Statistical NLP

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Lecture 5: WSD / Maxent

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Word Senses

- Words have multiple distinct meanings, or senses:
  - Plant: living plant, manufacturing plant, …
  - Title: name of a work, ownership document, form of address, material at the start of a film, …
- Many levels of sense distinctions
  - Homonymy: totally unrelated meanings (river bank, money bank)
  - Polysemy: related meanings (star in sky, star on tv)
  - Systematic polysemy: productive meaning extensions (organizations to their buildings) or metaphor
  - Sense distinctions can be extremely subtle (or not)
- Granularity of senses needed depends a lot on the task
- Why is it important to model word senses?
  - Translation, parsing, information retrieval?

Word Sense Disambiguation

- Example: living plant vs. manufacturing plant
- How do we tell these senses apart?
  - "context"

    The manufacturing plant which had previously sustained the town's economy shut down after an extended labor strike.

  - Maybe it's just text categorization
  - Each word sense represents a topic
  - Run the naive-bayes classifier from last class?
- Bag-of-words classification works ok for noun senses
  - 90% on classic, shockingly easy examples (line, interest, star)
  - 80% on senseval-1 nouns
  - 70% on senseval-1 verbs

Verb WSD

- Why are verbs harder?
  - Verbal senses less topical
  - More sensitive to structure, argument choice
- Verb Example: "Serve"
  - [function] The tree stump serves as a table
  - [enable] The scandal served to increase his popularity
  - [dish] We serve meals for the homeless
  - [enlist] He served his country
  - [jail] He served six years for embezzlement
  - [tennis] It was Agassi's turn to serve
  - [legal] He was served by the sheriff

Various Approaches to WSD

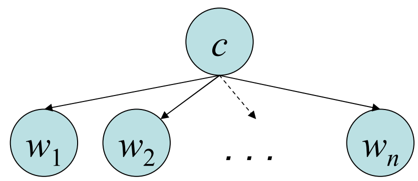
- Unsupervised learning
  - Bootstrapping (Yarowsky 95)
  - Clustering
- Indirect supervision
  - From thesauri
  - From WordNet
  - From parallel corpora
- Supervised learning
  - Most systems do some kind of supervised learning
  - Many competing classification technologies perform about the same (it's all about the knowledge sources you tap)
  - Problem: training data available for only a few words

Resources

- WordNet
  - Hand-build (but large) hierarchy of word senses
  - Basically a hierarchical thesaurus
- SensEval
  - A WSD competition, of which there have been 3 iterations
  - Training / test sets for a wide range of words, difficulties, and parts-of-speech
  - Bake-off where lots of labs tried lots of competing approaches
- SemCor
  - A big chunk of the Brown corpus annotated with WordNet senses
- OtherResources
  - The Open Mind Word Expert
  - Parallel texts
  - Flat thesauri

Knowledge Sources

- So what do we need to model to handle "serve"?
  - There are distant topical cues
    - …. point … court ………………… serve ……… game …



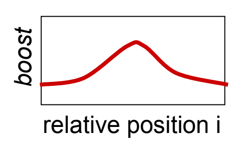
$$P(c, w_1, w_2, \ldots w_n) = P(c) \prod_i P(w_i \mid c)$$

Weighted Windows with NB

- Distance conditioning
  - Some words are important only when they are nearby
  - …. as …. point … court ……………………………… serve ……… game …
  - …. ………………………………………………………… serve as……………..

$$P(c, w_{-k}, \ldots, w_{-1}, w_0, w_{+1}, \ldots w_{+k'}) = P(c) \prod_{i=-k}^{k'} P(w_i \mid c, bin(i))$$

- Distance weighting
  - Nearby words should get a larger vote
  - … court …… serve as……… game …… point



$$P(c, w_{-k}, \ldots, w_{-1}, w_0, w_{+1}, \ldots w_{+k'}) = P(c) \prod_{i=-k}^{k'} P(w_i \mid c)^{boost(i)}$$

Better Features

- There are smarter features:
  - Argument selectional preference:
    - serve NP[meals] vs. serve NP[papers] vs. serve NP[country]
  - Subcategorization:
    - [function] serve PP[as]
    - [enable] serve VP[to]
    - [tennis] serve <intransitive>
    - [food] serve NP {PP[to]}
  - Can capture poorly (but robustly) with local windows
  - … but we can also use a parser and get these features explicitly
- Other constraints (Yarowsky 95)
  - One-sense-per-discourse (only true for broad topical distinctions)
  - One-sense-per-collocation (pretty reliable when it kicks in: manufacturing plant, flowering plant)

Complex Features with NB?

