Turkish Universal Conceptual Cognitive Annotation

Necva Bölücü, Burcu Can
Hacettepe University, University of Wolverhampton
Department of Computer Engineering, Research Group in Computational Linguistics (RGCL)
Ankara Turkey, Wolverhampton UK
necvaa@gmail.com, b.can@wlv.ac.uk

Abstract

Universal Conceptual Cognitive Annotation (UCCA) is a cross-lingual semantic annotation framework that provides an easy annotation without any requirement for linguistic background. UCCA-annotated datasets have been already released in English, French, and German. In this paper, we introduce the first UCCA-annotated Turkish dataset that currently involves 50 sentences obtained from the METU-Sabanci Turkish Treebank. We followed a semi-automatic annotation approach, where an external semantic parser is utilised for an initial annotation of the dataset, which is partially accurate and requires refinement. We manually revised the annotations obtained from the semantic parser that are not in line with the UCCA rules that we defined for Turkish. We used the same external semantic parser for evaluation purposes and conducted experiments with both zero-shot and few-shot learning. This is the initial version of the annotated dataset and we are currently extending the dataset. We are releasing the current Turkish UCCA annotation guideline along with the annotated dataset.

Keywords: UCCA, semantic parsing, semantic annotation, Turkish, low-resource languages

1. Introduction

Semantics is concerned with anything related to meaning and explores answers to such questions (Vigliocco and Vinson, 2007): 1) How do we represent the meaning of each word? 2) How do the meanings of words form a semantic structure? 3) How are words related to each other in a semantic structure? Word embeddings allow the meaning of a word to be represented in a compact low-dimensional space. It is a learned representation where words with a similar meaning have similar representations. The first breakthrough in neural word representation is word2vec (Mikolov et al., 2013), a statistical-based method (built on a shallow neural architecture) for learning word embeddings via their contextual information obtained from a preferably large corpus. Learning high-quality word embeddings using neural methods rather than statistical methods such as co-occurrence matrices has improved the performance of all natural language processing (NLP) tasks such as text classification (Wensen et al., 2016; Li et al., 2018) and machine translation (Jansen, 2017; Qi et al., 2018), which applies to all languages with available large resources. Contextualised word embeddings such as BERT (Devlin et al., 2018) and its variations (Sanh et al., 2019; Yang et al., 2019) have recently been introduced, and have shown even better performance in almost any NLP task.

Better word representation techniques have paved the way for semantic representation for compositional semantics for bigger text units, such as phrases and sentences. Semantic representation is the process of mapping a given text into a formal or abstract form that can be understood by machines. Semantic representation is widely dominated by graph and tree-structured representations. Since graphs have the flexibility and

ability to express and generate adequate and variable target structures, they have been used for semantic representation schemes such as Abstract Meaning Representation (AMR) (Banarescu et al., 2013), Universal Conceptual Cognitive Annotation (UCCA) (Abend and Rappoport, 2013a), bilexical Semantic Dependencies (SDP) (Oepen et al., 2016), Universal Decompositional Semantics (UDS) (White et al., 2016), and Parallel Meaning Bank (PMB) (Abzianidze et al., 2017). Graph-based semantic representation frameworks have been used in various NLP applications such as text summarisation (Liao et al., 2018; Zhang et al., 2020; Liu et al., 2018), question answering (Xu et al., 2021; Kapanipathi et al., 2020; Naseem et al., 2021), and machine translation (Song et al., 2019; Sulem et al., 2020; Nguyen et al., 2021), which have shown promising performance.

UCCA (Abend and Rappoport, 2013a) is a recently proposed semantic representation for depicting the "meaning" of a sentence within a multilayer framework in which each layer corresponds to a semantic module. The ultimate goal of UCCA is to provide a semantic representation that is applicable across languages and domains. It also allows rapid annotation by non-experts in linguistics. With all these benefits, UCCA representation has recently gained attention in the field and it has been already part of some shared tasks (SemEval 2019; (Hershcovich et al., 2019), MRP 2019; (Oepen et al., 2019), MRP 2020; (Oepen et al., 2020)). According to the UCCA specification, the annotation framework is designed as cross-lingual. For example, the French corpus is extracted by implementing cross-lingual methods on an English-French parallel corpus obtained from *Twenty Thousand Leagues Under the Sea* by Jules Verne (Sulem et al., 2015). Apart

from French, there are also available UCCA-annotated datasets in English and German. However, there is not any available UCCA-annoted dataset for Turkish, which is a morphologically rich and low-resource language.

