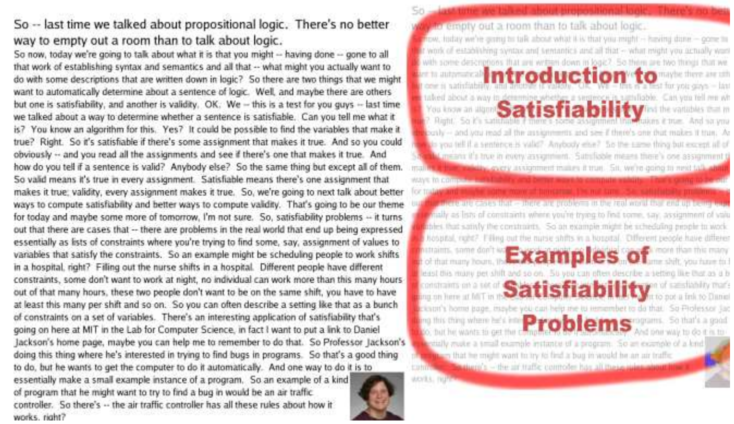
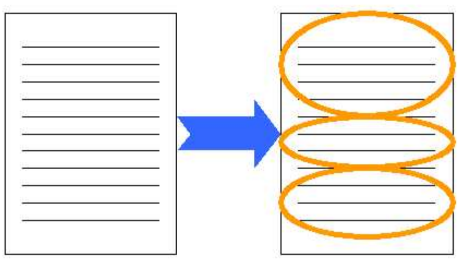
Text Segmentation

Example



Text Segmentation

Goal: Partition a text into a sequence of topically coherent blocks



Applications: Information Retrieval, Summarization, Question Answering

Flow model of discourse

Chafe'76:

> "Our data ... suggest that as a speaker moves from focus to focus (or from thought to thought) there are certain points at which they may be a more or less radical change in space, time, character configuration, event structure, or even world ... At points where all these change in a maximal way, an episode boundary is strongly present."

Discourse Exhibits Structure!

- Discourse can be partitioned into segments, which can be connected in a limited number of ways
- Speakers use linguistic devices to make this structure explicit
  cue phrases, intonation, gesture
- Listeners comprehend discourse by recognizing this structure
  - Kintsch, 1974: experiments with recall
  - Haviland&Clark, 1974: reading time for given/new information

Types of Structure

- Linear vs. hierarchical
  - Linear: paragraphs in a text
  - Hierarchical: chapters, sections, subsetions

- Typed vs. untyped
  - Typed: introduction, related work, experiments, conclusions

Our focus: Linear segmentation

Segmentation: Agreement

Percent agreement — ratio between observed agreements and possible agreements

A	B	C
−	−	−
−	−	−
+	−	−
−	+	+
−	−	−
+	+	+
−	−	−
−	−	−

$$\frac{22}{8 * 3} = 91\%$$

Results on Agreement

People can reliably predict segment boundaries!

Grosz&Hirschbergberg'92	newspaper text	74-95%
Hearst'93	expository text	80%
Passanneau&Litman'93	monologues	82-92%

Linguistic Basis: Lexical Cohesion

- Common assumption of unsupervised algorithms
  - Word repetition indicates topical cohesion [Halliday & Hasan,'76]
  - Variations in lexical distribution signal topic changes

> What is the instantaneous **speed**?
> Well, **speed** is not sign sensitive.

> It's like a spacecraft in orbit or an elevator with a cut cable .

Example

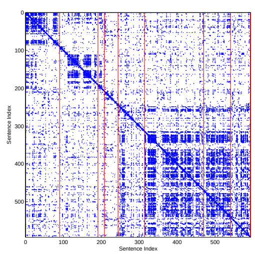
Stargazers Text(from Hearst, 1994)

- Intro - the search for life in space
- The moon's chemical composition
- How early proximity of the moon shaped it
- How the moon helped life evolve on earth
- Improbability of the earth-moon system

DotPlot Representation

Key assumption: change in lexical distribution signals topic change (Hearst '94)

