# Shallow Parsing, Named Entities, and Machine Learning

Adam Meyers
New York University

# Outline

- Shallow Parsing
- What is a Named Entity?
- Converting Shallow Parsing Tasks to Sequence Labeling Tasks (like POS tagging)
- Applying Machine Learning Packages to Sequence Labeling Tasks

# Shallow or Partial Parsing

- Finding constituents in a sentence, but not parsing the whole sentence
- Shallow Parsing identifies “short phrases”:
  - Noun Group and Verb Group Chunking
  - NE tagging
  - Identifying Time Expressions
  - Identifying other phrases in text

# 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.

# Annotating Names in Sample Documents

- Sample Documents to be annotated with Mae with name.dtd
  - State of the Union addresses by Obama and Trump
  - Einstein's Theory of Relativity
- Named Entity Definitions
  - GPE = location with government or set of GPEs
  - PER = person or set of people
  - ORG = organization, club, society, etc. – set of people with (governing) structure
  - Other = Word sequence widely recognized as name (not a good definition)
- Attempts at annotation of samples illustrate:
  - Difficulty of applying these criteria
  - Suggests need for more detailed specifications
  - Specifications may be influenced by goal of research, e.g., is the "name" of a scientific theory a type of "name"?

# What is a Proper Noun (Phrase)?

- Definition: A name of something that is (in English) capitalized even in non-initial position, typically representing a unique individual object. 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)
  - https://www.ldc.upenn.edu/sites/www.ldc.upenn.edu/files/english-entities-guidelines-v6.6.pdf
- GPE – location with a government
  - city, state, county, country
  - people, physical location, government
  - ***US, New York City, Queens, Greenwich Village***
    - ***The US attacked Sweden***
    - ***The US likes quacamole***
    - ***The US is in North America***
- Location – geographical location
  - lake, mountain, natural structure
  - ***Hudson River, Mt. McKinley, the Grand Canyon***

# ACE Named Entities 2

- Facility – man-made structure
  - bridge, street, building
  - ***The Brooklyn Bridge, 12 Street, The Forbes building***
- Person – person or group of people
  - ***Adam Meyers, The Smiths*** (meaning a group of people with the last name ***Smith***)
- Organization – group of people with structure
  - commercial, government, club, non-profit
  - ***New York University, the Glee Club, the NYU Fencing Team, New York Police Department, Alphabet, Inc., Google, Inc., The Dungeons and Dragons Club***

# 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, (plus limited Spanish)

# 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)
- **For NE for final projects**
  - **NYUClasses (Resources) or Linguistic Data Consortium**

# BIO Tagging and HMM

- HW 3 used an HMM to identify POS tags
- Property of POS tagging:
  - Each token has exactly one Tag
- BIO Tags (see also limits_of_sequence_labeling slides)
  - Provide a way to analyze short phrases using one tag per token
  - Example with Noun Group Identification
    - ***The***/B-NG ***blue***/I-NG ***book***/I-NG ***is***/O ***in***/O ***the***/B-NG ***box***/I-NG ***.***/O
    - BGs from annotated sentence: "***The blue book***" & "***the box***"
  - B-X = Beginning X, I-X = Inside X, O = Outside of constituent (or other)
  - Tags can be specific to phrase type: B-Per, I-Per, B-GPE, I-GPE, … etc.

# More Examples of BIO Tags

- NE Annotation:
  - ***Adam***/B-PER ***Meyers***/I-PER ***is***/O ***at***/O ***New***/B-ORG ***York***/I-ORG ***University***/I-ORG **.**/O
- Noun Group Chunking:
  - ***He***/B-NG ***teaches***/O ***NLP***/B-NG ***in***/O ***the***/B-NG ***Department***/I-NG ***of***/O ***Computer***/B-NG ***Science***/I-NG **.**/O
- Time Expressions
  - ***It***/O ***was***/O ***10***/B-TMP ***o'clock***/I-TMP ***on***/O ***Saturday***/B-TMP.
- Typically, only 1 task is covered at a time

# Shallow Parsing as Sequence Labeling

- POS tagging is a sequence labeling task
  - Assigning labels to tokens in a seqeunce
- We used an HMM for POS tagging
  - HMM uses the following “features” to predict POS:
    - Previous POS
    - Current word
- BIO tags (like POS) are labels on individual words
- Can we use an HMM or something like it to predict BIO tags and therefore short phrases?

