Named Entities, Named Entity Tagging and Machine Learning

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Outline

- What is a Named Entity?
- HMM NE tagging
- Inferences based on less Information
- Combining Evidence: Maximum Entropy

What is a Named Entity?

- Definition 1: A single or multi-word expression that meets any of the following criteria:
  - is a proper noun phrase phrase
    - *Adam L. Meyers, PhD.*
    - *Professor Meyers*
    - *New York University*
  - is a proper adjective phrase, e.g., *Latin American*
  - has external distribution of NP, but different internal structure
    - January 3, 2012
    - Five Hundred Thirty
    - waffles@cs.nyu.edu
- Definition 2: A class of words and multi-word expressions defined by specifications tuned to information extraction tasks (can conflict with 1 by including "normal" nouns)
  - http://nlp.cs.nyu.edu/ene/ is a large NE hierarchy following definition 2.

What is a Proper Noun (Phrase)?

- Definition: A name of something that is (in English) capitalized even in non-initial position, typically representing unique individual objects. Proper nouns don't typically take determiners.
- What's unique?
  - Is *Adam Meyers* a proper NP even though there are more than one person with that name?
  - Are *Thursday* or *September 3* proper NPs even though there are more than one instance of these days?
  - What about car models such as the *Fiesta* which represent a type of objects rather than a specific object.
  - Color terms, e.g., *azure, salmon, peach*, … identify unique types, just like car models, yet they are not technically proper nouns
- Capitalization can be inconsistent
  - fields of study (like *computer science*) are capitalized inconsistently
  - different languages use different capitalization conventions

Internal Structure of Person Names

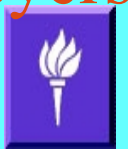
- NP → First_Name
- NP → (TitleP)?(First_Name)? (Middle_Name|Initial)?Last_Name (Post_Honorific)?
- TitleP →(Mod)* Title
- Mod → *vice* | *assistant* | *assist.* | *deputy*, …
- Title → *Mr.* | *Ms.* | *Mrs.* | *Miss* | *Master* | *Dr.* | *President*, …
- First_Name → *Adam* | *Jenny* | *Joshua* | *Nurit* | *Giancarlo* | *Ralph* | *Cristina* | *Satoshi* | *Heng* | *Xiang* | *Shasha* | *Wei* | *Ang* | *Bonan* | …
- Last_Name → *Meyers* | *Matuk* | *Lee* | *Grishman* | *Mota* | *Sekine* | *Ji* | *Li* | *Liao* | *Xu* | *Min* | …
- Post_Honorific → *Esq.* | *Jr.* | *Sr.* | *I* | *II* | *III* | *PhD.* | ...
- Note: specifications vary about whether titles and Post_Honorifics are or are not part of the name (ACE excludes titles, but includes post-honorifics)

Structure of Organization/Location/… Names

- Many Different Structures Possible
  - *Advanced Micro Devices* (ORG, normal NP)
  - *Council of Indian Nations* (ORG, normal NP)
  - *Yucatan Pennisula* (LOC, normal NP)
  - *United States of America* (GPE, normal NP)
  - *Ford Motors, Inc.* (ORG, NP plus right modifier)
  - *Alcoholics Anonymous* (ORG, NP plus right modifier)
  - *Head, Heart, Hands, Health* (list of nouns)
  - *Alfac* (ORG, newly coined single word)
  - *Addis Abba* (GPE, two foreign words)
  - *Merrill Lynch* (ORG, Person name structure)
  - *Nobody Can Beat the Wiz* (ORG, normal S)
  - *Hi Ho* (SONG, idiom)
- Unambiguous (like fixed phrases)
  - Name of ORG: *Advanced Micro Devices* (Advanced modifies Devices)
  - *[Advanced biology] textbook* vs. *Advanced [biology textbook]*

Some Other Entities

- Numbers and Quantities
  - Twenty Five Thousand, Five Hundred Fifty Eight
  - $200 million
- Times and Dates (not always names)
  - January 3, 2011
  - Ten o'clock
  - 10:30
  - last Thursday
  - St. Valentine's Day
- Addresses (street, email, url, …)
  - 1313 Mockingbird Lane, New York, NY 10003
  - hm1313@cs.nyu.edu
  - http://nlp.cs.nyu.edu/people/meyers.html



