# Distributed Representation of Documents with Explicit Explanatory Features: Background Research

## Kusner, Matt J., et al. "From Word Embeddings To Document Distances."

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# Background

<u>Need for representing "distance" between documents</u>

- Accurately representing the distance between two documents is crucial in document retrieval, news categorization and clustering and multilingual document matching
- Suggested Methods:
  1. Bag of Words & TF-IDF
     - Due to high dimensionality of the vectors, near-orthogonality frequently occurs among the vector representations
     - Do not capture the distance between individual words
     - Example: "Obama speaks to the media in Illinois" vs. "The President greets the press in Chicago"
     - Variations of BOW models with different features exist
  2. Latent Semantic Indexing (LSI)
     - Eigendecomposes BOW feature space
  3. Latent Dirichlet Allocation (LDA)
     - Probabilistically groups similar words into topics and represent the documents as distribution over these topics
- Yet, no models improve the empirical performance of BOW on distance-based tasks

# Suggested Method

Word Mover's Distance (WMD)

- A new metric for the distance between text documents
- Utilizes word2vec embedded word vectors as semantic relationships are often preserved in vector operations
- Distance between two text documents A & B is the minimum cumulative distance that words from document A need to travel to match exactly to the words from document B
- Uses Earth Mover's Distance transportation problem to find the optimal solutions

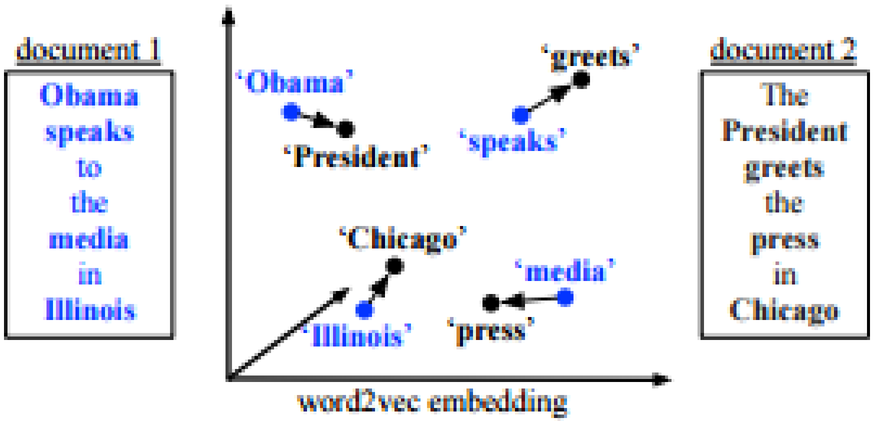
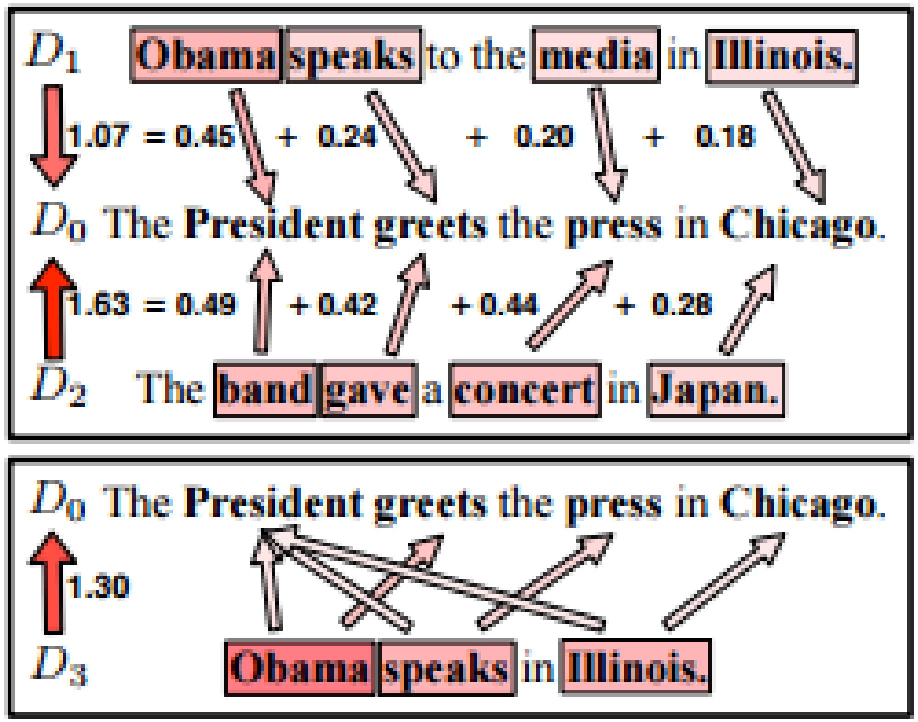



*Figure 1.* An illustration of the *word mover's distance.* All non-stop words (***bold***) of both documents are embedded into a *word2vec* space. The distance between the two documents is the minimum cumulative distance that all words in document 1 need to travel to exactly match document 2. (Best viewed in color.)

