Lexical Coherence Graph Modeling Using Word Embeddings

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Abstract

Coherence is established by semantic connections between sentences of a text which can be modeled by lexical relations. In this paper, we introduce the lexical coherence graph (LCG), a new graph-based model to represent lexical relations among sentences. The frequency of subgraphs (coherence patterns) of this graph captures the connectivity style of sentence nodes in this graph. The coherence of a text is encoded by a vector of these frequencies. We evaluate the LCG model on the readability ranking task. The results of the experiments show that the LCG model obtains higher accuracy than state-of-the-art coherence models. Using larger subgraphs yields higher accuracy, because they capture more structural information. However, larger subgraphs can be sparse. We adapt Kneser-Ney smoothing to smooth subgraphs' frequencies. Smoothing improves performance.

1 Introduction

The concept of coherence is based on cohesive semantic relations connecting elements of a text. Cohesive relations are expressed through grammar and the vocabulary of a language. The former is referred to as *grammatical coherence*, the latter as *lexical coherence* (Halliday and Hasan, 1976). Grammatical coherence encompasses coreference, substitution, ellipsis, etc. Lexical coherence comprises semantic connections among words of a text.

In this paper we measure text coherence by modeling *lexical coherence*. Lexical relations specify cohesive relations over the sentences of a text. These lexical relations can be any kind of semantic relation: repetition, synonymy, hyperonymy, meronymy, etc. These lexical items may or may not have the same reference (Halliday and Hasan, 1976).

> *Why does the little boy wriggle all the time? Girls don't.*

In this example the lexical items *boy* and *girls* are semantically related. Although they do not refer to the same entity, they still connect these two sentences.

There is coherence between any pair of lexical items that stand to each other in some lexico-semantic relation (Halliday and Hasan, 1976). For textual purposes it is not required to determine the type of the relation. It is only necessary to recognize semantically related lexical items, and these relations can be learned by cooccurring lexical items.

One can use world knowledge resources to determine semantic relations. This way is expensive in terms of determining the best resource, e.g. WordNet vs. Freebase. WordNet lacks broad coverage in particular with proper names, Freebase is restricted to nominal concepts and entities.

Recent improvements in embedding representations of words let us efficiently compute semantic relations among lexical items in the vector space. These models use a vector of numbers to encode the meaning of words. We use these vectors to check the existence of any kind of semantic relations between two words.

In the following example the sentences are connected because of the semantic relation between *king* and *queen* which can be induced by word em-

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bedding models (Mikolov et al., 2013; Pennington et al., 2014).

> *. . . The king was in his counting-house,*
> *counting out his money,*
> *The queen was in the parlour, eating bread*
> *and honey.*

We model lexical coherence between sentences by a lexical coherence graph (LCG). We consider subgraphs of this graph coherence patterns and use their frequency as features representing the connectivity of the graph and, hence, the coherence of a text (Mesgar and Strube, 2015).

An important task for evaluating a coherence model is readability assessment. The goal of this task is to rate texts based on their readability. The more coherent a text, the faster to read and easier to understand it is. Other coherence models (Barzilay and Lapata, 2008; Guinaudeau and Strube, 2013; Mesgar and Strube, 2014) are also evaluated on this task. Pitler and Nenkova (2008) use the entity grid (Barzilay and Lapata, 2008) to capture the coherence of a text for readability assessment. Mesgar and Strube (2015) extend the entity graph (Guinaudeau and Strube, 2013) as coherence model to measure the readability of texts. They encode coherence as a vector of frequencies of subgraphs of the graph representation of a text. We build upon their method and represent the connectivity of sentences in our LCG model by a vector of frequencies of subgraphs.

Although using the frequency of subgraphs of the lexical coherence graph encodes coherence features well, the subgraph frequency method, in general, is suffering from a sparsity problem when the subgraphs get larger. Large subgraphs capture more structural information, but they occur only rarely. We resolve this sparsity issue by adapting Kneser-Ney smoothing (Heafield et al., 2013) to smooth subgraph counts (Section 3). We estimate the probability of unseen subgraphs, i.e. coherence patterns. This prediction lets us measure the coherence of a text even when its corresponding graph representation contains a subgraph which does not occur in the training data. If the unseen coherence pattern is similar to seen ones, smoothing gives it closer probability to seen coherence patterns in comparison to dissimilar unseen ones. This is due to the base probability factor in Kneser-Ney smoothing.

