Towards Improving Machine Translation and Speech Recognition with Discriminative Fluency Classification

Roee Aharoni, Moshe Koppel
Bar Ilan University
ICRI-CI Retreat, May 24th, 2016

Motivation

- Evaluation of automatic speech recognition (ASR) systems and Machine Translation (MT) systems requires manually aligned speech-to-text or text-to-text examples (Word Error Rate, BLEU)

- Such examples are expensive to obtain, especially for specific domains and resource-poor languages

- We would like to create an evaluation and re-ranking method for MT and ASR which does not depend on such aligned examples

The Generative Approach to Fluency Estimation

- Generative n-gram language models are a core component in today's state of the art ASR and MT systems (e.g. Baidu's Deep Speech, Hannun et. al. 2015)

- Usually used as a scoring model in the sequence decoding process - better LM score = more likely hypothesis

- Enables the use of massive amounts of unlabeled data

Our Approach: Discriminative Fluency Estimation

- If we look at the data:
  - "Good" ASR outputs:
    - GO TO THE LOUNGE
    - LOOK FOR MY MOBILE PHONE
    - ROBOT CAN YOU TURN THE OVEN ON
  - "Bad" ASR outputs:
    - ROEDEL CAN YOU OPEN THE WATUSI
    - WHO THE GLASS FROM THE SCENE
    - ROBOT CAN RETURN MY LAPTOP ONE FTP
- **Can we train a classifier to discriminate good ASR/MT outputs from bad ones?**

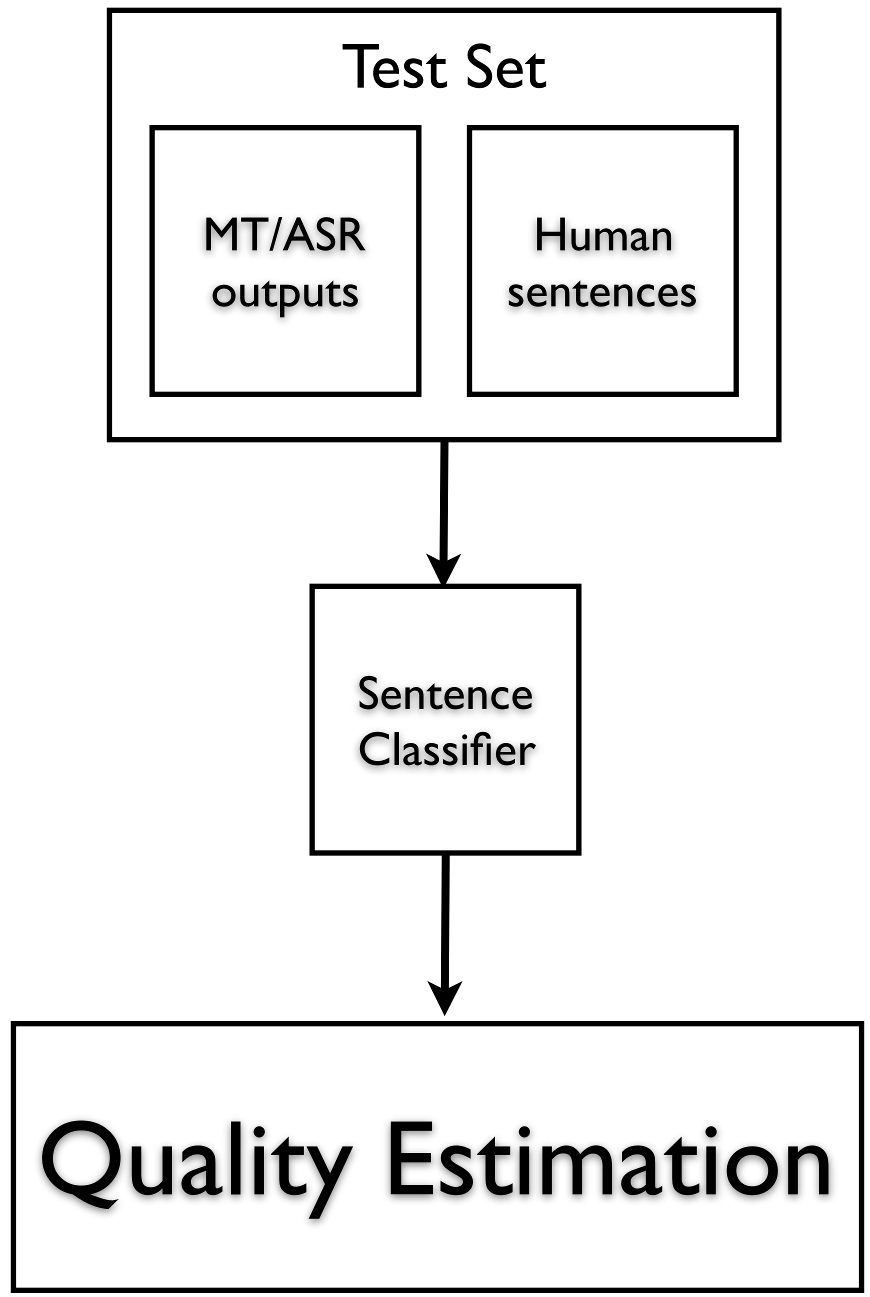
Our Approach: Discriminative Fluency Estimation

- Classify text, at sentence level, into Machine or Human Language
- Use the classification accuracy as a “proxy” for quality estimation
- The hypothesis (over a large enough dataset):

