A Two Step Process for Generating Sentences from the Sums of their Embeddings

Abstract

Converting a sentence to a meaningful vector representation has uses in many NLP tasks, however very few methods allow that representation to be restored to a human readable sentence. Being able to generate sentences from the vector representations is expected to open up many new applications. We introduce such a method for moving from sum of word embedding representations back to the original sentences. This is done using a greedy algorithm to convert the vector to a bag of words. We then show how the bag of words can be ordered using simple probabilistic language models to get back the sentence. To our knowledge this is the first work to demonstrate qualitatively the ability to reproduce text from a large corpus based on its sentence embeddings. As well as practical applications for sentence generation, the success of this method has theoretical implications on the degree of information maintained by the sum of embeddings representation.

1 Introduction

We present a method for generating sentences based on vector representations of the sum of their word embeddings. The generation task, going from any vector representation back to a sentence, is quite challenging. It has not received a lot of attention.

Dinu and Baroni (2014) motivates this work from a theoretical perspective given that a sentence encodes its meaning, and the vector encodes the same meaning, then it must be possible to translate in both directions between the natural language and the vector representation. An implementation, such as the work reported in this paper, which demonstrates the truth of this dual space theory has its own value. There are also many potential practical applications of such an implementation, often ranging around certain types of "translation" tasks.

There are a number of techniques for learning to associate various media and sentences to a common vector space. Such as Farhadi et al. (2010) and Socher et al. (2014) for images; Kågebäck et al. (2014) and Yogatama et al. (2015) for multi-document summaries, and Zhang et al. (2014) for sentences in multiple languages. However, all of these techniques are tied to being able to use the vector space to compare the sentences and other media for similarities. With appropriate generative models for sentence vectors, these "matching" tasks – that can find the most similar sentence to a vector from a list; become "generative" tasks – that can generate a new sentence.

There are currently three existing methods for sentence regeneration – each tied to different machine learnt vector representations. The current state of the art for full sentence generation are the works of Iyyer et al. (2014) and Bowman et al. (2015). Both these have been demonstrated to produce full sentences – advance beyond the original work in the area of Dinu and Baroni (2014). These sentences are qualitatively shown to be loosely similar in meaning to the original sentences. Neither works has produced quantitative evaluation, making it hard to compare their performance. Both are detailed further in the next section.

The two step method proposed in this paper takes in a sum of word embeddings (SOWE) sentence vector, and outputs the sentence which it corresponds to. The input is a vector for example $\tilde{s} = [0.11, 0.57, -0.21, ..., 1.29]$, which approximates a SOWE vector, and outputs a sentence: for example "The boy was happy.". That input vector

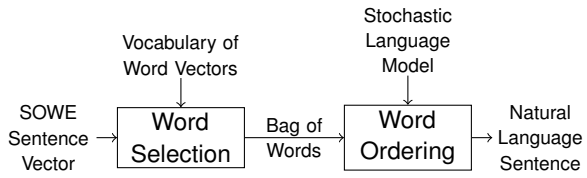

Figure 1: The Two Step process for the regenerating sentences from SOWE-type sentence vectors.

could come direct as the SOWE representation of a reference sentence (as is the case for the evaluation presented here). More practically it could come as the output of some other process; for example a machine learnt mapping from an image to the vector representation of its textual description. This vector representation is transformed through our process into a human readable sentence.

Our method performs the sentence generation in two steps, as shown in Figure 1. It combines the work of White et al. (2016) on generating bags of words (BOW) from SOWE (Word Selection); with the work of Horvat and Byrne (2014) on ordering BOW into sentences (Word ordering). The overall two step approach can generate proper sentences from SOWE vectors.

The rest of the paper is organized into the following sections. Section 2 introduces the area, discussing in general sentence models, and prior work on generation. Section 3 explains the problem in detail and how the Two Step method is used to solving it. Section 4 describes the settings used for evaluation. Section 5 presents the results on this evaluation. The paper concludes with Section 6 and a discussion of future work on this problem.

2 Related Works

2.1 Embedding Models

There are two general types of embedding methods for sentences: compositional, and non-compositional.

Compositional modules use a hierarchical breakdown of a sentence into clauses, phrases and words. Compositional models produce embeddings for each component which is then composed (merged) produce the embeddings for its super component and so forth up the syntactic tree. Compositional models include the works of Mitchell and Lapata (2008), Socher (2014) and Yu and Dredze (2015), and in the generative sense Dinu and Baroni (2014) and Iyyer et al. (2014). They use the inherent structure of the sentence to produce embeddings. This structure is disregarded by most non-compositional models.

Non-compositional models do not combine substructure embeddings to produce a sentence embeddings. This is a wide and varied class. It includes simple methods like the bag of words (BOW), and the sum of word embeddings (SOWE). It also includes the more advanced methods of Le and Mikolov (2014), and the generative method of Bowman et al. (2015). By disregarding structure, there is less indirection in the transfer of information from words vectors to sentence vectors. Even though some information is lost – e.g. all word order in the case of BOW and SOWE – overall they can perform better than the compositional models.

