Evaluating Hierarchical Discourse Segmentation of Expository Speech

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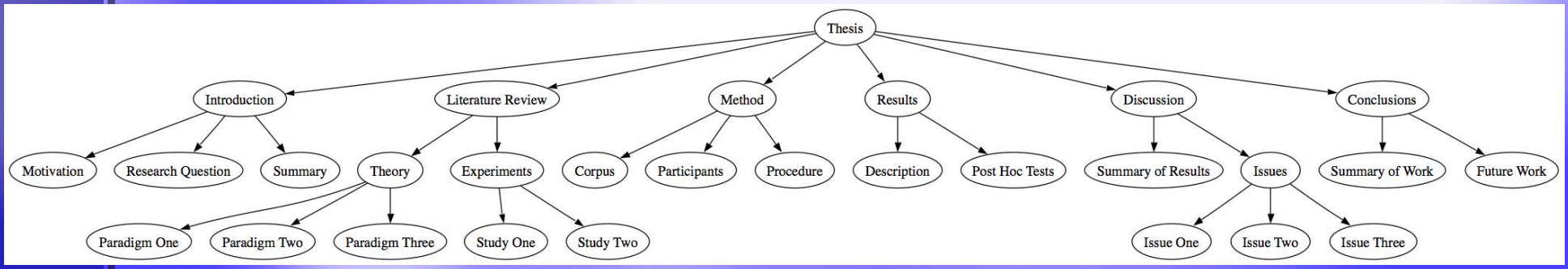
What is Discourse Segmentation?

- It's like finding sensible paragraph breaks and/or section breaks, but not just in expository writing
- It's shallow parsing of discourse structure
- Discourse structure:
  - Answers the question: how do people organize language beyond the sentence?
  - Is described in terms of: schemas (e.g. story grammars), informational and interactional purposes, topics and subtopics, logical or rational relations, functions of cohesive devices

Example: A Thesis



- Discourse parsing seeks the whole structure starting with individual clauses
- Linear discourse segmentation seeks the bracketing for just one level of structure
- Hierarchical discourse segmentation seeks the bracketing corresponding to just the tree above

What is it good for?

- Assists in
  - Automatic summarization (Angheluta et al., 2002)
  - Information retrieval (Kaszkiel & Zobel, 1997)
  - Anaphora resolution (Walker, 1997)
  - Question answering (Chai & Jin, 2004)
- Helps test theories of discourse structure (Passonneau & Litman, 1997)
- Enriches linguistic corpora (Csomay, 2004)

Overview

- Look at three holes in discourse segmentation research
  - Lack of diversity in genres
  - Little work in hierarchical segmentation algorithms
  - No work in quantitative measures for HDS
- Describe what I've done to address them
- Examine how well this fulfills the need
- Discuss what more is needed

Hole One: Genre Diversity

- Discourse structure theory has been interested in conversation, spoken and written narrative, and expository text
- Empirical discourse segmentation research has focused overwhelmingly on news data, some expository text and narrative, little of anything else
  - News data has been the most available data
  - Evaluating on speech data is hard because it doesn't come with headlines or headings to use as evaluation reference (a “gold standard”)

Hole Two: Hierarchical Segmentation

- Discourse structure theories are explicitly hierarchical (many theories resemble syntactic structures)
- Discourse parsing is hierarchical but has focused on small scale—a few hundred words or smaller
- Linear segmentation (i.e. like paragraph breaks alone) addresses large scale structure but isn't hierarchical
- Only three algorithms for hierarchical segmentation are published

Hole Three: Evaluating Hierarchical Segmentation

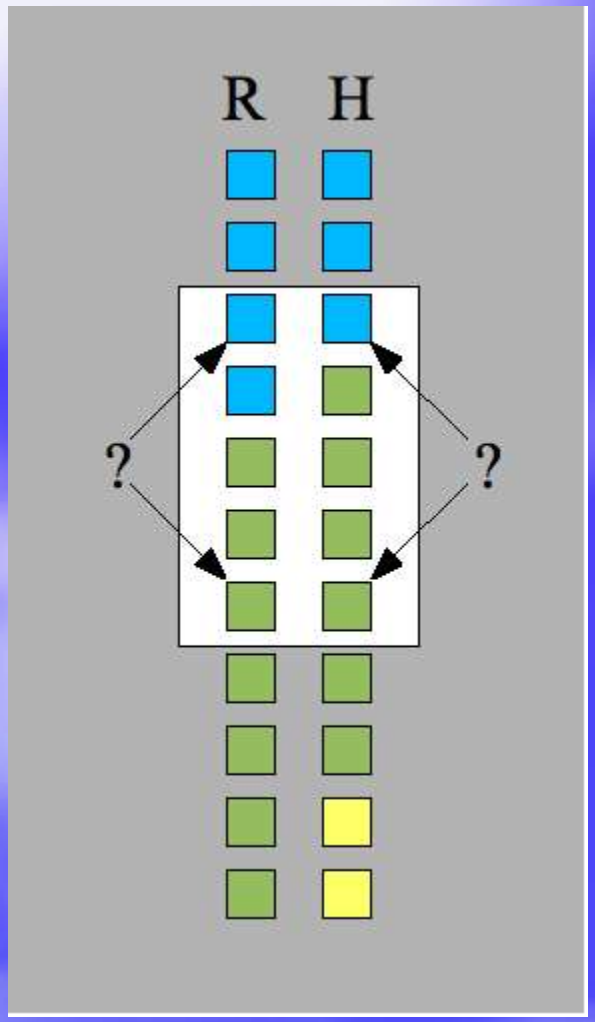
- Discourse segments are fuzzy: imprecise boundaries and debatable number
- Traditional measures like precision, recall, and crossing brackets overpenalize small errors in bracket placement
- Beeferman et al. (1999) and Pevzner & Hearst (2002) proposed probabilistic error measures to allow for variation in linear segmentation
- No comparable error measure has been offered for hierarchical segmentation

