A Hierarchical Book Representation of Word Embeddings for Effective Semantic Clustering and Search

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Keywords: Word Vectors, Deep Learning, Semantic Matching, Multidimensional Scaling, Clustering.

Abstract: Semantic word embeddings have shown to cluster in space based on linguistic similarities that are quantifiably captured using simple vector arithmetic. Recently, methods for learning distributed word vectors have progressively empowered neural language models to compute compositional vector representations for phrases of variable length. However, they remain limited in expressing more generic relatedness between instances of a larger and non-uniform sized body-of-text. In this work, we propose a formulation that combines a word vector set of variable cardinality to represent a verse or a sentence, with an iterative distance metric to evaluate similarity in pairs of non-conforming verse matrices. In contrast to baselines characterized by a bag of features, our model preserves word order and is more sustainable in performing semantic matching at any of a verse, chapter and book levels. Using our framework to train word vectors, we analyzed the clustering of bible books exploring multidimensional scaling for visualization, and experimented with book searches of both contiguous and out-of-order parts of verses. We report robust results that support our intuition for measuring book-to-book and verse-to-book similarity.

1 INTRODUCTION

The attraction of using vector spaces for analyzing natural language semantics, stems primarily from providing an instinctive relation mechanism by subscribing to lexical distance and similarity concepts. In a large corpora of text, the structure of a semantic space is created by evaluating the various contexts in which words occur. Thus leading to distributional models of word meanings with the underlying assertion that words who transpire in similar contexts tend to have similar interpretations (Turney and Pantel, 2010). Distributed words, also known as word embeddings, are each represented with a dense, low-dimensional real-valued vector, and follow efficient similarity calculations directly from the known Vector Space Model (Salton et al., 1975). Word vectors have been widely used as features in a diverse set of computational linguistic tasks, including information retrieval (IR) (Manning et al., 2008), parsing (Socher et al., 2013), named entity recognition (Guo et al., 2014), and question answering (Iyyer et al., 2014).

In recent years, neural network architectures have inspired the deep learning of word embeddings from large vocabularies to avoid a manual labor-intensive design of features. The work by Bengio *et al.* (2003) introduced a statistical language model formulated by the conditional probability of the next word given all its preceding words in a sequence, or a context. However, the time complexity of the neural model renders the scheme inefficient due to the non-linear hidden layer. The succeeding Word2Vec (Mikolov et al., 2013a) and GloVe (Pennington et al., 2014) methods, preserve the probabilistic hypotheses founded in Bengio *et al.* (2003) approach, and further eliminate the hyperbolic tangent layer entirely, thus becoming more effective and feasible tools for language analysis. Notably, these methods expand on the input context window to include the words that both precede and follow the target word. Word embeddings are typically constructed by way of minimizing the distance between words of similar contexts, and encode various simple lexical relations as offsets in vector space. Our work investigates the linguistic structure in raw text, and explores clustering and search tasks using Word2Vec to train the underlying word representations.

Applying unsupervised learning (Duda et al., 2001) of distributed word embeddings to a broader set of semantic tasks has not yet been fully established and remains an active research to date. In their recent work, Fu *et al.* (2014) utilize word embeddings to discover hypernym-hyponym type of linguistic relations.

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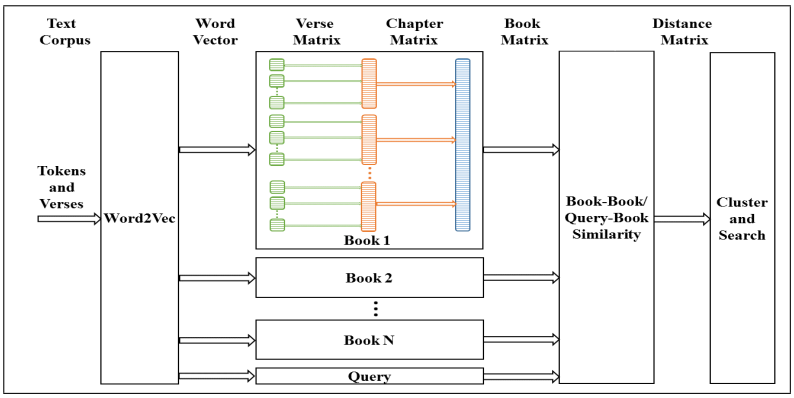


Figure 1: Framework overview: on the left, tokens and context from a text corpus are used to train word vectors. A collection of word vectors is constructed to represent word-for-word the source text of every book. Word vectors are first row bound into a matrix to represent a verse. Then, verse matrices are concatenated into chapter matrices that are further coalesced into a hierarchical book matrix. We run all-book-pairs and all-query-book-pairs similarity process on matrices of a non-uniform row count, and generate a distance matrix that we use for cluster analysis and search ranking, respectively.