# Features that May Predict Short Phrases

- Previous BIO Tag
- Word Related: Previous word (or Beg_Sentence), 2 words previous, Current Word, Following Word (or End Sentence), 2 words ahead, etc.
- Previous POS, POS of 2 words previous, Current POS, Next POS, etc.
- Captial or lowercase properties, last letter of current word, class in dictionary class, member of word list, etc.

# Can we use lots of features in an HMM, like our POS tagger?

- Nymble: an HMM-style NE tagger
  - Replaces words with sets of features about orthography of word, e.g., ***TwoDigitNum, ContainsDigitandAlpha, allCaps, firstWord, initCap, …***
  - Different probabilities for beginning, ending and inside elements of NE differently
  - OOV model based on 20% sample from corpus
- Bikel, et. al. (1996). *Nymble: A High-performance Learning Name-finder*. in ANPL 1997

# 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
- HMM (and Nymble's approach) are ways of doing machine learning, but now we will discuss machine learning more generally
- Algorithm Used for Homework 5: ***Maximum Entropy***
- 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
  - Semi-supervised: Methods that combine supervised and Unsupervised

# High Level Description of Supervised ML

- Input = Data correctly annotated with observable set of features
  - Training Corpus
  - Development Corpus
  - Test 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 HW5
    - WEKA: http://www.cs.waikato.ac.nz/ml/weka/
    - MALLET: http://mallet.cs.umass.edu/
  - Python
    - NLTK's classication package (Chapter 6)
    - Scikit-learn: http://scikit-learn.org/stable/

