Evaluating Bilingual Embeddings in Bilingual Dictionary Alignment

Çift Dilli Kelime Temsilleri ile Sözlük Eşlenmesi

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Declaration of Authorship

I, Yiğit Sever, declare that this thesis titled, "Evaluating Bilingual Embeddings in Bilingual Dictionary Alignment" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.

- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.

- Where I have consulted the published work of others, this is always clearly attributed.

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Abstract

Yiğit SEVER

*Evaluating Bilingual Embeddings in Bilingual Dictionary
Alignment*

Dictionaries catalog and describe the semantic information of a lexicon. WordNet provides an edge by presenting distinct concepts with the hierarchy information among them. Research in computer science has been using this hand crafted tool in natural language applications such as text summarization and machine translation. Original WordNet has been compiled for English yet counterparts for other languages are not as readily available nor as comprehensive. In order for research on languages other than English to benefit from the power of a WordNet, machine assisted creation and evaluation methods are essential.

Word embeddings can provide a mapping between words and points in a real valued vector space. Using these vectors, representing documents as well as forming geometric relationships between them is a well studied area of research. In this thesis we start by hypothesizing that a dictionary definition captures the semantic basis of the described word. We used word embeddings as building blocks to map dictionary definitions into a multidimensional space. These spaces can be aligned to accommodate two languages, allowing the transfer of information from one language to another. We investigate the success of retrieving and matching discrete senses across languages by employing supervised and unsupervised methods. Our experiments show that dictionary alignment can be evaluated successfully by using both unsupervised and supervised methods but corpora sizes should be taken into consideration. We further argue that some methods are not viable considering their poor performance.

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The acknowledgments and the people to thank go here, don't forget to include your project advisor...

Contents

List of Figures

List of Tables

For/Dedicated to/To my...

Chapter 1

Introduction

1.1 Dictionaries

Dictionaries are living records of a society's language usage. Languages change over time, people adopt new words for new senses while others fall out of use. Concepts appear as a result of technological advancements or social shifts, giving birth to new senses and words to define them. Meanwhile, the term *dictionary* is a broad one to define. On its own, it brings forth the monolingual dictionary into consideration [1]. This type of dictionary presents words alongside their definitions following an alphabetical order. The intention is to inform the user about the words [2]. Other types of dictionaries vary with regard to their use case, target audience, and scope. For instance, bilingual dictionaries present words alongside their translations in the target language, often used by language learners or translators. Domain specific dictionaries list technical terms that target people who are familiar with the terminology.

The term that precedes the entries is called *headword* or *lemma*. Usually, lemmas are the form of a word without inflections. The sense they convey is as comprehensive as possible, reducing the number of otherwise redundant entries that would have been the derivatives of the unmarked form [3].

Dictionaries also inform the user about how senses relate to each other. **Polysemous** words share the same spelling while having related, often derivative meanings. For example; under the entry for the term *bank*, a definition might clarify the meaning *financial institution* while another can define *the building of a financial institution.* In contrast, **homonymous** words have distinct meanings while having identical spellings through coincidence. Formal definition of homonymy separates sound based and spelling based homonymy differently as homophones and homographs but for the

purposes of our text based arguments, we do not delve into the specifics. The *bank of a river* is homonym to the given examples. Homonyms are often shown in discrete blocks of descriptions.

Synonymity is another lexical relation we are interested in. A word is synonymous to another if they share the same meaning but are not spelled alike, such as the terms *right* and *correct*. However, synonymity is seldom shown in dictionaries.

Dictionaries take an immense amount of time and expertise to prepare. We can talk about the examples after narrowing our scope down to the dictionaries that are still available today. A survey by Uzun [4] notes that the first instalment of the modern Turkish dictionary, led by a team of experts, has taken over 6 years to prepare. Kendall [5] talks about how Noah Webster, the writer of the *An American Dictionary of the English Language* had to mortgage off his home in order to finish his project which took over 26 years. The bulk of this effort is collecting documents and other written material in order to establish a *corpus* [4]. This endeavour is necessary since a corpus is crucial to create the vocabulary of a language. Once the corpus is at hand, researchers can extract the lemmas. The resulting wordstock is called the *lexicon* of the language.

The internet radically changed the way researchers aggregate data. The advancements in digital storage technology allowed the data to be persistent. Improvements in networking ensured that people can share the volume of it among themselves. With the popularization of social media, the internet generates everyday conversations at an unprecedented rate that researchers are using for natural language applications. Moreover, efforts on open, collaborative, web based encyclopedias generate structured, multilingual data often used in machine translation and text categorization tasks. Once the cumbersome task of corpus attainment is now akin to web crawling. With the digitized data, it was only natural for dictionaries to go digital as well since it's generally acknowledged that they are no longer viable if they are not electronic [1].

1.2 WordNet

George A. Miller started the WordNet project in the mid-1980s. On its early days, project members studied theories that were aimed towards enabling computers to understand natural language as intrinsically as humans do. While working on then popular semantic networks and sense graphs, they have started something that will evolve into an expansive, influential resource [6].

Traditional dictionaries are rigid, constrained by the nature of the printed form. Today, people can browse WordNet via queries, like an online dictionary or a thesaurus. Behind the scenes, a sprawling lexical database has relationship information for more than 117000 senses. Figure 1.1 shows a brief result for the query string "run".

Noun

S: (n) **run**, tally (a score in baseball made by a runner touching all four bases safely) *"the Yankees scored 3 runs in the bottom of the 9th"; "their first tally came in the 3rd inning"*

direct hyponym / full hyponym

- S: (n) earned run (a run that was not scored as the result of an error by the other team)
- S: (n) unearned run (a run that was scored as a result of an error by the other team)
- S: (n) run batted in, rbi (a run that is the result of the batter's performance) *"he had more than 100 rbi last season"*

direct hypernym / inherited hypernym / sister term

- S: (n) score (the act of scoring in a game or sport) *"the winning score came with less than a minute left to play"*

derivationally related form

- W: (v) run [Related to: run] (make without a miss)
- W: (v) tally [Related to: tally] (keep score, as in games)
- W: (v) tally [Related to: tally] (gain points in a game) *"The home team scored many times"; "He hit a home run"; "He hit .300 in the past season"*

S: (n) test, trial, **run** (the act of testing something) *"in the experimental trials the amount of carbon was measured separately"; "he called each flip of the coin a new trial"*

S: (n) footrace, foot race, **run** (a race run on foot) *"she broke the record for the half-mile run"*

Verb

- S: (v) **run** (move fast by using one's feet, with one foot off the ground at any given time) *"Don't run--you'll be out of breath"; "The children ran to the store"*
- S: (v) scat, **run**, scarper, turn tail, lam, run away, hightail it, bunk, head for the hills, take to the woods, escape, fly the coop, break away (flee; take to one's heels; cut and run) *"If you see this man, run!"; "The burglars escaped before the police showed up"*

FIGURE 1.1: WordNet result for the query "run", truncated for brevity.

WordNet lists terms, much like a traditional dictionary, alongside its polysemes but also their homonyms. Additionally, there is a horizontal association; for any sense, the lemmas that share the row with the target term are synonyms. This set of synonyms is aptly named *synsets*. A short description is also provided to clarify the meaning. These descriptions, hence the meanings for any synset is unique within the WordNet. During this discussion, we have used sense and synset interchangeably.

WordNet also includes other relationships such as *hypernymy* and *hyponymy*, semantic

relation of senses being type-of one another [7].[1] For instance, the term "building" is a hyponym of "restaurant" since it encompasses a more general sense; the restaurant is type of a building. While coffee shop is a hypernym to the restaurant since it is a more specific sense.
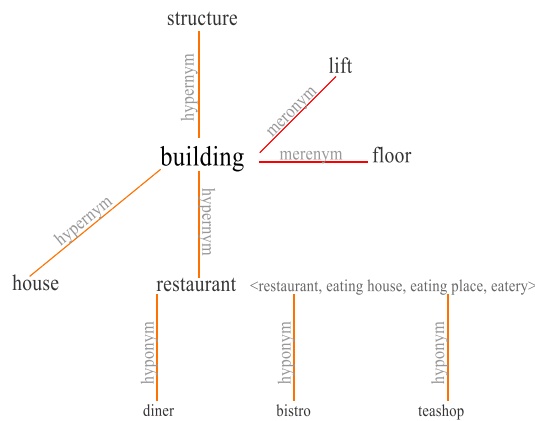
FIGURE 1.2: Example of a WordNet relationship graph. Hyponymy/hypernymy relations are shown from the heiarchy level of

One other relation is the meronymy, defined as a sense being part of or a member of another [8]. Keeping to our building example, windows are meronym to buildings. Other relationships exist but listing them is outside the scope of this thesis. Bottom line is the effort that has gone through to map 117,000 senses according to different semantic relationships. Sagot & Fišer [9] argue that the semantic relationships between senses are not tied to a specific language. With this assumption at hand, we can infer the effort behind the WordNet does not need to be repeated but can be translated to other languages.

Since it's inception, other projects built lexical databases, using the same WordNet design. Fellbaum [10] talks about the correct terminology that we abide for the thesis; "As WordNet became synonymous with a particular kind of lexicon design, the proper name shed its capital letters and became a common designator for semantic networks

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[1]not to be confused with homonymy

4

of natural languages". Hence *WordNet* refers to English Princeton WordNet, while *wordnets* created for other languages are not stylized.

1.3 Multilingual Wordnets

Authorities list more than 7000[2] living languages but only 40[3] of them have a sizeable presence on the internet. Among this small fraction, English is the dominant language of the web. English in not the centrepiece for natural language processing research because of any linguistic attribute. It is simply the most abundant language on web, giving researchers data to work with.

Natural language processing library spaCy [4] resorts to lemmatizations such as *=PRON=* to denote pronouns in order to collapse the senses for "I" "you", "them" etc.. The sense and the accompanying word for the brother of a person's father or mother differs in Turkish, Danish, Chinese and Swedish among other languages while both collapse to "uncle" in English. Studying other languages can provide insight towards concepts that are not present in English.

Translation, information transfer from foreign languages is a valid way of enriching a language's corpora; if a term that for a sense does not have a match in the target language, it is a good indication for the linguists of that language to look into their lexicons and work towards expanding it [3]. Further research in the area contributes to languages other than English having access to tools that will incorporate them into the literature.

Open Multilingual WordNet [11] set out to discover the effects related to the choice of license for wordnets. Their criteria for usefulness is the number of citations a publication tied to the wordnet has gotten on literature. They identified two major problems with the current distributions;

- some projects have picked restrictive licenses, effectively barring access to their tools for research purposes.

- the structures of the wordnets are not standardized, creating additional cost for creating programs to parse and use the wordnets.

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[2]https://www.ethnologue.com/statistics
[3]https://w3techs.com/technologies/history_overview/content_language/
[4]https://spacy.io/

In order to overcome the standardization issue, Bond & Paik have aligned the wordnets according to their English Princeton WordNet lemma ids and have written individual scripts to parse them. They are currently hosting the results from a single source.[5]

With alignment information at hand, we have created our dataset that we will assume to be perfectly aligned; a golden corpus. Among the 34 wordnets available on Open Multilingual WordNet, only 6 of them have gloss information available. Given this thesis will only investigate the ability to map senses using definitions of the sense, we used the subset of Albanian [12], Bulgarian [13], Greek [14], Italian [15], Slovenian [16] and Romanian [17] wordnets. Table 1.1 shows brief statistics about them. We should note that the languages of the wordnets used in the thesis are all present in the 40 languages that have a significant presence on the internet that we have mentioned before. We have constrained this study to use only the freely available wordnets and not considered wordnets that are gated behind restrictive licenses.