Noting that offsets of word pairs distribute into structured clusters, they modeled fine-grained relations by estimating projection matrices that map words to their respective hypernyms, and report a reasonable test F1-score of 73.74%. Socher *et al.* (2013) proposed a recursive neural network to compute distributed vector representations for phrases and sentences of variable length. Their model outperforms state-of-the-art baselines on both sentiment classification and accuracy metrics, however, its supervised method requires extensive manual labeling and makes scaling to larger sized text non trivial. A representation more rooted in a convolutional neural architecture (Kim, 2014), produces a feature map for each possible window in a sentence, and follows with a max-over-time pooling (Collobert et al., 2011) to capture the most important features. Pooling has the apparent benefit of naturally adapting to variable length sentences. At the higher document level, Le and Mikolov (2014) introduced a paragraph vector extension to the learning framework of word vectors. Given their different dimensionality, paragraph and word vectors are concatenated to yield fixed sized features, however, unique paragraph vectors constrain context sharing across the document.

For a composition of words, most of the techniques discussed tend to reshape the varying dimensionality of input sentences into uniform feature vectors. Rather, our implementation retains the word vectors as distinct rows in a matrix form to construct any of the verse, chapter, or book data structures for performing our set of linguistic tasks. The main contribution of our work is a framework (Figure 1) with a lexical representation that abides word-for-word by the corpus source sequence, to facilitate a generic evaluation of relationships among entities of non-uniform text size. The rest of this paper is organized as follows. In section 2, we briefly review the neural models to found Word2Vec, and proceed with motivating our choice for a verse matrix representation that leads to our chapter and book hierarchies. Section 3 derives our book similarity measure as it applies to a pair of non-conforming concatenations of verse embeddings, whereas Section 4 profiles the compiled format of the bible corpus we used for evaluation. We then present our methodology for analyzing clusters of bible subdivisions and ranking book searches of unsolicited keywords, and report extensive quantitative results of our experiments, in section 5. We conclude with a discussion and future prospect remarks in section 6.

2 EMBEDDING HIERARCHY

In Word2Vec, Mikolov *et al.* (2013a) proposed a shallow neural-network structure for learning useful word embeddings to support predictions within a local bi-directional context-window. Both the skip-gram and continuous bag-of-words (CBOW) models offer a simple single-layer architecture based on the inner product between a pair of word vectors. In the skip-gram version the objective is to predict the not necessarily immediate context words given the target word, and conversely, CBOW estimates the target word based on its neighboring context. As a context window scans over the corpus, the models attempt to maximize the log probability of the generated objective function, based on their respective multi and single output layers, and training word vectors proceeds in a stochastic manner using back propagation. To improve upon accuracy and training time, Mikolov *et al.* (2013b) introduced both randomly discarding of frequent words that exceed a prescribed count threshold,

and the concept of negative sampling that measures how well a word pairs with its context drawn from a noise distribution of a small sample of tokens. Empirically, neural model performance shown mainly governed by tunable parameters, including the word vector dimension, d, the symmetric context-window size, c_w, and the number of negative samples, s_n. Overall, skip-gram works well with a small amount of training data, while CBOW is several times faster to train.

The corpus we used for our study comprises a set of tens of books and to train word embeddings we first flattened the entire corpus into a linear array of verses, or sentences. We then proceeded to construct our basic data structures that culminate in an effective hierarchical representation of a book object, which is perceived nameless across subsequent clustering and search analysis. Let $w^{(k)} \in \mathbb{R}^d$ be the d-dimensional word vector corresponding to the k-th word in a verse. A verse S of length n is represented as a matrix

$$S = w^{(1)} \oplus w^{(2)} \oplus \ldots \oplus w^{(n)}, \quad (1)$$

where $\oplus$ is a row-wise binding operator and $S \in \mathbb{R}^{n \times d}$. S is thus regarded as a vector set and rows of S are considered atomic. To index a word vector in a verse, we use the notation s_k. Similarly, a book chapter C of m verses becomes a concatenation of verse matrices, $C = S^{(1)} \oplus S^{(2)} \ldots \oplus S^{(m)}$, where $C \in \mathbb{R}^{r_c \times d}$ and $r_c = \sum_{j=1}^{m} |S^{(j)}|$, and a book B comprises l chapter matrices, $B = C^{(1)} \oplus C^{(2)} \ldots \oplus C^{(l)}$, where $B \in \mathbb{R}^{r_b \times d}$ and $r_b = \sum_{i=1}^{l} r_c^{(i)}$. Respectively, c_j itemizes a verse matrix in a chapter, and b_i enumerates a chapter matrix in a book. Equation 2 provides an alternate matrix notation for each a verse, chapter, and book.

$$S = \begin{bmatrix} w^{(1)} \\ w^{(2)} \\ \vdots \\ w^{(n)} \end{bmatrix} \qquad C = \begin{bmatrix} S^{(1)} \\ S^{(2)} \\ \vdots \\ S^{(m)} \end{bmatrix} \qquad B = \begin{bmatrix} C^{(1)} \\ C^{(2)} \\ \vdots \\ C^{(l)} \end{bmatrix}. \quad (2)$$

The length of a verse, $|S^{(j)}|$, and the number of verses per chapter, $|C^{(i)}|$, are varying parameters that we track and keep in a book map for traversing the book hierarchy. For book similarity computations, we often iterate a book matrix and access the entire collection of word vectors. Conveniently, we use a three dimensional indexing scheme, b_{ijk}, where each of i, j, and k points to a chapter matrix, verse matrix, and word vector, respectively. Space complexity for book embeddings is linear, $O(lmn)$, and for a vocabulary that permits storing a 16-bit token enumeration instead, memory area required is reduced by a half. We further denote the corpus book set $T = \{B^{(1)}, B^{(2)}, \ldots, B^{(N)}\}$, where N, or cardinality $|T|$, is the number of books.

