Modeling ESL Word Choice Similarities By Representing Word Intensions and Extensions

Huichao Xue, Rebecca Hwa

Department of Computer Science

University of Pittsburgh

Outline

- Task – Building Confusion Sets for Grammatical Error Correction (GEC) systems
- Idea – Simulating ESL Word Learning
  - Words have *Intensions* and *Extensions*
  - We simulate learning both components
- Simulation Models
- Experimental Results

Grammatical Error Correction(GEC)

- English as Second Language (ESL) learners make grammar errors.

ESL(English as Second Language speakers) TEXT

…

~~Beside~~ the factor of the lead user, …

… Besides

With the help modern technology, …

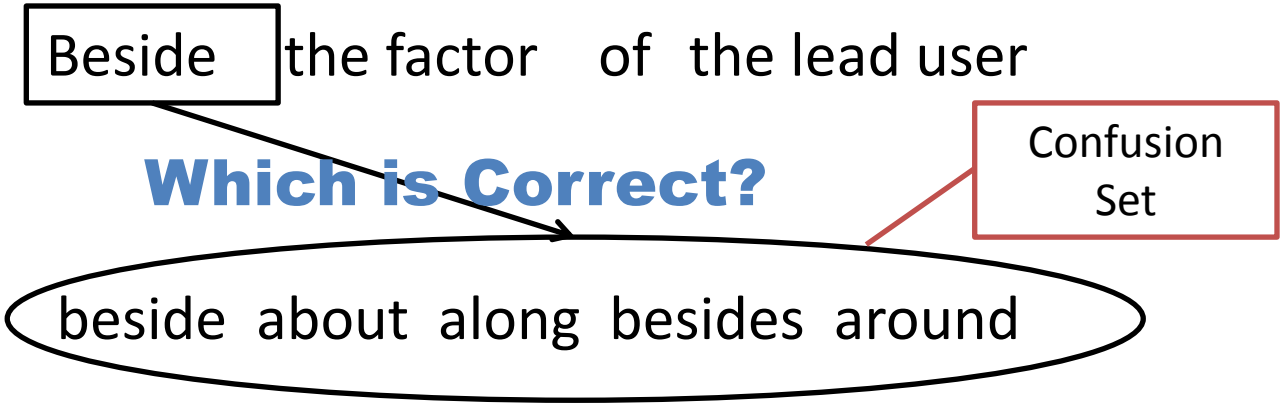
of

…

- We try to build systems that automatically detect and correct these mistakes.

Confusion Sets in GEC systems

- Grammatical Error Correction by Classification

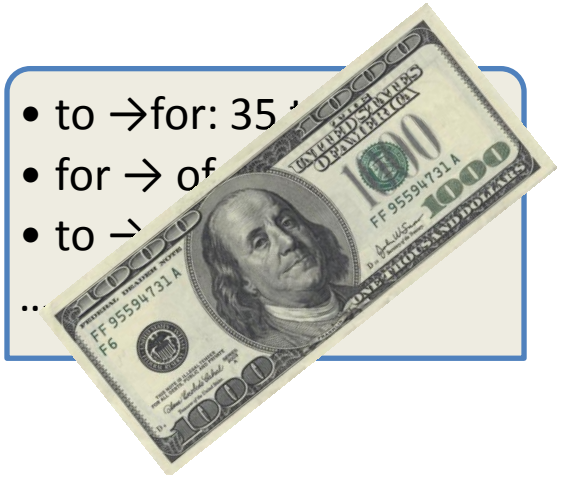


- Confusion sets need to be pre-defined

Ways to build Confusion Sets?

Hiring human experts to filter the initially large sets (Liu, 2010)

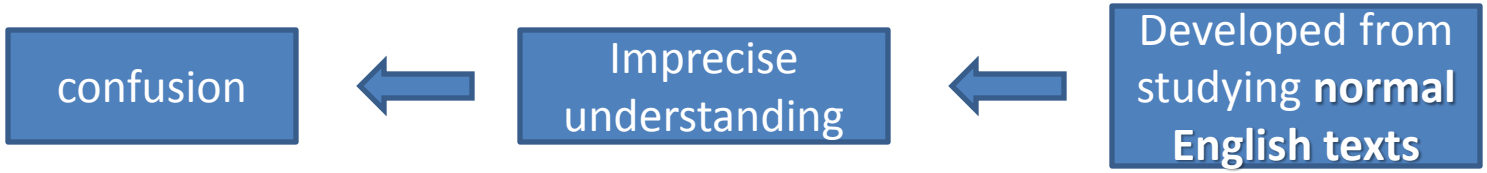
Count from annotated ESL corpora (Rozovskaya, 2010)



Is there a better (cheaper) way?