Approach

- Generalize the probabilistic error measures from linear segmentation for hierarchical segmentation
- Take two algorithms for linear segmentation that use hierarchical clustering and alter them to produce hierarchical segmentation
- Evaluate the algorithms on monologic lectures (i.e. expository speech); derive gold standard based on Passonneau & Litman (1997)

Linear Error Measure

- P_k (Beeferman et al.)
  - Looks through window at reference and hypothesized segs (width k is half average segment length in ref. seg.)
  - Asks if they agree about ends of window being in same segment
- WindowDiff (Pevzner & Hearst)
  - Asks if they agree about number of boundaries in window



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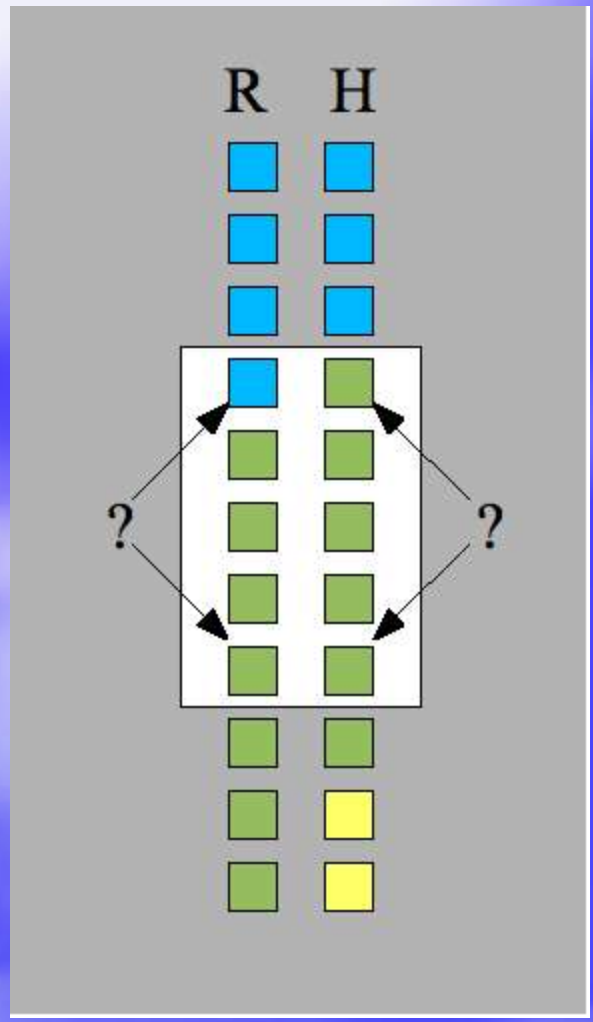

