



Chapter 9: Topic Detection and Tracking (TDT)

Some slides from "Overview NIST Topic Detection and Tracking

-Introduction and Overview" by G. Doddington

-http://www.itl.nist.gov/iaui/894.01/tests/tdt/tdt99/presentations/index.htm



TDT Task Overview

- 5 R&D Challenges:
 - Story Segmentation
 - Topic Tracking
 - Topic Detection
 - First-Story Detection
 - Link Detection

- TDT3 Corpus Characteristics:†
 - Two Types of Sources:
 - Text

- Speech
- Two Languages:
 - English 30,000 stories
 - Mandarin 10,000 stories
- 11 Different Sources:
 - _8 English__ 3
 Mandarin
 ABC CNN VOA
 PRI VOA XIN
 NBC MNB ZBN
 APW NYT

^{*} see http://www.itl.nist.gov/iaui/894.01/tdt3/tdt3.htm for details

[†] see http://morph.ldc.upenn.edu/Projects/TDT3/ for details



Preliminaries



A topic is ...

a seminal **event** or activity, along with all directly related events and activities.

A story is ...

a topically cohesive segment of news that includes two or more DECLARATIVE independent clauses about a single event.





Example Topic

Title: Mountain Hikers Lost

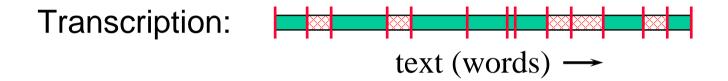
- WHAT: 35 or 40 young Mountain Hikers were lost in an avalanche in France around the 20th of January.
- WHERE: Orres, France
- WHEN: January 1998
- RULES OF INTERPRETATION: 5.
 Accidents





The Segmentation Task:

To segment the source stream into its constituent stories, for all audio sources.



Story: Non-story:

(for Radio and TV only)

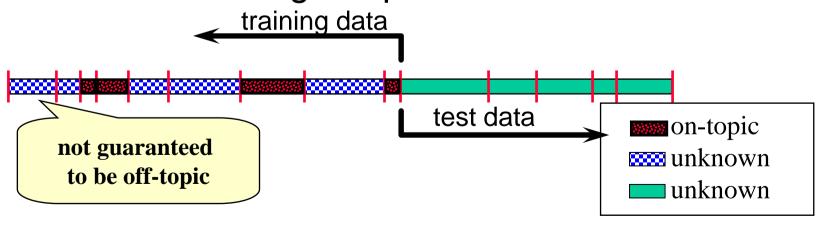




The Topic Tracking Task:

To detect stories that discuss the target topic, in multiple source streams.

- Find all the stories that discuss a given target topic
 - Training: Given N_t sample stories that discuss a given target topic,
 - Test: Find all subsequent stories that discuss the target topic.







Topic Tracking Conditions

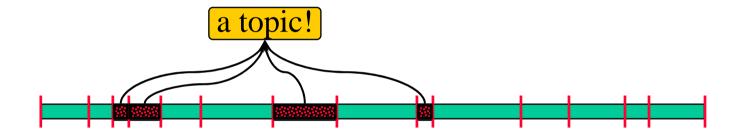
- 3 Source Conditions:
 - text sources and manual transcription of the audio sources
 - text sources and ASR transcription of the audio sources
 - text sources and the sampled data signal for audio sources
- 2 Story Boundary Conditions:
 - Reference story boundaries provided
 - No story boundaries provided





The Topic Detection Task:

To detect topics in terms of the (clusters of) stories that discuss them.



- Unsupervised topic training
- New topics must be detected as the incoming stories are processed.
- Input stories are then associated with one of the topics.





Topic Detection Conditions

Decision Deferral Conditions:

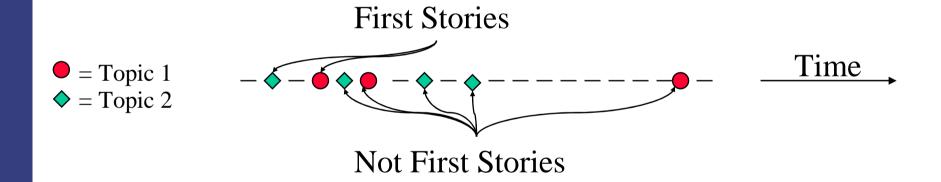
Maximum decision deferral period in # of source files			
1			
10			
100			





The First-Story Detection Task:

To detect the first story that discusses a topic, for all topics.



