

ARIEL UNIVERSITY

MASTER THESIS PROPOSAL

Word Sense Induction with Attentive Context Clustering

Author:
Moshe Stekel

Supervisor:
Amos Azaria, Shai Gordin

Data Science Group
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February 17, 2023

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Acknowledgements

This research was supported by the Ministry of Science & Technology, Israel, Grant 3-16464.

I would like to express my sincere gratitude to my advisors Prof. Amos Azaria and Dr. Shai Gordin for introducing me to the world of Deep Learning and to the advanced research tools and methodologies as well as to the world of the ancient Middle East history and linguistics, for their patience and guidance in the last two years.

I would like to thank Ariel University for the privilege of learning and researching at the department of Computer Science, for the familial environment and the generous scholarship.

My deep and everlasting thanks to my supportive family, my wonderful children and my loving and supportive wife Avigail.

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Ariel University

Abstract

Faculty of Natural Sciences
Department of Computer Science

Master

Word Sense Induction with Attentive Context Clustering

by Moshe Stekel

This thesis presents ACCWSI (Attentive Context Clustering WSI), a method for Word Sense Induction, suitable for languages with limited resources. Pretrained on a small corpus and given an ambiguous word (a query word) and a set of excerpts that contain it, ACCWSI uses an attention mechanism for generating context-aware embeddings, distinguishing between the different senses assigned to the query word. These embeddings are then clustered to provide groups of main common uses of the query word. We show that ACCWSI performs well on the SemEval-2 2010 WSI task. ACCWSI also demonstrates practical applicability for shedding light on the meanings of ambiguous words in ancient languages, such as Classical Hebrew and Akkadian. In the near future, we intend to turn ACCWSI into a practical tool for linguists and historians.

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Chapter 1

Introduction

Natural language expresses human concepts, thoughts, emotions, and insights. That is, natural language represents a model of extremely high complexity - the human mind (at least, its communication-driven layers). Some researchers believe that natural language is an environment in which compromise is inevitable when projecting the infinite number of dimensions of human thinking onto the much smaller number of dimensions of human speech [Fedorenko and Varley \[2016\]](#). The multiplicity of the meaning of a single word, such as polysemy (similarity obtained from a common source) or homonymy (accidental similarity), is, therefore, an expected product of this compromise. Below are two common examples of word sense ambiguity:

- “I can hear *bass* sounds” versus “They like grilled *bass*”
- “We crossed the river to the other *bank*” versus “Mike deposited the money in his *bank* account”

Humans are able to disambiguate the polysemy/homonymy or understand contextual nuances by using the clues that come from the context of the ambiguous word. One of the fundamental tasks of natural language processing is Word Sense Induction (WSI), a task of automatic discrimination of the different senses of words by finding these contextual clues.

It is difficult to overestimate the importance of accurate Word Sense Induction when dealing with common Natural Language Processing (NLP) tasks, such as Information Retrieval or Search Clustering. Furthermore, historical research seeks to correctly induce the meaning of words in order to resolve doubts about many historical issues. As a good example, we can refer to the Akkadian lemma “galû”, the meaning of which ranges between the negative shade of “exile” or “deportation”, the neutral shade of “relocation” and the rare positive one of “appointment”. Another example is the Hebrew lemma “zakar”, which takes on both the meanings of “memory” and “male”. Accurate Word Sense Induction is essential for the correct understanding of ancient documents.

In this thesis, we present an Attentive Context Clustering WSI (ACCWSI). ACCWSI first creates a word embedding for each word, which is identical for any context that it appears in. ACCWSI uses the cosine similarity between the words in the context and the word in focus to determine the attention that each word should achieve to form a context-aware vector representation for each appearance of the word in focus. ACCWSI then clusters the resulting vectors, such that each cluster represents a different meaning of the word. ACCWSI has demonstrated high practical applicability in languages with limited resources and obtained a very high score by the evaluation framework of SemEval-2 2010 Task 14 [Manandhar et al. \[2010\]](#) (we conducted a post-event evaluation using the original evaluation scripts). ACCWSI achieved a high score not only with the original training dataset but also with a training dataset reduced to a fraction of 2.6% of the original dataset, which is comparable to the size of the Hebrew Bible.

Chapter 2

Related Work

Word Sense Induction and Word Sense Disambiguation provide fertile ground for researchers, starting from very early attempts to tackle these non-trivial tasks, such as “simulated annealing” according to a human-edited dictionary [Cowie et al. \[1992\]](#) and employing the “conceptual distance” between contexts [Agirre and Rigau \[1996\]](#), later going through unsupervised methods, that use patterns of word co-occurrence [Bordag \[2006\]](#) or bigrams of web search results [Udani et al. \[2005\]](#), continuing with “hidden concepts” of the contextual words, that not necessarily overlap with the sense of the ambiguous word [Chang et al. \[2014\]](#), and ending with the most recent solutions like [Eyal et al. \[2021\]](#), that uses word substitutions of modern Masked Language Models, such as Google BERT MLM. In addition, the technique of pipelining a clustering algorithm and cosine distance (note that we do this in reverse order) is used by [Hämäläinen and Alnajjar \[2019\]](#) for dividing words (not necessarily polysemous or even similar) into semantic fields. This idea is not directly related to the Word Sense Induction task but it is another approach to dividing a given text into different semantic groups by using clustering and cosine distance. Our research was inspired by two main works: the context-group discrimination algorithm [Schütze \[1998\]](#) from the Context Clustering category and the Google BERT language model [Vaswani et al. \[2017\]](#). [Amrami and Goldberg \[2019\]](#) utilize Google BERT for their WSI method. However, their method does not meet our requirement of being able to induce word senses in languages with limited resources, as training Google BERT on small corpora does not provide sufficient accuracy [Ezen-Can \[2020\]](#). The high scores achieved by the BertWSI model in the SemEval-2 2010 Task 14 [Manandhar et al. \[2010\]](#) metrics are credited to the fact that the underlying model was pre-trained by Google on a huge corpus of text. Our solution takes advantage of the basic mechanism of attention [Galassi et al. \[2020\]](#) underlying BERT without applying the complex process of learning attention weights and thus achieves good results when applied to small datasets. The only weight learning process we use is the Word2Vec [Goldberg and Levy \[2014\]](#) model training that requires far fewer resources than attention-based learning. Thus, we provide a practical tool for the study of the meanings of words in resource-limited languages, such as ancient dead languages. The Clustering by Committee work [Pantel and Lin \[2002\]](#) gave us the idea to use a threshold of 0.5 as an acceptable proportion of orphan instances when measuring the quality of a clustering solution (see Section 3.4.3). We also explored Lin’s algorithm [Lin \[1998\]](#), which uses the word clustering approach by combining words with similar semantics into sense representations, but it was found less effective when it came to discriminating senses of words in resource-constrained languages.