Recently the works of Ritter et al. (2015) and White et al. (2015) found that when classifying sentences into categories according to meaning, simple SOWE outperformed more complex models. Both works used sentence embeddings as the input to classifiers. Ritter et al. (2015) classified challenging artificial sentences into categories based on the positional relationship described using Naïve Bayes. White et al. (2015) classified real-world sentences into groups of semantically equivalent paraphrases. In both cases, they found the best SOWE-type sentence embeddings to be amongst the highest performing representations. In the case of Ritter et al. (2015) it outperformed the next best representation by over 5%. In the case of White et al. (2015) it was within a margin of 1% from the very best performing method. These results suggest there is a lot of consistency in the relationship between a point in the SOWE space, and the meaning of the sentence. Thus this simple method is worth further consideration. SOWE is the basis of the work presented in this paper.

2.2 Sentence Generation from Vector Embeddings

To the best of our knowledge only three prior works exist in the area of sentence generation from embeddings. The first two of which are based on compositional embeddings, while the most recent work at the time of this writing, is based on a non-compositional approach.

Dinu and Baroni (2014) extends the models described by Zanzotto et al. (2010) and Guevara (2010) for generation. The composition is described as the sum of pair of linear transformations of the input word vectors to get a output vector, and another pair to reverse the composition reconstructing the input. The linear transformation matrices are solved for using least squares. This method of composing, can be applied recursively from words to phrases to clauses and so forth. It theoretically generalises to whole sentences, by recursive application of the composition or decomposition functions, however in Dinu and Baroni's work is quantitatively assessed only on direct reconstruction for decomposing Preposition-Noun and Adjective-Noun 2 word phrases. In the case where the decomposition function was trained on vectors generated using the compositional function they were able to get perfect reconstruction on the word embedding based inputs.

The work of Iyyer et al. (2014) extends the work of Socher et al. (2011) defining an unfolding recursive dependency-tree recursive autoencoder (DT-RAE). Recursive neural networks are jointly trained for both composing the sentence's words into a vector, and for decomposing that vector into words. This composition and decomposition is done by reusing a composition neural network at each vertex, the dependency tree structure with different weight matrices for each dependency relation. The total network is trained based on the accuracy to reproduce its input word vectors, through back-propagation. It can be used to generate sentences, if a dependency tree structure for the output is provided. This method was demonstrated quantitatively on five examples (shown in Table 3); they found generated sentences to be loosely semantically similar to the originals.

Bowman et al. (2015) uses a a modification of the variational autoencoder (VAE) (Kingma and Welling, 2013) with natural language inputs and outputs, to learn the sentence representations. These input and output stages are performed using long short-term memory recurrent neural networks (Hochreiter and Schmidhuber, 1997). They demonstrate a number of uses of this technique, only one of which is sentence generation, in the sense of this paper. While it is a generative model it does not seek to recreate a sentence purely from its vector input, but rather to produce a series of probability distributions on the words in the sentence. These distributions can be evaluated greedily, which the authors used to give three quantitative examples of resynthesis (also shown in Table 4). They found the sentence embeddings created were storing largely syntactic and loose topical information.

None of the existing methods have demonstrated recreation of the full sentence input close enough to allow for quantitative evaluation on a full corpus. They tend to output lose paraphrases, or roughly similar sentences – itself a separately useful achievement. That is not the case for our method described in the next section, which can often exactly recreate the original sentence from its vector representation.

Unlike current sentence generation methods, the BOW generation method of White et al. (2016) generally outputs a BOW very close to the reference for that sentence – albeit at the cost of loosing all word order information. It is because of this accuracy that we base our method on it (as detailed in Section 3.1). The Word Selection step we used is directly based on their greedy BOW generation method. We improve it for sentence generation by composing with a word ordering step to create the two step sentence generation process.

3 General Framework: Two Step Generation

As discussed in Section 1, and shown in Figure 1, the approach taken to generate the sentences from the vectors comes in two steps. First selecting the words used – this is done deterministically, based on a search of the embedding space. Second is to order them, which we solve by finding the most likely sequence according to a stochastic language model. The separating of the process into two steps is unlike any of the existing methods for sentence generation from vectors. The two subproblems which result from this split resemble more classical NP-Hard computer science problems; thus variations on known techniques can be used to solve them.

3.1 Word Selection

White et al. (2016) solves the BOW generation problem, by solving what they call the vector selection problem – selecting the vectors that sum up closest to a given vectors. This is related to the knapsack

and subset sum problems. They formally define the vector selection problem as:

$$(\tilde{s}, \mathcal{V}, d) \mapsto \underset{\{\forall \tilde{c} \in \mathbb{N}_0^V\}}{\operatorname{argmin}} d(\tilde{s}, \sum_{\tilde{x}_j \in \mathcal{V}} \tilde{x}_j c_j)$$

to find the bag of vectors selected from the vocabulary set $\mathcal{V}$ which when summed is closest to the target vector $\tilde{s}$. Closeness is assessed with distance metric d. $\tilde{c}$ is the indicator function for that multi-set of vectors. As there is a one to one correspondence between word embeddings and their words, finding the vectors results in finding the words. White et al. (2016) propose a greedy solution to the problem.

