Hybrid Information Extraction Systems

Class 2: Entity Linking

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What are Named Entities?

- At its core, proper names
- Nowadays generalized to nouns and multi-word expressions within a semantic class
  - 200 categories including "color" which contain common nouns
- Useful outside IE
  - Reduce the vocabulary space, instead of every name of every person have a token "NAME_OF_PERSON"

Some Example NEs

[Fred Flintstone]$^{\text{person}}$ was named [CTO]$^{\text{position}}$ of [Time Bank Inc.]$^{\text{organization}}$ in [2031]$^{\text{date}}$. The [next year] [he] got married and became [CEO]$^{\text{position}}$ of [Dinosaur Savings & Loan]$^{\text{organization}}$.

NE in the Context of IE

- NEs are the entries in the DB
- Events are the DB schema

Named Entity Recognition Techniques

- We will discuss them in class 2 (tomorrow)
    - Regular Expressions
    - Lists of names (gazzetteers)
    - Machine learning

Regular Expressions

- Regular Expressions are a succint way to encode an automaton that accepts a regular language
- Constructs:
  - literal (e.g. /RÉSOLU/)
  - character class (e.g., /[0-9]/)
  - quantifiers (e.g., /,?/)
  - groups (e.g., /([0-9][0-9][0-9])/)

RE: Literal

- Literals are characters or sequences of characters that need to be matched verbatim
  - In perl code from the baseline: /(concernant)/
- Characters that have a meaning in the RE language (e.g., '?') need to be escaped (e.g., '\?')
  - In Java you will need to double escape (e.g., "\\?")
- Special quotation to escape unknown sequences: \E ... \Q
  - In perl code from the baseline: /\Q$amount\E\spour/

RE: Character Classes

- Succint way to describe a set of characters
  - Either by listing all members (e.g, /[xyz]/)
  - Or by using a range (e.g., /[0-9]/)
- There are also patterns for most common sets
  - /\d/ for digits
  - /\s/ for white space
  - special class /./ that matches any character

RE: Quantifiers

- Extend the smaller regular recursively

?	one or nothing
*	nothing, one or more
+	one or more
{n,m}	at lest n, at most m

- From perl baseline /.*RÉSOLU À L'UNANIMITÉ:/

RE: Groups

- Concatenate other regular expressions
  - /concernant?\spour/ means the t is optional!
  - /(concernant)?\spour/ means concernant is optional
- The regular expressions inside a group could be of any complexity, including groups
  - /(concertnant\s)?pour/
- By default groups are capturing which means the match is returned by the system
  - Non-capturing groups are indicated with ?:
  - /(?:concernant\s)?pour/

RE: Alternatives

- Indicates two or more regular expressions could be matched
  - /((du\scontrat\sde)|(requis\spour)|(concernant)/
  - Character classes are a succint way to representing many alternatives
- Watch out the need for grouping
  - /du\scontrat\sde|requis\spour/ means (du\scontrat\sd)[er](equis\spour) which is not what you want

Amount RE

- /(\d?\d?(?:\s?|\.?)\d{3}(?:\s?|,?)(?:\d{3})?(?:\,\d{2})?\s?\$)/
- (\d?\d? // two digits (optional)
  - (?:\s?|\.?) // a space or a period (optional)
  - \d{3} // three digits (required)
  - (?:\s?|,?) // a space or a period (optional)
  - (?:\d{3})? // three digits (optional)
  - (?:\,\d{2})? // an optional comma followed by two digits
- \s?\$) // an optional space with a required dollar sign

What is Machine Learning?

- A new way of programming
- Magic!
- Leaving part of the behavior of your program to be specified by calculating unknown numbers from "data"
  - Two phases of execution: “training” and “application”

The ultimate TDD

- If you're using a library, you almost do no coding, just test!
- But every time you test, your data becomes more and more obsolete
  - No peeking!
- Have met people who didn't have any tests and considered
  - Bugs in the code same are the same as model issues
  - My experience has been quite the opposite, the code you write on top of machine learning algorithms has to be double and triple checked

Taxonomy of Machine Learning Approaches

- **Supervised learning**

  Monkey see, monkey do

  - Classification
- **Unsupervised learning**

  Do I look fat?