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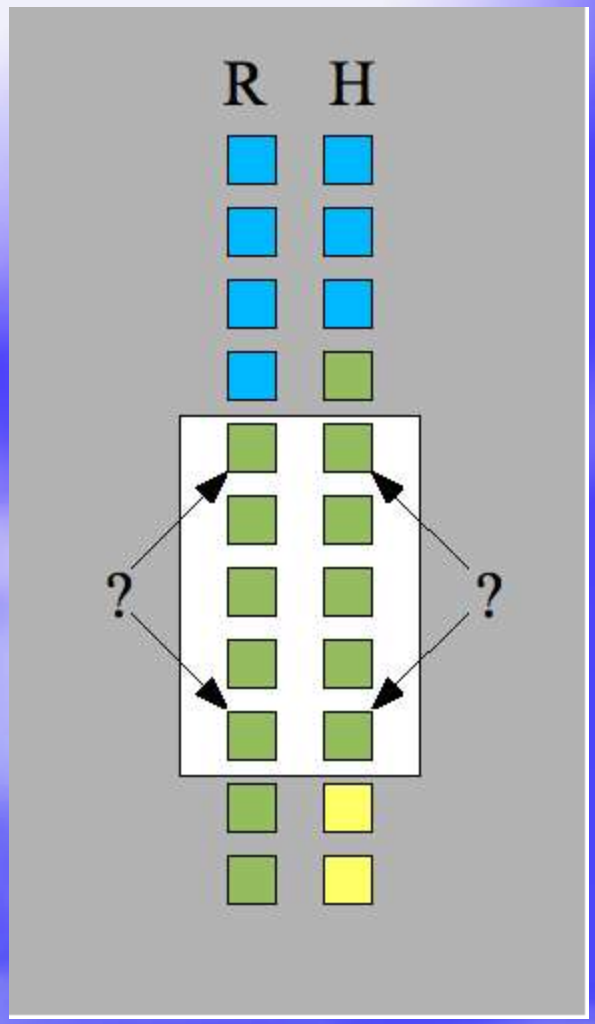