We evaluate our LCG model on the two readability datasets provided by Pitler and Nenkova (2008) and De Clercq et al. (2014), respectively (Section 4). The results (Section 5) indicate that the LCG model outperforms state-of-the-art systems. By applying Kneser-Ney smoothing we solve the sparsity problem. Smoothing allows us to exploit the high informativity of large subgraphs which leads to new state-of-the-art results in readability assessment.

2 Related Work

The entity grid model (Barzilay and Lapata, 2008) is based on entity transitions over sentences. It uses a two dimensional matrix to represent transitions of entities among adjacent sentences. The entity grid is applied to readability assessment by Pitler and Nenkova (2008). The entity graph (Guinaudeau and Strube, 2013) is a graph-based, mainly unsupervised interpretation of the entity grid. This model represents the distribution of entities over sentences in a text with a bipartite graph. Connections between sentences are obtained by information on entites shared by sentences. Guinaudeau and Strube (2013) perform a one-mode projection on sentence nodes and use the average out-degree of the one-mode projection graph to quantify the coherence of the given text. Mesgar and Strube (2015) represent the connectivity of the one-mode projection graph by a vector whose elements are the frequencies of subgraphs in projection graphs. This encoding works much better than the entity graph for the readability task on the *P&N* dataset and even outperforms Pitler and Nenkova (2008) by a large margin. Zhang et al. (2015) state that the entity graph model is limited, because it only captures mentions which refer to the same entity (the entity graph uses a very restricted version of coreference resolution to determine entities). Zhang et al. (2015) use world knowledge *YAGO* (Hoffart et al., 2013), *WikiPedia* (Denoyer and Gallinari, 2006) and *FreeBase* (Bollacker et al., 2008) to capture the semantic relatedness between entities even if they do not refer to the same entity. Main issues with using world knowledge are: the choice knowledge sources, selection of knowledge from the source, coverage, and language-dependence.

Word embedding approaches like *word2vec* and

GloVe (Mikolov et al., 2013; Pennington et al., 2014) show that the semantic connection between words can be captured by word vectors which are obtained by applying a neural network. The ability to train on very large data sets allows the model to learn complex relationships between words.

3 Method

We introduce a new graph representation of semantic connections over lexical items in texts. Afterwards we compute the frequency of all subgraphs, i.e. coherence patterns. The intuition is that subgraphs capture how sentence nodes are connected and, respectively, encode text coherence.

3.1 Graph Model

We model semantic relations between sentences by a graph $G = <V, E>$ where V is the set of sentence nodes and E is the set of edges between sentence nodes. Two nodes of G are adjacent if there is a semantic connection between the corresponding sentences. Two sentences are semantically connected if there is at least one strong semantic relation between the words of these sentences. We model semantic relations between words by their corresponding word embeddings (Pennington et al., 2014). Given word vectors v_a for word a of sentence A and v_b for word b of sentence B, the cosine similarity value, $cos(v_a, v_b)$, between the two word vectors is a measure of semantic connectivity of the two words. The range of $cos(v_a, v_b)$ is between $[-1, +1]$. One interpretation of cosine is the normalized correlation coefficient, which states how well the two words are semantically correlated (Manning and Schütze, 1999). The absolute value of cosine, $|cos(v_a, v_b)|$, encodes how strongly the two words are connected.

The connection between sentences is obtained from connections between their words (Figure 1). Assume sentence A precedes sentence B, each word b of sentence B is connected with word a^* of A, where

$$a^* = \underset{a \in A}{\operatorname{argmax}}\, cos(b, a)$$

Then from all connections between the words of sentences A and B, the connection with the maximum weight among the words of B is selected to connect these two sentences (Figure 2).

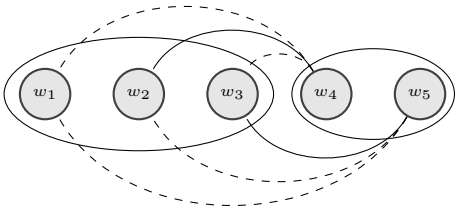


Figure 1: Sentence A with three words $\{w_1, w_2, w_3\}$ and sentence B with two words $\{w_4, w_5\}$. w_4 is highly related to w_2 and w_5 is highly related to w_3.