The key approach proposed by White et al. (2016) is greedy addition. The idea is to greedy add vectors to a partial solution building towards a complete bag. This starts with an empty bag of word embeddings, and at each step the embedding space is searched for the vector which when added to the current partial solution results in the minimal distance to the target – when compared to other vectors from the vocabulary. This step is repeated until there are no vectors in the vocabulary that can be added without moving away from the solution. Then a fine-tuning step, n-substitution, is used to avoid some simpler greedy mistakes.

The n-substitution method avoids mistakes by examining partial solutions (bags of vectors) and seeing if it is possible to find a better solution by removing n elements and replacing them with up-to n different elements. The replacement search is exhaustive over the n-ary cartesian product of the vocabulary. Only for $n = 1$ is it currently feasible for practical implementation outside of highly restricted vocabularies. Never-the-less even 1-substitution can be seen as lessening the greed of the algorithm, though allowing early decisions (of which vectors to being include) to be reconsidered in the full context of the partial solution. The algorithm does remain greedy, but many simple mistakes are avoided by n-substitution. The greedy addition and n-substitution processes are repeated until the solution converges.

3.2 The Ordering Problem

After the bag of words has been generated by the previous step, it must be ordered. For example “are how , today hello ? you”, is to be ordered into the sentence: “hello , how are you today ?”. This problem can not always be solved to a single correct solution. Mitchell and Lapata (2008) gives the example of "It was not the sales manager who hit the bottle that day, but the office worker with the serious drinking problem." which has the same word content (though not punctuation) as "That day the office manager, who was drinking, hit the problem sales worker with a bottle, but it was not serious.". However, while a unique ordering can not be guaranteed, finding the most likely word ordering is possible.

Horvat and Byrne (2014) formulated the word ordering problem an a generalised asymmetrical travelling salesman problem (GA-TSP). Figure 2 shows an example of the connected graph for ordering five words. We extend beyond the approach of Horvat and Byrne (2014) by reformulated the problem as a linear mixed integer programming problem (MIP). This lets us take advantage of the efficient existing solvers for this problem. Beyond the GA-TSP approach, direct MIP formulation allows for increased descriptive flexibility and opens the way for further enhancement. The description is freed of some of the constraints of a TSP. For example, word ordering does have distinct and known start and end nodes (as shall be detailed in the next section). To formulate it as a GA-TSP it must be a tour without beginning or end. Horvat and Byrne (2014) solve this by simply connecting the start to the end with a zero cost link. This is not needed if formulating as a MIP problem, the start and end nodes can be treated as a special case. Being able to special case them as nodes known always to occur allows some simplification in the subtour elimination step (as will follow). The formulation to mixed integer programming is otherwise reasonably standard.

3.2.1 Notation

The following notion is used:

For $\mathcal{W}$ the bag of words to be ordered, including the start ($w_{\blacktriangleright}$,$w_{\triangleright}$) and end pseudo-words.($w_{\triangleleft}$, $w_{\blacktriangleleft}$)

We will write $w_i \in \mathcal{W}$ to represent a word from the bag, with arbitrarily assigned subscripts. Where a word occurs with multiplicity greater than 1, it is assigned multiple subscripts, and each is treated as a distinct word.

Each vertex is a sequence of two words, $\langle w_i, w_j \rangle \in \mathcal{W}^2$. This is a Markov state, consisting of a word and its predecessor word.

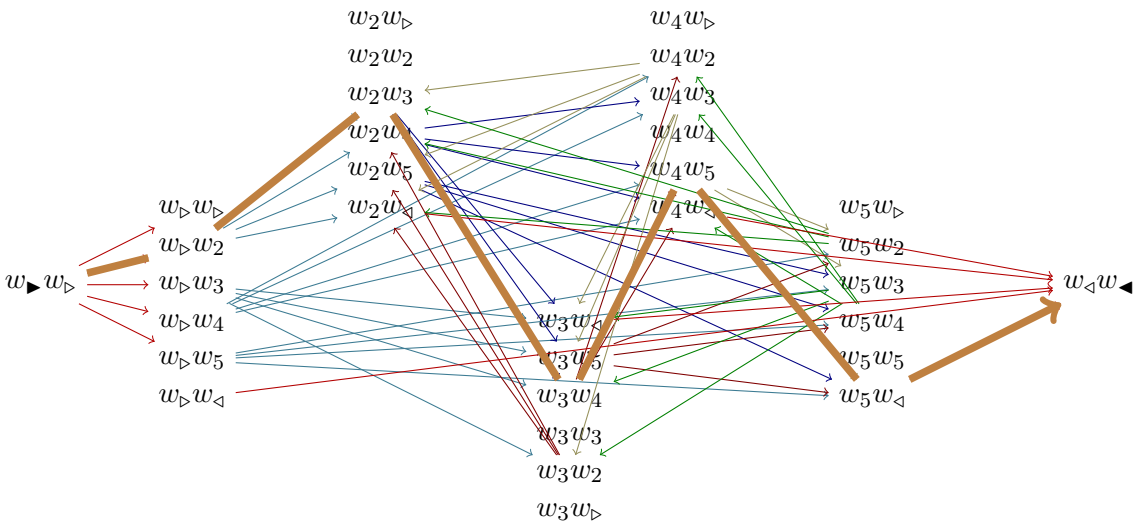

Figure 2: A graph showing the legal transitions between states, when the word-ordering problem is expressed similar to a GA-TSP. Each edge $(w_aw_b) \to (w_bw_c)$ has cost $-\log(P(w_c \mid w_aw_b)$. The nodes are grouped into columns for each district (word). In bold is shown one legal path which goes from beginning, to end, and covers all districts (words).