Name of the Project	Language	Number of Definitions
Albanet	Albanian	4681
BulTreeBank WordNet	Bulgarian	4959
Greek Wordnet	Greek	18136
ItalWordnet	Italian	12688
Romanian Wordnet	Romanian	58754
SloWNet	Slovenian	3144

TABLE 1.1: Summary of the Wordnets used.

1.4 Thesis Goals

In this thesis, we will study document matching and document retrieval methods.

We will evaluate existing methods for their performance on cross-lingual document retrieval but our documents are dictionary definitions which are short, descriptive snippets of text. At the end of this study, we will answer the following research questions;

1. Is it possible to create wordnet like lexical databases using unsupervised document matching and retrieval techniques.

2. How well does the studied techniques perform.

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[5]http://compling.hss.ntu.edu.sg/omw/

3. What attributes need to be considered regarding the available data.

1.5 Thesis Outline

Fill later…

Chapter 2

Background Information & Related Work

Somers puts down modern dictionaries in their article *You're Probably Using the Wrong Dictionary*; "The definitions are these desiccated little husks of technocratic meaningese, as if a word were no more than its coordinates in semantic space." [18]. From the perspective of an author, the efficiency of dictionaries might be worrisome but we will build this thesis on the presumption that dictionary definitions can indeed be represented in some semantic space using the words they are written with as the elements of their vectors.

2.1 Word Embeddings

Word embeddings are real valued dense vectors that represent words. Recently, language modelling studies have been focusing on explicitly learning word embeddings in order to show words or phrases as points on a low dimensional latent space. On the other hand, earlier research had been obtaining what we can call feature vectors for words while studying natural language processing tasks such as named entity recognition or part of speech tagging [19, 20]. The vector representation allows researchers access to the tools of the broad literature in linear algebra and machine learning, since they are intuitive for humans to interpret, more so for machines. Vectors can be compared as a measure of semantic similarity or composed together to build more expansive sentence, paragraph or document representations.

Induced embeddings can be saved to the disk in matrix notation. Each row is labelled with a token which is shown in some space by the following n real numbers, as popularized by the open source package *word2vec*. Researchers have been sharing their models on the internet so that other researchers can simply download and use them in their own applications [21–23]. Word embeddings available in this manner are often called as *pre-trained* models. Examples of pre-trained word embeddings are *word2vec* [24], *GloVe* [25], *Numberbatch* [23] and *fastText* [26].

In the following section, we will briefly present the history of word embeddings. Research on word embeddings is a sprawling subject that researchers has been building upon using the ideas from probabilistic, statistical and neural network models. We have omitted crucial contributions that optimized models and brought the literature where it is today due to space constraints, following a path that will lead into the preliminary behind the models we have chosen.

2.1.1 History of Word Representations

In order to talk about how words can be mapped to a multidimensional space, we should first talk about how the idea that *they can* has came about.

Linguistic Background

In his 1954 article, Harris [27] introduced his ideas which later came to known as *distributional hypothesis* in the field of linguistics. He argued that similar words appear within similar contexts. The famous quote by Firth [28] captures the idea as; "You shall know a word by the company it keeps!". For instance, the semantic similarity or relatedness between the terms *jacket* and *coat* can be theoretically shown since they will be accompanied by similar verbs, such as *wear*, *dry clean* or *hang*, and similar adjectives such as *warm* or *leather*. We should note that similarity and relatedness differ from each other such that *car* and *motorcycle* are similar to each other while *car* and *road* are related.

Early attempts to show words on a semantic space is studied in Osgood *et al.* [29]. Authors suggested representing concepts using orthogonal scales and relying on human judgement to score meanings on the axes. An example human annotated concept from their study is given in Figure 2.1.
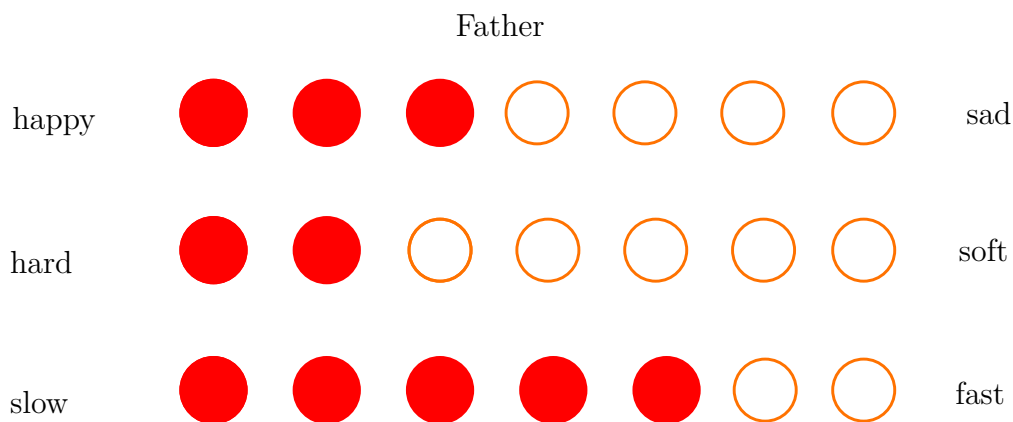
FIGURE 2.1: Sense representation using human judgement scores for the concept "Father" [29]

However, for a researcher to pick appropriate scales or have meaning extracted by hand would be infeasible for natural language processing tasks [30].

Even though Harris argued that "language is not merely a bag of words" [27], using just the word counts of a collection to capture the semantic information without regarding the order of the words will be used in the literature and be known as the *bag-of-words* model.

Vector Space Model

The history of word embeddings is tightly coupled with *vector space models* that initially appeared in the field of information retrieval. The intent was to extract vectors that represented *documents*. First vector space model developed by Salton *et al.* [31] was presented in "A Vector Space Model for Automatic Indexing". It was the first application of bag-of-words hypothesis on a corpus to extract semantic information [32]. Salton *et al.* presented the novel idea of a *document space*. The document space is built using a term document matrix. The rows of the matrix represent individual documents using the whole vocabulary as their dimension.

In this space, a document D_i is represented using t distinct terms;

$$D_i = (d_{i1}, d_{i2}, \ldots, d_{it})$$

The elements d_{ix} can be raw term counts. They can be weighted using inverse document frequency measure introduced by Jones [33]. Since this weighting scheme uses term frequency and the inverse document frequency, if is shortened as *tf-idf*. *tf-idf* is the multiplication of two metrics;

tf the number of times a term k occurs in a document

idf the inverse of the number of documents that contain k.

The weighting scheme was selected to "assign the largest weight to those terms which arise with high frequency in individual documents, but are at the same time relatively rare in the collection as a whole" [31].

The vector space model allowed Salton *et al.* to handle the similarity between documents as the angle between two vectors. Cosine similarity measure is often used since inner product of two normalized vectors is equivalent to the angle between them. Salton *et al.* have shown that there is merit to handling documents as real valued vectors.

2.1.2 Latent Semantic Analysis

Deerwester *et al.* [34] introduced latent semantic analysis in order to address a crucial problem with the vector space model. They have identified that the term document matrix approach cannot handle synonyms and homonyms due to the fact that vector space model requires the words to match exactly between the two documents. Synonymity is an issue because the query can have terms that have the same meaning as the target word, without getting matched. On the other hand, homonyms can match with an unrelated word. In order to answer these issues, their model seeks the higher order latent semantic structure in order to learn the *similarity between words*.

Latent semantic analysis starts with a word co-occurrence matrix X. An element $x_{i,j}$ of X is the number of times term i co-occurs with term j in a predefined context. Initially, whole documents were used for the context. Like term document matrices, the terms of the co-occurrence matrix is weighted by some weighting scheme. While original study by Deerwester *et al.* used raw term frequencies, *tf-idf* is a possibility while Levy *et al.* [35] reports pointwise mutual information (PMI) [36] as a popular choice. A term document matrix X is then factorized into three matrices using singular

value decomposition [37];

$$X = T_0 S_0 D_0'$$

Where the columns of T_0 and D_0' are orthogonal to each other and S_0 is the diagonal matrix of singular values. The singular values of S_0 can be ordered by size to keep only the k largest elements, setting others to zero [34]. The resulting matrix is shown as S. The similarity tasks that are solved with S can employ the representative k dimensional vectors such that $k << |V|$. Latent semantic analysis was used to the solve document similarity task while *word similarity* was mentioned briefly. Landauer & Dumais [38] later studied word similarity in full using latent semantic analysis, reducing the dimensions of the terms instead of documents.

2.1.3   Building Upon Distributional Hypothesis

While Deerwester *et al.* studied relatedness between words using vectors, their approach used the whole document for the co-occurrence information while the focus was clearly still on the document similarity. Schütze [39] proposed "to represent the semantics of words and contexts in a text as vectors" and built upon word co-occurrence. They theorized a context window of 1000 *characters* in order to consider words that are close to the target word instead of the whole document in co-occurrence calculations. The choice of a character window is justified with the claim that lower number of representative long words are more discriminative than numerous short words. Schütze claimed that the computation power available was not suitable yet to fully tackle the task.

Lund & Burgess [30] took the challenge and experimented with 160 million *words* taken from the Usenet, a precursor to the internet. They used a context window of 10 words and provided a method to obtain feature vectors to represent the meaning of words. However, intricate tuning of word co-occurrence generated associatively similar vectors instead of semantically similar ones.

2.1.4   Distributed Vector Representations

Bengio *et al.* [40] proposed learning word representations using a feedforward neural network. Their model learns feature vectors for words using a predictive approach instead of counting based approaches we have presented until now. Although neural networks have been proposed to learn a language model by Xu & Rudnicky [41], the
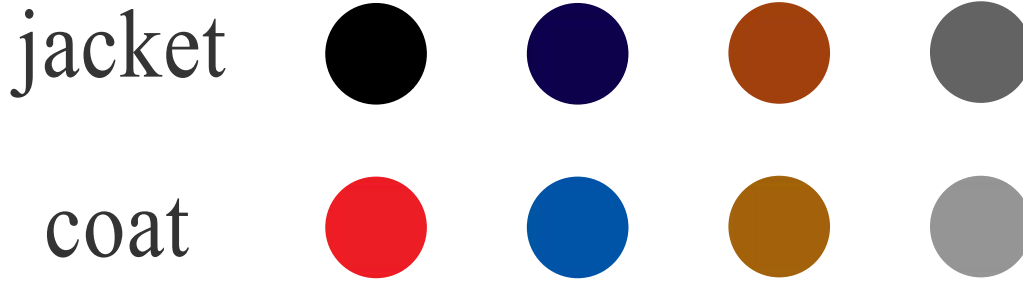
FIGURE 2.2: How semantic similarity can be shown using similarity of two vectors, the colour gradient represents similar values for elements of the vector

main contribution of Bengio *et al.* is to use an *embedding layer*, in order to attack *curse of dimensionality*. Their approach was also motivated exponentially increasing size of the vocabularies caused by *n-grams*. n-grams are representations that are built using multiple tokenized words. For instance, as well as showing *new* and *york* in the vocabulary, *New York* is handled as a single unit. For a corpus with vocabulary V, there are $|V|$ dimensions for the language model to learn and taking *n-gram* representations into consideration, the problem grows exponentially. Using m dimensions in the embedding layer allowed Bengio *et al.* to represent words using manageable, more representative dimensions and the problem scaled linearly as a result.