- Dotplot Representation: (i, j) – similarity between sentence i and sentence j



Example

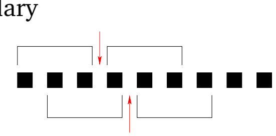
```
-------------------------------------------------------------------------------------------------------------+
Sentence:        05   10   15   20   25   30   35   40   45   50   55   60   65   70   75   80   85   90   95|
-------------------------------------------------------------------------------------------------------------+
14       form    1     111 1   1                               1 1     1   1       1     1     1    1        |
 8  scientist                   11            1   1               1          1      1  1                     |
 5      space 11    1     1                                                            1                     |
25       star    1             1                                       1122  111112  1 1  1   11 1111     1 |
 5     binary                                                          11  1          1                    1|
 4    trinary                                                           1   1         1                    1|
 8 astronomer 1                1                                        1 1           1   1    1  1          |
 7      orbit   1                    1                                     12    1 1                         |
 6       pull                          2     1 1                               1  1                          |
16     planet   1    1       11               1           1                21  11111                  1     1|
 7     galaxy    1                                                  1                 1  11     1           1|
 4      lunar            1  1     1       1                                                                  |
19       life 1  1  1                              1    11 1  11  1      1                 1 1    1 111  1 1 |
27       moon        13  1111   1 1 22 21  21    21           11 1                                           |
 3       move                                       1   1   1                                                |
 7  continent                                       2 1 1 2 1                                                |
 3  shoreline                                             12                                                 |
 6       time                      1               1  1  1     1                                          1  |
 3      water                                 11            1                                                |
 6        say                                 1 1        1        11                1                        |
 3    species                                         1  1  1                                                |
-------------------------------------------------------------------------------------------------------------+
Sentence:        05   10   15   20   25   30   35   40   45   50   55   60   65   70   75   80   85   90   95|
-------------------------------------------------------------------------------------------------------------+
```

Outline

- Local similarity-based algorithm
- Global similarity-based algorithm
- HMM-based segmentor

Segmentation Algorithm of Hearst

- Initial segmentation
  - Divide a text into equal blocks of k words
- Similarity Computation
  - compute similarity between m blocks on the right and the left of the candidate boundary



- Boundary Detection
  - place a boundary where similarity score reaches local minimum

Similarity Computation: Representation

Vector-Space Representation

SENTENCE$_1$: I like apples

SENTENCE$_2$: Apples are good for you

Vocabulary	Apples	Are	For	Good	I	Like	you
Sentence$_1$	1	0	0	0	1	1	0
Sentence$_2$	1	1	1	1	0	0	1

Similarity Computation: Cosine Measure

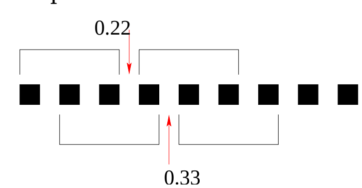
Cosine of angle between two vectors in n-dimensional space

$$sim(b_1, b_2) = \frac{\sum_t w_{y,b_1} w_{t,b_2}}{\sqrt{\sum_t w_{t,b_1}^2 \sum_{t=1}^n w_{t,b_2}^2}}$$

SENTENCE$_1$: 1 0 0 0 1 1 0
SENTENCE$_2$: 1 1 1 1 0 0 1

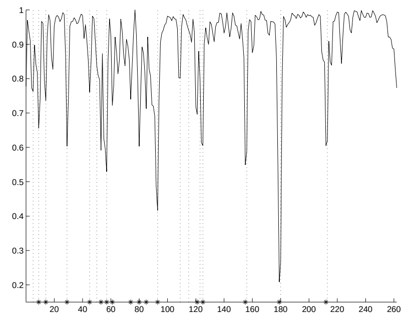
$$\mathrm{sim}(S_1,S_2) = \frac{1*0+0*1+0*1+0*1+1*0+1*0+0*1}{\sqrt{(1^2+0^2+0^2+0^2+1^2+1^2+0^2)*(1^2+1^2+1^2+1^2+0^2+0^2+1^2)}} = 0.26$$

Output of Similarity computation:



Boundary Detection

- Boundaries correspond to local minima in the gap plot



- Number of segments is based on the minima threshold ($s - \sigma/2$, where s and σ correspond to average and standard deviation of local minima)