Chapter 3

Task and Algorithm

3.1 WSI task definition

The general definition of WSI is automatic detection of the set of senses denoted by a word. A simplified version of WSI can be defined as follows: given a list of lemmatized sentences and a query lemma, find all the sentences in the list that contain the query lemma, and group them so that the instances of the query lemma in one group are semantically similar to each other and noticeably different from the instances in other groups. This is a simplified definition because, when lemmatizing, we ignore some input information, such as the part of speech, tense, etc. Note that ignoring the part of speech information of the target word is not necessarily a disadvantage, especially for ancient genres in which the archaic syntactic forms of words may provide no part of speech information (for instance, refer to the words of uncertain meanings and part of speech information in the Hebrew Bible, such as "amen" or "sela").

3.2 Attention mechanism

Our method uses the following "basic attention" mechanism: given a target word (query) and its "context", either the whole sentence or some "window" of words containing the query word, each element of the context is evaluated by its cosine similarity to the query word. The result is optionally multiplied by a constant factor and eventually softmaxed. We refer to the result as the "weights of similarity" or "weights of relevance". The semantically closer two words are, the greater is the cosine similarity between their embeddings and, therefore, the appropriate weights of relevance are greater. The original word embeddings of the context members are multiplied by the appropriate weights of relevance and thus the power of every context member is improved or worsened according to its relevance to the query word. When these new context-sensitive embeddings are summed into a single vector, this sum represents a context-aware vector of the query word that embeds its "local sense" with respect to this specific context, where the relevance of each context member is taken into consideration. Figure 3.1 illustrates this mechanism.

3.3 The ACCWSI algorithm

We now present our Attentive Context Clustering WSI (ACCWSI) algorithm (Algorithm 1). The algorithm first replaces the lemmas with their Word2Vec embeddings [Goldberg and Levy \[2014\]](#). It then uses the attention mechanism described above (Section 3.2), resulting in context-aware vectors, that are used as input to the DBSCAN clustering algorithm [Schubert et al. \[2017\]](#), producing clusters of different "shades of meaning" of the query lemma. Since different contexts are best defined by different most relevant context members, and conversely - similar contexts are defined by similar context members, the result vectors can be easily clustered. Figure 3.2 illustrates this idea.

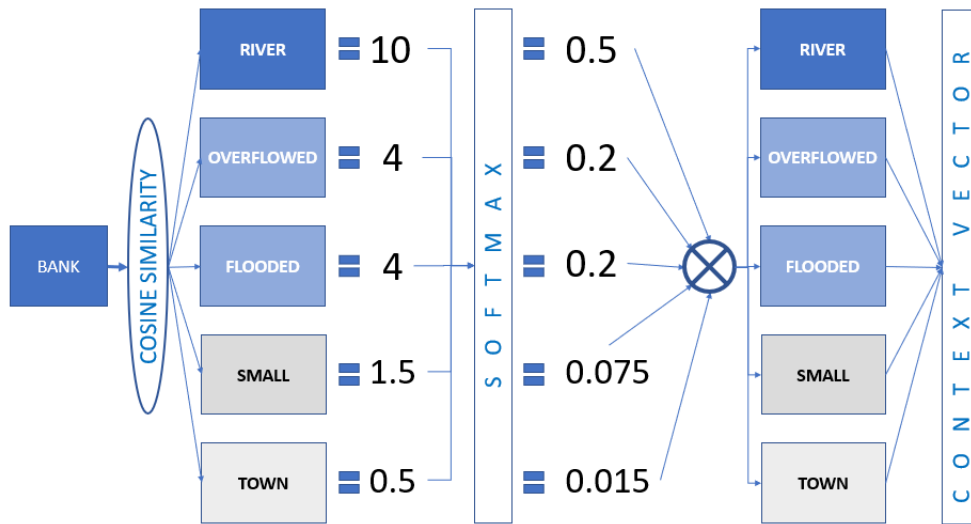


FIGURE 3.1: Illustration of the attention mechanism

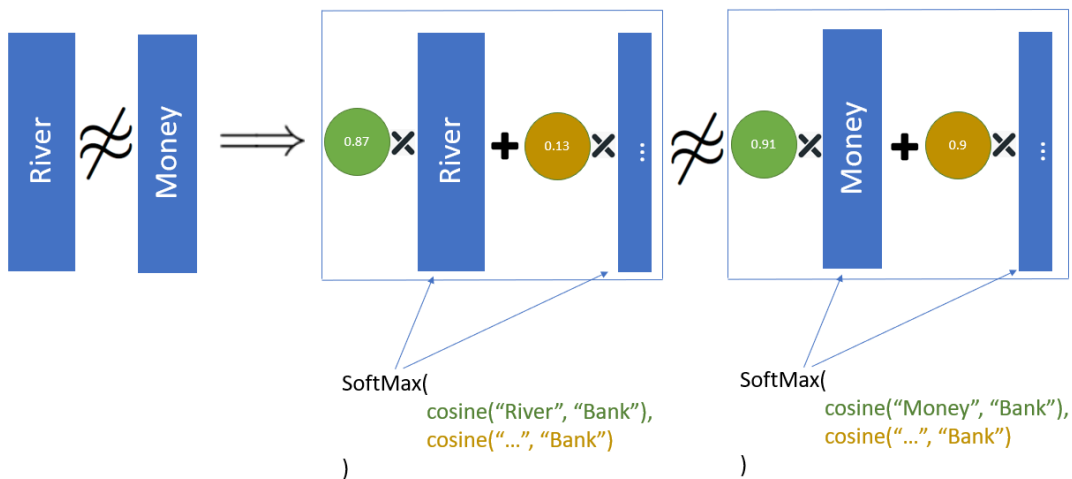


FIGURE 3.2: An illustration of separability of context-aware vectors generated by ACCWSI: the most relevant terms (green weights) with respect to the query term “bank” are “river” in the first context and “money” in the second context. They are different and therefore the result context-aware vectors are different. Less relevant terms are multiplied by smaller weights (light brown) and thus have a smaller effect on the final context-aware vector.

