Measuring Semantic Relatedness using Mined Semantic Analysis

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ABSTRACT
Mined Semantic Analysis (MSA) is a novel distributional semantics approach which employs data mining techniques. MSA embraces knowledge-driven analysis of natural languages. It uncovers implicit relations between concepts by mining for their associations in target encyclopedic corpora. MSA exploits not only target corpus content but also its knowledge graph (e.g., “See also” link graph of Wikipedia). Empirical results show competitive performance of MSA compared to prior state-of-the-art methods for measuring semantic relatedness on benchmark data sets. Additionally, we introduce the first analytical study to examine statistical significance of results reported by different semantic relatedness methods. Our study shows that, top performing results could be statistically equivalent though mathematically different. The study positions MSA as one of state-of-the-art methods for measuring semantic relatedness.

Categories and Subject Descriptors
H.3.1 [Information Storage and Retrieval]: Content Analysis and Indexing—Linguistic processing

General Terms
Algorithms, Measurement

Keywords
semantic relatedness, text mining, information retrieval, association rules, wikipedia

1. INTRODUCTION
For decades semantic analysis (SA) has gained enormous attention in the computational linguistics (CL) and Natural Language Processing (NLP) community. Automating natural language understanding (NLU) has been and still the core goal of semanticists. To this end, evaluating lexical semantic similarity/relatedness has attracted many researchers as an approach for NLU. Semantic relatedness is a knowledge intensive task as it requires huge amount of world knowledge to accomplish its goal [1].

Although semantic similarity and relatedness are often used interchangeably in the literature, they do not represent the same task [2]. Evaluating genuine similarity is, and should be, concerned with measuring the similarity or resemblance in meanings and hence focuses on the synonymy relations (e.g., smart, intelligent). Relatedness, on the other hand, is more general and covers broader scope as it focuses on other relations like antonymy (old,new), hypernymy (cock,bird), and other functional associations (money, bank).

Semantic relatedness has many applications in NLP and Information Retrieval (IR) for addressing problems like word sense disambiguation, paraphrasing, text categorization, dimensionality reduction, and others. Most semantic relatedness methods are inspired by the distributional hypothesis [3] which emphasizes the idea that similar words tend to appear in similar contexts and thus have similar contextual distributions. Those methods often develop a Distributional Semantics (DS) model which represents each linguistic term as a vector derived from contextual information of that term in a large corpus of text or knowledge base [1,6-8]. After constructing such distributional vectors, relatedness is calculated using an appropriate vector similarity measure (e.g., cosine similarity).

In this paper we propose Mined Semantic Analysis (MSA), a novel DS approach for evaluating semantic relatedness using data mining techniques. MSA is a mixture of corpus-based and knowledge-based methods. Unlike other explicit SA methods which look for direct associations between concepts and terms through statistical co-occurrence [1,6,8]. MSA discovers latent associations by mining for concept-concept association rules [9]. MSA uses these rules subsequently to enrich term concept space with latent concepts.

MSA utilizes a search index built using encyclopedic corpus text. The concept space of a given term is constructed through two phases. First, an initial set of candidate concepts is retrieved from the index. Second, the candidates set is augmented with other related concepts using discovered concept-concept association rules. Following this strategy, MSA identifies not only concepts directly related to the given linguistic term but also other latent concepts associated implicitly with them.

The contributions of this paper are threefold: First, we introduce a novel DS method for semantic analysis which augments explicit semantics with conceptual associations through data mining techniques. Second, we demonstrate the effectiveness of this method for evaluating semantic relatedness on benchmark data sets. Third, we present the first analytical study to examine statistical significance of results reported by different semantic relatedness methods. Our study shows that, top performing results could be statistically
2. RELATED WORK
Several semantic representation models have been proposed in the literature. Some of them utilize text corpora from which world knowledge is acquired and used to represent linguistic terms as high-dimensional "meaning" vectors. As pointed out by [1], those vectors are either estimated by means of statistical modeling like LSA [7] and LDA [10], or more recently through neural embeddings like CW vectors [11], Word2Vec [12], and GloVe [14].

Another set of corpus-based models constructs those vectors directly from explicit concepts represented in encyclopedic corpora like ESA [6], SSA [11], and NASARI [8]. Semantic relatedness models usually employ these corpus-based semantic vectors to measure relatedness using appropriate similarity measure between the vectors.