Proposal: Building Confusion Sets from Normal English Corpora

- Normal English corpora is enough



- Our idea:
  - Simulate how learners learn English words.
  - Find out which words are similar
- Test our idea on **prepositions**

36 most frequent prepositions

about, along, among, around, as, at, beside, besides, between, by, down, during, except, for, from, in, inside, into, of, off, on, onto, outside, over, through, to, toward, towards, under, underneath, until, up, upon, with, within, without.

Knowledge of a word – Intension and Extension

What do people learn about words?

Intension

Any property or quality connoted by a word.

Extension

Things the word applies to.

Characterized by contexts it appears in.

Intension

[1]of *preposition* \əv, *before consonants also* ə; ˈəv, ˈäv\

Definition of OF

1 —used as a function word to indicate a point of reckoning <north *of* the lake>

2 a —used as a function word to indicate origin or derivation <a man *of* noble birth>

b —used as a function word to indicate the cause, motive, or reason <died *of* flu>

c : BY <plays *of* Shakespeare>

Extension

Three Views on Word Learning

1. Concentrating on intensions
   - E.g. lexical semantics
   - Words with similar meanings are confusable
2. Concentrating on extensions
   - E.g. language modeling
   - Words occur in similar contexts are confusable
3. Our view – both intensions and extensions
   - Ultimately, compatible intension and extension

Outline

- Task – Building Confusion Sets for Grammatical Error Correction (GEC) systems
- Idea – Simulating ESL Word Learning
- Simulation Models
  - Intension only
  - Extension only
  - Both (proposed model)
- Experimental Results

Intension Based Model

- Learners' main goal is to learn about words' meanings.

  Confusion is caused by *meanings' similarity*.
- Meanings are learned from reading text. (Fischer, 1990)
  - We simulate using *Distributional Models* (Pereira et al., 1993; Lee, 1999)
    - The similarities are shown to correlate with word meaning similarities
  - We then fill in confusion sets with the most similar words

Intension Based Model (distributional models)

Corpus
… need of …
… need for …
… of you …
… to you …
… to you …
… for you …
… of course …
…

Dimensions are contexts (very many):

	__ that	__ you	__ course	…
of	0.50	0.25	1.00	…
to	0.0	0.50	0.00	…
for	0.50	0.25	0.00	…

Words are Vectors of Distributions: Pr(word|context)

Normal Metrics for Similarities:

1. Euclidean Distance
2. KL-Divergence
3. Cosine Similarities

Intension Based Model

Corpus
… need of …
… need for …
… of you …
… to you …
… to you …
… for you …
… of course …
…

