Improving automated oral testing: identifying features and enhancing speech recognition

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Elicited imitation (EI) testing

- NNS oral proficiency test for English
- Subjects repeat isolated sentences of varying complexity (60 / testing session)
- Responses are recorded and scored, usually at syllable (σ), item levels
- Rationale: subjects can't process linguistic vocabulary, structures they don't know yet

EI advantages: can be

- Administered to multiple learners at the same time
- Administered in a computer lab
- Administered with less cost/time
- Scored by a reasonably proficient speaker of English
- "A reasonable measure of global proficiency" (Bley-Vroman & Chaudron, 1994)

EI testing so far

- Developed about 280 sentences
  - Varying length, complexity, features
- 1500 tests administered to about 1050 subjects since Fall 2006
- Random sampling of subjects also given other tests (ECT speaking, OPI, oral placement, LAT speaking)
- Relatively simple application, standard language lab setting

Sample EI sentences

Discriminate well

- Perhaps he works there.
- Had you ever flown that high before?
- Good cars will never break down.
- When she went to Las Vegas, did she like the shows that she saw?
- If her heart were to stop beating, we might not be able to help her.

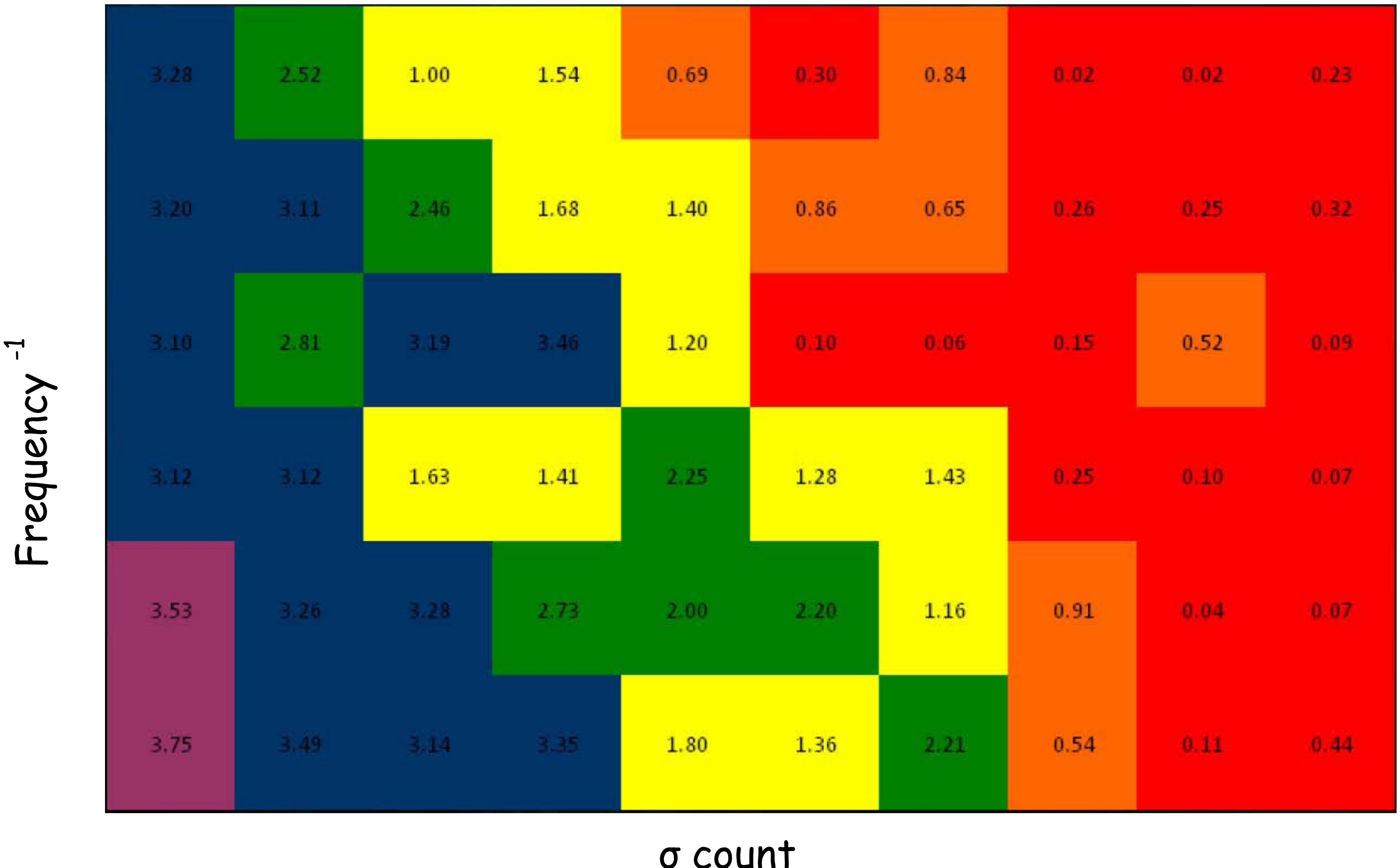
Don't discriminate well

- Have you slept?
- Maybe she likes cats.
- We eat cookies.
- How do good children play baseball?
- Chris has yelled louder than ten sheep.
- He should have walked away before the fight started.

Assessing lexical features

- New items engineered to investigate lexical complexity
  - Lexical density, lexical difficulty (frequency, morphological composition)
  - Characteristics reflect:
    - 6 frequency bands (ranges)
    - 5 σ-count bands (4-6, 7-9, 10-12, 13-15, 16+)
- Items scored, IRT analysis
- Factors: σ-count (.73), frequency (.08), lexical density/complexity (.02)

