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CS47300: Web Information Search and Management

More on Machine Learning in IR

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ML in IR: We've talked about:

- Classification
  - Topic categorization
  - Sentiment analysis
- Clustering
  - Topic detection
- *And a few others*

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Types of ML

- Supervised learning
  - Classification
  - Regression
- Unsupervised learning
  - Clustering
  - Anomaly detection
- Pattern Discovery
  - Association rules, …

Regression

- Goal: Learn to predict a numeric score
- Approaches
  - Linear Regression
    - Ax + By + Cz = output
    - Choose A+B+C to minimize error
  - CART (Classification and Regression Tree)
    - Piecewise linear regression
  - Neural networks
    - With some caveats

Regression for Retrieval Models

- Challenge: Training Data
  - What would training data look like?

Query
Regression
Information
Retrieval

Word	Count
Retrieval	4
Model	3
Training	7
Data	2

Score
0.73

- Is this feasible?

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Where is Regression Appropriate?

- Advertising?
  - Predict revenue from an ad?
- Search engine revenue models
  - Pay per view (rather simple)
  - Pay per click (need probability of click)
- Advertiser bidding
  - Revenue expectation per ad: Conversion rate

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Pattern Discovery

- Identify recurring patterns in the data
- Examples:
  - Correlation (Information and Retrieval occur together frequently)
  - Association rules (A & B → C)
- Where is this useful in IR?
  - Summarization
  - Topic identification / naming
  - Feature selection

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Feature Selection Example: Word2vec

- Word Embedding: Map a word to a vector of numbers
  - Words with similar means should have similar vectors
- Similar goal to Latent Semantic Indexing
  - But word level rather than document level
- Word2vec: Neural Network approach

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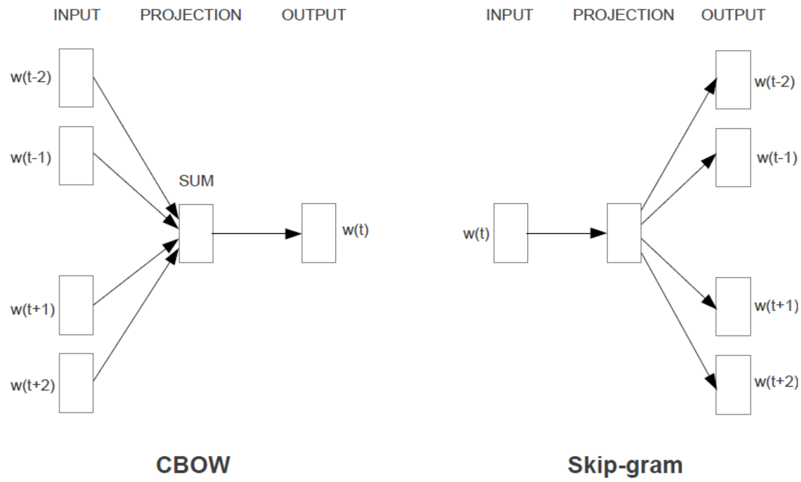
Word2vec: Basic Idea *(Mikolov et al. 2013)*



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Word2vec: Key contributions

- Neural networks for word embedding not new
  - Mikolov et al. point to Morin & Bengio '86
- Key contribution: Scale
  - Google has a lot more data
  - Authors figured out how to train network much more efficiently
- Increasing the amount of data dramatically improved results

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TopCat: Data Mining for Topic Identification

Chris Clifton
Robert Cooley

16 September, 1999

MITRE

Goal: Automatically Identify Recurring Topics in a News Corpus

- Started with a user problem: Geographic analysis of news
- Idea: Segment news into ongoing topics/stories

  How do we do this?
- What we need:
  - Topics
  - "Mnemonic" for describing/remembering the topic
  - Mapping from news articles to topics
- Other goals:
  - Gain insight into collection that couldn't be had from skimming a few documents
  - Identify key players in a story/topic

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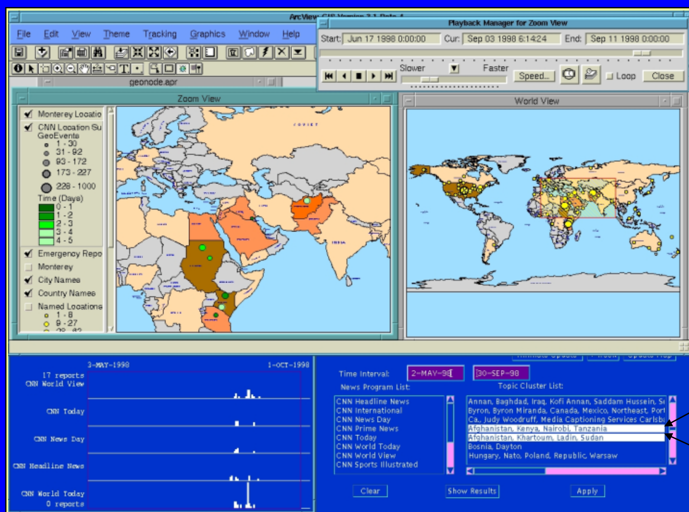
User Problem: Geographic News Analysis



TopCat identified separate topics for U.S. embassy bombing and counter-strike.