Each edge between two vertices represents a transition from one trigram state to another. The Start vertex is given by $\langle w_{\blacktriangleright}, w_{\triangleright}\rangle$, and the end by $\langle w_{\triangleleft}, w_{\blacktriangleleft}\rangle$.

The GA-TSP districts are given by the sets of all states that have a given word in the second position. The district for word w_j is given by $S(w_j) \subseteq \mathcal{W}^2$, defined as $S(w_j) = \{\langle w_i, w_j\rangle \mid w_i \neq w_j \wedge w_i \in \mathcal{W}\}$. It is required to visit every district, thus it is required to use every word.

3.2.2 Optimization Model

The path and its costs are modelled by:

A transition from $\langle w_i, w_j\rangle$ to $\langle w_j, w_k\rangle$ transitions has cost

$$C[\langle w_i, w_j\rangle, \langle w_j, w_k\rangle] = -\log\left(P(w_k|w_i, w_j\rangle\right)$$

The table of transitions to be optimized is

$$\tau[\langle w_a, w_b\rangle,\ \langle w_c, w_d\rangle] = \begin{cases} 1 & \text{if transition from } \langle w_a, w_b\rangle \to \langle w_c, w_d\rangle \text{ occurs} \\ 0 & \text{otherwise} \end{cases}$$

The total cost to be minimized, is given by

$$C_{total}(\tau) = \sum_{\forall[\langle w_a,w_b\rangle,\langle w_c,w_d\rangle]\in(\mathcal{W}^2)^2} \tau[\langle w_a, w_b\rangle,\ \langle w_c, w_d\rangle]\cdot C[\langle w_a, w_b\rangle,\ \langle w_c, w_d\rangle]$$

The probability of a particular path (i.e. of a particular ordering) is thus given by

$$P(\tau) = e^{-C_{total}(\tau)}$$

The word order can be found by following the links. The function $f(n, \tau)$ gives the word that, according to τ occurs in the nth position.

$$f(n,\tau) = \begin{cases} \{w_a \mid \tau[\langle w_{\blacktriangleright}, w_{\triangleright}\rangle, \langle w_{\triangleright}, w_a\rangle] = 1\}_1 & n = 1 \\ \{w_b \mid \tau[\langle w_{\triangleright}, f(1,\tau)\rangle, \langle f(1,\tau), w_b\rangle] = 1\}_1 & n = 2 \\ \{w_c \mid \tau[\langle f(n-2,\tau), f(n-1,\tau)\rangle, \langle f(n-1,\tau), w_c\rangle] = 1\}_1 & n \geq 3 \end{cases}$$

Note that if τ follows the constraints that follow then valid then, then each set is a singleton, $\{\}_1$ indicates taking the singleton set's only element.

3.2.3 Constraints

The requirements of the problem, place various constraints on to τ:

The Markov state must be maintained: $\forall\langle w_a, w_b\rangle, \langle w_c, w_b\rangle \in \mathcal{W}^2$:

$$w_b \neq w_c \implies \tau[\langle w_a, w_b\rangle, \langle w_c, w_d\rangle] = 0$$

Every node entered must also be left – except those at the beginning and end.

$$\forall\langle w_i, w_j\rangle \in \mathcal{W}^2 \backslash \{\langle w_\blacktriangleright, w_\triangleright\rangle, \langle w_\triangleleft, w_\blacktriangleleft\rangle\} :$$
$$\sum_{\forall\langle w_a, w_b\rangle \in \mathcal{W}^2} \tau[\langle w_a, w_b\rangle, \langle w_i, w_j\rangle] = \sum_{\forall\langle w_c, w_d\rangle \in \mathcal{W}^2} \tau[\langle w_i, w_j\rangle, \langle w_c, w_d\rangle]$$

Visit (enter) every district exactly once. i.e. use every word exactly once.

$$\forall w_j \in \mathcal{W} \backslash \{w_\blacktriangleright, w_\triangleright\} :$$
$$\sum_{\substack{\forall\langle w_i, w_j\rangle \in S(w_j) \\ \forall\langle w_a, w_b\rangle \in \mathcal{W}^2}} \sum \tau[\langle w_a, w_b\rangle, \langle w_i, w_j\rangle] = 1$$

To allow the feasibility checker to detect if ordering the words is impossible, transitions of zero probability are also forbidden. i.e. if $P(w_n|w_{n-2}, w_{n-1}) = 0$ then $\tau[\langle w_{n-2}, w_{n-1}\rangle, \langle w_{n-1}, w_n\rangle] = 0$. These transitions, if not expressly forbidden, would never occur in an optimal solution in any case, as they have infinitely high cost.

Lazy Subtour Elimination Constraints The problem as formulated above can be input into the MIPS solver. However, like similar formulation of the travelling salesman problem, some some solutions will have subtours. We take the usual method for handling this an use callbacks to impose lazy constraints to forbid such solutions at run-time. However the actual formulation of those constraints are different to a typical GA-TSP.

