Simple Semantics in Topic Detection and Tracking

Juha Makkonen, Helena Anonen-Myka, and Marko Salmenkivi

Introduction

- Topic Detection and Tracking (TDT) focuses on organizing news documents
- Split documents into stories, spotting new stories, tracking development of an event, and grouping together stories describing the same event
- A TDT systems runs on-line without knowledge of incoming stories
- Short duration events cause changing vocabulary

Introduction (cont.)

- Use *semantic classes*, groups consisting of terms that have similar meaning: location, proper names, temporal expressions, and general terms
- Similarity metric is applied class-wise: compare names in one document with names in the other, the locations in one document with locations in the other, etc.
- Allows a semantic similarity between terms rather than binary string matching
- Results in a vector of similarity measures, which is combined via weighted sum to produce a yes/no decision

Topic Detection and Tracking

- Compilation of on-line news and transcribed broadcasts from one or more sources and one or more languages
- TDT consists of five tasks:
  1. Topic tracking monitors news streams for stories discussing given target topic
  2. First story detection makes binary decisions on whether a document discusses a new, previously unreported topic
  3. Topic detection forms topic-based clusters
  4. Link detection determines whether two documents discuss the same topic
  5. Story segmentation finds boundaries for cohesive text fragments
- TDT presents unique challenges: on-line, few assumptions, small number of documents, changing vocabulary

Definitions

- An **event** is an unique thing that happens at some specific time and place
  - Definition neglects events with either long timelines, escalating directions, or lack of tight spatio-temporal constraints
- A **topic** is an event or activity, along with all related events or activities
  - A topic is a set of documents that related strongly to each other via a seminal event

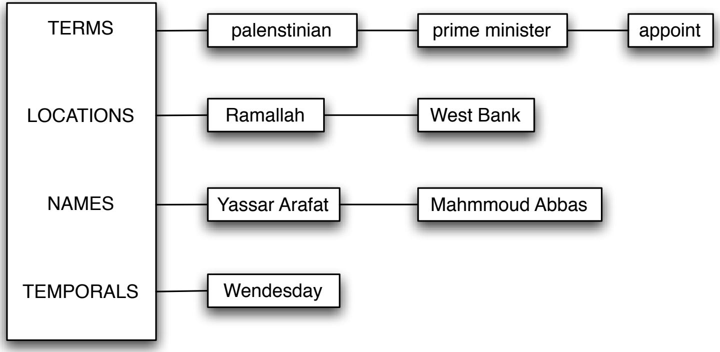
Document Representation

- Four types of terms: locations, temporal expressions, names, and general terms
- Introduces simple semantics since all terms in a given type are compared

Event Vector

- *Semantic classes* are are assigned to basic questions in news article: who, what, when, where
  - Called NAMES, TERMS, TEMPORALS, and LOCATIONS
- An *event vector* is formed by combining multiple semantic classes

Event Vector



An example event vector for AP news article starting "RAMALLAH, West Bank — Palestinian leader Yassar Arafat appointed his longtime deputy Mahmoud Abbas as prime minister Wednesday..."

Comparing Event Vectors

- Comparison is done class-wise, i.e, via corresponding sub-vectors of two event representations
- Similarity metric can be different for each class
  - Use a weighed sum of the similarity measures for final binary decision
- Results in a vector in $\mathbf{v} = \{v_1, v_2, v_3, v_4\} \in \mathbb{R}^4$

Similarity for NAMES and TERMS

- Use the term-frequency inverted document frequency
- Let $T = \{t_1, t_2, \ldots, t_n\}$ denote the terms, $D = \{d_1, d_2, \ldots, t_m\}$ denote the documents. Then, the weight $w : T \times D \to \mathbb{R}$ is defined as:

$$w(t, d) = f(t, d) \cdot \log\left(\frac{|D|}{g(t)}\right),$$

  where $f : T \times D \to \mathbb{N}$ represents the number of occurrences of term t in document d, $|D|$ is the total number of documents, and $g : T \to \mathbb{N}$ is number of documents in which term t occurs (i.e., the document frequency of term t).
- The similarity of two sub-vectors X_k and Y_k of semantic class k is based on the cosine of the two:

$$\sigma(X_k, Y_k) = \frac{\sum_{i=1}^{|k|} w(t_i, X_k) \cdot w(t_i, Y_k)}{\sqrt{\sum_{i=1}^{|k|} w(t_i, X_k)^2} \cdot \sqrt{\sum_{i=1}^{|k|} w(t_i, Y_k)^2}}$$

  where $|k|$ is the number of terms in semantic class k.