3 BOOK SIMILARITY

Measuring similarity and relatedness between distributed terms is an important problem in lexical semantics (Agirre et al., 2009). Recently, the process of learning word embeddings transpired compelling linguistic regularities by simply probing the linear difference between pairs of word vectors. This evaluation scheme exposes relations that are adequately distributed in a multi-clustering representation (Fu et al., 2014). However, a single offset term is insufficient to assess similarity between a pair of books represented by non-conforming matrices, each potentially retaining many thousands of word vectors. For evaluating semantic closeness of a pair of books, $b^{(u)}$ and $b^{(v)}$, we explored a similarity concept that expands on the Chebychev matrix distance and is defined by

$$d(u,v) = \frac{1}{|b^{(u)}|} \sum_{xyz} \left\{ \max_{ijk} \left(sim(b_{xyz}^{(u)}, b_{ijk}^{(v)}) \right) \right\}, \quad (3)$$

where $|b^{(u)}|$ is the book cardinality that amounts to the total number of distributed word vectors for representing the book, and $|b^{(u)}| \neq |b^{(v)}|$. Whereas *sim* is a similarity function that operates on two word vectors and takes either a Euclidean or an angle form. We chose cosine similarity (Baeza-Yates and Ribeiro-Neto, 1999) that performs an inner product on a pair of normalized vectors g and h, $\frac{g \cdot h^T}{\|g\|_2 \|h\|_2}$, and returns a scalar value as a measure of proximity. The time complexity of the distance algorithm is roughly quadratic, as for each word vector in book $b^{(u)}$, we find the closest word vector in book $b^{(v)}$, and then calculate the mean of all the closest distances derived formerly.

In our system, all possible pairs of the corpus books, T, are evaluated for similarity in the context of a $|T|$-dimensional squared distance-matrix, D. Elements of the distance matrix are considered directional and hence imply $d(u,v) \neq d(v,u)$. Matrix D facilitates unsupervised learning for clustering books that apart from knowing their individual representations, they are perceived as a collection of unlabeled objects. Following an identical vein, as the distance metric provided by Equation 3 is generic and assumes opaque matrix pairs, our framework extends the semantic distance intuition to express a query-book type of relations for conducting a search. A query, q, comprises an unsolicited keyphrase and as such abides by our verse matrix formulation, S. The distance $d(q,u)$, where $u \in \{1,2,\ldots,|T|\}$, thus conveys a distinct relevancy measure for ranking the search of a query in each of the corpus books, T. Our system reports back search results as a table of sorted distances paired with the book enumeration (Cormen et al., 1990).

4 BIBLE CORPUS

We evaluated the performance of our model on raw bible text we acquired online from the publicly available repository provided by Google (2008). Among the editions offered, we chose the American Standard version of the Old Testament that is distributed in constructive book folders, each with a list of chapter files. The bible script comprises three major book collections termed Torah, Neviim, and Ketuvim, also known correspondingly as Pentateuch, Prophets, and Writings. Compactly, we denote the compilation into three timeline related components with the commonly used acronym, TNK. Table 1 lists the book names associated with each of the TNK partitions.

Table 1: Book names for each of the TNK partitions.

Torah	**Neviim**		**Ketuvim**
Genesis	Joshua	Hosea	Psalms
Exodus	Judges	Joel	Proverbs
Leviticus	1 Samuel	Amos	Job
Numbers	2 Samuel	Obadiah	Song of Solomon
Deuteronomy	1 Kings	Jonah	Ruth
	2 Kings	Micah	Lamentations
	Isaiah	Nahum	Ecclesiastes
	Jeremiah	Habakkuk	Esther
	Ezekiel	Zephaniah	Daniel
		Haggai	Ezra
		Zechariah	Nehemiah
		Malachi	1 Chronicles
			2 Chronicles

The bible dataset contains 39 titles, as 5, 21, and 13 books subscribe to each of the TNK groups, respectively. In total, the corpus incorporates 929 chapters and 23,145 verses, with over one and a half million tokens. Table 2 provides further TNK summarizations of books-per-partition, chapters-per-book, and verses-per-chapter, whereas the visualization of both chapter and stacked verse distribution across all the TNK books is outlined in Figure 2 and Figure 3, respectively. To derive our word vectors, we trained 11,319 unique tokens that include stop words and punctuation marks, with no preprocessing to attend to any exclusion or exception. Notably, most tokens are of a low frequency term with 3,536 tokens that occur only once in the dataset, and 8,254, or about 73%, come up each under ten incidents. To construct a context window, we randomly select an unlabeled book enumeration in the $[1, 39]$ range, and traverse our hierarchy top-to-bottom by arbitrarily sampling chapter and verse indices that are confined to the limits set by the singled out book. In the chosen verse, a random target-word position is used to extract from left and right context words that are delimited by the verse start and end words. One of our system goals is to discover semantic relations that closely align learned book clusters with the handmade TNK partitions.

