MRR: an Unsupervised Algorithm to Rank Reviews by Relevance

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Introduction

- Many works address the problem of ranking documents by their relevance.
- Most of them rely on supervised algorithms such as classification and regression.
  - Annotated: Neural Network, SVM
  - Statistics: TF-IDF, Readability, POS-Tag

Introduction

- The quality of results produced by supervised algorithms is dependent on the existence of a large, domain-dependent training data set.
  - Amazon, Yelp
  - Netflix, IMDB
- Unsupervised methods are an attractive alternative to avoid the labor-intense and error-prone task of manual annotation of training datasets.

Graph-based

- Vertices are the documents (review), and the edges are defined in terms of the similarity between pairs of documents (ratings score and textual).

$$f(u, v) = \alpha * sim\_txt(u, v) + (1 - \alpha) * sim\_star(u, v) \tag{1}$$

- α : tune similarity function

Similarity Functions

- Textual
  Cosine similarity of TF-IDF vectors

$$sim\_txt(u, v) = cos(tfidf(t.t), tfidf(v.t)) \tag{2}$$

- Stars
  Euclidean distance normalized by Min-Max scaling

$$sim\_star(u, v) = 1 - \frac{|u.rs - v.rs| - min(rs)}{max(rs) - min(rs)} \tag{3}$$

MRR - Ranking documents by their relevance

Graph Centrality

- Hypothesis: a relevant document has a high centrality index since it is similar to many other documents.
- Centrality index produces a ranking of vertices' importance, indicating the ranking of the most relevant document.

MRR - Graph-Specific Similarity Threshold

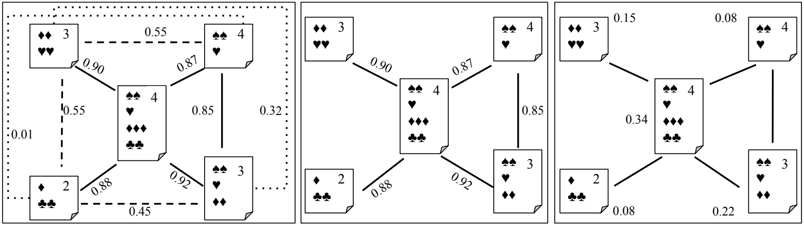
Graph Pruning

- Centrality is dependent on the existence of edges between nodes.
- Prune the graph based on a minimum similarity between review.
- $\overline{E}$: mean of graph similarity

$$W'(u,v) = \begin{cases} 1, & f(u,v) \geq \overline{E} * \beta \\ 0, & otherwise \end{cases} \tag{4}$$

- β : tune prune function

Main steps of the MRR algorithm



(A) Similarity Function (B) Graph-Specic Threshold (C) PageRank Scores

- (A) Builds a similarity graph G between pairs of documents;
- (B) Prune by removing all edges lower than the similarity threshold;
- (C) Employ PageRank to obtain the centrality scores;

MRR Algorithm

Algorithm 1 - MRR Algorithm (R, α, β): S

for each $u, v \in R$ **do**
    $W[u, v] \leftarrow \alpha * sim\_txt(u, v) + (1\text{-}\alpha) * sim\_star(u, v)$
end for
$\overline{E} \leftarrow mean(W)$
for each $u, v \in R$ **do**
    if $W[u, v] \geq \overline{E} * \beta$ **then**
        $W'[u, v] \leftarrow 1$
    else
        $W'[u, v] \leftarrow 0$
    end if
end for
$S \leftarrow PageRank(W')$
Return S

Experiment Design

- Dataset: reviews (rating score and text) of electronics and books from the Amazon website.
- Gold Standard: Human perception of helpfulness:

$$h(r \in R) = \frac{vote_{+}(r)}{vote_{+}(r) + vote_{-}(r)} \tag{5}$$

- Metric: Normalized Discounted Cumulative Gain as NDCG@n

Amazon Dataset

	Electronics	Books
Votes	48.20 ($\pm$ 302.84)	29.71 ($\pm$ 73.58)
Positive	40.12 ($\pm$ 291.99)	20.60 ($\pm$ 64.18)
Negative	8.08 ($\pm$ 22.27)	9.11 ($\pm$ 21.44)
Rating	3.73 ($\pm$ 1.50)	3.41 ($\pm$ 1.54)
Words	350.32 ($\pm$ 402.02)	287.44 ($\pm$ 273.75)
Products	383	461
Total	19,756	24,234

Table: Profiling of the Amazon dataset.