The setup for the neural network starts with the one hot encoded vector representation of the context for a word w, essentially a one dimensional vector where context words of w are set while the rest of the vocabulary are zero. This context window is similar to those used in statistical models that predicts the word w_t using the words that lead up to w_t. In other words, context window of w_t is T words on the left of w_t. In the following equation, we present the problem algebraically with an arbitrary probability function P.

$$P(w_1^T) = \prod_{t=1}^{T} P(w_t|w_1^{t-1})$$

In short, the input layer is projected into an embedding layer, later to a softmax layer to get a probability distribution in order to minimize the following softmax cost function.

$$\hat{P}(w_t|w_{t-1}, \ldots, w_{t-n+1}) = \frac{e^{y_{w_t}}}{\sum_i e^{y_i}} \tag{2.1}$$

However, this formulation is too computationally expensive since all vocabulary needs to be considered for the sum in the denominator. The curse of dimensionality problem is shifted to the final layer of the neural network. It will be solved later using hierarchical softmax. Authors reported training times around 3 weeks using 3 to 5 context window sizes and vocabulary sizes around 17000.

Collobert & Weston [20] suggested a deep neural network model in order to learn feature vectors for various natural language processing tasks. Their proposed approach for language model is important for our case since it explicitly learned distributed word representations or simply *word embeddings*. They have introduced two key ideas;

- Instead of using a context window that used words left of the target word to estimate the probability of the target word, they have placed the context window *on* the target window, using n words for left and right of the target word.

- They introduced negative examples, where they randomly changed the middle word with a random one. As well as keeping their model from overfitting, this allowed them to use the ranking cost;

$$\sum_{s \in S} \sum_{w \in D} \max\big(0, 1 - f(s) + f(s^w)\big)$$

2.1.5 Pre-trained Embeddings

P. Turian *et al.* [42] evaluated the performance of different word representations as word features that researchers can include into an existing task. Their contribution is elegantly summarized in their work as;

> Word features can be learned in advance in an unsupervised, task-inspecific, and model-agnostic manner. These word features, once learned, are easily disseminated with other researchers, and easily integrated into existing supervised NLP systems.
> […]

With this contribution, word embeddings can now be used off-the-shelf as word features, with no tuning.

2.1.6 Popularization of Word Embeddings

word2vec package [24, 43, 44] popularized word embeddings. There are two aspects of the work done by Mikolov *et al.* that contributed to the fact;

- Their model captures the semantic and syntactic attributes of words and phrases on a large scale with good accuracy, trained on billions of words using a shallow neural network, keeping the computational cost down.

- They published their code as well as their pre-trained embeddings as an open source project[1].

The second point is self explanatory but in order to argue about the first one, we should report the algorithms behind word2vec.

The *skip-gram model* introduced by Mikolov *et al.* [43] differs from the previous methods by predicting the surrounding words given the target word (Figure 2.3).
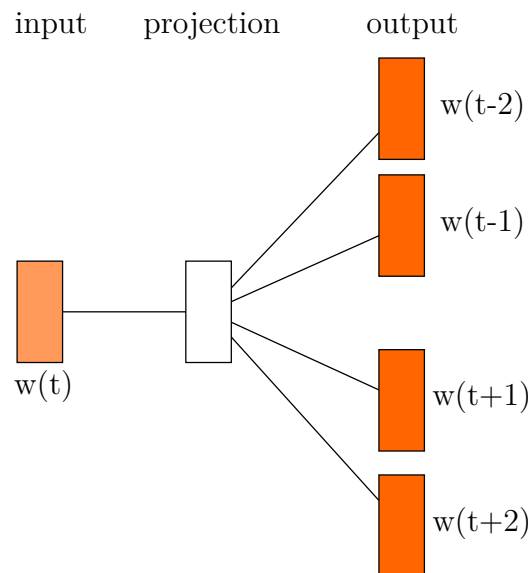
FIGURE 2.3: Skipgram architecture by Mikolov *et al.* [24]

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[1]https://code.google.com/archive/p/word2vec/

In "Distributed Representations of Words and Phrases and Their Compositionality", it is defined as follows;

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j}|w_t) \tag{2.2}$$

The $w_1, w_2, \ldots, w_T$ are the context of the word w_t. We should note that, Levy *et al.* [35] has identified that this window size is *dynamic* in the open source implementation of word2vec, where the actual window size is sampled between 1 and T.

Levy *et al.* [35] compared the performance of count based and prediction based word representation models. Representation algorithms they considered are;

- Positive pointwise mutual information (PPMI) [36, 45]

- Singular Value Decomposition on PPMI Matrix (Latent Semantic Analysis) [34]

- Skip-Gram with Negative Sampling [24]

- Global Vectors for Word Representation [25]

They found out that choice of a particular algorithm played an insignificant role compared to choosing the right approach during training, mainly picking correct *hyperparameters*. Besides, the amount of data the models are trained on were more important than the model itself. They used this finding to counter the results reported by Baroni *et al.* [46]. Baroni *et al.* claimed that predictive models outperformed count based models. On the other hand, Levy *et al.* noted that Baroni *et al.* used count based models without hyperparameter tuning, denying them from "tricks" developed in the word representation literature.

2.1.7 fastText

Armed with the fact that a good word representation model should tune their hyperparameters and should be trained on a large dataset, we set our sights on *fastText*. On their website, authors define fastText as a "Library for efficient text classification and representation learning". The ideas behind it are presented in Mikolov *et al.* [47]. Overall, it builds upon word2vec [24] by adding position dependent features presented in Mnih & Kavukcuoglu [48] and character n-grams suggested on Bojanowski *et al.* [26].

Let us turn our focus towards "Enriching Word Vectors with Subword Information" [26]. Instead of using a context window to learn the representation of the target word or predicting surrounding words given the centre word like in the the skip-gram model, Bojanowski *et al.* learn representations for character n-grams. We have mentioned that n-grams consider sequences like *New York* as a single token. Character n-grams start with parsing the corpus into c character long sequences. We will use 3 as the c value. The boundaries of the words are marked with "<>" characters for later and the whole corpus is transformed into tokens where the phrase "lecture slide" is now "<lecture> <slide>". Then, sequences of 3 characters are extracted such that "<slide>" is broken down into "<sl, sli, lid, ide, de>". Note that "lid" character n-gram is different from word "<lid>". These character n-grams are called subword vectors, they are trained using the skip-gram architecture.
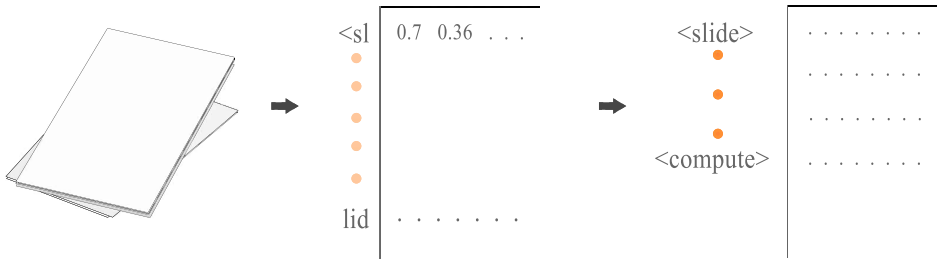
FIGURE 2.4: Overview of character n-gram model

With the subword vectors z_g for every n-gram g at hand, authors take a dictionary of n-grams of size G and for a given word w, they denote $G_w \subset 1, \ldots, G$ as the n-grams of w.

$$s(w,c) = \sum_{g \in G_w} z_g^T v_c$$

Grave *et al.* [49] trained fastText model on different languages using Wikipedia and Common Crawl data. Wikipedia is a curated encyclopaedia that can be used as a multilingual corpora with 28 languages that have over *100 million* tokens and 82 languages

with 10 million tokens [49]. Considering the original word2vec was trained on *100 billion* tokens, Grave *et al.* also used Common Crawl, a non profit project that collocates web pages and publishes the data publicly. This data can be inadvertently noisy which Grave *et al.* addressed using linewise language identification and by removing duplicate lines that often appear as leftover boilerplate on many sites. While Wikipedia provided them with a curated signal, Common Crawl data helped with capturing as many contexts as possible to train their distributed model. They are currently hosting the pre-trained word embeddings on their website [2].

2.1.8 ConceptNet Numberbatch

As an alternative to purely distributional models, Speer *et al.* [23] suggested *numberbatch* embeddings built in conjugation with ConceptNet.[3] ConceptNet is a knowledge graph. Like the WordNet, it presents semantic relationships between concepts but the defined relationships are more fine grained. The relationships are collocated from various resources like English Princeton WordNet, Open Mind Common Sense [50] and DBPedia [51]. ConceptNet stylizes its relations with the `/r/Relationship` syntax. For instance, being distinct members of a set relation is defined as `/r/DistinctFrom` which includes concepts like August and September.[4] Compared to WordNet, more subjective, human centric relations are defined such as `/r/MotivatedByGoal`, relationship between *compete* and *win* or `/r/ObstructedBy`, the relationship between *sleep* and *noise*. Total number of relations that are available between two concepts is 36. Moreover, these relationships are *weighted* depending on how present they are. For example, the concept *run* is related to *fast* with a weight of `9.42` but the similarity between *race* and *run* is weighted at `2.54`. Finally, the ConcepNet is multilingual, encompassing 304 languages in total with 77 of them reported as having moderate support that can be used in downstream tasks. Details of the knowledge graph and the procedure is explained by Speer *et al.* [23] in the paper "ConceptNet 5.5: An Open Multilingual Graph of General Knowledge".

Speer *et al.* also present their resource in word embedding matrix form for ease of use in the current plug-and-play environment. In order to get word embeddings from the knowledge graph, first they prepare a symmetric term-term matrix X where an element $w_{i,j}$ is the sum of all edge weights between terms i and j. This is similar to a word

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[2] https://fasttext.cc/
[3] http://conceptnet.io/
[4] https://github.com/commonsense/conceptnet5/wiki/Relations

co-occurrence matrix but instead of constructing the matrix using unstructured text, this approach builds upon semantic connections between senses. Speer *et al.* reports that their approach learns *relatedness* more so than *similarity* which was reported by the word co-occurrence approaches before.

With the term-term matrix at hand, Speer *et al.* weigh the terms using positive point-wise mutual information (PPMI) as suggested by Levy *et al.* [35] and reduce it to 300 dimensions, as is standard set by word2vec, using truncated SVD. Resulting matrix is similar to approaches set by Deerwester *et al.* [34] or Pennington *et al.* [25] but Speer *et al.* enrich it further using *retrofitting* as proposed by Faruqui & Dyer [52]. Pre-trained word2vec and GloVe embeddings are incorporated into the reduced term-term matrix to finally obtain embeddings that include both distributional and semantic relatedness signal. Authors call their finalized model *ConceptNet numberbatch*. Speer *et al.* reports state of the art results compared to word2vec embeddings on word relatedness and models built using their embeddings get scores equivalent to humans on SAT-style analogy tasks.