Table 2: Summarizations of TNK books-per-partition, chapters-per-book, verses-per-book, and corpus tokens.

Books			
Torah	Neviim	Ketuvim	Total
5	21	13	39
Chapters			
Min	Max	Mean	Total
1	150	23.8	929
Verses			
Min	Max	Mean	Total
21	2,461	593.5	23,145
Tokens			
	Unique	Total	
	11,319	1,507,790	

5 EMPIRICAL EVALUATION

Previously, we discussed vector embedding techniques, such as Word2Vec (Mikolov et al., 2013a) and GloVe (Pennington et al., 2014), and their role to transform natural language words into a semantic vector space. In this section, we proceed to quantitatively evaluate the intrinsic quality of the produced set of latent vector representations, and analyze their impact on the performance of our unsupervised learning tasks that comprise book clustering and search. As an aid to tune our system level performance, we explored varying some of the hyperparameters designed to control the neural models incorporated in the word embedding methods. In practice, we have implemented our own Word2Vec technique natively in R (R, 1997) for better integration with our software framework. Across all of our experiments we trained word vectors employing mini-batch stochastic gradient descent (SGD) with an annealed learning rate, and semantic similarity results we report on both book-to-book and verse-to-book relations presume anonymous books.

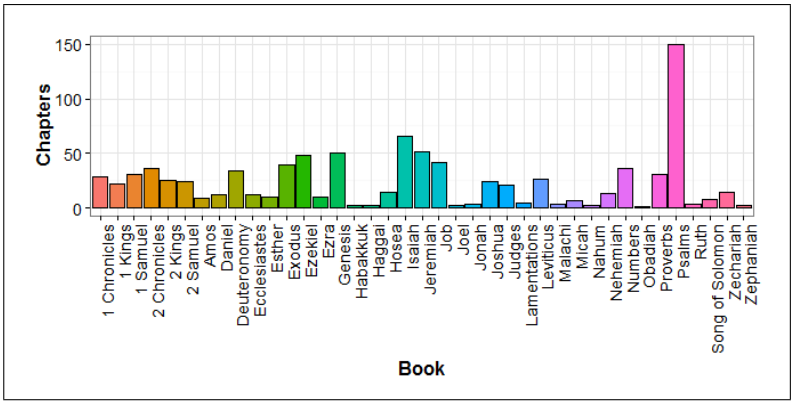


Figure 2: Chapter distribution across the entire TNK book suite.

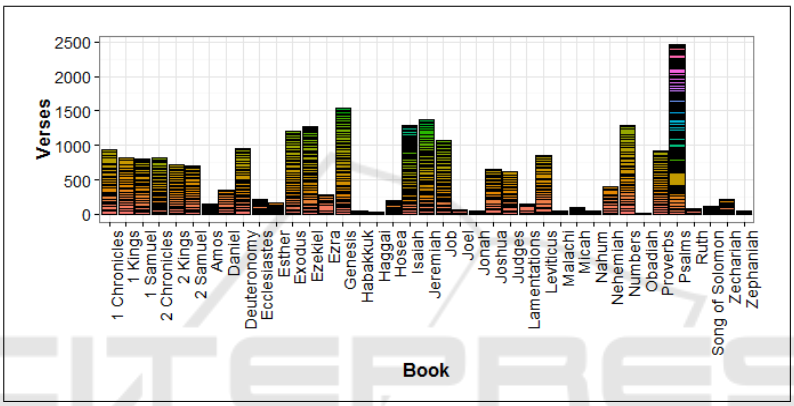


Figure 3: Stacked verse distribution for chapters across the entire TNK book suite.

5.1 Experimental Setup

The raw bible text (Google, 2008) underwent a data cleanup preprocess to properly space words from punctuation marks and introduce a more definite separation symbol between a verse ID and the verse text. We then tokenized the corpus using the R tokenizer and built a maximal vocabulary of size $|V| = 11,319$. Each word in this sparse 1-of-$|V|$ encoding is represented as a one-hot vector $\in \mathbb{R}^{|V|\times 1}$, with all 0s and a single 1 bit at the word index in the vocabulary, that is further mapped onto a lower-dimensional semantic vector-space. Projecting onto the denser formulation transpires preceding the hidden layer of the neural models that underlie the embedding technique.

