

# Contextually Mediated Semantic Similarity Graphs for Topic Segmentation

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StreamSage/Comcast



# Outline of talk

- Motivations
- Relevance intervals
- Graphs representing documents
  - Application to segmentation
- Experiments and Evaluation
  - Comparison with other systems
- Conclusions and future work

# Topic segmentation

- Topic segmentation defined: dividing a document into topically coherent segments
  - Typically a partition (exhaustive, non-overlapping segments)
  - But could vary (e.g., hierarchical, overlapping, “fuzzy”, etc.)
  - Labeling the segments with good terms is a separate problem
- Advantages of segmenting video (e.g., news broadcasts)
  - Viewers can select only the portions of a program they want to watch
  - They can browse in the order they want

# Related Work on Segmentation

- Previous work has used several approaches
  - Discourse features
    - Some signal a topic shift; others a continuation
    - Highly domain-specific
  - Similarity measures between adjacent blocks of text
    - Typical document similarity measures used, as in TextTiling (Hearst, 1994) or Choi's algorithm (Choi, 2000)
    - Choi measures lexical similarity among neighboring sentences
    - Posit boundaries at points where similarity is low
  - Lexical chains: repeated occurrences of a term (or of closely related terms)
    - Again, posit boundaries where cohesion is low (few lexical chains cross the boundary (e.g., Galley, et al., 2003))

# Motivations behind our approach

- Model both the influence of a term beyond the sentence it occurs in and semantic relatedness among terms
  - The range of a term's influence extends beyond the sentence it occurs in, but how far? (relevance intervals)
  - Semantic relatedness among terms (contextually mediated graphs)
- Apply this model to topic-based segmentation



# Relevance Intervals

# Relevance Intervals (RIs)

- Each RI is a contiguous segment of audio/video deemed relevant to a term
- Developed originally to improve audio/video search and retrieval
- RI calculation relies on a pointwise mutual information (PMI) model of term co-occurrence (built from 7 years of *New York Times* text, 325M words)
- Previously evaluated on radio news broadcasts, and currently deployed in Comcast video search

$$PMI(x,y) = \log \frac{P(x,y)}{P(x)P(y)}$$

Anthony Davis, Phil Rennert, Robert Rubinoff, Tim Sibley, and Evelyne Tzoukermann. 2004. Retrieving what's relevant in audio and video: statistics and linguistics in combination. *Proceedings of RIAO 2004*, 860-873.

# Relevance Intervals (RIs)

- Each RI is a contiguous segment of audio/video deemed relevant to a term
  - RIs are calculated for all content words (after lemmatization) and common multi-word expressions
  - An RI for a term is built outwards, forward and backward from a sentence containing that term, based on:
    - PMI values between pairs of terms across sentences; high PMI values suggest semantic similarity between terms
    - Discourse markers which extend or end an RI
    - Synonym-based query expansion, using information from WordNet
    - Anaphor resolution – roughly based on Kennedy and Boguraev (1996)
    - Nearby RIs for the same term are merged
    - Large-scale vocabulary shifts (as determined by a modified version of Choi (2000) to indicate boundaries) \*\*\*\*\*



# Relevance Intervals: an Example

- Index term: **squatter**  
among the sentences containing this term are these two, near each other:

Paul Bew is professor of Irish politics at Queens University in Belfast.  
In South Africa the government is struggling to contain a growing demand for land from its black citizens.

Authorities have vowed to crack down and arrest **squatters** illegally occupying land near Johannesburg.

In a most serious incident today more than 10,000 black South Africans have seized government and privately-owned property.

Hundreds were arrested earlier this week and the government hopes to move the rest out in the next two days.

NPR's Kenneth Walker has a report.

Thousands of **squatters** in a suburb outside Johannesburg cheer loudly as their leaders deliver angry speeches against whites and landlessness in South Africa.

“Must give us a place...”

- We build an RI for **squatter** around each of these sentences...

# Relevance Intervals: an Example

- Index term: **squatter**  
among the sentences containing this term are these two, near each other:

Paul Bew is professor of Irish politics at Queens University in Belfast.

[Stop RI Expansion]

In South Africa the government is struggling to contain a growing demand for land from its black citizens. [PMI-expand]

Authorities have vowed to crack down and arrest **squatters** illegally occupying land near Johannesburg.

In a most serious incident today more than 10,000 black South Africans have seized government and privately-owned property. [PMI-expand]

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# Relevance Intervals: an Example

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In South Africa the government is struggling to contain a growing demand for land from its black citizens. [PMI-expand]

Authorities have vowed to crack down and arrest **squatters** illegally occupying land near Johannesburg.

In a most serious incident today more than 10,000 black South Africans have seized government and privately-owned property. [PMI-expand]

Hundreds were arrested earlier this week and the government hopes to move the rest out in the next two days. [merge nearby intervals]

NPR's Kenneth Walker has a report. [merge nearby intervals]

Thousands of **squatters** in a suburb outside Johannesburg cheer loudly as their leaders deliver angry speeches against whites and landlessness in South Africa.


[Stop RI Expansion]

“Must give us a place...”

