Foundations of Natural Language Processing
Lecture 10
Methods in Annotation and Evaluation

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(Based on slides from Sharon Goldwater, with slides from Alex Lascarides and Nathan Schneider)

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Today we will look at. . .

- Annotation
  - Why "gold" $\neq$ perfect
  - Quality Control
- Evaluation
  - Experimental setup
  - Significance testing
  - Error analysis
  - Evaluating without Gold Standards:
    How do we evaluate when there is more than one right answer?

Factors in Annotation

Suppose you are tasked with building an annotated corpus. (E.g., with part-of-speech tags.) In order to estimate **cost** in time and money, you need to decide on:

- Source data (genre? size? licensing?)
- Annotation scheme (complexity? guidelines?)
- Annotators (expertise? training?)
- Annotation software (graphical interface?)
- Quality control procedures (multiple annotation, adjudication?)

Annotation Scheme

- Assuming a competent annotator, some kinds of annotation are straightforward for most inputs.

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- Assuming a competent annotator, some kinds of annotation are straightforward for most inputs.

- Others are not.
  - Text may be ambiguous
  - There may be gray area between categories in the annotation scheme

You play annotator

Noun or adverb?

- **Yesterday** was my birthday .
- **Yesterday** I ate a cake .
- He was fired **yesterday** for leaking the information .
- I read it in **yesterday** 's news .
- I had not heard of it until **yesterday** .

You play annotator

Verb, noun, or adjective?

- We had been **walking** quite briskly
- **Walking** was the remedy, they decided
- In due time Sandburg was a **walking** thesaurus of American folk music.
- we all lived within **walking** distance of the studio
- a woman came along carrying a folded umbrella as a **walking** stick
- The **Walking** Dead premiered in the U.S. on October 31, 2010, on the cable television channel AMC

Annotation: Not as easy as you might think

Pretty much any annotation scheme for language will have some difficult cases where there is gray area, and multiple decisions are plausible.

- Because human language needs to be **flexible**, it cuts corners and is reshaped over time.

- Not just syntax: wait till we get to semantics!

Annotation Guidelines

However, we want a dataset's annotations to be as clean as possible so we can use them reliably in systems.

Documenting conventions in an annotation manual/standard/guidelines document is important to help annotators produce **consistent** data, and to help end users interpret the annotations correctly.

Annotation Guidelines

- Penn Treebank: 36 POS tags (excluding punctuation).
- Tagging guidelines (3rd Revision): 34 pages
  - "The temporal expressions *yesterday*, *today* and *tomorrow* should be tagged as nouns (NN) rather than as adverbs (RB). Note that you can (marginally) pluralize them and that they allow a possessive form, both of which true adverbs do not." (p. 19)
  - An entire page on nouns vs. verbs.
  - 3 pages on adjectives vs. verbs.
- Penn Treebank bracketing (tree) guidelines: $>$300 pages!

Annotation Quality

But even with extensive guidelines, human annotations won't be perfect:

- Simple error (hitting the wrong button)
- Not reading the full context
- Not noticing an erroneous pre-annotation
- Forgetting a detail from the guidelines
- Cases not anticipated by or not fully specified in guidelines (room for interpretation)

"Gold" data will have some tarnish. How can we measure its quality?

Inter-annotator agreement (IAA)

- An important way to estimate the reliability of annotations is to have multiple people independently annotate a common sample, and measure **inter-annotator/coder/rater agreement**.
- **Raw agreement rate**: proportion of labels in agreement
- If the annotation task is perfectly well-defined and the annotators are well-trained and do not make mistakes, then (in theory) they would agree 100%.
- If agreement is well below what is desired (will differ depending on the kind of annotation), examine the sources of disagreement and consider additional training or refining guidelines.
- The agreement rate can be thought of as an upper bound (**human ceiling**) on accuracy of a system evaluated on that dataset.

IAA: Beyond raw agreement rate

- Raw agreement rate counts all annotation decisions equally.

- Some measures take knowledge about the annotation scheme into account (e.g., counting singular vs. plural noun as a minor disagreement compared to noun vs. preposition).