In the absence of a large supervised training set of word vectors, the use of pre-trained word vectors obtained from an unsupervised neural model became a favorable practice to boost system performance (Collobert et al., 2011; Iyyer et al., 2014; Kim, 2014). While proven useful for word analogy and multi-class classification tasks, clustering and search over a rather unique dataset requires however randomly initialized word-vectors. Hence our model generates distinct input and output sets of word vectors, W and $\tilde{W}$, that only differ as a result of their random initialization. To help reduce overfitting and noise, we used their sum, $W + \tilde{W}$, as our final vectors and that typically yields a small performance gain. To better assess the space complexity of our book representation made of the trained word embeddings, Figure 4 provides a visual interpretation of a flattened book hierarchy, outlined as a single linear matrix with up to several tens-of-thousands rows of word vectors, and shown distributed across the entire TNK book suite.

Recent study by Baroni *et al.* (2014) alluded to neural word-embedding models that consistently outperform the more traditional count-based distributional methods on many semantic matching tasks and by a fair margin. Furthermore, much of the achieved performance gains cited are mostly attributed to a system design choice of the configured hyperparameters. Motivated by these results, we evaluated task performance comparing distinct book hierarchies generated by each skip-gram and CBOW, and choose negative sampling that typically works better than hierarchical softmax (Mikolov et al., 2013b). For the learning hyperparameters, there seems no single selection for an

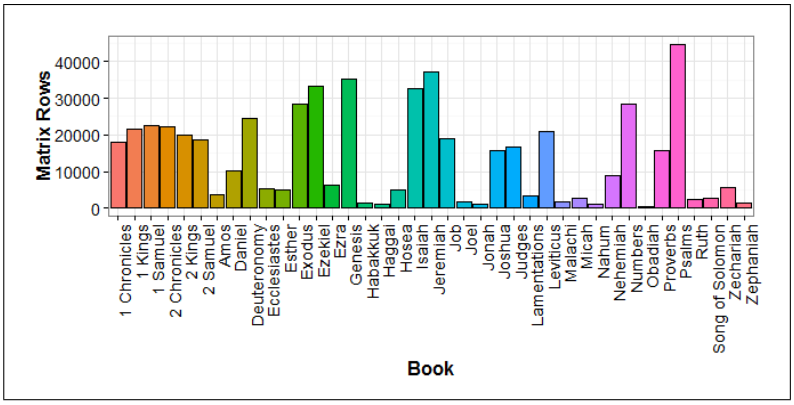


Figure 4: Flattened book hierarchy into a single linear matrix of word vectors $w^{(k)} \in \mathbb{R}^d$. Showing distribution of matrix row count across the entire TNK book suite.

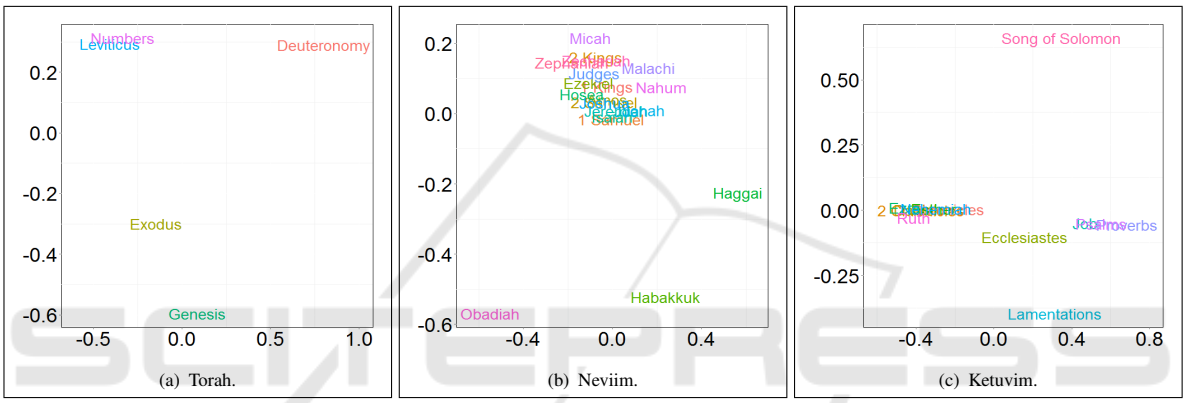


Figure 5: Visualization of book distance matrices using Multidimensional Scaling, representing the TNK subsets of Torah, Neviim, and Ketuvim with 5, 21, and 13 books, respectively.

optimal word-vector dimension, d, as it tends to be highly task dependent and varies from 25 for semantic classification (Socher et al., 2013) up to 300 for word analogy (Mikolov et al., 2013a). Rather, we set $d = 10$ and traded-off word vector dimension to attain more tractable computation in building the distance matrix that is inherently of a quadratic time complexity, $O(|T|^2)$. Whereas, to better assess the impact of the context window on our system performance, we varied discretely its size $c_w = \{5, 15, 25, 50\}$, in a wide range of word counts. Evidently, Word2Vec performance tends to decrease as the number of negative samples increases beyond about 10 (Pennington et al., 2014), thereby we used $s_n = 10$. For our mini-batch SGD to train word vectors, we used a batch size of 25 and an initial learning rate $\alpha = 0.1$, as we ran 100 iterations and updated parameters after each window.

