSON *saw Sue*

- Models will assign to each feature a *weight:*
  - A positive weight votes that this configuration is likely correct
  - A negative weight votes that this configuration is likely incorrect

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Features

- Very commonly, a feature specifies
  1. an indicator function – a yes/no boolean matching function – of properties of the input *and*
  2. a particular class

$$f_i(c, d) \equiv [\Phi(d) \wedge c = c_j] \qquad \text{[Value is 0 or 1]}$$

- Each feature picks out a data subset and suggests a label for it

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Feature-Based Models

- The decision about a data point is based only on the features active at that point.

Data BUSINESS: Stocks hit a yearly low …	Data … to restructure bank:MONEY debt.
Label: BUSINESS Features {…, stocks, hit, a, yearly, low, …}	Label: MONEY Features {…, w_{-1}=restructure, w_{+1}=debt, Leng=12, …}
Text Categorization	Word-Sense Disambiguation

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Feature-Based Linear Classifiers

- Linear classifiers at classification time:
  - Linear function from feature sets $\{f_i\}$ to classes $\{c\}$.
  - Assign a weight λ_i to each feature f_i.
  - We consider each class for an observed datum d
  - For a pair (c,d), features vote with their weights:
    - $\text{vote}(c) = \Sigma\lambda_i f_i(c,d)$

PERSON *in Québec* LOCATION *in Québec* DRUG *in Québec*

  - Choose the class c which maximizes $\Sigma\lambda_i f_i(c,d)$

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Feature-Based Linear Classifiers

- Linear classifiers at classification time:
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  - For a pair (c,d), features vote with their weights:
    - $\text{vote}(c) = \Sigma\lambda_i f_i(c,d)$

PERSON *in Québec* 1.8 LOCATION *in Québec* -0.6 0.3 DRUG *in Québec*

  - Choose the class c which maximizes $\Sigma\lambda_i f_i(c,d)$ = LOCATION

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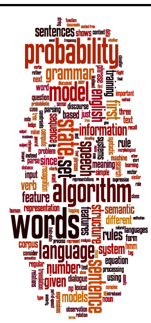
Feature-Based Linear Classifiers

There are many ways to chose weights for features

- Perceptron: find a currently misclassified example, and nudge weights in the direction that corrects classification
- Margin-based methods (Support Vector Machines)
- Maximum entropy models ("softmax regression"; roughly logistic regression), which we will look at next



Feature-based Discriminative Classifiers

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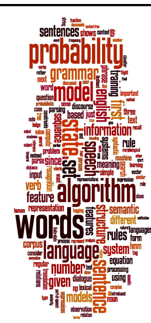

Feature-based Linear Classifiers

How to put features into a classifier

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Feature-Based Linear Classifiers

- Linear classifiers are a linear function from feature sets $\{f_i\}$ to classes $\{c\}$
- At test time, we consider each class c for a datum d
  - We generate a feature set $\{f_i\}$ for an observed datum-class pair (c,d)
  - Each feature f_i has a weight λ_i
  - We then score each possible class assignment: $\text{vote}(c) = \Sigma\lambda_i f_i(c,d)$
  - We choose the class c which maximizes $\Sigma\lambda_i f_i(c,d)$
- At training time we have observed (c,d) pairs from labeled examples
  - We generate sets of features $\{f_i(c,d)\}$ for them
  - We use information about what features occur and don't occur to set a weight λ_i for each feature

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Example features

- $f_1(c, d) \equiv [c = \text{LOCATION} \wedge w_{-1} = \text{"in"} \wedge \text{isCapitalized}(w)]$
- $f_2(c, d) \equiv [c = \text{LOCATION} \wedge \text{hasAccentedLatinChar}(w)]$
- $f_3(c, d) \equiv [c = \text{DRUG} \wedge \text{ends}(w, \text{"c"})]$

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Feature-Based Linear Classifiers

- Maxent (softmax, multiclass logistic, exponential, conditional log-linear, Gibbs) models:
  - Make a probabilistic model from the linear combination $\Sigma\lambda_i f_i(c,d)$

$$P(c \mid d, \lambda) = \frac{\exp \sum_i \lambda_i f_i(c,d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}$$

Makes votes positive

Normalizes votes

  - P(LOCATION|*in Québec*) = $e^{1.8}e^{-0.6}/(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.586$
  - P(DRUG|*in Québec*) = $e^{0.3}/(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.238$
  - P(PERSON|*in Québec*) = $e^{0}/(e^{1.8}e^{-0.6} + e^{0.3} + e^{0}) = 0.176$
  - The weights are the parameters of the probability model, combined via a "soft max" function

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Feature-Based Linear Classifiers

- Maxent models:
  - Given this model form, we choose parameters $\{\lambda_i\}$ that *maximize the conditional likelihood* of the data according to this model (as discussed later)
  - We construct not only classifications, but probability distributions over classifications.
    - There are other (good!) ways of discriminating classes – SVMs, boosting, even perceptrons – but these methods are not as trivial to interpret as distributions over classes.

