Maxent Models and Discriminative Estimation

Generative vs. Discriminative models

Christopher Manning

Introduction

- So far we've looked at "generative models"
  - Language models, Naive Bayes
- But there is now much use of conditional or discriminative probabilistic 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

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 (gene-rate the observed data from hidden stuff):

  $P(c, d)$

  - All the classic StatNLP models:
    - n-gram models, Naive Bayes classifiers, hidden Markov models, probabilistic context-free grammars, IBM machine translation alignment models

Joint vs. Conditional Models
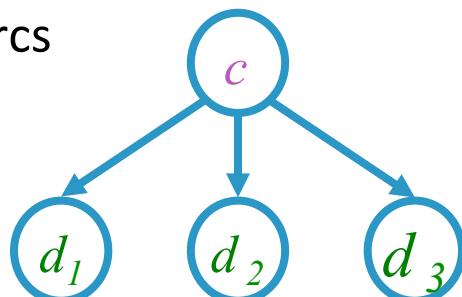
- **Discriminative (conditional) models** take the data as given, and put a probability over hidden structure given the data:

  $P(c|d)$

  - Logistic regression, conditional loglinear or maximum entropy models, conditional random fields
  - Also, SVMs, (averaged) perceptron, etc. are discriminative classifiers (but not directly probabilistic)
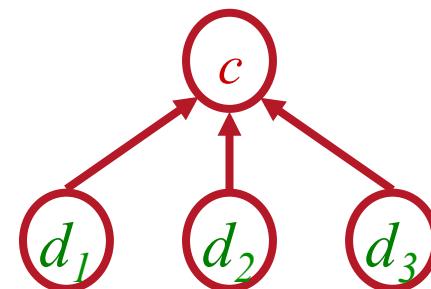
Bayes Net/Graphical Models

- Bayes net diagrams draw circles for random variables, and lines for direct dependencies

- Some variables are observed; some are hidden

- Each node is a little classifier (conditional probability table) based on incoming arcs
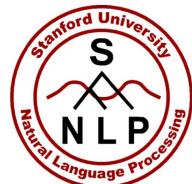
Naive Bayes

Generative

Logistic Regression

Discriminative

Conditional vs. Joint Likelihood

- A *joint* model gives probabilities P(*d,c*) and tries to maximize this joint likelihood.
  - It turns out to be trivial to choose weights: just 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
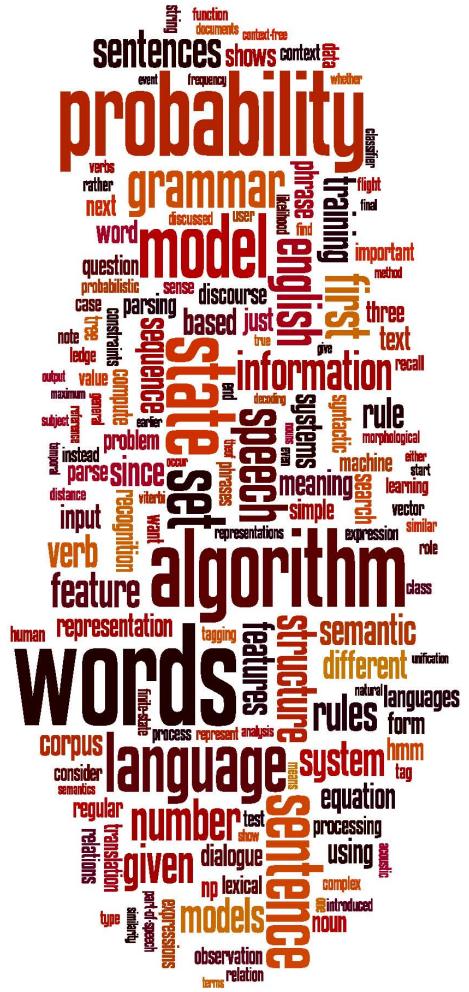
Training Set	
Objective	Accuracy
Joint Like.	86.8
Cond. Like.	98.5

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)

Maxent Models and Discriminative Estimation

Generative vs. Discriminative models

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Discriminative Model Features

Making features from text for discriminative NLP models

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Features

- In these slides and most maxent work: *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: $f: C \times D \rightarrow \mathbb{R}$

Features

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- A feature is a function with a bounded real value

Example features

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

LOCATION
in Arcadia

LOCATION
in Québec

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

Example features

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LOCATION	LOCATION	DRUG	PERSON
in Arcadia	*in Québec*	*taking Zantac*	*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

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:

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

Features

- In NLP uses, usually a feature specifies (1) an indicator function – a yes/no boolean matching function – of properties of the input and (2) a particular class

  - $f_i(c, d) \equiv [\Phi(d) \wedge c = c_j]$ [Value is 0 or 1]
  - They pick out a data subset and suggest a label for it.