- What if some decisions (e.g., POS tags) are far more frequent than others?
  - If 2 annotators both tagged *hell* as a noun, what is the chance that they agreed **by accident**? What if they agree that it is an interjection (rare tag)—is that equally likely to be an accident?
  - **Chance-corrected** measures such as Cohen's kappa (κ) adjust the agreement score based on label probabilities.
  - . . . but they make modeling assumptions about how "accidental" agreement would arise; important that these match the reality of the annotation process!
  - More below on hypothesis testing/statistical significance.

Crowdsourcing

- Quality control is even more important when eliciting annotations from "the crowd".

- E.g., **Amazon Mechanical Turk** facilitates paying anonymous web users small amounts of money for small amounts of work ("Human Intelligence Tasks").

- Need to take measures to ensure annotators are qualified and taking the task seriously.
  - Redundancy to combat noise: Elicit 5+ annotations per data point.
  - Embed data points with known answers, reject annotators who get them wrong.

The Nature of Evaluation

- Scientific method rests on making and testing hypotheses.

- Evaluation is just another name for testing.

- Evaluation not just for public review:
  - It's how you manage internal development
  - And even how systems improve themselves (see ML courses).

What Hypotheses?

About existing linguistic objects:

- Is this text by Shakespeare or Marlowe?

About output of a language system:

- How well does this language model predict the data?
- How accurate is this segmenter/tagger/parser?
  - Is this segmenter/tagger/parser better than that one?

About human beings:

- How reliable is this person's annotation?
- To what extent do these two annotators agree? (IAA)

Gold Standard Evaluation

- In many cases we have a record of 'the truth':
  - The best human judgement as to what the correct segmentation/tag/parse/reading is,
    or what the right documents are in response to a query.
- Gold standards used both for training and for evaluation
- But testing must be done on unseen data (held-out test set; train/test split)

Don't ever train on data that you'll use in testing!!

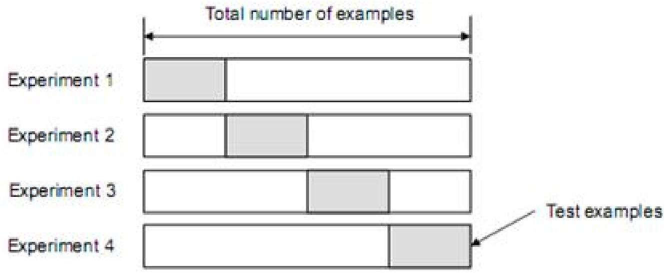
Tuning

- Often, in designing a system, you'll want to **tune** it by trying several configuration options and choosing the one that works best empirically.
  - E.g., Lidstone (add-λ) smoothing; choosing features for text classification.
- If you run several experiments on the test set, you risk **overfitting** it; i.e., the test set is no longer a reliable proxy for new data.
- One solution is to hold out a second set for tuning, called a **development** ("dev") set. Save the test set for the very end.

Cross-validation

What if my dataset is **too small** to have a nice train/test or train/dev/test split?

- ***k*-fold cross-validation**: partition the data into k pieces and treat them as mini held-out sets. Each **fold** is an experiment with a different held-out set, using the rest of the data for training:



- After k folds, every data point will have a held-out prediction!

- If tuning the system via cross-validation, still important to have a separate blind test set.

Measuring a Model's Performance

Accuracy: Proportion model gets right:

$$\frac{|\text{right}|}{|\text{test-set}|} \times 100$$

E.g., POS tagging (state of the art $\approx 96\%$).

Measuring a Model's Performance

Precision, Recall, F-score

- For isolating performance on a particular label in multi-label tasks, or
- For chunking, phrase structure parsing, or anything where word-by-word accuracy isn't appropriate.
- F_1-score: Harmonic mean of
  precision (proportion of model's answers that are right) and
  recall (proportion of test data that model gets right).
- E.g., for the POS tag `NN`:

$$
\begin{aligned}
P &= \frac{|\text{tokens correctly tagged } \texttt{NN}|}{|\text{all tokens automatically tagged } \texttt{NN}|} &&= \frac{\text{TP}}{\text{TP+FP}} \\
R &= \frac{|\text{tokens correctly tagged } \texttt{NN}|}{|\text{all tokens gold-tagged } \texttt{NN}|} &&= \frac{\text{TP}}{\text{TP+FN}} \\
F_1 &= \frac{P \cdot R}{P+R}
\end{aligned}
$$

Upper Bounds, Lower Bounds?

Suppose your POS tagger has 95% accuracy? Is that good? Bad??