Let’s explain the algorithm in detail: line 1 runs the language model creation - the process that generates multi-dimensional vectors that correspond to the words in the text. The distances between the vectors are supposed to express the semantic distances between the corresponding words. Line 2 finds the sentences in which the query lemma occurs. The flow in lines 4-11 iterates over these sentences, computes the similarity of their members to the query lemma (line 7), normalizes the similarity values (SOFTMAX - line 8), and then uses these normalized weights to generate the weighted (with respect to the query lemma) values of the sentence members and sums them (dot product - line 9), resulting in a list of weighted context vectors. These context vectors are eventually clustered in line 12.

Algorithm 1 ACCWSI Algorithm.**Input:** $\$text$ ▷ a list of lemmatized sentences $\$query_lemma$ ▷ the query lemma**Output:** context groups of the query lemma

```

1:  $word2vec \leftarrow$  train a Word2Vec model using  $\$text$ 
2:  $query\_lemma\_sentences \leftarrow$  sentences from  $\$text$  that contain  $\$query\_lemma$ 
3:  $context\_vectors \leftarrow$  an empty list
4: for each  $sentence \in query\_lemma\_sentences$  do
5:    $sentence\_member\_vectors \leftarrow word2vec.get\_vectors(sentence)$ 
6:    $query\_lemma\_vector \leftarrow word2vec.get\_single\_vector(query\_lemma)$ 
7:    $similarity\_vector \leftarrow$ 
       $COSINE\_SIMILARITY(sentence\_member\_vectors, query\_lemma\_vector)$ 
8:    $similarity\_weights \leftarrow SOFTMAX(similarity\_vector)$ 
9:    $context\_vector \leftarrow$ 
       $sentence\_member\_vectors \cdot similarity\_weights$  ▷ dot product
10:   $context\_vectors.push(context\_vector)$ 
11: end for
12: return  $DBSCAN(...).fit(context\_vectors)$ 

```

3.4 Hyperparameters

Algorithm 1 uses several hyperparameters: Word2Vec window, the choice of the clustering algorithm, and the internal hyperparameters of the latter. The optimal values of these parameters can be found either empirically or by using well-known optimization methods. In this section, we explain these hyperparameters, briefly overview the optimization methods, and present the method that achieved the best accuracy in our case. Note that in our online tool we will use our recommendations for these parameters as their default values allowing the end-users to modify these default values according to the characteristics of their datasets.

3.4.1 Word2Vec Window

This parameter determines the size of the context to be scanned from each direction around the target word when training the Word2Vec model to perform the missing word prediction task (CBoW architecture) or the context prediction task (Skip-Gram architecture). The optimal value of this parameter intuitively depends on the native average “density of context” inherent to the target language. We found the optimal value empirically by iterating over the range from 2 to 10 and evaluating the result by manually checking the semantic similarity of words suggested by the model. The best values were 5 for English and 2 for Classical Hebrew. This difference is probably due to the specific syntactic structures of Classical Hebrew verses, which are statistically much shorter than the syntactic structures of typical Modern English sentences.

3.4.2 The choice of the clustering algorithm

We evaluated several clustering algorithms on our task, including KMeans [Hamerly and Elkan \[2004\]](#), Gaussian-Mixture model [Reynolds et al. \[2009\]](#) and DBSCAN [Schubert et al. \[2017\]](#). DBSCAN, the density-based clustering algorithm, performed slightly better and was therefore selected as our clustering algorithm for this thesis. In our online tool, we will present a list of clustering algorithms to choose from

and the end-users will be able to choose the best clustering algorithm that suits their datasets.

3.4.3 Optimizing DBSCAN-eps

This parameter is a key one for the density-based clustering proposed by DBSCAN. It defines the maximum distance between two points to be considered as neighbors. There are several methods in the literature for optimizing the value of this parameter, such as the Kneedle algorithm for finding the maximum curvature in the graph of distances, the Silhouette Score for evaluating the clustering quality, and more. Although these optimization methods demonstrated good performance (unsupervised V-Measure of 15.3%), we propose an optimization search heuristic that performed better. The rationale behind the heuristic is that text can contain instances of ambiguous words with highly clear context, in addition to other instances with more obscure context. Decreasing the value of *eps* results in clearer but tighter clusters, filtering out distant “noisy” instances. In our case, narrowing the clusters while keeping the number of the “noisy” instances below 50% gave good results¹. Algorithm 2 demonstrates this heuristic.

For other datasets, the heuristic above may be less effective because there should not be a direct correlation between the amount of noise and the distribution of word senses, so it can always be a good idea to let the user adjust the value of this parameter empirically. In our future online tool for researchers, summarizing this research (see Chapter 6.1), we plan to add dedicated controls to tune all ACCWSI hyperparameters.

Algorithm 2 Fine-tuning the DBSCAN *eps* hyperparameter - the value of *eps* is iteratively decreased until the noise (the fraction of the outlier instances) becomes greater than $\frac{1}{2}$

```

1: best_eps ← 0.95
2: for each xrange(90, 0, -5) do ▷ from 90 to 0 with step -5
3:   eps ← x/100
4:   labels ← DBSCAN(eps = eps).fit(context_vectors)
5:   noise ← labels.count(OUTLIERS)/len(labels)
6:   if noise ≤ 0.5 then
7:     best_eps ← eps
8:   else
9:     break
10:  end if
11: end for
12: return

```

¹Note that any parameter optimization search method should only be performed on the training data to prevent test data bleeding and overfitting

Chapter 4

Experimental evaluation

We ran an experiment to evaluate the algorithm on **Sem-Eval 2010 Task 14** [Manandhar et al. \[2010\]](#), which aims to objectively measure and compare the quality of WSI systems. Both training and test data are English sentences containing polysemous or homonymous nouns and verbs. The goal of the task is to split the instances of each ambiguous word and their contexts into clusters representing different meanings. The result is assessed by comparison with the “Gold Standard” clustering performed by human experts. In Section 4.1 we present the Unsupervised V-Measure and F-Score metrics of this assessment as well as the Supervised Recall metric.

