Language and Computers
LTS: Grammatical Error Detection

Based on slides from Ross Israel
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Spring 2016
What Is Grammatical Error Detection?

We will be talking about errors made by learners in a second language acquisition context.

Language Learners often make non-native-like mistakes when constructing sentences:

- We arrived to the station.
- There is the garden in my house.
- I eat rice, nikujaga and salada yesterday.

**Grammatical error detection** entails trying to find these mistakes automatically.

Recommended reading: Leacock et al 2014, *Automated Grammatical Error Detection for Language Learners*
Where Is This Useful?

- Automatic grading
  - Language teachers
  - Standardized testing
- Analysis and annotation of learner data for research
- Language learning software (ICALL)
Where Error Detection Fits In
(a bit of a review)

- **CALL: Computer Assisted Language Learning**
  - Using computers and media in language learning and teaching
  - e.g., Rosetta Stone, eLanguage
  - Exercises are typically very simple in design, and offer little feedback

- **ICALL: Intelligent Computer Assisted Language Learning**
  - Utilize computational linguistics tools, such as POS tagging & parsing along with statistical language modeling strategies (e.g., n-grams)
    - These tools often need to be altered to expect and diagnose errors, or at least handle learner data better
    - We can also build software for specific kinds of errors. *(today’s discussion)*
  - Focus on precision; we don’t want to tell a learner that they’ve made a mistake when they haven’t!
Learners typically make different kinds of mistakes than native speakers.

- **Content Word Choice (19.9% of all errors in CLC)**
  - We need to deliver the merchandise on a daily *base/basis*.

- **Preposition Error (13.4%)**
  - Our society is developing *in/at high* speed.

- **Determiner Error (11.7%)**
  - There is *the/a garden in my house.*

*CLC = Cambridge Learner Corpus*
Motivation

Some common areas of research in English error detection are articles, prepositions, and collocations. We’ll look a little more in depth at prepositions.

- Because prepositions make up a large portion of errors commonly made by learners, there has been a good deal of research on how to find and diagnose preposition errors.
- Also, prepositions are a closed set, so it’s a problem that’s easier to define than a more open error type like use of the wrong content word.
  - Prepositions can be treated as a confusion set where we know that one is being substituted for another.
  - This is not the case with many parts of the grammar.
Choosing the correct preposition can be a tough task even for native speakers.

There has been concern about syncing phone contacts on Facebook. "As long as you are aware of who is the group it can be a great privacy tool. If it gets out hand it could give you a sense of false security." The roll out of new products comes reports that a syncing feature on the iPhone lets Facebook access contact data and share it with the site. "It’s very possible that your private phone numbers - and those lots of your and their friends - are the site," said Charles Arthur of the Guardian newspaper.
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Challenges with Prepositions

- Negative Transfer: *in the garden, at home, on (the) campus*: same preposition in Arabic
- Adjuncts: *on the beach vs. at the beach*
- Arguments: *The loaded the hay on the wagon vs. The loaded the wagon with hay*
- Phrasal Verbs: *add up the numbers, add the numbers up*
- Idioms: *on the house*
- PP Attachment: *I put the ring on the table in the safe*
- Lexical Ambiguity: *eat with a fork, view with anxiety, strike with fear, combine with others, furnish with supplies*

See section 3.3.1 of Leacock et al (2014)
Commonly Used Techniques

A sampling ...

- **Language Model** - Gamon et al. (2008)
  - Build $n$-grams of POS and/or parsing labels from native text and check if learner $n$-grams align with that model

- **Web-based methods** - Gamon and Leacock (2010)
  - Take a few words of context on either side of a preposition to generate a web query
  - Replace the preposition with neighbors from a confusion set and search those queries
  - The search with the greatest number of hits is selected as the right answer

  - Write linguistic rules designed to find errors in learner data

- **Statistical** - Tetreault and Chodorow (2008)
  - Statistical methods means building a classifier
  - So, what is a classifier?
Machine Learning: give examples to a computer system & have it learn what the patterns are

- We will explore this topic in more detail when we get to the *document classification* unit

Example: based on your previous purchases, what coupons should you receive?

Understanding Classifiers

Machine learning is not as scary as it sounds!

▶ There are a number of algorithms for classification that we could talk about
  ▶ Maximum Entropy, Support Vector Machines, Memory Based Learning
  ▶ Each method requires different representations of information
  ▶ These slides are indicative of Memory Based Learning
▶ TiMBL http://ilk.uvt.nl/timbl/ - Daelemans et al. (2007)
  ▶ Easy-ish to install
  ▶ Easy to use
  ▶ Works well with language data
We will need two sets of data:
- Training Set - needs to be big
- Testing Set - usually smaller

The data sets are full of events *(instances)* that contain *features* that describe the circumstances of the event and a *class* that is the answer we are trying to guess.

With a little bit of a language like python, you can extract features pretty easily to train and run TiMBL:
- Open a file (e.g. a POS tagged file)
- Extract bits of text (features) that you deem useful
- Print those bits of text on a single line for each instance
- The real trick is selecting appropriate features
Let’s consider a real-world example:

- **The Task:** We want to classify the weather as either **good** or **bad**.

- **We would want features like**
  - temperature
  - sunny?
  - cloudy?
  - windy?
  - humidity level
  - rain/snow/none
Running the Classifier

- Then, we would build **vectors** for every measurement we take and **label** them to build training data:
  - 75, yes, no, no, 70%, none, **good**
  - 35, no, no, yes, 50%, none, **bad**
  - 105, yes, no, no, 98%, rain, **bad**
  - 68, yes, yes, no, 75%, none, **good**

- Now, when we give the classifier an unknown feature vector, we hope that it makes a wise decision
  - 85, yes, no, no, 65%, none - classifier’s guess = **good** yay!
  - 15, no, no, yes, 70%, snow - classifier’s guess = **bad** yay!
  - 75, yes, no, yes, 70%, none - classifier’s guess = **bad** oops!
Tetreault and Chodorow used a maximum entropy classifier to try to find preposition confusions and extraneous uses.

They extracted 25 features including:
- words/POS tags in a 2 word window(+-) around preposition
- the head verb and noun of the preceding VP and NP
- the head noun of the following NP

John went to the store this morning.
- word+POS bigrams: went_VBD, the_DET
- head of previous VP = went
- head of previous NP = John

Their system achieved 84% precision and 19% recall.
- This might sound low, but keep in mind, we want to get the best possible precision, even if it means losing recall.
Types of systems

Summary

Systems differ in terms of:

1. the kinds of features they use
   ▶ surface level features, syntactic features, L1 information, etc.

2. the training data they use
   ▶ correct usage, artificially generated errors, real errors

3. the kinds of models (e.g., classifiers) they use
   ▶ classifiers, language models, web counts, etc.