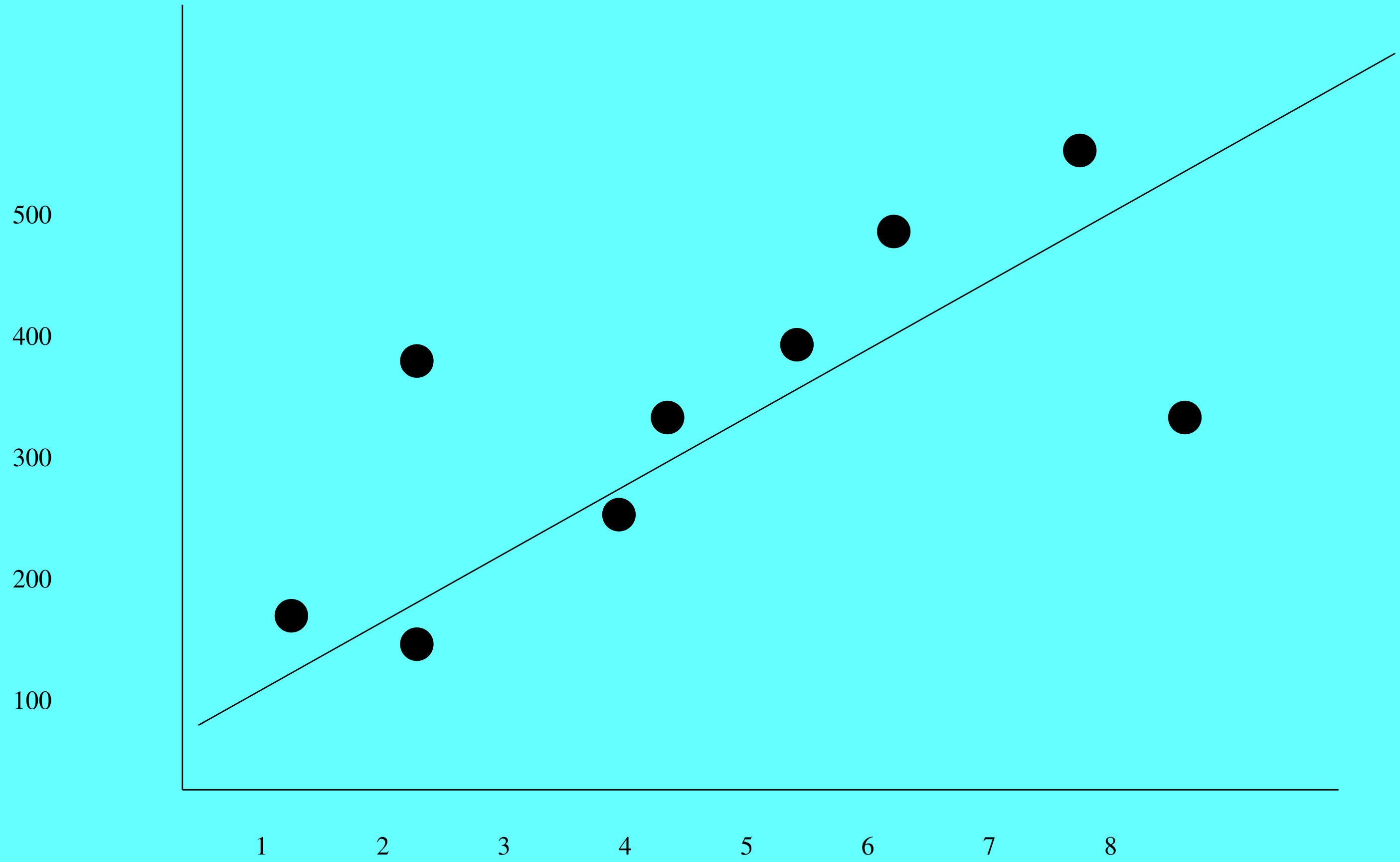
# Making and Tuning ML Systems

- Experiment with Different ML Algorithms
  - Use the same set of features
  - Toolkits make switching easy
  - May help to understand differences between algorithms
    - 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 features
  - Easy to explain success if you use features that can be expected to make a prediction
  - May be more effective to use as many features as possible (regardless of expectations)
    - When these systems work, it cannot always be explained why
- Possible to make an excellent ML system while treating algorithms as black boxes

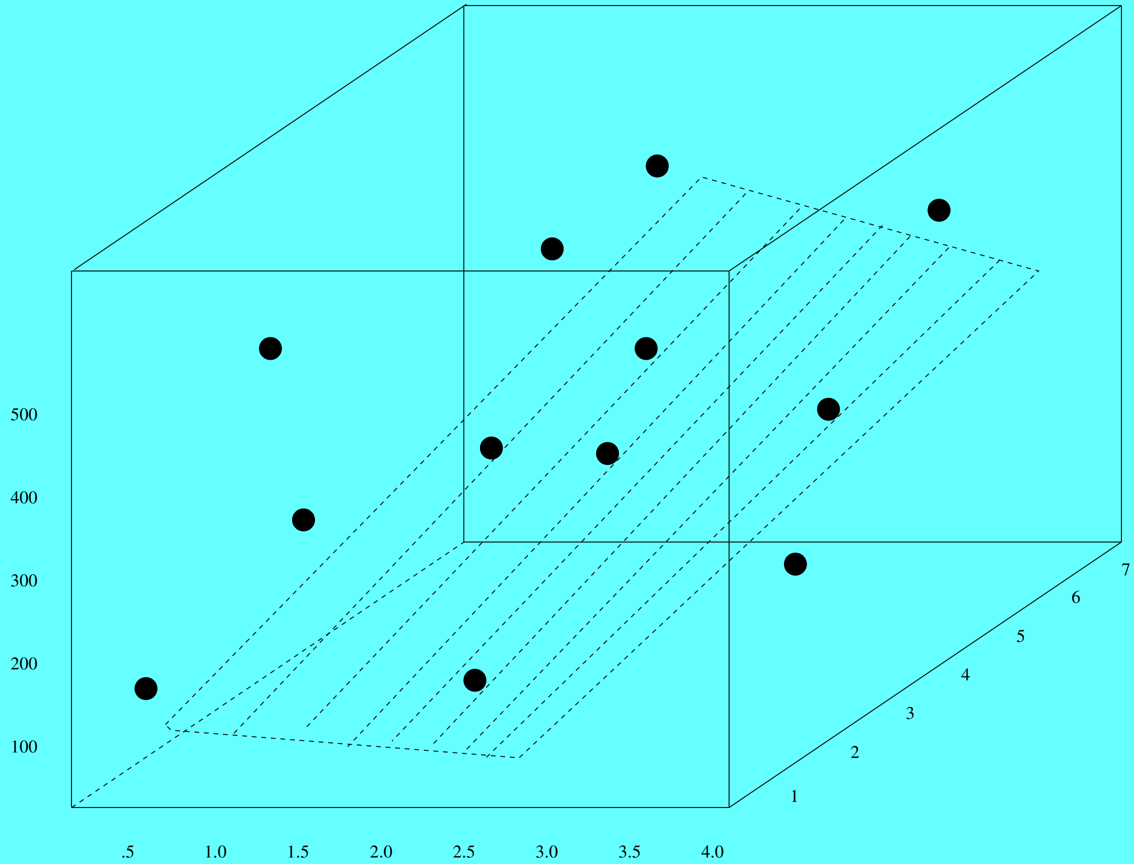
# Regression Analysis (Used in many ML Algorithms)

