A Comparative Evaluation of Deep and Shallow Approaches to the Automatic Detection of Common Grammatical Errors

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DCU IBM National Centre for Language Technology School of Computing, Dublin City University embarkinitiative

Talk Outline

- Motivation
- Background
- Artificial Error Corpus
- Evaluation Procedure
- Error Detection Methods
- Results and Analysis
- Conclusion and Future Work

Why Judge the Grammaticality?

- Grammar checking
- Computer-assisted language learning
  - Feedback
  - Writing aid
  - Automatic essay grading
- Re-rank computer-generated output
  - Machine translation

Why this Evaluation?

- No agreed standard
- Differences in
  - What is evaluated
  - Corpora
  - Error density
  - Error types

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Deep Approaches

- Precision grammar
- Aim to distinguish grammatical sentences from ungrammatical sentences
- Grammar engineers
  - Avoid overgeneration
  - Increase coverage
- For English:
  - ParGram / XLE (LFG)
  - English Resource Grammar / LKB (HPSG)

Shallow Approaches

- Real-word spelling errors
  - vs grammar errors in general
- Part-of-speech (POS) n-grams
  - Raw frequency
  - Machine learning-based classifier
  - Features of local context
  - Noisy channel model
  - N-gram similarity, POS tag set

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Common Grammatical Errors

- 20,000 word corpus
- Ungrammatical English sentences
  - Newspapers, academic papers, emails, …
- Correction operators
  - Substitute (48 %)
  - Insert (24 %)
  - Delete (17 %)
  - Combination (11 %)

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Common Grammatical Errors

- 20,000 word corpus
- Ungrammatical English sentences
  - Newspapers, academic papers, emails, …
- Correction operators
  - Substitute (48 %) { Agreement errors / Real-word spelling errors
  - Insert (24 %)
  - Delete (17 %)
  - Combination (11 %)

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Chosen Error Types

Agreement: She steered Melissa around a **corners.**

Real-word: She could **no** comprehend.

Extra word: Was that in the summer **in**?

Missing word: What the subject?

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Automatic Error Creation

Agreement: replace determiner, noun or verb

Real-word: replace according to pre-compiled list

Extra word: duplicate token or part-of-speech, or insert a random token

Missing word: delete token (likelihood based on part-of-speech)

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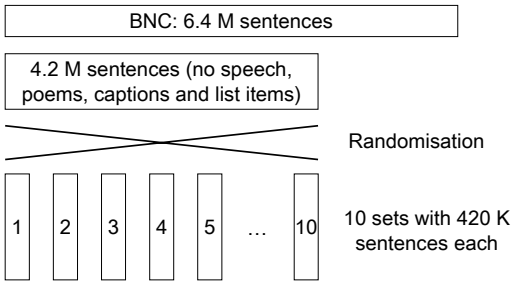
BNC Test Data (1)



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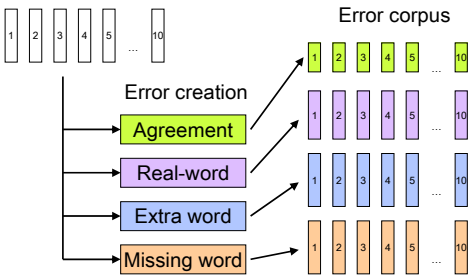
BNC Test Data (2)



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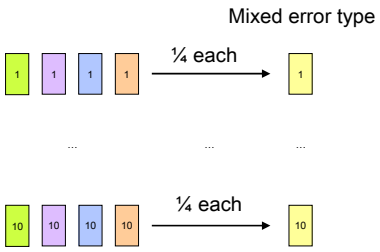
BNC Test Data (3)



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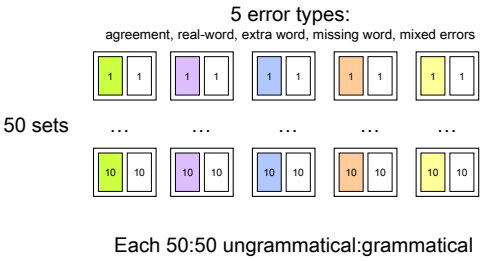
BNC Test Data (4)