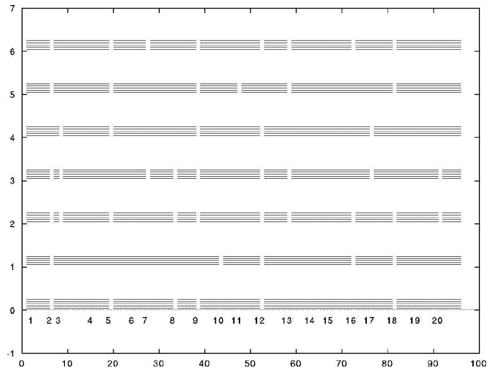
Evaluation Results

Methods	Precision	Recall
Random Baseline 33%	0.44	0.37
Random Baseline 41%	0.43	0.42
Original method+thesaurus-based similarity	0.64	0.58
Original method	0.66	0.61
Judges	0.81	0.71

Segmentation Evaluation

Comparison with human-annotated segments(Hearst'94):

- 13 articles (1800 and 2500 words)
- 7 judges
- boundary if three judges agree on the same segmentation point



More Results

- High sensitivity to changes in parameter values
  - Parameters: Block size, window size and boundary threshold
- Thesaural information does not help
  - Thesaurus is used to compute similarity between sentences — synonyms are considered to be identical
- Most of the mistakes are "close misses"

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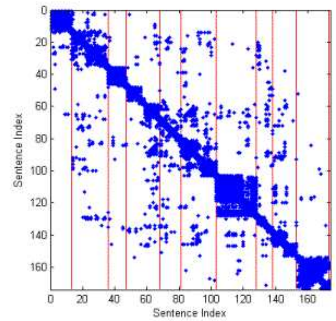
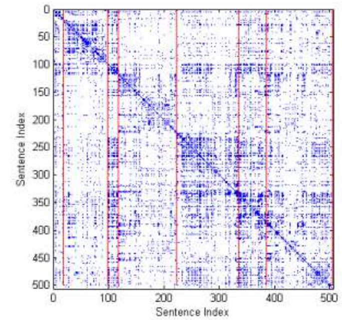
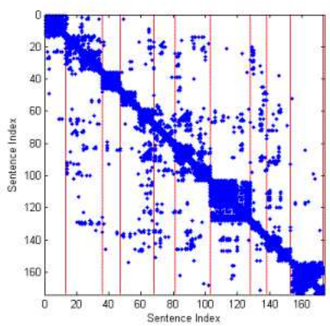
Synthetic vs. Real Data





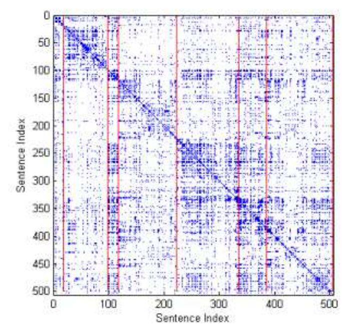
Synthetic Text Dotplot

- Broadcast News, synthetic document collections
  - Exhibit sharp segment transitions



Physics Lecture Dotplot

- Spoken Lecture Data
  - Exhibit very subtle topical transitions



Motion → Instantaneous Velocity → Average Acceleration → Numerical Example

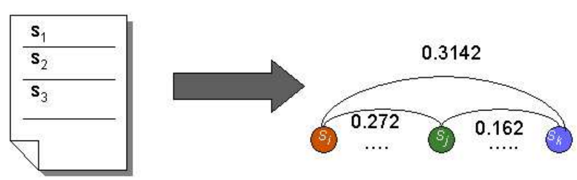
Minimum Cut Segmentation

- New graph-theoretic formalization of the segmentation objective
  - jointly maximizes within-cluster similarity and minimizes between-cluster similarity
  - Incorporates long-range lexical dependencies
- Exact, fast decoding using dynamic programming

Key Strength: Can detect subtle topic changes

Graph Based Representation

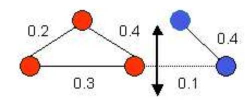
- Let *G(V,E)* be a weighted, undirected, fully-connected graph
- Graph nodes represent textual units (e.g. sentences)
- Edge weights $w(s_i, s_j)$ indicate pairwise sentence similarity