The two intervals for **squatter** are merged, because they are so close



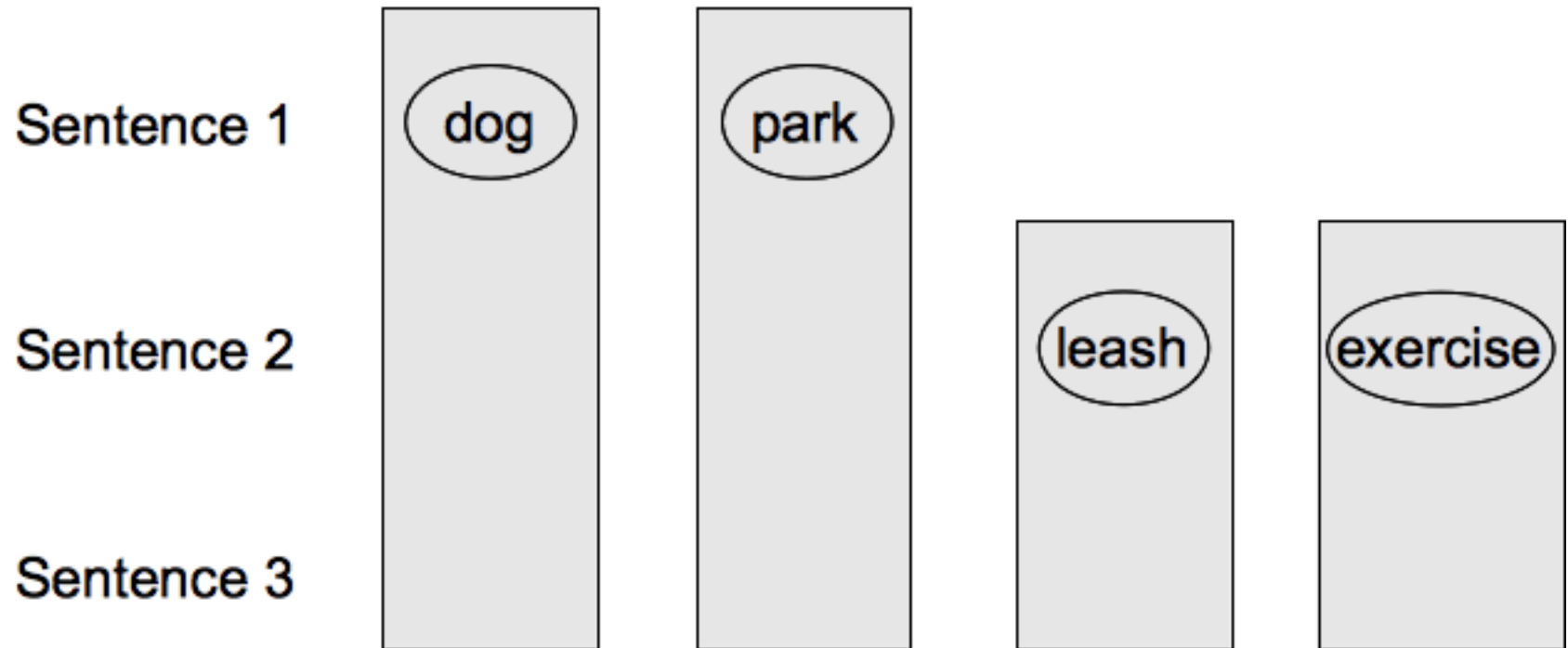
Documents → Graphs →  
Segmentation

- 
- (S\_1) Yesterday, I took my dog to the park.
  - (S\_2) While there, I took him off the leash to get some exercise.
  - (S\_3) After 2 minutes, Spot began chasing a squirrel.
  - \_\_\_\_\_(Topic Shift)\_\_\_\_\_
  - (S\_4) Then, I needed to go grocery shopping.
  - (S\_5) So I went later that day to the local store.
  - (S\_6) Unfortunately, they were out of cashews.

# RIs → Nodes

- Construct a graph in which each node represents a term and a sentence, iff the sentence is contained in an RI for that term