Distributional vectors

of	0.50	0.25	1.00	…
to	0.0	0.50	0.00	…
for	0.50	0.25	0.00	…

Calculate distance

	of	to	for
of	0	1.5	2.0
to	1.5	0	2.5
for	2.0	2.5	0

Pick the closest

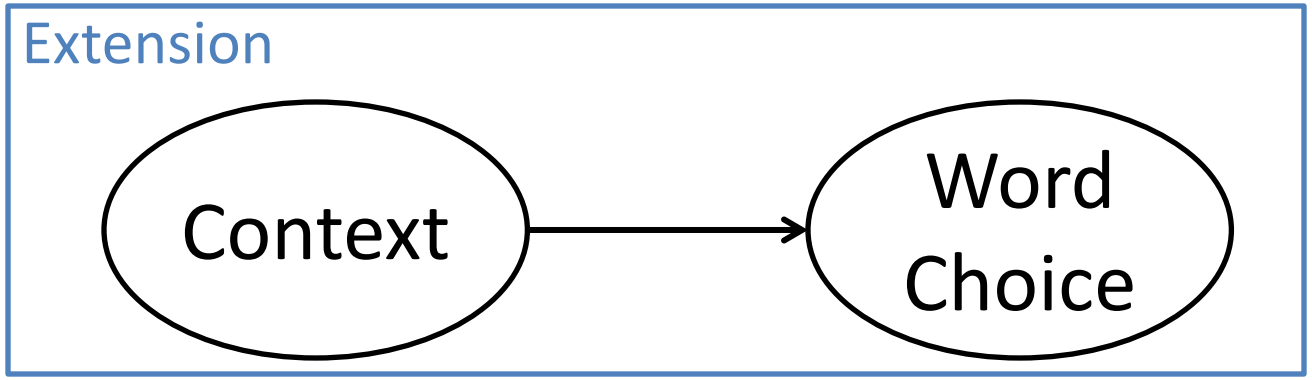
Word	Confusion set
of	of, to
to	to, of
for	for, of

Outline

- Task – Building Confusion Sets for Grammatical Error Correction (GEC) systems
- Idea – Simulating ESL Word Learning
- Simulation Models
  - Intension Only
  - Extension Only
  - Both (Proposed model)
- Experimental Results

Extension Based Model (Word Selector)

- Learners' main goal is to learn how to choose words.



- We use classifiers to simulate learners

  Rerun the trained classifier on training data to collect mistakes

Extension Based Model

Corpus
… need of …
… need for …
… of you …
… to you …
… to you …
… for you …
… of course …
…

Train a word selector

Word Selector		
need __	⇒	of
__ you	⇒	to
__ course	⇒	of
…	…	…

Rerun on training corpus

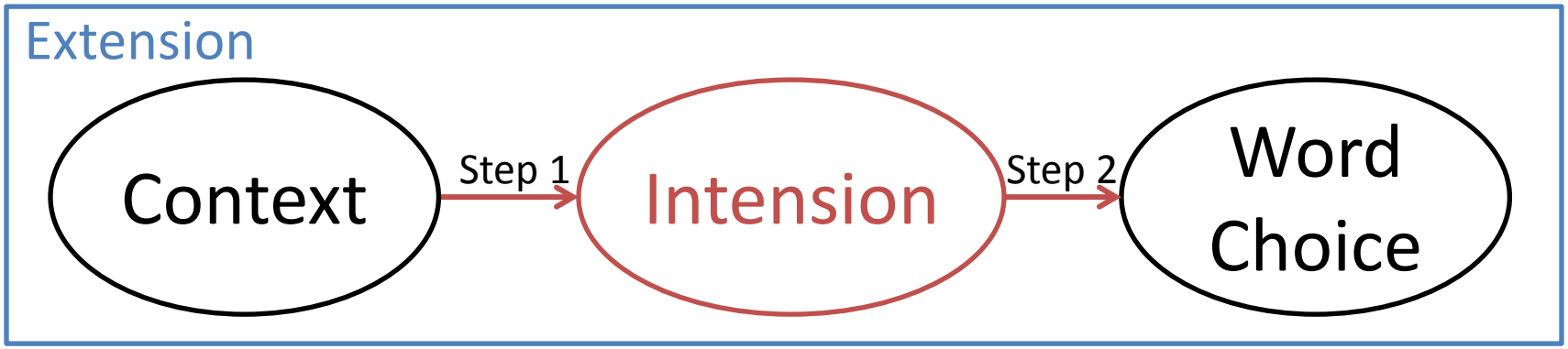
		true		
selector		of	to	for
	of	200	150	10
	to	0	400	100
	for	5	10	100

Word	Confusion set
of	of, to
to	to, for
for	for, to

Outline

- Task – Building Confusion Sets for Grammatical Error Correction(GEC) systems
- Idea – Simulating ESL Word Learning
- Simulation Models
  - Intension Only
  - Extension Only
  - Both(Proposed model)
- Experimental Results

Proposed method: Combine Intension and Extension



Example:

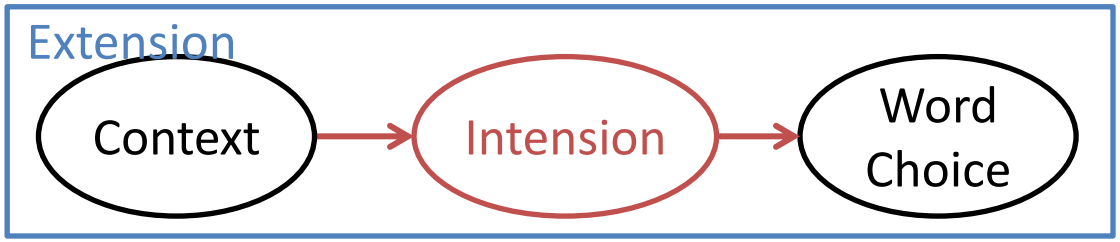
country's needs ___ water

1. water is the object
2. water is necessary for the country

√of
to
…

Word usages (extension) involve the understandings of words' meanings (intension).

Combining Intension and Extension
Mathematical Formulation



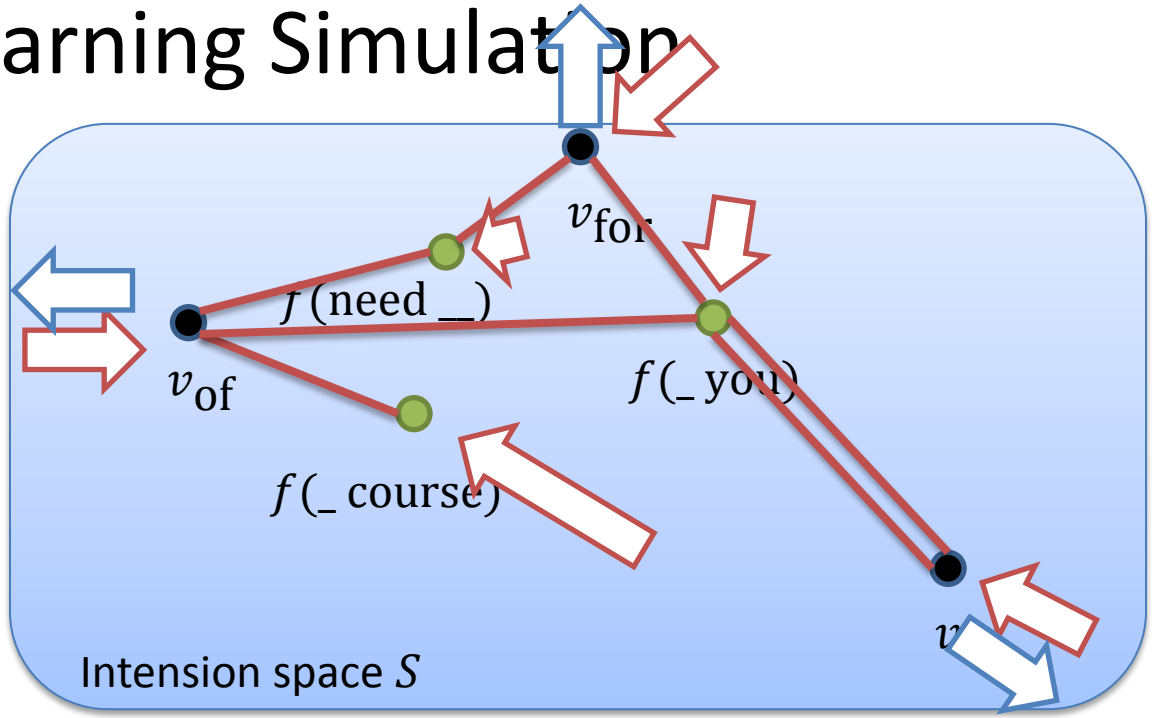
- Intensions are represented as points in an Euclidean space S:
  - Prepositions are vectors in S: $v_{\text{of}}, v_{\text{to}}, \ldots$
  - We assume $S = R^{36}$
- The first step of word choice decision is formalized as $f: \text{Context} \rightarrow S$

e.g. Need __ $\rightarrow$ $[1.2, 3.5, -1.2, \ldots, 1]^T$

Combining Intension and Extension

Learning Simulation

Corpus
… need of …
… need for …
… of you …
… to you …
… to you …
… for you …
… of course …
…



$$\min_{f, v_{\text{of}}, v_{\text{for}}, \ldots} \left\| f(\text{need }\_) - v_{\text{of}} \right\|^2 + \cdots \quad \text{s.t. } \text{Area}(v_{\text{of}}, v_{\text{for}}, \ldots) \geq 1$$