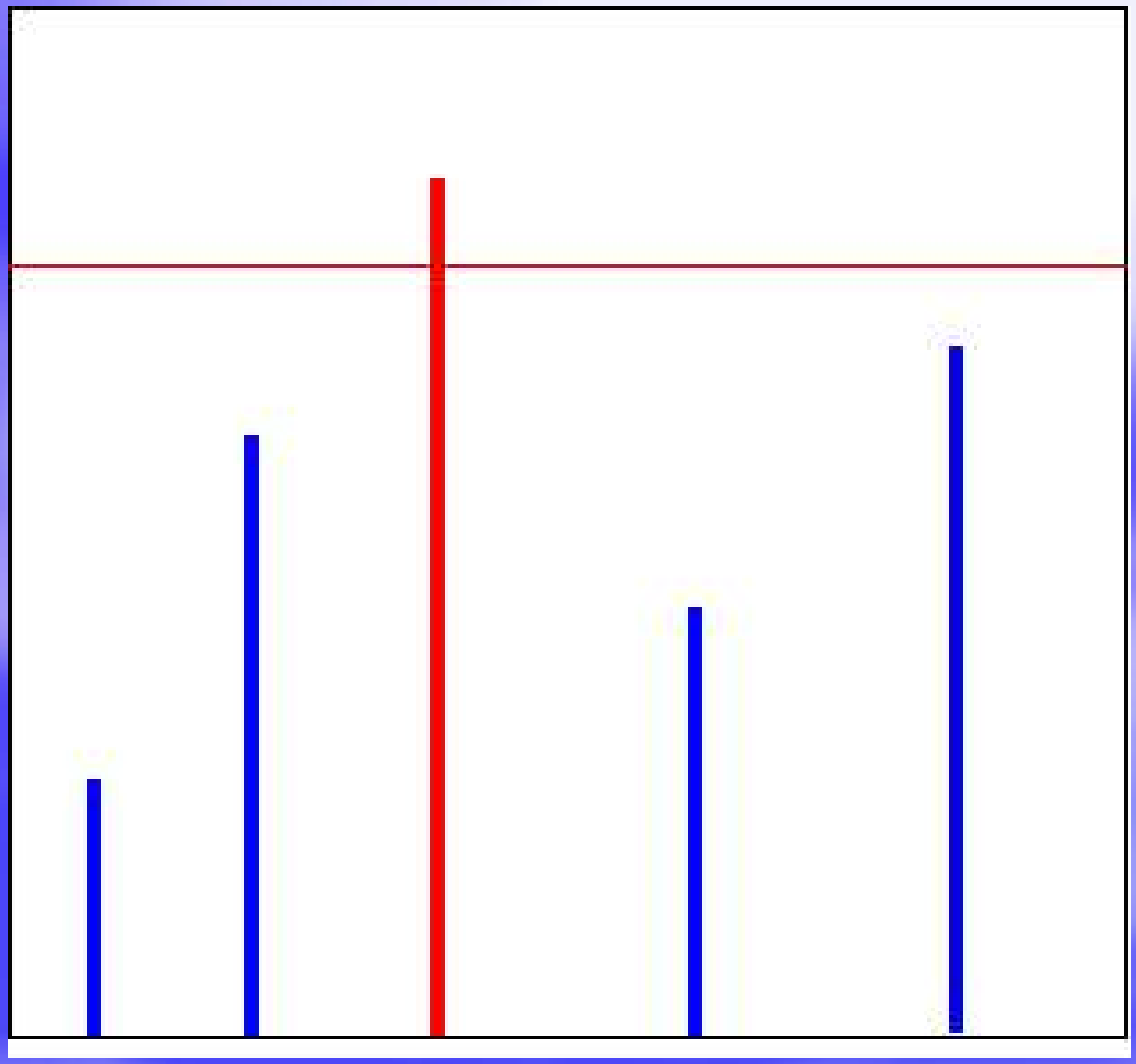
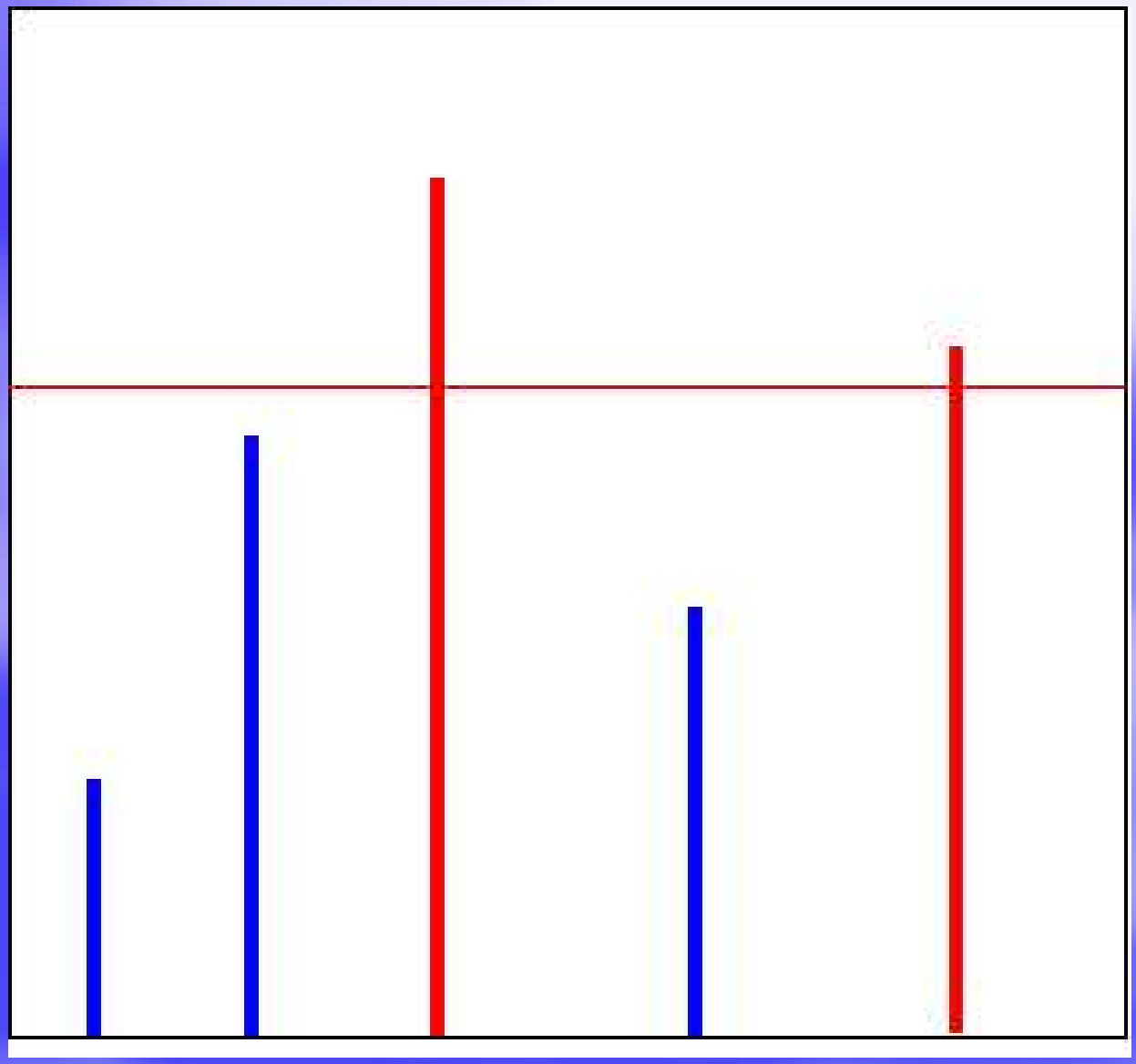
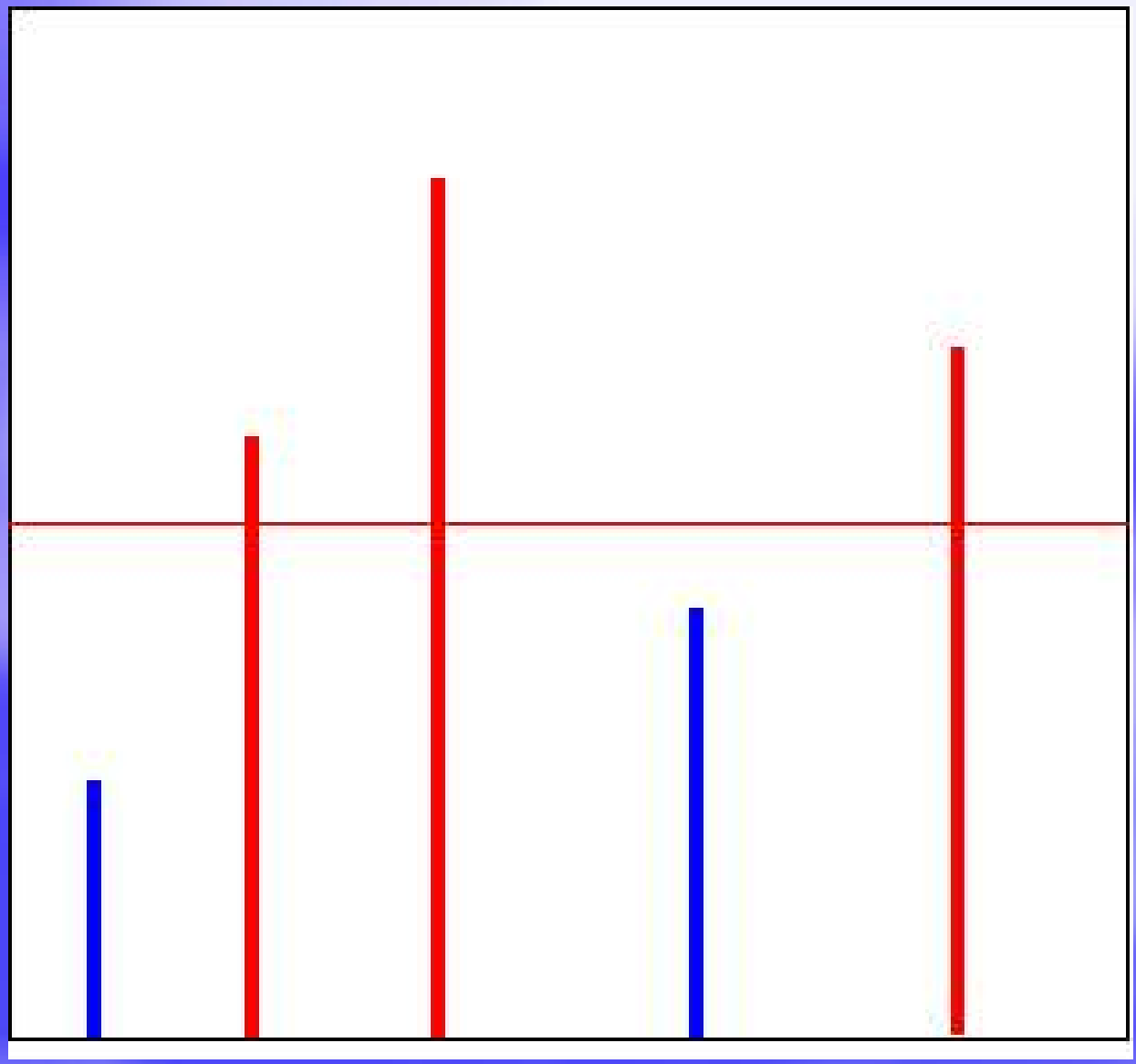