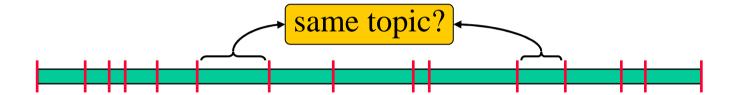
 There is no supervised topic training (like Topic Detection)





The Link Detection Task

To detect whether a pair of stories discuss the same topic.



- The topic discussed is a free variable.
- Topic definition and annotation is unnecessary.
- The link detection task represents a basic functionality, needed to support all applications (including the TDT applications of topic detection and tracking).
- The link detection task is related to the topic tracking task, with Nt = 1.





TDT3 Evaluation Methodology

- All TDT3 tasks are cast as statistical detection (yes-no) tasks.
 - Story Segmentation: Is there a story boundary here?
 - Topic Tracking: Is this story on the given topic?
 - Topic Detection: Is this story in the correct topic-clustered set?
 - First-story Detection: Is this the first story on a topic?
 - Link Detection: Do these two stories discuss the same topic?
- Performance is measured in terms of detection cost, which is a weighted sum of *miss* and *false alarm* probabilities:

$$\mathbf{C}_{\mathsf{Det}} = \mathbf{C}_{\mathsf{Miss}} \bullet \mathsf{P}_{\mathsf{Miss}} + \mathbf{C}_{\mathsf{FA}} \bullet \mathsf{P}_{\mathsf{FA}}$$

(e.g. $\mathsf{C}_{\mathsf{Miss}} = 0.2$, $\mathsf{C}_{\mathsf{FA}} = 0.98$)

Detection Cost is normalized to lie between 0 and 1:

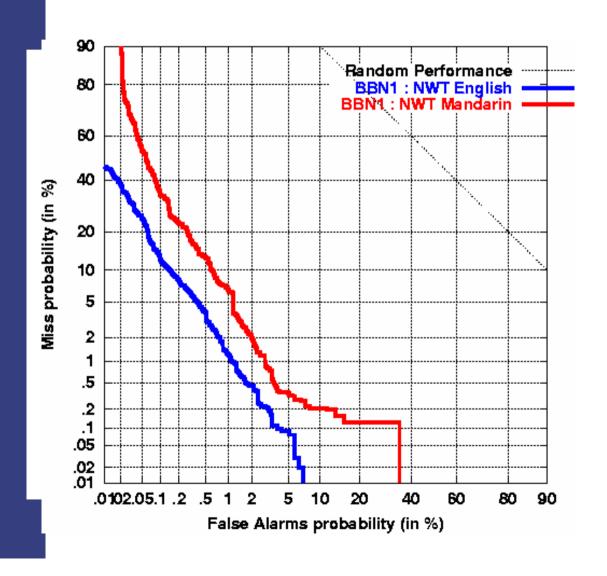
$$(C_{Det})_{Norm} = C_{Det} / min\{C_{Miss}, C_{FA}\}$$

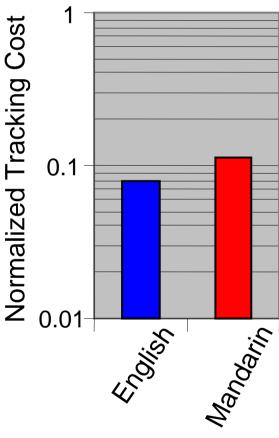


Example Performance Measures:



Tracking Results on Newswire Text (BBN)