Graph Cut Definitions

- Graph Cut - partitioning of the graph into two disjoint sets of nodes *A,B*
- **Between-segment similarity** (Cut Value) - sum of the edge weights between A,B
- **Within-segment similarity** (Volume) - sum of the edge weights for nodes in A
- Normalized Cut Value [Shi & Malik '00] :

$$Ncut(A,B) = \frac{cut(A,B)}{vol(A)} + \frac{cut(A,B)}{vol(B)}$$



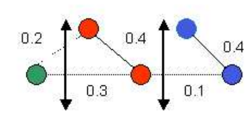
Normalized Cut Value = 0.6

Multi-way Graph Cuts

- K-way Graph Cut: partitioning of the graph into K disjoint sets, $A_1, \ldots A_k$
- K-way Normalized Cut Value:

$$Ncut_k(A_1, \ldots A_k) = \frac{cut(A_1, V - A_1)}{vol(A_1)} + \ldots + \frac{cut(A_k, V - A_k)}{vol(A_k)}$$

- 3-way Cut Example:



Normalized Cut Value = 1.8

Optimization Objective

- For given k, we seek the k-way cut that minimizes the normalized cut value:

$$\min_{A_1,\ldots A_k} \frac{cut(A_1, V-A_1)}{vol(A_1)} + \ldots + \frac{cut(A_k, V-A_k)}{vol(A_k)}$$

- With this objective, we jointly
  - minimize the Cut Value ~ similarity between segments
  - maximize the Volume ~ similarity within segments

Dynamic Programming Solution

Exact solution can be found using dynamic programming in $O(kn^2)$ time:

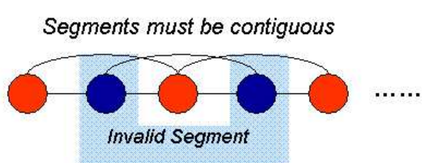
- $C[i,m]$: Minimum normalized cut of the segmentation of the first m sentences into i segments

- $C[i,m]$ can be computed recursively by choosing the best sentence *j* prior to *m* to begin the *i*th segment:

$$C[i,m] = \min_{j<m} \left[C[i-1,j] + \frac{cut[A_{j,m}, V - A_{j,m}]}{vol[A_{j,m}]} \right]$$

Linearity Constraint

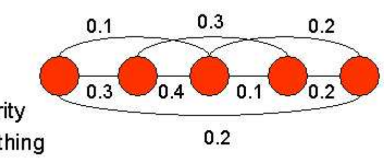
- Without further constraints, this optimization is *NP*-complete [Papadimitriou '00]
- However, the segmentation problem imposes a natural **linearity** constraint on the form of the solution:



- Reformulation: $\min_{A_1,\ldots A_k} Ncut_k(A_1,\ldots A_k)$
  s.t. linearity constraint

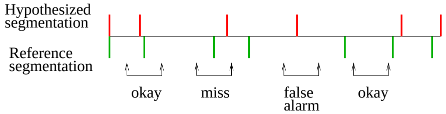
Graph Construction

- Node representation
  - Fixed blocks of text
- Topology
  - Fully-connected Graph
- Edge Weights
  - Weighted Cosine Similarity
  - Word Occurrence Smoothing



$$\tilde{s}_i = \sum_{j=i}^{i+k} e^{-\alpha(j-i)} s_j,$$

Evaluation Metric: P_k Measure



P_k: Probability that a randomly chosen pair of words k words apart is inconsistently classified (Beeferman '99)

- Set k to half of average segment length
- At each location, determine whether the two ends of the probe are in the same or different location. Increase a counter if the algorithm's segmentation disagree
- Normalize the count between 0 and 1 based on the number of measurements taken