- We will say that $\Phi(d)$ is a feature of the data d, when, for each c_j, the conjunction $\Phi(d) \wedge c = c_j$ is a feature of the data-class pair (c, d)

Features

- In NLP uses, usually 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

Feature-Based Models

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

Data	Data	Data
BUSINESS: Stocks hit a yearly low …	… to restructure bank:MONEY debt.	DT JJ NN … The previous fall …
Label: BUSINESS Features {…, stocks, hit, a, yearly, low, …}	Label: MONEY Features {…, w_{-1}=restructure, w_{+1}=debt, L=12, …}	Label: NN Features {w=fall, t_{-1}=JJ w_{-1}=previous}
Text Categorization	Word-Sense Disambiguation	POS Tagging

Example: Text Categorization
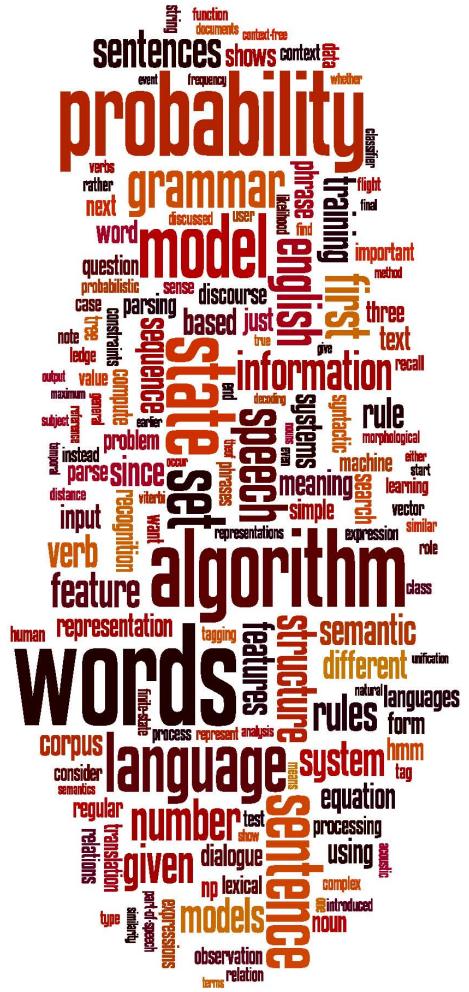
(Zhang and Oles 2001)

- Features are presence of each word in a document and the document class (they do feature selection to use reliable indicator words)

- Tests on classic Reuters data set (and others)
  - Naïve Bayes: 77.0% F_1
  - Linear regression: 86.0%
  - Logistic regression: 86.4%
  - Support vector machine: 86.5%

- Paper emphasizes the importance of *regularization* (smoothing) for successful use of discriminative methods (not used in much early NLP/IR work)

Other Maxent Classifier Examples
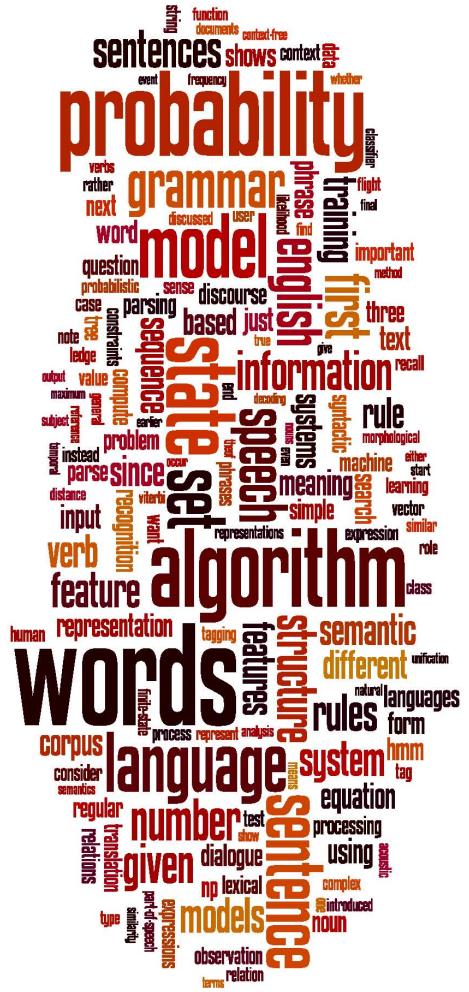
- You can use a maxent classifier whenever you want to assign data points to one of a number of classes:

  - Sentence boundary detection (Mikheev 2000)

    - Is a period end of sentence or abbreviation?