ACE Named Entities

- ACE Specifications online (name mentions only)
  - http://projects.ldc.upenn.edu/ace/docs/English-Entities-Guidelines_v6.6.pdf
- GPE – location with a government
  - city, state, county, country
  - people, physical location, government
- Location – geographical location
  - lake, mountain, ..
- Facility – man-made structure
  - bridge, street, building
- Person – person or group of people
- Organization – group of people with structure
  - commercial, government, club, non-profit

The ACE Task

- 2000-2008 Government-sponsored shared tasks (or bake-offs)
- Full Entity task
  - Annotation of mentions
    - Names, common noun, pronoun phrases that fall into the semantic classes (ultimately a superset of previous slide)
  - Coreference
    - Entity = Sets of mentions that refer to the same thing
- Other tasks
  - Relations: between two entities
    - located, part-whole, family, employment, ...
  - Events: entities are arguments of predicates
    - Movement, attack, be_born, marry, die, business_merge, declare_backruptcy, …
- Languages: English, Chinese, Arabic

Some Historical Notes

- Before ACE, NEs were introduced in 1995 as part of the MUC6 government task
  - http://www.cs.nyu.edu/cs/faculty/grishman/muc6.html
- The ACE task and several other NE tasks extended MUC6 in various ways.
- Other NE tasks, both government and SIG sponsored:
  - CONLL 2002-2003: English, Dutch, German, Spanish
  - IREX 1998-1999: Japanese (co-chairs: Sekine at NYU and Isahara at CRL)
  - SIGHan 2006: Chinese
  - TAC/KBP 2009 – Present: English (NIST)

Markov Chains (review)

- Markov chain is a WFSA in which an input string uniquely determine path through the Automaton
  - Q = set of states: q0 (start state), …, qF (final state)
    - q0 and qF are special in that they are not associated with observations
  - A = transition probability matrix A, each $a_{i,j}$ representing the probability of moving from state i to state j, such that $\sum_{j=1}^{n} a_{i,j}=1 \; \forall i$
- Assumptions
  - In an N-order markov model, a particular state depends on the previous N states. So far we have focused on first-order models (bigrams)
  - All outgoing edges from a node sum to 1
    - $\sum_{j=1}^{n} a_{i,j}=1 \forall i$
- Alternative (equivalent) formulation regarding initial/final states
  - Substitute transition probabilities from initial states and from final states with probabilities that particular states will be initial or final.

HMM (review)

- Hidden Markov model combines hidden events (indirect predictions) with Markov chains (transition probabilities are called **prior probabilities**)
- Adds following 2 things to Markov chains
  - $O_1 \ldots O_T$ – a sequence of T observations
  - $B=b_i(O_t)$ – observation **likelihoods** – each likelihood that observation O_t will occur, given state i
- Additional Assumption: Likelihoods depend only on the states in which they occur

Named Entity Task

- Similar to POS tagging and Chunking
- Typical manual markup
  - <LABEL> … </LABEL> (label = PER, GPE, ...)
  - States in HMM could correspond to:
    - Being inside constituents of each of the labeled types and being outside.
- Example POS/Chunking-like tagset:
  - B_PER, I_PER, B_GPE, I_GPE, B_ORG, I_ORG, B_LOC, I_LOC, … , NOT_NAME
  - A popular way to label transitions for HMM (and other) NE taggers.

Nymble: an HMM NE tagger

- NEs: organization, person, location, time, date, percent, money
- Bikel, et. al. (1996) – basis of next few slides
- MUC: http://www.cs.nyu.edu/cs/faculty/grishman/muc6.html
- Name Classes (NC): NE classes + other
- Begin and Internal tags are implied
  - *John/PER Smith/PER ,/OTHER Mary/PER Smith/PER*
  - No B-PER tag is mentioned in paper, but priors for initial words in a PER sequence are different than for subsequent elements of PER
- HMM using Viterbi algorithm
- Each word is an ordered pair: <word, features>
  - True/False features involving upper/lowercase/capitalization, digit/letter/punctuation, 1st word, etc.
  - <***John*** *<False,...,True,True,...>>* Only f*irstWord* and *initCap* are True
  - <***Smith*** *<False,...,False,True,...>>* *Only initCap* is True
  - <**,** *<False,...,True,...>>* Only *Other* is True
- Includes Backoff Model:
  - different (weighted) levels of prior probabilities are combined
  - bigrams, NCs, words, features, …