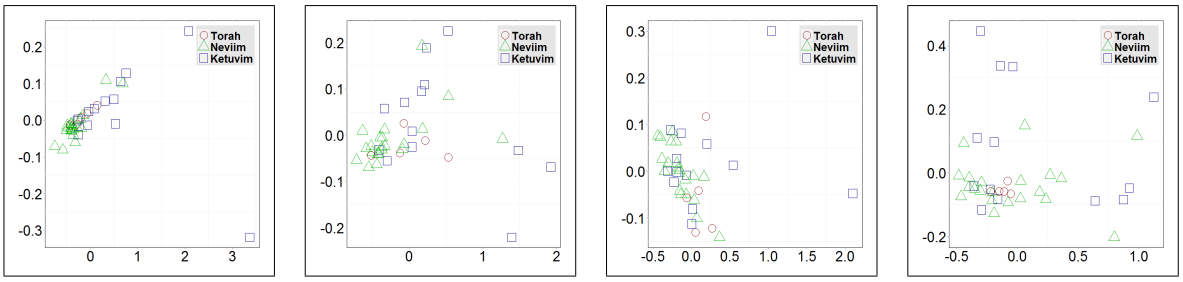
5.2 Experimental Results

We present book clustering results of our own trained TNK corpus at both the component level and for the entire suite of $|T| = 39$ books. To visualize TNK clusters we used Multidimensional Scaling (MDS) (Torgerson, 1958; Hofmann and Buhmann, 1995) that extracts patterns of semantic proximities from our book distance-matrix representation, D. The distance matrix is composed of a set of pairwise book-similarity values with $O(|T|^2)$ scaling that MDS further compiles and projects onto an embedding p-dimensional Euclidean-space. This mapping is intended to faithfully preserve the clustering structure of the original distance data-points, and often, data visualization quality of clusters is directly proportional to the ratio $\frac{p}{|T|}$. In our experiments, we consistently rendered similarity measures of book pairs onto a two-dimensional coordinate frame to inspect and analyze formations of TNK book clustering.

In Figure 5, we provide baseline visualization of MDS applied to our book distance matrices that represent each of the TNK components of Torah, Neviim, and Ketuvim with dimensionality $|T| = \{5, 21, 13\}$, respectively. For this experiment, we used the CBOW neural model to train word vectors, as hyperparame-

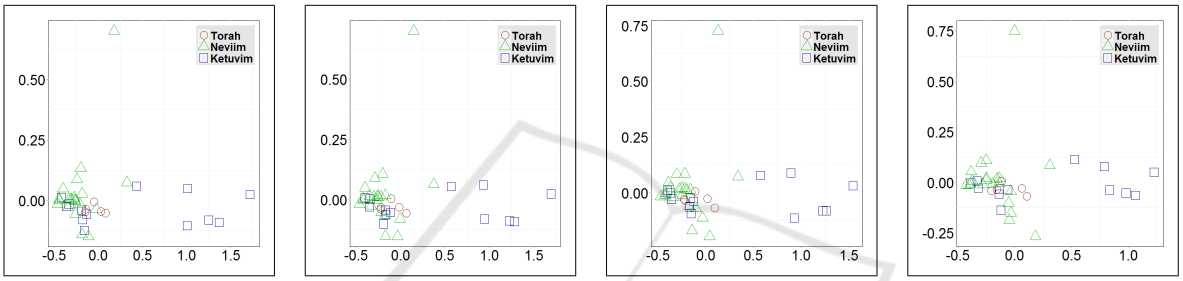
Table 3: Visualization of clustering the entire TNK book suite using Multidimensional Scaling, as each book is assigned its formal TNK-subset legend post projecting onto the displayable embedding space. Shown as a function of a non-descending context window-size, c_w, for both the skip-gram and CBOW neural models.

Skip-gram



$c_w = 5$ $c_w = 15$ $c_w = 25$ $c_w = 50$

CBOW



$c_w = 5$ $c_w = 15$ $c_w = 25$ $c_w = 50$

ters were uniformly set to their defaults, using 5 words for the context window size, c_w. The Torah collection shows Leviticus and Numbers semantically closely related, as Genesis, Exodus, and Deuteronomy are each of some distance apart. Given the Neviim largest number of 21 book samples, clusters appear more statistically sound, with 18 books grouped together and only leaving the books of Habakkuk, Haggai, and Obadiah somewhat disjoint. On the other hand, Ketuvim formed two major clusters with the book of Ecclesiastes close to both, whereas the books of Lamentations and Song of Solomon are notably outliers.

A much broader interest of our work underscores the cluster analysis of a single distance matrix with dimensionality $|T| = 39$ that represents the entire TNK book suite. Through this evaluation, our main objective is to predict unsupervised book clustering and assess its matching to the TNK formal subdivisions. Table 3 shows the clustering produced by applying MDS to the single matrix that captures all-book-pairs semantic similarities, as each book is assigned its formal TNK-subset legend post projecting onto the displayable embedding space. In these experiments, we compared unique word-vector sets generated by each skip-gram and CBOW, as we stepped over the fairly large extent of discrete values prescribed for the context window size, c_w. Expanding the context window scope has a rather mild impact on cluster construction with word vectors trained by the CBOW neural model, however for skip-gram, group formations are considerably susceptible and affected by even a moderate change of c_w. Furthermore, the book partitions we generated under CBOW training persistently resemble the official subdivision of TNK collections, although for visualization in a 2D embedding space, the Torah and Neviim sets do overlap each other.

