### The Ups and Downs of Preposition Error Detection in ESL Writing

Joel Tetreault [Educational Testing Service]

#### What does ETS do?

Standardized Assessment

**EVIL** 

• GRE

TOEFL

SAT

Others

Educational Tools

Criterion, Text Adaptor

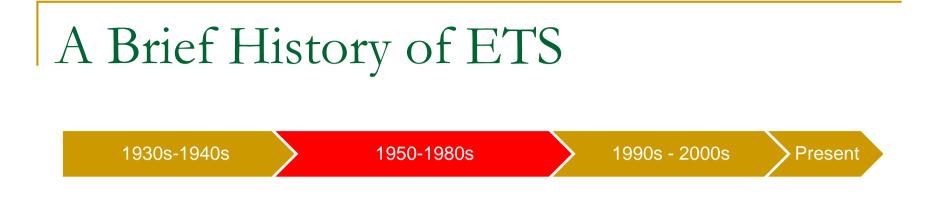
Educational Policy

## A Brief History of ETS

- 1930s: to get into university, one had to be wealthy or attend top prep schools
- Henry Chauncey believed college admission should be based on achievement, intelligence
- With other Harvard faculty, created standardized tests for military and schools

Present

ETS created in 1947 in Princeton, NJ



- ETS grows into the largest assessment institution
- SAT and GRE are biggest tests, with millions of students over 180 countries taking them each year
- Make move from multiple choice to more natural questions (essays)

#### NLP Meets Assessment



#### Revenue

- Cost Savings for Large-Scale Assessments
- Market for Practice Instruction & Assessments

#### Classroom Teacher Support for Writing

- More practice writing possible
- Individual and classroom performance assessment
- Electronic writing portfolios

#### NLP Meets Assessment



- E-rater / Criterion<sup>SM</sup> (essay scoring)
- C-rater (short answer content scoring)
- Speech Rater (speech scoring)
- Text Adaptor (teacher assistance tools)
- Plagiarism Detection

#### E-rater

- First deployed in 1999 for GMAT Writing Assessment
- System Performance:
  - *E-rater*/Human agreement: 50% exact, 90% exact (+1 adjacent)
  - Comparable to two humans
- Massive collection of 50+ weighted features organized into 5 high level features
- Combined using stepwise linear regression

#### E-rater Features

Grammar	<ul><li>Sentence fragments, garbled words</li><li>Pronoun, possessive errors</li></ul>
Usage	<ul><li>Wrong word form, double negative</li><li>Incorrect article/preposition</li></ul>
Mechanics	<ul><li>Spelling</li><li>Punctuation</li></ul>
Style	<ul><li>Sentence length, word repetition</li><li>Passives</li></ul>
Organization	<ul><li>Discourse sequences</li><li>RST &amp; Syntactic structures</li></ul>

#### Criterion

- E-rater as classroom instruction/feedback tool
- Used in 3200+ schools
- Over 3M submissions since 2001
- Over 1M student registrations
- International Use:
  - Canada, Mexico, India, Puerto Rico, Egypt, Nepal, Taiwan, Hong Kong, Japan, Thailand, Vietnam, Brazil, UK, Greece, Turkey

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Click on each bolded item below to see the corresponding feedback.	() Roll over the highlighted text in your passage to displ	ay comments specific to your writing.		
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Trait Feedback Analysis Menu		Revise Essay	Printer-Friendly Version	Writer's Handbook	Help
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## What's Next for ETS? 1930s-1940s 1950-1980s 1990s - 2000s

- Assessment/tools for learners of English as a Second Language (ESL)
  - 300 million ESL learners in China alone
  - 10% of US students learn English as a second language
  - Teachers now burdened with teaching classes with wildly varying levels of English fluency

# What's Next for ETS? 1930s-1940s 1950-1980s 1990s - 2000s Present

- Increasing need for tools for instruction in English as a Second Language (ESL)
- Other Interest:
  - Microsoft Research (ESL Assistant)
  - Publishing Companies (Oxford, Cambridge)
  - Universities
  - Rosetta Stone

### Objective

- Long Term Goal: develop NLP tools to automatically provide feedback to ESL learners about grammatical errors
- Preposition Error Detection
  - □ Selection Error ("They arrived *to* the town.")
  - Extraneous Use ("They came to outside.")
  - Omitted ("He is fond this book.")