4.1 SemEval-2 2010 Task 14 Evaluation

In Task 14 of the SemEval-2 2010 workshop [Manandhar et al. \[2010\]](#), participants were asked to train their models on the corpus of training data provided by the organizers, and then perform word sense induction for a set of sentences containing both ambiguous nouns and ambiguous verbs. The results were assessed against the “Gold Standard” clusters compiled by human experts. The tables below show the metrics achieved with ACCWSI trained on the full training corpus (**ACCWSI full** in the tables). By training ACCWSI we mean training its internal Word2Vec model), as well as the metrics achieved with the reduced ACCWSI (**ACCWSI reduced** in the tables), which was trained on a randomly selected 2.6% of the training data, along with those of the participants with the highest scores in every metric.

System	VM % (All)	VM % (Nouns)	VM % (Verbs)
ACCWSI full	17.3	20.7	12.3
Hermit	16.2	16.7	15.6
UoY	15.7	20.6	8.5
KSU KDD	15.7	18	12.4
ACCWSI reduced	15.4	18.8	10.4
Duluth-WSI	9	11.4	5.7
...			
...			
Duluth-WSI-SVD-Gap	0	0	0.1

TABLE 4.1: V-Measure (VM) unsupervised evaluation. V-Measure assesses the quality of a clustering solution by explicitly measuring its homogeneity and its completeness. Homogeneity refers to the degree how much each cluster consists of data points primarily belonging to a single Gold Standard class, while completeness refers to the degree how much each Gold Standard class consists of data points primarily assigned to a single cluster. V-Measure is the harmonic mean of homogeneity and completeness.

System	FS % (All)	FS % (Nouns)	FS % (Verbs)
Duluth-WSI-SVD-Gap	63.3	57	72.4
KCDC-PT	61.8	57	72.4
...			
...			
ACCWSI reduced	55.9	51.3	62.7
...			
...			
ACCWSI full	53.8	47.2	63.4
Duluth-WSI-SVD	41.1	37.1	48.2
Duluth-WSI	41.1	37.1	48.2
...			
...			
Duluth-R-110	16.1	15.8	16.4

TABLE 4.2: Paired F-Score (FS) unsupervised evaluation: two sets of instance pairs are generated - a set of all possible instance pairs within each induced cluster and a set of all possible instance pairs within each Gold Standard class. Precision is the number of common instance pairs between the two sets to the total number of pairs in the induced clusters, while recall is the number of common instance pairs between the two sets to the total number of pairs in the Gold Standard classes. F-Score is the harmonic mean between precision and recall.

System	SR % (All)	SR % (Nouns)	SR % (Verbs)
ACCWSI full	63.7	59.6	71.1
ACCWSI reduced	62.7	57.5	69.8
UoY	62.4	59.4	66.8
Duluth-WSI	60.5	54.7	68.9
...			
...			
Duluth-Mix-Uni-Gap	18.7	1.6	43.8

TABLE 4.3: Supervised recall (SR) using a test set split with 80% mapping and 20% evaluation. In this evaluation, the testing dataset is split into a mapping and an evaluation corpus. The first one is used to map the automatically induced clusters to Gold Standard senses, while the second one is used to evaluate methods in a WSD setting.

Chapter 5

Application examples

In this section, we present examples of applying our method to a relatively small Hebrew corpus—the Hebrew Bible. These examples are far from constituting definitive proof of applicative effectiveness and, as we will show later for Akkadian texts, there can be many instances of applicative failure. But the high scores obtained in SemEval-2 2010 Task 14 and the directions listed in Section 6.1 give us hope for creating a highly applied tool in the near future.

We used the text-fabric version of the BHSA project to generate the appropriate dataset and run the ACCWSI algorithm on it. Figure 5.1 shows the operation of the ACCWSI algorithm used to obtain two different meanings of “bank” in English. Figure 5.2 and Figure 5.3 present the induced classes for two ambiguous Hebrew Biblical lemmas: **khalal** (dead body/desecrate) and **zakar** (male/memory). The instances of the first lemma were split into 2 sense clusters while the instances of the second lemma were split into 5 sense clusters. ACCWSI seems to perform well and provide satisfactory clusters despite the small training corpus.

5.1 ACCWSI performance on ancient Akkadian texts

Another experiment we did was Word Sense Induction in ancient Akkadian texts. Between the 9th to the late 7th centuries BCE, the Assyrian Empire deported millions of people across the Near East. By even the most humble estimates, around 1.3 million people were moved around as a result of conquest, labour recruitment, or as punishment, just to name the central reasons for this dire process (Sano 2020). However, the records for these deportations are numerous and came down to us in different genres that deal with the act of deportation, or forced migration, from different points of view: contemporaneous Assyrian royal inscriptions, letters, and administrative texts, as well as Babylonian historical chronicles, written many years after the events in question. All were written in Assyrian and Babylonian, two close dialects of Akkadian, the oldest known (East-)Semitic language in the world. In total, 19 different verbs deal with various stages of the forced migration, like the capture of people or forced recruitment, their change of location, and resettlement. Even then, there are differences across meanings for specific verbs, sometimes minute ones, but also quite substantial in terms of semantics.

A good example of such a complicated verb is *galû* which the Chicago Assyrian Dictionary (CAD), the most comprehensive dictionary of Akkadian, translates as “1. to go into exile, 2. to deport, to exile (Š-stem, causative)” (CAD Š/3, 201). Its usage is limited to a Babylonian context, either in Assyrian letters dealing with Babylonia or Babylonian chronicles (Sano 2020, 34). As text 1 below shows, *galû*, much like Biblical Hebrew *GLY/H*, is used in consequence of a military conflict. However, a single instance in a letter from the time of Tiglath-pileser III (c. 731-730 BCE), here text 2, shows a rare nuance of the verb. Under certain political circumstances, people could ask for someone to deport them to Assyria, likely referring to the safety of being a protected refugee under the direct responsibility of the Assyrian king. This might also be the meaning of certain cases in Aramaic, where *gly* in G-stem active participle

means “exile, refugee”, or in D-stem means “to emigrate”, ([Comprehensive Aramaic Lexicon](#), s.v. gly D and C).

Text 1: SAA 19, 27 rev. 4'-8a' ([online edition](#), Luukko 2012)

4' LUGAL? lu? ú-di NIM.MA.KI-a-[a] 5' LÚ.ERIM-MEŠ-šú-nu TA DUMU ^mGIN—
NUMUN la? 6' i-du-ku ù ša—da-a-ni 7' ú-sag-li-šú-nu šú-nu-ú-ma 8' ig-da-al-ú

(rev. 4'-5') The Elamites killed their soldiers with the son of Mukin-zeri and (6'-8') **deported them by force**. They too **went into exile**.

