

A 5W1H Based Annotation Scheme for Semantic Role Labeling of English Tweets

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Abstract. Semantic Role Labeling (SRL) is a well researched area of Natural Language Processing. State-of-the-art lexical resources have been developed for SRL on formal texts that involve a tedious annotation scheme and require linguistic expertise. The difficulties increase manifold when such complex annotation scheme is applied on tweets for identifying predicates and role arguments. In this paper, we present a simplified approach for annotation of English tweets for identification of predicates and corresponding semantic roles. For annotation purpose, we adopted the 5W1H (*Who, What, When, Where, Why and How*) concept which is widely used in journalism. The 5W1H task seeks to extract the semantic information in a natural language sentence by distilling it into the answers to the 5W1H questions: *Who, What, When, Where, Why and How*. The 5W1H approach is comparatively simple and convenient with respect to the ProBank Semantic Role Labeling task. We report on the high inter-annotator agreement of our annotation scheme for SRL on tweets and show that non-expert annotators can produce quality SRL data for tweets. This paper also reports the difficulties and challenges involved with semantic role labeling on twitter data and propose solutions to them.

1 Introduction

Recently, research and development in natural language understanding on social media texts has significantly taken a momentum. Semantic role labeling(SRL) is one such natural language understanding task that involves shallow semantic parsing and has wide applications in other natural language processing areas such as question and answering(QA), information extraction(IE), machine translation, event tracking and so on. For understanding an event from a given sentence means being able to answer “*Who did what to whom when where why and how*”. To answer such questions of “*who,what*”etc., it is important to identify each syntactic constituents of a sentence such as predicates, subjects, objects etc. In SRL, the task is to assign syntactic constituents called arguments with semantic roles of predicates (mostly verbs) at sentence level. The relationship that a syntactic constituent has with a predicate is considered as a semantic role. For instance, for a given sentence, the SRL task consists of analyzing the propositions expressed by some target verbs of the sentence. Particularly, the task is to recognize the semantic role of all the constituents of a sentence for each target verb. Typical semantic

arguments include Agent, Patient, Instrument, etc. and also adjuncts such as Locative, Temporal, Manner, Cause, etc.

The study of semantic roles was first proposed by the Indian grammarian Panini [1] in his “*Karaka*” theory. *Karaka* theory assigns generic semantic roles to words in a natural language sentence. The relationship of the arguments with the verb is described using relations called *Karaka* relations. *Karaka* relations describe the way in which arguments participate in the action described by the verb. [2] describes a syntactic annotation scheme for English based on Panini’s concept of *Karakas*. Subsequent work [3] revived Panini’s *Karaka* theory and developed state-of-the-art SRL system.

There are several lexical resources available for SRL such as PropBank [4], FrameNet [5], VerbNet [6]. In this paper, we discuss about an annotation scheme for SRL on Social Media Texts, particularly Twitter³ texts (also called tweet) which are informal in nature. Twitter is a micro-blogging site which allows users to post a message(tweet) within the limitation of 140 characters. However, the 140 character restriction may be increased in the near future. Due to the restriction of maximum 140 characters, use of abbreviations, word play, phonetic typing, emoticons are often found in tweets. For example, in the below given tweet

Tweet(1):

- *You made me ROFL ... pls doooooon’t do it again*

“ROFL” is the abbreviated form of *rolling on the floor laughing*, “pls” for *please* and “doooooon’t” (for don’t) is a word play. It is evident that tweets are free form and may not contain grammatically correct phrases. Therefore, performing SRL on such texts is a difficult task and state-of-the-art SRL systems do not perform well on them. The concept of “5W1H”(Who, What, When, Where, Why, How) adopted in this paper, aims at developing an annotation scheme for semantic role labeling of English tweets. The major contributions of our work are:

- Prepare a corpus for SRL on tweets.
- Propose a simple annotation scheme for SRL on tweets based on 5W1H concept.