Given a potential solution τ meeting all other constraints:

- The core path – which starts at the beginning $\langle w_\blacktriangleright, w_\triangleright\rangle$ and ends at $\langle w_\triangleleft, w_\blacktriangleleft\rangle$the end can be found. This is done by practically following the links from the start node, and accumulating them into a set $T \subseteq \mathcal{W}^2$
- From the core path, the set of words covered is given by $\mathcal{W}_T = \{w_i \mid \forall\langle w_i, w_j\rangle \in T\} \cup \{w_\blacktriangleleft\}$. If $\mathcal{W}_\mathcal{T} = \mathcal{W}$ then there are no subtours and the core-path is the full. Otherwise, there is a subtour to be eliminated.
- If there is a subtour, then to eliminate it, a constraint must be added. This constraint is that there must be a connection from at least one of the nodes in the district covered by the core path to one of the nodes in the districts not covered.
- The districts covered by the tour are given by $S_T = \bigcup_{w_t \in W_T} S(w_t)$,
- subtour elimination constraint is given by

$$\sum_{\substack{\forall\langle w_{t1}, w_{t2}\rangle \in S_T \\ \forall\langle w_a, w_b\rangle \in \mathcal{W}^2 \backslash S_T}} \sum \tau[\langle w_{t1}, w_{t2}\rangle, \langle w_a, w_b\rangle] \geq 1$$

- i.e. There must be a transition from one of the states featuring a word that is in the core path, to one of the states featuring a word not converted by the core path.

It is the formulation around the notion of a core-path that differs this from typical subtour elimination in a GA-TSP. True GA-TSP problems are not guaranteed to have any nodes which must occur. However every word ordering problem is guaranteed to have such a node – the start and end nodes. This thus makes it possible to identify what is generally the path that requires the least modification to get to a complete solution, as the path to require changes on. Other heuristics, and subtour elimination constraints do exist however.

4 Experimental Setup and Evaluations

This experimental data used in this evaluation was obtained from the data released with .

4.1 Word Embeddings

GloVe representations of words are used in our evaluations (Pennington et al., 2014). There are many varieties of word embeddings which function with our algorithm. GloVe was chosen simply become of the availability of a large pre-trained vocabulary of vectors. The representations used for evaluation were pretrained on pre-trained on 2014 Wikipedia and Gigaword 5[1]. Other vector representations are presumed to function similarly.

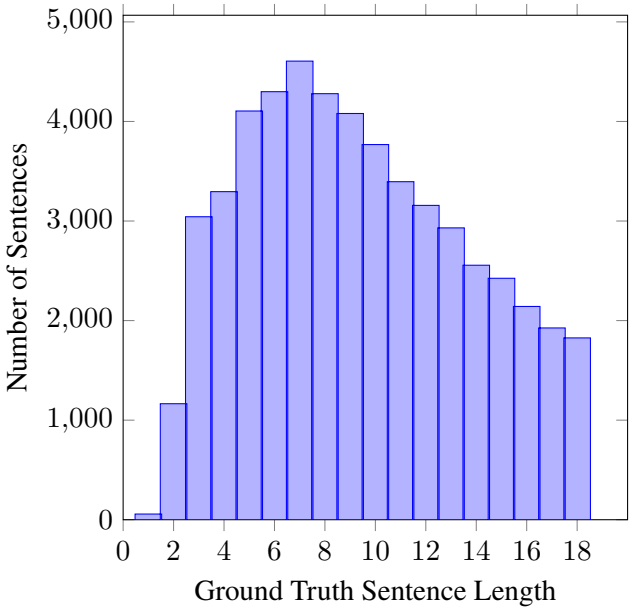

Figure 3: the distribution of the evaluation corpus after preprocessing.

Process	Portion Perfect	Mean Precision	Mean Jaccard Score
Word Selection	75.6%	0.912	0.891

Table 1: The performance of the word selection step, on the Books corpus. Note that the performance of the word selection step, bounds the overall performance shown in Table 2. This table shows a subset of the results reported by White et al. (2016).

Process	Portion Perfect	BLEU Score	Portion Feasible
Ordering Only	66.6%	0.806	99.6%
Two Step	62.2%	0.745	93.7%

Table 2: The overall performance of the Two Step sentence generation process when evaluated on the Books corpus. The Input column indicates whether the bag of words input to the ordering step was generated using the word selection process, or if it was provided an by an Oracle word sector.

4.2 Corpus

The evaluation was performed on a subset of the Books Corpus (Zhu et al., 2015). The corpus was preprocessed as per in the work of White et al. (2016). This meant removing any sentences which use words not found in the embedding vocabulary.

After preprocessing, the base corpus, was split 90:10. 90% (59,694,016 sentences) of the corpus was used to find a trigram model. The remaining 10% of the corpus was kept in reserve. From the 10%, 1% (66,464 sentences) were taken for testing. From this any sentences with length over 18 words were discarded – the time taken to evaluated longer sentences is too long to be feasible. This left a final test set of 53,055 sentences. Figure 3 shows the distribution of the evaluation corpus in terms of sentence length.