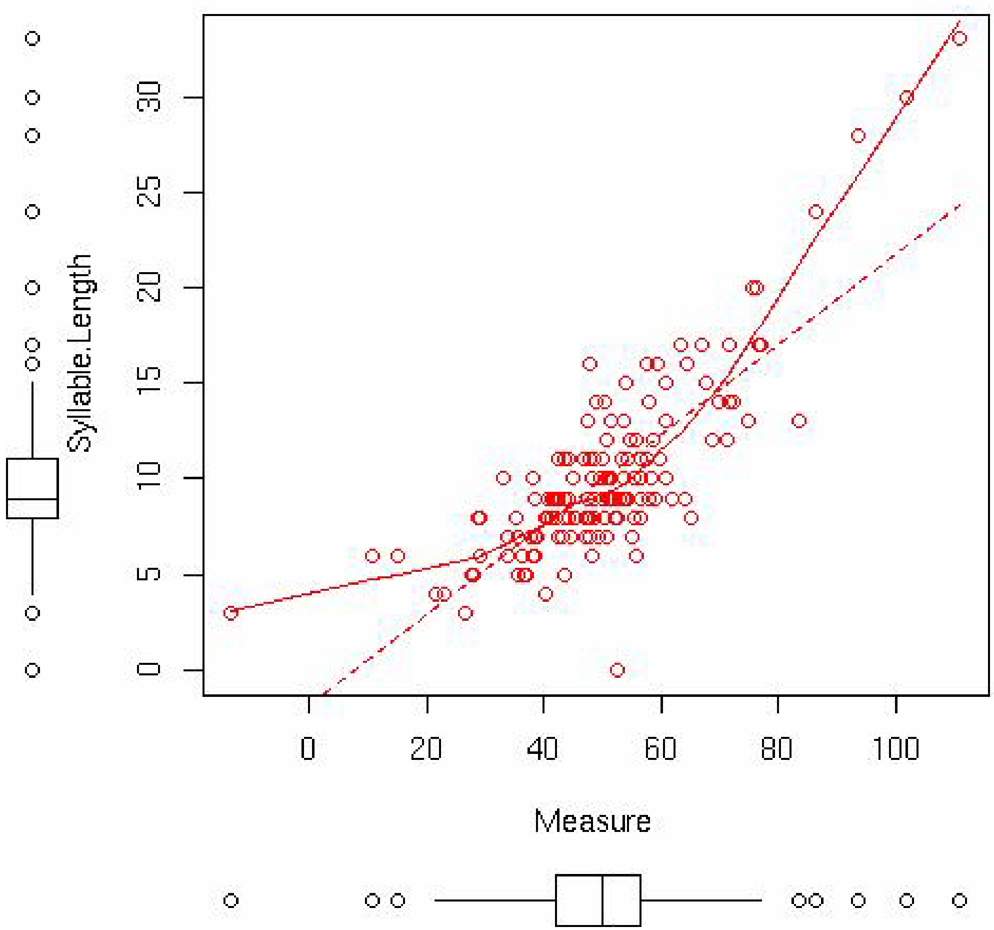
Lexical features: interaction



Assessing syntactic features

- New items engineered to investigate role of syntactic features
  - 44 features from L2 acquisition studies, OPI test guidelines
    - Tense, modality, aspect, transitivity, articles, agreement, contractions, possessives, etc.
- Items scored, IRT analysis
- Factors: σ-count (.68), 3rdPersAgr (.02), negation, imperfect, copula… (≈.01 each)