The rest of the paper is organized as follows. Section 2 discusses related work. In section 3, the corpus collection and annotation process is discussed. Analysis of the annotation task is discussed in section 4. Section 5 discusses the ambiguities and limitations of our work which is followed by the concluding remarks and future work in section 6.

2 Related Work

We categorized the related work into two types: first, we discuss about previous work on 5W1H and second, SRL on tweets. Previous work on 5W1H such as [7] describe a verb-driven approach to extract 5W1H event semantic information from Chinese online news. [8] present different methodologies to extract semantic role labels of Bengali⁴ nouns using 5W distillation process. They used lexico-syntactic features such as POS

³ www.twitter.com

⁴ https://en.wikipedia.org/wiki/Bengali_language

and morphological features such as root word, gender, case and modality for identification of the 5W1H. [9, 10] describe a 5W1H based visualization system that facilitates users to generate sentiment tracking with textual summary and sentiment polarity. [11] describe a 5W1H based Cross-Lingual Machine Translation system from Chinese to English. [12] propose an algorithm named 5WTAG for detecting microblog topics based on the model of five Ws.

[13] are the first to study SRL on tweets. They considered only those tweets that reported news events. They mapped predicate-argument structures from news sentences to news tweets to get training data, based on which a tweet specific system is trained. Using hierarchical agglomerative clustering algorithm [14], news excerpts were divided into groups in terms of content similarity and predicate argument structures by removing all meta data from the tweets except the main text. [15] is an extension of [13] where similar tweets are grouped by clustering. Then for each cluster a two-stage SRL labeling is conducted. [16] describe a system for emotion detection from tweets. Their work mainly focuses on identification of roles for *Experiencer*, *State* and *Stimulus* of an emotion.

Our work presented in this paper, reports on the 5W1H based annotation process of English tweets for SRL task. Given a tweet, the objective is to identify the predicate p first and then extract the corresponding role arguments. The arguments of a predicate is the answer to the 5W1H entity <Who, What, When, Where, Why, How>. All the 5W1H may not be present in all the tweets.

3 Data Collection and Annotation

3.1 Data Collection

For collection of tweets, we crawled Twitter data related to the US elections held in 2016 using Twitter API⁵. We used query terms “Donald Trump”, “Donald”, “Trump”, “Hillary Clinton”, “Hillary” and hash tags such as #USElections, #USElections2016, #USElectionsUpdate, #ElectionNight, #HillaryClinton, #DonaldTrump, #hillary, #trump and #DonaldTrumpWins for fetching the tweets. We crawled a total of 38,984 tweets which are further reduced to 24,679 tweets after manually removing the Non-English tweets as well as re-tweets (tweets with RT). We randomly sampled 3000 tweets and tokenized them with CMU tokenizer [17]. We further manually segregated the 3000 tweets based on whether a tweet contains *@user mentions* or *hash tags* or both. The corpus distribution is shown in Table 1.

3.2 Annotation based on PropBank

We deployed five annotators for identifying predicates and PropBank role arguments from the tweets. The annotators are not linguists but well conversant in English. Our annotation task involve the following steps:

⁵ <http://twitter4j.org>

Table 1. Corpus statistics

Type of tweet	Numbers
Plain tweets	48
Tweets with only @mentions	28
Tweets with only # tags	2297
Tweets with both @mentions and # tags	627
Total	3000

Step 1: Automatic Predicate Identification and Argument Prediction:

We use a SRL system [18] for automatically identifying the predicates and labeling the semantic roles. Since the SRL system of [18] is not designed for tweets, a high accuracy is not desired. Therefore, the output of such a system requires manual evaluation.

