Modeling Factual Claims with Semantic Frames

Fatma Arslan, Josue Caraballo, Damian Jimenez, Chengkai Li
Department of Computer Science and Engineering
University of Texas at Arlington
Arlington, TX USA
{fatma.dogan, josue.caraballo, damian.jimenez}@mavs.uta.edu, cli@uta.edu

Abstract

In this paper, we introduce an extension of the Berkeley FrameNet for the structured and semantic modeling of factual claims. Modeling is a robust tool that can be leveraged in many different tasks such as matching claims to existing fact-checks and translating claims to structured queries. Our work introduces 11 new manually crafted frames along with 9 existing FrameNet frames, all of which have been selected with fact-checking in mind. Along with these frames, we are also providing $2,540$ fully annotated sentences, which can be used to understand how these frames are intended to work and to train machine learning models. Finally, we are also releasing our annotation tool to facilitate other researchers to make their own local extensions to FrameNet.

Keywords: frame-semantics, frame-annotated corpus, factual claims, fact-checking

1. Introduction

In recent years, the proliferation of misinformation has reached a staggering pace eroding people's confidence in politics and even affected democracies (Bennett and Livingston, 2018). For example, during the 2016 elections, propagated misinformation was shown to be highly in favor of one side (Allcott and Gentzkow, 2017). A recent survey[1] conducted by the Pew Research Center found that 68% of respondents reported that misinformation hurt their belief in the government and 51% reported a belief that misinformation can impede progress in politics. Many efforts have emerged in response to the urgent need to fight the dissemination of misinformation. According to a recent report[2] from the Duke Reporters' Lab, the number of active fact-checking outlets has reached 226 in 73 countries. There has also been a considerable response from the academic research communities within computer science, political science, and journalism.

These research communities have made significant efforts in studying misinformation and in aiding fact-checking. Many such efforts led to the development of computational methods and tools in countering misinformation on various fronts, such as identifying claims worth fact-checking from a myriad of sources of digital or traditional media (Hassan et al., 2015; Patwari et al., 2017; Jaradat et al., 2018; Jimenez and Li, 2018; Hansen et al., 2019), debunking repeated claims by matching them against a collection of already checked claims[3] (Hassan et al., 2017; Adair et al., 2019), and vetting claims by using supporting, refuting, and related evidence sentences from documents (Miranda et al., 2019). Several studies aimed at understanding misinformation on several aspects such as its diffusion model (Allcott et al., 2019), correlations between different predictors and an individual's tendency to reject or accept a factual claim (Pennycook and Rand, 2019), the effects of different corrective strategies on a person's recollection of misinformation and its degradation over time (Berinsky, 2017), and how influencers wield social media to spread misinformation (Bovet and Makse, 2019).

Research and development efforts on these fronts can benefit from structural representations of factual claims that capture various aspects of such claims, including the entities involved and their relationships, quantities, points and intervals in time, comparisons, and aggregate structures. With such a modeling capability in place, fact-check assisting tools can exploit the idiosyncrasies of different forms of factual claims. For instance, in translating claims into verification queries over knowledge bases (Thorne and Vlachos, 2017; Jo et al., 2019), query templates can be carefully crafted beforehand for different types of claims, and methods can be designed to replace the variables in the query templates by entities and elements from the structured representations. By modeling factual claims, we can also explore and uncover common semantic structures present in misinformation. An example of this can be seen in a recent study (Faasse et al., 2016) that analyzed pro- and anti-vaccine comments and found that in both sets of comments, risk-related and causation type words were used more. Such studies could attain greater granularity by identifying semantic structures that correlate with or represent particular sentence elements, e.g., risk-related or causation type words, through modeling of claims.

This paper presents our work on the structured and semantic representation of factual claims. Our approach is to extend the Berkeley FrameNet[4] project, a lexical resource for English built on a theory of meaning called *frame semantics* (Baker et al., 1998). This theory "asserts that people understand the meaning of words largely by virtue of the frames which they evoke." (Ruppenhofer et al., 2006) In frame semantics, *lexical units* (LUs, i.e., words, phrases, and linguistic patterns) evoke frames. A *frame* describes a type of event, action, situation, or relation, together with *frame elements* (FEs). Frame elements are frame-specific seman-

[1] https://pewrsr.ch/37ykPcs
[2] https://reporterslab.org/tag/fact-checking-database/
[3] Duke Reporters' Lab in-house fact-checking app https://www.factstream.co/
[4] https://framenet.icsi.berkeley.edu/fndrupal/