For Turkish, there is only one available annotated dataset based on graph-based AMR semantic representation (Azin and Eryiğit, 2019). The goal of this study is to build a UCCA-annotated dataset for Turkish. One of the main challenges in developing language models for morphologically rich languages with productive derivational morphology such as Hungarian, Finnish, or Turkish is the number of different word forms derived from a root. Here, we analyse the meaning of words without considering the morphological information. We leave morphological semantic annotation as a future goal. We initially annotated 50 sentences obtained from METU-Sabanci Turkish Treebank (Atalay et al., 2003; Oflazer et al., 2003). The annotation was performed in a semi-automatic pipeline in two steps. 1. In the first step, we train an external semantic parsing model on a dataset that is a combination of English, German, and French UCCA-annotated datasets to parse Turkish sentences using a zero-shot learning method, where the results are partially correct. 2. In the second step, we revised and corrected the annotations obtained from the semantic parsing model and defined new UCCA annotation rules in line with the Turkish syntax, if required. We also performed experiments on zero-shot and few-shot learning settings using the annotated dataset for training and evaluation purposes to better analyse the errors caused by the parsing model.

This is the first UCCA-annotated dataset for Turkish and we introduce a set of UCCA annotation rules that are followed during the annotation along with our initial findings about the differences between the Turkish and other languages that have UCCA-annotated datasets available. The next step will be to extend the current Turkish UCCA annotation guideline that covers all types of sentence structures and grammatical phenomena, which will be based upon the differences in Turkish and English morphology and grammar.

The paper is organised as follows: Section 2 discusses the related work on UCCA parsing, Section 3 describes the UCCA representation, Section 4 explains the semantic parser model used in the first step of the semi-automatic annotation. Section 5 defines the rules that are defined while revising the output of the semantic parser. Section 6 presents the results obtained using the semantic parser model in zero-shot and few-shot settings on the new Turkish dataset, and finally Section 7 concludes the paper with some future goals.

2. Related Work

The approaches that are followed for UCCA-based semantic parsing can be categorised in 3 classes: transition-based, graph-based, end-to-end.

Transition-based approaches employ new features of the UCCA framework such as discontinuity and reentrancy. The first parser model introduced for UCCA-based semantic representation is a transition-based model called TUPA parser. The TUPA parser defines new transition operations (e.g. `NODE`, `LEFT-EDGE`, `RIGHT-EDGE`, `LEFT-REMOTE`, `RIGHT-REMOTE`, `SWAP`) (Hershcovich et al., 2017) in addition to the standard operations (e.g. `SHIFT` and `REDUCE`). The second model introduced for UCCA parsing is based on the TUPA parser, which extends the TUPA parser for other graph-based semantic representation frameworks (i.e. UCCA, AMR, DM, and UD) (Hershcovich et al., 2018). With the shared tasks conducted at SemEval (Hershcovich et al., 2019) and MRP (Oepen et al., 2019; Oepen et al., 2020), new transition-based methods are introduced, and many of them are an extension of the TUPA parser (Lai et al., 2019; Arviv et al., 2020).

Graph-based approaches (Cao et al., 2019; Koreeda et al., 2019; Droganova et al., 2019) aim to generate a graph with the highest score among all possible graphs in the graph space. The proposed methods are generally utilised for all graph-based frameworks. One of the graph-based approaches is to tackle the parsing task as a constituency parsing problem (Jiang et al., 2019; Li et al., 2019; Bölücü and Can, 2021). End-to-end neural models are usually complex systems based on deep learning models that parse the input by passing through intermediate layers (Chen et al., 2018; Wang et al., 2019a) that eventually generate the semantic parsing of the given input sequence.