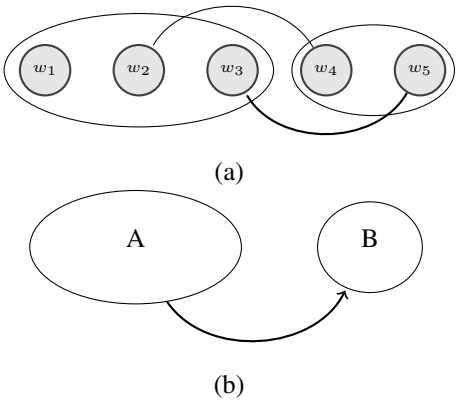


Figure 2: The word relation with the maximum weight (a) represents the connections between sentences (b).

The output of this phase is a graph whose edge weights model the strength of connections between sentences. The edges in this graph are directed to model the order of sentences.

Word embeddings relate each word in sentence A with each word in sentence B. Since the resulting graph is very dense, we filter out edges whose weights are below a threshold[1].

3.2 Coherence Features

Mesgar and Strube (2015) propose that the connection style of an entity graph can be captured by the frequency of all k-$node$ subgraphs in this graph. Larger[2] subgraphs[3] can capture more information about the structure of graphs and are more informative coherence patterns than smaller ones. We experiment with $k \in \{3, 4, 5, 6\}$. Text coherence is repre-

[1] We set this threshold to 0.9 to connect only sentences with high confidence.

[2] The size of a subgraph is the number of its nodes.

[3] We compute *induced subgraphs* (Mesgar and Strube, 2015). However, we use the term *subgraph* for brevity.

sented by a vector whose elements are the frequency of subgraphs (coherence patterns) with k-$node$.

3.3 Smoothing

Although increasing the size k of subgraphs captures more structural information about the connections of sentence nodes, a main risk with large subgraphs is sparsity. Given a sentence graph, many large subgraph types do not occur in this graph. Small subgraph types occur frequently in most sentence graphs in the dataset, but these subgraphs do not capture enough information about the connectivity style of the graphs.

Inspired by Kneser-Ney smoothing in language models (Heafield et al., 2013), each feature vector of a sentence graph can be smoothed. Smoothing deals with the problem of zero counts in the feature vector. It also lets the model having feature values for unseen subgraphs (like OOV in language modeling) which may be seen in the testing phase.

Kneser-Ney smoothing uses a discount factor to discount the raw count of each event (subgraph) and distributes the total discount to all event (subgraph) probabilities by means of a base probability.

The estimated frequency of subgraph sg in a given sentence graph is computed as follows:

$$KN(sg) = \frac{\max\{count(sg) - \alpha, 0\}}{Z} + \frac{M \cdot \alpha}{Z} P_b(sg),$$

where α is the discount factor and M is the number of times that discount factor is applied. Z is a normalization factor to ensure that the distribution sums to one and is obtained as follows:

$$Z = \sum_{sg \in A} count(sg),$$

where A is the set of all subgraphs with k-$nodes$ and function $count(\cdot)$ computes the number of instances of subgraph sg in the given sentence graph.

$P_b(sg)$ in Kneser-Ney smoothing is the base probability of subgraph sg among all k-$node$ subgraphs (A). The base probability can be computed based on hierarchical (parent-child) relations in subgraphs. k-$node$ subgraph sg_i is a parent of (k+1)-$node$ subgraph sg_j, if sg_i is a subgraph of sg_j. Figure 3 shows the parent-child relation between subgraphs via a weighted tree. The root of this tree is a null graph[4]. The weight of a parent-child relation connecting the parent subgraph sg_i and child subgraph sg_j is shown by w_{ij} and computed as follows:

$$w_{ij} = \frac{count(sg_i, sg_j)}{\sum_{sg_l \in A} count(sg_i, sg_l)},$$

where A is all subgraphs with k-$node$ and k equals the number of nodes of sg_j. Interpretation of weight w_{ij} is the normalized count of sg_i in sg_j with respect to all outgoing edges from sg_i.