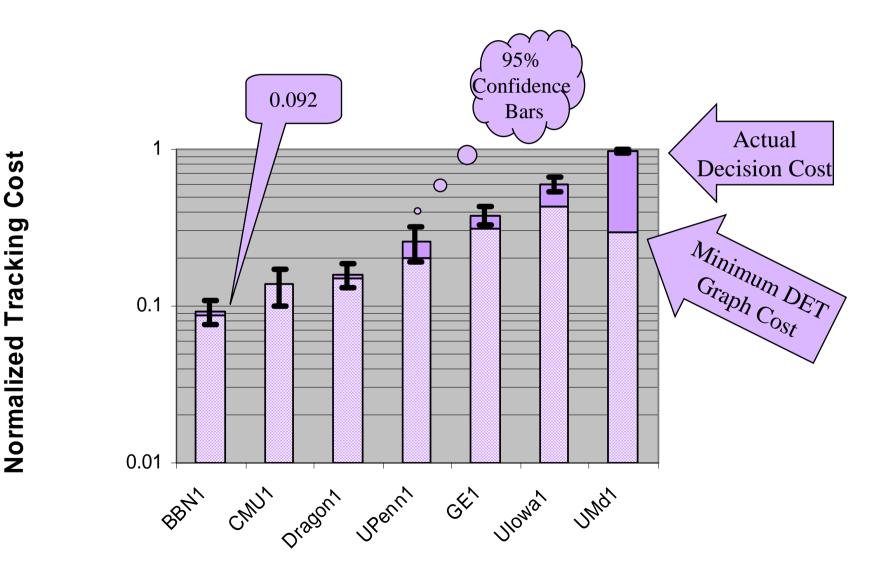
1999 TDT3 Tracking Results



Required Evaluation Condition

4 English Training Stories, Multilingual Test Texts,

Newswire Text+Broadcast News ASR, Given ASR Boundaries

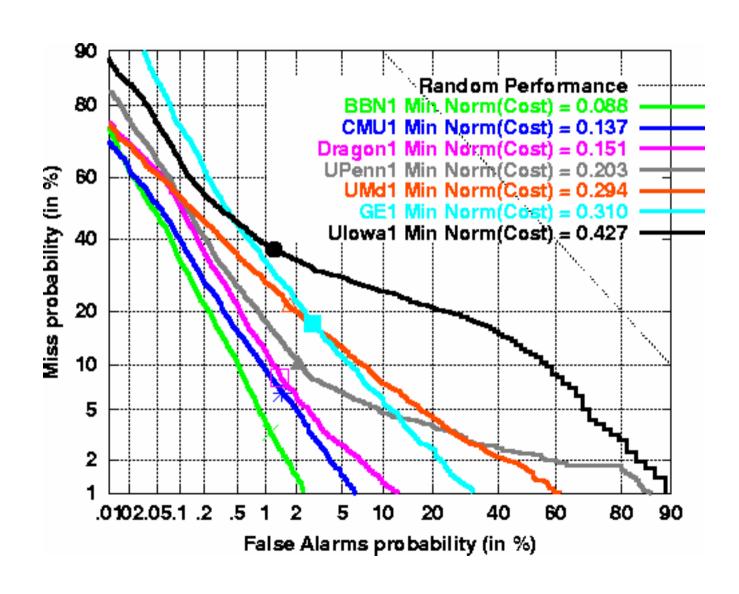




1999 TDT3 Tracking Results



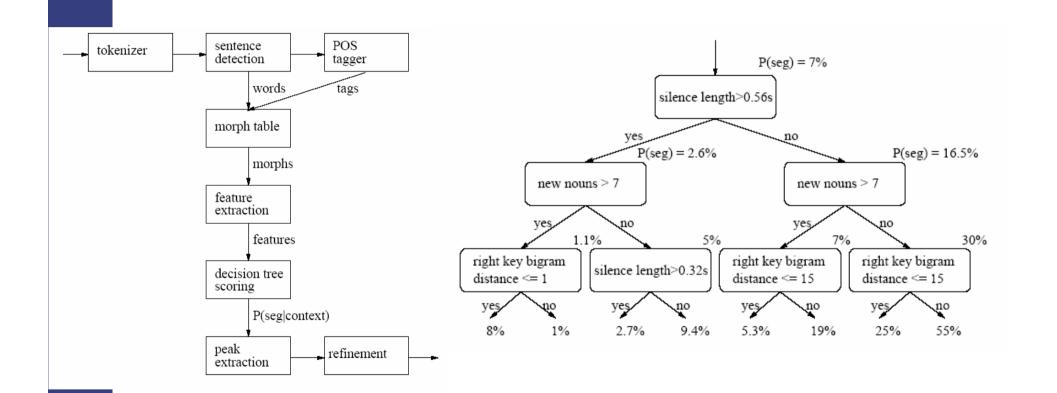
Required Evaluation Condition





Story Segmentation using **Decision Trees**





Story Segmentation and Topic Detection in the Broadcast **News Domain**

S. Dharanipragada

J.S. McCarley

S. Roukos T. Ward

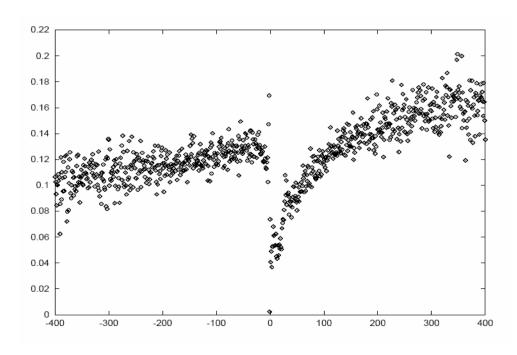
IBM T.J. Watson Research Center P.O. Box 218 Yorktown Heights, NY 10598



