# 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]$^{\text{organization}}$ .

from Grishman (2012)

# 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 $p\left(F_i \mid C, F_j\right) = p(F_i \mid C)$

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

# 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

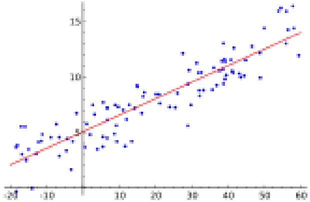
  *previous=succeeds current=Terrence next=D. currentWordIsCapitalized*

- 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




from Wikipedia

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

# Least-squares Estimation

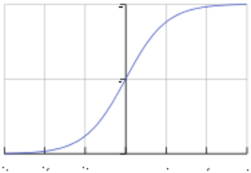
Representing the problem as $\mathbf{y} = \mathbf{X}\beta + \varepsilon$ where

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

a closed solution for$\beta$ 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



from Wikipedia

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

# 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
   2.1 What information would **you** us to solve that problem?
   2.2 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/

# NER 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
- Dependency management and build cycle is usually managed with the Apache Maven tool:
  - mvn clean
    - mvn compile
    - mvn test
    - mvn appassembler:assemble
    - pom.xml (Project Object Model)

# Running the Pipeline

- ./target/appassembler/bin/run-pipeline-tsv or run-pipeline-xmi
- Focus on Company annotations
- OpenNLP pipeline:
  - ./target/appassembler/bin/run-pipeline-xmi org/ie4opendata/octroy/OctroyEngineOpenNLP.xml ./docs/dev32 /tmp/dev32/
- ConceptMapper pipeline:
  - ./target/appassembler/bin/run-pipeline-xmi org/ie4opendata/octroy/OctroyEngineCM.xml ./docs/dev32 /tmp/dev32

# Evaluating the Results

- https://github.com/IE4OpenData/ruta_testing_standalone
  - mvn package appassembler:assemble
  - ./target/appassembler/bin/ruta-evaluate
- Evaluating XMI annotated with different pipelines (output on /tmp/dev32)

```
$ /path/to/ruta_testing_standalone/target/appassembler/bin/ruta-evaluate \
      --gold data/gold32 --eval /tmp/dev32 \
      --include org.ie4opendata.octroy.Company \
      --typesystem ./src/main/resources/org/ie4opendata/octroy/octroy_eval_ts.xml
```

# The Entities

- Amount
- Company

- Two approaches:
  - Dictionary using UIMA Concept Mapper (with linking)
  - Machine Learning MEMM using OpenNLP NameFinder

# Linking Approach

- We use ConceptMapper with the NEQ code as a field in the dictionary
- http://duboue.net/download/neq_dict.xml.gz
  - 289Mb decompressed
  - ~2 million canonical entries over 3.6 million variants

# The Types

- DocumentAnnotation
- Token
- Sentence
- Amount
- Company

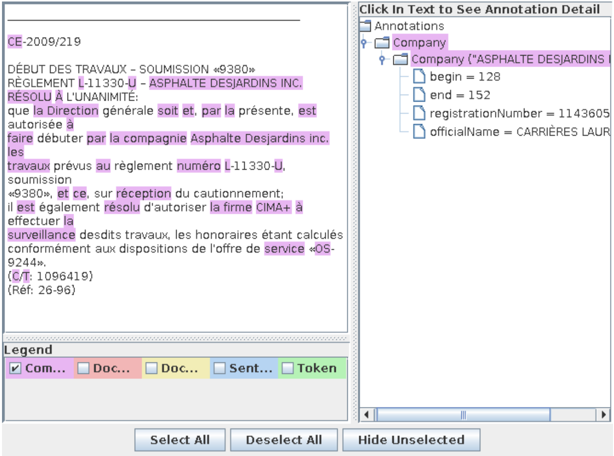
# The AEs

- ContractClassifier
- ContractFlowController
- AmountAnnotator
- NeqConceptMapper