The base probability of each subgraph sg_j is the inner product of the Kneser-Ney probabilities of sg_j's parents by the weights of the corresponding relations:

$$P_b(sg_j) = P \cdot W, \tag{1}$$

where P is the vector of probabilities of all parents of sg_j and W is the vector of all corresponding edge weights connecting the parents of sg_j to sg_j.

Since the root node of this tree is the null subgraph, and it is a subgraph of all possible sentence graphs, its base probability is one. Because the edge weights are in the range $[0, 1]$ the sum of the probabilities of all subgraphs with k-$node$ is always equal to one.

Proof. Assume I and J are the set of all k-$node$ and (k+1)-$node$ subgraphs. We also assume that I has n subgraphs and $\sum_{i=1}^{n} p(sg_i) = 1$. Considering these assumptions we prove that

$$\sum_{j=1}^{m} p(sg_j) = 1,$$

where m is the number of subgraphs in J.

We start from the left and compute the value of

$$\sum_{j=1}^{m} p(sg_j).$$

Based on the definition of base probability, the value of $p(sg_j)$ is computed based on its parents in I,

$$p(sg_j) = \sum_{i=1}^{n} w_{ij} p(sg_i),$$

where w_{ij} is the weight of the parent-child relation between sg_i and sg_j. Now we have:

[4] A null graph is a graph with no nodes.

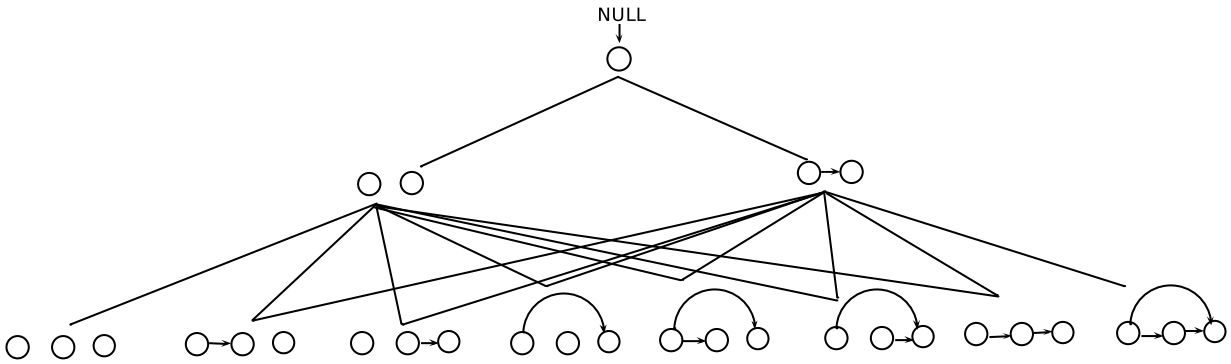


Figure 3: parent child relation.

$$\sum_{j=1}^{m} p(sg_j) = \sum_{j=1}^{m} \sum_{i=1}^{n} w_{ij} p(sg_i).$$

If we exchange the place of the sums and re-write the equation, we have:

$$\sum_{j=1}^{m} p(sg_j) = \sum_{i=1}^{n} \sum_{j=1}^{m} w_{ij} p(sg_i).$$

In this equation $p(sg_i)$ is independent of j (index of the inner sum), so it can be moved out of the inner sum:

$$\sum_{j=1}^{m} p(sg_j) = \sum_{i=1}^{n} p(sg_i) \sum_{j=1}^{m} w_{ij}$$

The inner sum equals 1.

$$\sum_{j=1}^{m} p(sg_j) = \sum_{i=1}^{n} p(sg_i).$$

Based on our assumption the right side of the equation is 1 and

$$\sum_{j=1}^{m} p(sg_j) = 1.$$

So we proved that the sum of the base probability of all k-$node$ subgraphs is 1. □

This way, Kneser-Ney smoothing distributes the total discount value by considering the weights of parent-child relations among the subgraphs. The result of applying smoothing is an estimation of the frequency of each subgraph in the sentence graph.

4 Experiments

4.1 Evaluation Task

We evaluate our coherence model on the task of ranking texts by their readability. The intuition is that more coherent texts are easier to read.

Datasets. We run our experiments on two datasets annotated with readability information provided by human annotators: *P&N* (Pitler and Nenkova, 2008) and *De Clercq* (De Clercq et al., 2014).