Note that the books corpus contains many duplicate common sentences, as well as many duplicate books: according to the distribution site [2] only 7,087 out of 11,038 original books in the corpus are unique. We did not perform any further deduplication, which means there is a strong chance of a small overlap between the test set, and the set used to fit the trigrams.

4.3 Mixed Integer Programming

During evaluation we used Gurobi MIP solver version 6.5.0. During preliminary testing we found Gurobi to be significantly faster than the open source GLTK. Particularly for longer sentences, we found two orders of magnitude difference in speed for sentences of length 18. This is inline with the more extensive evaluations of Meindl and Templ (2012). It was run under default settings, other than being restricted to a single thread. Restricting the solver to a single thread allowed for parallel processing.

Processing was done on a 12 core AMD Opteron 6300 virtual machine with 45Gb of RAM. Implementation was done in the Julia programming language (Bezanson et al., 2014). The MIP solver was invoked though the JuMP library (Lubin and Dunning, 2015). The implementation, and non-summarised results are available for download online.[3]

5 Results and Discussion

The overall results the Two Step sentence generation are shown in Table 2. It includes further break down showing the Ordering step only results. Table 1 shows

[1]Kindly made available online at `http://nlp.stanford.edu/projects/glove/`

[2]`http://www.cs.toronto.edu/~mbweb/`

[3][[URL Blinded for Review]]

		Sel.	Ord.
3A Reference	name this 1922 novel about leopold bloom written by james joyce .		
Ref. BOW+Ord.	written by name this . novel about 1922 bloom leopold james joyce	–	✖
Sel. BOW+Ord.	written novel by name james about leopold this bloom 1922 joyce .	✓	✖
DT-RAE Ref.	name this 1906 novel about gottlieb_fecknoe inspired by james_joyce		
DT-RAE Para.	what is this william golding novel by its written writer		
3B Reference	ralph waldo emerson dismissed this poet as the jingle man and james russell lowell called him three-fifths genius and two-fifths sheer fudge .	**Sel.**	**Ord.**
Ref. BOW+Ord.	sheer this as james two-fifths emerson fudge lowell poet genius waldo called russell the and ralph and him . dismissed jingle three-fifths man	–	✖
Sel. BOW+Ord.	him " james great as emerson genius ralph the lowell and sheer waldo three-fifths man fudge dismissed jingle russell two-fifths and gwalchmai 2009 vice-versa _____ prominent called 21.25 explained	✗	✖
DT-RAE Ref.	henry_david_thoreau rejected this author like the tsar boat and imbalance created known good writing and his own death		
DT-RAE Para.	henry_david_thoreau rejected him through their stories to go money well inspired stories to write as her writing		
3C Reference	this is the basis of a comedy of manners first performed in 1892 .	**Sel.**	**Ord.**
Ref. BOW+Ord.	this is the basis of a comedy of manners first performed in 1892 .	–	✓
Sel. BOW+Ord.	this is the basis of a comedy of manners first performed in 1892 .	✓	✓
DT-RAE Ref.	another is the subject of this trilogy of romance most performed in 1874		
DT-RAE Para.	subject of drama from him about romance		
3D Reference	in a third novel a sailor abandons the patna and meets marlow who in another novel meets kurtz in the congo .	**Sel.**	**Ord.**
Ref. BOW+Ord.	kurtz and another meets sailor meets the marlow who abandons a third novel in a novel in the congo in patna .	–	✗
Sel. BOW+Ord.	kurtz and another meets sailor meets the marlow who abandons a third novel in a novel in the congo in patna .	✓	✗
DT-RAE Ref.	during the short book the lady seduces the family and meets cousin he in a novel dies sister from the mr.		
DT-RAE Para.	during book of its author young lady seduces the family to marry old suicide while i marries himself in marriage		
3E Reference	thus she leaves her husband and child for aleksei vronsky but all ends sadly when she leaps in front of a train .	**Sel.**	**Ord.**
Ref. BOW+Ord.	train front of child vronsky but and for leaps thus sadly all her she she in when aleksei husband ends a . leaves	–	✖
Sel. BOW+Ord.	she her all when child for leaves front but and train ends husband aleksei leaps of vronsky in a sadly micro-history thus , she the	✗	✖
DT-RAE Ref.	however she leaves her sister and daughter from former fianc and she ends unfortunately when narrator drives into life of a house		
DT-RAE Para.	leaves the sister of man in this novel		

Table 3: A comparison of the output of the Two Step process proposed in this paper, to the example sentences generated by the method of Iyyer et al. (2014). Ref. BOW+Ord. shows the word ordering step on the reference BOW. the Sel. and Ord. columns indicate if the output had the correct words selected, and ordered respectively. ✖ indicates not only that ordering was not correct, but that the MIP problem had no feasible solutions at all. In DT-RAE Ref. is shown the result of the method of Iyyer et al. (2014), when the dependency tree of the output is provided to the generating process. Where-as in DT-RAE Para. an arbitrary dependency tree of the is provided to the generating process.Note that the reference used as input to Sel. BOW+Ord. and Ref. BOW+Ord. sentence was varied slightly from that used in Iyyer et al. (2014) and from White et al. (2016), in that punctuation was not removed, and multiword entity references were not grouped into single tokens.