2.2 Approaches in Wordnet Generation

2.2.1 History of Wordnet Generation

We have mentioned the lexical database WordNet created by Princeton University. To reiterate, WordNet is a lexical database with human annotated collection of senses and relationships among them. The relationships are hierarchical so they can be followed along to reach new nodes due to the transitive property (shown in Figure 1.2). The format itself has become the standard for databases that present meanings and concepts [53].

Glosses or the definitions that go along with synsets were not initially part of the WordNet design. Authors believed that "definition by synonymity" would be enough. In other words, definition of a synset can be derived from the lemmas that make up the synset. As the number of items in the WordNet grew, only then short glosses, later followed by longer definitions got included in WordNet [6].

WordNet has been used in various natural language processing applications over the years such as text summarization [54] or word sense disambiguation [55]. Since the original WordNet was prepared for English over many years of work, efforts for creating

Synset	Gloss
{glossary, gloss}	an alphabetical list of technical terms in some specialized field of knowledge; usually published as an appendix to a text on that field
{dog, domestic dog, Canis familiaris}	(a member of the genus Canis (probably descended from the common wolf) that has been domesticated by man since prehistoric times; occurs in many breeds)
{university}	(the body of faculty and students at a university)
{depository financial institution, bank, banking concern, banking company}	(a financial institution that accepts deposits and channels the money into lending activities)

TABLE 2.1: Example synsets and their respective glosses

an equivalent resource for other languages has been initiated. Arguably, EuroWordNet set the standard for creating wordnets for languages other than English [56, 57].

EuroWordNet[5] project was initiated to introduce the benefits of English Princeton WordNet for other languages. Additionally, an interlinked semantic network can be a research topic on lexicalization patterns of languages, finding conceptual clusters of vocabularies or cross lingual text retrieval [56, 58]. EuroWordNet project included 7 wordnets for languages other than English and an adapted English wordnet. Due to the effort needed to create a wordnet from scratch, Vossen averted the EuroWord-Net project from creating full scale semantic lexicons and prioritized the connectivity between wordnets. All in all, Vossen [56] defines the aims as;

1. to create a multilingual database;

2. to maintain language-specific relations in the wordnets;

3. to achieve maximal compatibility across the different resources;

4. to build the wordnets relatively independently (re)-using existing resources;

One challange in achieving compatability is the shortcomings of using the original WordNet as the anchor. On one hand, since the WordNet is the first and the most comprehensive, it is a natural hub for new wordnets. On the other hand, a sense

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[5]http://projects.illc.uva.nl/EuroWordNet/

in one language might not have a direct equivalent in an other. Cultural differences or linguistic differences between languages contribute to this fact [59] which is called a lexical gap or untranslatability. EuroWordNet addresses lexical gaps using Inter-Lingual-Index (ILI). ILI is a higher order list of meanings just for wordnet synsets to align themselves to, elevating the burden for alignment from English Princeton WordNet. The introduction of ILI allowed language specific structures to exist in wordnets while keeping the connections among themselves.

Two approaches for wordnet generation were defined by "Introduction to EuroWord-Net";

Merge Approach where a wordnet structure is formed in the target language with synset selection and relation mapping. Then the connections between the new wordnet and English Princeton WordNet can be established.

Expand Approach where English Princeton WordNet is (machine) translated to target language [60], preserving connection information with a trade-off where the target language wordnet will be biased towards the relationships of the English Princeton WordNet and may not include target language specific lexical connections.

In order to maintain as much language specific lexical connections as possible while having a starting point for evaluation of target wordnets, EuroWordNet project offered "Base Concepts". This idea evolved into 1000 and later to 5000 core synsets that are compiled from most frequent, connected and representetive synsets to be used for evaluating wordnet generation [61].

2.2.2 Examples of Wordnet Generation

Following the EuroWordNet project, several studies were published on wordnet generation with proposals heavily leaning towards the expand approach. Diab [62] explored whether an Arabic wordnet is attainable or not using a parallel corpora. Arabic differs from the languages explored in EurowordNet due to its unusual morphological nature. Using their proposed method, they observed 52.3% of words they processed are sufficient for a future Arabic wordnet. They have also reiterated that semantic relationships in a language are transferable to a target language's wordnet.

Further approaches using parallel corpora to align the target language with English Princeton WordNet were used by Sagot & Fišer [9] in order to create a production ready French wordnet and by Fiser [63] to create a Slovene wordnet.

Approaches that used machine translation to get potential synsets for the target language was explored by Lam *et al.* [64]. They proposed two approaches for this task. First approach uses a single bilingual dictionary to translate English Princeton WordNet lemmas to target language to form synsets. Second approach translates existing wordnet synsets to English and then translates them to target language.

Following the publication of word2vec, approaches that use word embeddings gained traction and are interest to us. Sand *et al.* [65] used word embeddings to extend Norwegian wordnet by adding new relationships on existing synsets or by introducing new synsets all together. First, cosine similarity measure is used to discover nearest neighbours to a potential synset. Then a threshold value is used to cut off any new synsets below a certain similarity value. They evaluated their approach against accuracy, the percentage of relations that were correct and attachment which is similar to a recall score. It is the percentage of considered synsets that were above the threshold value. Overall, Sand *et al.* reported.

Arguably most relevant to our study, Khodak *et al.* [66] proposed an unsupervised method for automated construction of wordnets. In their paper "Automated WordNet Construction Using Word Embeddings" they present 3 approaches and compare their precision, recall and coverage.

First off, they picked 200 French and Russian adjectives, nouns and verbs, totalling 2 corpora with 600 items in each. These words are selected based on if they have a translation in the core sense list provided by English Princeton WordNet. Their approach starts with the processing of a word w. Initially, the presented method collects the possible translations of w using a bilingual dictionary and uses them as lemmas to query English Princeton WordNet. As we have mentioned, lemmas that query the WordNet retrieve synsets in the form `<lemma.pos.offset>`. Furthermore, every synset includes possible lemmas that can represent the sense of the synset (Refer to Table 2.1). These lemmas form the set S. By translating the English Princeton WordNet lemmas to target language, they obtain the set T_S Elements of T_S and w are both in target language so a monolingual word embeddings can be used; As a baseline,

they calculate the average cosine similarity between word embeddings of every element of S and w.

$$\frac{1}{S} \sum_{w' \in S} v_w \cdot v_{w'}$$

In order to improve the discriminative power of their target vectors, they use synsets relations, definitions and example sentences. These are used to get a more representative vector v_L. Given resources can be thought as sentences and sentence embeddings are calculated by getting a weighted average of word vectors of words that make up the sentence. The weighting is called smooth inverse frequency which was suggested by Arora *et al.* [67];

$$v_L = \sum_{w' \in L} \frac{a}{a + Pw'} v_{w'}$$

We will talk about sentence embeddings in detail for our approach in Section 3.1.

Third approach is word sense induction [68].

Gordeev *et al.* [69] uses unsupervised cross-lingual embeddings to match cross-lingual product classifications. Working on taxonomy matching, they use out of domain pre-trained embeddings due to small size of their corpora and investigate methods using untranslated and translated text.

Lesk [70] represent words using their gloss. Relied upon traditional dictionaries.

Banerjee & Pedersen [55] developed on lesk algorithm and included WordNet definitions.

Metzler *et al.* [71] talked about short text retrieval and lexical matching. They reported that lexical matching is good for finding semantically identical matches.

Chapter 3

Unsupervised Matching

3.1   Linear Assignment Using Sentence Embeddings

Word embeddings represent single tokens or in some cases n-grams such as *San Francisco*. Yet, word2vec suggested and proved that word embeddings are compositional [24]. Research then moved on to study the representation of longer pieces of text like documents, paragraphs and sentences. Implementations like Le & Mikolov [72] extended the skip-gram idea of Mikolov *et al.* [24] to learn the feature vectors for *paragraphs* and used them to predict surrounding paragraphs in the text. Approaches like Kiros *et al.* [73] trained an encoder that constructed surrounding sentences to learn sentence representations. However, text in question for the given studies are continuous. When the text that we would like to show on a latent space is not part of a longer piece of text but *discrete* pieces, that assumption does not hold. Regarding dictionary definitions, we cannot rely on continuous models. Our dictionary definitions are comprised of 10 to 11 words each with no relation from one distinct dictionary definition to another. One other case where a similar situation occurs is *twitter*.[1] *Tweets* are short pieces of text due to the 280 character constraint imposed by the platform. With such short pieces of text, considering the scope of a possible model could fit in, instead of paragraph embeddings, we can talk about *sentence embeddings*. A sentence embedding model should ideally capture the collective meaning of the short text where every word is potentially informative and discriminative.

Wieting *et al.* [74] studied sentence embeddings and reported that averaging word embeddings that make up a sentence to get sentence embeddings is a valid and surprisingly effective approach. Arora *et al.* [67] built upon the simple model and has shown that

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[1] https://twitter.com

weighed average of word vectors perform so well, their publication is called; "A Simple but Tough-to-Beat Baseline for Sentence Embeddings". In the suggested approach, word embeddings that make up a sentence is weighed with a scale called *smooth inverse frequency* and averaged with respect to the sentence. Smooth inverse frequency is suggested as

$$\text{SIF (w)} = \frac{a}{a + p(w)}$$

where a is a hyperparameter and $p(w)$ is the estimated word probability.

Using smooth inverse frequency weighting, word embeddings $v_w \in R^d$ where word w is in a vocabulary V can be averaged over a sentence S such that $S \subset V$ to get sentence embedding v_S in the same dimensionality R^d.

$$v_S = \frac{1}{|S|} \sum_{w \in S} \text{SIF (w)} v_w \tag{3.1}$$

The authors point out that the metric is similar to *tf-idf* weighting scheme if "one treats a 'sentence' as a 'document' and make the reasonable assumption that the sentence doesn't typically contain repeated words" [67]. These assumptions hold for us so we scaled our word embeddings using *tf-idf* weights to get sentence embeddings.

$$v_S = \frac{1}{|S|} \sum_{w \in S} \text{tfidf}_{w,S} v_w \tag{3.2}$$

Parallel to Arora *et al.*, Zhao *et al.* [75] used two approaches for sentence embeddings in order to solve SemEval-2015 Task 2: Semantic Textual Similarity [2]. First, for a sentence $S = (w_1, w_2, \ldots, w_s)$ where the length of the presumably small sentence is $|S| = s$ and the word embedding of a w_t is v_t;

- They summed up the word embeddings of the sentence $\sum_{t \in S} v_t$

- Used information content [76] to weigh each word's LSA vector $\sum_{t \in S} I(w_t) v_t$

Both approaches results in a vector that is in the same dimensions R^d as the original word representations.

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[2]http://alt.qcri.org/semeval2015/task2/

TABLE 3.1: Some definitions from English Princeton WordNet

turn red, as if in embarrassment or shame
a feeling of extreme joy
a person who charms others (usually by personal attractiveness)
so as to appear worn and threadbare or dilapidated
a large indefinite number
distributed in portions (often equal) on the basis of a plan or purpose
a lengthy rebuke

Edilson A. Corrêa *et al.* [77] expanded upon this simple yet effective idea to tackle the SemEval-2017 Task 4[3], Sentiment Analysis in Twitter. In order to acquire embeddings that represented *tweets*, they weighed the word embeddings that made up a tweet; tweet$_i = (w_{i1}, w_{i2}, \ldots, w_{im})$ with the *tf-idf* weights. For the *tf-idf* calculation, they cast individual weights as documents so that term frequency become the term count in a single tweet while document frequency become the number of tweets the term w_t occurs.