Nymbol – Probabilities Used

- Probability assumed to consist of:
  - Likelihood (of the word/prob sequence) X Priors (transitions between states)
- Probability of Tag Sequence *NC* given Input Token Sequence *W*
  - $Pr(NC|W) = \frac{Pr(W|NC)}{Pr(W)} \times Pr(NC)$ # Bayes Rule
  - $\frac{Pr(W|NC)}{Pr(W)} \times Pr(NC) \approx Pr(W|NC) \times Pr(NC)$ # Pr(W) ignored (same for any tag seqs)
  - $Pr(W|NC) = Liklihood \quad Pr(NC) = Prior$
- Likelihood Approximated is based only on its NC (as with HMM)
  - $Pr(W|NC) \approx \prod_{i=1}^{n} P(w_i|nc_i)$
  - Backoff: withhold 10–20% of training data for OOV model
    - Base probabilities above on words in this subcorpus, but not in the regular training corpus.
    - Assume words found **only** in the held-out (10-20%) are "unknown words" and calculate all of the above probabilities based on the occurrence of these words in this subcorpus.
- Prior calculated differently for different parts of the sequence
  - Otherwise, same as HMM used for POS tagging
  - Details on next Slide

Nymbol – Prior Probabilities

- Prior for 1st word of a NC: $Pr(NC|NC_{-1}, w_{-1}) \times Pr(<w, f>_{first}|NC, NC_{-1})$
  - $Pr(NC|NC_{-1}, w_{-1})$ # e.g., *Mr.* precedes B-PER
  - $Pr(<w, f>_{first}|NC, NC_{-1})$ # e.g., O precedes capitalized B-PER
- Prior for subsequent words of NC:
  - $Pr(<w, f>|<w.f>_{-1}, NC)$ # sequences of same/diff class
- Probability that the current word ends an NC:
  - $Pr(<+end+, other>|<w, f>_{final}, NC)$
- Main difference with POS tagging HMM (HW4): substitute words with a vector of features <word, baseform, first, capitalized, ...>

Nymbol – Backoff for Prior Probabilities

- High Weight on More Specific Info
- Name Class Bigrams
  - $Pr(NC|NC_{-1},w_{-1}) \subset Pr(NC|NC_{-1}) \subset Pr(NC) \ldots \frac{1}{number\ of\ NCs}$
- First Word Bigrams
  - $Pr(<w,f>_{first}|NC,NC_{-1}) \subset Pr(<w,f>|<+begin+,other>,NC) \subset$
    $Pr(<w,f>|NC) \subset \ldots Pr(w|NC) \times Pr(f|NC) \subset \frac{1}{\text{vocab\_size}} \times \frac{1}{\text{number\_features}}$
- Non-First Word Bigrams
  - $Pr(<w,f>|<w,f>_{-1},NC) \subset Pr(<w,f>|NC) \subset$
    $Pr(w|NC) \times Pr(f|NC) \ldots \subset \frac{1}{\text{vocab\_size}} \times \frac{1}{\text{number\_features}}$

Smoothing (in Nymbol)

- Order Models by amount of Info: $M_1 \subset M_2 \subset M_3 \subset M_4 \ldots$
- Apply weight Λ to the back-off model and 1 – Λ to the initial model
  - This is called smoothing
- Λ based on relative sample sizes of M and M'
  - In model M, Pr(X|Y) is based on the count of Y (more info)
  - In model M', Pr(X|Y') is based on the count of Y' (backoff model)
  - c(Y') > c(Y) e.g., suppose Y = NC_{-1},w_{-1} and Y' = NC_{-1}
- Λ favors backing off to more frequent and less diverse models
  - $$\lambda = \left(1 - \frac{c(Y)}{c(Y')}\right) \times \frac{1}{1 + \frac{\text{unique\_outcomes}(Y')}{c(Y')}}$$
  - 1st factor: Positive if Y' > Y and increases as Y' increases
  - 2nd factor: .5 if Y' is maximally diverse and approaches 1 as the number of diverse outcomes decreases to 1

If Lots of Evidence, Do Machine Learning

- Suppose you want to combine lots of features together and take advantage of any correlation to predict outcomes
- Methods for doing this fall into the area called machine learning
- These methods include: Maximum Entropy, Support Vector Machines, Naive Bayes, Conditional Random Fields, Neural Networks, and several others.
- Supervised or Unsupervised
  - **Supervised**: **Methods in which statistical models are "trained" based on manually annotated text. ***
    - We will focus on these.
  - Unsupervised: Methods in which statistical models are based on assumptions about un-annotated data