- Example: Washington County jail served 11,166 meals last month - a figure that translates to feeding some 120 people three times daily for 31 days.
- So we have a decision to make based on a set of cues:
  - context:jail, context:county, context:feeding, …
  - local-context:jail, local-context:meals
  - subcat:NP, direct-object-head:meals
- Not clear how build a generative derivation for these:
  - Choose topic, then decide on having a transitive usage, then pick “meals” to be the object’s head, then generate other words?
  - How about the words that appear in multiple features?
  - Hard to make this work (though maybe possible)
  - No real reason to try

A Discriminative Approach

- View WSD as a discrimination task (regression, really)

  P(sense | context:jail, context:county,
  context:feeding, …
  local-context:jail, local-context:meals
  subcat:NP, direct-object-head:meals, ….)

- Have to estimate multinomial (over senses) where there are a huge number of things to condition on
  - History is too complex to think about this as a smoothing / back-off problem
- Many feature-based classification techniques out there
- We tend to need ones that output distributions over classes (why?)

Feature Representations

d

Washington County jail served 11,166 meals last month - a figure that translates to feeding some 120 people three times daily for 31 days.

$\{f_i(d)\}$

context:jail = 1
context:county = 1
context:feeding = 1
context:game = 0
…
local-context:jail = 1
local-context:meals = 1
…
subcat:NP = 1
subcat:PP = 0
…
object-head:meals = 1
object-head:ball = 0

- Features are indicator functions f_i which count the occurrences of certain patterns in the input
- We map each input to a vector of feature predicate counts

Linear Classifiers

- For a pair (c,d), we take a weighted vote for each class:

$$vote(c \mid d) = \exp \sum_i \lambda_i(c) f_i(d)$$

Feature	Food	Jail	Tennis
context:jail	-0.5 * 1	+1.2 * 1	-0.8 * 1
subcat:NP	+1.0 * 1	+1.0 * 1	-0.3 * 1
object-head:meals	+2.0 * 1	-1.5 * 1	-1.5 * 1
object-head:years = 0	-1.8 * 0	+2.1 * 0	-1.1 * 0
TOTAL	+3.5	+0.7	-2.6

- There are many ways to set these weights
  - Perceptron: find a currently misclassified example, and nudge weights in the direction of a correct classification
  - Other discriminative methods usually work in the same way: try out various weights until you maximize some objective

Maximum-Entropy Classifiers

- Exponential (log-linear, maxent, logistic, Gibbs) models:
  - Turn the votes into a probability distribution:

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

Makes votes positive.

Normalizes votes.

  - For any weight vector $\{\lambda_i\}$, we get a conditional probability model P(c | d,λ).
  - We want to choose parameters that *maximize the conditional (log) likelihood* of the data:

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

Building a Maxent Model

- How to define features:
  - Features are patterns in the input which we think the weighted vote should depend on
  - Usually features added incrementally to target errors
  - If we're careful, adding some mediocre features into the mix won't hurt (but won't help either)

- How to learn model weights?
  - Maxent just one method
  - Use a numerical optimization package
  - Given a current weight vector, need to calculate (repeatedly):
    - Conditional likelihood of the data
    - Derivative of that likelihood wrt each feature weight

The Likelihood Value

- The (log) conditional likelihood is a function of the iid data (C,D) 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:

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

- We can separate this into two components:

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

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

The Derivative I: Numerator

$$\frac{\partial N(\lambda)}{\partial \lambda_i(c)} = \frac{\partial \sum_k \log \exp \sum_i \lambda_i(c_k) f_i(d_k)}{\partial \lambda_i(c)} = \frac{\partial \sum_k \sum_i \lambda_i(c_k) f_i(d_k)}{\partial \lambda_i(c)}$$

$$= \sum_{k:c_k=c} \frac{\partial \sum_i \lambda_i(c) f_i(d_k)}{\partial \lambda_i(c)} = \sum_{k:c_k=c} f_i(d)$$

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

E.g.: we actually saw the word “dish” with the “food” sense 3 times (maybe twice in one example and once in another).