Each 50:50 ungrammatical:grammatical

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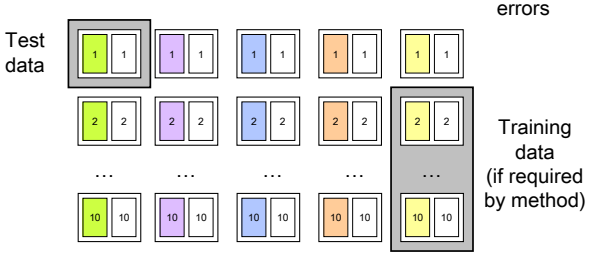
BNC Test Data (5)

Example: 1st cross-validation run for agreement errors



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Evaluation Measures

tp = true positive
tn = true negative
fp = false positive
fn = false negative

- Precision tp / (tp + fp)
- Recall tp / (tp + fn)
- F-score 2*pr*re / (pr + re)
- Accuracy (tp + tn) / total
- tp := ungrammatical sentences identified as such

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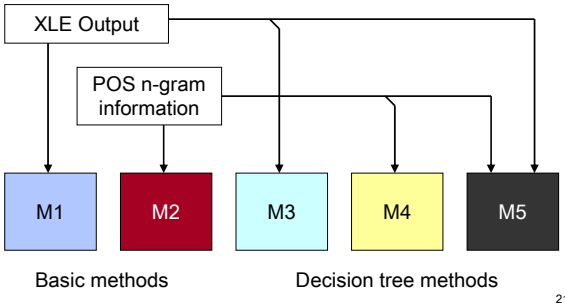
Overview of Methods



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M1

Method 1: Precision Grammar

- XLE English LFG
- Fragment rule
  - Parses ungrammatical input
  - Marked with *
- Zero number of parses
- Parser exceptions (time-out, memory)

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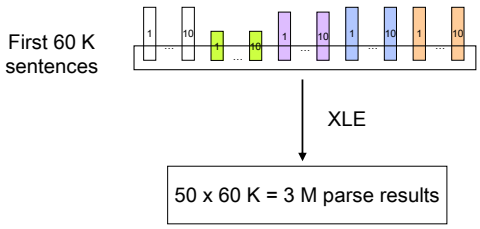
M1

XLE Parsing



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M2

Method 2: POS N-grams

- Flag rare POS n-grams as errors
- Rare: according to reference corpus
- Parameters: n and frequency threshold
  - Tested n = 2, …, 7 on held-out data
  - Best: n = 5 and frequency threshold 4

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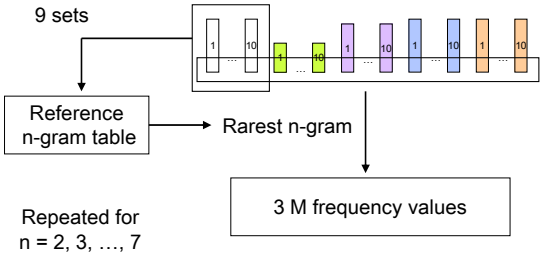
M2

POS N-gram Information



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M3

Method 3: Decision Trees on XLE Output

- Output statistics
  - Starredness (0 or 1) and parser exceptions (-1 = time-out, -2 = exceeded memory, …)
  - Number of optimal parses
  - Number of unoptimal parses
  - Duration of parsing
  - Number of subtrees
  - Number of words

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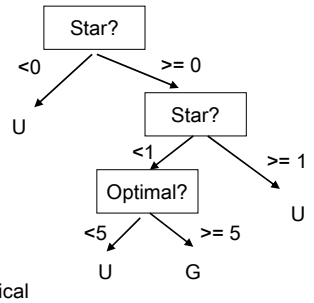
M3

Decision Tree Example



U = ungrammatical
G = grammatical

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M4

Method 4: Decision Trees on N-grams

- Frequency of rarest n-gram in sentence
- N = 2, …, 7
  - feature vector: 6 numbers

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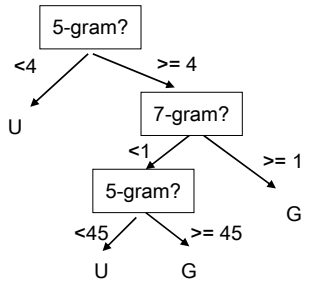
M4