Hierarchical Error Measure

- Average P_k/WindowDiff over best linearizations of tree
  - Take *n* highest ranked boundaries, for *n* between 1 and total number of boundaries in gold standard
  - Calculate linear error for each one and average them
  - When ranks aren't all unique, average over representative sampling at each rank level







Segmentation Algorithms

- HC99: Hierarchical version of C99 (Choi, 2000)
- HCWM: Hierarchical version of CWM (Choi et al., 2001)
- NONE: Baseline with no boundaries
- BIN: Baseline made by recursive bisection
- RAND: Baseline made by a random process

Reference Segmentation

- Corpus:
  - Portions of the 7 most monologic lectures in MiCASE
  - Pauses assumed to delimit prosodic phrases
- Procedure:
  - Based on that of Passonneau & Litman (1997)
  - Untrained readers mark topic changes
  - Statistical significance of interannotator agreement identifies reference boundaries

In the following text, please check off all boxes where a "paragraph break" should go (where the topic changes).

1 S1: please remember that there 's another field trip coming up this Sunday if you 'd like to go you could sign up with Larry Henderson by the end of the week .
☐ -----

2 also um ,
☐ -----

3 in the ,
☐ -----

4 coming events category Lorna Simpson is going to be speaking at the University Museum of Art tomorrow night .
☐ -----

5 and she 's a contemporary um ,
☐ -----

6 photography conceptual artist who 's now moving into video ,
☐ -----

7 and is very articulate and interesting .
☐ -----

8 so ,
☐ -----

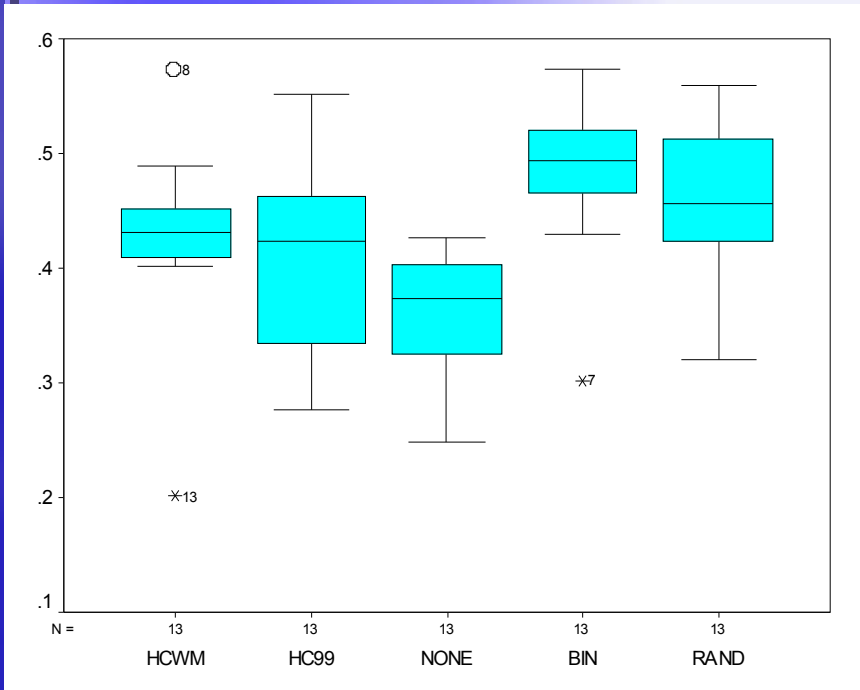
9 since we 've been spending all term on dead artists here 's a chance to hear a living one .
☐ -----