In our book search experiments, we explored three types of keyphrase queries including fixed verses drawn from a known book and chapter, reordered words of random partial verses distributed uniformly in each of the books of the TNK suite, and randomly selected tokens from the TNK vocabulary composed into a set of keywords that exclude stop words and punctuation marks. Every search is preceded by converting the query composition into a matrix of word vectors and then pairing the query matrix with each of the book hierarchies to compute similarity distances. Thus resulting in a process of linear time complexity, $O(|T|)$. Unless otherwise noted, for the search experiments we used CBOW-based trained word-vectors.

In Table 4, we list search queries of fixed verses and correspondingly enumerate their book origins. Overall, for each of the five verses searched the predicted book title matched the expected label and was

Table 4: Search queries of fixed verses from known books.

Book	Search Query
Psalms	*Fret not thyself because of evil doers*
Esther	*king delight to do honor more than to myself*
Genesis	*his sons buried him in the cave of Machpelah*
Jonah	*go unto Nineveh that great city*
Proverbs	*lips of the wise disperse knowledge*

ranked highest with a score of 1.0. Surprisingly, and without any advanced knowledge, our search uncovered that some of the fixed keyphrases were sourced by unlisted TNK books that equally claimed the top rank. For example, the first verse listed from the book of Psalms, also shows up contiguously and in its entirety to overlap a verse of the Proverbs book (chapter 24, verse 19). Alternately, keyphrase words may extend over chapters non-adjacently and would still be ranked high for relevance in the context of a book search. For instance, the book of Nahum scored high on the keyphrase from the book of Jonah, while having its keywords split to the subsets $\{Nineveh,great\}$ and $\{go,unto,that,city\}$ that appear in chapters 1 and 3, respectively. Figure 7(a) provides visualization to our fixed-verse search results in the form of a confusion matrix, with actual and predicted books listed at the bottom and to the left of the grid, respectively.

In the second search experiment, we selected from each of the TNK books five random samples of partial verses, each with eight unordered context words. We ran a total of $5 \times 39 = 195$ search episodes and constructed a search matrix by computing all directional pairs of query-book distances, and then averaged the score for multiple queries per book. In Figure 7(b), we show our results for the random sub-verse search and demonstrate consistent top ranking for when the source book of the queries matches the predicted book along the confusion matrix diagonal.

Our third task deployed cumulatively a total of 200 searches using a query keyphrase that is a composite of randomly selected tokens from our entire vocabulary, and thus implies a weak contextual relation to any of the TNK books. Distributed non uniformly, our token based keyphrases are evidently biased towards affiliation with books of the largest content. Figure 6 shows non-zero query allocations that result in occupying only a subset of 20 out of 39 books. As a preprocess step, we iterated over the extended search matrix of dimensionality 39×200 and identified the book that is closest to a given query. We followed by averaging the distances in the case of multiple queries per book, and ended up with a reduced search matrix of dimensionality 39×20. Figure 7(c) shows the results of random token search as the straddling bright line along the confusion matrix diagonal highlights our best ranks. In this experiment, expected diverse search-scores span a rather wide range of $[0.15, 0.86]$.

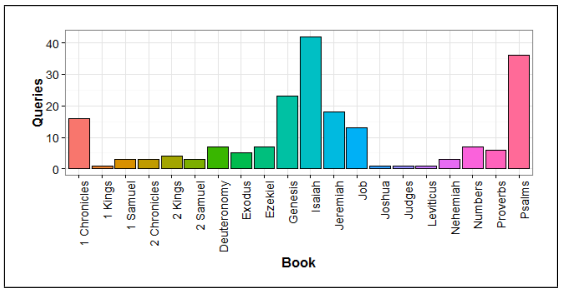


Figure 6: Distribution of queries in random token search, presented across 20 TNK books of the largest content.