Step 2: Manual Argument and Predicate Identification:

Annotators are trained on PropBank role labels and asked to curate the output of Step 1. It took approximately three to four weeks to train the annotators to get acquainted with the PropBank argument role set. We call them the “Experienced Annotators (EA)”. In this step, we ask annotators to either *accept* or *reject* or *correct* the predicates identified and arguments predicted in step 1. Each predicate identified in step 1 is manually checked in the PropBank database for the correct arguments. On an average, it took 6 minutes to annotate one tweet. As an illustration, in the below given tweet,

Tweet(2):

- *Hillary Clinton lost because of being Hillary Clinton!*

the SRL system[18] in step 1 identified predicate *lose* with verb sense *lose.02*. As per PropBank, the predicate *lose.02* means “no longer have” with arguments ARG0:*entity losing something*, ARG1:*thing lost* and ARG2:*benefactive or entity gaining thing lost*. This suggests that in the example tweet, “Hillary Clinton” is ARG0 and “because of being Hillary Clinton” is ARG-CAU. In this example, argument ARG1 is missing.

Step 3: Identify Missing Arguments and Predicates:

In this step, annotators are asked to identify the missing arguments and predicates. As an example, the SRL system in step 1 could not identify the predicate *provide.01* for the below given tweet

Tweet(3):

- *Trump’s Pyrrhic Victory Provides a BIG Silver Lining for Democrats*

As per PropBank, predicate *provide.01* means “to give” with arguments ARG0:*provider*, ARG1:*thing provided* and ARG2:*entity provided for (benefactive)* .

An annotation is considered “*accept*” only if all the five annotators agree on the annotation. The annotation agreement is reported in Table 3.

3.3 5W1H Annotation

The concept of 5W1H (Who, What, When, Where, Why and How) was first introduced by [19] and widely used in journalism. In journalism, a news article or a story is considered to be complete and correct only when the 5W1H are present. The 5W1H provide the facts about a news article or a story being written such as:

- Who?: Who was involved?
- What?: What happened?
- When?: When did it happen?
- Where?: Where did it happen?
- Why?: Why did it happen?
- How?: How did it happen?

For 5W1H annotation, we adopted a Question and Answer (QA) based approach similar to [20] and [21] to extract the answers to the 5W1H questions. The following steps explain our approach.

Step 1: Predicate Identification:

The first task in the annotation process is to identify the predicates. For this task, we deployed three new annotators without any training on PropBank argument role set. We call them the "Inexperienced Annotators (IA)". In this step, we deployed both the EA and IA Annotators for the said task. Both EA and IA are instructed to look for the main verbs in a tweet.

Step 2: Semantic Role Identification with QA:

We prepared QA pairs with the help of two Post Graduate Scholars in English Language. For every predicate identified in the previous step, QA pairs are provided to the annotators. Each question has one of the wh-words (*who, what, when, where and why*) and *how*. Every answer to a question is a phrase in the sentence (tweet). An example is illustrated in Table 2 and the IA agreement is reported in Table 3.

3.4 Handling @user mentions

The major difference between a formal sentence and a sentence in a tweet is the presence of *@user mentions*. On Twitter, a username also known as "*handle*", is a user's identity. Twitter usernames typically appear with an at sign (@) before the name. A username could be an individual's name or name of an organization. In a tweet, one twitter user sometime may prefer to mention another twitter user's name either to emphasize on an opinion expressed or for some other reasons. Twitter has a restriction on the length of usernames to 15 characters. The presence of @user mentions creates difficulty in identifying semantic role arguments. Let us consider the following tweet:

Tweet(4):

- @abc @xyz @pqr⁶ Y'all should chill . I wanted Hillary , too . But she lost . Move on ...