		Sel.	Ord.
4A Reference	we looked out at the setting sun .	**Sel.**	**Ord.**
Ref. BOW+Ord.	we looked out at the setting sun .	–	✓
Sel. BOW+Ord.	we looked out at the setting sun .	✓	✓
VAE Mean	they were laughing at the same time .		
VAE Sample1	ill see you in the early morning .		
VAE Sample2	i looked up at the blue sky .		
VAE Sample3	it was down on the dance floor .		
4B Reference	i went to the kitchen .	**Sel.**	**Ord.**
Ref. BOW+Ord.	i went to the kitchen .	–	✓
Sel. BOW+Ord.	i went to the kitchen .	✓	✓
VAE Mean	i went to the kitchen .		
VAE Sample1	i went to my apartment .		
VAE Sample2	i looked around the room .		
VAE Sample3	i turned back to the table .		
4C Reference	how are you doing ?	**Sel.**	**Ord.**
Ref. BOW+Ord.	how are you doing ?	–	✓
Sel. BOW+Ord.	how 're do well ?	✗	✗
VAE Mean	what are you doing ?		
VAE Sample1	are you sure ?		
VAE Sample2	what are you doing, ?		
VAE Sample3	what are you doing ?		

Table 4: A comparison of the output of the Two Step process proposed in this paper, to the example sentences generated by the method of Bowman et al. (2015). Ref. BOW+Ord. shows the word ordering step on the reference BOW. the Sel. and Ord. columns indicate if the output had the correct words selected, and ordered respectively. VAE Sample performs the decoding from a sample from the posterior distribution.

		Sel.	Ord.
5A Reference	it was the worst of times , it was the best of times .	**Sel.**	**Ord.**
Ref. BOW+Ord.	it was the worst of times , it was the best of times .	–	✓
Sel. BOW+Ord.	it was the best of times , it was the worst of times .	✓	✗
5B Reference	please give me directions from paris to london .	**Sel.**	**Ord.**
Ref. BOW+Ord.	please give me directions to london from paris .	–	✗
Sel. BOW+Ord.	please give me directions to london from paris .	✓	✗

Table 5: A pair of example sentences, where the correct order is particularly ambiguous. Ref. BOW+Ord. shows the word ordering step on the reference BOW. the Sel. and Ord. columns indicate if the output had the correct words selected, and ordered respectively

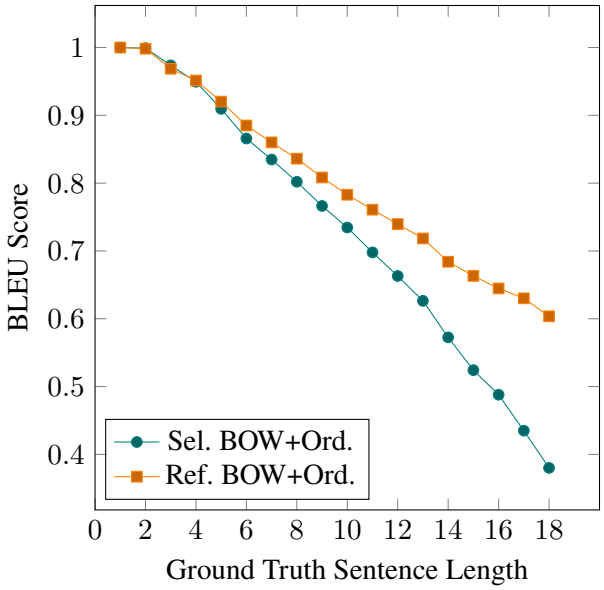

Figure 4: the BLEU score of the entire two step process, vs just the ordering step (with reference BOW).

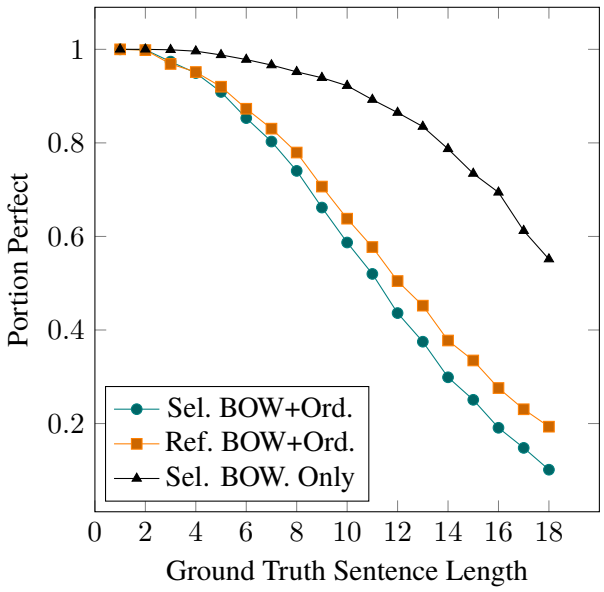

Figure 5: The portion of sentences reconstructed perfectly by the Two Step process. Shown also is the results on ordering only, which orders the reference BOWS, and the results from the Word Selection Step only (the input to the ordering step).

the results for the Word Selection step only. Both these results place an upper bound on the performance of the overall. The Ordering step only results show the best performance the ordering step can attain if given the reference BOW. The Word Selection results bound the over accuracy as no matter how good the word ordering method is, it can not recreate perfectly accurate sentences with imperfect words.