3. Universal Conceptual Cognitive Annotation (UCCA)

UCCA (Abend and Rappoport, 2013a; Abend and Rappoport, 2013b) is a cross-lingual semantic annotation scheme influenced by the basic linguistic theory (Dixon, 2005; Dixon, 2010a; Dixon, 2010b; Dixon, 2012) and the cognitive linguistic theory (Langacker, 2008). It is a multi-layered framework, where each layer corresponds to a "module" of semantic distinctions of a sentence or a paragraph. The foundational layer of UCCA focuses on grammatically relevant information. It covers predicate-argument relations for predicates of grammatical categories (verbal, nominal, adjectival, and others). It is depicted by a directed acyclic graph (DAG) with leaves corresponding to tokens and multi-tokens in the text. The nodes of the graph are called units that can be either a terminal or multiple tokens considered together as a single entity according to some semantic or cognitive consideration. The edges of the graph indicate the role of a child in the relation (i.e. semantic categories) such as scene elements (Process (P), State (S), Participant (A), Adverbial (D)), elements of non-scene units (Center (C), Elaborator (E), Connector (N), Relator (R)), inter-scene relations (Parallel Scene (H), Linker (L), Ground (G)), and other roles (Function (F)).
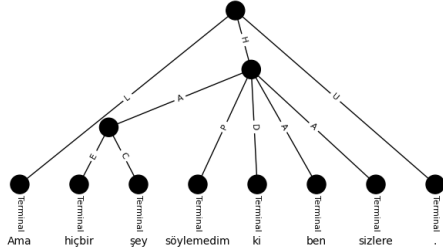
Figure 1: The UCCA annotation graph of the Turkish sentence "Ama hiçbir şey söylemedim ki sizlere." (in English, *"But I did not say anything to you."*)

Initially, an English UCCA-annotated dataset was released (Abend and Rappoport, 2013a) that follows other UCCA-annotated datasets in several languages. For English, the *Wikipedia* corpus and the English-French parallel corpus obtained from the first five chapters of *Twenty Thousand Leagues Under the Sea* were annotated. The extension of the UCCA dataset into other languages has been implemented initially starting with the English-French parallel corpus, which is used to annotate the French dataset (Sulem et al., 2015). German dataset (Hershcovich et al., 2019) consists of the entire book, *Twenty Thousand Leagues Under the Sea*. All of these datasets are annotated according to v2.1 of the UCCA guideline (Abend et al., 2020) and we followed the same version in our annotation [1].

An example of an UCCA annotation graph of a Turkish sentence is given in Figure 1. In the example, there is a **Linker** (L) "Ama" (meaning *"but"*) that links the event to the previous events (i.e. scenes) and a Scene "hiçbir şey söylemedim ki ben sizlere" (in English, *"I did not say anything to you"*), which corresponds to the main clause in the sentence. The Scene has a relation called **Process** (P) that corresponds to the main action in the scene: "söylemedim" (in English, *"I did not tell"*), three **Participant**s (A) "hiçbir şey" (in English, *"anything"*), "ben" (in English, *"I"*) and "sizlere" (in English, *"to you"*) which are the arguments of the action and finally an **Adverbial** (D) "ki" that modifies the Scene.

4. Neural Semantic Parser for UCCA

We followed a semi-automatic annotation approach that involves two steps. First, we parsed the dataset using a neural UCCA semantic parser (Bölücü and Can, 2021) that is based on self-attention mechanism (Vaswani et al., 2017). The adopted neural semantic parser model follows a chart-based constituency parsing approach. The neural model is based on an encoder/decoder architecture. Self-attention layers are used within the encoder along with a multilayer perceptron (MLP) classifier with two fully-connected layers and Rectified Linear Unit (ReLU) non-linear activation function in the output layer. The final output of

the encoder gives the per-span scores where spans correspond to constituents in the constituency tree. The decoder adopts CYK (Cocke-Younger-Kasami) algorithm (Chappelier and Rajman, 1998) that generates the tree with the maximum score using the scores obtained from the encoder.