  - Sentiment analysis (Pang and Lee 2002)

    - Word unigrams, bigrams, POS counts, …

  - PP attachment (Ratnaparkhi 1998)

    - Attach to verb or noun? Features of head noun, preposition, etc.

  - Parsing decisions in general (Ratnaparkhi 1997; Johnson et al. 1999, etc.)

Discriminative Model Features

Making features from text for discriminative NLP models

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Feature-based Linear Classifiers

How to put features into a classifier

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

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

Feature-Based Linear Classifiers

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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

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 of its correct classification

- Margin-based methods (Support Vector Machines)

Feature-Based Linear Classifiers

- Exponential (log-linear, maxent, logistic, 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

Feature-Based Linear Classifiers

- Exponential (log-linear, maxent, logistic, Gibbs) models:
  - Given this model form, we will choose parameters $\{\lambda_i\}$ that *maximize the conditional likelihood* of the data according to this model.
  - 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.

Aside: logistic regression

- Maxent models in NLP are essentially the same as multiclass logistic regression models in statistics (or machine learning)
  - If you haven't seen these before, don't worry, this presentation is self-contained!
  - If you have seen these before you might think about:
    - The parameterization is slightly different in a way that is advantageous for NLP-style models with tons of sparse features (but statistically inelegant)
    - The key role of feature functions in NLP and in this presentation
      - The features are more general, with f also being a function of the class – when might this be useful?

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Quiz Question
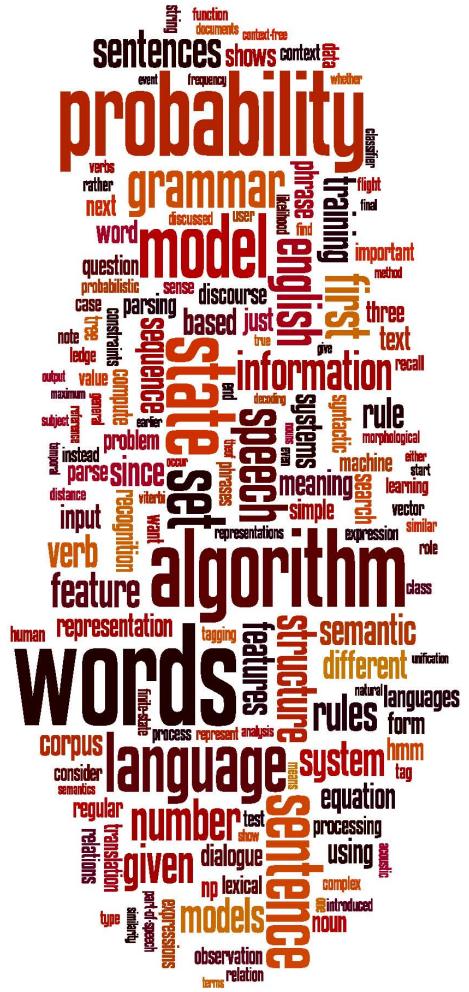
- Assuming exactly the same set up (3 class decision: LOCATION, PERSON, or DRUG; 3 features as before, maxent), what are:
  - P(PERSON | *by Goéric*)   =
  - P(LOCATION | *by Goéric*) =
  - P(DRUG | *by Goéric*)   =

  - 1.8 $f_1(c, d) \equiv [c = \text{LOCATION} \wedge w_{-1} = \text{``in''} \wedge \text{isCapitalized}(w)]$
  - -0.6 $f_2(c, d) \equiv [c = \text{LOCATION} \wedge \text{hasAccentedLatinChar}(w)]$
  - 0.3 $f_3(c, d) \equiv [c = \text{DRUG} \wedge \text{ends}(w, \text{``c''})]$