Text 2: SAA 19, 87 obv. 8b'-13a' ([online edition](#), Luukko 2012)

8' ... e-gir-tum ša ina UGU 9' [^{md}]AMAR.UTU—A—SUM-na na-šú-ni-ni it-tab-lu-ni
10' [ina] pa-ni-ni i-si-si-ú : ù ^mba-la-su 11' [ip]-ta-la-a a—da-niš ma-a an-nu-rig x+[x x]
12' [at]-tu-nu tal-la-ka ma-a ša-ga-la-ni [o] 13' [i]-si-ku-nu la-al-lik ...

(obv. 8'-9') They intercepted the letter which was brought to Merodach-baladan (10') and read it [in] our [pr]esence. But Balassu (11') [g]ot very scared, saying: (12') “You (pl.) must come this moment and **deport me!** (13') I will go [wit]h you (pl.).”

Figure 6.1 (shortened) shows that ACCWSI produces a single cluster only for a limited number of instances of *galû* found in the [State Archives of Assyria Online at ORACC](#). In stark comparison, Figure 5.4 demonstrates that applying ACCWSI to the polysemous lemma *kayyānu*, which is more common in Akkadian texts, produces much better distinction of different clusters of meaning. Three possible reasons might lead to the difference in the resulting clusters between *galû* and *kayyānu*:

1. The meanings of a cultural lemma like *galû* are close to each other, at least in terms of their contexts, and even humans do not necessarily agree on them.
2. The source cuneiform tablets contain many discontinuations, breaks and names of peoples and places, providing contexts of very different quality from one another.
3. ACCWSI focuses on careful reading and does not rely on the experience gained from reading a large number of texts. Although this was previously considered its main advantage, it becomes a stumbling block when disambiguating very minute nuances.

Sentence	Attention Highlights	Cluster			
Her bank account was rarely over two hundred.	account, rarely	0			
After breakfast, she closed her account at the bank and turned in her resignation.	account, close, turn	0			
How could a man with four million in the bank be in financial danger?	financial, man, danger	0			
Seating herself on a low bank, she studied the souls.	seat, study, low	0	A stream bank is the terrain alongside the bed of a stream	stream, stream, bed	1
If you would know the history of these homesteads, inquire at the bank where they are mortgaged.	mortgage, homestead, history	0	He walked up and down the river, leading his house behind him; but he kept his eyes turned always toward the dim, dark spot which he knew was the old North Church.	river, church, spot	1
I guess he had some bucks at one time – back when he bought all this land – but his bank account never held a candle to mine.	account, hold, buy	0	She waded to the bank and picked up he shoes and stockings.	stocking, shoe, wade	1
			The town of Barwani is situated near the left bank of the Nerbudda	town, near, left	1
			Cushing himself swam to the swamps on the river bank, and after wading among them for hours reached a Federal picket boat.	river, boat, swamp	1
			Within an hour, there were riding side-by-side down the south bank of the creek, searching for the blocked area.	creek, area, south	1

FIGURE 5.1: Two different meanings of **bank**, the financial institute and the geographic terrain, are represented by the clusters in the figure. The “attention highlight” column shows the most relevant context words. The first cluster contains an interesting failure: the fourth sentence is clustered as a financial institute even though a human would cluster it as a geographic terrain. The reason is that the most relevant context words “seat, study, low” are not sufficiently indicative.

Sentence	Attention Highlights	Cluster
וּמִזְרָעֶךָ לֹא תִתֵּן לְהַעֲבִיר לְמַלְךְ וְלֹא תִחַלֵּל אֶת־שֵׁם אֱלֹהֶיךָ אֲנִי יְיָ-וְהָ.	נתן, י-ה-ו-ה, עבר	0
לִכֵּן אָמַר לְבֵית יִשְׂרָאֵל כִּה אָמַר אֲדֹנָי יְיָ-וְהָ לֹא לְמַעַנְכֶם אֲנִי עֹשֶׂה בַּיִת יִשְׂרָאֵל כִּי אִם לְשֵׁם קֹדֶשׁ אֲשֶׁר חָלַלְתֶּם בְּגוֹיִם אֲשֶׁר בְּאַתְּמֵי שָׁמַיִם.	גוי, ישראל, קדש	0
וְאַחֲמַל עַל שֵׁם קֹדֶשׁ אֲשֶׁר חָלַלְוּהוּ בַּיִת יִשְׂרָאֵל בְּגוֹיִם אֲשֶׁר בָּאוּ שָׁמָּה.	חמל, גוי, ישראל	0
וַיָּבֹאוּ אֵלַי הַגִּזְיֹת אֲשֶׁר בָּאוּ שֵׁם וַיְחַלְלוּ אֶת שֵׁם קֹדֶשׁ בְּצִמְרֵי לֶהֱם עִם יְיָ-וְהָ אֵלֶּה וּמֵאַרְצוֹ יָצְאוּ.	עם, גוי, קדש	0
וַיִּפְּלוּ סִלְלִים בְּאַרְץ כְּשָׂדִים וּמִדְּקָרִים בְּחֻצוֹתֶיהָ.	דקר, חוץ, נפל	1
כִּי נִתְּתִי אֶת חֲתִיתִי בְּאַרְץ סַיִים וְהִשְׁכַּב בְּתוֹךְ עֲרָלִים אֶת סִלְלֵי חֶרֶב פְּרָעָה וְכָל הַמִּזְוָה נָאֵם אֲדֹנָי יְיָ-וְהָ.	ערל, חרב, נאם	1
אוֹתָם יִרְאֶה פְּרָעָה וְנָחַם עַל כָּל הַמִּזְוָה סִלְלֵי חֶרֶב פְּרָעָה וְכָל חֵילָא נָאֵם אֲדֹנָי יְיָ-וְהָ.	חרב, נאם, כל	1
שָׁמָּה נִסִּיכִי צִפּוֹן כָּל־וְכָל אֲדֹנָי אֲשֶׁר יִרְדּוּ אֶת סִלְלִים בְּחֲתִיתָם מִגְּבוּרַתְּם בּוֹשִׁים וַיִּשְׁכְּבוּ עֲרָלִים אֶת סִלְלֵי חֶרֶב וַיִּשְׁאוּ כְלִמְתָם אֶת יִרְדֵי בֹר.	ערל, כל, כל	1

FIGURE 5.2: In the Hebrew Bible, the lemma **khalal** normally takes on the sense of either **dead body**(as a noun) or **desecrate**(as a verb). This figure presents the appropriate clusters generated by ACCWSI. The “attention highlight” column shows the most relevant context words. In the context of **desecrate** (cluster 0), the attention is paid to words like **God, sacred, nation** etc. while in the context of **dead body** (cluster 1), the attention is paid to **sword, stab, fall**, etc.