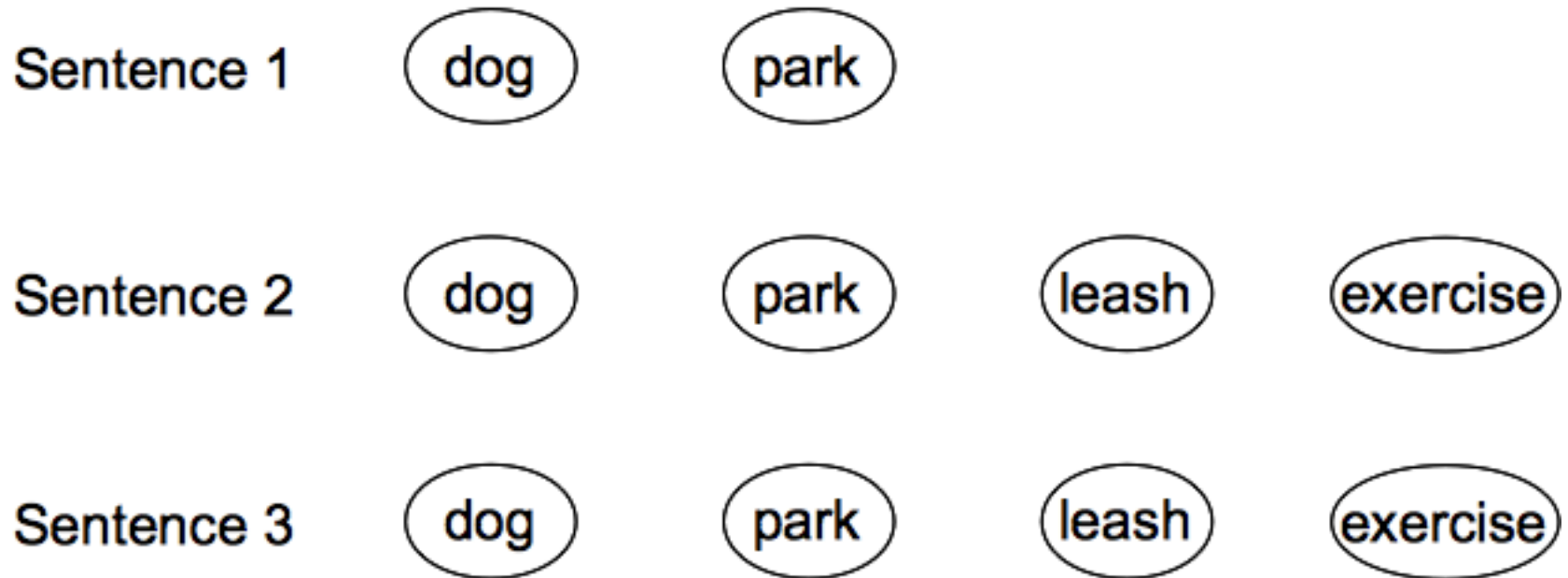
## Relevance Intervals for sample terms in the discourse



# RIs → Nodes

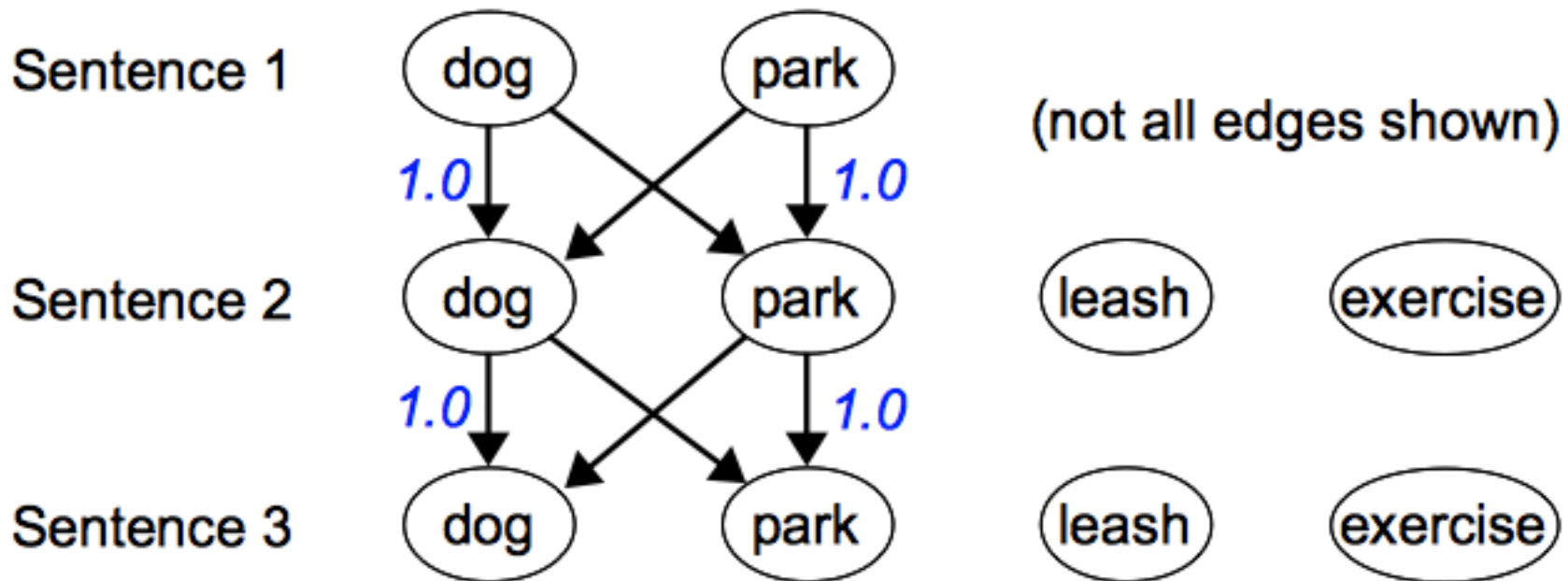
- Construct a graph in which each node represents a term and a sentence, iff the sentence is contained in an RI for that term