Several Knowledge-based models were introduced for semantic relatedness [2][4][6]. Those models utilize dictionaries like WordNet [17] and Wiktionary and use explicit word relations to infer semantic relatedness. Hybrid models which incorporate knowledge from corpora and dictionaries were widely used to evaluate semantic relatedness [8][13][19].

MSA builds an explicit semantics model where each linguistic term is represented as a high-dimensional vector of concepts obtained from encyclopedic corpus. A closely related method is Explicit Semantic Analysis (ESA) [6]. ESA constructs the concept space of a given term by searching an inverted index of term-concept co-occurrences. ESA is mostly the traditional IR vector space model applied to Wikipedia articles.

ESA is effective in retrieving concepts which explicitly mention target search terms. However, it fails to identify other latent concepts which do not contain the search terms. MSA bridges this gap by mining for concept-concept associations and thus can augment the concept space identified by ESA by more relevant concepts.

Salient Semantic Analysis (SSA) was proposed by [11] and uses Wikipedia concepts to build semantic profiles of words. SSA is more conservative than ESA as it defines word meaning by its immediate context and therefore might yield concepts of higher relevance. However, it is still limited to surface semantic analysis because it, like ESA, utilizes only direct associations between words and concepts and fails to capture other latent concepts not directly co-occurring with corpus words in the same context.

Table 1: The concept space of “Computational Linguistics”

| Explicit Concepts                  | Latent Concepts                                      |
|-----------------------------------|------------------------------------------------------|
| Parse tree                        | Universal Networking Language                        |
| Temporal annotation               | Translation memory                                   |
| Morphological dictionary          | Systemic functional linguistics                      |
| Textanalytics                      | Semantic relatedness                                 |
| Bracketing                         | Quantitative linguistics                             |
| Lemmatisation                     | Natural language processing                          |
| Indigenous Tweets                 | Internet linguistics                                 |
| Statistical semantics              | Grammar induction                                    |
| Treebank                          | Dialog systems                                       |
| Light verb                        | Computational semiotics                              |

Another closely related model is Latent Semantic Analysis (LSA) [7][20]. LSA is a statistical model that was originally proposed to solve the vocabulary mismatch problem in IR. LSA first builds a term-document co-occurrence matrix from textual corpus and then maps that matrix into a new space using singular-value decomposition. In that semantic space terms and documents that have similar meaning will be placed close to one another. Though its effectiveness, LSA has been known to be hard to explain because it is difficult to map the computed space dimensions into meaningful concepts. MSA, alternatively, generates conceptual mappings that are interpretable by humans making it more intuitive than LSA.

3. MSA: MINED SEMANTIC ANALYSIS
We call our approach Mined Semantic Analysis (MSA) as it utilizes data mining techniques in order to discover the semantic concept space of a given linguistic term. The motivation behind our approach is to mitigate a notable gap in prior corpus-based explicit semantics models which are limited to direct associations between words and concepts. Therefore those models lack the ability to transfer the association relation to other latent concepts which contribute to the meaning of the given term.

To demonstrate our approach, we provide an example of exploring the concept space of “Computational Linguistics”. Column 1 in Table 1 represents concepts retrieved by searching Wikipedia [1]. Column 2 represents latent concepts retrieved by mining “See also” section hyperlinks in corresponding Wikipedia articles of Column 1 concepts. As we can notice, those latent concepts could enrich the explicit concept space with more related concepts which contribute to understanding “Computational Linguistics”. It is worth mentioning that not all latent concepts are equally relevant, therefore we need an automated mechanism for ranking these concepts in a way that reflects their relatedness to the original search term.

3.1 The Search Index
MSA starts constructing the concept space of a term by searching for an initial set of candidate concepts. For this purpose, we build a search index of all Wikipedia articles. This is similar to the idea of the inverted index introduced in ESA [6]. We build the index using Apache Lucene [4], an open-source indexing and search engine. For each article we index title, content, length, and the “See also” section.

During search we use some parameters to limit the search space. Specifically, we define the following parameters to provide more control over search:

Article Length (L): minimum length of Wikipedia article in bytes excluding sections like “References”, “See also”, “Categories”...etc.