Experiments

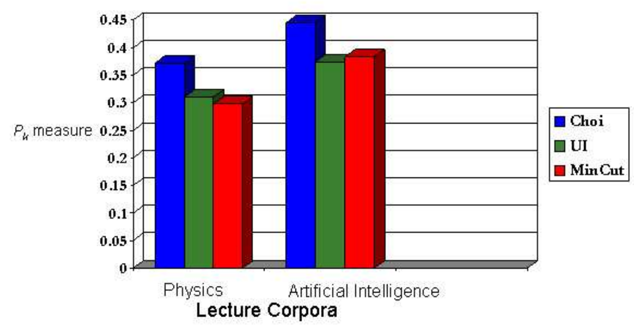
- Data: MIT Physics and AI Lecture Corpus
  - Verbose and colloquial language
  - Subtle topic transitions
  - Automatic Speech Recognition Error
- Baselines: State-of-the-art unsupervised segmentation systems
  - Utiyama & Isahara (UI) 2001 - language modeling approach
  - Choi 2000 - local similarity-based approach

To control for segmentation granularity, the target number of segments for the baselines and our system is fixed

Notes on P_k measure

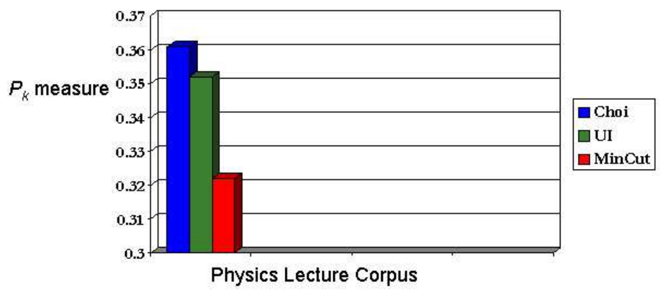
- $P_k \in [0, 1]$, the lower the better
- Random segmentation: $P_k \approx 0.5$
- On synthetic corpus: $P_k \in [0.05, 0.2]$
- On real segmentation tasks: $P_k \in [0.2, 0.4]$

Results: Manually Transcribed Data



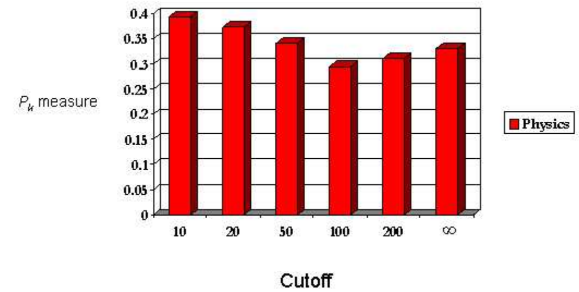
Human Agreement: $P_k \in [0.22; 0.42]$

Results: ASR Data (WER = 20%)



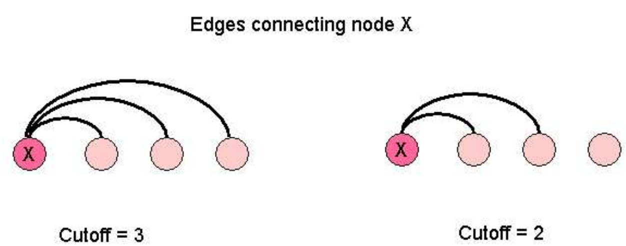
Impact of Long-range Dependencies

- Long-range dependencies improve performance



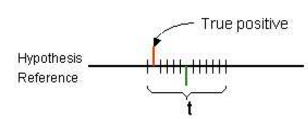
Impact of Long-range Dependencies

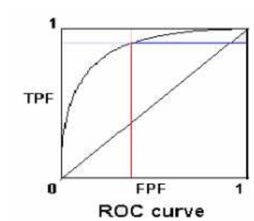
- Experiment: remove edges between nodes separated by a specified cutoff



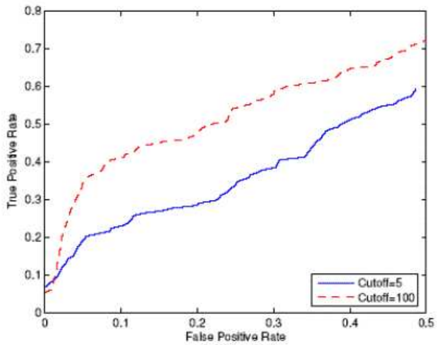
Evaluation Metrics - ROC

- Receiver Operating Characteristic Curve – represents tradeoff between true positives and false positives
- In segmentation, a true positive is a hypothesized boundary that occurs within a threshold *t* of the true boundary
- By varying *t*, we obtain points along the ROC curve





