Pairwise Webpage Coreference Classification using Distant Supervision

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Introduction

A person or other entity is often associated with multiple URL endpoints on the web

- Barack Obama $\Leftrightarrow$ barackobama.com/ and en.wikipedia.org/wiki/Barack_Obama
- Donald Trump $\not\Leftrightarrow$ twitter.com/realDonaldTrump and instagram.com/ivankatrump

Motivates the task of **webpage coreference classification** for a given entity!

Problem Setup

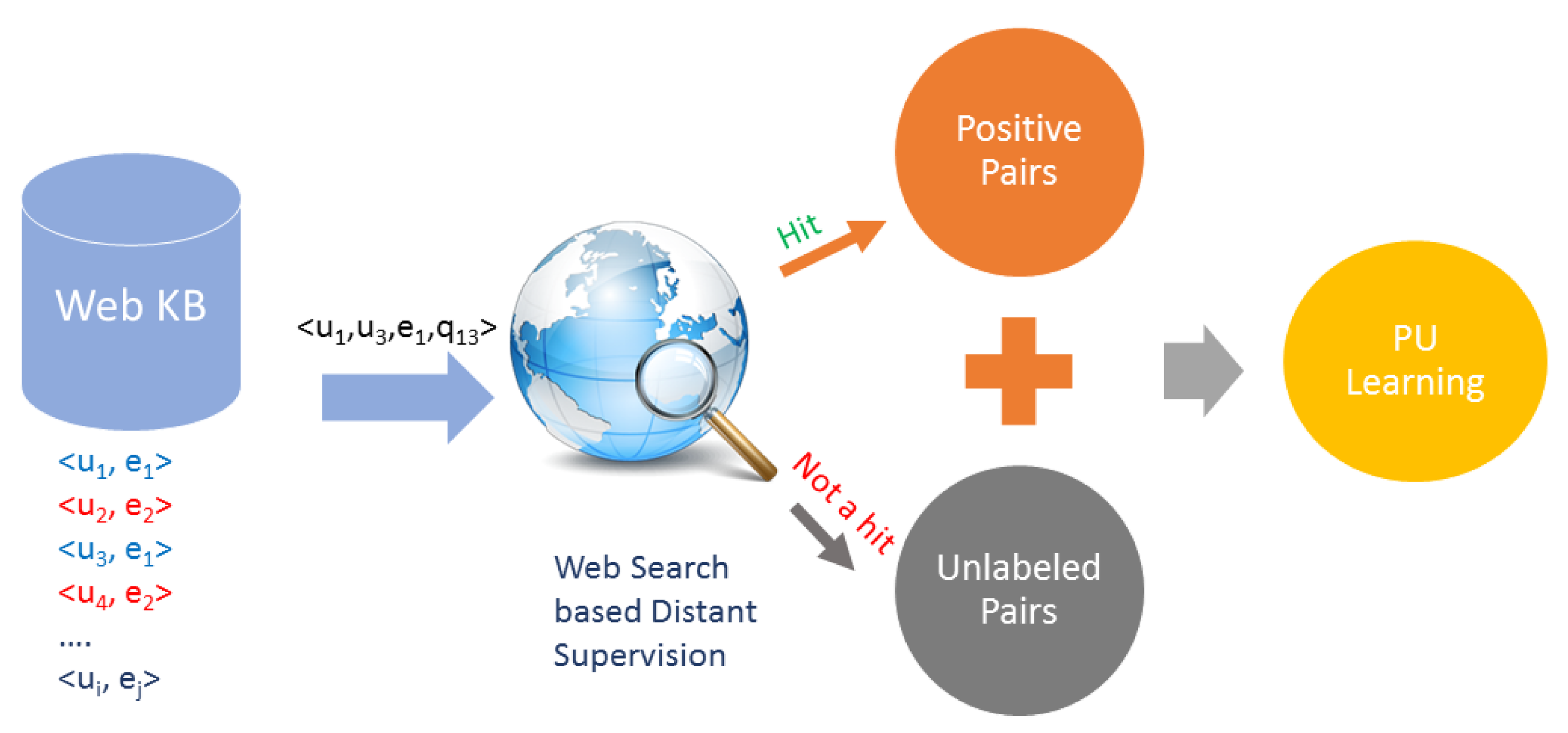
- We assume access to web KBs based on automatic crawling
  - social networks (e.g. facebook.com/*), news aggregation endpoints (e.g. nytimes.com/topic/person/*) and organisation directories (e.g. gtlaw.com/People/*)
- Given a training dataset D with pairs of web URLs
  - Initially all the pairs are unlabeled ($D_u \leftarrow D$, $D_p, D_n = \phi$)
  - Learn a model $f(\phi(U_i, U_j)) \rightarrow y$, for URL pair U_i and U_j
  - Target $y \in \{0, 1\}$

