# Topic Detection and Tracking

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## Topic Detection and Tracking

Wayne (1997) - automatic techniques for finding topically related materials in streams of data

- EMMNewsExplorer
- EMMNewsBrief



# Terminology

Story an article or news broadcast with an underlying focus

Event a unique thing that happens at some point in time

Topic a set of highly-related events

Input a continuous stream of real-time text (stories)

Output clusters organized by topic with a leading story

## **Terminology**



### Subtasks

- Topic Detection
  - 1st story
- Topic Tracking
  - Finding additional stories about a particular topic
  - Clustering

### Feature Selection

Lexical Words, Noun Phrases, Named Entities

Syntactic POS tagging (nouns, verbs, proper names)

Semantic Temporal language cues (verb tense and temporal NPs)(Makkonen and Ahonen-Myka, 2003)

Metadata Timestamps

## Similarity Measures and Model Selection

Similarity measures such as TF-IDF and language models such as smoothed Bayes are used to compare documents.

Vector space TF-IDF (Carbonell et al., 1999)

Probabilistic Chi-square(Swan and Allan, 1999)

Graph-based Edge weights from word cooccurrences (Saha and Sindhwani, 2012)

Language Models Probability of a story given a topic (Allan et al., 2000)

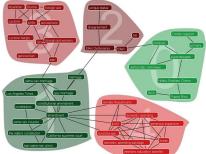


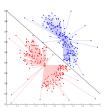
Figure: source: http://www.cs.umd.edu/~sayyadi/keygraph.html

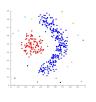


#### Cluster

Stories are grouped through clustering using distance metrics based on the model (probabilistic, cosine similarity, etc.):

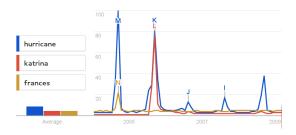
- K-means:
  - ullet Selecting small k with small variance
  - Centroid represents dominant features
- Hierarchical agglomerative clustering:
  - Provides a hierarchy of clusters
- KeyGraph link based clustering:
  - Network of features and relations
  - Topics are identified using network theory
- Advanced Techniques:
  - Latent Dirichlet Allocation (LDA)
  - Non-negative Matrix Factorization (NMF) (Sayyadi et al., 2009)





# Time-Span (Swan and Allan, 1999)

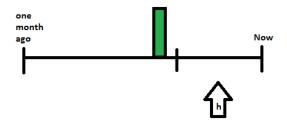
- Entities & noun phrases with overlapping time-spans constitute a topic.
- Calculate probabilities of time-span overlap for features if independence is assumed.
- Merge features, which are statistically dependent  $(\chi^2)$  in terms of doc occurrence.



Examples

# Topic Tracking in Tweet Streams (Lin et al., 2011)

- High arrival rate (up to 4000+ tweets per second)
- Foreground model: tracks recent topic counts
  - History of h events
  - Smoothed with the background model
- Background model: long-term estimates of term distributions
  - Handles sparsity from limited history of foreground model
- Evaluation based off hashtags



## Conclusion

- Topic Detection
- Topic Tracking
- ullet Implementation: Feature o Model o Cluster
- Current Application:
  - EMM
  - Google News

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