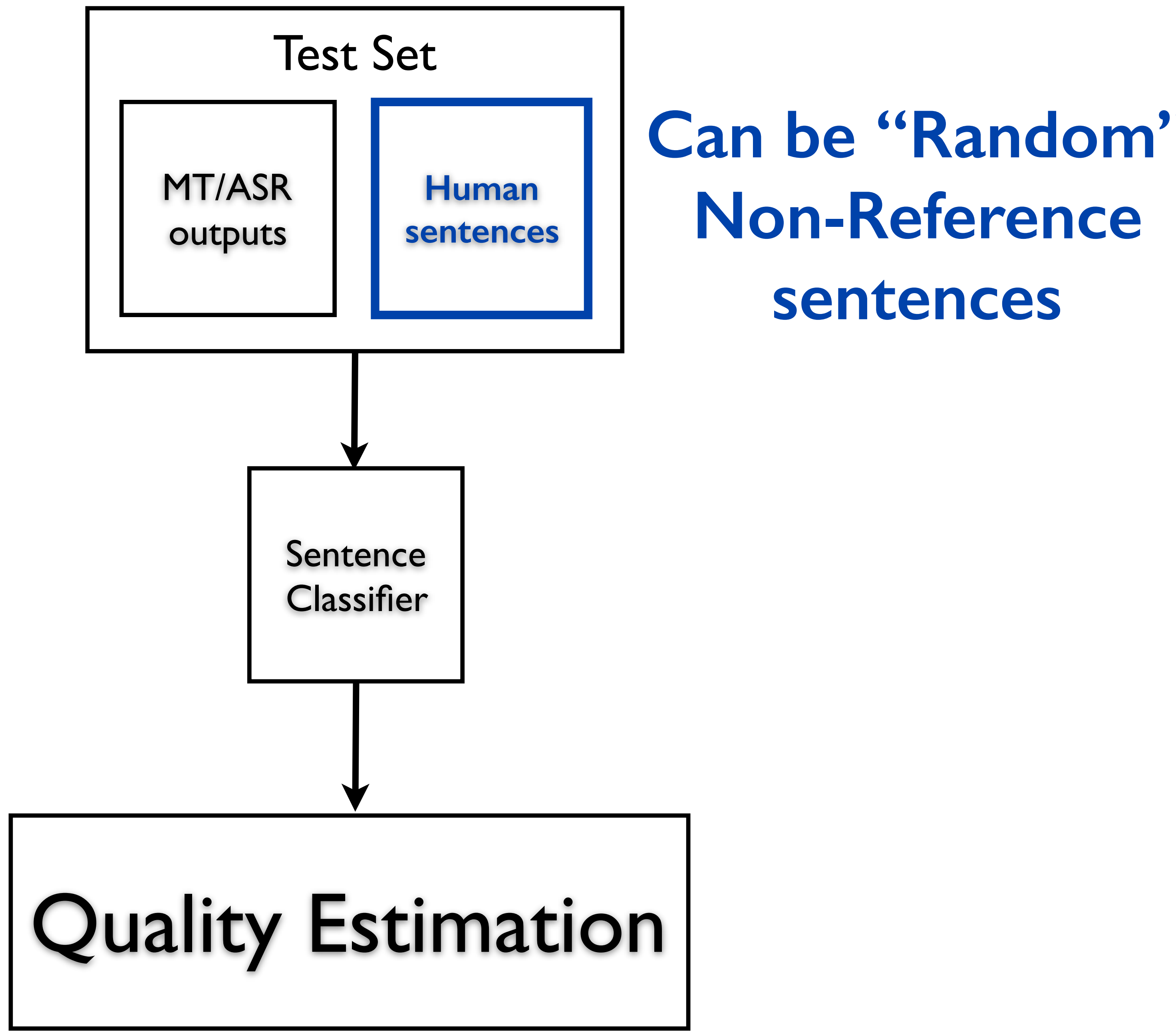
high classification accuracy = bad quality output,

low classification accuracy = high quality output

Our Approach: Discriminative Fluency Estimation



Our Approach: Discriminative Fluency Estimation



Experiments Outline

- Divide the machine output sentences into variable quality sets (from poor quality to high quality)
- For a given sentence sets:
  - Perform a 10-fold cross-validation experiment using a linear SVM classifier that classifies the sentences into human vs. machine, the machine sentence set vs. a human sentence set
  - Measure the correlation between the classification accuracy and the output quality for the set (WER/BLEU/human evaluation)

MT Experiments

Features - MT

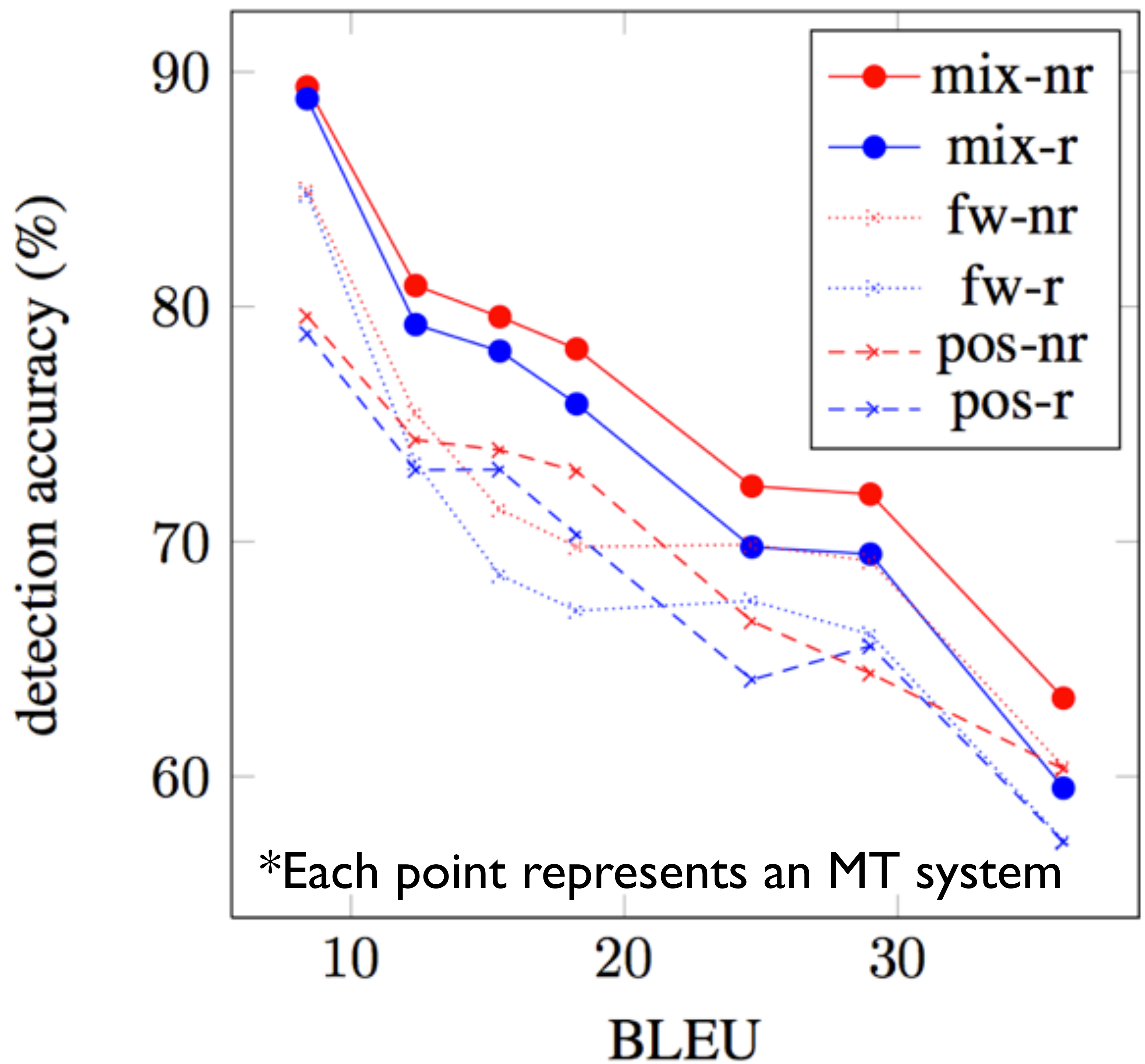
- Use common linguistic, domain-independent features to discriminate MT outputs from human sentences:
    - Function Words
    - Parts of Speech
    - Syntax
- Inspired by works on:
    - “Translationese” (Koppel and Ordan, 2011)
    - Machine Translation Detection (Arase and Zhou, 2013)