Search Field (F): either text or line1 where text represents all article content, and line1 represents the first paragraph only.

Number of Concepts (M): maximum number of concepts (articles) to retrieve as initial candidates.

Title Length (τ): this threshold is important for pruning all articles that have long irrelevant titles. It represents maximum number of

1We search Wikipedia using a term-concept inverted index and limit the search space to articles with min. length of 2KB and max. title length of 3 words.

2http://lucene.apache.org/core/
words in the title, for example, if \( \tau = 3 \), then all articles with more than three words in title will be pruned.

### 3.2 Association Rules Mining

In order to discover latent concepts, we employ association rules mining \cite{9} to learn implicit relations between concepts using Wikipedia “See also” link graph.

Formally, given a set of concepts \( C = \{c_1, c_2, ..., c_N\} \) of size \( N \) (i.e., all Wikipedia articles). We build a dictionary of transactions \( T = \{t_1, t_2, t_3, ..., t_M\} \) of size \( M \) such that \( M \leq N \). Each transaction \( t \) in \( T \) contains a subset of concepts in \( C \). \( t \) is constructed from each article in Wikipedia that contains at least one hyperlink in its “See also” section. For example, if an article representing concept \( c_1 \) with hyperlinks in its “See also” section referring to concepts \( \{c_2, c_3, ..., c_n\} \), a transaction \( t = \{c_1, c_2, c_3, ..., c_n\} \) will be constructed and added to \( T \). A set of rules \( R \) are then created by mining \( T \). Each rule \( r \) in \( R \) is defined as in equation \( 1 \):

\[
 r(s, f) = \left\{ (X \Rightarrow Y) : X, Y \subseteq C \text{ and } X \cap Y = \emptyset \right\}
\]

Both \( X \) and \( Y \) are subsets of concepts in \( C \). \( X \) are called the antecedents of \( r \) and \( Y \) are called the consequences. Rule \( r \) parameterized by two parameters: 1) \( s \) which is support (i.e., how many times both \( X \) and \( Y \) appeared together in \( T \)), and 2) \( f \) which is the confidence (i.e., \( s \) divided by number of times \( X \) appeared in \( T \)).

After learning \( R \), we end up having concept(s)-concept(s) associations. Using such rules, we can tell exactly how strong this association is based on the calculated support and confidence.

As the number of rules grows exponentially with the number of concepts, we define the following parameters to provide more fine grained control on participating rules during concept expansion:

- **Consequences Size** \( |Y| \): number of concepts in rule consequences part (right hand side).
- **Minimum Support** \( c \): minimum rule support, it defines the minimum strength of the association between rule concepts. For example, if \( c = 2 \), then all rules whose support \( s \geq 2 \) will be considered during concept expansion.
- **Minimum Confidence** \( v \): this threshold defines the minimum strength of the association between rule concepts compared to other rules with same antecedents. For example, if \( v = 0.5 \), then all rules whose confidence \( f \geq 0.5 \) will be considered during concept expansion. In other words, consequent concept(s) must have appeared in at least 50\% of the times antecedent concept(s) appeared in \( T \).

### 3.3 Constructing the Concept Space

Given a set of concepts \( C \) of size \( N \), MSA constructs the concept vector \( C_t \) of a given term/text \( t \) through two phases: Search and Expansion. In the search phase, \( t \) is represented as a search query and is searched for in the Wikipedia search index. Searching the index in this phase is constrained by the target search field \( F \). This returns a weighted set of articles that best matches \( t \) based on the vector space model. We call the set of concepts representing those articles \( C_{ts} \) and is represented as in equation \( 2 \):

\[
 C_{ts} = \{ (c_i, w_i) : c_i \in C \text{ and } i < N \} \quad \text{subject to:} \quad \text{title}(c_i) \leq \tau, \text{length}(c_i) \geq L, |C_{ts}| \leq M
\]

Note that we search all articles whose content length and title length meet the thresholds \( L \) and \( \tau \) respectively. \( w_i \) is the weight of \( c_i \), it represents the match score between \( t \) and \( c_i \) returned by the search engine.