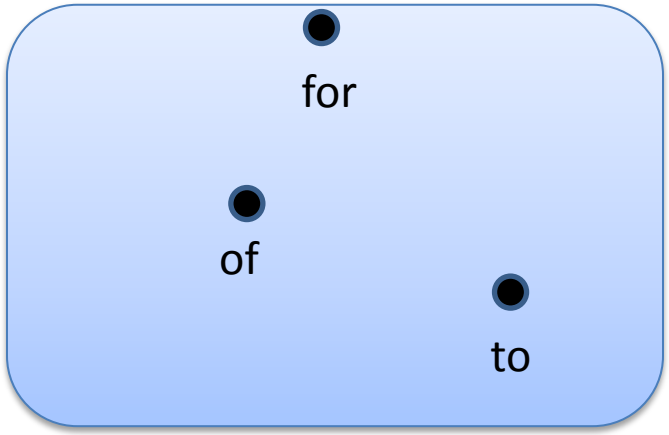
Optimal $v_{\text{of}}, v_{\text{for}} \ldots$ indicate the ultimate understandings of prepositions' intensions

Relevance Component Analysis (RCA) (Bar et al., 2006) solves this optimization problem

Combining Intension and Extension (RCA)

Corpus
… need of …
… need for …
… of you …
… to you …
… to you …
… for you …
… of course …
…

RCA



Calculate distance

	of	to	for
of	0	2.0	1.5
to	2.0	0	2.5
for	1.5	2.5	0

Pick the closest

Word	Confusion set
of	of, for
to	to, of
for	for, of

Outline

- Task – Building Confusion Sets for Grammatical Error Correction (GEC) systems
- Idea – Simulating ESL Word Learning
  - Words have *Intensions* and *Extensions*
  - We simulate learning both components
- Simulation Models
- Experimental Results

Experimental Setup – task

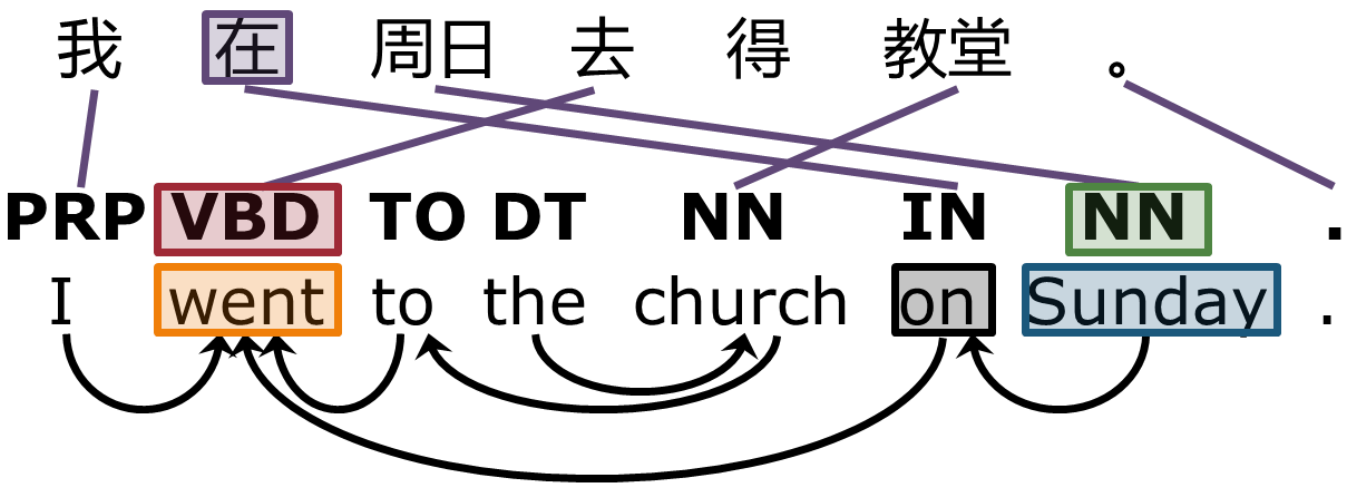
- Constructing confusion sets for the 36 most frequent prepositions
- Evaluate extrinsically – end-to-end GEC system
  - On NUCLE corpus (Chinese ESL speakers)
  - filter training samples using the confusion set (Rozovskaya et al., 2010)
  - Evaluate by F_1 score