Upper Bound: Turing Test:

- When using a human Gold Standard, check the agreement of humans against that standard.

Lower Bound: Performance of a 'simpler' model (**baseline**)

- Model always picks most frequent class (**majority baseline**).

- Model assigns a class randomly according to:

  1. Even probability distribution; or
  2. Probability distribution that matches the observed one.

Suitable upper and lower bounds depend on the task.

Measurements: What's Significant?

- We'll be measuring things, and comparing measurements.

- What and how we measure depends on the task.

- But all have one issue in common:

  Are the differences we find significant?

- In other words, should we interpret the differences as down to pure chance? Or is something more going on?

- Is our model significantly better than the baseline model?
  Is it significantly worse than the upper bound?

Example: Tossing a Coin

- I tossed a coin 40 times; it came up heads 17 times.
- Expected value of fair coin is 20. So we're comparing 17 and 20.
- If this difference is *significant*, then it's (probably) not a fair coin.
  If not, it (probably) is.

Normal distributions

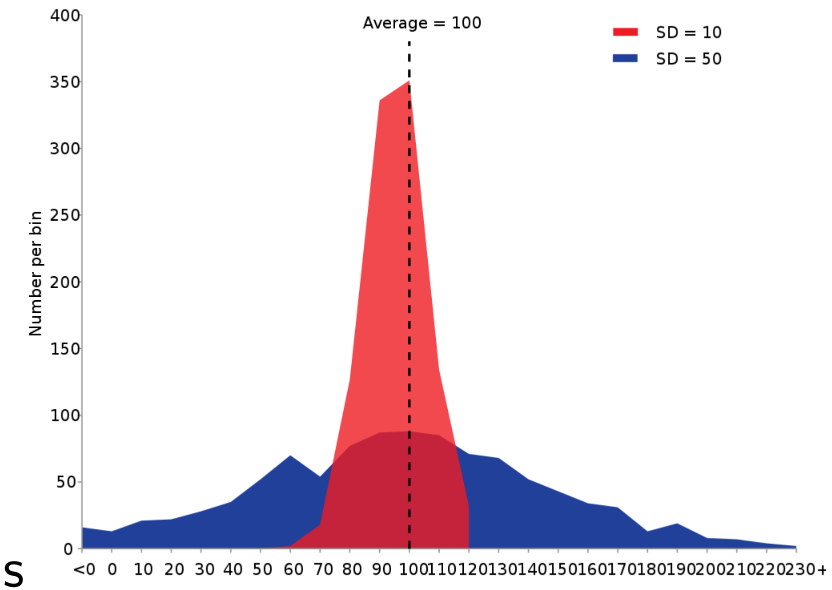
Significance measurement can be complex to understand, but the basic idea is simple (for normal distributions):

- Measure difference in terms of standard deviation

Standard deviation is essentially a measure of how representative the mean is

- The more outliers, and the further they are from the mean
- The less representative the mean is

- The standard deviation quantifies this



Mean and standard deviation

Definitions:

Mean of N measurements

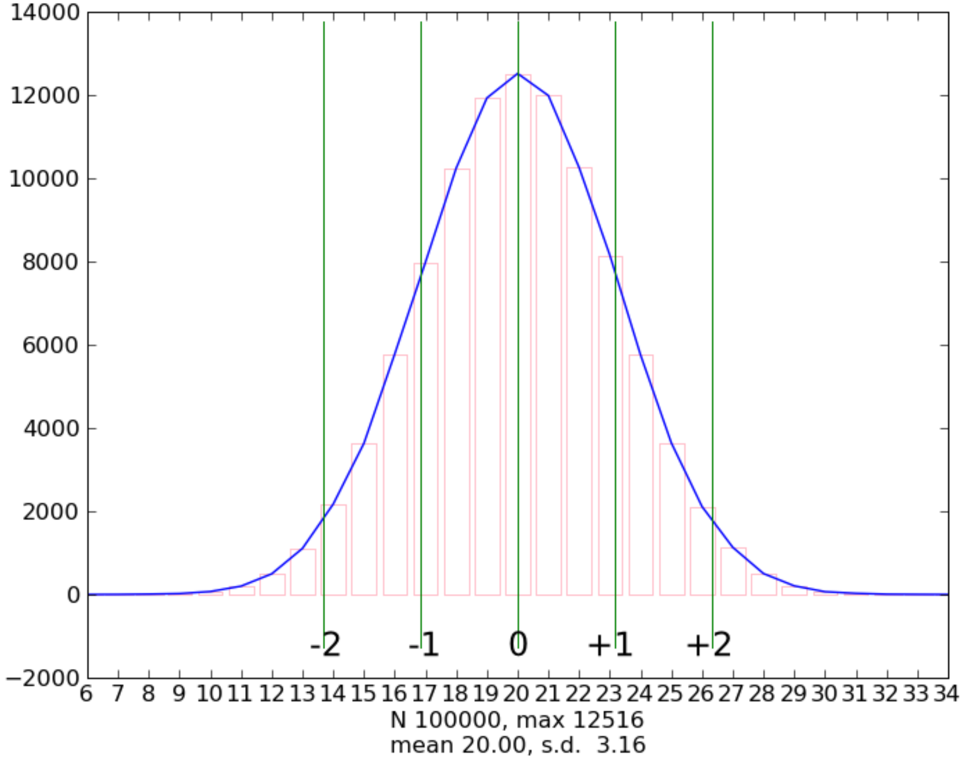
$\frac{n_1+n_2+n_3+\cdots+n_N}{N}$ Call this μ