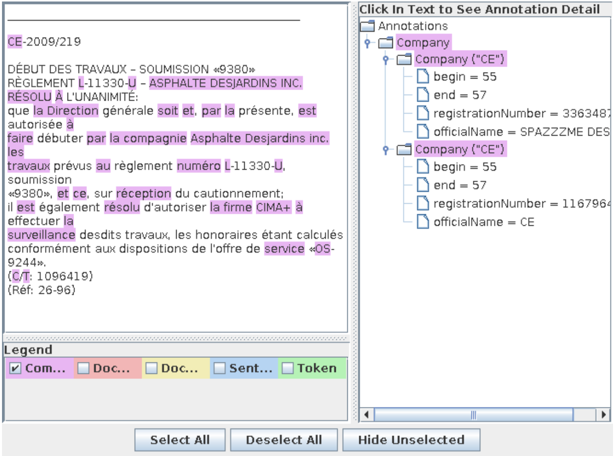
# Some Results

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

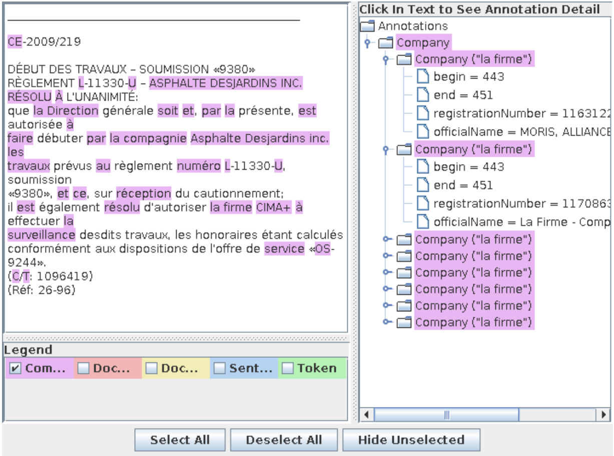
# Some Results (cont.)



# Some Results (cont.)



# Some Results (cont.)



# Evaluation

- JAVA_OPTS=-Xmx6G ./target/appassembler/bin/run-pipeline-xmi org/ie4opendata/octroy/OctroyEngineCM.xml ./docs/dev32 ./output/dev32-cm
- ../ruta_testing_standalone/target/appassembler/bin/ruta-evaluate --gold data/gold32 --eval ./output/dev32-cm --typesystem ./src/main/re-sources/org/ie4opendata/octroy/octroy_eval_ts.xml --include org.ie4opendata.octroy.Company
- FP 522 / FN 8 / TP 11
- Prec 0.021 (very, very low!)
- Rec 0.579 (good)
- F1 0.04 (very, very low)
- Overgenerates

# MEMM Approach

- Annotate the named entities
- Train a Maximum Entity model
- opennlp.tools.namefind.NameFinderME

```
private static AdaptiveFeatureGenerator createFeatureGenerator() {
  return new CachedFeatureGenerator(
    new AdaptiveFeatureGenerator[]{
    new WindowFeatureGenerator(new TokenFeatureGenerator(), 2, 2),
    new WindowFeatureGenerator(new TokenClassFeatureGenerator(true), 2,
2),
    new OutcomePriorFeatureGenerator(),
    new PreviousMapFeatureGenerator(),
    new BigramNameFeatureGenerator(),
    new SentenceFeatureGenerator(true, false)
  });
}
```

# Generate Training File

- OpenNLP has a standalone model generating capabilities, based on "semi-structured text files"
  - This approach encodes tokens as white-space separated terms
  - And sentences as full lines
  - NER tokens are marked with pseudo SGML tags as `<START:person> <END>`
- This format clearly does not uses stand-off annotation but we will look into it to build up towards using ClearTk
  - Annotating training data with this format will render the annotations useless if the tokenizer / sentence boundary detector is changed!
- You can generate the training file (empty file, the annotations have to be added by hand using a text editor) using
  - `./target/appassembler/bin/opennlp-trainer-extractor <folder with txt files> <output file>`
- An annotated file is in data/company.training36
  - Note the sentence boundaries are very poor

# Available Models

- Trained MEMM models for multiple tasks (NER but also tokenization and sentence boundary detection) are made available by the OpenNLP project only at
  - http://opennlp.sourceforge.net/models-1.5/