# Suggested Method

Properties and Advantages

1. Hyper-parameter free
2. Highly interpretable as the distance between two documents can be broken down and explained
3. High retrieval accuracy as it incorporates the effective knowledge encoding of word2vec



# Earth Mover's Distance

- A method to evaluate dissimilarity between two multi-dimensional distributions in some feature space where a distance measure between single features is given
- Intuitively, two distributions can be thought of as earth and hole, and EMD measures the least amount of work needed to fill the holes with earth
- Can be thought of as a transportation problem (suppliers supplying to several consumers)
- If two multidimensional data is given as:

$$P = \{(p_1, w_{p_1}), \ldots, (p_m, w_{p_m})\} \qquad Q = \{(q_1, w_{q_1}), \ldots, (q_n, w_{q_n})\}$$

  - Can be thought of as (coordinate, weight)
- If $f_{ij}$ represents a flow from $p_i$ to $q_j$, following linear programming problem can be set up

$$\mathrm{WORK}(P, Q, \mathbf{F}) = \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d_{ij}$$

Minimizing Objective Function

Constraints

$$f_{ij} \geq 0 \qquad 1 \leq i \leq m,\ 1 \leq j \leq n$$

$$\sum_{j=1}^{n} f_{ij} \leq w_{p_i} \qquad 1 \leq i \leq m$$

$$\sum_{i=1}^{m} f_{ij} \leq w_{q_j} \qquad 1 \leq j \leq n$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = \min\left(\sum_{i=1}^{m} w_{p_i}, \sum_{j=1}^{n} w_{q_j}\right),$$

# WMD Formulation

- Difference between words (cost associated with travelling from one word to another): Euclidean distance difference in the word2vec embedding space

$$c(i,j) = \| x_i - x_j \|_2$$

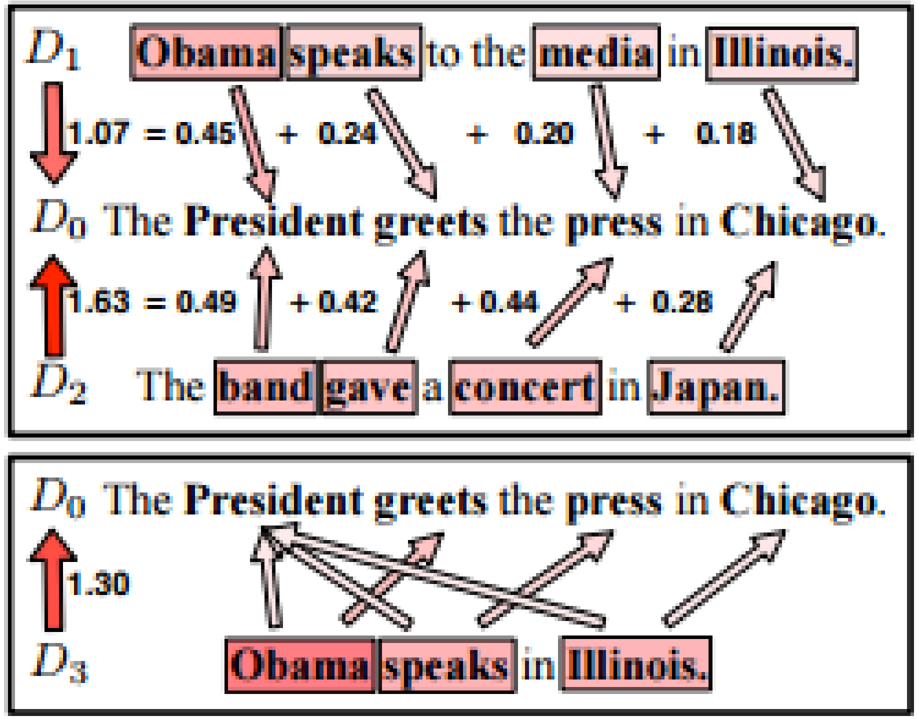
- Allow each word in document $d$ to be transformed into any word in document $d'$
- Let $\boldsymbol{T} \epsilon R^{n \times n}$ be a (sparse) matrix that denotes how much of word i in document $d$ travels to word j in $d'$
- $d_i$ : the number of word appearance in a document ($d_i = \frac{c_i}{\sum_{j=1}^{n} c_j}$)