We have mentioned that our dictionary definitions are not continuous. Yet, we advocate using *tf-idf* weights to weigh our word embeddings to get sentence embeddings. In order to clarify, let us present Table 3.1.

For the *tf-idf* calculations, we followed a similar approach. The term frequency is the raw count of a term in a dictionary definition. While the document frequency is the number of dictionary definitions where w_t occurs.

Then, with the term-embedding matrix at hand, we have calculated definition embeddings using;

$$S_{\text{emb}}(S) = \sum_{w_i \in S} tf_{w_i,S}\text{-}idf_{w_i} \cdot Emb_w(w_i) \tag{3.3}$$

Every word that makes up a definition is scaled by its vector in $\mathbb{R}^n$, then concatenated to form sentence embeddings on $\mathbb{R}^n$. Given the N vectors from source and target language, we hypothesize that there exists a matching where every source definition vector is perfectly mapped to one target vector. Given that this problem naively iterates over $N!$ matchings, we have looked into an algorithm to handle the problem. Our problem is an instance of an linear assignment problem, where the nodes of our graph are

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[3]http://alt.qcri.org/semeval2017/task4
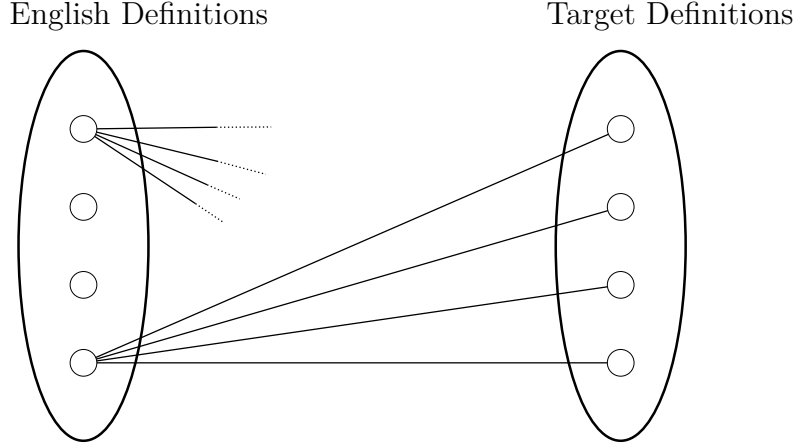
FIGURE 3.1: Matching sentence embeddings can be shown as finding the minimum flow in a bipartite graph. Connections are similarity between sentences and not all connections are shown

3.2 Linear Assignment Algorithm

Linear assignment problem is an optimization problem where a cost matrix is solved. A cost matrix is formulated such that each row corresponds to a task and each column corresponds to a solver agent. The aim is to find an assignment such that each task is solved by one agent and the total cost is minimized.

In our case, this formulation corresponds to two sets of wordnet definitions. The definitions are disjoint and independent with respect to their source wordnet. The weights among the sets are the similarity between individual dictionary definitions. Refer to Figure 3.1 for a representation of this notation.

We have calculated sentence embeddings such that each node of the graph is an d dimensional sentence vector $v_S \in R^d$. The weights that connect one definition to another in this bipartite graph is the cosine similarity between two sentence's sentence vectors. Cosine similarity is constrained in $[0, 1]$ where 1 is perfect similarity and 0 is two orthogonal vectors. This is crucial for our task such that we set out to maximize the total weight in this matching.

We use Jonker & Volgenant [78] solver for the problem. Jonker & Volgenant improve

upon the Hungarian Algorithm proposed by Kuhn [79] using heuristics for initialization and shortest path algorithm of Dijkstra [80].

Chapter 4

Dictionary Alignment as Pseudo-Document Retrieval

Document retrieval is the prototypical information retrieval task. Bush [81] theorized the possibilities of the automatic information retrieval by machines in his essay titled "As We May Think". On his "Modern Information Retrieval", Singhal [82] gives due credit to Luhn [83] for the initial suggestion of using word overlap in document retrieval.

Modern information retrieval techniques are far from the scope of this thesis. Yet, we can still benefit from the tried and tested methods of the early information retrieval. Considering the small collection of documents at hand, first we will investigate if we can handle the task using approaches that were available to the researchers when the size of corpora that were available to them were small as well [82]. However, we will get leverage from a state of the art tool from the modern computer science; *Google Translate.*

4.1 Monolingual Retrieval

First of all, we created a corpora suitable for the task by translating the target language's definitions to English using Google Translate. We used the Google Cloud API[1] in order to automate the process.

Table 4.1 presents some definitions and their automated translations to English. While the translations can inform the user about the general sense of the word, sentence

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[1] https://cloud.google.com/translate

Original Definition	Translated Definition
bila pri starih Grkih in Rimljanih vojna ladja s tremi vrstami vesel	with the ancient Greeks and Romans, a three-wheeled war ship was happy
znanstvena veja matematike, ki se ukvarja s prostorskimi lastnostmi teles in njihovimi medsebojnimi odnosi	the scientific branch of mathematics, which deals with the spatial properties of the bodies and their interrelations
circumstanțe, stări de fapte, lucruri luate în calcul într + o discuție sau dezbatere	circumstances, facts, things taken into account in a discussion or discussion
Fază a lunii în care este complet iluminată	Phase of the month in which it is fully illuminated
Persoană care se ocupă cu pescuitul și uneori cu conservarea peștelui pescuit	A person who deals with fishing and sometimes with the conservation of fish fishing
E bëj diçka që të shkojë e të përputhet me një qëllim të caktuar, i bëj ndryshimet e ndreqjet e nevojshme, që t'u përgjigjet kushteve e rrethanave të caktuara.	I do something to go and match a certain purpose, make the necessary adjustments and adjustments, to respond to certain conditions and circumstances.
pohoj, a paraqit dikujt një gjë për ta parë, për t'u njohur me të a për të gjykuar për të; zbuloj diçka që të shihet; tregoj	I assure you, did someone present a thing to see, to know him or to judge him? I find something to be seen; show

TABLE 4.1: Example definitions and translations

structure is flawed at times. We can also see word duplication when synonyms collapse into single words. These shortcomings are also reported by Groves & Mundt [84].

With the English Princeton WordNet definitions and 6 target wordnet definitions at hand, we can handle the task as *monolingual document retrieval.* We will use the vector space model that was mentioned in Chapter 2 to have real valued vectors that represent the definitions.

To begin with, the definitions that were extracted from English Princeton WordNet and the target wordnet have been collocated to form a corpora. This process includes one target wordnet at a time and experiments were simply repeated for each wordnet. The vocabulary of this corpora is shared between the wordnet pairs as they have been joined in a single language.

4.1.1 Term Document Matrix

With the definition collection and the vocabulary at hand, we created a *term-document* matrix. In this instance of the term-document matrix, rows represent the documents and columns denote individual vocabulary entries. Such a matrix C is m by n while m is the number of documents and n is the size of the vocabulary $|V|$. Our definitions are just short documents so we use the terms *definition* and *document* interchangeably with the added benefit of using d to denote either of them.

For any element of C, $c_{i,j}$ is the number of times j occurs in the document i. This matrix is sparse since documents use a fraction of the available vocabulary V. Our case with definitions is no different with an average of 10.62 words per definition with vocabulary sizes well over 10,000s.

4.1.2 Term Weighting

Elements of a term-document matrix is scaled in order to assign weights to elements according to their discriminative power [85]. Stopwords like "the", "and" have virtually no significance and terms that are common in the corpora's domain will have no discriminating power either, as explained by Manning *et al.* [85]. We have opted out of stopword removal considering our short definitions.

What is a good scaling method for term weighing? *tf-idf* is composed of two scores; term frequency *tf* and inverse document frequency *idf.* *idf* was initially

suggested by Jones [33] and is highlighted by Manning *et al.* [85]. Term frequency $tf_{w,d}$ is the number of times term w occurs in a document d. Inverse document frequency idf_w is calculated using the number of documents that contain the term w which is also known as the document frequency of w, df_w. We have used the smooth variant of idf as follows;

$$idf_w = \log \frac{N+1}{df_w + 1} \tag{4.1}$$

Where N is the number of documents in the corpus. $\log(\cdot)$ is used to dampen the effect of the *idf*.

Manning *et al.* explains the intuition behind the *tf-idf* in his *Introduction to Information Retrieval* as follows;

[...], tf-idf$_{t,d}$ assigns to term t a weight in document d that is

1. highest when t occurs many times within a small number of documents (thus lending high discriminating power to those documents);

2. lower when the term occurs fewer times in a document, or occurs in many documents (thus offering a less pronounced relevance signal);

3. lowest when the term occurs in virtually all documents.

By weighing our term-document matrix C, for any term $x_{i,j}$

$$x_{i,j} = \text{tf}_{td} \cdot \text{idf}_t \tag{4.2}$$

Such that term $x_{i,j}$ shows the importance of term t with relation to its general significance throughout the corpus.

4.1.3   Similarity Measure

Using the term-document matrix, similarity between two documents can be calculated by assigning a scoring scheme that uses rows as document vectors. *Cosine similarity* is such a measure that can be used to find the cosine of the angle between two vectors and scales to multidimensional case trivially. Moreover, since the majority of the dimensions between the vectors are zero, cosine similarity ignores these dimensions and implicitly prioritizes the non-zero dimensions.

For the row vector $\vec{d_t}$ and $\vec{d_p}$, cosine similarity between definitions t, p is

$$\cos(\theta) = \text{sim}(d_t, d_p) = \frac{\vec{d_t} \cdot \vec{d_p}}{|\vec{d_t}||\vec{d_p}|} \qquad (4.3)$$

4.1.4 Retrieval

With definition vectors and a similarity measure at hand, we split the *tf-idf* weighted term-document matrix C' as English Princeton WordNet definitions and target wordnet definitions. The target wordnet definitions were used as pseudo-queries and English Princeton WordNet definitions were used as the document collection to retrieve definitions from.
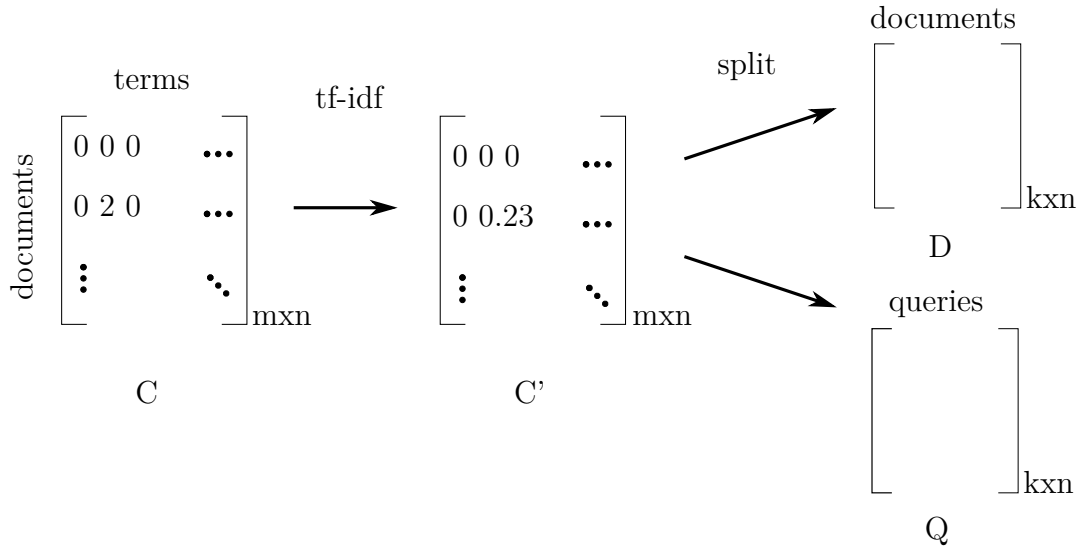
FIGURE 4.1: Term document matrix to queries and documents

In order to retrieve and rank definitions given the query definition, cosine similarity between query and each corpus definition is calculated. The similarity scores that range between 0 and 1 are sorted in descending order with the definition index attached. The retrieved documents are ranked according to their similarity score. Since the definitions are aligned across wordnets, a correctly retrieved definition will have the same index as the query definition.