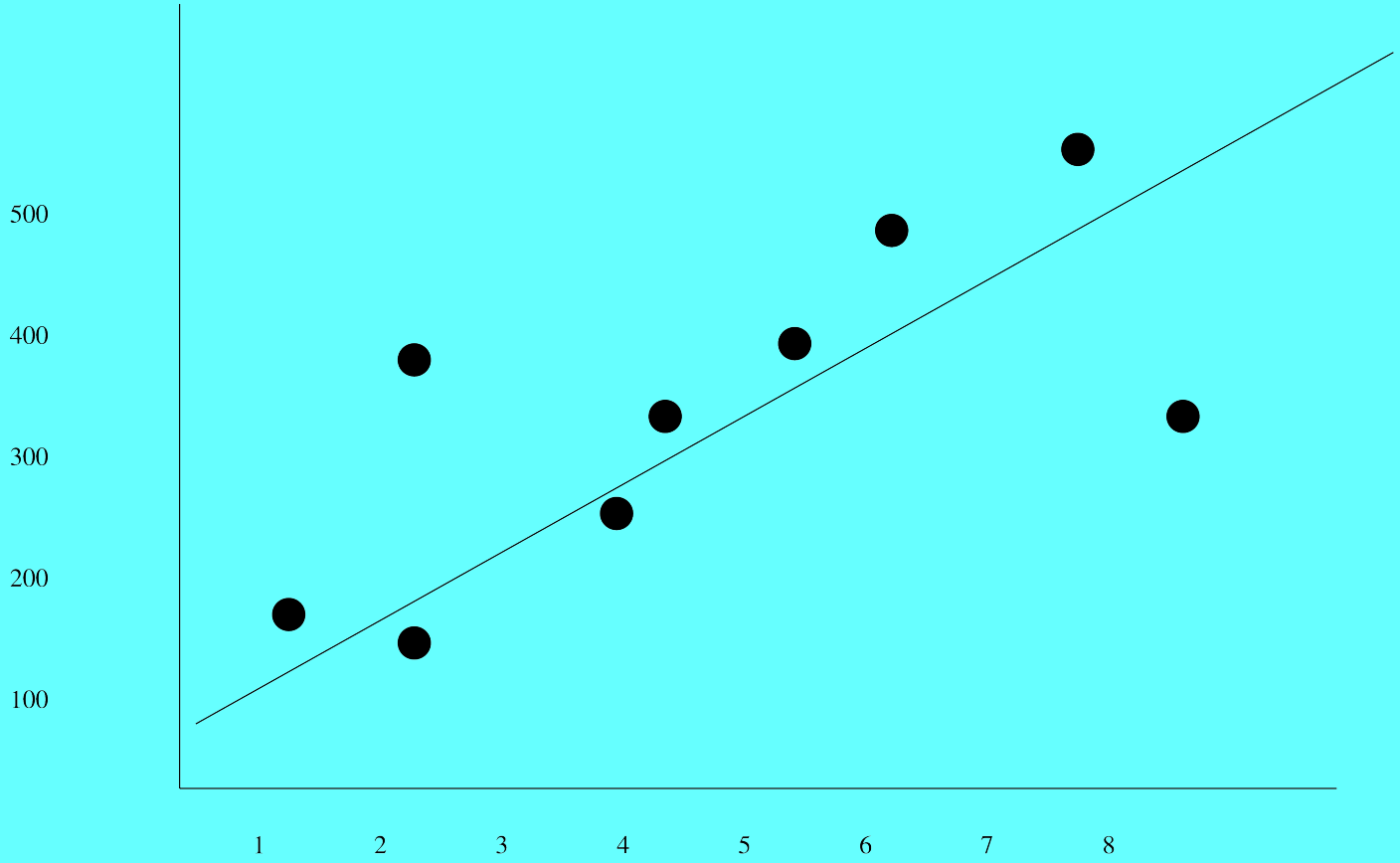
High Level Description of ML

- Input = Data correctly annotated with observable set of features
  - Training Corpus
  - Test or Development Corpus
- Machine Learning Algorithms
  - Methods for combining evidence and making predictions
- Tookits for Multiple Machine Learning Algorithms
  - JAVA
    - OpenNLP maxent package: http://maxent.sourceforge.net/howto.html
      - Default for HW6
    - WEKA: http://www.cs.waikato.ac.nz/ml/weka/
    - MALLET: http://mallet.cs.umass.edu/
  - Python
    - NLTK's classication package (Chapter 6)
    - Also: http://scikit-learn.org/ [I know less about this one]