Decision Tree Example



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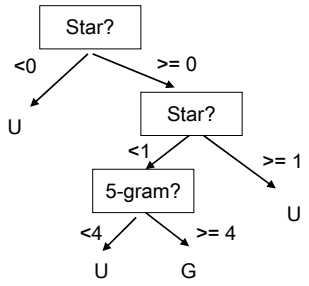
M5

Method 5: Decision Trees on Combined Feature Sets



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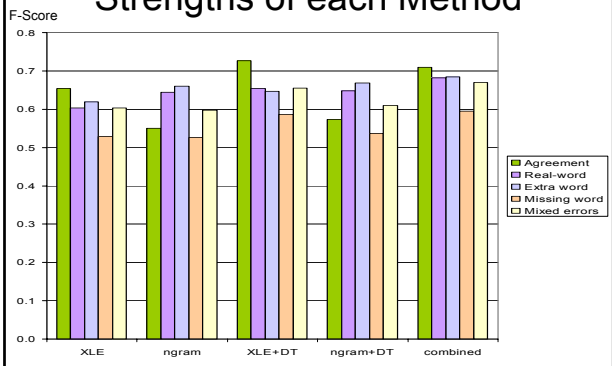
Strengths of each Method



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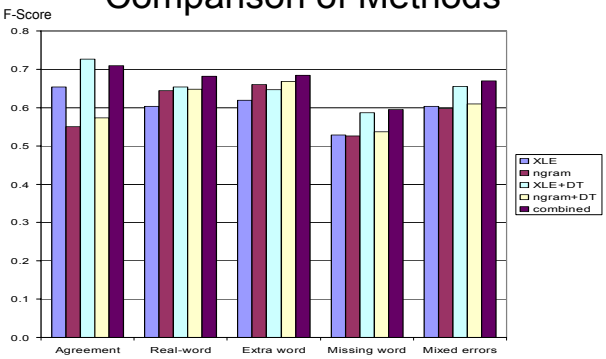
Comparison of Methods



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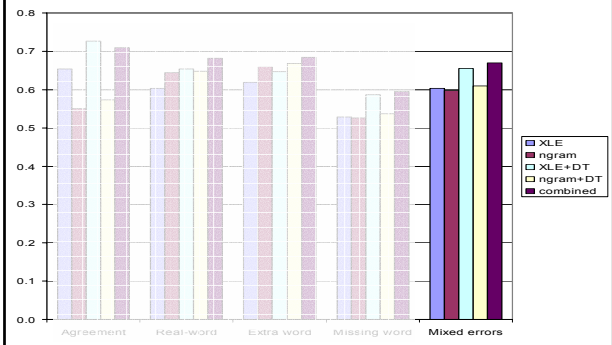
Results: F-Score



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Conclusions

- Basic methods surprisingly close to each other
- Decision tree effective with deep approach
- Combined approach best on all but one error type

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Future Work

- Error types:
  - Word order
  - Multiple errors per sentence
- Add more features
- Other languages
- Test on MT output
- Establish upper bound

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Thank You!

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Irish Centre for High-End Computing

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Investing in People and Ideas

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Extra Slides

- P/R/F/A graphs
- More on why judge grammaticality
- Precision Grammars in CALL
- Error creation examples
- Variance in cross-validation runs
- Precision over recall graphs (M3)
- More future work

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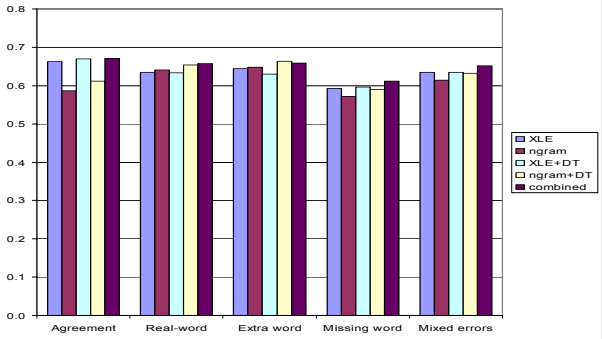
Results: Precision