4.1.5 Evaluation

Information retrieval literature usually uses *precision* and *recall* as the evaluation metric with the assumption that the user wants to receive as many relevant documents as possible [86]. However, we only have one correct definition we are interested in and cannot access relevance any further for any other retrieved definitions anyway. As a result, we used a tweaked version of *Mean reciprocal rank* (MRR) as introduced by Voorhees [87] in "The TREC-8 Question Answering Track Report". In the report, mean reciprocal rank was used in order to evaluate a question answering track where a singular correct answer was sought among other answers and is rewarded according to the returned rank. In other words, mean reciprocal rank evaluates a system's retrieval score with respect to the rank of a single correct answer.

$$\text{MRR} = \frac{1}{|Q|} \cdot \sum_{q}^{|Q|} \frac{1}{\text{rank}_q} \tag{4.4}$$

Where rank_q is the ranking of the *correct* definition for the query q.

4.1.6 Results

4.2 Cross Lingual Document Retrival

4.2.1 Word Movers Distance

Following the popularization of the word2vec [24], Kusner *et al.* [22] introduced *Word Mover's Distance*. By adapting the optimal transport theorem into using distances between word embeddings and documents as probability distributions that are composed of words, he suggested the following;

For an embedding matrix $X \in R^{n \times d}$ d is the dimension the embedding was learned at and n is the size of the vocabulary. In this configuration, a row $\vec{x_i} \in R^d$ of the matrix X is the embedding for the ith word w_i.

Given a a separate term-document matrix $C \in R^{m \times n}$, a row $\vec{d_j} \in R^n$ is the row vector for the jth document d_j. In the original paper "From Word Embeddings to Document

English Princeton WordNet Definition	Translated Definition
ancient Greek or Roman galley or warship having three tiers of oars on each side	with the ancient Greeks and Romans, a three-wheeled war ship was happy
the pure mathematics of points and lines and curves and surfaces	the scientific branch of mathematics, which deals with the spatial properties of the bodies and their interrelations
everything stated or assumed in a given discussion	circumstances, facts, things taken into account in a discussion or discussion
the time when the Moon is fully illuminated	Phase of the month in which it is fully illuminated
someone whose occupation is catching fish	A person who deals with fishing and sometimes with the conservation of fish fishing
make fit for, or change to suit a new purpose	I do something to go and match a certain purpose, make the necessary adjustments and adjustments, to respond to certain conditions and circumstances.
admit (to a wrongdoing)	I assure you, did someone present a thing to see, to know him or to judge him? I find something to be seen; show

TABLE 4.2: English Princeton WordNet definitions and the target word-net definitions we want to match

Language	MRR	Top 10	Top 10 %	Top 1	Top 1 %
bg	0.087	674	0.337	403	0.202
el	0.122	1006	0.503	709	0.355
it	0.016	476	0.238	250	0.125
ro	0.051	988	0.494	728	0.364
sl	0.073	584	0.292	317	0.159
sq	0.056	979	0.490	767	0.384

TABLE 4.3: Experiment results for monolingual retrieval

Distances", the elements of the term-document matrix C are given as normalized bag-of-words representations. Given the ith word in a document;

$$d_i = \frac{tf}{\sum_{j=1}^{n} tf_j} \tag{4.5}$$

Where $\text{tf}_{i,j}$ is the term frequency or the number of times term i appears in document j.

We have studied the *tf-idf* weighted case for using term-document matrices for document retrieval tasks. Kusner *et al.* gives a brilliant example on a case where word overlap scoring nature of term-document matrices fall short;

> Recall the earlier example of two similar, but word-different sentences in one document: "Obama speaks to the media in Illinois" and in another: "The President greets the press in Chicago". After stop-word removal, the two corresponding nBOW vectors d and d' have no common non-zero dimensions and therefore have close to maximum simplex distance, although their true distance is small.

In order to use the innate similarity between words provided by word embeddings, Kusner *et al.* first introduces a flow matrix $T \in R^{n \times n}$.

4.3 Balikas *et al.* Implementation

4.3.1 Optimal Transport

4.3.2 Sinkhorn

Chapter 5

Supervised Validation

The approaches we have presented so far work fully unsupervised. Given two collections of definitions, we have tried to retrieve the definition(s) that represented the same meaning. However, given the moderately sized data in our hands we have accepted as "golden", we studied the feasibility of training an encoder [88], where the objective is to learn whether the pair of definitions entail the same sense across languages.

Recurrent Neural Network (RNN) architectures improve upon the prototypical neural network model by introducing a *memory* for the connections in the network [89]. By updating the hidden unit over time using the output of the previous time step, the model can *remember* features of the input signal for later inputs. One particular architecture of RNNs propsed by Hochreiter & Schmidhuber [90] is *long short-term memory* (LSTM). LSTM models have been successful on language modelling tasks [88], handwriting recognition [91, 92] and machine translation with a focus on rare words [93] to name a few. Highlight of these results are that LSTM has an advantage on tasks that require contextual information to persist over long periods of time [94]. Furthermore, LSTMs do not require fixed input vectors, which is a necessity for us since our definition pairs do not have to be the same size.

5.0.1 Vanishing Gradient Problem

LSTM is borne out of the need to address the *vanishing gradient problem* [90, 95]. On the original publication by Hochreiter & Schmidhuber [90], a crucial shortcoming of RNNs have been identified as their slow rate of training which may not converge in the end at all. Independently, Bengio *et al.* [95] suggested that the problem stems from the choice between the conservation of the previous inputs versus resisting against the

noise they accumulate. Figure 5.1, adapted from Graves [94] illustrates the problem using shades as the influence of input over neural network units.
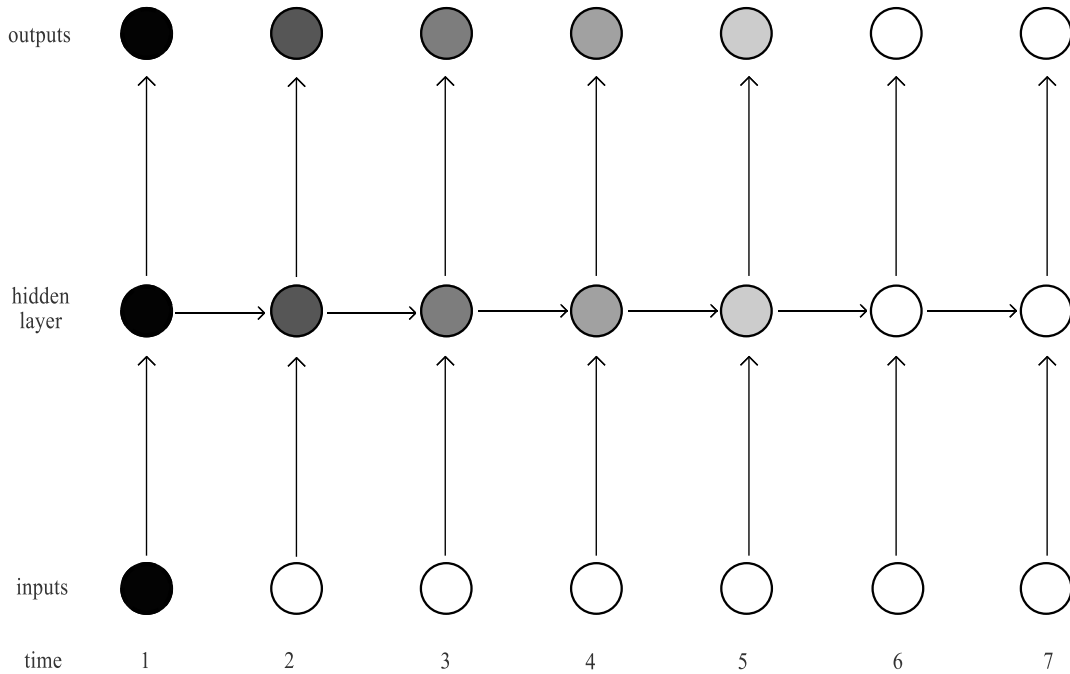
FIGURE 5.1: Graphical representation of vanishing gradient problem where the shades of the nodes represent the influence of the input signal, adapted from Figure 4.1 of Graves [94]

As the input signal traverses the units of an RNN, it either diminishes or blows up [94]. A long line of solutions were proposed such as decomposing structures so that only unexpected ones can be relevant.

5.0.2 Long Short-Term Memory

LSTM is the solution highlighted by Graves [94] as a recurrent neural network model that can work over temporally distant input signals while preserving their influence or diminishing their noise. The centrepiece idea is to use a *constant error carousel*, special cells that enforce a constant error flow. In the original paper, this complex unit is named *memory cell* [90]. Using an *input gate*, the cell is updated if the current input is relevant and using an *output gate*, the unit will not update other cells if the current input is not relevant. A simplified overview of the suggested model is presented in Figure 5.2.

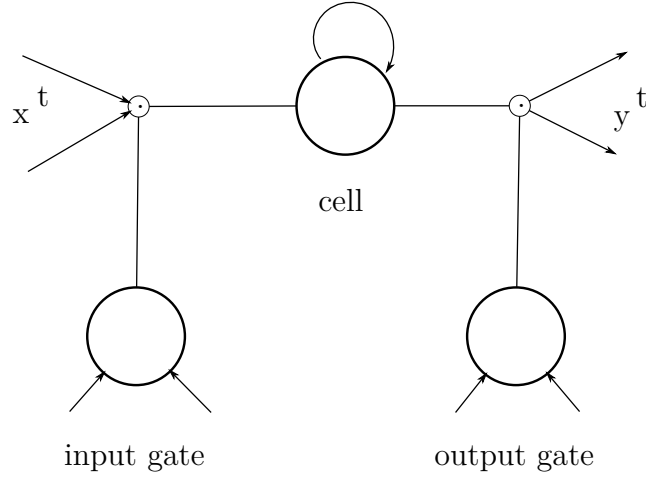FIGURE 5.2: Simplified long short-term memory cell architecture

Multiple arrows denote input from current time frame and recurrent connections. $\odot$ symbol denotes multiplication. By weighing the input and output gates between 0 and 1, the impact of the current input can be adjusted. Overall, input gate controls how much cell will learn and output gate controls how much the cell will propagate. Figure 5.3 adapted from Graves [94] illustrates how the LSTMs operate against vanishing gradient.