Zero-shot learning allows learning without using any training data on a particular domain or language by transferring information from another domain or language. By means of the large pre-trained models made available especially using transformer networks (Devlin et al., 2018; Sanh et al., 2019), the popularity of zero-shot learning has increased due to its outstanding success in various NLP tasks such as dependency parsing (Wang et al., 2019b; Tran and Bisazza, 2019) and text classification (Pushp and Srivastava, 2017; Chalkidis et al., 2020). Since there is not any UCCA-annotated dataset available for Turkish, we utilised the encoder/decoder model with zero-shot learning by transferring information from the UCCA-datasets available in other languages. We initially trained the parser on merged datasets (in English, German, and French) and then we parsed the Turkish UCCA dataset using the trained model. Once the partial parsing results were obtained from zero-shot learning, we manually revised the Turkish parsing results by concurrently defining our Turkish-specific rule set for UCCA annotation in Turkish. Eventually, we obtained 50 Turkish sentences that are annotated using UCCA representation. Example outputs of the parser are shown in Figure 2 and 3. As seen, most of the relations and their labels are identified correctly apart from the adverbial ("ki") that is confused with a Relator [2] in Figure 2, and the participant and ground ('oğlum', meaning "my son") that is confused with a static scene in Figure 3.

Data annotation might be a burden particularly when started from zero-resource. However, beginning with a semi-automatic annotation with only a small number of annotated sentences does not only speed the annotation process, but also helps understanding the general discrepancies between the annotated sentences in different languages. Thus, we designed more experiments using the annotated Turkish dataset as part of the training set for few-shot learning.

5. A UCCA-Annotated Dataset for Turkish

We annotated 50 sentences obtained from METU-Sabanci Turkish Treebank (Atalay et al., 2003; Oflazer et al., 2003). Here, we explain the annotation process, annotation rules that are specific to Turkish, and the statistical distribution of the labels in the dataset.

5.1. Turkish UCCA Annotation Rules

Once we analysed the output of the semantic parsing model manually, we either applied the rules already defined in UCCA guideline (Abend et al., 2020) or de-
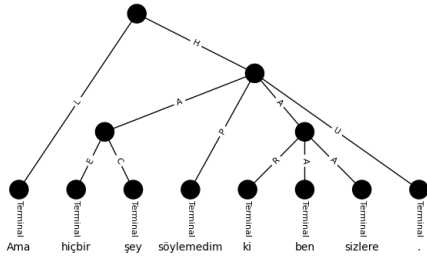

Figure 2: The output of the parsing for sentence "Ama hiçbir şey söylemedim ki sizlere." (in English, *"But I did not say anything to you."*)
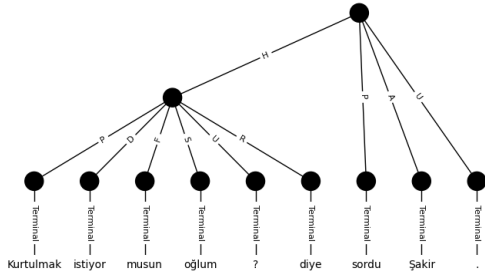

Figure 3: The output of the parsing for sentence "Kurtulmak istiyor musun oğlum? diye sordu Şakir."(in English, *"Do you want to be saved, son? asked Şakir."*)

fined new annotation rules for syntactic components in Turkish, which are not covered by any of the available rules in the official UCCA guideline. We do not re-describe the existing UCCA annotation rules here, but we only describe the new UCCA annotation rules with example sentences in Turkish that have been all encountered during the annotation of the dataset[3]:

- **Pronoun-dropping (Göçmen et al., 1995):** Pronoun subjects are usually omitted in Turkish, since it is a pro-drop language. In UCCA annotation, omitted pronoun subjects are identified with the label A-IMPLICIT:
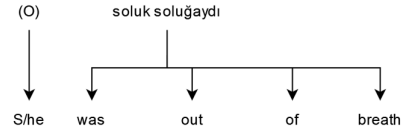
Example 5.1

(Ben)$_{A-IMPLICIT}$ özgür kalmak istemiyorum (in English, "I don't want to stay free")
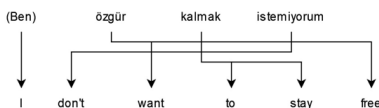

Example 5.2

(O)$_{A-IMPLICIT}$ soluk soluğaydı (in English, "S/he was out of breath")

- **Genitive case:** To express possession in Turkish, the genitive suffix is added to the possessor and the possessive suffix is added to the possessed noun. Pronominal possessors of possessive nouns are also usually omitted since possessive suffix already bears the possession meaning. Omitted pronominal possessors of possessive nouns are identified with the label E-IMPLICIT:
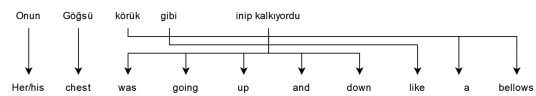
Example 5.3