Experiments:

- Baselines comparison;
- Graph-Specific Threshold Assessment;
- Parameter Sensibility; and
- Run-time Performance.

Experiment Design

Baselines:

- TSUR et al. (2009) as REVRANK;
  - Core Virtual Review (200 most frequent words),
  - Rank by similarity distance to Core
- Wu et al. (2011) as PR_HS_LEN;
  - Sentences similarity based on POS-Tags,
  - PageRank, Hits and Length
- SVM Regression:
  - a) textual features TF-IDF and the star score,
  - b) the same features used by Wu et al. (2011)

Relevance Ranking Assessment

	NDCG@1	NDCG@5
SVM_WU	0.80770	0.91817
SVM_TFIDF	**0.85539**	**0.93119**
REVRANK	0.66052	0.68172
PR_HS_LEN	0.72689	0.77131
MRR	0.79877	0.81876

Table: Mean Performance on Book Reviews

- MRR statistically outperformed all unsupervised baselines

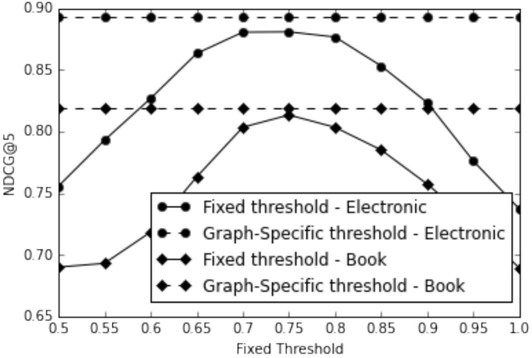
Relevance Ranking Assessment

	NDCG@1	NDCG@5
SVM_WU	0.76416	0.91535
SVM_TFIDF	0.88986	**0.94621**
REVRANK	0.67903	0.72133
PR_HS_LEN	0.87434	0.87184
MRR	**0.89403**	0.89246

Table: Mean Performance on Electronic Reviews

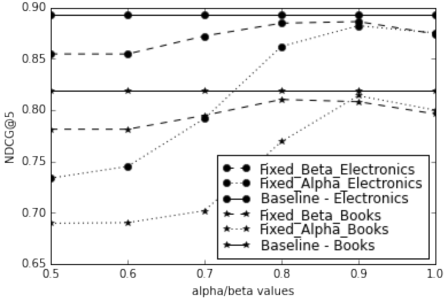
- MRR statistically outperformed all unsupervised baselines
- MRR is comparable to supervised methods

Graph-Specific Threshold Assessment



- MRR performance is always better using a Graph-Specific threshold.

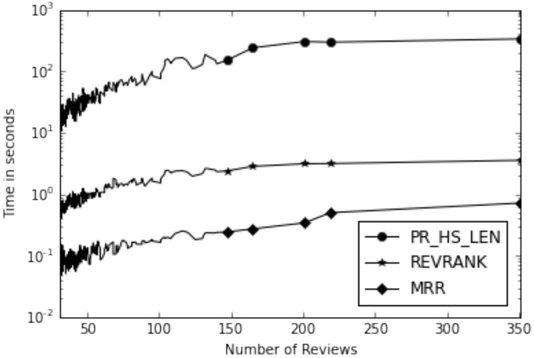
Parameter Sensibility: α and β



- α in all settings had a low influence (4%)
- β produced the highest variation (17%).
- Nevertheless when $0.8 \leq \beta \leq 0.9$, the MRR varying only 6% .

Run-time Assessment

Time required for producing a ranking for 383 products (log scale)



- MRR presents a significantly lower running time

Final Remarks

Contributions:

- Unsupervised method: does not depend on an annotated training set;
- Faster than other graph-centrality methods;
- It performs well in different domains (e.g. closed vs. open-ended);
- Significantly superior to the unsupervised baselines, and comparable to a supervised approach in a specific setting.

Further Work

Next steps:

- Others clustering techniques for graph;
- Methods to select the most relevant reviews;
- Segmented Bushy Path widely explored in text summarization;

Thanks

Thank You! Question?

source: https://github.com/vwoloszyn/MRR

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