Sentence	Attention Highlights	Cluster
וּבֶן שָׁמֹנֶת יָמִים מוּל לֶכֶם כֹּל זָכָר לְדַבְרֵיכֶם יָלִיד בֵּית וּמְקַנֵּת כֶּסֶף מִכֹּל בֶּן זָכָר אֲשֶׁר לֹא מִזְרַעְךָ הוּא.	דור, יום, כל	0
פְּקֻדֵיהֶם בְּמִסְפָּר כֹּל זָכָר מִבֶּן חֹדֶשׁ וּמַעֲלָה פְּקֻדֵיהֶם שִׁבְעַת אֲלָפִים וְחֲמֵשׁ מֵאוֹת.	מספר, שבע, פקד	0
בְּמִסְפָּר כֹּל זָכָר מִבֶּן חֹדֶשׁ וּמַעֲלָה שָׁמֹנֶת אֲלָפִים וְשֵׁשׁ מֵאוֹת שְׁמֹרֵי מִשְׁמֶרֶת הַקֹּדֶשׁ.	מספר, מעל, כל	0
וּפְקֻדֵיהֶם בְּמִסְפָּר כֹּל זָכָר מִבֶּן חֹדֶשׁ וּמַעֲלָה שִׁשַּׁת אֲלָפִים וּמֵאוֹת.	מספר, פקד, מעל	0
זָכָר רִחְמִיךָ יְיָ-הוֹיָה וְנִסְדִּיךָ כִּי מַעֲלֹם הָפָה.	עולם, חסד, רחמים	1
חֲטָאוֹת נְעוּרַי וּפְשָׁעַי אֵל תִּזְכֹּכ כְּחִסְדְּךָ זָכָר לִי אֲתָה לְמַעַן טוֹבֵךְ יְיָ-הוֹיָה.	פשע, חסד, נעורים	1
פָּנִי יְהוָה בְּעֵשִׂי רַע לְהִכְרִית מֵאֶרֶץ זָכְרָם.	כרת, ה', רע	1
אֲלֵהֶם, אֲזַכְרְךָ מֵאֶרֶץ יִרְדּוֹ וּמִגִּבְעוֹתֶיךָ מֵהַר מֵאֲוֵר.	אלהם, נפש, כן	1
וְאִם מִן הַצֹּאן קָרְבַּנְךָ לְזִבְחֵי שְׁלָמִים לִי-הוֹיָה זָכָר אוֹ נִקְבָּה תָּמִים יִקְרִיבוּ.	נקבה, תמים, ה'	2
אוֹ הוֹדַע אֵלָיו חֲטָאוֹת אֲשֶׁר חָטָא בָּהּ וְכִיבִיא אֶת קָרְבָּנוֹ שְׁעִיר עִזִּים זָכָר תָּמִים.	חטא, תמים, קרבן	2
לְהִיבְרָתָם תָּמִים זָכָר בְּבָקָר בְּשֵׁשֶׁבַע וּבְעִזִּים.	תמים, רצון, כשב	2
וְאִם זִבְחֵי שְׁלָמִים קָרְבַּנְךָ אִם מִן הַבָּקָר הוּא מִקְרִיב אִם זָכָר אִם נִקְבָּה תָּמִים יִקְרִיבוּ לִפְנֵי יְהוָה.	נקבה, תמים, ה'	2
וַיֵּבֵא אֱלֹהִים בֶּן טֹלְקָהוּ אֲשֶׁר עַל הַבַּיִת וְשִׁבְנָא הַסּוֹפֵר וַיֹּאמֶר בֶּן אֶסְף הַמְּזַכֵּיר אֵל חֻקֵּיהֶם: הֲכַמְנָא בְּגָדִים וַיֵּאָדוּ לוֹ אֶת דְּבַר רַב שְׁקָה.	סופר, בן, אסף	3
וַיֵּבֵא אֵלָיו אֱלֹהִים בֶּן חֻלְקֵיהוּ אֲשֶׁר עַל הַבַּיִת וְשִׁבְנָא הַסּוֹפֵר וַיֹּאמֶר בֶּן אֶסְף הַמְּזַכֵּיר.	סופר, בן, אסף	3
אֶלְחִנָּגָה וְאַחִיהֶם בְּנֵי שְׁלֹשָׁה סָפְרִים יְהוֹשֻׁפֵט בֶּן אֶסְמֵלָה הַמְּזַכֵּיר.	ספר, בן, יהושפט	3
וַיִּקְרְאוּ אֵל הַמְּלַךְ וַיֵּבֵא אֲלֵהֶם אֱלֹהִים בֶּן חֻלְקֵיהוּ אֲשֶׁר עַל הַבַּיִת וְשִׁבְנָא הַסּוֹפֵר וַיֹּאמֶר בֶּן אֶסְף הַמְּזַכֵּיר.	סופר, בן, אסף	3
וְהַיָּמִים הָאֵלֶּה נִזְכָּרִים וְנִעְשִׂים בְּכָל דּוֹר נְדָר מִשְׁפָּטָה וּמִשְׁפָּטָה מְדִינָה וּמְדִינָה וְעִיר וְעִיר וְעַכְשָׁיו יָמֵי הַפּוֹרִים הָאֵלֶּה לֹא יִעָבְרוּ מִתּוֹךְ הַיְּהוּדִים וְזָכְרָם לֹא יִסָּפֵחַ מִזְרַעֲכֶם.	דור, דור, יום	4
יְיָ-הוֹיָה שְׁמֶךָ לְעוֹלָם יְיָ-הוֹיָה זָכְרְךָ לְדֶרֶךְ נְדָר.	דור, דור, עולם	4
אֲזַכִּירָה שְׁמֶךָ בְּכָל דֶּרֶךְ נְדָר עַל כֵּן עַמִּים יִהְיוּ לְעוֹלָם וָעֶד.	דור, דור, שם	4
וְאַתָּה יְהוָה לְעוֹלָם תִּשָּׁב זָכְרְךָ לְדֶרֶךְ נְדָר.	דור, דור, עולם	4