  - Clustering
- Others
  - Reinforcement learning: learning from past successes and mistakes (good for game AIs and politicians)
  - Active learning: asking what you don't know (needs less data)
  - Semi-supervised: annotated + raw data

Concepts

- Trying to learn a function $f(x_1, \ldots, x_n) \rightarrow y$
  - x_i are the **input** features.
  - y is the **target** class.
- The key here is *extrapolation*, that is, we want our learned function to **generalize** to unseen inputs.
  - Linear interpolation is on itself a type of supervised learning.

Data

- Collecting the data
  - Data collection hooks
  - Annotating data
    - Annotation guidelines
    - Cross and self agreement
- Representing the data (as **features**, more on this later)
- Understanding how well the system operates over the data
  - Testing on **unseen** data
- A DB is a rather poor ML algorithm
  - Make sure your system is not just memorizing the data
  - "Freedom" of the model

Evaluating

- Held out data
  - Make sure the held out is representative of the problem and the overall population of instances you want to apply the classifier
- Repeated experiments
  - Every time you run something on eval data, it changes you!
- Cross-validation
  - Training and testing on the same data but not quite
  - data = {A,B,C}
    - train in A,B, test in C
    - train in A,C, test in B
    - train in B,C, test in A

Metrics

- Measuring how many times a classifier outputs the right answer ("accuracy") is not enough
  - Many interesting problems are very biased towards a background class
  - If 95% of the time something doesn't happen, saying it'll never happen (not a very useful classifier!) will make you only 5% wrong
- Metrics:

$$precision = \frac{|correctly\ tagged|}{|tagged|} = \frac{tp}{tp + fp}$$

$$recall = \frac{|correctly\ tagged|}{|should\ be\ tagged|} = \frac{tp}{tp + fn}$$

$$F = 2 \cdot \frac{P \cdot R}{P + R}$$

Naive Bayes

- Count and multiply
- How spam filters work
- Very easy to implement
- Works relatively well but it can seldom solve the problem completely
  - If you add the target class as a feature, it will still has a high error rate
  - It never "trusts" anything too much

Why Naive?

- Bayes Rule

$$p(C \mid F_1, \ldots, F_n) = \frac{p(C)\,p(F_1, \ldots, F_n \mid C)}{p(F_1, \ldots, F_n)}$$

$$posterior = \frac{prior \times likelihood}{evidence}$$

- Naive Part
  - Independence assumption of the F_x, that is $p(F_i \mid C, F_j) = p(F_i \mid C)$

$$p(C|F_1, \ldots, F_n) \propto p(C)\,p(F_1 \mid C) \ldots p(F_n \mid C)$$

Maximum Entropy

- Tons and tons of (binary) features
- Very popular at beginning of 2000's
  - CRF has taken some of its glamour
    - Mature code
- OpenNLP MaxEnt uses strings to represent its input data

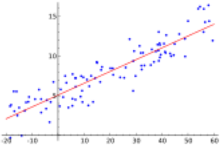
  previous=succeeds current=Terrence next=D. currentWordIsCapitalized

- Training with `trainModel(dataIndexer, iterations)` and using it with `double[] eval(String[] context)`

Maximum Entropy Details

- A maximum entropy classifier is a multi-class generalization of a logistic regression, so we will discuss them instead
  - Multi-class can be obtained by a number of techniques, e.g., using a pivot class
- Related to Naive Bayes if we think of it as not estimating the probability of the features given the class, but the probability of the class given the features directly
  - So we don't need to make an independence assumption between the features anymore

Linear Regression



$$y_i = \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i = \mathbf{x}_i^{\mathrm{T}} \beta + \varepsilon_i, \qquad i = 1, \ldots, n$$

Least-squares Estimation

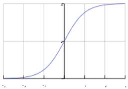
Representing the problem as $\mathbf{y} = \mathbf{X}\beta + \varepsilon$ where

$$\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \quad \mathbf{X} = \begin{pmatrix} \mathbf{x}_1^{\mathrm{T}} \\ \mathbf{x}_2^{\mathrm{T}} \\ \vdots \\ \mathbf{x}_n^{\mathrm{T}} \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix}, \quad \beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

a closed solution forβ is given by:

$$\hat{\beta} = (\mathbf{X}^{\mathrm{T}}\mathbf{X})^{-1}\mathbf{X}^{\mathrm{T}}\mathbf{y} = \left(\sum \mathbf{x}_i \mathbf{x}_i^{\mathrm{T}}\right)^{-1} \left(\sum \mathbf{x}_i y_i\right)$$