Experiment 1 - Commercial MT Systems

- 7 French-English commercial MT system outputs (Google Translate and 6 others via the itranslate4.eu website)
- 3 different feature settings (POS, function words and both)
- Compared use of reference and random non-reference human sentences
- 20,000 sentences per class (human/MT) taken from the Hansard Corpus (Germann, 2001)

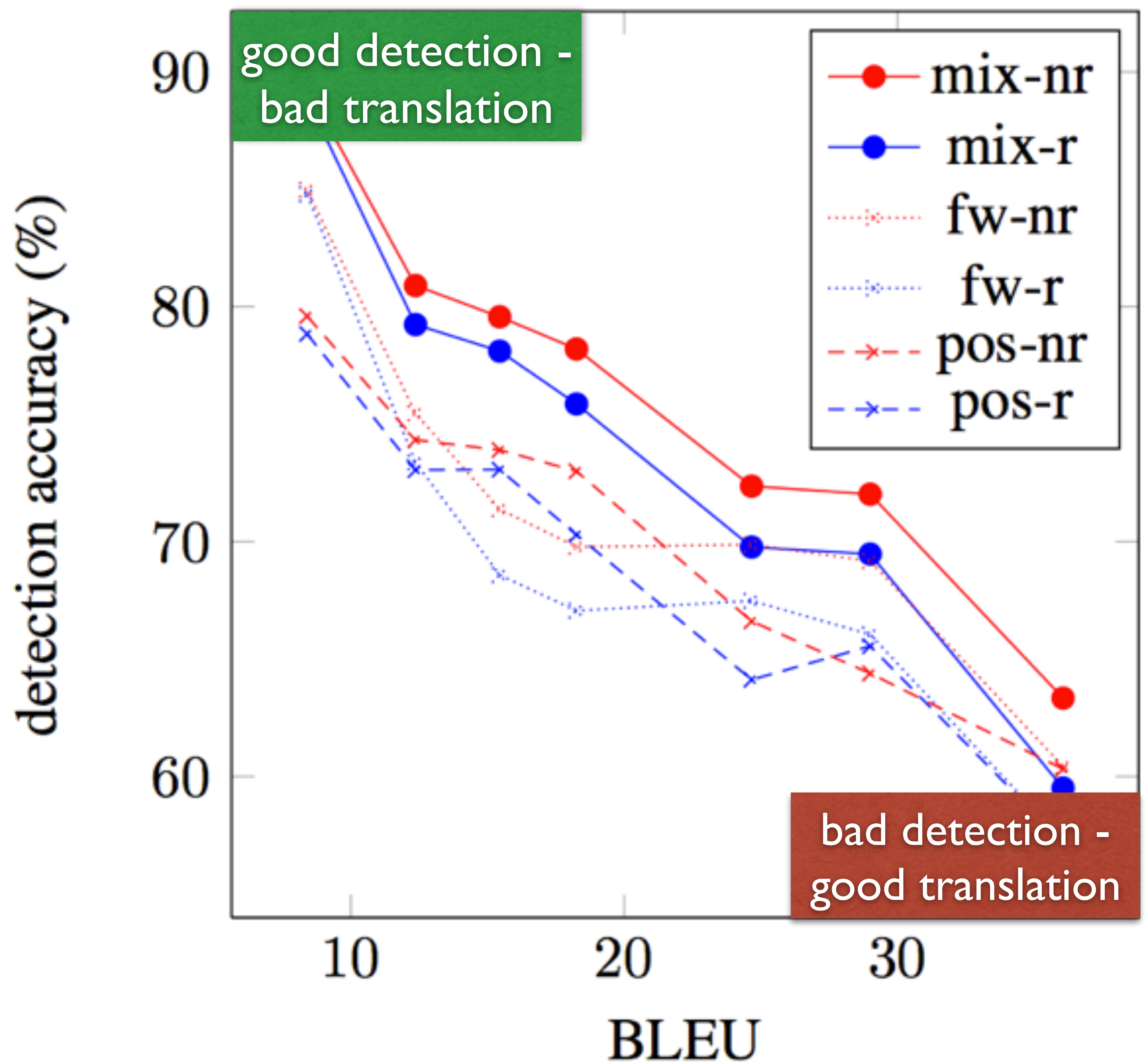
Results - Commercial MT Systems

- Very strong negative correlation with BLEU - R^2: 0.78 to 0.98
- Up to ~90% detection accuracy



Results - Commercial MT Systems

- Very strong negative correlation with BLEU - R^2: 0.78 to 0.98
- Up to ~90% detection accuracy
- The better the translation quality is, the harder it is to correctly detect it