Two gates on top of the cell structure model got extended with a third *forget gate* by Gers *et al.* [96]. The aim was to handle input sequences that are not segmented in a predictable manner. The error signals were getting carried too far back in time which deteriorated the performance on tasks with continuous input streams. The proposed forget gate is implemented to *reset* the cell. When a cell state got irrelevant due to a change in problem domain, forget gate gradually resets the cell state instead of erroneous activations from the input gate.

Another extension came in the form of *peephole connections* by Gers *et al.* [97]. With this addition, the gates can use the cell state to increase their sensitivity to *timining* in the input data. By allowing internal gates to inspect the cell state, they have shown improvements on non-linear tasks.

The finalized model with input, forget and output gates as well as the internal peephole
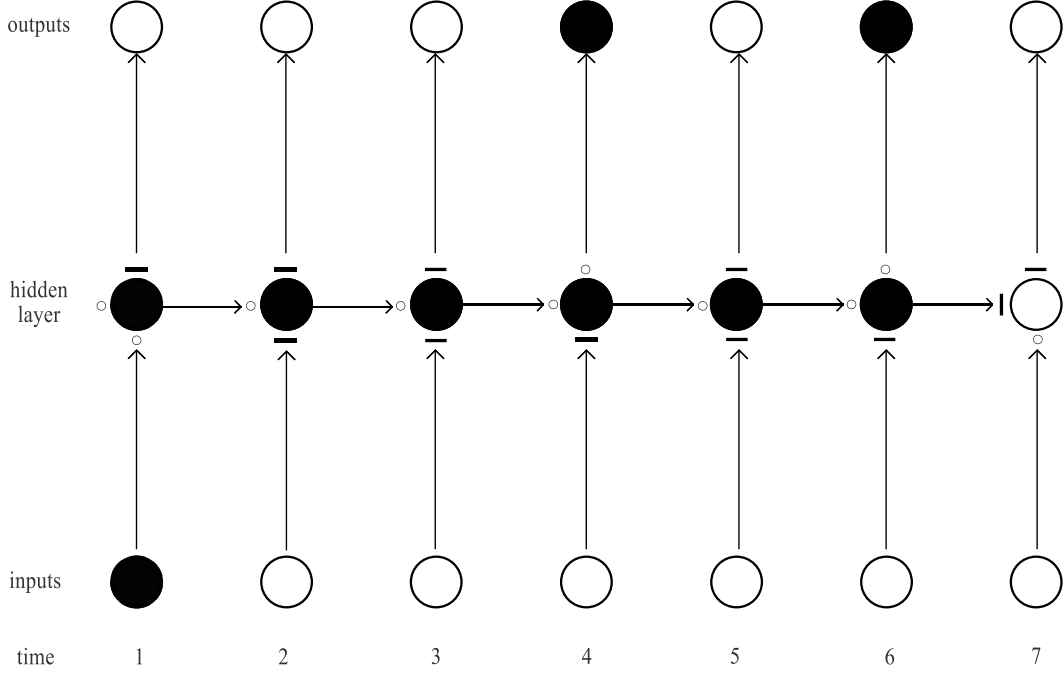
FIGURE 5.3: Preserving the input signal through blocking (-) or allow-
ing (O) the input signal, adapted from Figure 4.4 of Graves [94]

connections was debuted in Graves & Schmidhuber [98]. In their expansive study
comparing 8 LSTM variants over 15 years of CPU time, Greff *et al.* [99] named this
model the "vanilla LSTM". This particular form of LSTM is commonly used [88].
The real valued vectors are denoted alongside their update time step $(\cdot)_t$ such that
$t \in 1, \ldots, T$. Updates are performed on the input gate i_t, memory cell c_t, forget gate
f_t and output gate o_t. We show the updates over weight matrices W_i, W_f, W_c and
W_o via the use of recurrent weights R_i, R_f, R_c and R_o and bias vectors b_i, b_f, b_c and b_o.
Peephole connections are shown using $p.$ for input, forget and output gates as p_i, p_f and
p_o respectively. Finally, the input is a sequence of data in the form of $(x_1, x_2, \ldots, x_T)$
and the model outputs real valued vector y_t at the time step t.

$$i^t = \sigma \left(W_i x^t + R_i y^{t-1} + p_i \odot c^{t-1} + b_i \right) \tag{5.1}$$

$$f^t = \sigma \left(W_f x^t + R_f y^{t-1} + p_f \odot c^{t-1} + b_f \right) \tag{5.2}$$

42

$$\overline{c}^t = W_c x^t + R_c y^{t-1} + b_c \tag{5.3}$$

$$c_t = \tanh\left(i^t \odot \overline{c}^t + f_t \odot c^{t-1}\right) \tag{5.4}$$

$$o^t = \sigma\left(W_o x^t + R_o y^{t-1} + p_o \odot c^t + b_o\right) \tag{5.5}$$

$$y^t = \tanh(o_t) \odot c^t \tag{5.6}$$

Where $\sigma(\cdot)$ is the *logistic sigmoid* function $\sigma(x) = \frac{1}{1+e^{-x}}$ and pointwise vector multiplication is denoted using $\odot$. The recurrence holds via the usage of signals from the previous time steps $(\cdot)^{t-1}$.

5.0.3 Siamese Long Short-Term Memory

Recently, Mueller & Thyagarajan [100] proposed a *siamese* model to solve sentence similarity problem. They suggest using two networks and denote them as LSTM_a and LSTM_b. The weights are shared between the networks such that $\text{LSTM}_a = \text{LSTM}_b$. The Manhattan distance is used as the measure of similarity between the sentences.

We extend the siamese network architecture by using bilingual word embeddings. Our learning objective encodes a sense to be represented across languages using bilingual word embeddings.

We used a similarity function that relies on cosine similarity over the outputs of the LSTM units that handled source (English) definition's word embeddings and target language's definitions.

$$\exp\left(\sum ||y^s \cdot y^t||_2\right) \tag{5.7}$$

Zeiler [101]

Chapter 6

Experiments and Evaluation

We experimented with in domain *fasttext* embeddings. We have trained Romanian and Bulgarian embeddings and ran the WMD and Sinkhorn experiments. The performance dropped to the quarter of pre-trained embeddings so we have not repeated the experiments for other language corpora.

We have evaluated our embeddings using the standard bilingual lexicon extraction as a general measure for their performance. Although Ruder *et al.* [102] and Glavas *et al.* [103] both say you should evaluate them using downstream tasks.

Language	FastText 1M	FastText 500k	numberbatch
bg	33.61	35.17	51.97
el	37.37	39.58	30.35
it	58.20	59.28	50.37
ro	37.33	38.71	64.17
sl	21.42	22.91	74.74
sq	24.46	25.36	58.63

TABLE 6.1: Accuracy Scores of the Vectors Aligned Using VecMap

Language	FastText 1M	FastText 500k	numberbatch
bg	96.43	93.36	17.53
el	94.44	90.28	12.15
it	97.93	95.97	41.08
ro	97.06	94.91	16.4
sl	94.67	90.73	9.23
sq	83.59	80.92	9.51

TABLE 6.2: Coverage Scores for the Vectors Aligned Using VecMap

6.1 Results

	Percentage of Correctly Matched Definitions		
Language	**fastText 1M**	**fastText 500k**	**Numberbatch**
bg	0.39	0.41	0.19
el	0.37	0.38	0.14
it	0.28	0.28	0.36
ro	0.39	0.39	0.20
sl	0.15	0.15	0.06
sq	0.55	0.54	0.27

TABLE 6.3: Linear Assignment Using 2000 Definitions

	Percentage of Correctly Matched Definitions		
Language	**fastText 1M**	**fastText 500k**	**Numberbatch**
bg	0.35	0.36	0.18
el	0.36	0.36	0.12
it	0.25	0.25	0.32
ro	0.36	0.37	0.19
sl	0.11	0.11	0.05
sq	0.39	0.40	0.19

TABLE 6.4: Linear Assignment Using 3000 Definitions

	fastText 1M	**fastText 500k**	**Numberbatch**
Best	0.55	0.54	0.36
Worst	0.11	0.11	0.05
Average	0.33	0.33	0.19

TABLE 6.5: Summary of Linear Assignment

Chapter 7

Conclusion

Italian is a core language in numberbatch, the performance skyrockets!

Appendix A

Case Study - Aligning a Turkish Dictionary and English Princeton WordNet

Turkish Definition	English WordNet Definition
birdenbire duyulan ağrı ya da türlü heyecanları anlatır	an absence of emotion or enthusiasm
meyve bisküvi vb ile yapılan bir ingiliz tatlısı	a small hard fruit
yalıtım tecrit	a thin coating or layer
bulgu araz	a pattern of symptoms indicative of some disease
42195 m'lik en uzun yaya koşusu uzunkoşu	any long ditch cut in the ground
benzer olma durumu müşabehet	the quality of being similar
var olan bulunan	something that is lost
parmakların kapanmasıyla elin aldığı biçim	handwear covers the hand and wrist
zayıf olma durumu	any strong feeling
bir süreç içindeki durumlardan her biri basamak aşama rütbe mertebe	the effect of one thing or person on another

Turkish Definition	English WordNet Definition
bir birimin bölündüğü eşit parçalardan birini ya da birkaçını anlatan sayı	a unit of spoken language larger than a phoneme
haşhaş sütünü toplamakta kullanılan kaşık	grass mowed and cured for use as fodder
bir şeyi yapmayı önceden isteyip düşünme maksat	an act of intending a volition that you intend to carry out
ipekböceği kozaları çözülerek çıkarılan ve dokumacılıkta kullanılan çok ince esnek ve parlak tel	a very strong thick rope made of twisted hemp or steel wire
anadolu'nun doğu ve kuzey bölgelerinde en çok erzurum yöresinde el ele tutuşarak oynanan bir oyun	game a players turn to take some action permitted by the rules of the game
başkalarından saklanan duyurulmayan saklı kalan mahrem	a consecrated place where sacred objects are kept
bir kimseye ya da bir şeye karşı belli tavır takınmak	a feeling of sympathy for someone or something
tarihsel gelişme içinde belirli bir üretim ilişkisinin belirli bir aşamasında bir arada yaşayan insanların tümü	a large number of things or people considered together
bir cismin herhangi bir yöndeki uzanımı	a relatively small granular particle of a substance
organizmada birtakım değişikliklerin ortaya çıkmasıyla fizyoloji görevlerinin bozulması durumu sayrılık maraz esenlik" karşıtı	an impairment of health or a condition of abnormal functioning
yolcu ve gezmenlere geceleme olanağı sağlamak bunun yanında yemek eğlence gibi türlü hizmetleri sunmak ereğiyle kurulmuş işletme	a building where travelers can pay for lodging and meals and other services