Logistic Function



$$F(t) = \frac{e^t}{e^t+1} = \frac{1}{1+e^{-t}}$$

Logistic Regression: Intuition

- We move from the target function space to the probability space for the target function being on a certain class
- Minimize the error for a linear combination of features approximating the logit of the said probability
- No close solution, use numerical methods to find an approximate solution

Logistic Regression, estimating p_i

$$Y_i \mid x_{1,i}, \ldots, x_{m,i} \sim \text{Bernoulli}(p_i) \tag{1}$$

$$\mathbb{E}[Y_i \mid x_{1,i}, \ldots, x_{m,i}] = p_i \tag{2}$$

$$\Pr(Y_i = y_i \mid x_{1,i}, \ldots, x_{m,i}) = \begin{cases} p_i & \text{if } y_i = 1 \\ 1 - p_i & \text{if } y_i = 0 \end{cases} \tag{3}$$

$$\Pr(Y_i = y_i \mid x_{1,i}, \ldots, x_{m,i}) = p_i^{y_i}(1 - p_i)^{(1-y_i)} \tag{4}$$

Estimating p_i and regression coefficients

- The p_i and the linear combination coefficients are all unknown so we resort to a search process that minimizes the error on training

$$\text{logit}(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_m x_{m,i}$$

  - Need some regularization process to avoid trivial or overtly complex solutions

How to Come Up with Features

1. Throw everything (and the kitchen sink) at it
2. Stop and think
    1. What information would **you** us to solve that problem?
    2. Look for published work
        - Papers: http://aclweb.org/anthology-new/
        - Blog postings
        - Open source projects
3. Add computable features
    - Learning to sum takes an incredible amount of training!

Improving the Classifier

- More data
- Better features
- Solve a different problem
- Shop around for a different classifier / parametrization
    - Procedural overfitting
- Add unlabelled data
- Drop ML and program it by hand

NE Detection

- Dictionary-based
- WSD
- Semi-supervised

Dictionary-based (Gazetteers)

- Gazzetteers and their problems
  - Spurious matches
  - In Octroy, "La Firme" was in some moment the name of a company
    - Same with "CE"

need annotated corpus for evaluation, otherwise more rules hurt performance

Simple Rules

- All capitalized sequences that end in "Inc." are companies
  - Work well as a starting point
- Need annotated corpus for evaluation, otherwise more rules hurt performance

WSD-based

- The context around an occurrence determines its function
- If we can segment the text around likely NEs, we can then use the context to determine its type

Biology: Problem

- "Disambiguating proteins, genes, and RNA in text: a machine learning approach," Hatzivassiloglou, Duboue, Rzhetsky (2001)
- The same term refers to genes, proteins and mRNA:
  - "By UV cross-linking and immunoprecipitation, we show that **SBP2** specifically *binds* selenoprotein *mRNAs* both in vitro and in vivo."
  - "The **SBP2** *clone* used in this study generates a 3173 nt transcript (2541 nt of coding sequence plus a 632 nt 3' UTR truncated at the polyadenylation site)."
- This ambiguity is so pervasive that in many cases the author of the text inserts the word "gene", "protein" or "mRNA" to disambiguate it itself
  - That happens in only 2.65% of the cases though

Biology: Features

- Take a context around the term, use the occurrence of words before or after the term as features.
- Keep a tally of the number of times each word has appear with which target class:

term	gene	protein	mRNA
PRIORS	0.44	0.42	0.14
D-PHE-PRO-VAL-ORN-LEU		1.0	
NOVAGEN	0.46	0.46	0.08
GLCNAC-MAN	1.0		
REV-RESPONSIVE	0.5	0.5	
EPICENTRE		1.0	
GENEROUSLY	0.33	0.67	

Biology: Methods

- Instead of multiplying, operate on logs

```
float[] predict = (float[]) priors.clone();
// ... for each word in context ...
if (wordfreqs.containsKey(word)) {
  float[] logfreqs = wordfreqs.get(word);
  for (int i = 0; i < predict.length; i++)
    predict[i] += logfreqs[i];
}
```


Biology: Results

- Used a number of variations on the features
    - Removed capitalization, stemming, filtered part-of-speech, added positional information
    - Changed the problem from three-way to two-way classification
- Results of Tree-learning and Naive Bayes were comparable (76% two-way and 67% three-way).
- Distilled some interesting rules from the decision trees:
    - after ENCODES is present
      before ENCODES is NOT present
      $\Longrightarrow$class gene [96.5%]

Sequence Tagging (IOB)