⁶ For privacy related issues, the @user mentions have been replaced with abc, xyz and pqr

Table 2. Comparison of PropBank role set and 5W1H

Tweet	Predicate	PropBank Argument	5W1H Question	Answer
(1) Trump's Pyrrhic Victory Provides a BIG Silver Lining for Democrats	provide.01	A0: Trump's Pyrrhic Victory	Who is the provider?	Trump's Pyrrhic Victory
		A1: a BIG Silver Lining for Democrats	What is being provided?	a BIG Silver Lining for Democrats
		A2: for Democrats	Who is being provided?	for Democrats
(2) Watch President Obama Address Nation Following Trump's Election Victory	watch.01	A0: not identified	Who is the watcher?	Viewers
	address.01	A1: President Obama Address Nation Following Trump's Election Victory	What is being watched?	President Obama Address Nation Following Trump's Election Victory
			When something is watched?	Following Trump's Election Victory
		A0: President Obama	Who is the addresser?	President Obama
		A1: Nation	What is the address about? Who is being addressed? When is it addressed?	Not defined Nation Following Trump's Election Victory

Tweet(4) has three @user mentions. For predicate *chill.02*, the 5W1H is extracted as; **Question:**Who should chill? **Answer:** Y'all. However, in this sentence, "Y'all" refers to the three usernames. So, for such cases, we adopted a simple approach of extending the span of the 5W1H to @user mentions. Therefore, in this case, the answer would be all the three usernames. But this approach is not uniform for every occurrence of @user mentions. Let us consider another example.

Tweet(5):

- *Thousands across the USA protest Trump victory <https://t.co/nsS5k4MoTV> via @uvwxyz*⁷

Tweet(5) is a news feed. The information delivered in this case is from external sources (<https://t.co/nsS5k4MoTV> and @uvwxyz). Moreover, the username "@uvwxyz", is not an argument of the predicate *protest.01*. Therefore, in this case, @user mention is ignored.

⁷ Actual @user mention has been replaced with uvwxyz

Table 3. Annotation agreement ratio of EA and IA annotators for identification of PropBank role set vs. 5W1H extraction

Agreement of EA on PropBank task	#Tasks	#Correct	# Incorrect	Accuracy
all 5 EA agree on answer	8375	6198	2177	0.74
4 out of 5 agree	2512	1733	779	0.69
3 out of 5 agree	1025	666	359	0.65
no agreement	52	0	52	0.0
Total	11964	8597	3367	0.72
Agreement of IA on 5W1H task	#Tasks	#Correct	#Incorrect	Accuracy
all 3 IA agree on answer	9368	8618	750	0.92
2 out of 3 agree	1405	1166	239	0.83
1 out of 3 agree	1172	833	339	0.71
no agreement	19	0	19	0.0
Total	11964	10617	1347	0.89
Agreement of EA on 5W1H task	#Tasks	#Correct	#Incorrect	Accuracy
all 5 IA agree on answer	9368	8900	468	0.95
4 out of 5 agree	1502	1307	195	0.87
3 out of 5 agree	1087	848	239	0.78
no agreement	7	0	7	0.0
Total	11964	11055	909	0.92

3.5 Handling hashtags (#)

A Twitter hash tag is simply a keyword phrase, spelled out without spaces, with a pound sign (#) in front of it. For example, #DonaldTrumpWins and #ILoveMusic are both hashtags. A Twitter hash tag ties the conversations of different users into one stream so that un-linked Twitter users could discuss on the same topic. Hash tags could occur anywhere in a tweet (beginning, in between words, end). In our corpus, we found 2297 tweets with hash tags. Handling hash tags is difficult when extracting 5W1H. Some hash tags are simple Named Entities such as #DonaldTrump, #HillaryClinton whereas, some are phrases such as #DonaldTrumpWins. The position and type of a hash tag is important while extracting the 5W1H. An example explains our approach for handling hash tags.

Tweet(6):

- *Will the GOP find a reason to impeach #Trump & usher in Pence ? #p2 #topprog*

For the predicate “impeach” with its sense *impeach.01*, 5W1H question is “Who is the impeacher?”, “Who is being impeached?”. Here, hash tag “#Trump” is the one being impeached. Therefore, we consider “#Trump” as the answer. The other two hash tags (#p2 and #topprog) do not play a significant role here. But this approach is not applicable for all the hash tags. The following example tweet explains the problem.