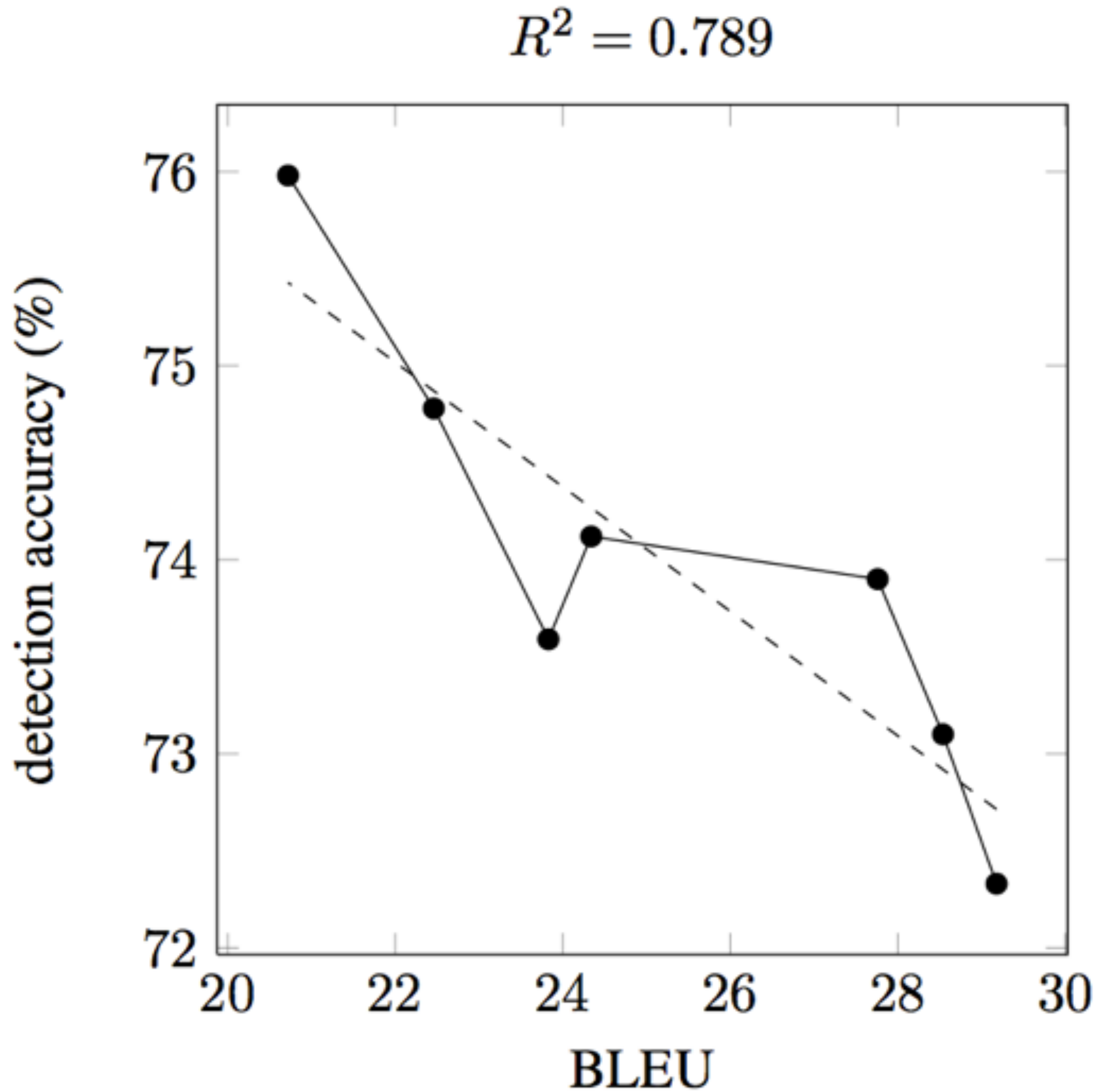
Experiment II - In-House MT Systems

- Trained 7 French to English phrase-based MT systems, using the Moses SMT toolkit (Koehn et al, 2007)
- Train data (LM + Translation): Europarl corpus (Koehn, 2005)
- Evaluation data: Hansard corpus (Germann, 2001)
- Varied both LM and translation model sizes, resulting in a wide variety of BLEU scores:

	Parallel	Monolingual	BLEU
SMT-1	2000k	2000k	28.54
SMT-2	1000k	1000k	27.76
SMT-3	500k	500k	29.18
SMT-4	100k	100k	23.83
SMT-5	50k	50k	24.34
SMT-6	25k	25k	22.46
SMT-7	10k	10k	20.72

Results - In-House MT Systems

- The correlation is consistent among the in-house systems as well
- High correlation with BLEU, **using only random, non-reference sentences**