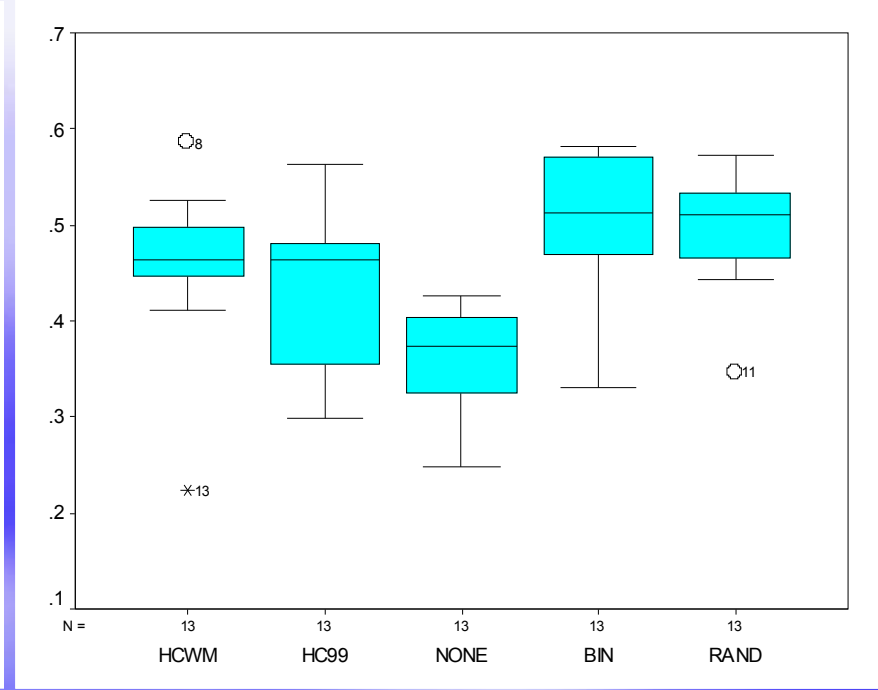
10 and her presentation i think is at seven thirty _
☐ -----

11 is there a question ?
☐ -----

One page of the web form annotation interface

Evaluation 1





- Stat. sig: matched-pair two-tailed t-tests; $p < .05$
- In P_k, s.s.d.s are: NONE < all, and HC99 < BIN
- In WD, s.s.d.s are: NONE < all, and HC99 < BIN, RAND