Using Maximum Entropy Language Models



Idea: compare perplexities of adaptive trigram with general English trigram



Relative position in segment

Statistical Models for Text Segmentation

School of Computer Science Carnegie Mellon University Pittsburgh, PA 15213 USA







$segmentation\\ model$	P_k	$miss\\probability$	$\begin{array}{c} false \ alarm \\ probability \end{array}$
exponential model	13.2%	16.0%	10.9%
decision tree	15.2%	19.3%	11.9%
interpolated (exp + dtree) models	11.8%	14.2%	9.8%
cue-word and $s = t$ trigger features	13.4%	16.9%	10.5%
cue-word and $s \neq t$ trigger features	13.6%	17.8%	10.1%
cue-word features only	18.3%	21.6%	15.5%
topicality features only	37.3%	42.1%	33.3%
TextTiling	34.6%	57.1%	18.6%



Relevance Models and Link Detection



- Given two stories A and B
 - Determine if topic(A)=topic(B)
- Estimate topics models of A and B
 - e.g. language models
- Measure distance between the models
 - e.g. Kullback-Leibler

Relevance Models for Topic Detection and Tracking

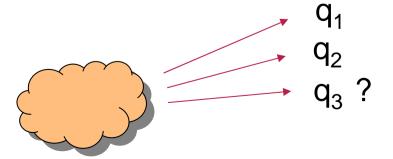




Generating Queries

- Suppose you have some source of queries
- You have generated several queries
 q₁...q_n from this source
- What is

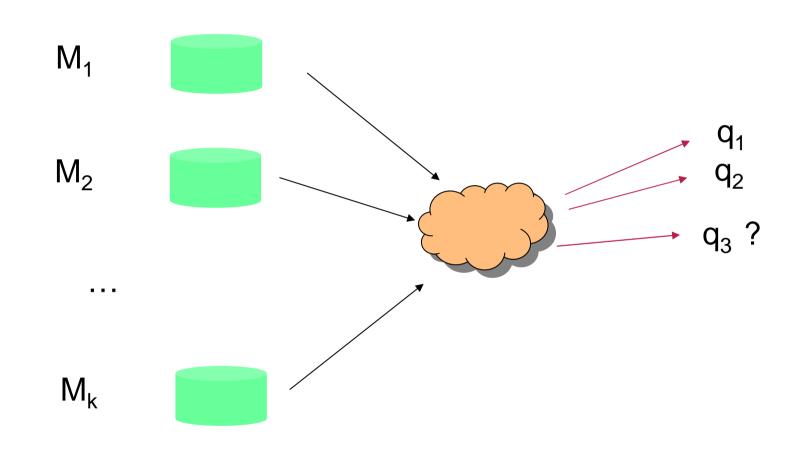
$$P(q_{N+1} | q_1....q_{N-1})$$







Universe of Models



$$P(q_{N+1} | q_1...q_N) = \sum_{i=1}^k P(q_{N+1} | M_i) P(M_i | q_1...q_N)$$



Using Relevance Models in Link Detection



- Question:
 - Are stories S₁ and S₂ linked?
- Approach
 - Create are relevance model for S₁ and S₂
 - Measure the distance between the models



Building Relevance Models as Topic Models



- S₁:
 - Generate queries from it
 - Retrieve documents from the collection
 - Estimate

$$P(w \mid D) = \lambda \frac{tf_{w,D}}{\mid D \mid} + (1 - \lambda) \frac{cf_{w}}{Coll.Size}$$

$$P(w | S_1) = P(w | q_1...q_N)$$

$$= \sum_{D \in R} P(w | D) P(D | q_1 ... q_N)$$





Measuring Distances

Kullback-Leibler Distance

$$D(S_1 || S_2) = \sum_{w} P(w | S_1) \log \frac{P(w | S_1)}{P(w | S_2)}$$

Symmetric Kullback-Leibler Distance

$$D_{sym}(S_1 \parallel S_2) = \frac{1}{2} (D(S_1 \parallel S_2) + D(S_2 \parallel S_1))$$

Kullback-Leibler Distance with "Clarity"