The dataset *P&N* contains 27 articles randomly selected from the Wall Street Journal corpus[5]. The average number of sentences is about 10 words. Every article is associated with a human score between $[0.0, 5.0]$ indicating the readability score of that article. We create pairs of documents, if the difference between their readability scores is greater than 0.5. If the first document in a pair has the higher score, we label this pair with $+1$, otherwise with -1. The resulting number of text pairs in this dataset is 209.

The dataset *De Clercq* consists of 105 articles from different genres: administrative (17 articles), journalistic (43 articles), manuals (14 articles) and miscellaneous (31 articles). The average number of sentences is about 12. This dataset was annotated by De Clercq et al. (2014) by asking human judges to compare two texts based on their readability. They use five labels:

[5]Pitler and Nenkova (2008)'s dataset contains 30 articles. They remove one. We assume this is `wsj-0382` which does not exist in the Penn Treebank. We furthermore remove `wsj--2090` which does not exist in the final release of the Penn Discourse Treebank. We also remove `wsj-1398` which is a poem and, hence, not very informative for readability assessment.

LME: left text is much easier,

LSE: left text is somewhat easier,

ED: both texts are equally difficult,

RSE: right text is somewhat easier,

RME: right text is much easier.

We map these labels to three class labels:

$+1$**:** for text pairs where the left text is easier to read (LME or LSE),

0**:** for text pairs where both texts are equally difficult to read (ED),

-1**:** for text pairs where the right text is easier to read (RSE or RME).

Properties of this dataset are shown in Table 1.

Genre	No. of articles	No. of text pairs
Administrative	17	272
Journalistic	43	1806
Manuals	14	182
Miscellaneous	31	931

Table 1: Properties of the different genres in the *De Clercq* dataset.

4.2 Experimental Settings

Word Embeddings and Classification. In order to reduce the effect of very frequent words, stop words are filtered by using the SMART English stop word list (Salton, 1971). We use a pretrained model of GloVe for word embeddings. This model is trained on Common Crawl with 840B tokens, 2.2M vocabulary. We represent each word by a vector with length 300 (Pennington et al., 2014). For handling out-of-vocabulary words, we assign a random vector to each word and memorize it for its next occurrence (Kusner et al., 2015). The classification task is done by the SVM implementation in WEKA (SMO) with the linear kernel function. All settings are set to the default values. The evaluation is computed by 10-fold cross validation.

Graph Processing and Smoothing. In order to compare the performance of LCG with the entity graph model, we follow Mesgar and Strube (2015) and use the gSpan method (Yan and Han, 2002) to compute all common subgraphs on each dataset and their frequencies. Note that gSpan does not count all possible k-$node$ subgraphs, whereas for applying Kneser-Ney smoothing it is necessary to count all possible k-$node$ subgraphs, because the probability should be distributed among all possible subgraphs. This also helps to estimate the probability of unseen patterns. We use a random sampling method (Shervashidze et al., 2009) to obtain the frequency of subgraphs in a sentence graph. In this regard, we take $10,000$ samples of the given sentence graph by randomly selecting k nodes of the graph to count the occurrence of k-$node$ subgraphs in this graph. We compute the base probability for at most $k = 6$. We find the best value for d in a greedy manner. First, we initialize d with 0.001. In each iteration we compute the performance. Then we multiply the discount factor by 10. We iterate as long as the discount factor is less than 1000. We report the best performance.

5 Results

In order to compare our method with related work, we run our model on the *P&N* dataset. Table 2 reports the accuracy of *LCG* with different values for k in k-$node$ subgraphs. This corresponds to coherence patterns spanning different numbers of sentences.

System		Accuracy	
ZeroR		50.24%	
EGrid		83.25%	
k-$node$	EGraph	EGraph+PRN	LCG
3-node	79.43%	80.38%**	78.95%
4-node	89.00%	89.95%	89.47%
5-node	96.17%**	95.69%**	97.13%

Table 2: *P&N* dataset.