(Onun)$_{E-IMPLICIT}$ gözleri kor gibi yanıyordu (in English, "Her/his eyes were burning like embers")
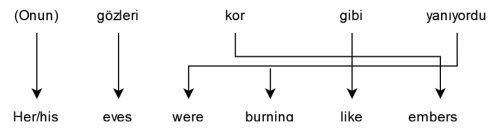
- **Postpositions:** Unlike English, Turkish has no prepositions (Göksel and Kerslake, 2004). While some English prepositions correspond to the case suffixes in English, other prepositions are formed by postpositions that follow their complement phrases. Such postpositions are identified with the label Relator (R):
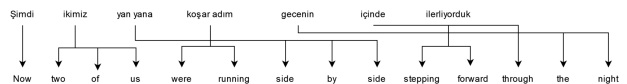
Example 5.4

Göğsü körük gibi$_R$ inip kalkıyordu (in English, "Her/his chest was going up and down like a bellows")


Example 5.5

Şimdi ikimiz yan yana koşar adım gecenin içinde$_R$ ilerliyorduk (in English, "Now the two of us were running side by side stepping forward through the night")

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[3]Please note that punctuation is not specified in the example sentences for simplicity purposes.

Example 5.6

Nasıl bir kadın o diye$_R$ sordum (in English, "I asked (that) what kind of a woman she is") [4]

(Ben) | Nasıl | bir | kadın | o | diye | sordum
I | asked | (that) | what | kind | of | a | woman | she | is
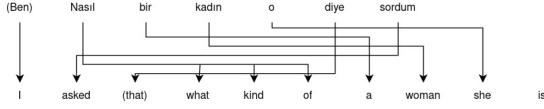
- **Negation** In Turkish, negation is formed by adding a suffix to the end of the verb. However, "değil" (in English, *"not"*) is used to negate a nominal sentence. The negation word is marked as an `Adverbial` (D) as defined in the English guideline since it does not refer to a participant or a relation:

Example 5.7

Onlar önemli değil$_D$ ki (in English, "They just don't matter")

Onlar | önemli | değil | ki
They | just | don't | matter
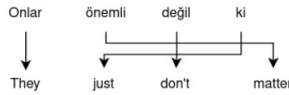
- **Clitics:** Clitics are free morphemes in Turkish (e.g. *"mı"*, *"ki"*) that are meaning-bearing units, but their meaning may change from one context to another. Therefore, the meaning of a clitic can only be determined within a particular context:

  1. **"mı"**[5] can be used in 3 different meanings depending on its context:

     (a) Yes/No condition: It is identified with the label `Function` (F) since it does not refer to a participant or a relation:

     Example 5.8

     Nereye gittiğimi biliyor musunuz$_F$ (in English, "Do you know where I'm going")

     (Siz) | nereye | gittiğimi | biliyor | musunuz
     Do | you | know | where | I'm | going
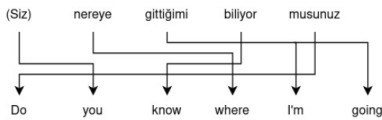
     (b) Adverbial clause marker: It is labeled with `Linker` (L) that also corresponds to the same category in the UCCA

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[4]Auxiliary verb *"is"* does not correspond to any word in Turkish.

[5]The clitic also involves the other forms of "mı", such as "mi", "mısın", "mısınız" etc depending on the vowel harmony and the person type.

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guideline. [6]

Example 5.9

Pazara gittin mi$_L$ bütün ihtiyaçlarını alırsın (in English, "When you go to market you buy all your needs")

(Sen) | Pazara | gittin | mi | bütün | ihtiyaçlarını | alırsın
When | you | go | to | market | you | buy | all | your | needs
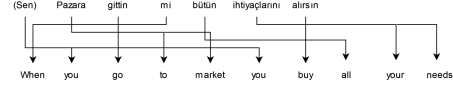
   (c) Intensifier in doubled forms: We combine the doubled forms for a more concise annotation. (e.g. sıcak_mı_sıcak) [6].