Experimental Setup – Confusion Set Construction Methods

- The three automatic methods
  - Intension only – **kl div, euc dist, cos sim**
  - Extension only – preposition **selector**
  - Combined – **RCA**
- **all preps**: containing all prepositions
- **gold**: containing the most frequently confused words according to real ESL corpus (NUCLE).

Experimental Setup – data and features

- FBIS corpus, GIZA++, Stanford Parser
- Indicative contextual features (Tetreault et al 2010):



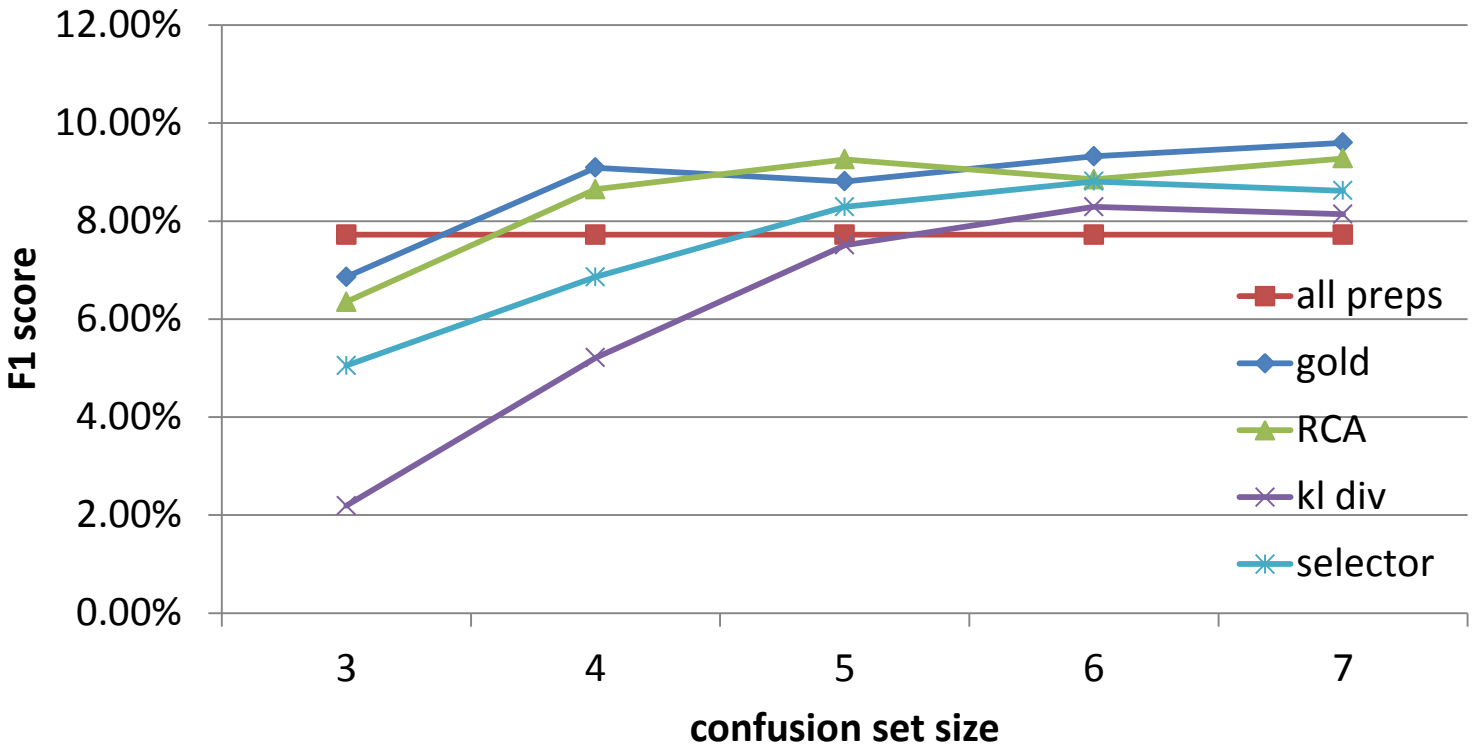
- **Gov**: dependency governors of the preposition
- **Obj**: dependency objects of the preposition
- **GovTag**: part-of-speech tags of Gov
- **ObjTag**: part-of-speech tags of Obj
- **L1-Trans**: L1 translation of the preposition

We incorporate **L1-Trans** to consider the L1 background of speakers.