Frame: Vote		
Definition	An Agent makes a voting decision on an Issue. Issues can be bills, resolutions, nominations, treaties, and others on procedural matters. A Frequency of the voting decision may be stated.	
Examples	GOP Rep. Joe Heck of Nevada VOTED 23 times against banning terrorists from buying guns.	
	They VOTED for a border wall in 2006.	
	Ann Kirkpatrick VOTES with her party nearly 90 percent of the time.	
FEs	Agent	The conscious entity, generally a person, that performs the voting decision on an Issue.
	Issue	The matter which the Agent has a positive or negative opinion about.
	Side	An entity which performs the voting decision on an Issue together with the Agent.
	Frequency	The number of times that the Agent made the same voting decision on an Issue.
	Position	The position that the Agent takes on an Issue.
	Support rate	The ratio of Agent's votes that are consistent with a Side.
	Place	The location where the voting decision took place.
	Time	The time when the Agent performs the voting decision.
LUs	vote.v, (a/the) deciding vote.n	

Table 1: The *Vote* Frame – One of the New Factual-Claim Specific Frames

tic roles that provide additional information to the semantic structure of a sentence.

In this study, we created factual-claim specific frames to represent claims in a structured format. We used claims from PolitiFact[5] and analyzed their internal structures. We grouped the claims sharing common syntactic and semantic patterns in order to form conceptual categories of claims that convey similar meanings. This process yielded a total of 20 claim categories. For each claim category, we identified all possible terms (words, phrases, and linguistic patterns) specific to the category that can become lexical units of frames. We mapped each of the identified terms to the LUs of frames in FrameNet so as to identify existing frames that represent our claim categories. For the claim categories where we found a matching frame, we used that frame to model factual claims belonging to the category. For the remaining claim categories, we created new frames. As a result, we identified nine matching frames and created 11 new frames. For each new frame, we provide its frame definition, a set of associated FEs along with their descriptions, a set of LUs, annotated example sentences, and frame-to-frame relations. Table 1 shows a new frame "Vote" created for characterizing claims about someone's voting decision towards an issue. "Agent" and "Issue" are two of the frame elements. "Agent", a conscious entity, holds a positive or negative opinion about an "Issue" and votes on it. The lexical units of the "Vote" frame are "vote" and "(a/the) deciding vote.n" in the verb and noun forms, respectively.

To support further studies that leverage the outcome of this work, we created a corpus of claims fully annotated with the aforementioned 20 factual-claim specific frames. We used 4,664 fact-checks from the "Share the Facts" database[6] that is regularly updated by several fact-checking organizations. Since some of these factual claims consist of multiple sentences, we split the claims into sentences. The corpus size thus became 6,017 individual sentences. For each lexical unit belonging to one of the 20 frames, we identified sentences containing these LUs and further annotated these sentences with their respective frame elements. A total of 2,540 sentences were annotated with a set of 3,616 frame instances.

To summarize, this paper describes our work on modeling factual claims using frame semantics—the first such study to the best of our knowledge.[7] We produced 20 factual-claim specific frames, including 11 new frames and nine existing ones from FrameNet, and 2,540 fully annotated factual claims. The frame files and annotated sentences are available at https://zenodo.org/record/3710507. We also built a publicly available and web-based frame annotation tool FrameAnnotator,[8] to aid annotating sentences. FrameAnnotator supports full-text annotation and

5 https://www.politifact.com

6 http://www.sharethefacts.org/

7 A non-archival publication describing the preliminary results of our study appeared in (Arslan et al., 2019).

8 https://idir.uta.edu/frameannotator/

encodes annotated sentences in the same XML format used in FrameNet. These resources enable other researchers to make their own local contributions to FrameNet. As FrameNet grows through these independent contributions, it will also be used in a wider range of domains. Thus its value to society will increase substantially beyond the scope of this research. This research specifically aims to aid in fact-checking, further the understanding of misinformation and its spread, and aiding in the automated verification of claims.

2. Related Work

Recently efforts have gone into developing taxonomies of political claims. One such effort was from fact-checkers in HeroX fact-checking challenge (Francis and Fact, 2016). During the course of this challenge, a taxonomy of political claims was presented. This taxonomy was comprised of four claim types: numerical claims, verification of quotes, position statements, and lastly, objects, properties, and events.