$$\min_{\mathbf{T} \geq 0} \sum_{i,j=1}^{n} \mathbf{T}_{ij} c(i,j)$$

$$\text{subject to: } \sum_{j=1}^{n} \mathbf{T}_{ij} = d_i \quad \forall i \in \{1, \ldots, n\} \qquad (1)$$

$$\sum_{i=1}^{n} \mathbf{T}_{ij} = d'_j \quad \forall j \in \{1, \ldots, n\}.$$

# WMD Formulation




<u>Observations</u>

- "Moves" the words to semantically similar words
- (D1, D2) = both have same TF-IDF distance from D0
- Still valid when the number of words in documents vary

# Complexity and Model Relaxation

- Complexity for solving WMD optimization problem: $O(p^3 \log p)$

  * p = number of unique words in the entire documents
- Can overcome the high complexity of the model via

  1. <u>Word Centroid Distance</u>
     - Represent each document by its weighted average vector and use that centroid vector to find the distance between the documents
     - Centroid distance serves as lower bound on WMD
     - Scales to $O(dp)$
     - Can incorporate this method to narrow down the search space in calculating exact WMD

# Complexity and Model Relaxation

2. <u>Relaxed Word Moving Distance</u>
   - To provide tighter bound, remove the two constraint from the original WMD formulation consecutively and take the maximum distance between the two
   - Need to find only the most similar word vector $x_j$ in document $d'$

$$\min_{\mathbf{T}\geq 0} \sum_{i,j=1}^{n} \mathbf{T}_{ij} c(i,j)$$

$$\text{subject to: } \sum_{j=1}^{n} \mathbf{T}_{ij} = d_i \quad \forall i \in \{1,\dots,n\}$$