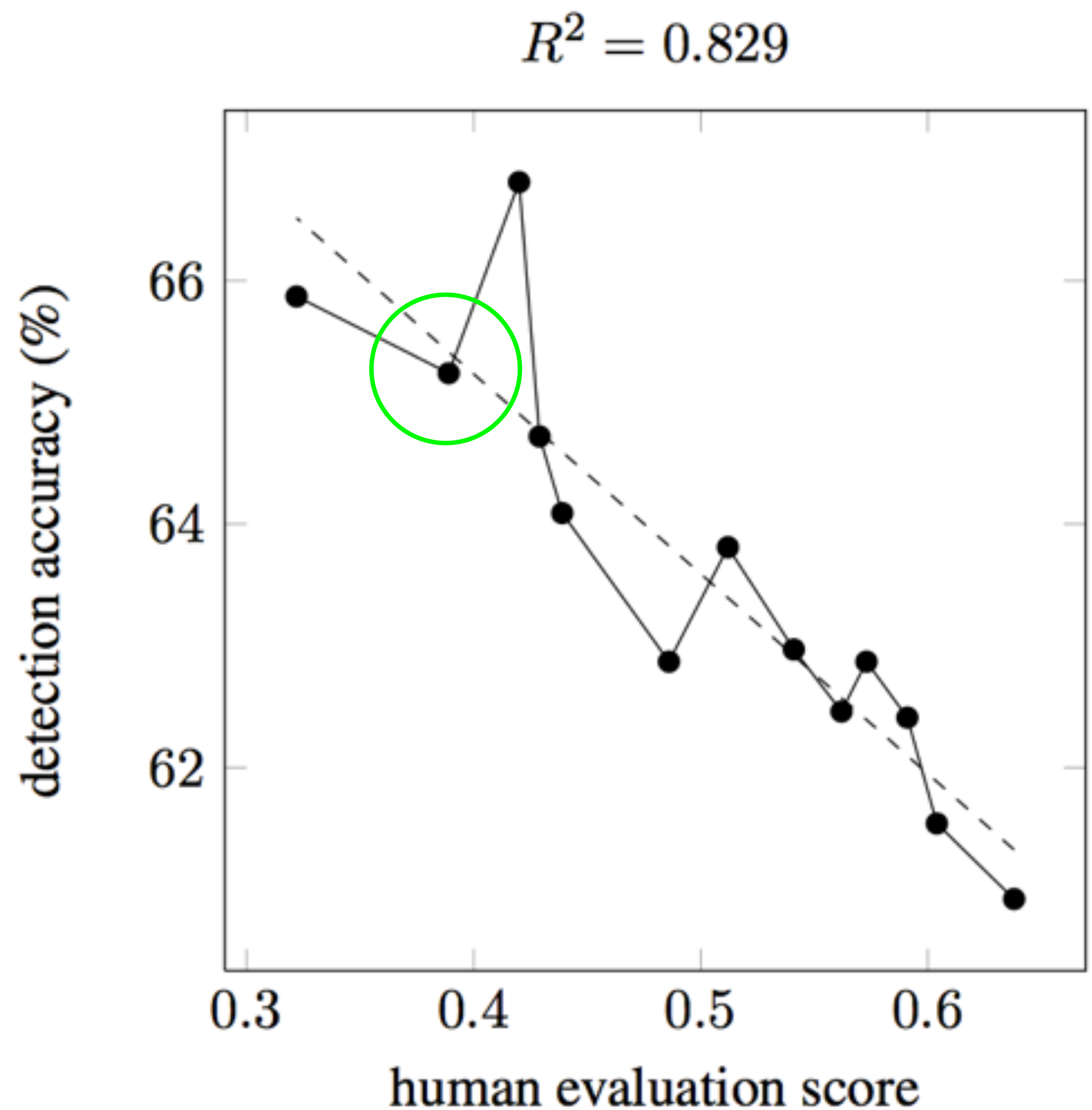


Experiment III - Correlation with Human Evaluation

- BLEU scores are nice, but how about correlation with real (human) evaluation?
- Examined 13 French-English MT systems and their human evaluations from WMT13’ (Bojar et al., 2013)
- Used reference sentences and random, non-reference sentences from WMT 12’ (Callison-Burch et al., 2012) as the human data

Results - Correlation with Human Evaluation

- High correlation with human evaluation score - R^2 = 0.829
- **No use of reference sentences in the process**



ASR Experiments

ASR Experiments Setup

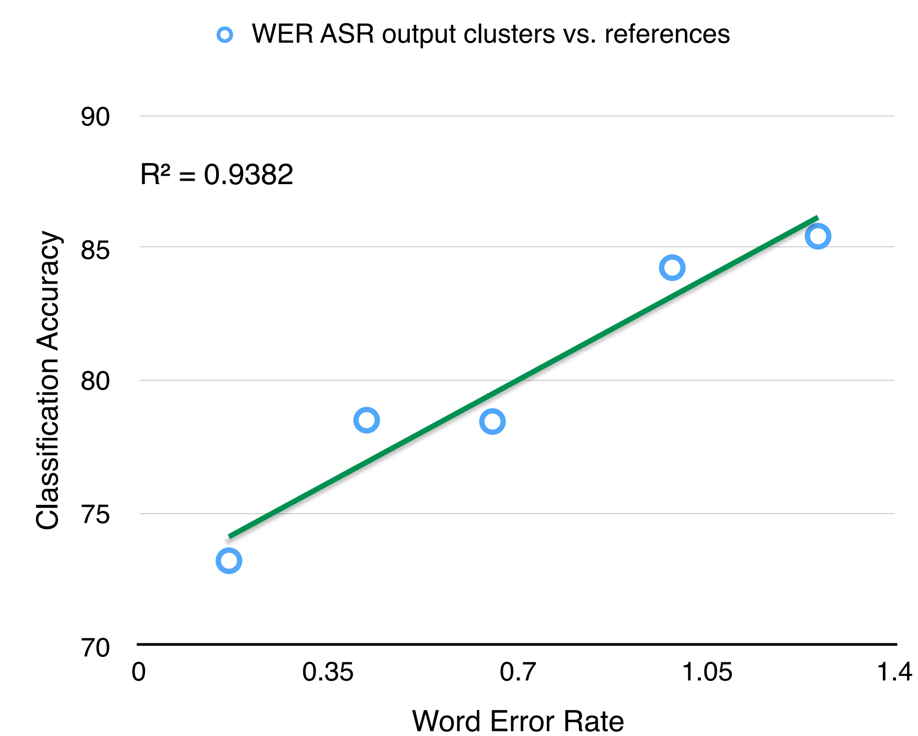
- Formal representation of ASR output and human-generated sentences
    - Lexical features only (most frequent words in corpus)
    - Syntactic and POS features not helpful
- Use SVM to distinguish human sentences from ASR output
- Use 10-fold cross-validation to measure success
- Compare success of discriminative model to WER