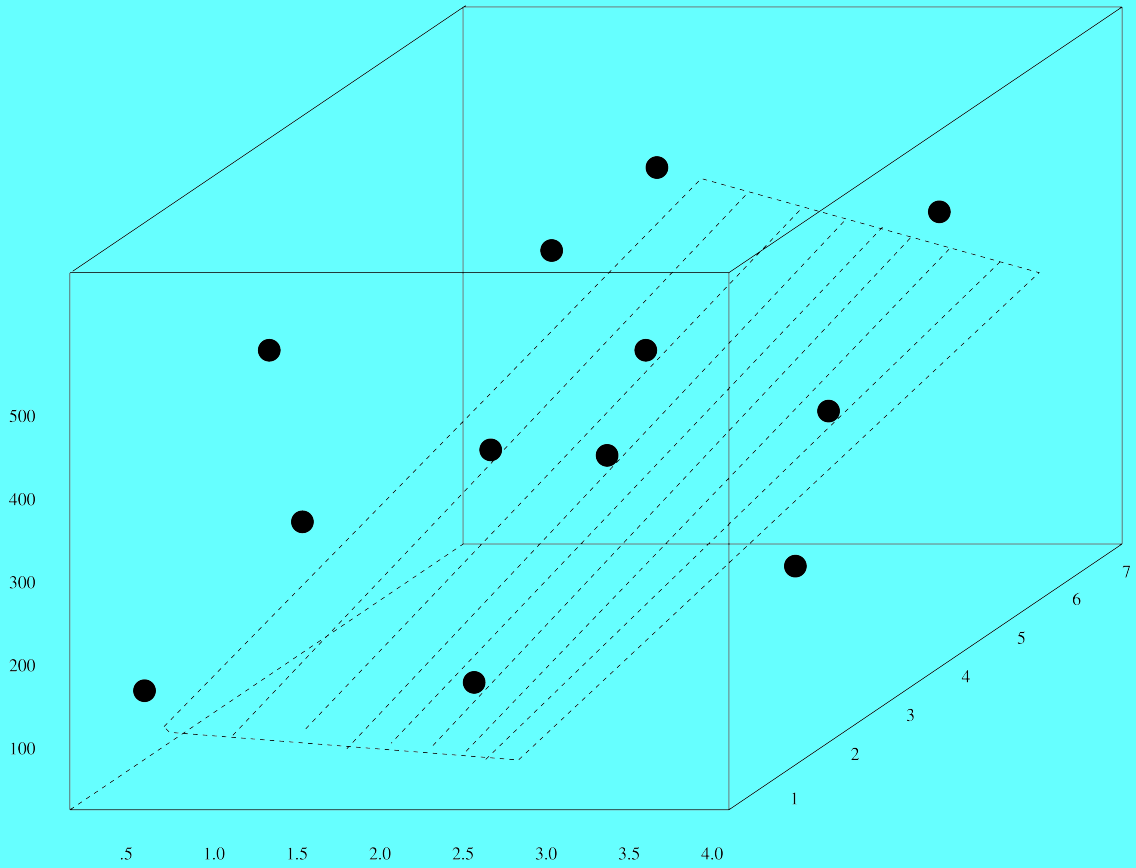
Making and Tuning ML Systems

- Experiment with Different ML Algorithms
  - Use the same set of features
  - Toolkits make switching easy
  - May help to understand some differences
    - Speed/complexity → limit size of training data
    - Assumptions about Feature Independence
  - Tweaking features, making new algorithms and making new more efficient versions of current ML algorithms
- Experiment with Different Sets of Features
  - Keep algorithm fixed
  - Vary numbers of features
  - Possible strategy: use as many features as possible
    - When these systems work, It cannot always be explained why
  - Possible strategy: use features that can be expected to make a prediction
- Possible to make an excellent ML system while treating algorithms as black boxes

Scatter Plot for 2 Features approximated by Regression Line:



Scatter Plot with 3 features approximated with a Regression plane



Regression Analysis

- Represent features as dimensions in a graph
- Approximate correlations using a figure with one fewer dimensions
- 2 dimensions/features – approximate with a line (a 1 dimensional representation)
- 3 dimensions/features
  - approximate with a plane (2 dimensions) or
  - a line (1 dimension)

Log Linear Classifiers (Important for Understanding Maximum Entropy)