Experiments – Questions

- Our proposed method V.S using annotated ESL corpus
- Intension/Extension only V.S Intension and Extension combined
- How do features affect our methods?

Experimental Result



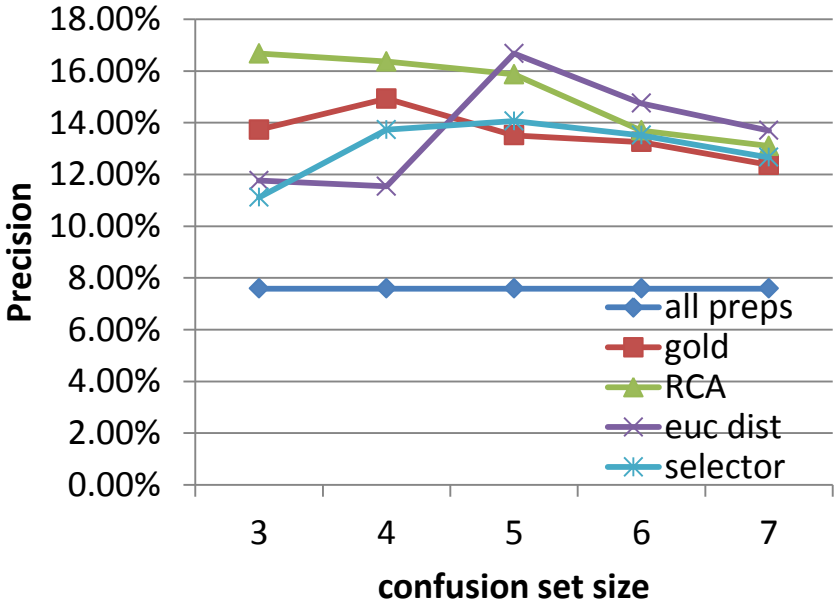
Using **Gov**, **Obj**, **L1-Trans**

1. Automatic method is competitive
2. Learning intension and extension together is helpful

A Deeper Comparison

Precision

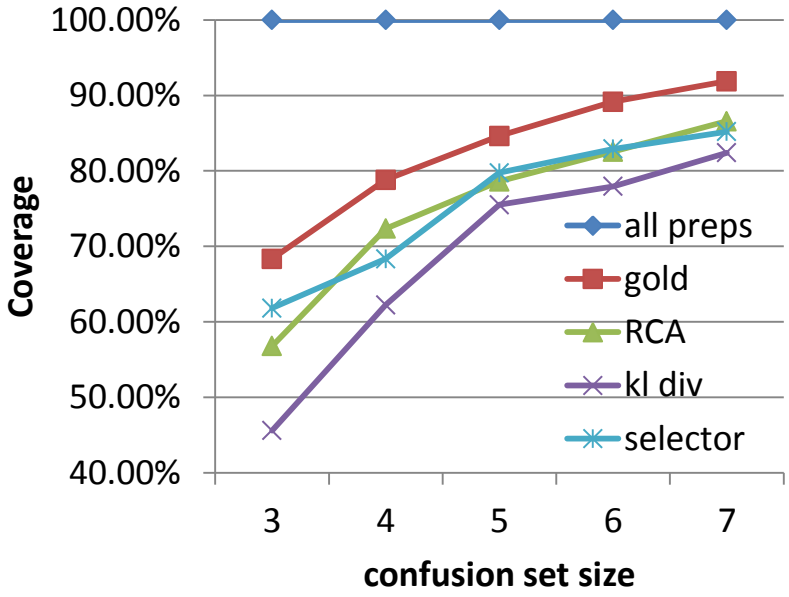
RCA and euc dist are more helpful



Coverage (Intrinsic Evaluation)