The Derivative II: Denominator

$$\frac{\partial M(\lambda)}{\partial \lambda_i(c)} = \frac{\partial \sum_k \log \sum_{c'} \exp \sum_i \lambda_i(c') f_i(d_k)}{\partial \lambda_i(c)}$$

$$= \sum_k \frac{1}{\sum_{c''} \exp \sum_i \lambda_i(c'') f_i(d_k)} \frac{\partial \sum_{c'} \exp \sum_i \lambda_i(c') f_i(d_k)}{\partial \lambda_i(c)}$$

$$= \sum_k \frac{1}{\sum_{c''} \exp \sum_i \lambda_i(c'') f_i(d_k)} \sum_{c'} \frac{\exp \sum_i \lambda_i(c') f_i(d_k)}{1} \frac{\partial \sum_i \lambda_i(c') f_i(d_k)}{\partial \lambda_i(c)}$$

$$= \sum_k \sum_{c'} \frac{\exp \sum_i \lambda_i(c') f_i(d_k)}{\sum_{c''} \exp \sum_i \lambda_i(c'') f_i(d_k)} \frac{\partial \sum_i \lambda_i(c') f_i(d_k)}{\partial \lambda_i(c)}$$

$$= \sum_k P(c \mid d_k, \lambda) f_i(d_k)$$ = predicted count(f_i, λ)

The Derivative III

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

		c	P(c | λ)
d	meal, jail, …	food	.4
	jail, term, …	prison	.8

The λ(prison) weight for the "context-word:jail" feature: actual = 1 empirical = 1.2

- 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 features counts are from actual data).

Summary

- We have a function to optimize:

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

- We know the function's derivatives:

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

- Ready to feed it into a numerical optimization package…
- What did any of that have to do with entropy?

Smoothing: Issues of Scale

- Lots of features:
  - NLP maxent models can have over 1M features.
  - Even storing a single array of parameter values can have a substantial memory cost.
- Lots of sparsity:
  - Overfitting very easy – need smoothing!
  - Many features seen in training will never occur again at test time.
- Optimization problems:
  - Feature weights can be infinite, and iterative solvers can take a long time to get to those infinities.

Smoothing: Issues

- Assume the following empirical distribution:

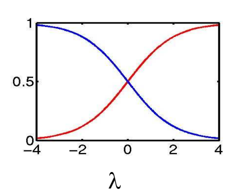
Heads	Tails
h	t

- Features: {Heads}, {Tails}
- We'll have the following model distribution:

$$p_{\text{HEADS}} = \frac{e^{\lambda_{\text{H}}}}{e^{\lambda_{\text{H}}} + e^{\lambda_{\text{T}}}} \qquad p_{\text{TAILS}} = \frac{e^{\lambda_{\text{T}}}}{e^{\lambda_{\text{H}}} + e^{\lambda_{\text{T}}}}$$

- Really, only one degree of freedom ($\lambda = \lambda_H - \lambda_T$)

$$p_{\text{HEADS}} = \frac{e^{\lambda_{\text{H}}} e^{-\lambda_{\text{T}}}}{e^{\lambda_{\text{H}}} e^{-\lambda_{\text{T}}} + e^{\lambda_{\text{T}}} e^{-\lambda_{\text{T}}}} = \frac{e^{\lambda}}{e^{\lambda} + e^{0}} \qquad p_{\text{TAILS}} = \frac{e^{0}}{e^{\lambda} + e^{0}}$$

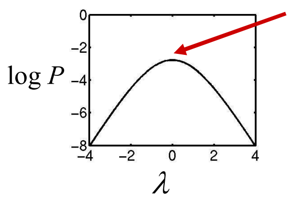


Smoothing: Issues

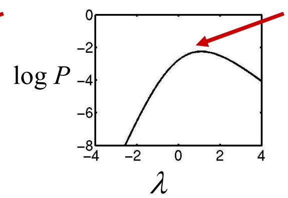
- The data likelihood in this model is:

$$\log P(h,t \mid \lambda) = h \log p_{\text{HEADS}} + t \log p_{\text{TAILS}}$$

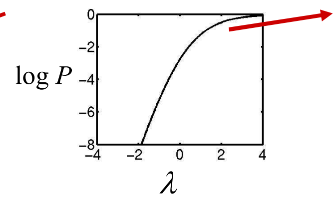
$$\log P(h,t \mid \lambda) = h\lambda - (t+h)\log(1+e^{\lambda})$$