We start in Table 2 with a majority class baseline (*ZeroR*). *EGrid* is our reimplementation of Pitler and Nenkova (2008) which we use as non-trivial baseline. The column *EGraph* is the entity graph model of Mesgar and Strube (2015). In *EGraph+PRN* we extend this model by a pronoun resolution system, so that entities mentioned by pronouns also enter the graph. We apply the Stanford coreference resolution system (Lee et al., 2013). Using the full coreference resolution system, however, decreases performance, hence we only use resolved pronouns. The enriched model with resolved pronouns works slightly better for *3-node* and *4-node* subgraphs,

and slightly worse for *5-node* subgraphs than the *EGraph*. The lexical coherence graph model, *LCG*, performs slightly worse than *EGraph* on *3-node* subgraphs. This could be because the graphs in *LCG* have more edges than the graphs in *EGraph*. When graphs are denser *3-node* subgraphs occur in every graph, hence their frequency is less discriminative. As shown in Table 2 larger subgraphs (*4-node* and *5-node*) capture more information and improve upon *EGraph* and for *5-node* subgraphs even upon *EGraph+PRN*. *LCG* significantly ($p\_value = 0.01$) works better than *EGraph+PRN* and *EGraph* using 5-node subgraphs. The difference between *LCG* and *EGraph+PRN* and *EGraph* using 4-node subgraphs is not significant.

Table 3 shows the performance of different models on the *De Clercq* dataset.

System	Accuracy	
ZeroR	42.312%	
k-$node$	EGraph+PRN	LCG
3-node	42.31%	42.31%
4-node	48.07%	49.12%**
5-node	65.77%	76.27%**

Table 3: *De Clercq* dataset.

Again, we use a majority baseline (*ZeroR*) to put our results in context. While the performance of both methods almost does not beat the baseline for *3-node* subgraphs, *4-node*-subgraphs work already better, and *5-node* subgraphs yield reasonable performance on this dataset. Although *EGraph+PRN* and *LCG* reach almost the same performance for *4-node*, the difference between them is statistically significant ($p\_value = 0.01$). With *5-node* subgraphs, *LCG* outperforms *EGraph+PRN* subgraphs by a large margin and gets a very reasonable performance on this dataset.

The general performance on the *De Clercq* dataset is lower than the performance on the the *P&N* dataset. This can have two reasons: first, the ranking task on the *De Clercq* dataset is three-label classification which is more difficult than the binary classification task on the *P&N* dataset. Second, texts in the *De Clercq* dataset are from different genres and coherence patterns may vary across genres. Hence, we take a closer look on the performance on the different genres.

5-node	EGraph+PRN	LCG
Administrative	69.49%	71.69%
Journalistic	65.01%	82.12%
Manuals	54.95%	61.54%
Misc.	70.68%	76.69%

Table 4: Accuracy of *EGraph+PRN* and *LCG* on different genres in the *De Clercq* dataset.

Table 4 shows the performance for *EGraph+PRN* and *LCG* using *5-node* subgraphs on the different genres in the *De Clercq* dataset. The performance of *LCG* is higher than *EGraph+PRN* on all genres. Unlike *EGraph+PRN*, *LCG* gets the best performance on journalistic articles. The lowest performance of both models is obtained on manuals. On administrative articles, performance of *LCG* is slightly better than *EGraph+PRN*. On miscellaneous articles *LCG* performs better than *EGraph+PRN*.

While large subgraphs are very informative for coherence modeling, extracting large subgraphs ($k > 4$) in relatively small datasets leads to a data sparsity problem, as there are very many possible subgraphs to be represented in a high dimensional vector space. Hence, many possible subgraphs have low or even zero counts. The problem for such a vector is that each graph is only similar to itself and not to any other graph. Hence, we observe a drop in performance when the model deals with large subgraphs (*6-node* subgraphs, *LCG1* for *P&N* in Table 5). We solve this problem by smoothing.

In order to apply Kneser-Ney smoothing we use a sampling method to create all possible (connected and disconnected) k-$node$ subgraphs (for *LCG1* and *LCG1** we use connected and disconnected subgraphs, for *LCG* only connected ones).

Table 5 shows the performance of *LCG1* when it is applied to ever larger subgraphs. As can be seen in Table 5, the performance on the *P&N* dataset suddenly drops for *6-node* subgraphs. This is could be caused by the sparsity problem.

When we apply Kneser-Ney smoothing as described in Section 3 the results for all tested values of k are superior for *LCG1** when compared to *LCG1* (Table 5).