It can be noted that the ordering step results, and indeed the overall two step results were significantly better than the best results reported by Horvat and Byrne (2014), on any dataset. We attribute this to Horvat and Byrne preprocessing the evaluation corpora to remove the easy sentences of with 4 or less words. We did not remove short sentences from the corpus. The performance on these sentences was very high, thus bring up the overall results on ordering.

The resynthesis of the two step process degrades as the sentence length increases. It can be seen from the Figure 5 that this is more significantly due to errors in the Ordering step, than in the selection step. Though the selection failures are responsible for the drop in performance of the Two Step processes below that of the Word Order of the reference sentences. The drop due to failed selection is much smaller than drop off, which indicated that many of the sentences which failed the word selection step, also would have failed the ordering step even if the words were perfectly selected.

The method is shown to be able to often exactly reproduce sentences based on their embeddings. Due to its exact and near exact resynthesis of whole sentences it is possible to assess it on a whole corpus, rather than having to demonstrate it only on a few examples. For comparison, results on the examples from Iyyer et al. (2014) and Bowman et al. (2015) are shown in Table 3 and Table 4 respectively. Table 5 shows two new examples.

The examples shown in Table 5 highlight sentences where the order is ambiguous. In both cases the Word Selection performs perfectly, but the ordering is varied. In the first example, the Ordering only output sentence and the overall Two Step sentence differ. This is because under the trigram language model both sentences have exactly identical probabilities, so it comes to which solution is found first. In the second the word order is switched – “from paris to london” vs “to London from paris”, which has the

same meaning. But, it could also reasonably have switch to “from london to paris”. In cases like this where two orderings are reasonable, the ordering method is certain to fail consistently for one of the orderings. Though it is possible to output the second (and third etc.) most probable ordering, which does ameliorate the failure somewhat.

The sentences in Table 3 are difficult. Of the five only two have a valid ordering found during the word ordering step – one of which was perfect, and the other of is garbled. Of the three failures, two had imperfections in the during the word selection step. The other fails only in ordering. Part of the difficulty in ordering these sentences can be associated with the large number of proper nouns – which are very sparse in any training corpus for language modelling. The large portion of the difficultly though can be attributed to length.

The sentences in Table 4, are short and easy to resynthesis. Of the three there were two exact match's and one near match. The near match in interesting, as it is not commonly produced by the Two Step process. In the near mean instead of "How are you doing ?" the sentence "How 're do well ?" was produced, this in interesting as normally mistakes in the word selection step result in an unorderable sentence. This sentence while garbled does convey the original meaning, however we attribute this ultimately to coincidence. The rigidity which allows for the exact reproduction is a limitation, where failures are likely to be ungrammatical e.g. missing conjunctions – which would cause finding a reasonable ordering to be impossible. This is not a problem for the methods of Iyyer et al. (2014) or Bowman et al. (2015).

Iyyer et al. (2014) guarantees grammatical correctness, as the syntax tree must be provided at an input for resynthesis. Bowman et al. (2015) on the other hand integrates the language model with the sentence embedding so that every point in the vector space includes information about word order. In general, it seems clear that incorporating knowledge about order, or at least co-occurrence probabilities, should be certain to improve the selection step. The simplicity of the two step approach, and capacity to get exact reproductions are clear.

6 Conclusion

A two step method was presented for how to regenerate sentences, from the sum of a sentence's word embeddings.

The first part of the two step method was the word selection problem, of going from the sum of embeddings to a bag of words. To solve this we utilised the method presented in White et al. (2016). White et. al. presented a greedy algorithm that was found to perform well at regenerating BOW. We extended that method with a second step, to order the words.

Word ordering was carried out by defining a task of finding the most likely sequence of trigrams. This was expressed as a MIP problem. This method was an extension to the work of Horvat and Byrne (2014), which expressed the word ordering problem as a GA-TSP. It was demonstrated that a probabilistic language model can be used to order the bag of words output to regenerate the original sentences; though it is certainly impossible to do this perfectly in every case, for many sentences the most likely ordering is correct.

Resynthesis degraded as sentence length increased. White et al. (2016) showed that the word selection degrades with sentence length, and improves with higher dimensional embeddings. Due to their findings, we only evaluated embeddings of 300 dimensions. It was found as expected that the accuracy of ordering also decreases, but remained strong with higher dimensional models up to reasonable length. The technique was only evaluated on sentences with up to 18 words (inclusive), due to computational time limitations. On these it performed quite well achieving perfect recreation in 62.2% of cases. This is to the authors knowledge the first method to report exact recreation of a substantive corpus. Performances, both accuracy and running time worsens as longer sentences were considered. With that said, short sentences are sufficient for many practical uses.

From a theoretical basis the resolvability of the selection problem shows that adding up the word vectors does preserve the information on which words were used; particularly for higher dimensional embeddings. This shows clearly that collisions do not occur (at least with frequency) such that two unrelated sentences do not end up with the same SOWE

representation.

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