$$\min_{\mathbf{T}\geq 0} \sum_{i,j=1}^{n} \mathbf{T}_{ij} c(i,j)$$

$$\text{subject to: } \quad (1)$$

$$\sum_{i=1}^{n} \mathbf{T}_{ij} = d'_j \quad \forall j \in \{1,\dots,n\}.$$

**Take the maximum distance between these two relaxed models**

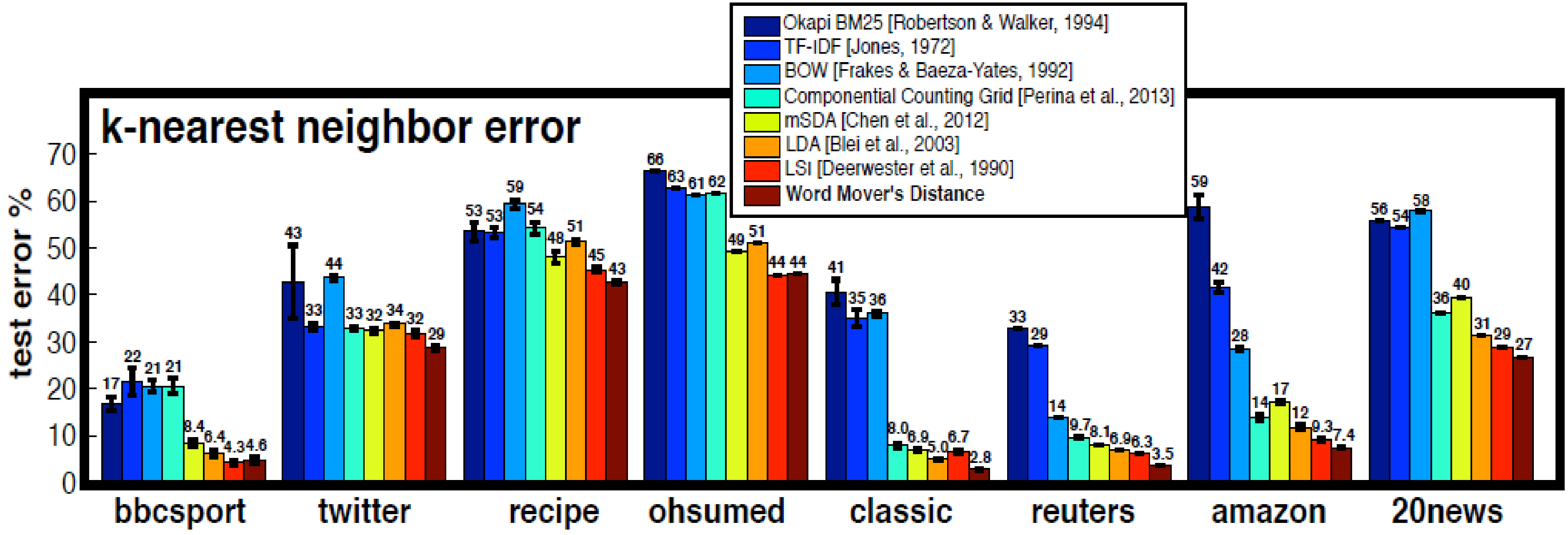
# Data

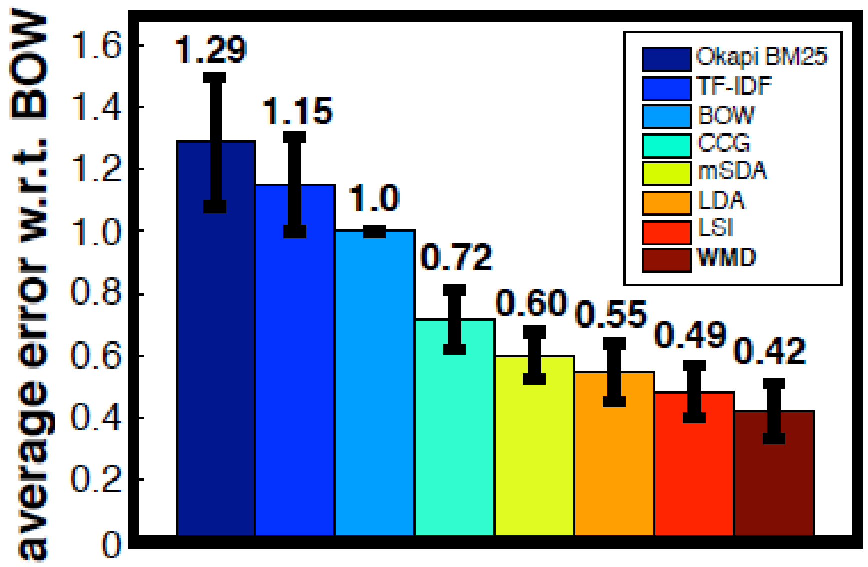
*Table 1.* Dataset characteristics, used in evaluation.

| NAME | $n$ | BOW DIM. | UNIQUE WORDS (AVG) | $\|\mathcal{Y}\|$ |
|---|---|---|---|---|
| BBCSPORT | 517 | 13243 | 117 | 5 |
| TWITTER | 2176 | 6344 | 9.9 | 3 |
| RECIPE | 3059 | 5708 | 48.5 | 15 |
| OHSUMED | 3999 | 31789 | 59.2 | 10 |
| CLASSIC | 4965 | 24277 | 38.6 | 4 |
| REUTERS | 5485 | 22425 | 37.1 | 8 |
| AMAZON | 5600 | 42063 | 45.0 | 4 |
| 20NEWS | 11293 | 29671 | 72 | 20 |

- Used the trained word2vec model from Google
- Words that are not present in the trained word2vec model is dropped during computing WMD metric

# K-NN Result


k-nearest neighbor error
test error %
Okapi BM25 [Robertson & Walker, 1994]
TF-IDF [Jones, 1972]
BOW [Frakes & Baeza-Yates, 1992]
Componential Counting Grid [Perina et al., 2013]
mSDA [Chen et al., 2012]
LDA [Blei et al., 2003]
LSI [Deerwester et al., 1990]
Word Mover's Distance
bbcsport
twitter
recipe
ohsumed
classic
reuters
amazon
20news