FIGURE 5.3: In the Hebrew Bible, the senses of the lemma **zakar** are related to either **male** or **memory**. This figure presents the five clusters generated by ACCWSI. The "attention highlight" column shows the most relevant context words. The first cluster represents the sense of **male human**, the second one - **God's memory**, the third one - **male animal sacrifice**, the fourth - **the role of scribe** and the fifth - **chronological memory**

origin	joined list of per-word senses	attention_highlight	cluster
P348683: Samsa eddésu nür ili kayyānu Marduk mušim šimāti murrik ūmī kurāti mupahhir niši saphāti muqerrubū ahāmes rūqūti artunuma	[] constantly self-renewing light god steady [] one who decrees one who lengthens day short one who gathers people scattered one who brings together far apart one you	šimāti, eddésu, ilu	0
Q004232: EN bēl bēli šar šarī Samsa Samsa dayyān šamē u eršeti bēl mātāti eddésu nür ili kayyānu mušēser elāti u šaplāti rē' ū kīnu ša tenēšeti attā Samsa dayyānu širu ša qibissu lā uttakkaru annāšu ilu mamman lā	incantation (label) lord lord king king [] [] judge sky and earth lord land constantly self-renewing light god constant good guide upper world and lower world shepherd true of people you [] judge exalted whose command not be(come) changed approval god anybody not	eddésu, ilu, nūru	0
Q004220: x eddésu nür ili kayyān mušēser elāti u šaplāti rē' ū kēnu ša tenēšeti attā Samsa dayyānu širu ša qibissu lā uttakkaru annāšu mamma lā	constantly self-renewing light god constant good guide upper world and lower world shepherd true of people you [] judge exalted whose command not be(come) changed approval anybody not	eddésu, ilu, nūru	0
Q005421: tēmēqu Samsa bēlyā ina supēšu ša ili rabūti puhur mārē ummāni temmēn labiti ippalissina papāhi u di' i ihūti zamar itūrdūm yāti iqūb appalissina temmēn labiti ša Naram-Sin šar ullu papāhi Samsa kayyānu mūšab ilūtūšu libbi ihdema immeri pānyā papāhi bēlūtūšu u di' i ušabbima ina	prayer [] lord through prayer of god great assembly citizen craftsman foundation original discover cella and (deity's) throne-platform check quickly return me say discover foundation original of king of Agade king distant past cella [] permanent residence divinity heart be(come) joyful be(come) bright face cella lordship and (deity's) throne-platform inspect during	hadū, ilūtu, nawāru	1
Q005490: Esagil u Ezida kaqdā kayyānāk asrāt Nabium u Marduk bēlyā astēne' a kayyānam isinātūšunu damqūtim akissunu rabūtim in gumābi paglūti alpū šuklulūti zuluhē damqūtim immer mīru gukkallam ušummu pelā nūnum iššurum simat appārīm tūbik sīrās lā nībi māmīs karānam šattīšam in nuhiš u hegallē in maharissunu etētiq nišim rapšāti ša	temple of Marduk at Babylon and temple of Nabū at Borsippa constantly constant shrine [] and [] lord constantly seek out constantly festival good (a cultic festival) great with prize bull massive ox perfect (a kind of long-fleeced sheep) good sheep fattening (process) fat-tailed sheep (a rodent) egg fish bird appropriate symbol marsh outpouring (a kind of) beer not number like water wine yearly in abundance and plenty in front parade people extensive that	kaqdā, ešertu, še' ū	1
Q005600: Nabium-kudurri-usur šar Babilī rē' ū kīnim migir Marduk iššakku siri narām Nabu rubām na dam ša alkakāt Marduk bēlu rabi' um ilu bānišu u Nabium apilūšū kīnim narām šarūtūšu itēne' ū kayyānam mūda u telē ša irammū puluhti ilūtūšunu ana tēnu ilūtūšunu bāzā ušāšu eršu itpēšu ša ana	Nebuchadnezzar II, king of Babylon king Babylon shepherd true favourite [] city-ruler exalted loved one [] prince attentive of way [] lord great god creator and [] heir true loved one kingship constantly seek out constantly one who knows very able one of love reverence divinity for decision divinity existing wisdom wise one expert of for	še' ū, puluhtu, mūdū	1
Q003704: rabēya astē' a asrāt ilāni rabūti šangūti ihšuhū irammū nadān zibīya Adad zunnišu umāššera Ea upattira nagbīšu 5 ammat ē i šqu ina absinnišu ērik šubultu 5/6 ammat ešer ebūri napās Nisaba kayyān ušahnabū gipāru šippāti šummuḫā inbu būlu šutēšur ina tālitti ina palēya nuhiš tūhdu ina šanātiya kummurū hegallum 10 imēr ē 3	adulthood constantly seek out shrine god great priestly office desire love giving food offering [] rain release [] loosen underground water a unit of length grain be(come) high in furrow be(come) long ear of corn a unit of length success harvest abundance [] constantly make grow luxuriantly pastureland fruit orchard very luxuriant fruit livestock success in offspring during reign (of a king) abundance abundance during year piled up plenty a unit of capacity grain	napāšu, ebūru, šummuḫa	2
Q003707: seheryya adi rubēya astē' a asrāt ilāni rabūti šangūti ihšuhū irammū nadān zibīya Adad zunnišu umāššera Ea upattira nagbīšu 5 ammat ē i šqu ina absinnišu ērik šubultu 5/6 ammat ešer ebūri napās Nisaba kayyān ušahnabū gipāru šippāti šummuḫā inbu būlu šutēšur ina tālitti ina palēya nuhiš tūhdu ina šanātiya kummurū hegallum 12	childhood to ruler constantly seek out shrine god great priestly office desire love giving food offering [] rain release [] loosen underground water a unit of length grain be(come) high in furrow be(come) long ear of corn a unit of length success harvest abundance [] constantly make grow luxuriantly pastureland fruit orchard very luxuriant fruit livestock success in offspring during reign (of a king) abundance abundance during year piled up plenty	napāšu, ebūru, šummuḫa	2
Q003703: absinnišu ērik šubultu 5/6 ammat ešer ebūri napās Nisaba kayyān ušahnabū gipāru šippāti šummuḫā inbu būlu šutēšur ina tālitti ina palēya nuhiš tūhdu ina šanātiya kummurū hegallu 10 imēr ē 1 imēr karāni BANMIN šamni 1	furrow be(come) long ear of corn a unit of length success harvest abundance [] constantly make grow luxuriantly pastureland fruit orchard very luxuriant fruit livestock success in offspring during reign (of a king) abundance abundance during year piled up plenty a unit of capacity grain a unit of capacity wine oil	napāšu, ebūru, šummuḫa	2
Q003705: niši āšibūti Qirbit kayyān ihtanabbatū hubut Yamutbali ālu šuātu ina tukulti Aššur Sin Samsa Bel Nabu Ištār ša Nimua Ištār ša Arba-ili akūsd ašlula šallatsu Tandaya itti	people inhabitant [] constantly constantly loot plunder [] city that through help [] [] [] [] of Nineveh [] of Arbela conquer carry off booty city ruler of Qirbit with	habātu, nišu, Yamutbal	3
Q006597: tūdāt mātūšu ušharrirūma U: x ŠU x x x x alāk gerri kayyān ihtanabbatū iprusū x	path land lay waste course road constantly constantly loot block	parāšu, habātu, mātu	3
Q003702: qereb Harehasta lū allik ša Tandaya ana šarrāni abbīya lā ikūšu ana niri u niši āšibūti Qirbit kayyān ihtanabbatū hubut Yamutbali ālu šuātu	interior [] may go of city ruler of Qirbit to king ancestor not bow down to yoke and people inhabitant [] constantly constantly loot plunder [] city that	habātu, nišu, Yamutbal	3