Example 5.10

Sıcak_mı_sıcak bir çay verdiler (in English, "They gave me a very hot tea")

(Onlar) | Sıcak mı sıcak | bir | çay | verdiler
They | game | me | a very hot | tea
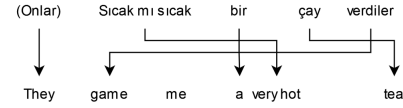
  2. **"ki"** can be used in 4 different meanings depending on its context:

     (a) Subordinator connecting: Since it is part of a larger construction that connects the subordinator to the main Scene, it is labelled with `Relator` (R), as defined in the English guideline.

     Example 5.11

     Anlıyorum ki$_R$ o gelmeyecek (in English, "I understand that s/he will not come")

     (Ben) | anlıyorum | ki | o | gelmeyecek
     I | understand | that | s/he | will | not | come
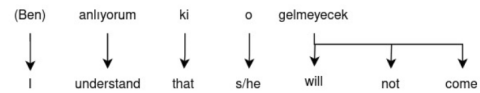
     (b) Repudiative discourse connective: It means "just", and therefore it is identified with the label `Adverbial` (D)[6].

     Example 5.12

     Onlar önemli değil ki$_D$ (in English, "They just don't matter")

     Onlar | önemli | değil | ki
     They | just | don't | matter

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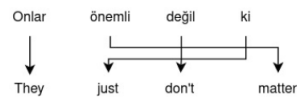
[6]During the annotation, we did not come across any example of this type of marker. Therefore, the example does not exist in the annotated dataset.

(c) Exclamations: It is identified with the label `Ground` (G) since it expresses the speaker's attitude towards the event. It usually appears at the end of a sentence and usually used along with *"o kadar (that much)"* or "öyle(sine) (so)". The exclamations do not correspond to a participant or relation [6]:

Example 5.13

Onun yemekleri o kadar lezzetli olur ki$_G$ (in English, Her/his food is so delicious") [7]

Onun yemekleri o kadar lezzetli olur ki
Her/his food is so delicious

(d) Relative clause marker: A relative clause modifies a noun and relative clause marker connects the clause to the top-level clause. It is identified with the label `Relator` (R)[6] as defined in the English guideline.
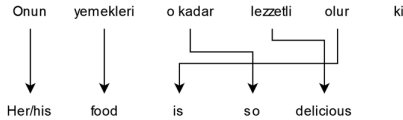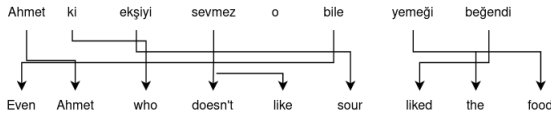
Example 5.14

Ahmet ki$_R$ ekşiyi sevmez o bile beğendi (in English, "Even Ahmet who doesn't like sour liked the food")

Ahmet ki ekşiyi sevmez o bile yemeği beğendi
Even Ahmet who doesn't like sour liked the food

5.2. Inter-annotator Agreement

We employed 2 annotators who are native speakers of Turkish and both from a computational linguistics background. The annotators were initially trained for the UCCA annotation based on the official UCCA guideline (Abend and Rappoport, 2013a). They annotated the sentences independently, and then all annotated sentences were compared with each other at the end. The percentage of the agreement between the two annotators during the annotation is 90.69%[8]. Using Cohen's Kappa (Cohen, 1960) (*100), we calculated the Inter-annotator Agreement (IAA) for the UCCA annotation to be 89.05. In case of disagreement, the sentence was labeled following a discussion, and if required, new rules were defined for a particular syntactic rule.

The general disagreement that recurs in the training procedure is mainly about the annotation of the clitics.

Since the morphology is out of scope in the current version of the annotation, we only consider clitics that are seen as a free morpheme. Consider the example *"Onlar önemli değil ki"* (in English, *"They just don't matter"*). The clitic *"ki"* gives repudiative meaning to the main Scene (*Onlar$_A$ önemli$_S$ değil$_D$ ki$_D$*). We refer to the Turkish grammar rules defined by (Göksel and Kerslake, 2004) to identify the clitics in the dataset.