- A log linear classifier
  - Extract features (real number) from input
  - Multiply each feature by a weight
  - Use this total as an exponent
- $$p(c|x) = \frac{1}{Z} \times e^{\sum_i w_i f_i}$$
- c = class, x = observation, Z normalizing factor, w_i and f_i are features and weights (both depending on c)
- Z makes all probabilities sum to 1
- e = mathematical constant, approximately 2.718

Linear Regression

- Tasks that map input features to output
  - linear regression (real numbers)
  - linear classifier (discrete classes)
- Combining feature weights
  - $y = \sum_{i=0}^{N} w_i \times f_i \qquad assuming\ f_0 = 1$
  - Expressed compactly in dot product notation: $y = w \cdot f$
- Regression line (y = mx + b) line that fits data (for features x,y)
  - m that minimizes cost of difference of predicted ($y^{(j)}_{pred}$) vs observed ($y^{(j)}_{obs}$)
  - $y^{(j)}_{pred} = \sum_{i=0} w_i \times f^{(j)}_i \qquad cost(W) = \sum_{j=0}^{M} (y^{(j)}_{pred} - y^{(j)}_{obs})^2$
  - Normalize cost by squaring, not absolute value
    - Outliers have an effect, adding absolute values would allow them to be ignored

Logistic Regression

- If we assume binary values (true|false or 1|0)
  - $p(y=true|x)=\frac{e^{w\cdot f}}{1+e^{w\cdot f}}$ and $p(y=false|x)=\frac{e^{-w\cdot f}}{1+e^{-w\cdot f}}$
  - The dot product of features:
    - $w\cdot f=\ln(\frac{p(true)}{p(false)})$
    - A number between positive and negative infinity
- Our observation should be labeled true if:
  - p(true|x) > p(false|x)
  - Or if $w\cdot f=\ln(\frac{p(true)}{p(false)})>0$
  - This equation is the hyperplane dividing the space of features into 2 predicted outcomes.
  - Learning these weights will not be covered here

Maximum Entropy

- Multinominal logistic regression: generalization of logistic regression to cover more than 2 classes, aka, Maximum Entropy
- Features have 2 values: 1 (True) or 0 (False)
- Linear regression for classes C = $\{c_1, \ldots, c_C\}$

$$p(c|x) = \frac{1}{Z} \times e^{\sum_i w_i f_i} \qquad Z = \sum_{c' \in C} e^{\sum_{i=0}^{N} W_{c'_i} f_i}$$

$$p(c|x) = \frac{e^{\sum_{i=0}^{N} w_{ci} f_i(c,x)}}{\sum_{c' \in C} e^{\sum_{i=0}^{N} wc'i f_i(c',x)}}$$

Maximum Entropy 2

- For each observation x and class c, we can find the probablity of c given x:

$$p(c|x)=\frac{e^{\sum_{i=0}^{N} w_{ci} f_i(c,x)}}{\sum_{c' \in C} e^{\sum_{i=0}^{N} wc'i f_i(c',x)}}$$

- We can choose the most probable classification:

$$\hat{c}=\underset{c \in C}{argmax}\, P(c|x)$$

- Or the most probable sequence of classifications as in a MEMM (Maximum Entropy Markov Model)
- Principle of Maximum Entropy: the principle best representing the current state of knowledge is the principle consistent with the data that has the highest entropy (level of uncertainty)

MEMM

- Most probable tag set T given the word sequence W

$$\hat{T} = \underset{T}{argmax}\, P(T|W)$$

- Prob of states Q = $q_1,\ldots,q_n$ given observations O=$o_1,\ldots, o_n$ when MEMM is simulating an HMM:

$$P(Q|O) = \prod_{i=1}^{n} P(q_i|q_{i-1}, o_i) = \prod_{i=1}^{n} P(o_i|q_i) \times \prod_{i=1}^{n} P(q_i|q_{i-1})$$

- MEMMs can and do incorporate more features.
  - HMM features, capitalization features, Nymbol-like features, prefixes, suffixes, letter combinations (which may indicate word origin), etc.
- Other "Machine Learning" paradigms: Baysean networks, Support Vector Machines, Perceptron, ...

Summary

- Named Entities: Classifications of names and sometimes other special noun phrases
- Supervised Machine Learning: Means of predicting a class in test data, given observed co-occurring features in training data
- Maximum Entropy – one such method

HW Assignment 6 – Due April 7

http://cs.nyu.edu/courses/spring16/CSCI-UA.0480-011/homework6.html