#### Preposition Error Detection

- Present a combined ML and rule-based approach:
  - State of the art performance in native & ESL texts
- Similar methodology used in:
  - Microsoft's ESL Assistant [Gamon et al., '08]
  - □ [De Felice et al., '08]
- This work is included in ETS's Criterion<sup>SM</sup> Online Writing Service and E-Rater (GRE, TOEFL)

## Outline

- 1. Motivation
- 2. Approach
  - Methodology
  - Feature Selection
- 3. Evaluation on Native Text (Prep. Selection)
- 4. Evaluation on ESL Text
- 5. Future Directions

#### Motivation

- Preposition usage is one of the most difficult aspects of English for non-native speakers
  - [Dalgish '85] 18% of sentences from ESL essays contain a preposition error
  - Our data: 8-10% of all prepositions in TOEFL essays are used incorrectly

#### Why are prepositions hard to master?

- Prepositions are problematic because they can perform so many complex roles
  - Preposition choice in an adjunct is constrained by its object ("on Friday", "at noon")
  - Prepositions are used to mark the arguments of a predicate ("fond of beer.")
  - Phrasal Verbs ("give in to their demands.")
    - "give in" ⇔ "acquiesce, surrender"

Why are prepositions hard to master?

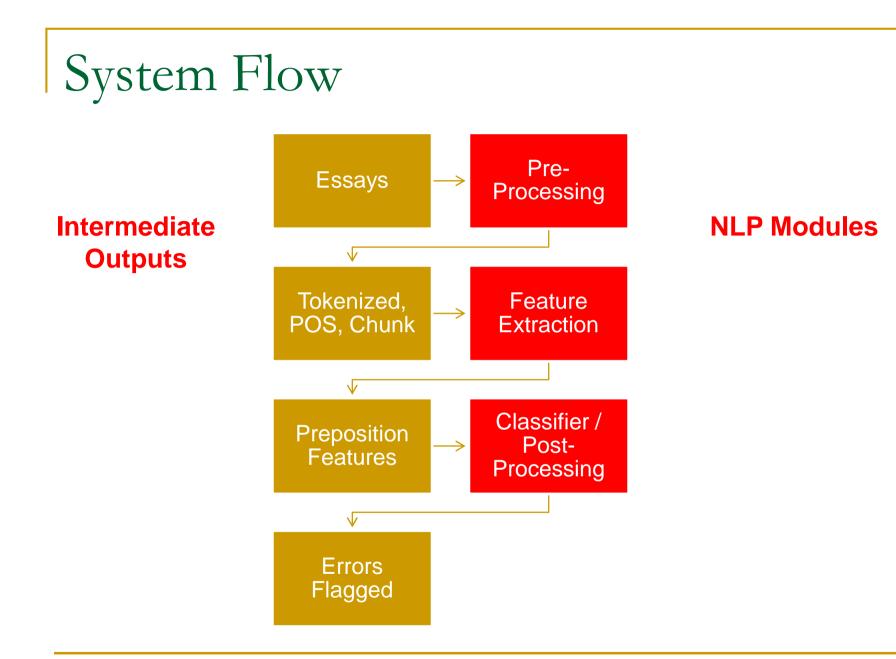
Multiple prepositions can appear in the same context:

"When the plant is horizontal, the force of the gravity causes the sap to move \_\_\_\_ the underside of the stem."



#### NLP & Preposition Error Detection

- 1. Methodology for Preposition Error Detection
  - [Tetreault & Chodorow, COLING '08]
  - [Chodorow, Tetreault & Han, SIGSEM-PREP '07]
  - [Tetreault & Chodorow, WAC '09]
- 2. Experiments in Human Annotation
  - Implications for system evaluation
  - Interval Chodorow, HJCL '08]



## Methodology

- Cast error detection task as a classification problem
- Given a model classifier and a context:
  - System outputs a probability distribution over 34 most frequent prepositions
  - Compare weight of system's top preposition with writer's preposition
- Error occurs when:
  - Writer's preposition  $\neq$  classifier's prediction
  - And the difference in probabilities exceeds a threshold

## Methodology

- Develop a training set of error-annotated ESL essays (millions of examples?):
  - Too labor intensive to be practical
- Alternative:
  - Train on millions of examples of proper usage
- Determining how "close to correct" writer's preposition is

#### Feature Selection

- Prepositions are influenced by:
  - Words in the local context, and how they interact with each other (lexical)
  - Syntactic structure of context
  - Semantic interpretation

#### Feature Extraction

- Corpus Processing:
  - POS tagged (Maxent tagger [Ratnaparkhi '98])
  - Heuristic Chunker
  - Parse Trees?
    - "In consion, for some reasons, museums, particuraly known travel place, get on many people."
- Feature Extraction
  - Context consists of:
    - +/- two word window
    - Heads of the following NP and preceding VP and NP
  - 25 features consisting of sequences of lemma forms and POS tags