## Nodes corresponding to these Relevance Intervals



# Connecting the Nodes ...

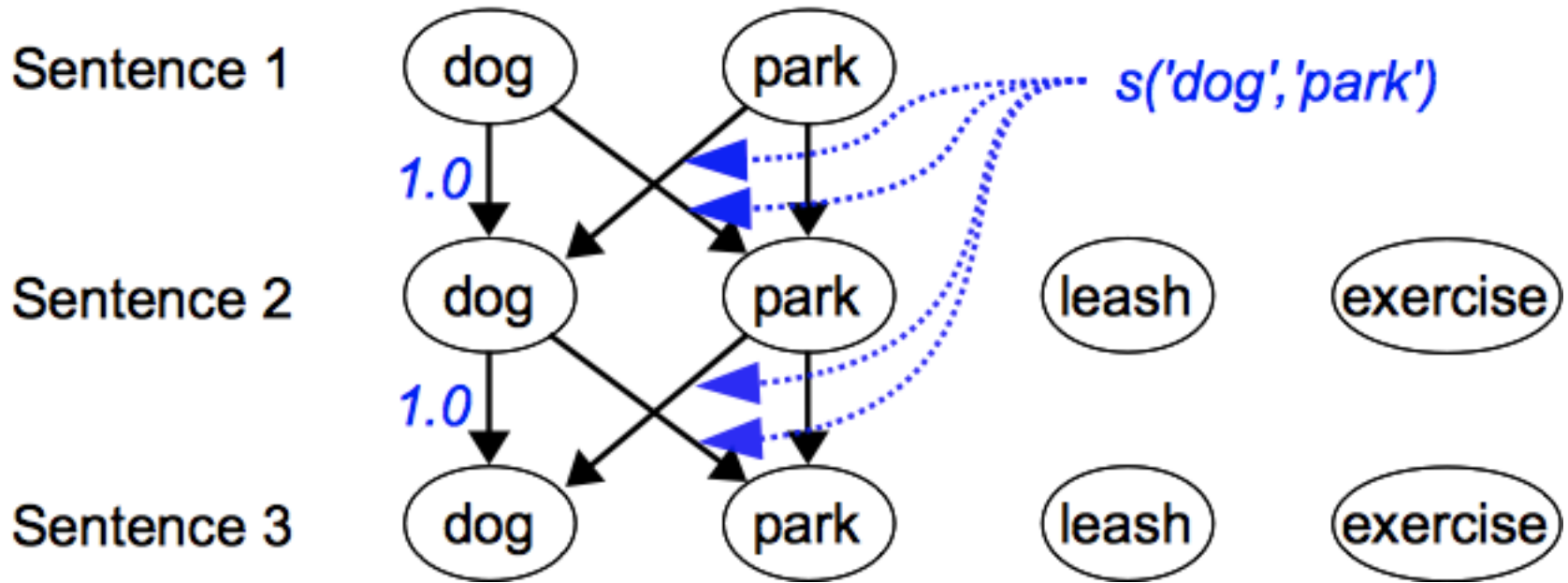
All edge strengths between a term and itself are initialized to 1.0





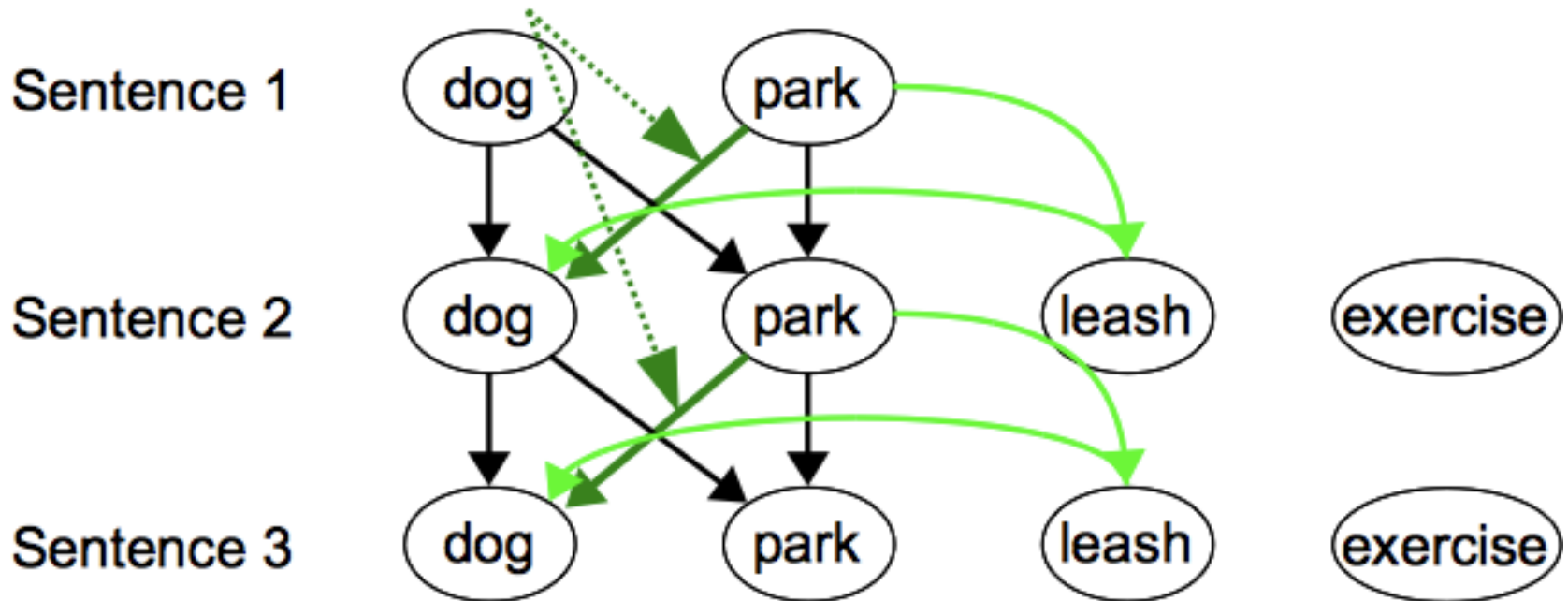
# Calculating connection strengths for edges