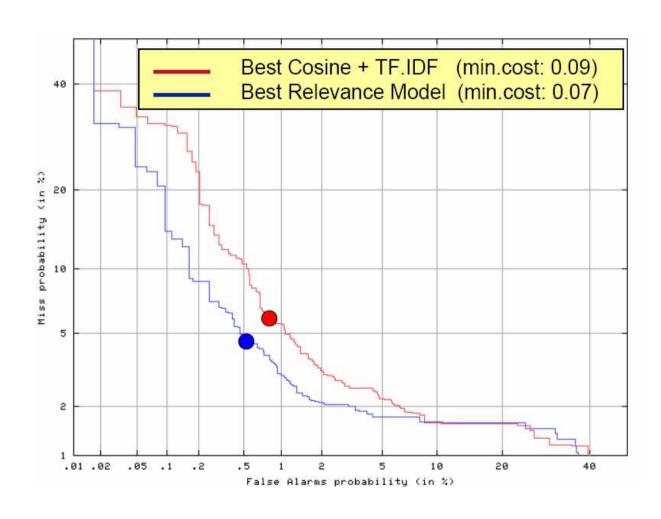
$$D_{Cl}(S_1 || S_2) = \sum_{w} P(w | S_1) \log \frac{P(w | S_2)}{P(w | GE)}$$

(GE: general english)





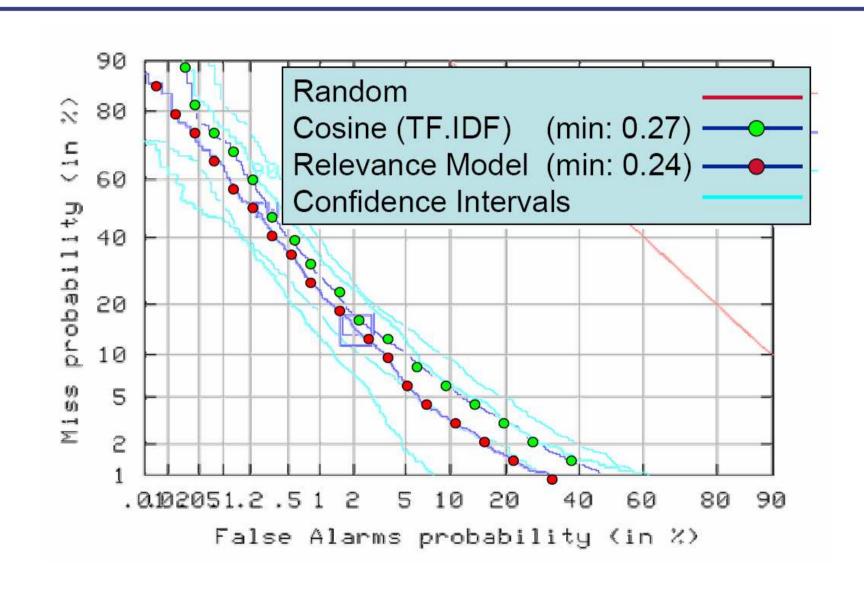
Comparison on Training Data







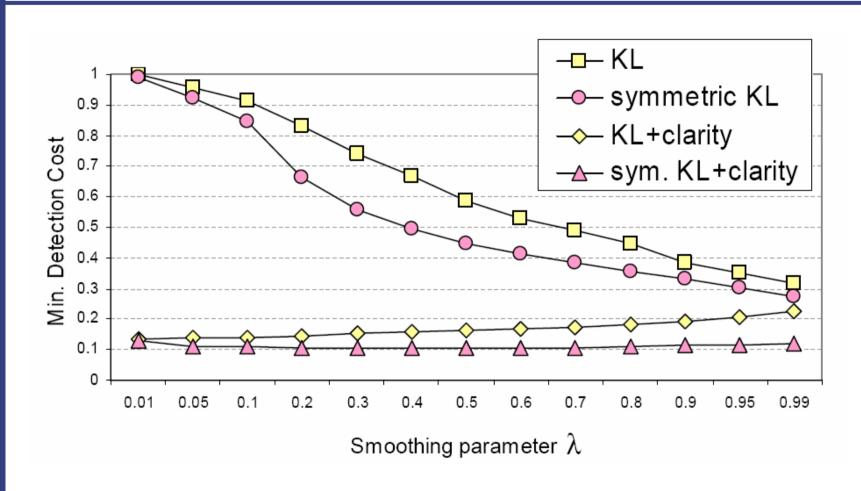
Comparison on Evaluation Data







Distance Metric /Smoothing



Sym. KL distance + clarity is not only the best method but also is robust against changes in the smoothing





Summary

- TDT:
 - International Benchmark
 - Various sub tasks
- Link detection