In the expansion phase, we use inferred association rules to expand each concept \( c \) in \( C \) by looking for its associated set of concepts in \( R \). Formally, the expansion set of concepts \( C_p \) is obtained as in equation \( 3 \):

\[
 C_p = \bigcup_{c \in C, c' \in C} \{ (c', w) : \exists r(s, f) = c \Rightarrow c' \} \\
 \text{subject to:} \quad |c'| = |Y|, s \geq c, f \geq v
\]

Note that we add all the concepts that are implied by \( c \) where this implication meets the support and confidence thresholds. \( w \) represents the weight of \( c' \), currently we use simple weight propagation mechanism where all concepts implied by \( c \) will inherit the same weight assigned to \( c \).

Finally, all obtained concepts from search and expansion phases are merged to construct the concept vector \( C_t \) of term \( t \) as in equation \( 4 \):

\[
 C_t = C_{ts} \cup C_p
\]

### 3.4 Relatedness Scoring

In order to calculate the relatedness score between a term pair \( (t_1, t_2) \), we first sparsify their concept vectors \( (C_{t_1}, C_{t_2}) \) to have same length. We then apply the traditional cosine similarity measure on their respective weight vectors \( (W_{t_1}, W_{t_2}) \) as in equation \( 5 \):

\[
 \text{Rel}_{\cos}(t_1, t_2) = \frac{W_{t_1} \cdot W_{t_2}}{|W_{t_1}| \cdot |W_{t_2}|}
\]

Like \cite{21}, we include a normalization factor \( \lambda \) as the cosine measure gives low scores for highly related terms due to their concept vectors sparsity. The final relatedness score will be adjusted as in equation \( 6 \):

\[
 \text{Rel}(t_1, t_2) = \begin{cases} 
 1 & \text{if } \text{Rel}_{\cos}(t_1, t_2) \geq \lambda \\
 \frac{1}{\text{Rel}_{\cos}(t_1, t_2)} & \text{if } \text{Rel}_{\cos}(t_1, t_2) < \lambda 
\end{cases}
\]

### 4. EXPERIMENTS AND RESULTS

#### 4.1 Data Sets

We use standard benchmark data sets for evaluating MSA. Each data set is a collection of word pairs along with human judged similarity/relatedness score for each pair.

**RG**: a similarity data set created by \cite{21}. It contains 65 noun pairs. Similarity judgments of each pair were conducted by 51 subjects. The highest performance on this data set is reported by \cite{16} by creating a semantic network from Wiktionary.

**MC**: a similarity data set created by \cite{22}. It contains 30 noun pairs taken from RG data set. Similarity judgments of each pair were done by 38 subjects at the same scale as RG. \cite{16} reports the highest performance on MC by integrating knowledge from Wikipedia and Wordnet.

\[ \text{http://www.cs.cmu.edu/~mfaruqui/word-sim/EN-RG-65.txt} \]
\[ \text{http://www.cs.cmu.edu/~mfaruqui/word-sim/EN-MC-30.txt} \]
WS; a relatedness data set created by [23]. It contains 353 word pairs. Relatedness score for each pair was judged by 13-16 human annotators ranging from 0 (totally unrelated) to 10 (very related). Annotators were not instructed to differentiate between similarity and relatedness. [23] reports the highest performance on WS using a supervised model combined with constraints of known related words.

WSS & WSR: [18] manually split WS data set into two subsets to separate between similar and related pairs. WSS contains 203 similar word pairs. WSR contains 252 related word pairs. [4] reports the highest performance on both data sets.

MEN: a relatedness data set created by [25]. We use the test subset of this data set which contains 1000 pairs. Relatedness scores of this data set range from 0 (totally unrelated) to 50 (totally related). [4] reports the highest performance on this collection using the popular neural language model Word2Vec proposed by [12].

4.2 Experimental Setup
We followed experimental setup similar to [4]. Basically, we implemented two sets of experiments. First, we evaluate MSA with different combinations of parameters to get the maximum performing combination on each data set. Second, we evaluate MSA in a more realistic settings where we use one of the data sets as a development set for tuning MSA’s parameters and then use tuned parameters to evaluate MSA’s performance on the other the data sets. In both sets of experiments, we set $|Y| = 1$, $F = text$, and $v = 0.0$.