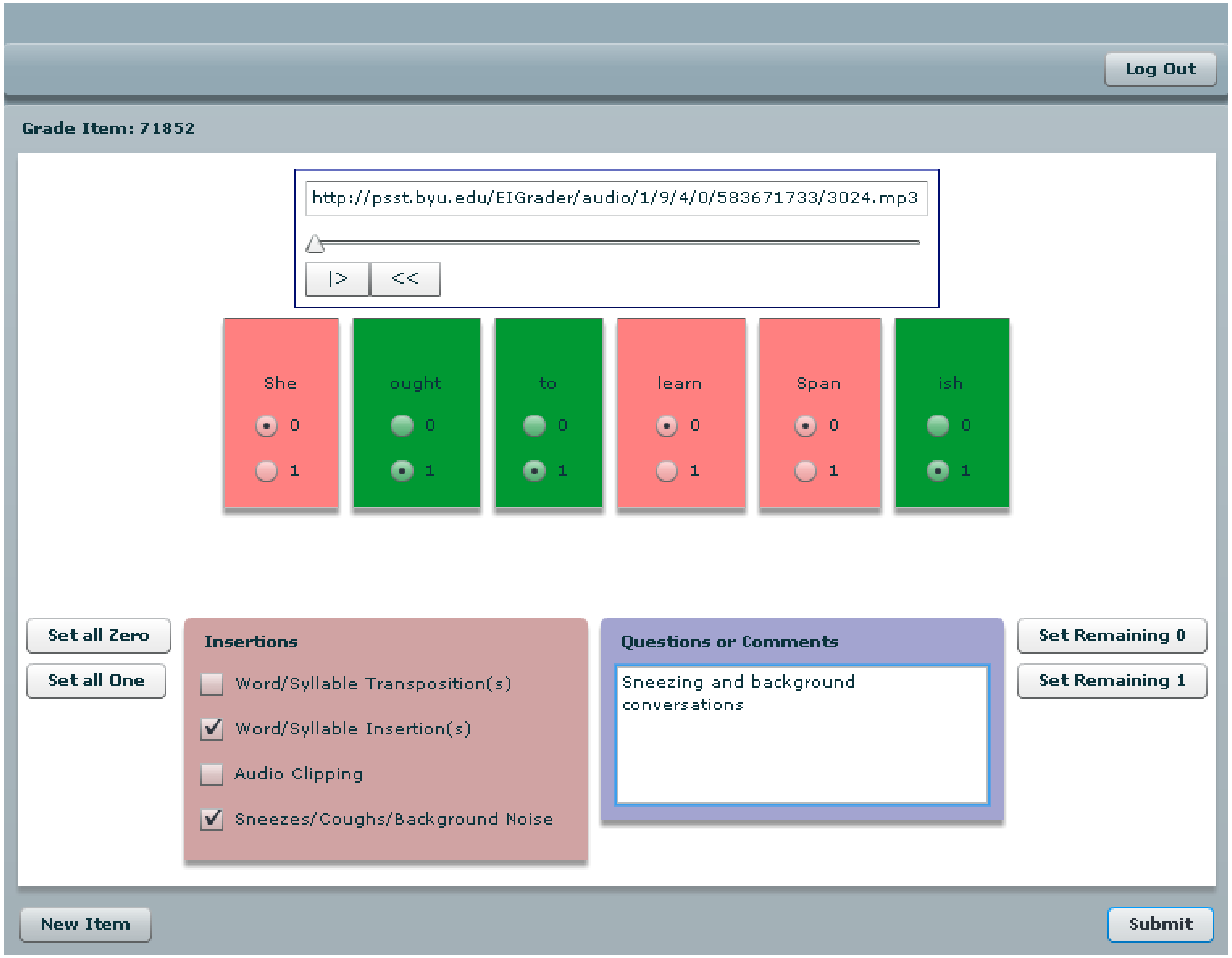
Discriminative value vs. σ count



Scoring since last workshop

- GUI tool developed to help human annotators score EI test items
- Deployed on the Web
- 1250 tests, 810 subjects, 44 graders
- ≈ 55,500 items graded, ≈ 596,000 σ
- Avg. time: ≈ 50 sec./item, 72 items/hr.

Scoring an EI item



Agreement among scorers

- ≈ 175,000 σ double-graded (so far)

- 91% agreement (raw %, Robinson's *A*)
- IRR: 0.82 (Krippendorff's α, Cohen's κ, mean of bivariate rank correlations, …)
- Rater bias coefficient: 0.576, χ^2=362
- Exploring team-wise analysis, arbitration, viability of single scoring

ASR and automatic EI scoring

- Discussed at length in last year's workshop, LREC 2008
- Sphinx, WSJ
- Correlations of between 0.85 and 0.88 with human scores
- Have now trained up acoustic model from EI native model utterances, evaluating
- Ongoing:
  - Develop NNS accented English acoustic models? w/rt L1? gender? both?
  - Fluency measures: pauses, filled pauses, restarts

Holistic evaluations

- Two ways of looking at EI scoring from a holistic perspective
  - Impressionistic ranking of overall intelligibility, grammaticality, fluency
  - Taking into consideration demographic information on test subjects
    - L1, age, scores for reading, writing, listening comprehension, etc.
- Machine learning
  - TiMBL (provides feature rankings)

Data mining for ranking items (1)

- Assumption: OPI score is gold standard
- Rank EI items for predictive value
  - Better item more predictive of OPI score?
  - Attributes: EI score, Item ID, Student ID
  - Label: OPI score
- 34 students, 2600 items
- 80%/20% training/testing split
- WEKA linear regression (default values)

Data mining for ranking items (2)

- Some feature selection on full set of items
- Reduced dataset of 15 items: lowest sum squared error, more predictive of OPI score
- LR model: $OPI = S_{1008} * 2.3414 + 3.0987$
- Item 1008: Had he ever played games well?
- Next: full range of data scored so far

Metric	All 60 sentences	15 selected sentences
Correlation coefficient	.4468	0.9225
Mean absolute error	1.5518	0.6277
Root mean squared error	1.668	0.7286

Summary

- Ongoing work on several fronts:
  - Administering tests
  - EI item development w/rt targeted feat's
  - Human scoring, annotation
  - Data analysis (machine learning, data mining)
  - ASR scoring of EI responses
  - Other language EI tests (Japanese, French)
- Ultimate goal: online, adaptive testing tool for assessing proficiency levels