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Feature Expectations

- We will crucially make use of two *expectations*
  - actual or predicted counts of a feature firing:
  - Empirical count (expectation) of a feature:

$$\text{empirical } E(f_i) = \sum_{(c,d)\in \text{observed}(C,D)} f_i(c,d)$$

  - Model expectation of a feature:

$$E(f_i) = \sum_{(c,d)\in(C,D)} P(c,d) f_i(c,d)$$

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Building a Maxent Model

- We define features (indicator functions) over data points
  - Features represent sets of data points which are distinctive enough to deserve model parameters.
    - Words, but also "word contains number", "word ends with *ing*", POS, syntactic structure, relation between two phrases, etc.
- We might simply encode each Φ feature as a unique String
  - A datum will give rise to a set of Strings: the active Φ features
  - Each feature $f_i(c, d) \equiv [\Phi(d) \wedge c = c_j]$ gets a real number weight
- We concentrate on Φ features but the math uses i indices of f_i

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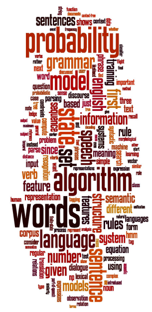
Building a Maxent Model

- Features are normally added in big batches via feature templates
  - E.g., one feature template adds $\forall i,j$ observed: lastWord=$w_i \wedge c = c_j$
  - Another is: nextWord=$w_i \wedge c = c_j$. Each may add tens of thousands of features
- A model may be specified by the set of feature templates used
- Features are often added during model development to target errors
  - Often, the easiest thing to think of are features that mark bad combinations



Maxent Models and Discriminative Estimation

Generative vs. Discriminative models

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Introduction

- So far we've mainly looked at "generative models"
  - Language models, IBM alignment models, PCFGs
- But there is much use of conditional or discriminative models in NLP, Speech, IR, and ML generally
- Because:
  - They give high accuracy performance
  - They make it easy to incorporate lots of linguistically important features
  - They allow automatic building of language independent, retargetable NLP modules

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Joint vs. Conditional Models

- We have some data $\{(d, c)\}$ of paired observations d and hidden classes c.
- Joint (generative) models place probabilities over both observed data and the hidden stuff $P(c,d)$
  - They generate the observed data from the hidden stuff
  - All the classic StatNLP models:
    - *n*-gram models, Naive Bayes classifiers, hidden Markov models, probabilistic context-free grammars, IBM machine translation alignment models

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Joint vs. Conditional Models

- Discriminative (conditional) models take the data as given, and put a probability/score over hidden structure given the data: $P(c|d)$
  - Logistic regression, conditional loglinear or maximum entropy models, conditional random fields
  - Also, SVMs, (averaged) perceptron, etc. are discriminative classifiers (but not directly probabilistic)

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Conditional vs. Joint Likelihood

- A *joint* model gives probabilities $P(d,c) = P(c)P(d|c)$ and tries to maximize this joint likelihood.
  - It ends up trivial to choose weights: just count! (relative frequencies)
- A *conditional* model gives probabilities $P(c|d)$. It takes the data as given and models only the conditional probability of the class.
  - We seek to maximize conditional likelihood.
  - Harder to do (as we'll see…)
  - More closely related to classification error.

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Conditional models work well: Word Sense Disambiguation

Training Set	
Objective	Accuracy
Joint Like.	86.8
Cond. Like.	98.5

Test Set	
Objective	Accuracy
Joint Like.	73.6
Cond. Like.	76.1

(Klein and Manning 2002, using Senseval-1 Data)

- Even with exactly the same features, changing from joint to conditional estimation increases performance
- That is, we use the same smoothing, and the same word-class features, we just change the numbers (parameters)

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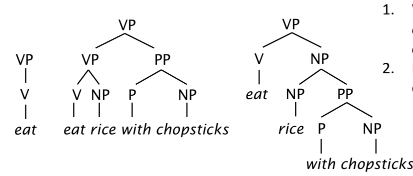
PCFGs Maximize Joint, not Conditional Likelihood



46 6 2

1. What parse for *eat rice with chopsticks?*
2. How can you get the other parse?

Based on an example by Mark Johnson

Maxent Models and Discriminative Estimation

Maximizing the likelihood

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Exponential Model Likelihood

- Maximum (Conditional) Likelihood Models :
  - Given a model form, we choose values of parameters λ_i to maximize the (conditional) likelihood of the data.
- For any given feature weights, we can calculate:
  - Data conditional likelihood
  - Derivative of the likelihood wrt each feature weight

$$\log P(C \mid D, \lambda) = \sum_{(c,d)\in(C,D)} \log P(c \mid d, \lambda) = \sum_{(c,d)\in(C,D)} \log \frac{\exp \sum_i \lambda_i f_i(c,d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}$$