### Features

Feature	No. of Values	Description
PV	16,060	Prior verb
PN	23,307	Prior noun
FH	29,815	Headword of the following phrase
FP	57,680	Following phrase
TGLR	69,833	Middle trigram (pos + words)
TGL	83,658	Left trigram
TGR	77,460	Right trigram
BGL	30,103	Left bigram

He will take our place in the line

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He will take our <mark>place in the</mark> line.			
TGLR			

#### Combination Features

- MaxEnt does not model the interactions between features
- Build "combination" features of the head nouns and commanding verbs
   PV, PN, FH
- 3 types: word, tag, word+tag
   Each type has four possible combinations
   Maximum of 12 features

#### Combination Features

Class	Components	+Combo:word
p-N	FH	line
N- <i>p-</i> N	PN-FH	place-line
V- <i>p-</i> N	PV-PN	take-line
V-N- <i>p-</i> N	PV-PN-FH	take-place-line

"He will take our place in the line."

#### Preposition Selection Evaluation

- Test models on well-formed native text
- Metric: accuracy
  - Compare system's output to writer's
  - Has the potential to underestimate performance by as much as 7% [HJCL '08]
- Two Evaluation Corpora:

#### WSJ

- test=106k events
- train=4.4M NANTC events

#### **Encarta-Reuters**

- test=1.4M events
- train=3.2M events
- Used in [Gamon+ '08]

## Preposition Selection Evaluation

Model	WSJ	Enc-Reu*
Baseline (of)*	26.7%	27.2%
Lexical	70.8%	76.5%
+Combo	71.8%	77.4%
+Google	71.6%	76.9%
+Both	72.4%	77.7%
+Combo +Extra Data	74.1%	79.0%

\* [Gamon et al., '08] perform at 64% accuracy on 12 prep's

#### Evaluation on Non-Native Texts

#### Error Annotation

- Most previous work used only one rater
- □ Is one rater reliable? [HJCL '08]
- Sampling Approach for efficient annotation
- Performance Thresholding
  - How to balance precision and recall?
  - May not want to optimize a system using F-score

#### ESL Corpora

- Factors such as L1 and grade level greatly influence performance
- Makes cross-system evaluation difficult

### Training Corpus for ESL Texts

- Well-formed text → training only on positive examples
- 6.8 million training contexts total
  - 3.7 million sentences
- Two training sub-corpora:

**MetaMetrics** Lexile

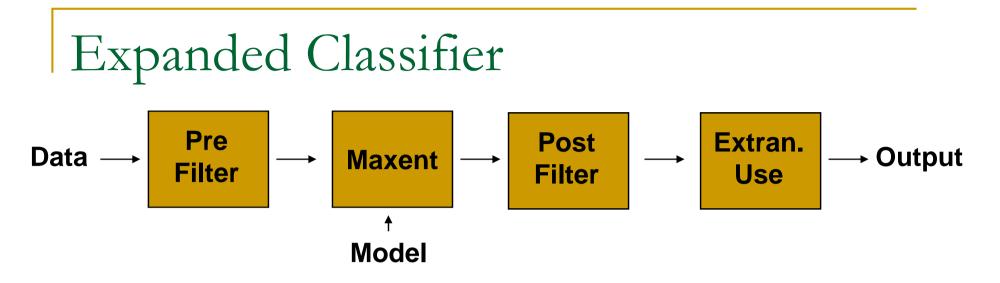
- 11<sup>th</sup> and 12<sup>th</sup> grade texts
- 1.9M sentences