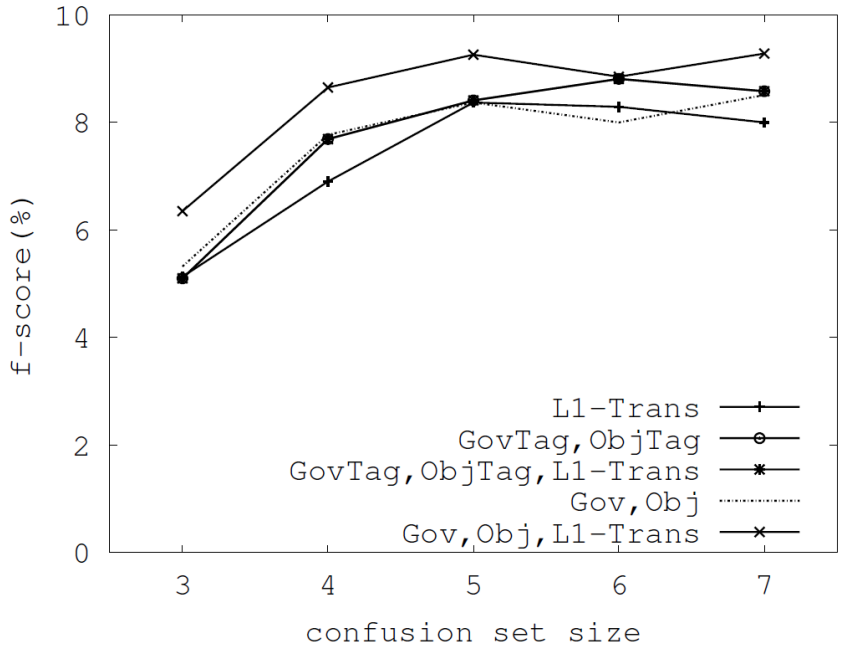
Proportion of ESL mistakes covered by the confusion sets

RCA and selector are better

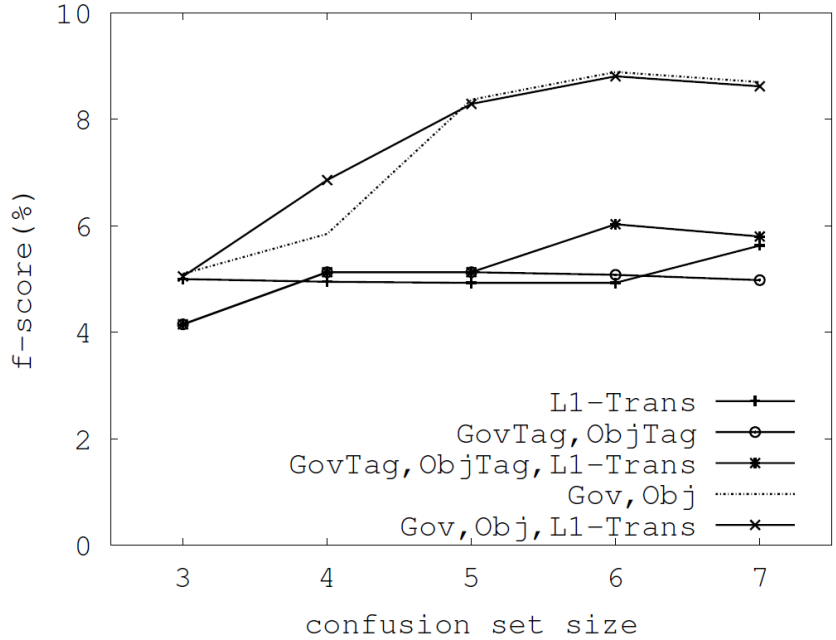


Feature Sets and Confusion Sets' Quality

***RCA* method's F_1 scores**



***Selector* method's F_1 scores**



RCA is more stable w.r.t. the feature set changes.

Conclusions

- A cheap method to automatically construct confusion sets
  - Simulation on **normal English text**
- The resulting confusion sets:
  - are able to improve GEC systems' performance
  - Correlate well with real ESL mistakes
- Benefits from modeling interaction between *intensional* and *extensional* knowledge

Thank you!