Turkish Definition	English WordNet Definition
hükümdar ailesinden olan erkeklere verilen san	female of any member of the dog family
orduda yazı işleri ile uğraşan er ya da erbaş	a verbal or written request for assistance or employment or admission to a school
düşmanın gelmesi beklenen yollar üzerinde askeri önem taşıyan kentlerde geçit ve darboğazlarda güvenliği sağlamak için yapılan kalın duvarlı burçlu mazgallı yapı	an area within a building enclosed by walls and floor and ceiling
içi su ya da hava dolu ufak kabartı ya da kürecik	water in small drops in the atmosphere blown from waves or thrown up by a waterfall
hava ya da herhangi bir akışkanı bir yerden başka bir yere basınç yoluyla aktarmaya yarayan makine	a vertical flue that provides a path through which smoke from a fire is carried away through the wall or roof of a building
başkalarınca bilinmesi sakıncalı görülen bir gerçeği saklamaktan vazgeçip açıklama söyleme bildirme	an acknowledgment of the truth of something
bir bilim sanat meslek dalıyla ya da bir konu ile ilgili özel ve belirli bir kavramı olan sözcük ıstılah	an occupation requiring special education especially in the liberal arts or sciences
bir kilidi açıp kapamak için kullanılan araç açar açkı	a fastener fitted to a door or drawer to keep it firmly closed
işletilmek için bir yere ödünç verilen paraya karşılık alınan kâr ürem işlenti nema	a fixed charge for borrowing money usually a percentage of the amount borrowed
yeryüzü parçası yerey yer toprak alan	sloping land especially the slope beside a body of water

Turkish Definition	English WordNet Definition
yiyecek koymaya yarar az derin ve yayvan kap	metal or earthenware cooking vessel that is usually round and deep often has a handle and lid
yerleşik toplumsal düzeni köklü hızlı ve geniş kapsamlı olarak niteliksel değiştirme ve yeniden biçimlendirme eylemi inkılap	an extended social group having a distinctive cultural and economic organization
duygusal olma durumu	an unstable situation of extreme danger or difficulty
özel bir bozukluğu belirleyen bir arada görülen tanıyı kolaylaştıran bulgu ve belirtilerin tümü	a pattern of symptoms indicative of some disease
dumanı ocaktan çekip havaya vermeye yarayan maden ya da tuğla yol	a vertical flue that provides a path through which smoke from a fire is carried away through the wall or roof of a building
bir canlının üstünü kaplayan ve onu dış etkilere karşı koruyan kendiliğinden oluşmuş sertçe bölüm kışır	the activity of protecting someone or something
bir olayın ilk duyurusu olan biten salık	following the first in an ordering or series
çoğunlukla kare ya da silindir biçimindeki yüksek yapı	a protective covering or structure
bir yazıya başka bir yazarın yazısından alınmış parça aktarma iktibas	the form in which a text especially a printed book is published
felsefeyle uğraşan ve felsefenin gelişmesine katkıda bulunan kimse felsefeci feylesof	a specialist in philosophy
bir vücudun ya da bir organın yapı öğelerinden birini oluşturan gözeler bütünü nesiç	part of an organism consisting of an aggregate of cells having a similar structure and function

Turkish Definition	English WordNet Definition
fiziksel güç takat	the property of lacking physical or mental strength liability to failure under pressure or stress or strain
ilgisini çekmek önem vermek ya da bir şeyle ilgili kılmak	an act of help or assistance
askeri olmayan	a nonmilitary citizen
bir olayı gören izleyen kimse izleyici	someone who takes part in an activity
yapıları ve ulaşım araçlarını tren vapur gibi aydınlatmak havalandırmak amacıyla yapılan çerçeve cam panjur perde gibi eklentilerle daha kullanışlı bir duruma getirilen açıklık	a vertical flue that provides a path through which smoke from a fire is carried away through the wall or roof of a building
insanda ve omurgalılarda içinde beyin bulunan başın kemik bölümü	the bony skeleton of the head of vertebrates
özellikle sokakta ayağı korumak için giyilen iskarpin çizme kundura mokasen sandalet patik galoş gibi türleri olan ayak giyeceği pabuç	a shoe consisting of a sole fastened by straps to the foot
yüzeyi belirli uzunlukta bırakılmış hammadde lifleriyle kaplı parlak yumuşak kumaş	fabric woven from cotton fibers
delik yırtık ya da eski bir yeri uygun bir parça ile onarma kapatma	a piece of cloth used as decoration or to mend or cover a hole
ciltli ya da ciltsiz olarak bir araya getirilmiş basılı ya da yazılı kâğıt yaprakların tümü	one side of one leaf of a book or magazine or newspaper or letter etc or the written or pictorial matter it contains

Turkish Definition	English WordNet Definition
kuvvetin bir cismi bir nokta ya da bir eksen yöresinde döndürme etkisini belirleyen vektör niceliği	the effect of one thing or person on another
bir evin en geniş bölümü	an outbuilding or part of a building for housing automobiles
bez tahta kâğıt gibi maddeler üzerine yapılmış yağlıboya suluboya pastel ya da karakalem resim	a three-dimensional work of plastic art
ilgisiz olma durumu aldırmazlık alakasızlık	an unstable situation of extreme danger or difficulty
sevgi ve bağlılık duyulan	an absence of emotion or enthusiasm
anahtar düğme gibi takılıp çıkarılabilen bir parça yardımıyla çalışan kimi zaman elektronik de olabilen kapatma aygıtı	electronic equipment consisting of a device providing access to a computer has a keyboard and display
evrende ya da düşüncede yer alan "yok" karşıtı bu sözcük hep yüklem olarak kullanılır ve üçüncü kişilerde koşaç almayabilir belirten olması için sonuna olan ortacı getirilir	something that should remain hidden from others especially information that is not to be passed on
bir yapının dışarıya doğru çıkmış çevresi duvar ya da parmaklıkla çevrili bölümü	a movable barrier in a fence or wall
evin ya da herhangi bir yapının oturmak çalışmak yatmak gibi işlere yarayan banyo salon giriş vb dışında kalan bir ya da birden fazla çıkışı olan bölmesi göz	a structure taller than its diameter can stand alone or be attached to a larger building
kurulanmaya yarar havlı bez	white goods or clothing made with linen cloth

Turkish Definition	English WordNet Definition
kamuyla ilgili işlerin yürütülmesi için gerekli gelirleri ve harcanan paraları düzenleyen kuralların tümü	the management of money and credit and banking and investments
bir doğal su birikintisinin yanındaki alan kıyı	an area of sand sloping down to the water of a sea or lake
tene yumuşaklık vermek ya da güneş yağmur gibi dış etkilerden korunmak için sürülen güzel kokulu merhem	fine powdery material such as dry earth or pollen that can be blown about in the air
sınırlamak eylemi	a rule or condition that limits freedom
bir sanata bir bilime temel olan yön veren ilke kaide	an occupation requiring special education especially in the liberal arts or sciences
il ilçe gibi yerleşim bölgelerinde iki yanında evler olan caddeye oranla daha dar ya da kısa olabilen yol	a deep and relatively narrow body of water as in a river or a harbor or a strait linking two larger bodies that allows the best passage for vessels
belli bir saatte belli bir yerde iki ya da daha çok kişi arasında kararlaştırılan buluşma	a time period usually extending from friday night through sunday more loosely defined as any period of successive days including one and only one sunday
araştırılıp öğrenilmesi düşünülüp çözümlenmesi bir sonuca bağlanması gereken durum mesele problem	a question raised for consideration or solution
alışılmış olandan umulandan ya da gerekenden eksik niceliği küçük "çok" karşıtı	the quality of having an inferior or less favorable position
herhangi bir iş bir görev için kendini ileri sürme ya da başkaları tarafından ileri sürülme namzetlik	the real physical matter of which a person or thing consists

Turkish Definition	English WordNet Definition
birini telefonla aramak ve bir şey söylemek	a seat for one person with a support for the back
denemek eylemi sınama tecrübe	the act of rejecting something
patlıcangillerden yaprakları tüylü çiçekleri salkım durumunda vitaminçe zengin kırmızı ürünü için yetiştirilen bir bitki lycopersicon esculentum	mildly acid red or yellow pulpy fruit eaten as a vegetable
bir görevi bir işi yasaların verdiği olanaklara göre belli koşullarla yürütmeyi sağlayan hak salahiyet mezuniyet	financial aid provided to a student on the basis of academic merit
bir konu ile ilgili bilgi vermek ve bu bilgiler üzerinde tartışmak amacıyla birkaç yetkilinin yönetimi altında düzenlenen toplantı	a prearranged meeting for consultation or exchange of information or discussion especially one with a formal agenda
kendi isteğiyle görevden ayrılma çekilme işinden ayrılma	withdrawal from your position or occupation
merkezde bulunan ve bir eksenin çevresinde dönebilir kurs ya da çember teker	an urban area with a fixed boundary that is smaller than a city
bireyle ilgili olan bireye özgü olan ferdi	a person who is a member of a partnership
yumuşakçalardan bahçelerde yaşayan sarmal kabuklu küçük hayvan helix	elongated crescent-shaped yellow fruit with soft sweet flesh
kadın ya da erkek çocuğun en ince sesi	the highest female voice the voice of a boy before puberty
omuz başının altında kolun gövde ile birleştiği yer	the part of the body between the neck and the upper arm
üzerinde sıcak ve soğuk su muslukları bulunan porselen sac emaye gibi maddelerden yapılan el yüz bulaşık yıkamaya yarar yer	metal or earthenware cooking vessel that is usually round and deep often has a handle and lid

Turkish Definition	English WordNet Definition
adaletle iş gören adaletten haktan ayrıl-mayan hakkı yerine getiren adaletli	a rule or condition that limits freedom
tanıtma filmi	gathering of producers to promote business
bir makinenin herhangi bir taşıtın hızını kesmeye ya da onu durdurmaya yarayan düzenek	a restraint used to slow or stop a vehicle
ara uzaklık	a large distance
kap kılıf sarma	small thin inflatable rubber bag with narrow neck
herhangi birinden	the effect of one thing or person on another
sinema ya da müzikhol sanatçısı yıldız	a three-dimensional work of plastic art
okuyup yazmadan başlayarak en yüksek düzeyde bilim ve sanat bilgisi vermeye değin çeşitli derecede toplu olarak öğren-imin sağlandığı yer mektep	an occupation requiring special education especially in the liberal arts or sciences
başın altına koymak ya da sırtı dayamak için kullanılan içi yün pamuk kuştüyü gibi şeylerle doldurulmuş küçük minder	a piece of cloth used as decoration or to mend or cover a hole
alt ve üst tabanları birbirine eşit daireler-den oluşan bir nesnenin eksenini dikey olarak kesen birbirine koşut iki yüzeyin sınırladığı cisim üstüvane	a support that consists of a horizontal surface for holding objects
bir kimsenin belli bir sürede ya da yaşam boyu edindiği bilgilerin tümü tecrübe	the real physical matter of which a person or thing consists
yaşantıları öğrenilen konuları bunların geçmişle ilişkisini bilinçli olarak saklama gücü hafıza	a storage device on which information sounds or images have been recorded

Turkish Definition	English WordNet Definition
geçmeye engel olacak biçimde uzunlamasına kazılmış derin çukur	the general feeling that some desire will be fulfilled
bıçak makas gibi bir araçla bir şeyi ikiye ayırmak	a top as for a bottle
yitme yitim	a feeling of restless agitation
eski çağlardan beri söylenegelen olağanüstü varlıkları olayları konu edinen imgesel öykü söylence	the series of events that form a plot

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