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The Likelihood Value

- The (log) conditional likelihood of iid* data (*C*,*D*) according to a maxent model is a function of the data and the parameters λ:

$$\log P(C \mid D, \lambda) = \log \prod_{(c,d)\in(C,D)} P(c \mid d, \lambda) = \sum_{(c,d)\in(C,D)} \log P(c \mid d, \lambda)$$

- If there aren't many values of *c*, it's easy to calculate:

$$\log P(C \mid D, \lambda) = \sum_{(c,d)\in(C,D)} \log \frac{\exp \sum_i \lambda_i f_i(c,d)}{\sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}$$

*A fancy statistics term meaning "independent and identically distributed". You normally need to assume this for anything formal to be derivable, even though it's never quite true in practice.

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The Likelihood Value

- We can separate this into two components:

$$\log P(C \mid D, \lambda) = \sum_{(c,d)\in(C,D)} \log \exp \sum_i \lambda_i f_i(c,d) - \sum_{(c,d)\in(C,D)} \log \sum_{c'} \exp \sum_i \lambda_i f_i(c',d)$$

$$\log P(C \mid D, \lambda) = N(\lambda) - M(\lambda)$$

- We can maximize it by finding where the derivative is 0
- The derivative is the difference between the derivatives of each component

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The Derivative I: Numerator

$$\frac{\partial N(\lambda)}{\partial \lambda_i} = \frac{\partial \sum_{(c,d)\in(C,D)} \log \exp \sum_i \lambda_{ci} f_i(c,d)}{\partial \lambda_i} = \frac{\partial \sum_{(c,d)\in(C,D)} \sum_i \lambda_i f_i(c,d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} \frac{\partial \sum_i \lambda_i f_i(c,d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} f_i(c,d)$$

Derivative of the numerator is: the empirical count(f_i, c)

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The Derivative II: Denominator

$$\frac{\partial M(\lambda)}{\partial \lambda_i} = \frac{\partial \sum_{(c,d)\in(C,D)} \log \sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} \frac{1}{\sum_{c''} \exp \sum_i \lambda_i f_i(c'',d)} \frac{\partial \sum_{c'} \exp \sum_i \lambda_i f_i(c',d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} \frac{1}{\sum_{c''} \exp \sum_i \lambda_i f_i(c'',d)} \sum_{c'} \frac{\exp \sum_i \lambda_i f_i(c',d)}{1} \frac{\partial \sum_i \lambda_i f_i(c',d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} \sum_{c'} \frac{\exp \sum_i \lambda_i f_i(c',d)}{\sum_{c''} \exp \sum_i \lambda_i f_i(c'',d)} \frac{\partial \sum_i \lambda_i f_i(c',d)}{\partial \lambda_i}$$

$$= \sum_{(c,d)\in(C,D)} \sum_{c'} P(c' \mid d,\lambda) f_i(c',d)$$

= predicted count(f_i, λ)

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The Derivative III

$$\frac{\partial \log P(C \mid D,\lambda)}{\partial \lambda_i} = \text{actual count}(f_i, C) - \text{predicted count}(f_i, \lambda)$$

- The optimum parameters are the ones for which each feature's predicted expectation equals its empirical expectation. The optimum distribution is:
  - Always unique (but parameters may not be unique)
  - Always exists (if feature counts are from actual data).
- These models are also called maximum entropy models because we find the model having maximum entropy and satisfying the constraints: $E_p(f_j) = E_{\tilde{p}}(f_j), \forall j$

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Finding the optimal parameters

- We want to choose parameters λ_1, λ_2, λ_3, … that maximize the conditional log-likelihood of the training data

$$CLogLik(D) = \sum_{i=1}^{n} \log P(c_i \mid d_i)$$

- To be able to do that, we've worked out how to calculate the function value and its partial derivatives (its gradient)

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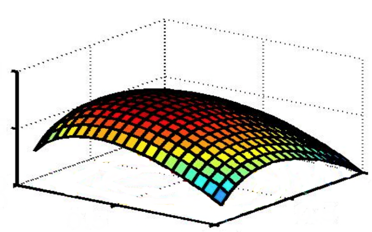
A likelihood surface



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Finding the optimal parameters

- Use your favorite numerical optimization package….
  - Commonly (and in our code), you **minimize** the negative of *CLogLik*

1. Gradient descent (GD); Stochastic gradient descent (SGD)
2. Iterative proportional fitting methods: Generalized Iterative Scaling (GIS) and Improved Iterative Scaling (IIS)
3. Conjugate gradient (CG), perhaps with preconditioning
4. Quasi-Newton methods – limited memory variable metric (LMVM) methods, in particular, L-BFGS