For edges between different terms, initialize their strengths to normalized PMI values:  $s(x,y) = 1 - 1/\exp(\text{PMI}(x,y))$

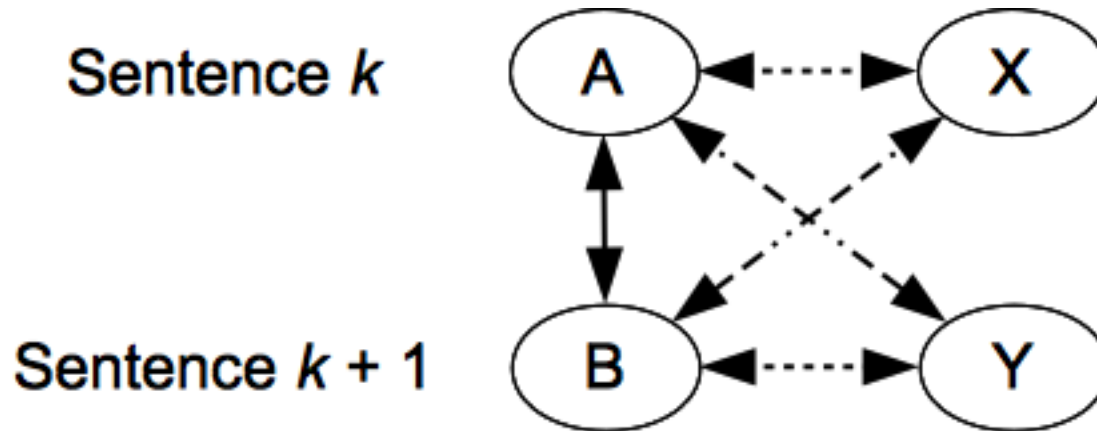


# Calculating connection strengths for edges

*Add  $s(\text{'park'}, \text{'leash'})s(\text{'leash'}, \text{'dog'})$  to edge strength between 'park' and 'dog'*



# Connection strength formula



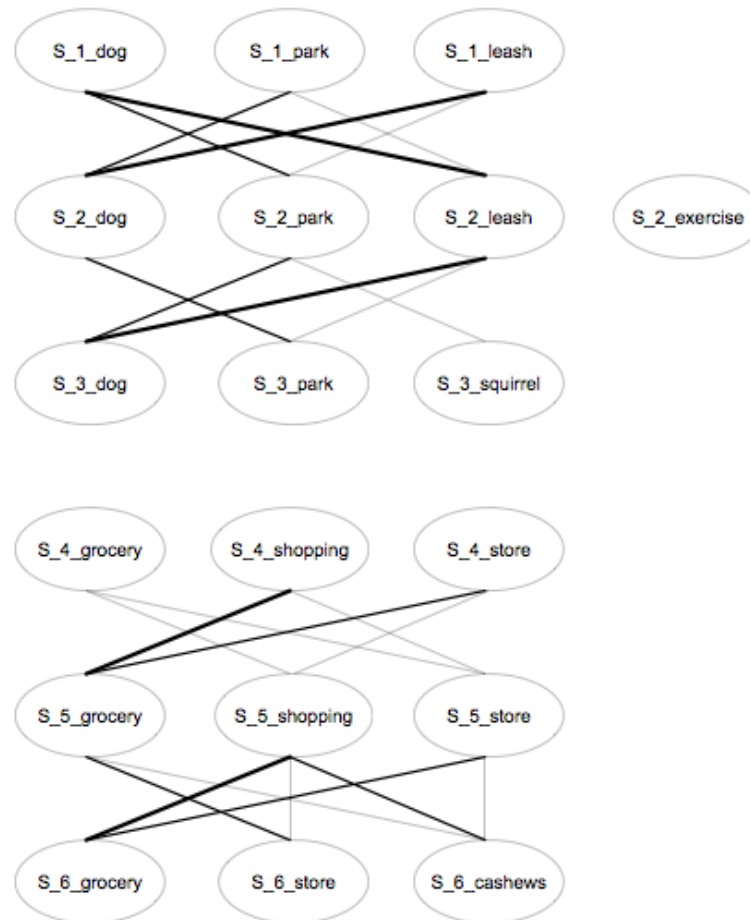
$$\text{Connection-strength}(A,B) = 2s(A,B) + s(A,X)s(X,B) + s(B,Y)s(Y,A)$$

and in general, for terms  $a$  and  $b$  in sentences  $i$  and  $i + 1$  respectively:

$$c(a,b) = \sum_{x \in W_i} s(x,a)s(x,b) + \sum_{x \in W_{i+1}} s(x,a)s(x,b)$$

# Filtering edges in the graph

- We filter out edges with a connection strength below a set threshold (we've tried a couple and usually use 0.5)