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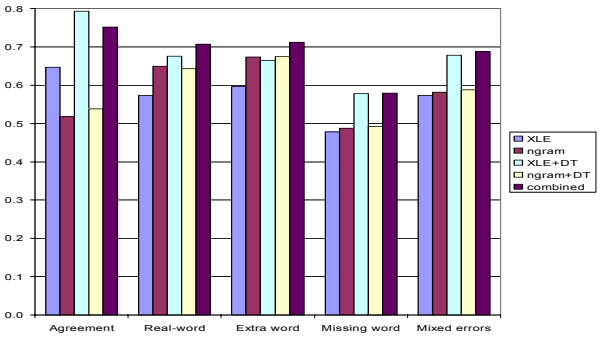
Results: Recall



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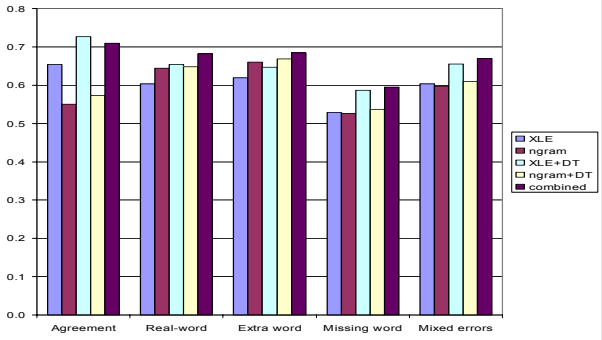
Results: F-Score



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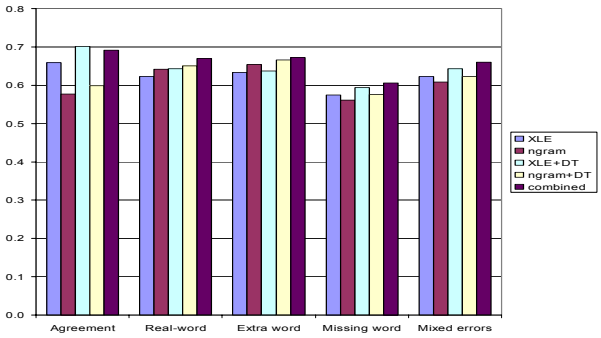
Results: Accuracy



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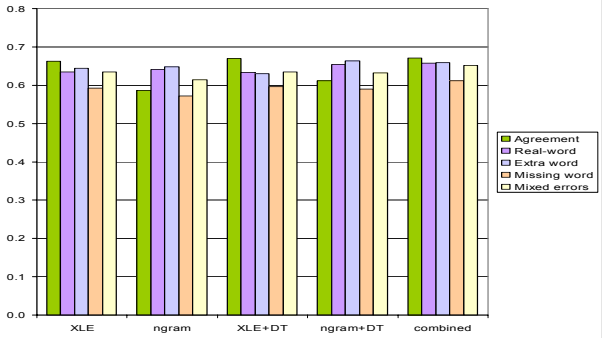
Results: Precision



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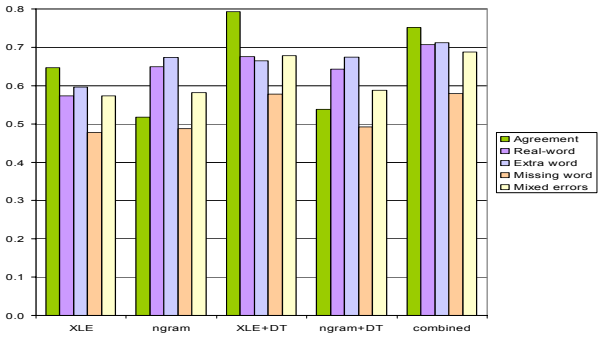
Results: Recall



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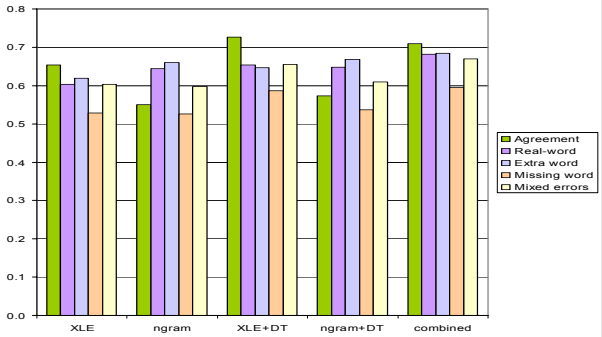
Results: F-Score