We built the search index using English Wikipedia articles dumped March 2014. The total uncompressed XML dump size was about 52GB representing about 7 million articles. We extracted the articles using a modified version of Wikipedia Extractor [13]. Our version extracts articles plain text discarding images and tables. We also discard References and External links sections (if any). We pruned both articles not under the main namespace and pruned all redirect pages as well. Eventually, our index contained about 4.8 million documents in total.

4.3 Evaluation
We report the results by measuring correlation between MSA’s computed relatedness scores and the gold standard provided by human judgments. Following prior studies, we report both Pearson correlation ($r$) [26] and Spearman rank-order correlation ($\rho$) [27].

We compare our results with those obtained from three types of semantic representation models. First, statistical co-occurrence models like LSA [7], CW and BOW [13], and ADW [16]. Second, neural language models like Collobert and Weston (CW) vectors [11], Word2Vec [4], and GloVe [13]. Third, explicit semantics models like ESA [6], SSA [11], and NASAIR [8].

4.4 Results
We report correlation scores of MSA from the two sets of experiments. MSA, represent maximum correlation scores obtained by grid search the parameter space for the best combination on each data set. MSA, represent scores obtained by using MC as a development set for tuning MSA’s parameters and then used them to calculate Pearson correlation scores. It is clear that, in absolute figures, MSA, consistently gives the highest correlation scores on all data sets compared to other methods. The results of the tuned model (MSA) are still very competitive to other methods. It comes first on MC, second on RG, WSR and WS, and third WSS.

Table 2 shows Pearson correlation ($r$) of MSA on five benchmark data sets. It also presents prior work results on same data sets. For Word2Vec, we obtained [4] predict vectors and used them to calculate Pearson correlation scores. It is clear that, in absolute figures, MSA, consistently gives the highest correlation scores on all data sets compared to other methods. The results of the tuned model (MSA) are still very competitive to other methods. It comes first on MC, second on RG, WSR and WS, and third WSS.

Table 3 shows MSA’s Spearman correlations compared to prior models on same datasets as in Table 2. As we can notice, MSA, give highest correlation scores on MC and WSR datasets. It comes second on RG, third on WSS, and fourth on WS. MSA, on the other hand, comes first on MC, second on WSR, third on RG, fourth on WS, and fifth on WSS.

On MEN data set, Pearson correlations for MSA, and MSA, were 0.75 and 0.69 respectively. Table 4 shows MSA’s Spearman correlation scores compared to other models (all are neural language models). As we can notice, MSA comes second after Word2Vec giving higher correlation than Skipgram, CW, and GloVe models. Results on this data set prove that MSA is a very advantageous method for evaluating semantic relatedness compared to the trendy deep learning models.

5. A STUDY ON STATISTICAL SIGNIFICANCE
Through the results section, we kept away from declaring state-of-the-art method. That was due two facts. First, the differences between reported correlation scores were very small. Second, the size of the data sets was not that large to accommodate for such small differences. These two facts raise a question about the statistical significance of improvement reported by some method A compared to another well performing method B.

We hypothesize that the best method is not necessarily the one that gives the highest correlation score. In other words, being state-of-the-art doesn’t require giving the highest correlation, rather giving a

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|}
\hline
 & MC & RG & WSS & WSR & WS \\
\hline
LSA* & 0.73 & 0.64 & – & – & 0.56 \\
ESA° & 0.74 & 0.72 & 0.45 & – & 0.49° \\
SSA° & 0.87 & 0.85 & – & – & 0.62 \\
SSA° & 0.88 & 0.86 & – & – & 0.59 \\
ADW° & 0.79 & 0.91 & 0.72 & – & – \\
NASARI° & 0.91 & 0.91 & 0.74 & – & – \\
Word2Vec° & 0.82 & 0.84 & 0.76 & 0.65 & 0.68 \\
MSA, & 0.96 & 0.88 & 0.72 & 0.64 & 0.65 \\
MSA, & 0.96 & 0.91 & 0.77 & 0.68 & 0.70 \\
\hline
\end{tabular}
\caption{MSA’s Pearson ($r$) scores on benchmark data sets vs. other techniques. (°) from [1], (○) from [4] predict vectors, (○) from [8].}
\end{table}
Tables 3 and 4 provide a comparison of MSA’s Spearman ($\rho$) scores on benchmark data sets and MEN data set, respectively, with other techniques. The scores are derived from various sources, including [1], [16], [18], [8], and [13]. For MSA’s scores, we used the tuned model ($MSA_t$) which produced the highest correlations on two data sets ($ADW$ and $NASARI$). Overall, $MSA_t$ produced the highest correlations ($\rho$ scores of 0.88 and 0.92 respectively). On WSS data set, no significant improvement was proved, whereas $WSR$, $WS$, and $MEN$ data sets, we could obtain pairwise similarities only for $Word2Vec_t$. The significance test results indicate that $MSA_t$, $Word2Vec_t$, and $NASARI_t$ are statistically equivalent on WSR and WS data sets. On $MEN$ data set, $Word2Vec_t$ is statistically better than $MSA_t$ (their $\rho$ scores on $MEN$ are 0.79 and 0.71 respectively).