- Represent features as dimensions in a graph
- Approximate correlations using a figure with fewer dimensions
- 2 dimensions/features – approximate with a line (a 1 dimensional representation)
  - 1 feature "predicts" the other, e.g., height predicts shoe size
- 3 dimensions/features
  - approximate with a plane (2 dimensions) or
    - 2 features (height and age) predicts a 3$^{rd}$ feature (shoe size)
  - a line (1 dimension)
    - 1 feature (age) predicts 2 features (height and shoe size)
- Correlations Used to Predict Values in ML

# Scatter Plot for 2 Features approximated by Regression Line:



# Scatter Plot with 3 features approximated with a Regression plane



# Machine Learning Algorithms

- Naive Bayes: Assumes that all features are independent of each other. Basically the probabilities of features in each category are multiplied together.
- Maximum Entropy: Combines features using weights that are adjusted via “smoothing”.
  - Normalizes result to a number between 0 and 1.
  - MEMM: Viterbi algorithm w/ Maximum entropy
- Other “traditional”: Support Vector Machines, Regression, Kernels, Conditional Random Fields, etc.
- Deep Learning: CNN, RNN, …

# Summary

- Named Entities: Classifications of names and sometimes other special noun phrases
- BIO Tags: Encoding Phrases as tags on tokens
- Supervised Machine Learning: Means of predicting a class in test data, given observed co-occurring features in training data

# HW 5

- https://cs.nyu.edu/courses/spring23/CSCI-UA.0480-057/homework5.html
- Due night of the 7th (Graduate) or 15th (Undergraduate) class

# Final Project (Undergraduate): Chunking

- Extend Methods in HW 5
  - Experiment with more ML algorithms
  - Versions of MEMM
  - Experiment with feature combinations
    - Incorporate Word Embeddings?
- Extend to additional types of Chunks
  - Extend Dataset – start with full parsed Penn Treebank and determine Chunks heuristically
  - Verb Groups, Preposition Groups, etc.
- Compare with previous work (cite)
- Evaluation
  - Split into training, development test
  - Use similar scoring as HW5

# Final Project: Build a NE Recognizer (Undergraduate)

- Use an annotated data set (e.g., ACE, BioNLP)
- Divide data into training, development & test sets
- Carefully orchestrated experiments to test
  - Different ML algorithms with same/similar features
  - Test particular features
  - Use manual rules
- Compare your work to cited work (academic papers)
- Do error analysis on your development set
  - Try to explain results and suggest ideas for future work

# Final Project (Undergraduate): Annotation

- Choose corpus
  - Licensing considerations
  - How do NEs apply to this data?
  - Research Questions: NEs in particular genre or NEs for a particular task
- Write specifications → test specifications → repeat
  - More than 1 annotator
  - Test for inter-annotator agreement
- Compare work to previous (cited) work
- Who will annotate:
  - expert annotators (NLP students)?
  - crowd source (Amazon Turk)?
- Pilot Project – may not have time for lots of annotation (unless Crowd Source)
- Evaluation:
  - inter annotator agreement
  - Precision and Recall vs. Adjudicated Results