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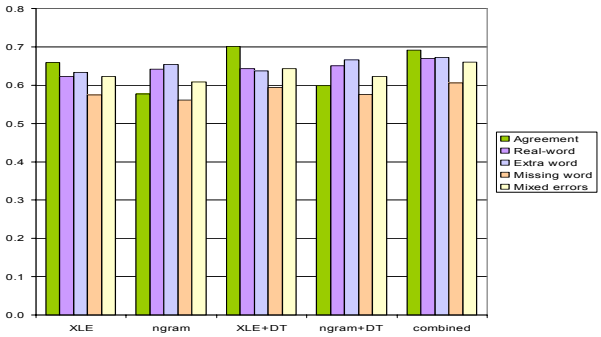
Results: Accuracy



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Why Judge Grammaticality? (2)

- Automatic essay grading
- Trigger deep error analysis
  - Increase speed
  - Reduce overflagging
- Most approaches easily extend to
  - Locating errors
  - Classifying errors

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Precision Grammars in CALL

- Focus:
  - Locate and categorise errors
- Approaches:
  - Extend existing grammars
  - Write new grammars

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Grammar Checker Research

- Focus of grammar checker research
  - Locate errors
  - Categorise errors
  - Propose corrections
  - Other feedback (CALL)

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N-gram Methods

- Flag unlikely or rare sequences
  - POS (different tagsets)
  - Tokens
  - Raw frequency vs. mutual information
- Most publications are in the area of context-sensitive spelling correction
  - Real word errors
  - Resulting sentence can be grammatical

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Test Corpus - Example

- Missing Word Error

She didn't **want** to face him

↓

She didn't to face him

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Test Corpus – Example 2

- Context-sensitive spelling error

I love **them** both

↓

I love **then** both

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Cross-validation

- Standard deviation below 0.006
- Except Method 4: 0.026
- High number of test items
- Report average percentage

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Example

Run	F-Score
1	0.654
2	0.655
3	0.655
4	0.655
5	0.653
6	0.652
7	0.653
8	0.657
9	0.654
10	0.653
Stdev	**0.001**

Method 1 – Agreement errors:
65.4 % average F-Score

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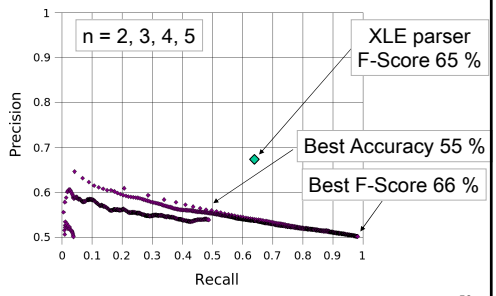
POS n-grams and Agreement Errors



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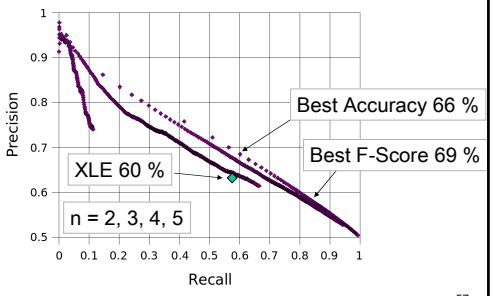
POS n-grams and Context-Sensitive Spelling Errors



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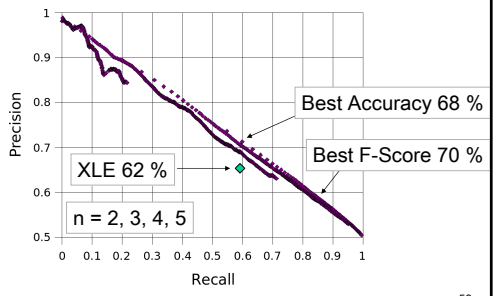
POS n-grams and Extra Word Errors



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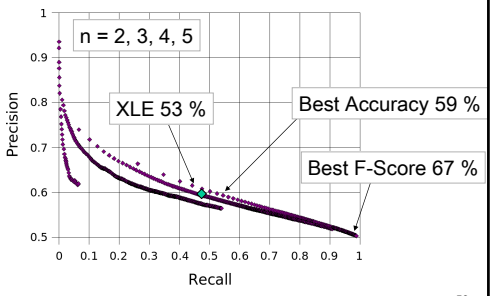
POS n-grams and Missing Word Errors



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