San Jose Mercury News

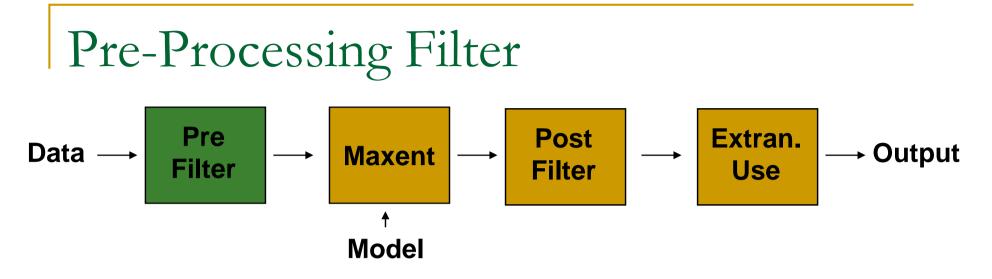
- Newspaper Text
- 1.8M sentences

### ESL Testing Corpus

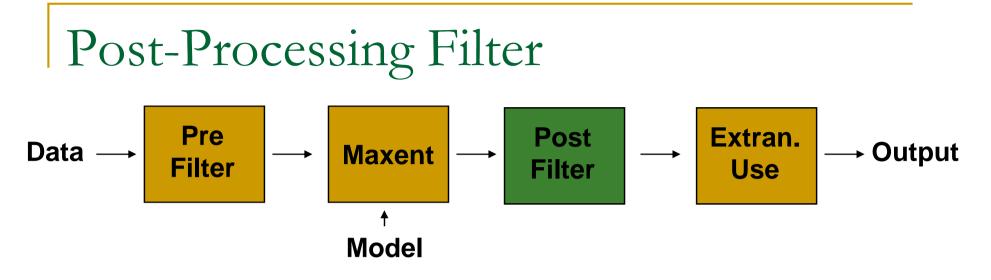
- Collection of randomly selected TOEFL essays by native speakers of Chinese, Japanese and Russian
- 8192 prepositions total (5585 sentences)
- Error annotation reliability between two human raters:
  - Agreement = 0.926
  - □ Kappa = 0.599



- Pre-Processing Filter
- Maxent Classifier (uses model from training)
- Post-Processing Filter
- Extraneous Use Classifier (PC)



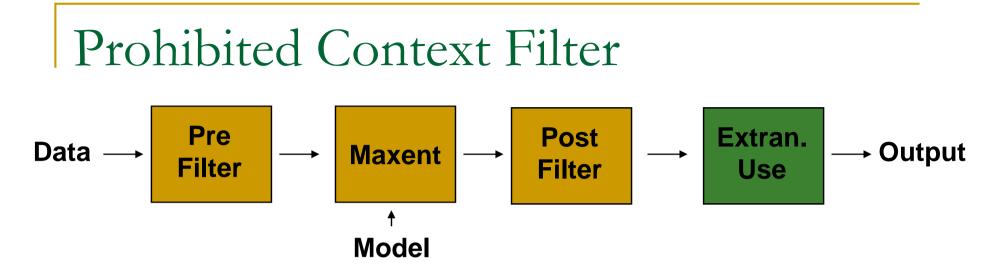
- Spelling Errors
  - Blocked classifier from considering preposition contexts with spelling errors in them
- Punctuation Errors
  - TOEFL essays have many omitted punctuation marks, which affects feature extraction
- Tradeoff recall for precision



- Antonyms
  - Classifier confused prepositions with opposite meanings (with/without, from/to)
  - Resolution dependent on intention of writer

#### Benefactives

- Adjunct vs. argument confusion
- Use WordNet to block classifier from marking benefactives as errors



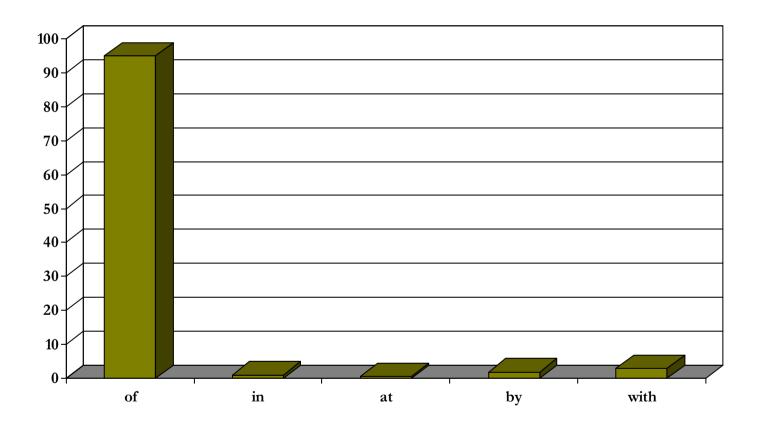
- Account for 142 of 600 errors in test set
- Two filters:
  - Plural Quantifier Constructions ("some of people")
  - Repeated Prep's ("can find friends with with")
- Filters cover 25% of 142 errors

Thresholding Classifier's Output

Thresholds allow the system to skip cases where the top-ranked preposition and what the student wrote differ by less than a prespecified amount