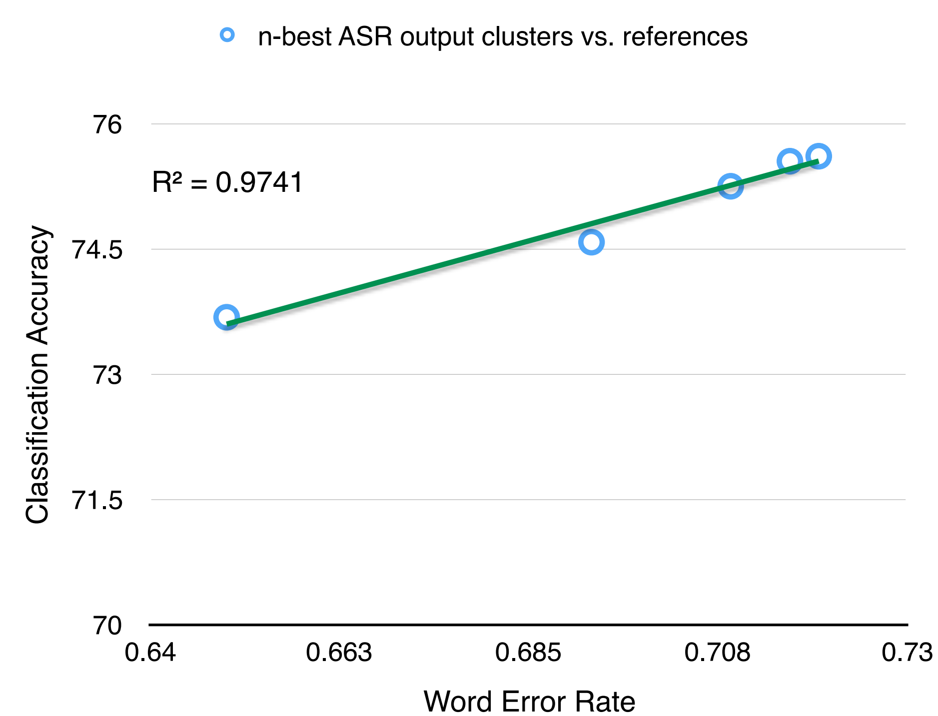
Datasets

- ICSI Meeting Transcripts Corpus
  - ~60k sentence transcriptions + corresponding 5-best lists from in-house ASR system
  - ~795k words; ~13k unique words
- TED talks corpus with NAIST ASR outputs
  - 1,770 manually transcribed sentences from TED talks
  - Corresponding 5-best lists produced by NAIST ASR system (Heck 2015)
- ROCKIN Robot Challenge Corpus
  - Robot instructions from 4 competitions
  - <700 transcribed instructions (very small!)
  - 5-best ASR outputs for only ~400 transcribed instructions

Results - ICSI Conversations Dataset

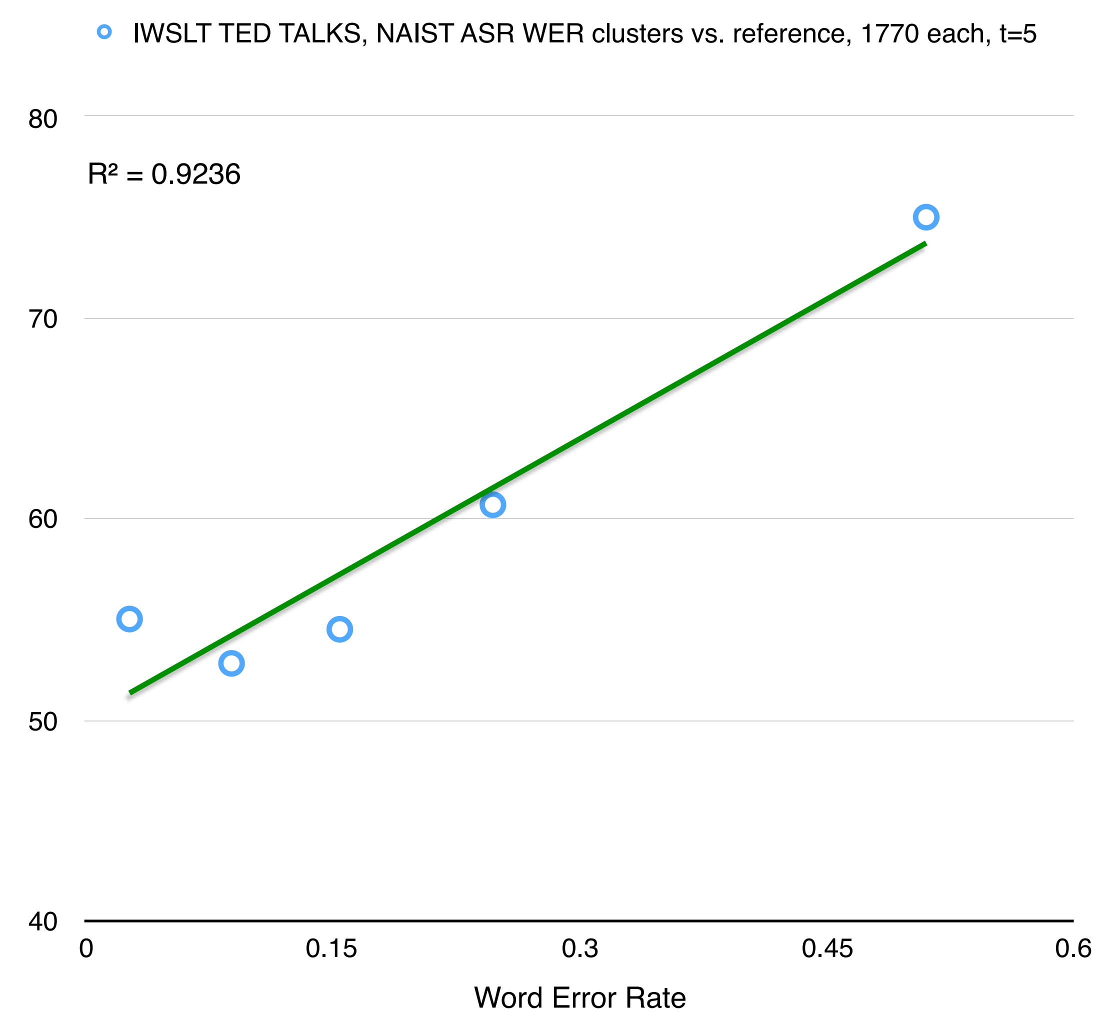
- X axis - WER, Y axis - classification accuracy, each point is a cluster
- Very high correlation (R^2 = 0.93-0.97) between classification accuracy and WER on both cluster types (n-best or sorted by WER)