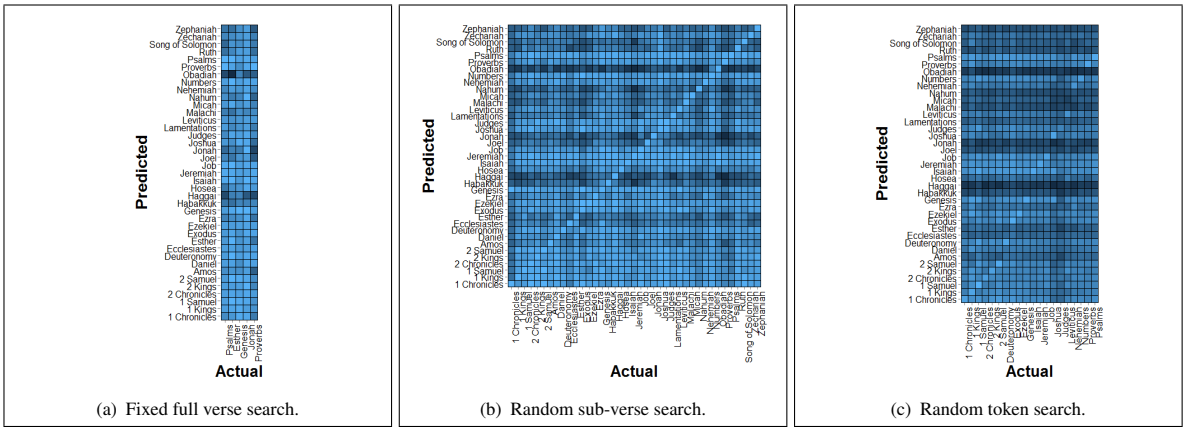
Table 5: Running time for key computational tasks in performing clustering and search. Figures shown in seconds.

Task	Min	Max	Mean	Total
Hierarchy Formation	0.01	1.25	0.29	11.52
Distance Matrix	1.03	107.68	28.01	1,092.62
Keyphrase Query	6.87	11.91	9.73	379.73

In table 5, we list computational runtime of our implementation for key tasks in performing linguistic clustering and search. All reported figures are in seconds and were obtained by running our software single-threaded on a Windows 10 mobile device, with Intel 4th generation Core™ processor at 1.8GHz, and 8GB of memory. Book hierarchy construction is linear with the number of verses per book, and as expected the book of Psalms claimed the slowest to generate the data structure at 1.25 seconds. The distance matrix item shows the time to compute a set of similarities for one book paired with each of the rest of the books in the TNK collection. On average, book-to-book distance derivation amortized across $T = 39$ books takes about 0.72 seconds. Launching a keyphrase query task typically involves a verse-to-book similarity operator that is linear in the total number of verses for the entire book collection. Query response times are shown for each search episode and they remain consistent regardless of the keyphrase originating book, with a small standard deviation of two percent of the mean. The total column of Table 5 further accumulates individual book processing times and is roughly the mean column value multiplied by the number of TNK books, $T = 39$.

6 CONCLUSIONS

In this study, we have demonstrated the apparent potential in a hierarchical representation of word embeddings to conduct effective book level clustering and



(a) Fixed full verse search. (b) Random sub-verse search. (c) Random token search.

Figure 7: Visualization of our search results in the form of confusion matrices for each of the experimental classes: fixed full verse search (a), random sub-verse search (b), and random token search (c).

search. We trained our system on a 39-book bible corpus that comprises a vocabulary of 1.5 million tokens, and generated our own word vectors for each of our experimental choices of model-hyperparameter configurations. We showed that the CBOW neural model outperforms skip-gram for the linguistic tasks we performed, and furthermore, clustering under CBOW proved sustainable to modifying the context window size in a fairly large extent. To evaluate any-pair semantic similarity of both book-to-book and query-to-book, we proposed a simple and generic distance metric between a pair of word vector sets, each of up to tens of thousands elements, that disambiguates non-matching matrix dimensionality. We reported robust empirical results on our tasks for deploying state-of-the-art unsupervised learning of word representations.

At first observation, our hierarchical representation of books might appear greedy storage wise, and rather than a matrix interpretation, we could have resorted to a more compact format by averaging all the verse word vectors and produce a single verse vector. While this approach seems plausible for the clustering tasks to both reduce footprint and streamline computations, the data loss incurred by doing so adversely impacted the performance of our search tasks. To address this shortcoming, our experimental choice of a modest 10-dimensional word vector appears as a reasonable system-design trade-off that aids to circumvent excessive usage of memory space.

To the best of our knowledge and based on literature published to date, we are unaware of semantic analysis systems with similar goals to evenhandedly contrast our results against. The more recent work by Yang *et al.* (2016), proposed a hierarchical attention network for document classification. Their neural model explores attention mechanisms at both a word and sentence levels in an attempt to differentiate content importance when constructing a document vector representation. However, for evaluation their work focuses primarily on topic classification of short user-review snippets. Unlike our system that reasons semantic relatedness between any full length books. On the other hand, Jiang *et al.* (2015) skip the sentence level construct altogether and combine a set of word vectors to directly represent a complete Yelp review. In their report, there is limited exposure to fine-grained control over the underlying neural models to show performance impact on business clustering.

Given that the training of word vectors is a one time process, a natural progression of our work is to optimize the core computations of constructing the distance matrix and performing a keyphrase query. The inherent independence of deriving similarity matrix elements and separating book search rankings, lets us leverage parallel execution, and we expect to reduce our runtime complexity markedly. For a larger number of corpus books, we contend that projecting the distance matrix onto a three-dimensional embedding space is essential to improve cluster perception for analysis. Lastly, we seek to apply our book distance matrix directly to methods that partition objects around medoids (Kaufman and Rousseeuw, 1990) and potentially avoid outliers.

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