5.3. Comparison of the Parses in Automatic and Manual Annotation

We analyse the common errors of the semantic parser model which were manually corrected once the automatic parsing was performed. Two example sentences that are parsed by the semantic parser model are given in Figure 4 and 5 along with their gold standard annotations. While in Figure 4, we added only the `IMPLICIT` edge, the `Parallel Scene` (H) and `Relator` (R) were not correctly labeled by the model in the second sentence in Figure 5.

While correcting the parses that are obtained from the semantic parser model, we did not make any additional corrections to short sentences (having less than 5 words). The labels of the terminal nodes were also mostly correct. We corrected most of the annotations for the Parallel Scene (H), which also affect the entire annotation of the sentence.
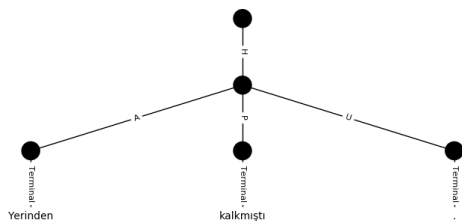
5.4. Annotation Statistics

The overall proportions of the UCCA edges and labels in the final annotation of the dataset along with the English datasets are given in Table 1[9]. In the Turkish dataset, the number of Participants (A) is the highest and the frequency of Adverbial (D) label is higher than that of Elaborator (E) and Center (C). We have not come across any Connectors (N) in the dataset. The distribution of the other labels is similar in the English and Turkish datasets, with the exception of the Elaborator (E). The reason for the low frequency of Elaborator (E) is the short length of the sentences in the Turkish dataset.

6. Experiments and Results

We used the annotated dataset for training and testing UCCA-based semantic parsing on Turkish. For this purpose, we conducted experiments with zero-shot and few-shot learning to understand the impact of the size of the training set for UCCA parsing.

We used the UCCA-annotated datasets provided by SemEval 2019 (Hershcovich et al., 2019) in English, German, and French for training the aforementioned neural semantic parser model. The details of the datasets are given in Table 2. We used the official evaluation metrics used in SemEval 2019, that are precision, recall, and the F_1 score in all experiments.

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[7]Clitics **"ki"** does not correspond to any word in English.

[8]There was disagreement in 38 out of 408 tokens in 50 sentences between the two annotators during annotation.

[9]The dataset is publicly available at `https://github.com/necvabolucu/semantic-dataset`.

(a) The output of the semantic parsing model
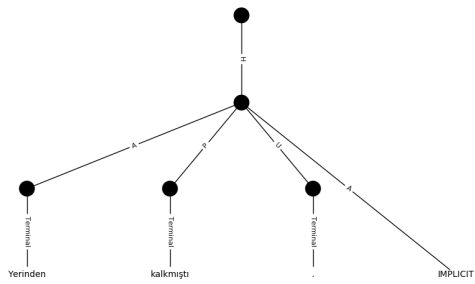
(b) The correct annotation of the sentence

Figure 4: The semantic parse tree obtained from the semantic parsing model and the gold standard annotation obtained from the manual annotation of the sentence, *Yerinden kalkmıştı.* (in English, *"S/he had gotten up."*)
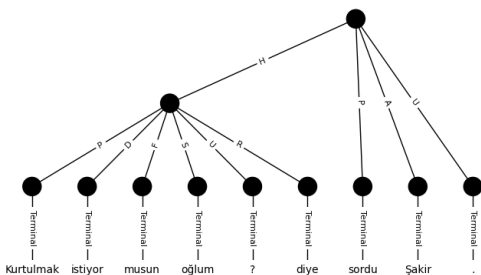

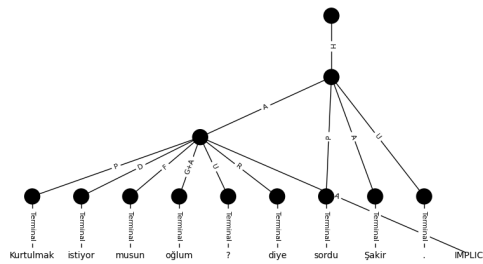(a) The output of the semantic parsing model

(b) The correct annotation of the sentence

Figure 5: The semantic parse tree obtained from the semantic parsing model and the gold standard annotation obtained from the manual annotation of the sentence, *Kurtulmak istiyor musun oğlum? diye sordu Şakir.* (in English, *"Do you want to be saved, son? asked Shakir."*)