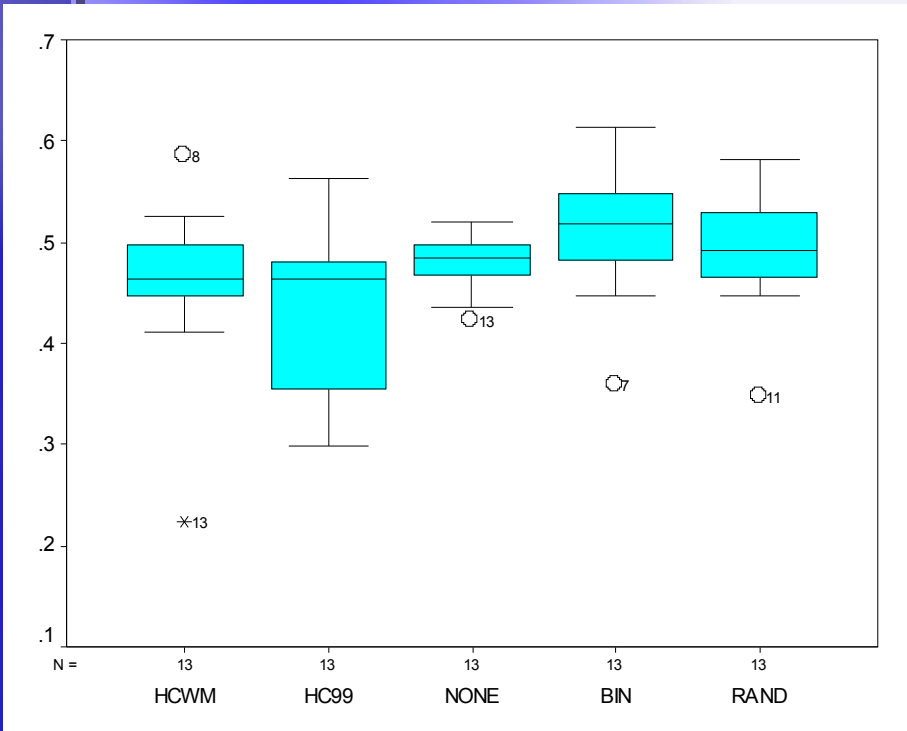
Analysis

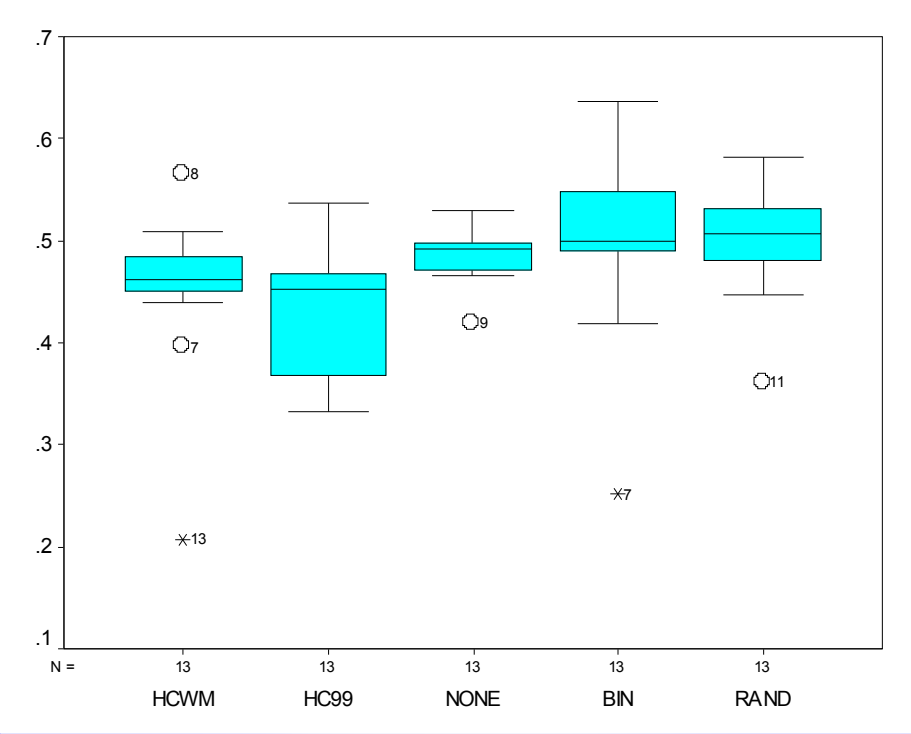
- Why is NONE judged with such low error?
  - Few boundaries in the reference seg, not evenly spaced
  - In this situation, the false positives produced by proposing a random boundary are generally more than the false negatives removed
  - The way P_k and WD are defined, boundaries near the head and tail of discourse are undercounted

Redefine Error Measure

- Fill: In context of hierarchical segmentation, “not a discourse boundary” really means, “lower importance than what's been marked”
- Wrap: Instead of stopping at end of text, wrap window end-point around to beginning

Evaluation 2





- WD+Fill: HC99 < NONE, BIN
- WD+Fill+Wrap: HC99 < NONE, RAND

Discussion

- Appears that WD+Fill(+Wrap) is a good measure
  - High discriminating power (s.d.d.s)
  - All baselines are close to .50
  - Algorithms appear better than baselines
- Algorithms perform poorly on this genre

Conclusions

- How well does this work fulfill the need?
  - Error Measure
    - Theoretically motivated
    - Based on corresponding best measure from linear seg
    - Distinguishes algorithms from baselines (it seems)
  - Segmentation Algorithms
    - These algorithms are not much good in this genre
  - Gold Standard
    - An alternative to trained annotators
    - Method is complex: should compare to trained annotators

Further Questions

- How do HC99 and HCWM compare to trained human annotators?
- How do human annotators compare?
- How do HC99 and HCWM compare to the other algorithms in the literature?
- How can algorithms be developed for handling non-news genres better?
- This is explicitly tree structure, whereas some theories favor DAGs or general graphs.

Supplementary Slides

- Algorithm Implementation
- Reference Segmentation Procedure
- References

Algorithm Implementation

- C99 (Choi, 2000) uses hierarchical clustering on a matrix of lexical vector similarities
- CWM (Choi et al., 2001) uses latent semantic indexing (LSI) vectors instead
- C99 was released for educational use as Java code, so to create HC99 I just altered Choi's code to make it keep track of the order of cluster splits
- For HCWM, I made a Java interface to an Infomap database. I tried a MiCASE LSI model, but a BNC model performed better.