Distant Supervision

- We obtain positive examples using web-search-based distant supervision
- Search query George Clinton AND P-Funk fetches en.wikipedia.org/wiki/George_Clinton_(musician)
  - But not biography.com/people/george-clinton-537674
- We build a positive and unlabelled (PU) learning model

Proposed Approach

- We generate queries for URL pairs that share same entity name
- Employ a label propagation technique to expand the set of positive examples



- Any binary classifier can be trained on the expanded labeled set

Query Generation

- We construct web search queries for distant supervision as follows:
  - Q_i: Using the target entity name and context information from U_i
  - Q_j: Similar to the above, we generate context information from U_j.
- E.g., for URL pairs: imperial.ac.uk/people/f.allen and linkedin.com/in/franklin-allen-0557906 a query constructed is "Franklin Allen Brevan Howard Centre"

Label Propagation using Distant Supervision

- Initialize Labels
  - For each query in Q_i, we check to see if U_j is present in the top-K search results S_{ij}
  - Conversely if U_i is present in the top-K results, S_{ji} for each query in Q_j
    - $[\exists q \in Q_i, \quad \exists S_{ji} \mid U_j \in S_{ji} \vee \exists q \in Q_j, \quad \exists S_{ij} \mid U_i \in S_{ij}] \implies \hat{y}_{ij} = 1$
    - $D_p \leftarrow D[\hat{y}_{ij} = 1]$, $D_u \leftarrow D_u \setminus D[\hat{y}_{ij} = 1]$.
- Expand Positive Labeled Set
  - Step 1: Randomly select N instances from D_p, and hold them out in S_p.
  - Step 2: Train a binary classifier θ, taking $D'_p = D_p \setminus S_p$ as positive instances and D_u as negative instances.
  - Step 3: $\mu_p = \frac{1}{|S_p|} \sum_{i:S_p} p(x_i = 1|\theta)$, (using Platt scaling)
    - $D^*_p = x_u \in D_u : p(x_u = 1) > \mu_p$.
    - $D_p \leftarrow D_p \cup D^*_p$, $D_n \leftarrow D_u \setminus D^*_p$

Datasets

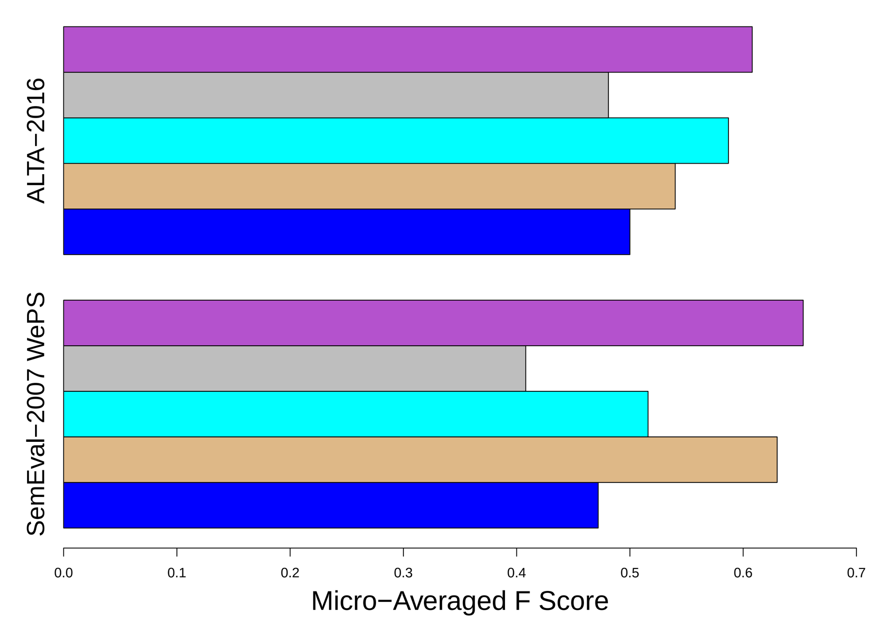
- SemEval-2007 WePS development set
  - Balanced 1000 end-point URL-pairs dataset from webpages for 49 people.
- ALTA-2016 shared task dataset
  - Balanced 400 end-point URL-pairs dataset that can refer to any entity

Feature Representation

- Structural features such as document length difference, URL path length difference
- Semantic features such as unigram cosine similarity, cosine similarity over an average word-level word2vec representation, machine translation scores (BLEU, METEOR, TER)

Experimental Results

- Benchmark Approaches
  - Biased SVM (BSVM) with costs for positive and negative classes
  - Spy-SVM (B. Liu et. al., ICML 2002)
  - SPUL (C. Elkan et. al., KDD 2008)
  - Hierarchical Clustering (HC) - Unsupervised Approach
- Proposed Approach
  - DP-SVM (Linear Kernel SVM built using propagated distant labels)



Conclusions

- Approach to determining whether two endpoint URLs refer to the same entity.
- Two key contributions:
  - use of distant supervision
  - application of PU Learning to the task