PERSON
by Goéric

LOCATION
by Goéric
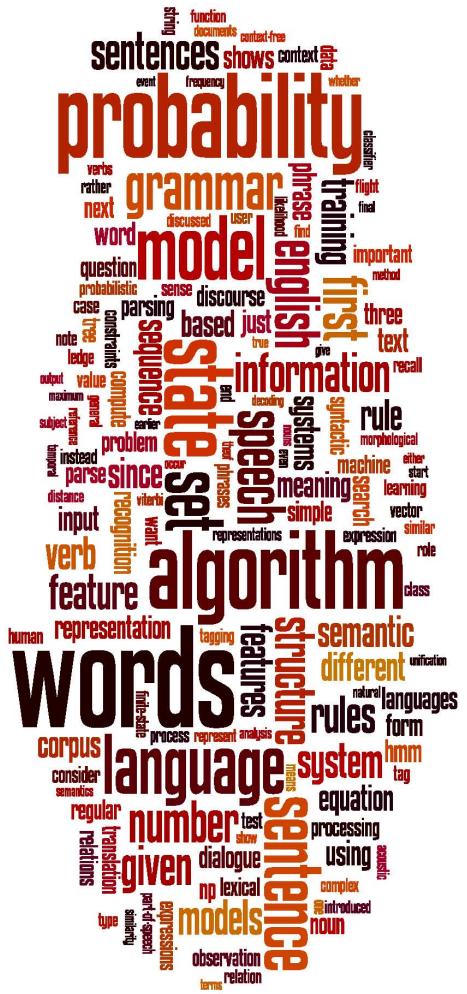
DRUG
by Goéric

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

Feature-based Linear Classifiers

How to put features into a classifier

Building a Maxent Model

The nuts and bolts
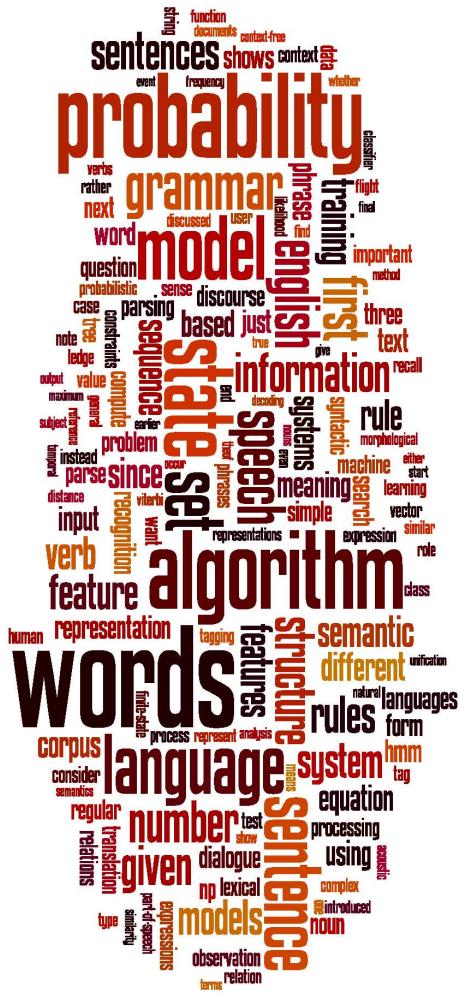
Building a Maxent Model

- 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*", etc.

- We will 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
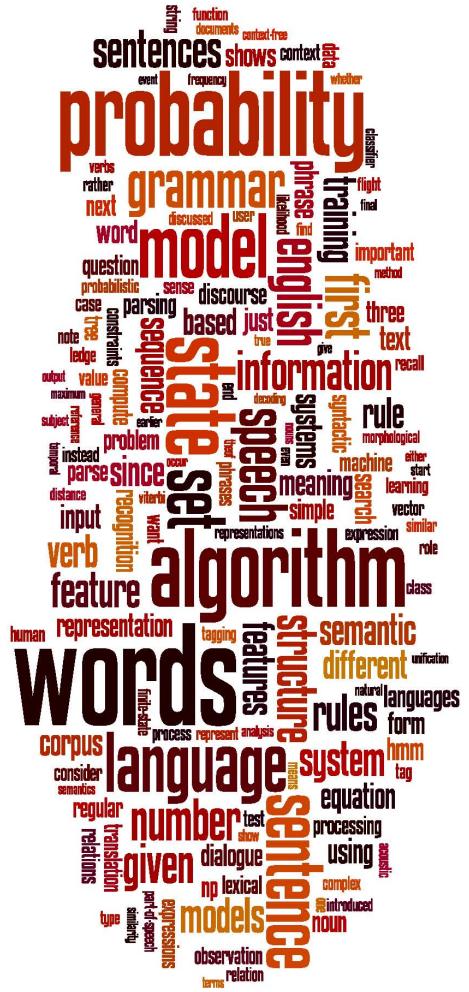
Building a Maxent Model

- Features are often added during model development to target errors
  - Often, the easiest thing to think of are features that mark bad combinations

- Then, for any given feature weights, we want to be able to calculate:
  - Data conditional likelihood
  - Derivative of the likelihood wrt each feature weight
    - Uses expectations of each feature according to the model

- We can then find the optimum feature weights (discussed later).