FIGURE 5.4: In the Oracc corpus, containing ancient Akkadian texts, the senses of the lemma **kayyānu** occur in various contexts related to **constant** or **permanent**. This figure presents the four clusters generated by ACCWSI. The “attention highlight” column shows the most relevant context words. The first cluster represents the sense of the stable expression of **self-renewing light god**, the second one means **permanent place of divinity/shrine**, the third one is also a stable expression **constantly make grow**, the fourth is also a stable notion of **permanent loot**. Note that the translation in the **joined list of per-word senses** is just a list of per-word translations that do not necessarily form a coherent sentence or phrase.

Chapter 6

Future work

6.1 Future work

In our future work, we will address these points without giving up the possibility of training the model on limited resources, while maintaining the main advantage of our method, which is to perform the Word Sense Induction task on a limited amount of text.

origin	joined list of per-word senses	attention_highlight	cluster
P363670:šumma šarru lū šarru x x ēribtu ušaglā x x SMA x	if king or king (palace-)enterer send into exile	ēribu, šarru, šarru	0
P334718:nišēšūni sahhir dīnaššu ina libbi ūme ša iglūni turtānu Zeru-ibni irtugumuniššu issa ulušu mā issurri ibašši memmēnika rēhe mā memmēniyāma lāšu lā rēhe ūmā atā	people return give in interior day that be(come) deported commander-in-chief [] call (out) ask saying perhaps exist somebody remaining saying anybody (there) is not not remaining now why?	Zeru-ibni, issurri, tartānu	0
P314272:bēlī lū ūda atā ina irti Arihi ūbbalūni ušaglanāši u šū iqṭibi mā Laqaya x	lord may know why? in breast [] bring be(come) deported and he say saying from Laqe	Arihu, wadū, wabālu	0
P334369:Kummaya'e dayālī ša issu Kumme ana nāgurtu illikūni udīni lā illakūni ammākamma šunu šarru bēlī liš' al luššīši issurri qanni ammūte ušagalušunu šarru bēlī ina	Kummean scout who from [] to hire come yet not come there they king lord ask investigate perhaps together with that be(come) deported king lord to	qannu, issurri, uššūšu	0
P237270:ana šar mātāti bēliya aradka Kudurru Aššur Šamaš Bel u Nabu ana šar mātāti bēliya likrubū ultu muhhi ūmu ša šarru bēlā ušeglanni šabtāk u ašbāk ūmussu ana šarri bēliya ušalla Nabu-killanni kī	to king land lord servant [] [] [] [] and [] to king land lord bless since skull day that king lord be(come) deported kept in confinement and sitting daily to king lord pray to [] when	ūmussu, ašbu, šarru	0
P334504:nušagli o issurri šarru bēlī iqabbi mā ša bēt lllumma-taklak Lahiraya šunu x x x	be(come) deported perhaps king lord say saying of house [] Lahiraeen they	issurri, šarru, qabū	0
P237257:x x x x akī hītu ša ana šarri bēliya ihtū ultegeli u	in accordance with crime which against king lord sin deport and	šarru, haṭū, hītu	0

FIGURE 6.1: ACCWSI produced a single cluster for some instances of the **galū** lemma, while resolving much of the results without any cluster. Some improvements should be applied to ACCWSI in order to detect subtle nuances, controversial even for humans. Note that the translation in the **joined list of per-word senses** is just a list of per-word translations that do not necessarily form a coherent sentence or phrase.

Iterating the process of generating context embeddings may improve the accuracy of the clustering. In our future work, we plan to develop a method for determining the “center of mass” (or “centroid” for convex clusters) of every cluster. These centers will be treated as new “query” embeddings and the ACCWSI attention-weighted technique will be reapplied within each cluster using its new query (its center). This should provide finer discrimination of meanings. This iterative process can be repeated many times until maximum accuracy is achieved.

The main practical goal of this study is to create an online tool for linguists and historians. This tool will allow the researcher to select a text corpus to scan, a word embedding generation algorithm to use (Word2vec/GloVe/BERT), and specify the values of various hyperparameters that control the ACCWSI flow.

Chapter 7

Conclusion

In this thesis, we proposed ACCWSI, an algorithm to automatically induce various senses of ambiguous words by automatically focusing on the most relevant words from their contexts. After learning generic word embeddings into a Word2Vec model, ACCWSI uses the basic attention technique for determining the most relevant context members and generating context-aware embeddings, each with a semantic direction that aggregates the directions of its context members. Distant meanings imply distant context embeddings and vice versa, and thus standard clustering techniques can be easily applied for grouping the context embeddings by their common semantic directions. ACCWSI has shown excellent performance even when trained on a small subset of the training data in the SemEval-2 2010 task 14. Furthermore, ACCWSI demonstrated high applicability in the disambiguation of word senses in ancient Semitic languages, such as Classical Hebrew and Akkadian.

The code of the Jupyter notebooks and other utilities we used during our research can be found in the GitHub repository below. The code resources are self-contained and reusable and can be useful in a variety of contexts¹.

¹<https://github.com/mstekel/accwsi>

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