Bombing

Counter-strike

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A Data Mining Based Solution
Idea in Brief

- A topic often contains a number of recurring players/concepts
  - Identified highly correlated named entities (frequent itemsets)
  - Can easily tie these back to the source documents
  - *But there were too many to be useful*
- Frequent itemsets often overlap
  - Used this to cluster the correlated entities
  - But the link back to the source documents is no longer clear
- Evaluated against manually-categorized “ground truth” set
  - Data for Topic Detection and Tracking (TDT2) program
  - Used “topic” (list of entities) as a query to find relevant documents to compare with known mappings

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Preprocessing

- Identify named entities (person, location, organization) in text
  - Alembic Natural Language Processing system
- Data Cleansing:
  - Coreference Resolution
    - Used intra-document coreference from NLP system
    - Heuristic to choose "global best name" from different choices in a document
  - Eliminate composite stories
    - Heuristic - same headline monthly or more often
  - High Support Cutoff (5%)
    - Eliminate overly frequent named entities (only provide "common knowledge" topics)

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Named Entities vs. Full Text

- Corpus contained about 65,000 documents.
- Full text resulted in almost 5 million unique word-document pairs vs. about 740,000 for named entities.
- Prototype was unable to generate frequent itemsets at support thresholds lower than 2% for full text.
  - At 2% support, one week of full text data took 30 times longer to process than the named entities at 0.05% support.
- For one week:
  - 91 topics were generated with the full text, most of which aren't readily identifiable.
  - 33 topics were generated with the named-entities.

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Frequent Itemsets

Israel	State	West Bank	Netanyahu	Albright	Arafat	*627390806*
Iraq	State	Albright				*479*
Israel	Jerusalem	West Bank	Netanyahu	Arafat		*4989413*
Gaza	Netanyahu					*39*
Ramallah	Authority	West Bank				*19506*
Iraq	Israel	U.N.				*39*

- **Query Flocks association rule mining technique**
  - *22894 frequent itemsets with 0.05% support*
- **Results filtered based on strength of correlation and support**
  - *Cuts to 3129 frequent itemsets*
- **Ignored subsets when superset with higher correlation found**
  - *449 total itemsets, at most 12 items (most 2-4)*

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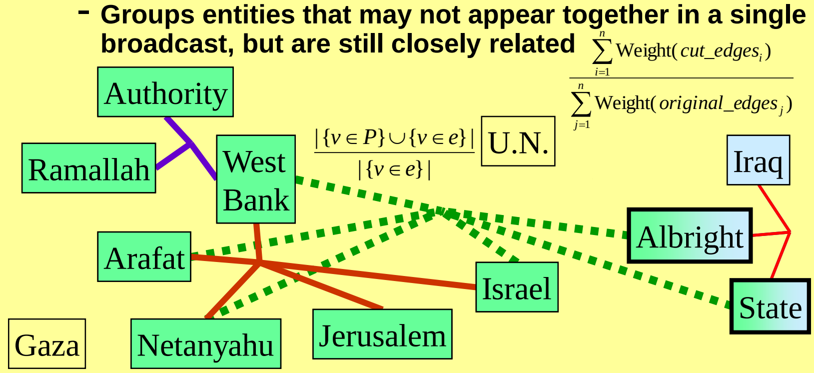
Clustering

- **Cluster similar associations**
  - **Hypergraph clustering based on hMETIS graph partitioning algorithm (adapted from (Han et. al. 1997))**
  - **Groups entities that may not appear together in a single broadcast, but are still closely related**



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TopCat Evaluation

- Tested on Topic Detection and Tracking Corpus
  - Six months of print, video, and radio news sources
  - 65,583 documents
  - 100 topics manually identified (covering 6941 documents)
- Evaluation results (on evaluation corpus, last two months)
  - Identified over 80% of human-defined topics
  - Detected 83% of stories within human-defined topics
  - Misclassified 0.2% of stories
- Results comparable to “official” Topic Detection and Tracking participants
  - Slightly different problem - retrospective detection
  - Provides “mnemonic” for topic (TDT participants only produce list of documents)