Heads	Tails
2	2



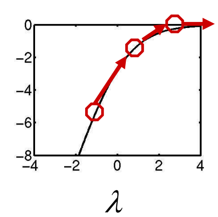
Heads	Tails
3	1



Heads	Tails
4	0

Smoothing: Early Stopping

- In the 4/0 case, there were two problems:
  - The optimal value of λ was ∞, which is a long trip for an optimization procedure.
  - The learned distribution is just as spiked as the empirical one – no smoothing.
- One way to solve both issues is to just stop the optimization early, after a few iterations.
  - The value of λ will be finite (but presumably big).
  - The optimization won't take forever (clearly).
  - Commonly used in early maxent work.



Heads	Tails
4	0

Input

Heads	Tails
1	0

Output

Smoothing: Priors (MAP)

- What if we had a prior expectation that parameter values wouldn't be very large?
- We could then balance evidence suggesting large parameters (or infinite) against our prior.
- The evidence would never totally defeat the prior, and parameters would be smoothed (and kept finite!).
- We can do this explicitly by changing the optimization objective to maximum posterior likelihood:

$$\log P(C, \lambda \mid D) = \log P(\lambda) + \log P(C \mid D, \lambda)$$

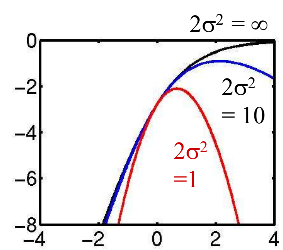
Posterior Prior Evidence

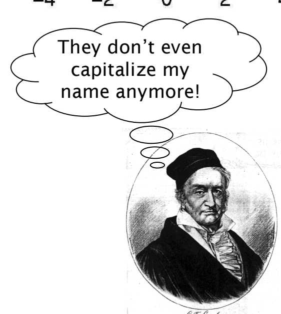
Smoothing: Priors

- Gaussian, or quadratic, priors:
  - Intuition: parameters shouldn't be large.
  - Formalization: prior expectation that each parameter will be distributed according to a gaussian with mean μ and variance σ^2.

$$P(\lambda_i) = \frac{1}{\sigma_i \sqrt{2\pi}} \exp\left(-\frac{(\lambda_i - \mu_i)^2}{2\sigma_i^2} \right)$$

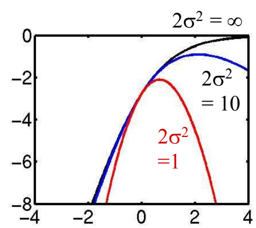
  - Penalizes parameters for drifting to far from their mean prior value (usually μ=0).
  - $2\sigma^2$=1 works surprisingly well (better to set using held-out data, though)





Smoothing: Priors

- If we use gaussian priors:
  - Trade off some expectation-matching for smaller parameters.
  - When multiple features can be recruited to explain a data point, the more common ones generally receive more weight.
  - Accuracy generally goes up!
- Change the objective:



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

$$\log P(C,\lambda \mid D) = \sum_{(c,d)\in(C,D)} P(c \mid d,\lambda) - \sum_i \frac{(\lambda_i-\mu_i)^2}{2\sigma_i^2} + k$$

- Change the derivative:

$$\partial \log P(C,\lambda \mid D)/\partial \lambda_i = \text{actual}(f_i,C) - \text{predicted}(f_i,\lambda) - (\lambda_i-\mu_i)/\sigma^2$$

Example: NER Smoothing

Because of smoothing, the more common prefixes have larger weights even though entire-word features are more specific.

Local Context

	Prev	Cur	Next
State	Other	???	???
Word	at	Grace	Road
Tag	IN	NNP	NNP
Sig	x	Xx	Xx

Feature Weights

Feature Type	Feature	PERS	LOC
Previous word	*at*	-0.73	0.94
Current word	*Grace*	0.03	0.00
Beginning bigram	*<G*	0.45	-0.04
Current POS tag	NNP	0.47	0.45
Prev and cur tags	IN NNP	-0.10	0.14
Previous state	Other	-0.70	-0.92
Current signature	Xx	0.80	0.46
Prev state, cur sig	O-Xx	0.68	0.37
Prev-cur-next sig	x-Xx-Xx	-0.69	0.37
P. state - p-cur sig	O-x-Xx	-0.20	0.82
…			
Total:		**-0.58**	**2.68**