ROC Plot: Physics Lecture Data



Mincut ROC Plot with edge cutoffs at 5 and 100 sentences

Typed Segmentation

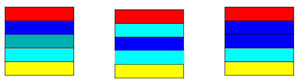
- Task: determining the positions at which topics change in a stream of text or speech and identify the type of each segment.
- Example: divide newsstream into stories about sports, politics, entertainment, etc. Story boundaries are not provided. List of possible topics is provided.
- Straightforward solution: use a segmentor to find story boundaries and then assign to each story a topic label.
  - Segmentation mistakes may interfere with the classification step.
  - Combining the two steps can increase the accuracy

Outline

- Local similarity-based algorithm
- Global similarity-based algorithm
- HMM-based segmentor

Types of Constraints

- "Local": *negotiations* is more likely to predict the topic **politics** rather than **entertaiment**
- "Contextual": **politics** is more likely to start the broadcast than to follow **sports**



Hidden Markov Models for Segmentation

- We have a text with sentences $s_1, s_2, \ldots, s_n$
  (s_i is the ith sentence in the text)
  - $s_i = \{w_{i,1}, w_{i,2}, \ldots, w_{i,m}\}$
- We have a topic sequence $T = t_1, t_2, \ldots, t_n$
- We'll use an HMM to define

$$P(t_1, t_2, \ldots, t_n, s_1, s_2, \ldots, s_n)$$

  for any text and tag sequence of the same length
- The most likely tag sequence for a text is

$$T^\star = argmax_T P(T, S)$$

- Topic breaks occur if $t_i \neq t_{i+1}$

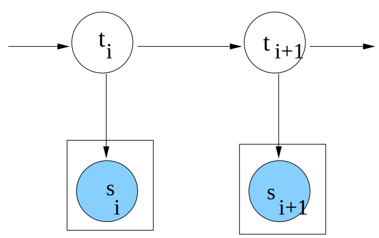
Hidden Markov Models for Segmentation

$$P(T,S) = P(END|t_1, t_2, \ldots, t_n, s_1, s_2, \ldots, s_n) \times$$
$$\prod_{j=1}^{n} [P(t_j|s_1, \ldots, s_{j-1}, t_1, \ldots, t_{j-1}) \times P(s_j|s_1, \ldots, s_{j-1}, t_1, \ldots, t_{j-1}, t_j)]$$
$$= P(END|t_n) \times \prod_{j=1}^{n} [P(t_j|t_{j-1}) \times P(s_j|t_j)]$$

Assumptions:

- Each topic t_i depends only on previous topic t_{i-1}
- Each sentence s_i only depends on topic t_i that generates it

Hidden Markov Models for Segmentation



- Choose a topic from an initial distribution of topics
- Generate a sentence from a distribution of words associated with a topic
- Choose another topic, possibly the same topic from a distribution of allowed transitions
- Repeat the process

Training the Models

- Fully supervised:
  - A newstream where stories are segmented and annotated with their type
- Partially supervised:
  - A newstream where stories are segmented but without type annotation
    - During the preprocessing, cluster the stories based on cosine similarity or other distributional similarity metric

Parameter Estimation and Decoding

- Emission probabilities are modeled using a smoothed unigram model
  (stop words are removed during preprocessing)

$$P(s|t) = \prod_i (w_i|t)$$

- Transition probabilities are based on ML estimates

$$P(sports|politics) = \frac{count(sports, politics)}{count(politics)}$$

- Using Viterbi algorithm, recover a tag sequence for a given sequence of sentences

Results

- Evaluation data: 2.2 million words (6,000 stories) from CNN and ABC
  The data is transcribed automatically
- Evaluation measures:
  - P_{Miss} — probability of missed boundary (within window of 50 words)
  - $P_{FalseAlarm}$ — probability of false segmentation (within window of 50 words)
  - $C_{Seg} = P_{Seg} * P_{Miss} + (1 - P_{Seg}) * P_{FalseAlarm}$, where P_{Seg} is the *a priori* probability of a segment boundary being within the window length ($P_{Seg} = 0.3$)
- Results:

Show	P_{Miss}	$P_{FalseAlarm}$	P_{Seg}
ABC	0.3453	0.088	0.158
CNN	0.3094	0.1022	0.164