This comparative study is one of the main contributions of this paper. To our knowledge, this is the first study that addresses evaluating the statistical significance of results across different semantic relatedness methods. Additionally, this study positioned MSA as one of the state-of-the-art methods for measuring semantic relatedness.

### Table 3: MSA’s Spearman ($\rho$) scores on benchmark data sets vs. other techniques. ($\ast$) from [1], ($\dagger$) from [16], ($\Upsilon$) from [18], ($\psi$) using pairwise similarities from [8], ($\psi$) from [13], ($\psi$) from [4]

| Method   | MC  | RG  | WSS | WSR | WS  |
|----------|-----|-----|-----|-----|-----|
| $LSA_t$  | 0.66| 0.61| –   | –   | 0.58|
| $ESA^\dagger$ | 0.70| 0.75| 0.53| –   | 0.75|
| $SSA_t$ | 0.81| 0.83| –   | 0.63| –   |
| $SSA_t^\ast$ | 0.84| 0.83| –   | –   | 0.60|
| $CW^\Upsilon$ | –   | 0.89| 0.77| 0.46| 0.60|
| $BOW^\psi$ | –   | 0.81| 0.70| 0.62| 0.65|
| $NASARI_t^\psi$ | 0.80| 0.78| 0.73| –   | –   |
| $ADW^\psi$ | 0.90| 0.92| 0.75| –   | –   |
| $GloVe^\psi$ | 0.84| 0.83| –   | –   | 0.76|
| $Word2Vec_t^\psi$ | 0.82| 0.84| 0.76| 0.64| 0.71|
| $Word2Vec_t^\ast$ | –   | 0.84| 0.80| 0.70| 0.75|
| $MSA_t$ | 0.93| 0.88| 0.72| 0.68| 0.69|
| $MSA_t^\ast$ | 0.93| 0.89| 0.75| 0.72| 0.73|

### Table 4: MSA’s Spearman ($\rho$) scores on MEN data set vs. other techniques. ($\ast$) from [28], ($\dagger$) from [4]

| Method   | MEN |
|----------|-----|
| Skipgram | 0.44|
| $CW^\gamma$ | 0.60|
| $GloVe^\psi$ | 0.71|
| $Word2Vec_t^\psi$ | 0.79|
| $Word2Vec_t^\ast$ | 0.80|
| $MSA_t$ | 0.71|
| $MSA_t^\ast$ | 0.75|

To measure statistical significance, we performed Steiger’s Z significance test [29]. The purpose of this test is to evaluate whether the difference between two dependent correlation measures obtained from the same sample is statistically significant or not, i.e., whether the two correlations are statistically equivalent.

Steiger’s Z test requires to calculate the correlation between the two correlations. We applied the tests using reported Spearman correlations ($\rho$) as it is more commonly used than Pearson correlation. We conducted the tests using correlation scores of MSA’s tuned model ($MSA_t$), Word2Vec’s tuned model ($Word2Vec_t$), ADW, and NASARI.

Table 5 shows the results using 1-tailed test with significance level 0.05. For each data set, we show method-method correlation ($\rho$) calculated using reported correlations in Table 3 and Table 4, and also show $p$-value of the test.

On MC data set, it is clear that $MSA_t$’s result is significant compared to both $Word2Vec_t$ and NASARI results ($p$-value<0.05). $ADW$’s result is also significant compared to NASARI. This implies that $MSA_t$ and $ADW$ could be considered state-of-the-art on MC data set (their $\rho$ scores are 0.93 and 0.90 respectively).