# Graph Representation of Document

- Lets look at a real example. 1<sup>st</sup> 8 minutes of an episodes of Bizarre Foods.
- [Bizarre\\_Foods\\_With\\_Andrew\\_Zimmern-Japan.pdf](#)

# Segmentation from graphs

- General idea: look for places in the graph where connections are sparse or weak
  - Typically, this will be where relatively few Ris cross a boundary
  - Edges with low connection strengths are unlikely to bear on topical coherence, so it's best to remove them from the graph
  - “Normalized novelty”: on the two sides of a potential boundary, the number of nodes labeled with the same terms, normalized by the total number of terms

# Graph representation of documents

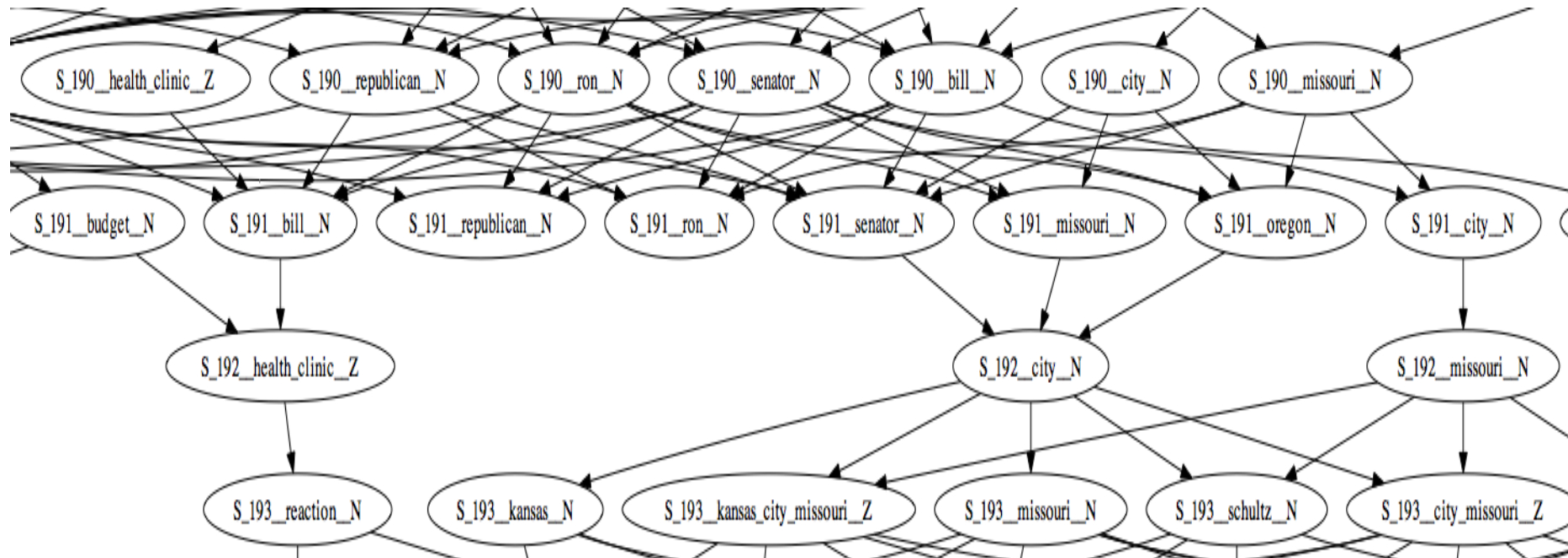
## Example snippet and graph from t.v. news broadcast