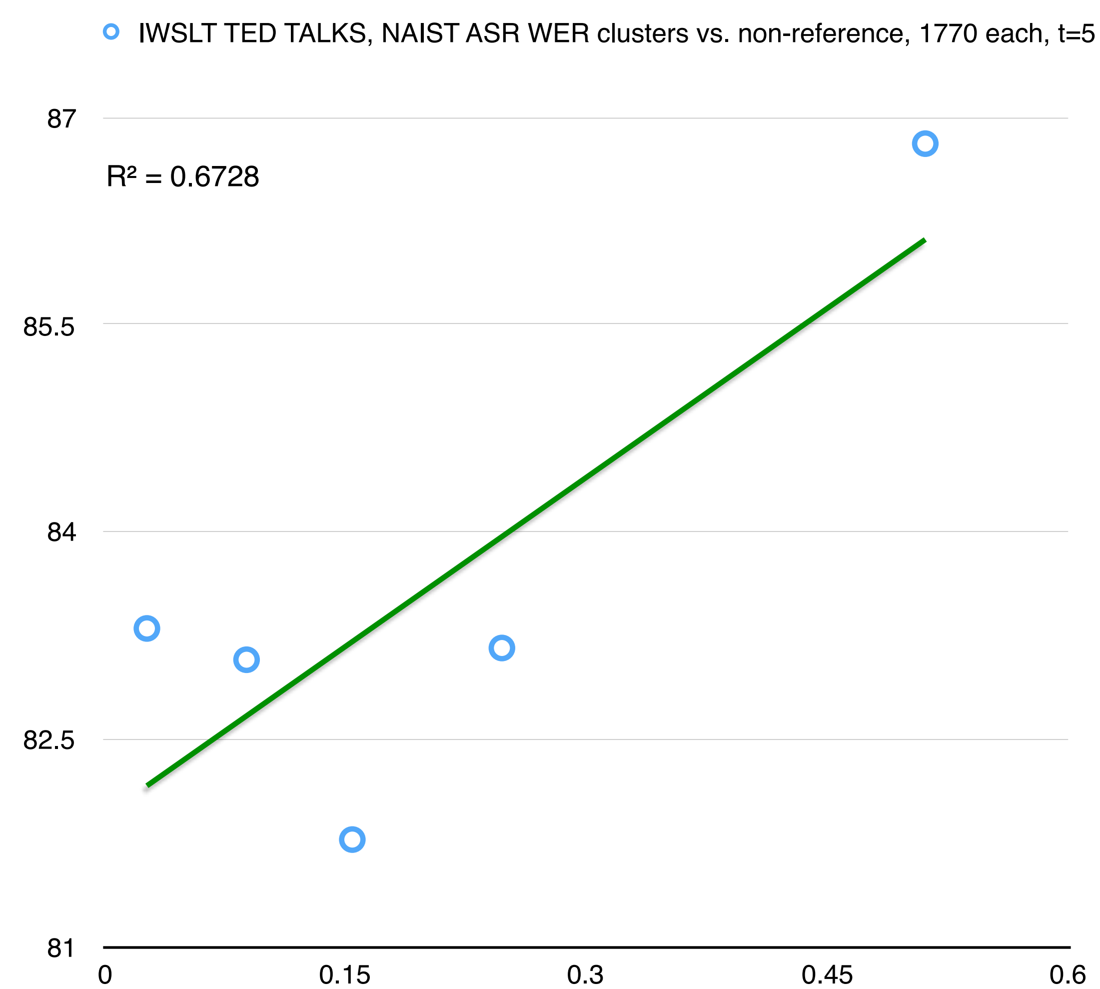
Results - TED talks dataset vs. references

- High correlation (0.92) with WER, even with a much smaller dataset and a very small WER variance (X axis, 0.18-0.22)



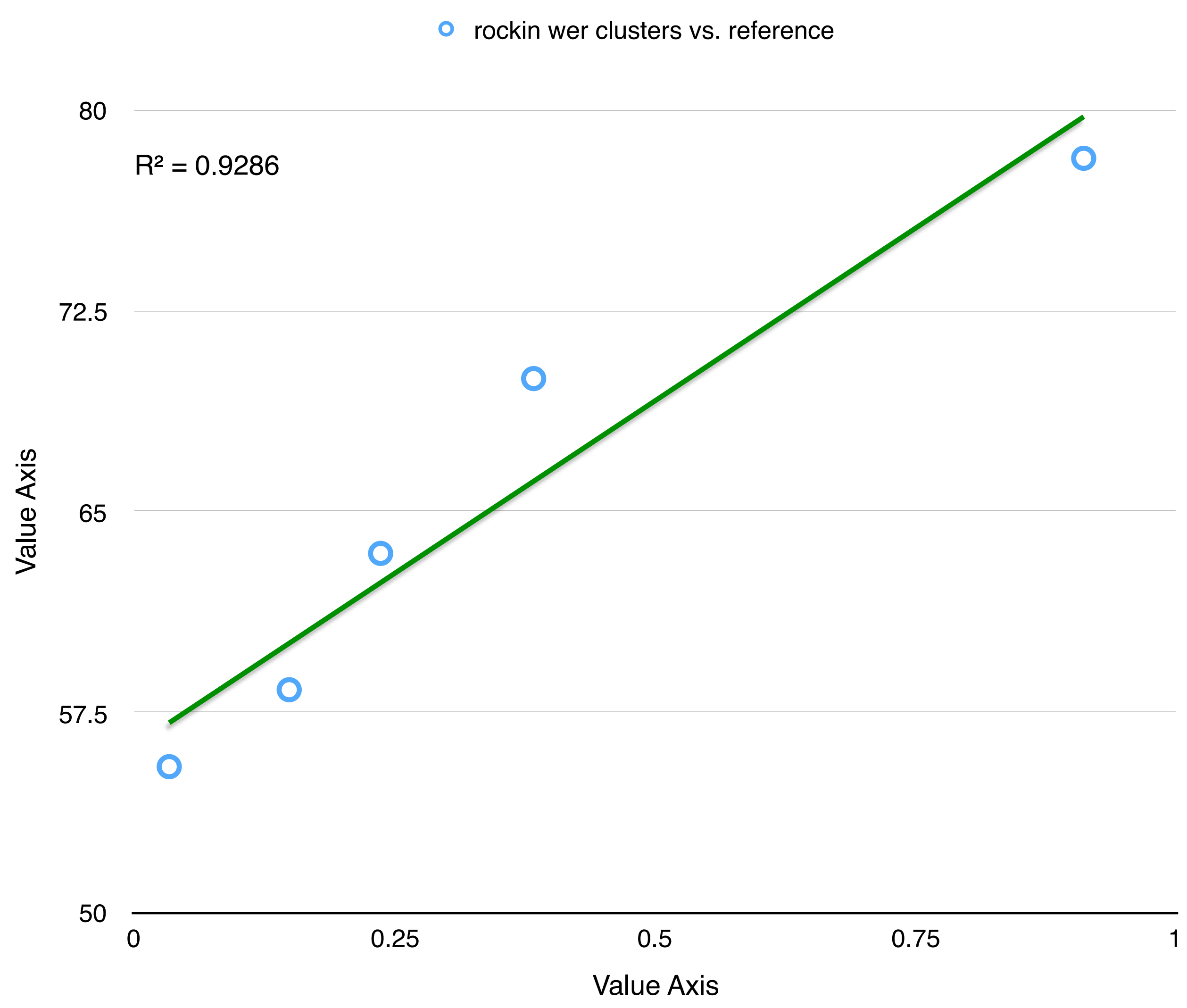
Results - TED talks dataset vs. non-reference data