Similarity for TEMPORALS

- Time intervals are mapped to a global calendar that defines a time-line and unit conversion
- Temporal similarity is based on comparison of intervals of each document. Let T be the global timeline, $x \subseteq T$ be a time interval with start- and end-points, x_s and x_e. Similarity between two intervals is

$$\mu_t(x, y) = \frac{2\Delta([x_s, x_e] \cap [y_s, y_e])}{\Delta(x_s, x_e) + \Delta(y_s, y_e)}$$

  where Δ is the duration of the interval in days.
- For each pair of intervals from TEMPORAL vectors $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_n\}$, determine the maximum value. The similarity is the average of all these maxima, i.e.,

$$\sigma_s(X, Y) = \frac{\sum_{i=1}^{n} \max\left(\mu_s(x_i, Y)\right) + \sum_{j=1}^{m} \max\left(\mu_s(X, y_j)\right)}{m + n}$$

Similarity for LOCATIONS

- Locations are split into a five-level hierarchy
  - Continent, region, country, administrative region, and city
  - Administrative region can be replaced by mountain, seas, lakes, or river
  - Represented by a tree
- Similarity between two locations, x and y is based on the length of the common path:

$$\mu_s(x, y) = \frac{\lambda(x \cap y)}{\lambda(x) + \lambda(y)}$$

  where $\lambda(x)$ is the length of the path from the root to the element x.
- The spatial similarity between two LOCATION vectors $X = \{x_1, x_2, \ldots, x_n\}$ and $Y = \{y_1, y_2, \ldots, y_m\}$ is

$$\sigma_s(X, Y) = \frac{\sum_{i=1}^{n} \max\left(\mu_s(x_i, Y)\right) + \sum_{j=1}^{m} \max\left(\mu_s(X, y_j)\right)}{m + n}$$

Topic Detection and Tracking Algorithms

- Class-wise comparison of two event vectors produces results in a vector $\mathbf{v} = \{v_1, v_2, v_3, v_4\} \in \mathbb{R}^4$
- Similarity is based on a weighted linear sum of class-wise similarity: $\langle \mathbf{w}, \mathbf{v} \rangle$
- Simplest algorithm uses a hyper-plane: $\psi(\mathbf{v}) = \langle \mathbf{w}, \mathbf{v} \rangle + b$, and a perceptron to learn $\mathbf{w}$ and b.
- Data is typically not linearly separable, so, transform $\mathbf{v}$ to higher dimensional space, and use a perceptron to learn a hyper-plan there
  - Define $\phi : \mathbb{R}^4 \rightarrow \mathbb{R}^{15}$ that expands $\mathbf{v}$ into its powerset
  - Then hyper-plane is $\psi(\mathbf{v}) = \langle \mathbf{w}', \phi(\mathbf{v}) \rangle + b$

Topic Tracking Algorithm

topic $\leftarrow$ buildVector()
For each new document d
  doc $\leftarrow$ buildVector(d)
  $\mathbf{v} \leftarrow$ (), decision $\leftarrow$ ()
  For each semantic class
    v[c] $\leftarrow sim_c(doc_c, topic_c)$
  If $(\langle \mathbf{w}', \phi(\mathbf{v}) \rangle + b \geq 0)$
    decision = 'YES'
  else
    decision = 'NO'

First Story Detection Algorithm

topics ← (); decision ← ()
For each new document d
  doc ← buildVector(d)
  max ← 0; max_topic ← 0
  For each topic
    For each semantic class
      v[c] ← $sim_c(doc_c, topic_c)$
    If $(\langle \mathbf{w}', \phi(\mathbf{v}) \rangle + b \geq max)$
      max ← $\langle \mathbf{w}', \phi(\mathbf{v}) \rangle + b$
      max_topic ← topic
    If (max $< \theta$)
      decision[d] ← 'first-story'
    else
      decision[d] ← max_topic
    add(topics, doc)

Experiments

- Text corpus contains 60,000 documents from two on-line newspapers, two TV broadcasts, and two radio broadcasts
- Automatic term extraction combined with automata and gazetteer to improve performance

Topic Tracking Results

Method	C_{det}	$(C_{det})_{norm}$	P_{miss}	P_{fa}	p	r	F_1
Cosine	0.0058	0.0720	0.0100	0.0470	0.2361	0.7900	0.2927
Weighted Sum	0.0471	0.5214	0.1818	0.0668	0.1646	0.8181	0.2741

Table: Using $(C_{det})_{norm}$

Method	C_{det}	$(C_{det})_{norm}$	P_{miss}	P_{fa}	p	r	F_1
Cosine	0.0524	0.6553	0.2582	0.0097	0.5297	0.7481	0.5481
Weighted Sum	0.0849	1.0621	0.4242	0.0015	0.8636	0.5758	0.6910

Table: Using F_1

First-Story Detection Results

Method	C_{det}	$(C_{det})_{norm}$	P_{miss}	P_{fa}	p	r	F_1
Cosine	0.0033	0.0414	0.0000	0.0414	0.4583	1.0000	0.6386
Weighted Sum	0.0036	0.0446	0.0000	0.0446	0.4400	1.0000	0.6111

Table: Using $(C_{det})_{norm}$

Method	C_{det}	$(C_{det})_{norm}$	P_{miss}	P_{fa}	p	r	F_1
Cosine	0.0381	0.4768	0.1818	0.0223	0.5625	0.8181	0.6667
Weighted Sum	0.0558	0.6977	0.2727	0.0159	0.6154	0.7272	0.6667

Table: Using F_1

Discussion

- In topic tracking, performance degrades due to lack of vagueness factor
  - For example, matching terms Asia and Washington produce the same similarity score, but does not account for indefiniteness of the terms.
- Including *a posteriori* approaches that examine all the data and the labels might improve performance

Conclusions

- Paper presents a topic detection and tracking algorithm based on semantic classes
- Comparison is class-wise
- Created geographical and temporal ontologies
- Semantic augmentation degraded performance, especially in topic tracking
    - Partially due to inadequate spatial and temporal similarity function