	Turkish	En-Wiki	En-20K
# edges	407	208,937	16,803
% primary	96.57	97.40	96.79
% remote	3.43	2.60	3.21
% Participant (A)	28.19	17.17	18.1
% Center (C)	8.09	18.74	16.31
% Adverbial (D)	8.82	3.65	5.25
% Elaborator (E)	4.41	18.98	18.06
% Function (F)	3.19	3.38	3.58
% Ground (G)	0.98	0.03	0.56
% Parallel Scene (H)	7.11	6.02	6.3
% Linker (L)	1.23	2.19	2.66
% Connector (N)	0.00	1.26	0.93
% Process (P)	15.44	7.1	7.51
% Relator (R)	2.70	8.58	8.09
% State (S)	4.17	1.62	2.1
% Punctuation (U)	15.69	11.28	10.55

Table 1: Statistics of the UCCA datasets in Turkish and English. Proportions of the edges and labels of each dataset are given.

In zero shot learning, we trained the semantic parser model on the combined datasets in English, German, and French. The trained model is used to parse the 50 sentences in Turkish, which is used as the test set. In few shot learning, we performed cross validation with 5-fold by adding 40 sentences to the combined training set and using 10 sentences only for testing. We report the average scores obtained from each fold. The results show that few-shot learning improves the results substantially. In particular, remote edges cannot be learning during zero-shot learning, but they are learned during few-shot learning even with a small number of annotated sentences.

The experimental results obtained from both zero-shot and few shot learning are given in Table 3. The results show that using even a small size of training set significantly improves the accuracy of the parser on Turkish. The results obtained from few-shot learning according to different sentence lengths are given in Table 4. Since the sentences from the METU dataset are shorter than the sentences in English, German and French datasets, the model performs well at parsing shorter sentences.

7. Conclusion and Future Work

In this study, we started annotating the first Turkish UCCA dataset with the first 50 sentences obtained from the METU-Sabanci Turkish Treebank. While we adopted the official UCCA guideline particularly defined for English, we either utilised the current specifications by describing how each linguistic construction should be annotated to ensure consistent annotation or

	English-Wiki	English-20K	German-20K	French-20K
Train	4,113	0	5,211	15
Validation	514	0	651	238
Test	515	492	652	239

Table 2: The number of sentences in each UCCA-annotated dataset provided by SemEval 2019 (Hershcovich et al., 2019)

		Primary			Remote			Average		
		P	R	F_1	P	R	F_1	P	R	F_1
Zero-shot	Labeled	73.55	80.25	76.76	0.00	0.00	0.00	73.04	77.89	75.39
	Unlabeled	76.80	83.80	80.15	0.00	0.00	0.00	76.80	81.33	79.00
Few-shot	Labeled	78.72	84.30	81.42	30.00	25.00	27.28	78.75	83.78	81.11
	Unlabeled	87.71	93.92	90.71	50.00	41.67	45.45	87.53	93.12	90.24

Table 3: Precision (P), Recall (R) and F-measure (F_1) results obtained from zero-shot and few-shot learning on the Turkish UCCA dataset

		Labeled			Unlabeled		
Sent. Len.	# of sentences	Primary	Remote	All	Primary	Remote	All
≤ 5	30	87.73	0.00	86.93	93.25	66.67	93.00
≤ 10	19	80.53	0.30	75.20	89.38	50.00	85.37
≤ 20	1	68.42	-	66.67	84.21	-	82.05

Table 4: F_1 Results obtained from few-shot learning according to their sentence length

we defined new rules that would cover syntactic rules that are peculiar to the Turkish language. Our annotation approach is semi-automatic, where we adopted a semantic parser model using zero-shot learning by training on other languages, and testing on Turkish to have partially correct UCCA representations for Turkish. Then we analysed the discrepancies between the annotated sentences and the English guideline to define new rules compatible with the Turkish grammar.

We also performed experiments with zero-shot and few shot learning using the annotated Turkish dataset. For this purpose, we again used the same neural semantic parser model. The results show that even a small amount of training data improves the accuracy of the semantic parsing substantially in few-shot learning.

Our future goal is to extend the dataset using a similar semi-automatic approach and create a more comprehensive Turkish UCCA annotation guideline for a larger Turkish UCCA-annotated dataset.

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