On RG data set, $MSA_t$ gives significant improvement over NASARI. $ADW$’s results are also significantly better than $Word2Vec_t$ and NASARI but not $MSA_t$. Overall, $MSA_t$ and $ADW$ results can be considered the best on RG data set (their $\rho$ scores are 0.88 and 0.92 respectively).

On WSS data set, no significant improvement was proved, therefore all results from the four methods can be considered statistically equivalent.

On WSR, WS, and MEN data sets, we could obtain pairwise similarities only for $Word2Vec_t$. The significance test results indicate that $MSA_t$ and $Word2Vec_t$ are statistically equivalent on WSR and WS data sets. On MEN data set, $Word2Vec_t$ is statistically better than $MSA_t$ (their $\rho$ scores on MEN are 0.79 and 0.71 respectively).

6. CONCLUSION

In this paper, we presented MSA, a novel approach for semantic analysis which employs data mining techniques. MSA is motivated by inability of prior explicit semantics models to capture implicit relations between concepts. To this end, MSA mines for implicit concept-concept associations through Wikipedia “See also” link graph. Intuitively, “See also” hyperlinks represent related concepts that might complement the conceptual knowledge about a given concept.

Through empirical results, we demonstrated MSA’s effectiveness to compute semantic relatedness on standard benchmark data sets. In absolute figures, MSA could consistently produce higher Pearson correlation scores than other explicit semantics approaches like ESA, SSA, and NASARI. MSA’s scores were also higher than predictive models built using deep learning like Word2Vec.

Regarding Spearman correlation, MSA produced the highest correlations on two data sets (MC and WSR). Results on other data sets were very competitive in absolute figures. Specifically, MSA gave higher Spearman correlations than GloVe and Word2Vec on RG data set. MSA also gave higher correlation on MEN data set than Skipgram, $CW$, and GloVe neural representations.

In this paper, we introduced the first comparative study which evaluates the statistical significance of results from across top performing semantic relatedness methods. We used Steiger’s Z significance test to evaluate whether reported correlations from two different methods are statistically equivalent even if they are mathematically different. We believe this study will help the research community to better evaluate and position state-of-the-art techniques at different application areas. The study proved that MSA results are sta...
|     | MC  | RG  | WSS | WSR | WS  | MEN |
|-----|-----|-----|-----|-----|-----|-----|
| ρ   | p-value | ρ   | p-value | ρ   | p-value | ρ   | p-value | ρ   | p-value | ρ   | p-value |
| Word2Vec*  | 0.84 | 0.004 | 0.79 | 0.126 | 0.72 | 0.108 | 0.67 | 0.134 | 0.68 | 0.238 | 0.76 | 0.0 |
| NASARI*    | 0.81 | 0.002 | 0.76 | 0.007 | 0.64 | 0.393 | –   | –     | –   | –     | –   | –     |
| ADW*       | 0.85 | 0.182 | 0.79 | 0.064 | 0.62 | 0.207 | –   | –     | –   | –     | –   | –     |
| Word2Vec  | 0.80 | 0.058 | 0.81 | 0.003 | 0.68 | 0.5   | –   | –     | –   | –     | –   | –     |
| NASARI     | 0.82 | 0.025 | 0.80 | 0.0   | 0.76 | 0.256 | –   | –     | –   | –     | –   | –     |
| NASARI     | 0.75 | 0.387 | 0.71 | 0.105 | 0.66 | 0.192 | –   | –     | –   | –     | –   | –     |

Table 5: Steiger’s Z significance test on the differences between Spearman correlations (ρ) using 1-tailed test and 0.05 statistical significance. (⋆) using [4] predict vectors, (*) using [8] pairwise similarity scores, (⋆) using [16] pairwise similarity scores.

MSA is a general purpose semantic analysis approach which builds an explicit semantics representation for linguistic terms. MSA’s concept vectors can be easily interpreted by humans. MSA could be leveraged in many applications like semantic search, textual entailment, word sense disambiguation, resolving vocabulary mismatch, concept tracking, technology mappings, and others. MSA is efficient because it employs a search index to retrieve semantically related concepts. Additionally, mining for concept-concept association rules is done offline making it scalable to huge amounts of data.

7. REFERENCES

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