Fullfact researchers (Konstantinovskiy et al., 2018) proposed a claim annotation schema based on their proprietary fact-checked claims. Their annotation schema consists of seven different categories: Personal experience, Quantity in the past or present, Correlation or causation, Current laws or rules of operation, Prediction, Other types of claim, and Not a claim. They assured that these claim categories cover an entire gamut of sentences used in political TV shows that they have come across over several years. The main difference between our work and Fullfact annotation is that while Fullfact assigns a claim to a single category only, in our schema, a claim can belong to multiple categories concurrently.

3. Modeling Factual Claims

3.1. Claim Modeling Process

To model factual claims, we began with a collection of 3,643 fact-checks sourced from PolitiFact. We chose PolitiFact because it is one of the most senior and prominent fact-checking organizations. Since its inception in 2007, it has fact-checked a significant volume of factual claims and published corresponding fact-checking articles online. Given that modeling would involve manually inspecting each fact-check individually, a randomly selected subset of 969 claims was chosen to begin with. The goal was to complete this in batches minimizing the amount of extra work done by not having to inspect the same types of sentences as often. If the selected 969 claims had been found to not be representative of the entire data-set then more claims would have been processed at that time. The steps in the process of factual claim modeling are explained below in detail. All of these steps were manually conducted.

Analyzing claims: We thoroughly examined all claims one by one in order to group the claims sharing common syntactic and semantic patterns. Throughout this process, we tried to maintain some generality to the groups, so as to avoid having many groups with a small number of sentences. Our goal was to capture a common concept in which a given group of claims can be expressed. The outcome of this process was a set of 20 conceptualized claim categories. It is worth mentioning that a claim may express multiple meanings, and therefore it could belong to various categories.

Identifying category specific terms: The process explained in this step was applied to each of the 20 claim categories generated in the previous step. For each claim category, we identified all possible terms (words, phrases, and linguistic patterns) specific to the category. We then enhanced the list of identified terms by including their relative words. For instance, one of our claim categories (hereafter, *oppose and support* category) is about an individual supporting or opposing an issue. The list of words that we identified for this claim category includes verbs “support”, “oppose”, and “back”; prepositions “for” and “against”; and nouns “supporter” and “opponent”. We then included “in favor of” and “pro” prepositions to the list as they are closely related to the previous words and support the conceptual background of the category. These identified terms are potential candidates for lexical units of a given frame. Identifying lexical units is a iterative process as the list can be expanded later by encountering new words.

Leveraging FrameNet frames: We used the following process to identify FrameNet frames that represent some of the 20 claim categories. For each claim category specific term, we identified all the corresponding lexical units that were present in FrameNet. This was followed by identifying all the frames evoked by these lexical units. We then analyzed all the identified frames to select the most frequently evoked frame. For instance, Table 2 shows the terms identified for one category and the corresponding FrameNet frames associated with each term. The most frequent frame is “Taking sides”. This process resulted in the identification of nine FrameNet frames (shown in Table 4) that matched our claim categories. Identifying the frames matching nine out of 20 claim categories shows indirect evidence of the robustness of our claim category creation process.

Term	FrameNet Frames
against.prep	Special contact, Taking sides
back.v	Funding, Self motion, Taking sides
for.prep	Duration relation, Taking sides
in favor.prep	Taking sides
support.v	Evidence, Funding, Supporting, Taking sides
supporter.n	Taking sides
opponent.n	Taking sides
oppose.v	Taking sides
pro.adv	Taking sides

Table 2: Terms from the Oppose and Support Categories and their corresponding FrameNet frames

Creating new frames: We created 11 new frames for the remaining claim categories. We used the previously identified terms of each of the claim categories as the lexical units for the frames that were created. We then manually identified frame elements for each of the 11 frames from the subset of sentences belonging to those frames. We further documented each of these frame elements based on their role in their parent frame. We then annotated some sample claims for each frame according to generated FEs. Finally, we wrote a definition for each of the new frames.

3.2. A Corpus of Factual-Claim Specific Frames

The outcome of this work resulted in 20 factual-claim specific frames, 171 FEs, and 284 LUs. Eleven of those frames along with 50 FEs and 27 LUs were newly created. Table 3 shows the distribution of FEs and LUs for each frame. The 9 frames we leveraged from FrameNet are listed in Table 4. In the following part of this section, we briefly describe each new frame and provided a sample annotated sentence with lexical units in boldface and frame elements in square brackets.