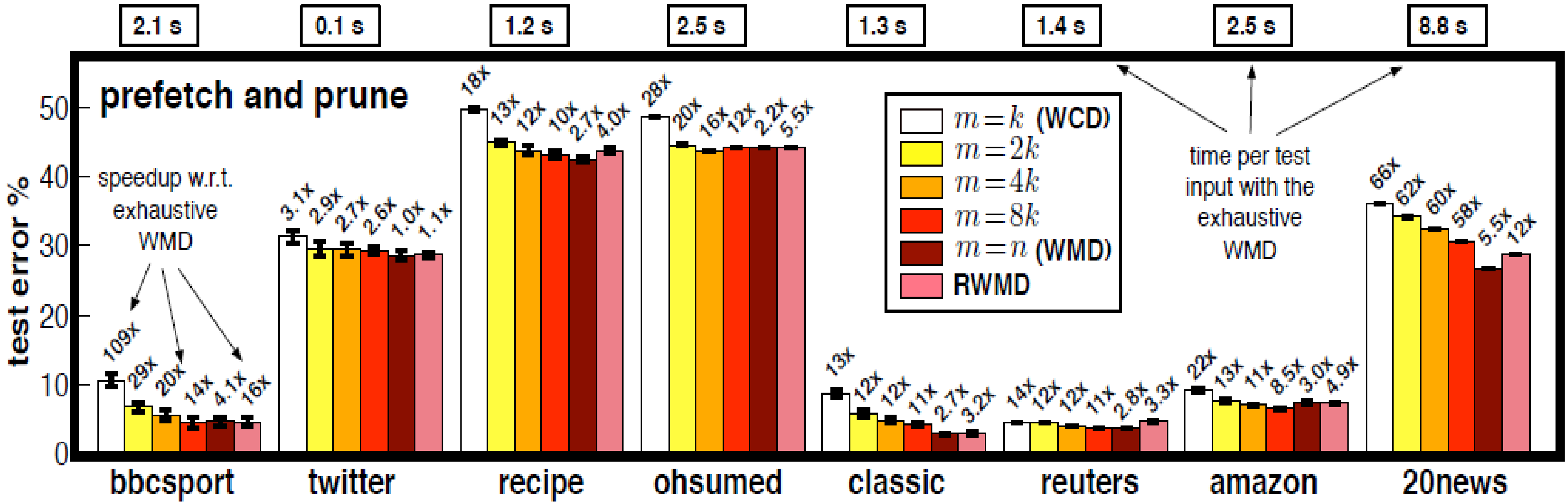

average error w.r.t. BOW
1.29
1.15
1.0
0.72
0.60
0.55
0.49
0.42
Okapi BM25
TF-IDF
BOW
CCG
mSDA
LDA
LSI
WMD

# Using Different Embedding Methods

| DOCUMENT $k$-NEAREST NEIGHBOR RESULTS | | | | | |
|---|---|---|---|---|---|
| DATASET | HLBL | CW | NIPS (W2V) | AMZ (W2V) | NEWS (W2V) |
| BBCSPORT | 4.5 | 8.2 | 9.5 | 4.1 | 5.0 |
| TWITTER | 33.3 | 33.7 | 29.3 | 28.1 | 28.3 |
| RECIPE | 47.0 | 51.6 | 52.7 | 47.4 | 45.1 |
| OHSUMED | 52.0 | 56.2 | 55.6 | 50.4 | 44.5 |
| CLASSIC | 5.3 | 5.5 | 4.0 | 3.8 | 3.0 |
| REUTERS | 4.2 | 4.6 | 7.1 | 9.1 | 3.5 |
| AMAZON | 12.3 | 13.3 | 13.9 | 7.8 | 7.2 |

- Used different embedding methods (Hierarchical log0bilinear model & Collobert Weston Model) and word2vec trained on different datasets to observe the change in k-nn performance
- WMD method seems to be very sensitive to the training set used in word2vec method
- Perhaps explains its reason behind very low k-nn error

# Using Different Embedding Methods




- When m = k, WCD metric for classification
- For all other results pre-fetch m instances via WCD, use RWMD to check if a document can be pruned and only if not compute the exact WMD distance until k documents are selected
- RWMD omits all WMD computations
- Relaxed models significantly decrease the computational time without the loss of accuracy

# Conclusion

- Compared to word2vec clustering, this method doesn't provide direct representation of documents
- Space generated by word2vec embedding space is effective in capturing semantic information, and can be applied to capturing the semantics of documents
- Although it didn't elaborate or list any examples to show the explanatory power of WMD method, it was enough to suggest a glimpse of such effect
- Yet, the experiment seemed biased, giving unfair advantage to WMD

# Reference

Kusner, Matt J., et al. "From Word Embeddings To Document Distances."

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