- Given n-tags, create $2n+1$ classes:
  - B-tag: this word starts a tag
  - I-tag: this word is inside a tag
  - O: this word is outside all tags (background model)
- Learn a classifier that goes from features around a word to these classes

IOB Example

- From WNUT NET competition
  - tonite O
  - " O
  - running B-tvshow
  - wit I-tvshow
  - mjd I-tvshow
  - " O
  - live O
  - from O
  - 7- O
  - 9pm O
  - eastern O
  - sirius B-company
  - 211 O
  - . O

Bootstrapping (Semisupervised)

- Use a seed set of entities to collect contexts around them on a corpus
- Apply the trained system to the corpus, collect more entities
- Repeat until no more entities are found
- As described, never seen working in practice
  - Need to clean the list of extracted entities by hand after each iteration or it ends up annotating everything
- Can be improved using co-training: using an alternative view of the data as a separate classifier (different features or different corpus or different approach)

Annotating Entities

- Interesting entities are rare, if you annotate a random sample you will need to annotate a very large number of documents to achieve coverage
- Alternative: Active Learning, let the trained system pick new things to annotate
  - Problem is that your system will be biased towards rare cases, need to weight the training samples

Evaluation

- Guidelines are usually straightforward to follow
- Problems:
  - Systematic polysemy (GPE vs location)
  - Corpus characterization (training on certain data, applying on different one)
  - Tags missing / spurious / partial match

Entity Linking

- Determine which occurrences refer to which entity
- Need a corpus of disambiguated references or at least text related to each entity

In-Document Linking

- In-document coreference
  - Pronouns detection is good (80-90%)

  [Fred Flintstone] was named CTO of Time Bank Inc. in 2031. The next year [he] ...

  - Nouns coreference is not that good

Open Data Taxonomies

- DBpedia
- Extracted from Wikipedia Info Boxes
- RDF triples

DBpedia Spotlight

from http://dbpedia-spotlight.github.io/demo/

Entity Linking in the End-to-End Case Study

- Continuing with the Octroy Pipeline, we will analyze code in branch class2 of
  - https://github.com/IE4OpenData/Octroy

The Entities

- Amount
- Company

The Linking

- We use ConceptMapper with the NEQ code as a field in the dictionary

The Types

- DocumentAnnotation
- Token
- Sentence
- Amount
- Company

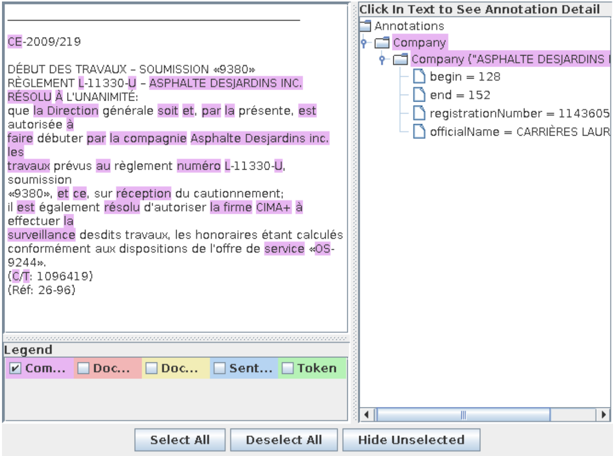
The AEs

- ContractClassifier
- ContractFlowController
- AmountAnnotator
- NeqConceptMapper

Some Results

- ContractClassifier works well
- ConceptMapper produces too many spurious matches
  - Add ML
  - Filter dictionary through general purpose corpus

Some Results (cont.)



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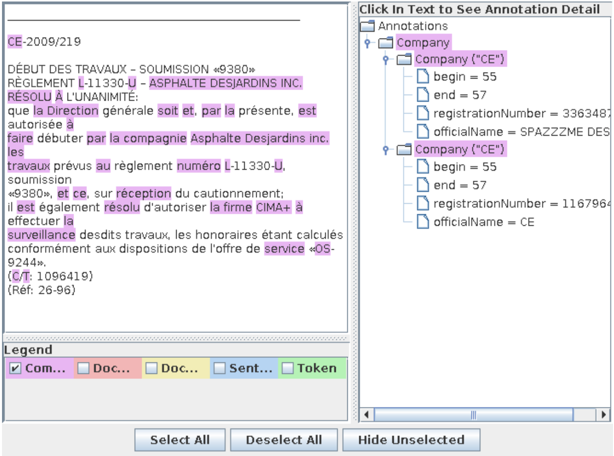

Some Results (cont.)