**S\_190** We've got to get this addressed and hold down health care costs.

**S\_191** Senator ron wyden, the optimist from oregon, we appreciate your time tonight.

**S\_192** Thank you.

**S\_193** Coming up, the final day of free health clinic in kansas city, missouri.





# Experiments and Evaluation



# Evaluation metrics

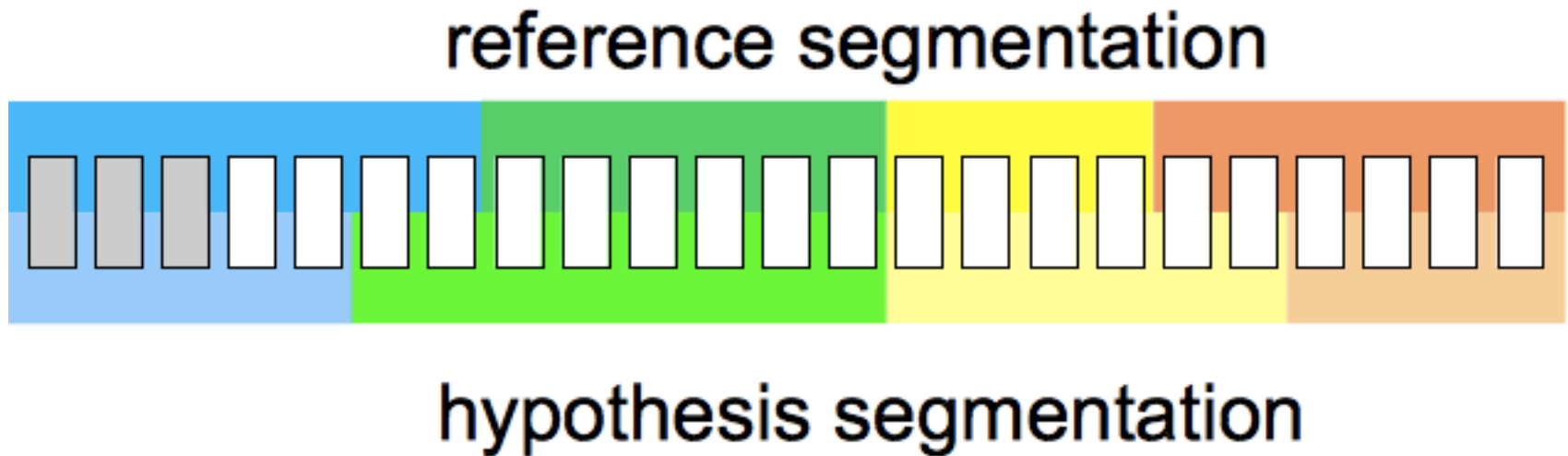
- How well does the hypothesized set of boundaries match the true (reference) set?
- $P_k$  (Beeferman, et al. 1997) and WindowDiff (Pevzner & Hearst, 2002)
  - Both compare hypothesis to reference segmentation within a sliding window
  - $P_k$  is the proportion of windows in which hypothesis and reference disagree on the number of boundaries
  - WindowDiff tallies the difference in the number of boundaries in each window
  - Both commonly used instead of precision and recall, because they take approximate matching into account
  - They have drawbacks of their own, however

Doug Beeferman, Adam Berger, and John Lafferty. 1997. Text Segmentation Using Exponential Models. *Proceedings of EMNLP 2*

Lev Pevzner and Marti A. Hearst. 2002. A critique and improvement of an evaluation metric for text segmentation. *Computational Linguistics*, 28:1

# Evaluation metrics

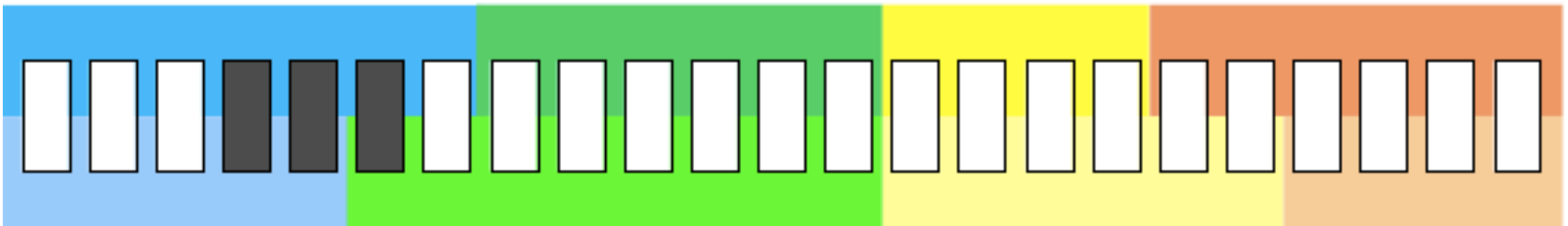
- $P_k$  and WindowDiff: sliding window is half the average reference segment size



# Evaluation metrics

- One black mark against the hypothesis segmentation, where it differs from the reference (mistakes closer to reference boundaries appear in fewer windows, and are thus penalized less)

**reference segmentation**



**hypothesis segmentation**

# Systems compared

Choi	Implementation from MorphAdorner*
SN	Our system, using a single node for each term occurrence (no extension)
FE	Our system, using an extension of a fixed number of sentences for each term from the sentence it occurs in
SS	Our system, using Ris without “hard” boundaries determined by the modified Choi algorithm
SS+C	Our full segmentation system, incorporating “hard” boundaries determined by the modified Choi algorithm

\* [morphadorner.northwestern.edu/morphadorner/-textsegmenter](http://morphadorner.northwestern.edu/morphadorner/-textsegmenter)