Passonneau & Litman

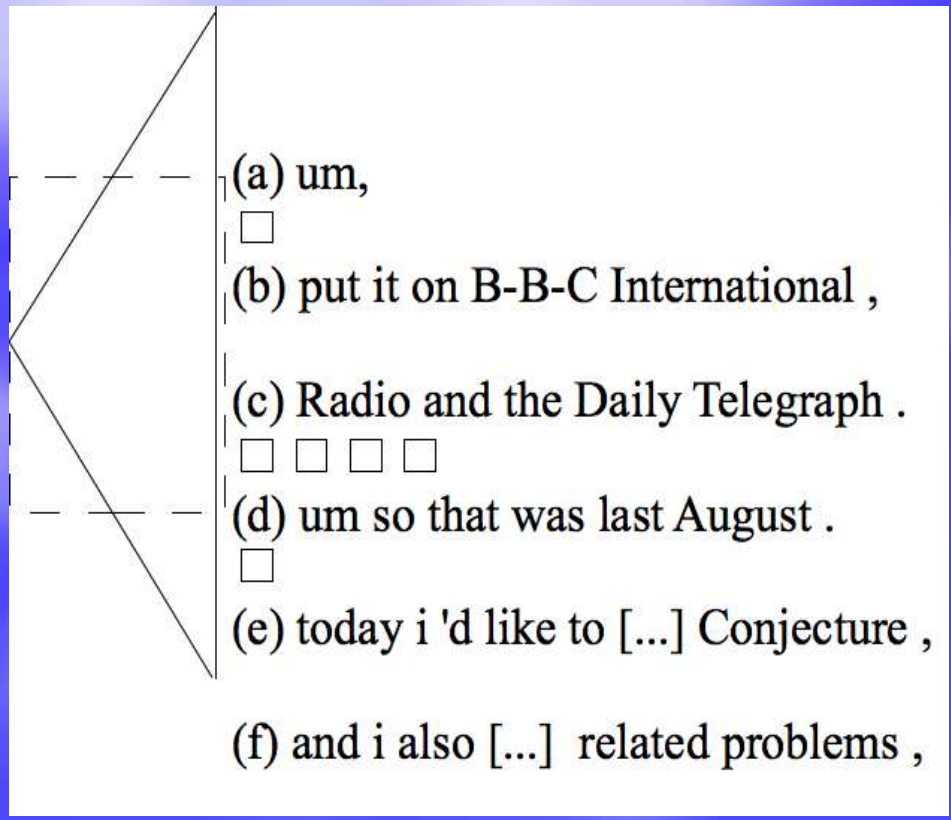
- Creating linear segmentation gold standard for Pear Narratives
- 7 untrained readers mark segment boundaries at any prosodic boundaries they like
- More than 3 readers in agreement is stat. sig.
- P&L note that
  - Readers often disagree by just one or two prosodic phrases
  - Readers differ widely about number of segments

Annotation

- Corpus:
  - Selected the seven most monologic lectures from MiCASE (highest word/turn ratios)
  - Each split into two or three sections of c.4000 words
  - One “prosodic phrase” per line (marked by punctuation in MiCASE)
- Participants: Native speakers of English, recruited from intro Ling classes, c.6 per sample
- Procedure: In internet web form, identify points where “topic changes” occur

Resolving Differences in Boundary Location

- Use a moving window for more flexible agreement criterion
- What shape?
  - Square is simple but has problems
  - Triangle behaves better
  - Gaussian is better theoretical model



Resolving Differences in Segment Count

- When some readers mark just a few boundaries and others mark many, what does that mean?
- Probably, fewer boundaries represents major branchings; many boundaries represents minor branchings
- Weight boundary marks by giving each annotator equal weight, divided evenly among that annotator's marks

Statistical Significance of Reference Boundaries

- Complex agreement criterion makes theoretical calculation of statistical significance difficult
- Calculate random agreement distribution empirically for each sample
  - Use same number of annotators and same numbers of boundary marks, but random placement
  - All agreement levels greater than minimum mark's weight go into distribution
  - All agreement levels with $p < .05$ go in gold standard, with higher stat. sig. as higher branchings

References

- Angheluta, R., Busser, R. D., and Moens, M.-F. (2002). The use of topic segmentation for automatic summarization. In *DUC 2002*.
- Beeferman, D., Berger, A., and Lafferty, J. D. (1999). Statistical models for text segmentation. *Machine Learning*, 34(1-3):177–210.
- Csomay, E. (2004). Linguistic variation within university classroom talk: A corpus-based perspective. *Linguistics and Education*, 15(3):243–274.
- Chai, J. Y. and Jin, R. (2004). Discourse structure for context question answering. In *HLT-NAACL 2004 Workshop on Pragmatics of Question Answering*, pages 23–30.
- Choi, F., Wiemer-Hastings, P., and Moore, J. (2001). Latent semantic analysis for text segmentation. In *Proceedings of 6th EMNLP*, pages 109–117.
- Choi, F. Y. Y. (2000). Advances in domain independent linear text segmentation. In *Proceedings of NAACL-00*, pages 26–33.
- Kaszkiel, M. and Zobel, J. (1997). Passage retrieval revisited. In *Proceedings of 20th ACM SIGIR*, pages 178–185.
- Passonneau, R. J. and Litman, D. J. (1997). Discourse segmentation by human and automated means. *Computational Linguistics*, 23(1):103–139.
- Pevzner, L. and Hearst, M. (2001). A critique and improvement of an evaluation metric for text segmentation. *Computational Linguistics*, 16(1).
- Simpson, R. C., Briggs, S. L., Ovens, J., and Swales, J. M. (2000). The Michigan corpus of academic spoken English.
- Walker, M. A. (1997). *Centering in Discourse*, chapter Centering, Anaphora Resolution, and Discourse Structure. Oxford University Press.