Standard deviation of N measurements

$\sqrt{\frac{(n_1-\mu)^2+(n_2-\mu)^2+(n_3-\mu)^2+\cdots+(n_N-\mu)^2}{N}}$

The outcomes if the coin is fair

The distribution over 100,000 trials (i.e., in each trial toss coin 40 times) is similar to a normal distribution curve.



- The peak is at 50% heads, but lots of other plausible outcomes.
- Even a result more than two standard deviations out will come up a bit less than 1 in 20 trials (i.e., 2,000/100,000)

Which Significance Test?

- Parametric when the underlying distribution is normal.
  - t-test, z-test,. . .
  - You don't need to know the mathematical formulae; available in statistical libraries!

- Non-Parametric otherwise.
  - Usually do need non-parametric tests: remember Zipf's Law!
  - Can use McNemar's test or variants of it.

See Smith (2011, Appendix B) for a detailed discussion of significance testing methods for NLP.

Error Analysis

- Summary scores are important, but don't always tell the full picture!
- Once you've built your system, it's always a good idea to dig into its output to identify patterns.
  - Quantitative *and* qualitative (look at some examples!)
  - You may find bugs (e.g., predictions are always wrong for words with accented characters)
  - Or think of ways to improve your system
- A **confusion matrix** can help in spotting problem areas

Confusion Matrices

		Estimated Emotion							
		Anger	Boredom	Disgust	Fear	Happiness	Sadness	Neutral	*Emotion Recog. Rate*
True Emotion	Anger	**19**	0	2	0	**3**	0	0	79.2%
	Boredom	1	**8**	1	1	0	1	**7**	42.1%
	Disgust	0	1	**6**	0	1	0	3	54.5%
	Fear	1	3	2	**7**	2	0	1	43.8%
	Happiness	**3**	0	3	2	**5**	0	2	33.3%
	Sadness	0	0	0	0	0	**14**	0	100.0%
	Neutral	0	**5**	1	0	0	0	**13**	68.4%
	HMM Recog. Rate	79.2%	47.1%	40.0%	70.0%	45.5%	93.3%	50.0%	

Figures on the main diagonal are for the correct answer

- Others are mistakes
- Mistakes in bold are perhaps large enough to worry about...

Tasks where there is > 1 right answer

Example: A Paraphrasing Task

- Estimate that *John enjoyed the book* means *John enjoyed reading the book*.

- Lots of closely related words to *read* are good too:
  skim through, go through, peruse, etc.

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Evaluation: 'Turing Test'

- Classify candidate paraphrases as high, medium or low probability.
- Measure correlation between human vs. machine's judgements.
- Result was 0.64. Is that good?
- Upper bound: average correlation between two human judges! That's 0.74.
- Can use above tests to measure if these are significantly different.

Summary

- Lots of things we might be evaluating.
- Generally, NLP systems evaluated against gold standard data, which is often quite expensive to collect.
- All that is "gold" does not glitter. Important to remember where the data came from and measure reliability.
- You compare performance of your model against: upper bound, baseline model, someone else's model, and use an appropriate significance test to see if differences are 'real' or within margin of error (i.e., likely due to chance).