Building a Maxent Model
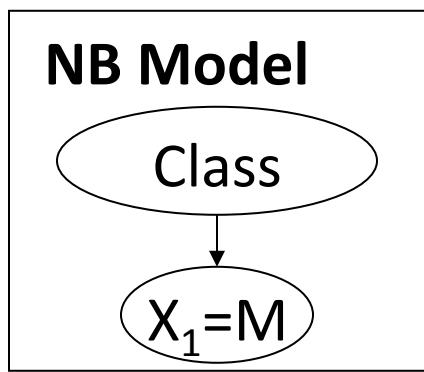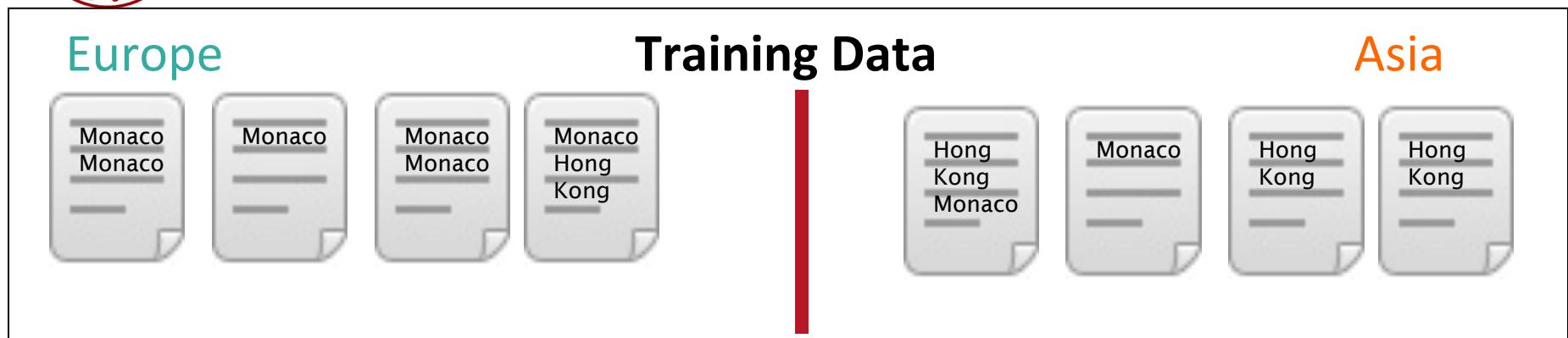
The nuts and bolts

Naive Bayes vs. Maxent models

Generative vs. Discriminative models: The problem of overcounting evidence

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Text classification: Asia or Europe

Training Data

Europe

Monaco Monaco	Monaco	Monaco Monaco	Monaco Hong Kong

Asia

|			
Hong Kong Monaco	Monaco	Hong Kong	Hong Kong

NB Model

Class → $X_1 = M$
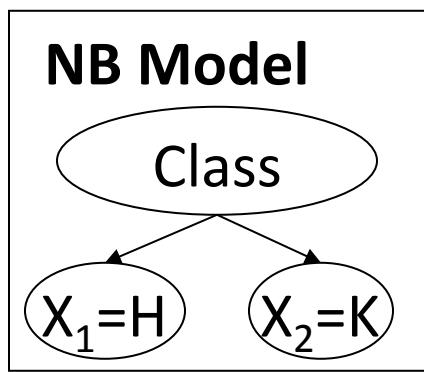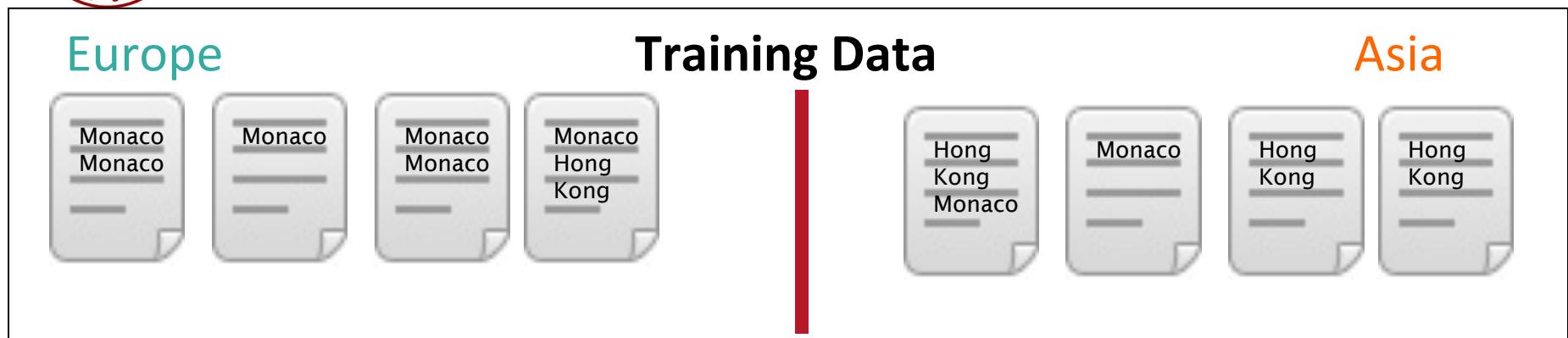
NB FACTORS:

- $P(A) = P(E) =$
- $P(M|A) =$
- $P(M|E) =$

PREDICTIONS:

- $P(A,M) =$
- $P(E,M) =$
- $P(A|M) =$
- $P(E|M) =$

Text classification: Asia or Europe

Training Data

Europe   **Asia**

| Monaco Monaco | Monaco | Monaco Monaco | Monaco Hong Kong |

| Hong Kong Monaco | Monaco | Hong Kong | Hong Kong |

## NB Model

Class

$X_1 = H$ $X_2 = K$
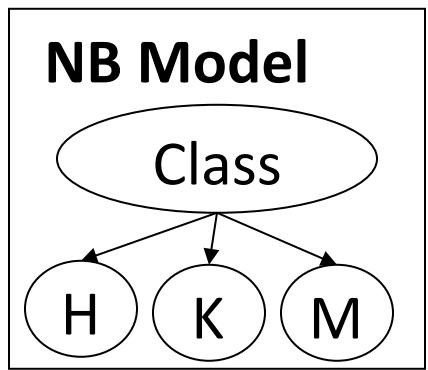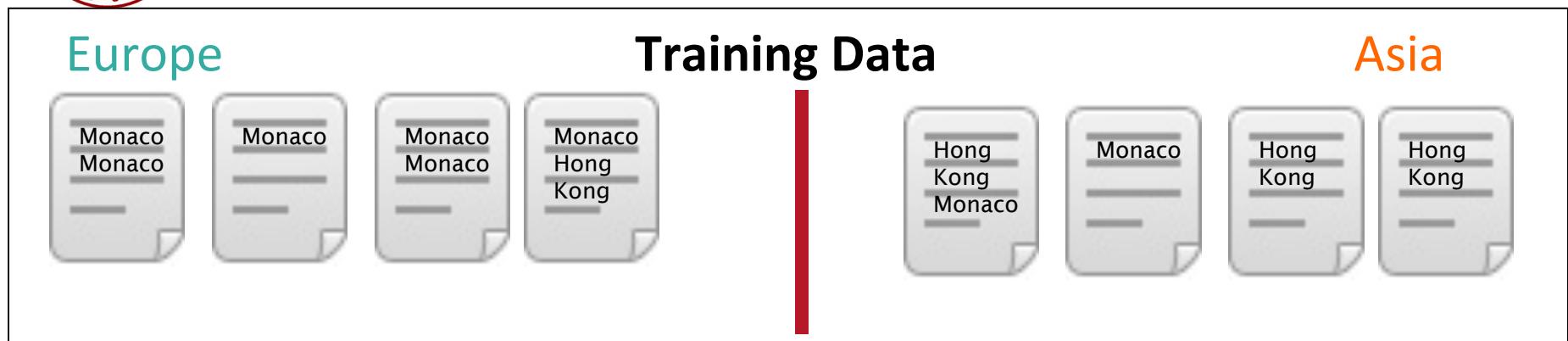
NB FACTORS:

- $P(A) = P(E) =$
- $P(H|A) = P(K|A) =$
- $P(H|E) = PK|E) =$

PREDICTIONS:

- $P(A,H,K) =$
- $P(E,H,K) =$
- $P(A|H,K) =$
- $P(E|H,K) =$

Text classification: Asia or Europe

Training Data

Europe

| Monaco Monaco | Monaco | Monaco Monaco | Monaco Hong Kong |

Asia

| Hong Kong Monaco | Monaco | Hong Kong | Hong Kong |

NB Model

Class

H K M

NB FACTORS:

- P(A) = P(E) =
- P(M|A) =
- P(M|E) =
- P(H|A) = P(K|A) =
- P(H|E) = PK|E) =
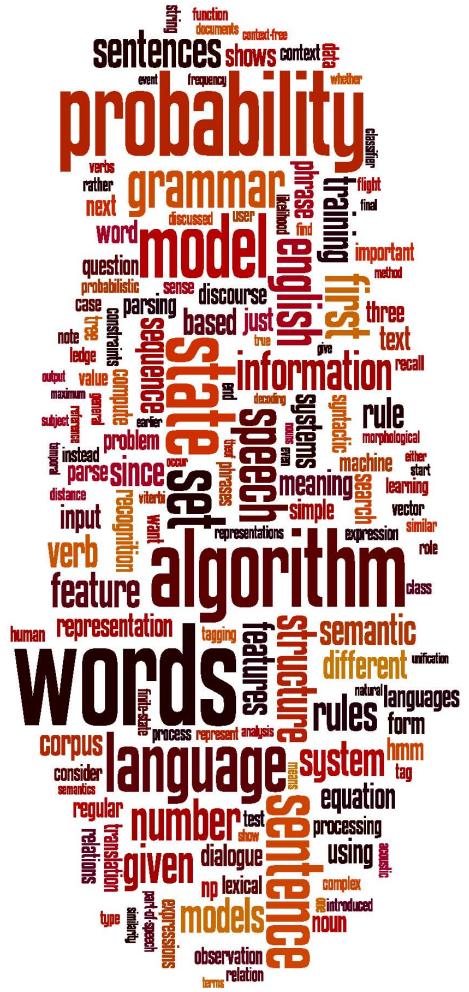
PREDICTIONS:

- P(A,H,K,M) =
- P(E,H,K,M) =
- P(A|H,K,M) =
- P(E|H,K,M) =

Naive Bayes vs. Maxent Models
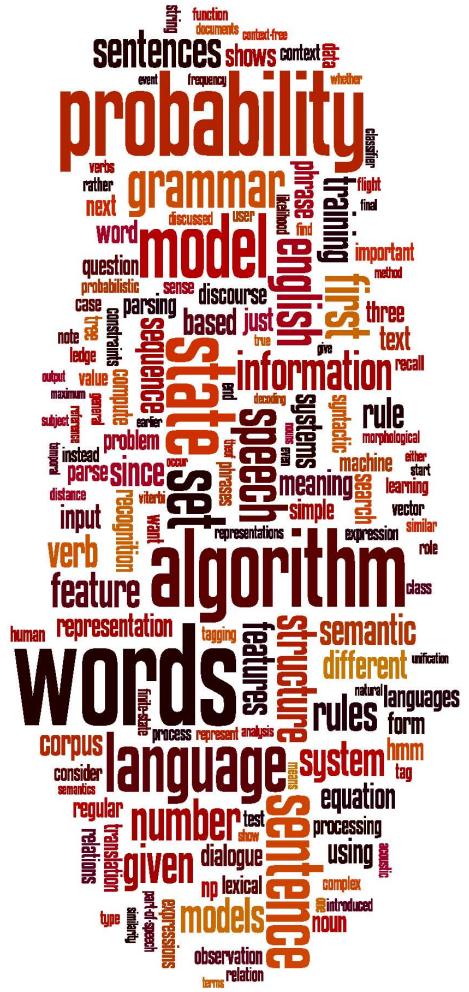
- Naive Bayes models multi-count correlated evidence
  - Each feature is multiplied in, even when you have multiple features telling you the same thing

- Maximum Entropy models (pretty much) solve this problem
  - As we will see, this is done by weighting features so that model expectations match the observed (empirical) expectations

Naive Bayes vs. Maxent models

Generative vs. Discriminative models: The problem of overcounting evidence

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Maxent Models and Discriminative Estimation

Maximizing the likelihood

Exponential Model Likelihood

- Maximum (Conditional) Likelihood Models :
  - Given a model form, choose values of parameters to maximize the (conditional) likelihood of the data.