Kneser-Ney smoothing improves the performance of the system even with *3-node* subgraphs by a large margin. Smoothing reduces the power of fre-

	P&N		*De Clercq*	
k-node	LCG1	LCG1*	LCG1	LCG1*
3-node	84.52%	89.00%	42.31%	49.60%
4-node	95.69%	96.17%	65.10%	66.23%
5-node	97.61%	98.08%	79.33%	79.85%
6-node	93.26%	95.69%	76.67%	78.03%

Table 5: Applying smoothing method yields to higher accuracy for larger subgraphs.

quency and makes the frequency distribution of subgraphs more even. Smoothing reduces the values through all subgraphs by considering parent-child relations between subgraphs to relate similar subgraphs. That is the advantage of the Kneser-Ney method in comparison to the other smoothing methods like Laplace-Smoothing.

For the *P&N* dataset we achieve the best results to date. Pitler and Nenkova (2008) reported 83.25% accuracy, Mesgar and Strube (2015) 89.95%. When smoothing *5-node* subgraphs we are able to report 98.08%. This, however, indicates that this dataset may not be the best one to report performance on. Hence, we now check whether smoothing also improves the performance on the more difficult *De Clercq* dataset.

On this dataset, we basically observe the same trends. Both settings result in better performance than *LCG* (see Table 3).

Note that none of the parameters in this work is tuned on the datasets. One may get better performance by tuning the parameters. The results confirm the intuition that the lexical coherence graph *LCG* captures coherence and models lexical coherence appropriately.

Applying smoothing on graphs of *EGraph+PRN* model increases the performance of this model. But this improvement is not as high as the improvement on the *LCG* graph.

Coherence Patterns. In this part we check the Pearson correlation coefficient between *LCG1* and human judgements of a few frequent subgraphs on the *P&N* dataset. In order to be consistent with Mesgar and Strube (2015), we use the exhaustive value of subgraph frequencies, i.e. *LCG1* for our work.

For the *3-node* subgraphs only one subgraph (Figure 4) in the *LCG1* representation is significantly (and positively) correlated ($p\text{-}value < 0.05$) with human scores. For the *4-node* subgraphs, we find six subgraphs which are significantly correlated with readability. Only one is positively correlated, while four are negatively correlated. Interestingly, both positively correlated *3-node* and *4-node* subgraphs have been determined as positively and significantly correlated by Mesgar and Strube (2015) as well. Both also capture a similar coherence pattern, indicating that our method is linguistically sound.

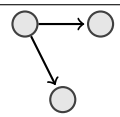
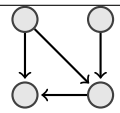
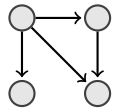
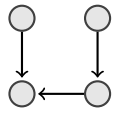
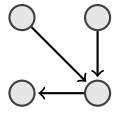
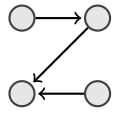
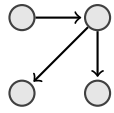
	Pattern	ρ	p-value
3-node		0.43	0.024
4-node		-0.45	0.018
		+0.39	0.047
		-0.43	0.024
		-0.59	0.001
		-0.55	0.003
		-0.55	0.003

Figure 4: Pearson correlation between *3-node* and *4-node* subgraphs and readability scores in the *P&N* dataset.

6 Conclusions and Future Work

In this paper we propose a new graph based coherence model, the lexical coherence graph, LCG. We view coherence as semantic connectedness between words which we model by word embeddings. We take only the strongest connection between sentences to create a graph with connected sentences. Then we extract large subgraphs capturing coherence patterns, which show similarity to patterns described in text linguistics (Daneš, 1974).

While the entity grid works only on sequences of up to three adjacent sentences, we are able to model relationships of up to six non-adjacent sentences. We solve the sparsity problem of large subgraphs by adapting Kneser-Ney smoothing to graphs. Smoothing prevents LCG from losing performance with large subgraphs and leads to superior performance on the Pitler and Nenkova (2008) dataset and to a first reasonable state-of-the-art on the De Clercq et al. (2014) dataset.

In future work we want to apply LCG to essay scoring as well. Also, we see that our adaption of Kneser-Ney smoothing to graphs may be useful for research in subgraph mining in general.

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