### Thresholds

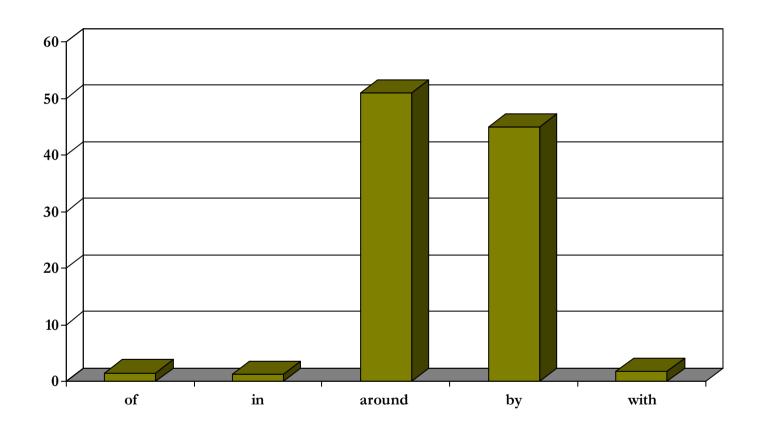
#### **FLAG AS ERROR**



"He is fond with beer"

### Thresholds

#### **FLAG AS OK**



"My sister usually gets home by 3:00"

# Results

Model	Precision	Recall
Lexical	80%	12%
+Combo:tag	82%	14%
+Combo:tag +Extraneous	84%	19%

# Typical System Errors

- Noisy context
  - Other errors in vicinity
- Sparse training data
  - Not enough examples of certain constructions
- Biased training data

## Related Work

	Method	Performance
[Eeg-Olofsson et al. '03]	Handcrafted rules for Swedish learners	11/40 prepositions correct
[Izumi et al. '03, '04]	ME model to classify 13 error types	25% precision 7% recall
[Lee & Seneff '06]	Stochastic model on restricted domain	80% precision 77% recall
[De Felice & Pullman '08]	ME model (9 prepositions)	~57% precision ~11% recall
[Gamon et al. '08]	LM + decision trees (12 prepositions)	80% precision

#### Future Directions

- Noisy Channel Model (MT techniques)
   Find specific errors or do sentence rewriting
   [Brockett et al., '06; Hermet et al., '09]
- Artificial Error Corpora
  - Insert errors into native text to create negative examples
  - □ [Foster et al., '09]
- Test long-range impact of error modules on student writing

#### Future Directions [WAC '09]

- Current method of training on well-formed text is not error-sensitive:
  - Some errors are more probable than others
    - e.g. "married to" vs. "married with"
  - Different L1's make different types of errors
    - German: "at Monday"; Spanish: "in Monday"
- These observations are commonly held in the ESL teaching/research communities, but are not captured by current NLP implementations

## "Region Web Counts" Approach

- In the absence of a large error-annotated ESL corpus, how does one find common errors?
  - ex: \*"married with John" vs. "married to John"
- Novel approach: use region-specific searches to gather data on how different L1's use certain English constructions

Region (or nation) searches = "advanced search"

Previous work has shown usefulness of webcounts for certain NLP tasks

□ [Lapata & Keller, '03; Kilgarriff, '07]

## Web-Counts Example

Region	"depends on"	"depends of"	Ratio
US	92,000,000	267,000	345:1
France	1,500,000	22,700	66:1

\* Counts using Google on March 6, 2009

- "depends of" is over 5 times more likely to appear in France than in the US
- France's small ratio may signal a potential error

## Summary

- Proof of Concept results appear promising:
  - Showed metric can detect known errors
  - Biasing training data could have a big impact
- Long Range Goal: Automatically determine common errors
  - Run methodology on thousands of constructions
    - Preliminary results on 8500 bigrams appear favorable
  - Add more training data for flagged constructions; determine performance improvement from new model

#### Conclusions

- Presented a state-of-the-art preposition error detection methodology
  - State-of-the-art preposition selection performance: 79%
  - Accurately detects preposition errors in ESL essays with P=0.84, R=0.19
- This work is included in ETS's Criterion<sup>SM</sup> Online Writing Service and E-Rater
- ESL error detection is a growing subfield with a more quickly growing demand
  - Great area for dissertation or project ideas!

# Acknowledgments

#### Researchers

- Martin Chodorow [Hunter College of CUNY]
- Na-Rae Han [University of Pittsburgh]

#### Annotators

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- Jill Burstein [ETS]
- Michael Gamon [Microsoft Research]
- Claudia Leacock [Butler Hill]

## Some More Plugs

#### NLP in ETS

- Postdocs
- Summer Interns
- 4<sup>th</sup> Workshop on Innovative Use of NLP for Educational Applications (NAACL-09)
  - http://www.cs.rochester.edu/u/tetreaul/naacl-bea4.html
- NLP/CL Conference Calendar
  - Google "NLP Conferences"
  - http://www.cs.rochester.edu/u/tetreaul/conferences.html