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

The Likelihood Value

- The (log) conditional likelihood of iid data (*C*,*D*) according to 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:

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

The Likelihood Value

- We can separate this into two components:

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

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

- The derivative is the difference between the derivatives of each component

The Derivative I: Numerator

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

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

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

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

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The Derivative II: Denominator

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

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

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

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

$$= \sum_{(c,d)\in(C,D)} \sum_{c'} P(c'|d,\lambda) f_i(c',d) \qquad \text{= predicted count}(f_i, \lambda)$$

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: $E_p(f_j) = E_{\tilde{p}}(f_j), \forall j$

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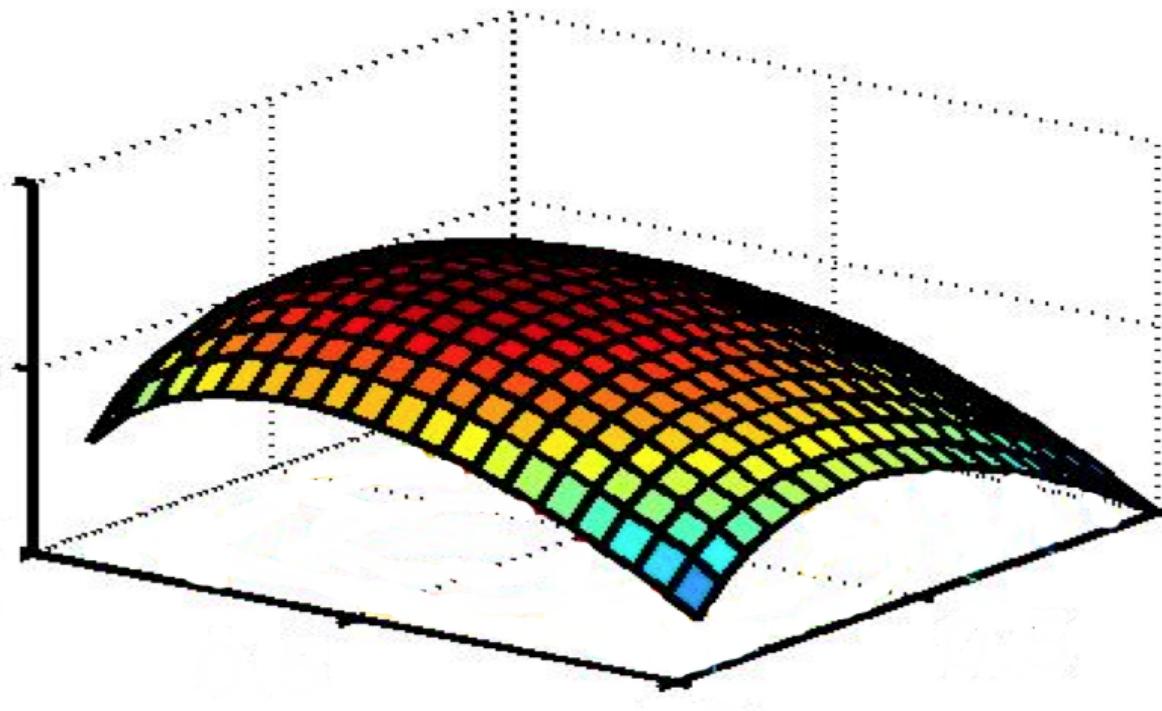
- We want to choose parameters λ_1, λ_2, λ_3, … that maximize the conditional log-likelihood of the training data

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

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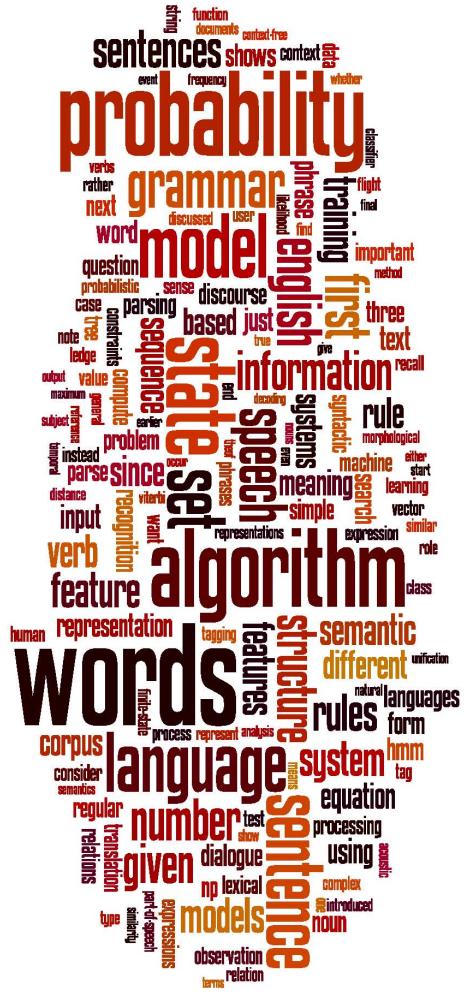
A likelihood surface

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

Maxent Models and Discriminative Estimation

Maximizing the likelihood