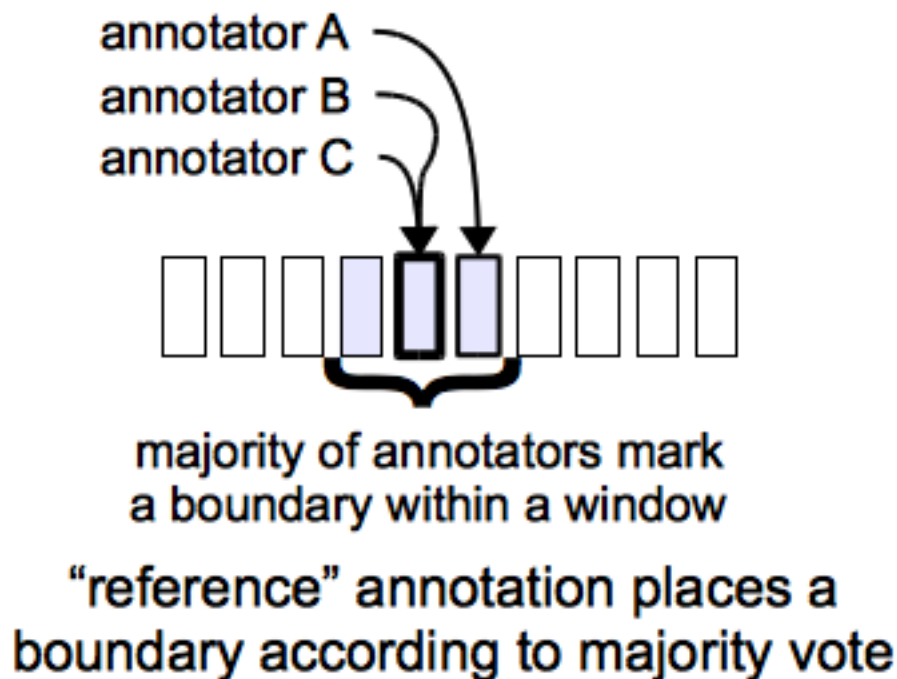
# Results on pseudodocuments

185 documents each containing 20 Concatenated *New York Times* articles  
Number of boundaries not specified to systems

system	precision	recall	F	<i>Pk</i>	WindowDiff
<b>Choi</b>	0.404	0.569	0.467	0.338	0.360
<b>SN</b>	0.096	0.112	0.099	0.570	0.702
<b>FE</b>	0.265	0.140	0.176	0.478	0.536
<b>SS</b>	0.566	0.383	0.448	0.292	0.317
<b>SS+C</b>	0.578	0.535	0.537	0.262	0.283

# Results on TV shows

- Data: Closed captions for 13 tv shows (News, talk shows, documentaries, lifestyle shows)
- 5 annotators manually marked up major and minor boundaries, using 1-5 rating scale
- As expected, IAA is low, so we create a reference annotation



# TV show closed-captions: inter-annotator agreement on segmentation

- *Pk* values between pairs of annotators: all boundaries and *major boundaries*
- Note that matrix is asymmetrical

	<b>A</b>	<b>B</b>	<b>C</b>	<b>D</b>	<b>E</b>	<b>Ref</b>
<b>A</b>		0.36 <i>0.48</i>	0.30 <i>0.45</i>	0.27 <i>0.44</i>	0.42 <i>0.67</i>	0.20 <i>0.38</i>
<b>B</b>	0.29 <i>0.40</i>		0.29 <i>0.32</i>	0.27 <i>0.33</i>	0.33 <i>0.55</i>	0.20 <i>0.25</i>
<b>C</b>	0.57 <i>0.48</i>	0.60 <i>0.44</i>		0.41 <i>0.20</i>	0.67 <i>0.61</i>	0.40 <i>0.18</i>
<b>D</b>	0.36 <i>0.46</i>	0.41 <i>0.46</i>	0.27 <i>0.20</i>		0.53 <i>0.63</i>	0.22 <i>0.26</i>
<b>E</b>	0.33 <i>0.35</i>	0.31 <i>0.34</i>	0.33 <i>0.30</i>	0.32 <i>0.31</i>		0.25 <i>0.27</i>
<b>Ref</b>	0.25 <i>0.39</i>	0.32 <i>0.35</i>	0.24 <i>0.17</i>	0.21 <i>0.22</i>	0.42 <i>0.58</i>	

# TV show closed-captions: segmentation

- Accuracy is low, which is unsurprising given the low IAA

system	precision	recall	F	<i>P</i> <sub>k</sub>	WindowDiff
<b>All topic boundaries</b>					
Choi	0.197	0.186	0.184	0.476	0.507
SS+C	0.315	0.208	0.240	0.421	0.462
<b>Major topic boundaries only</b>					
Choi	0.170	0.296	0.201	0.637	0.812
SS+C	0.271	0.316	0.271	0.463	0.621





# Conclusions and future work

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## Conclusions

- Graphs constructed from RIs do seem to help segmentation
- Semantic relatedness with reinforcement from neighboring terms
- Works decently on “noisy” material, such as TV shows
- Doesn't require any training; however, there are lots of parameters to play with (and we have started exploring training to optimize them)

## Future work

- Several ways to segment a graph: try community detection or learn boundary detection through various graph features
- Try to use graphs for more complex segmentation tasks, such as hierarchical segmentation; community structure in a graph might reflect hierarchical organization of discourse
- Try to find the most “central” terms in a subgraph, to use as segment labels



# We gratefully acknowledge...

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Thank you! Questions?