- To explore using non-reference data as the “fluent” part, we took 1770 sentences from another TED talks corpus
- Correlation still holds, but lower - R^2 = 0.67 (smaller datasets)



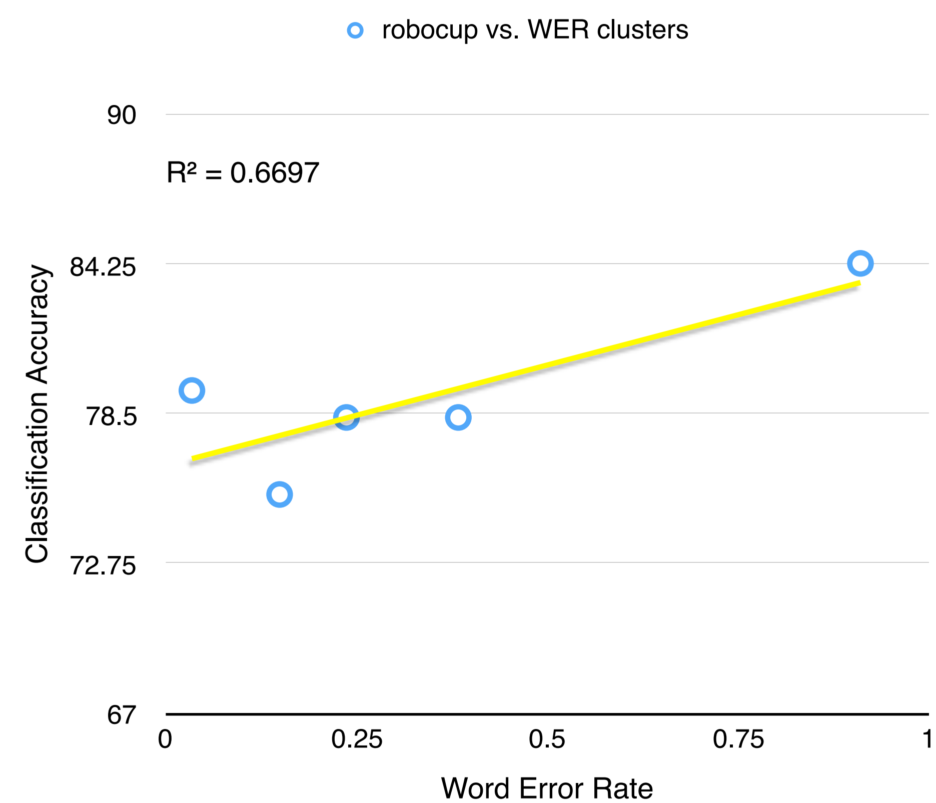
Results - Robot Instructions Dataset

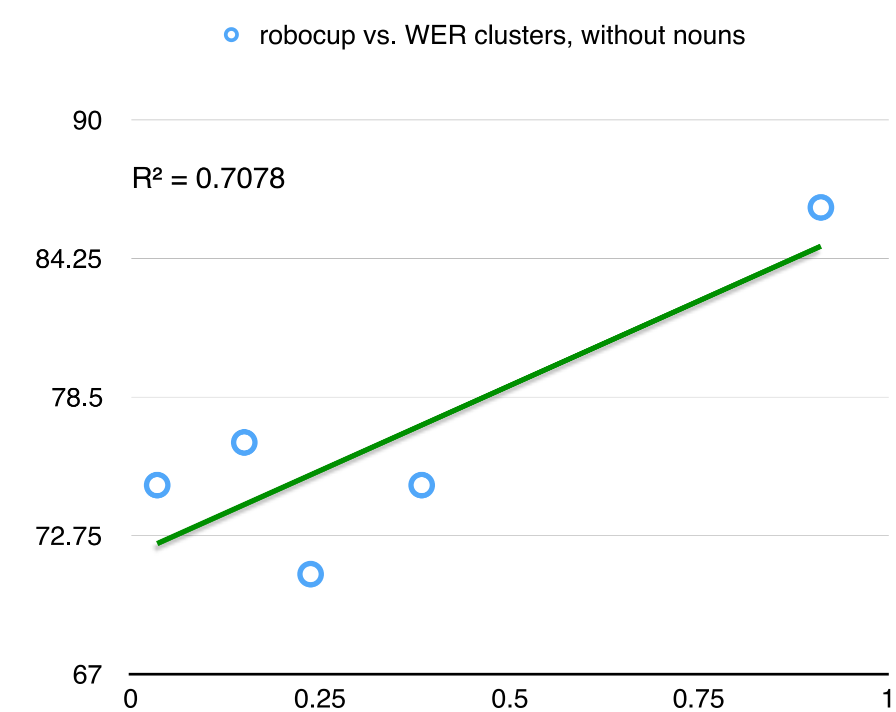
- High correlation (R^2=0.93) even with *very few* examples (382 per class) and a much more specific domain



Results - Using Non-Reference Data

- To explore using non-reference data as the “fluent” part, we took 292 instructions from a different robot competition
- Correlation still holds, but lower - R^2 = 0.67 (smaller datasets, slightly different language)
- Removing all the noun features (which are more domain specific), leaving only verbs and function words, improved correlation to 0.71





Conclusions

- It is possible to evaluate MT and ASR systems even in the absence of sentence-aligned data.

- This measure correlates with standard evaluation measures that use such data. The correlation holds on large, general domain datasets and on small, domain specific test sets

- Future work may include different classification techniques and the development of re-ranking components inspired by this approach.

Thank You