Tweet(7):

- *#DonaldTrumpWins I think ppl r fed up of traditional way of politics and governance . They r expecting radical changes , aggressive leadership .*

For phrase based hash tags, we simply segmented them into their semantic constituents. Therefore, #DonaldTrumpWins is expanded to *Donald Trump wins*. On expanding the hash tag, we get *win.01* as the predicate with “Donald Trump” as the argument. This further helps in finding the context for the argument of predicate *think.01* and the answer to the 5W1H question of “Why one thinks?”.

4 Analysis

On performing the three sets of annotation tasks, we observe that the agreement on the correct answers increases when more annotators agree. From Table 3, we observe that the overall accuracy of EA is only 72% for PropBank role identification task, whereas it is 89% for IA for the 5W1H task. This suggests that even without prior training, IAs could easily identify the presence of 5W1H. A comparison of the IA and the EA shows that when all three IA agreed for an answer, they identified more tasks while extracting the 5W1H. EA identified only 8375 tasks while identifying PropBank arguments. When all EA agreed for an answer, there is a significant increase in the Accuracy from 92% to 95% against the agreement when all IA agreed. Finally, we get an accuracy of 95% for EA which is a significant improvement over the previous annotation tasks. This suggests that our approach is comparatively easier to annotate with respect to ProbBank argument identification.

5 Discussion on Ambiguities and Limitations

In this section, we discuss the ambiguous cases where it is difficult to come to an agreement. While curating our corpus, we observed that certain tweets which are direct news feeds, mostly do not explicitly mention the AGENT of the predicate. As an example, let us consider the following tweet.

Tweet(8):

- *Watch President Obama Address Nation Following Trump’s Election Victory*

For the predicate *watch.01*, the AGENT or the ARG0 is explicitly not mentioned. However, there is an implicit AGENT or ARG0 present in the above tweet which semantically refers to the “viewers” or “readers” of the news feed. For such cases, it is difficult to extract an answer to a 5W1H question and difficult to come to an agreement for the annotators. The absence of proper punctuation is also a great concern while annotating the tweets. Some tweets do not have proper punctuation for marking the boundary of an utterance. For instance,

Tweet(9):

- *#DonaldTrump is a #racists liar & a #fascist do u really wanna vote for that America #USElections2016*

In Tweet(9), there are two possible utterances, one being “*#DonaldTrump is a #racists liar & a #fascist*” and the other being “*do u really wanna vote for that America #USElections2016*”. There are two possible annotations, one without breaking the utterances and the other after breaking the utterances. In all such cases, we instructed the EA and IA to treat them as two utterances. Detecting the boundary of utterances is itself a difficult task and currently outside the scope of our work. However, for better role identification, utterance boundary detection cannot be ignored. Our annotation scheme though simple to adopt but fails to identify the fine grain detail role labels such as discourse modifiers.

6 Conclusion and Future Work

In this paper, we described an annotation scheme to assign semantic roles on tweets by 5W1H extraction. Initially, we did not get satisfactory inter-annotator agreement for the PropBank predicate and argument identification task. The 5W1H based approach reported better annotator agreement without any expert level knowledge about the task as compared to the argument identification task based on PropBank. This suggests that our approach is simpler and convenient for identification of semantic roles. There is no single universal set of semantic roles that can be applied across all domains. Our annotation scheme though simple to adopt but loses on the fine grain level detail role identification. On the other hand, though the PropBank semantic role labels are too specific and complex in nature, they provide fine grain role identification. However, assigning such complex semantic role labels on tweets are ambiguous in certain cases. The simple and convenient approach for annotation discussed in the paper for SRL can be useful to some NLP application areas such as opinion mining, textual entailment and event detection. In the near future, we intend to incorporate a system for utterance boundary detection and evaluate how SRL could be done.

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