1. Taking sides consistency. This frame is about the consistency of an "Agent's" "Stance" towards an "Issue". The "Agent" either alters or maintains his/her "Stance". The "Stance" may not be explicitly stated.

[Republicans Chuck Grassley, John Boehner and John Mica $_{AGENT}$] **flip-flopped** [on providing end-of-life counseling for the elderly $_{ISSUE}$].

2. Recurring action. The Recurring action frame describes a repetitive "Action" that is performed by an "Agent" at the interval of a "Time_span".

[Last year $_{TIME}$], [Exxon $_{AGENT}$] [pocketed nearly $4.7 million $_{ACTION}$] **every** [hour $_{TIME\_SPAN}$].

3. Recurring action with frequency. This frame is about a repetitive "Action" that is performed by an "Agent" at a given "Frequency".

[Chemical weapons have been used $_{ACTION}$] probably [20 $_{FREQUENCY}$] **times** [since the Persian Gulf War $_{TIME}$].

4. Vote. See Table 1 for the definition and annotated examples for this frame.

5. Correlation. It shows the connection or relationship between the occurrences of "Event_1" and "Event_2".

Whenever [we raise the capital gains tax $_{EVENT\_1}$], [the economy has been damaged $_{EVENT\_2}$].

6. Comparing two entities. This frame is about comparing two entities using a "Comparison_criterion" while qualifying with a "Degree".

[Hillary Clinton $_{ENTITY\_1}$] [has been in office and in government longer $_{COMPARISON\_CRITERION}$] **than** [anybody else running here tonight $_{ENTITY\_2}$].

7. Comparing at two different points in time. This frame is about comparing an "Entity" with itself at two different points in time using a "Comparison_criterion" while qualifying with a "Degree".

[The average family $_{ENTITY}$] is [now $_{FIRST\_TIME\_POINT}$] [bringing home $4,000 less $_{COMPARISON\_CRITERION}$] **than** they did [just five years ago $_{SECOND\_TIME\_POINT}$].

8. Occupy rank via ordinal numbers. This frame is about "Items" in the state of occupying a certain "Rank" specified by an ordinal number within a hierarchy.

[The United States $_{ITEM}$] is [**65th** $_{RANK}$] [out of 142 nations and other territories $_{COMPARISON\_SET}$] [on equal pay $_{DIMENSION}$].

9. Occupy rank via superlatives. This frame is about "Items" in the state of occupying a certain "Rank" specified by a superlative within a hierarchy.

[Job growth in the United States $_{ITEM}$] is [now $_{TIME}$] at [the **fastest** $_{RANK}$] [pace $_{DIMENSION}$] [in this country's history $_{COMPARISON\_SET}$].

10. Ratio. In this frame, a "Criterion" determines a "Ratio" that quantifies the size of the subset of a larger "Group".

[More than 72 $_{RATIO}$] **percent of** [children in the African-American community $_{GROUP}$] are [born out of wedlock $_{CRITERION}$].

11. Uniqueness of trait. This frame distinguishes a "Unique entity" from a "Generic entity" based on a specific "Trait" where a "Trait" is some property, quality, point-of-view, or an arbitrary construct which is generally understood to be an attribute of an entity.

[The United States $_{UNIQUE\_ENTITY}$] is the **only** [advanced country on Earth $_{GENERIC\_ENTITY}$] [that doesn't guarantee paid maternity leave to our workers $_{TRAIT}$].

4. Annotation

This section discusses the source of the annotated sentences, the annotation process, the annotation tool that we created to assist this process, and the statistics of annotated sentences.

4.1. Data Source

In order to construct a sizable corpus of annotated sentences, we used fact-checked claims from the "Share the Facts" database. The "Share the Facts" database contains fact-checks annotated with the ClaimReview[9] schema–a schema.org standard which specifies a standardized format for fact-checks. The initial dataset had around 18,000 fact-checks compiled from 34 different fact-checking organizations.[10] The distribution of fact-checks from the top contributors is as follows: Gossip Cop (9082),[11] PolitiFact (4644),[5] the Washington Post (3100),[12] FactCheck.org (928),[13] and Snopes (31).[14] We removed redundant fact-checks and irrelevant fact-checks, such as those from international organizations and those associated with Hollywood gossip magazine sections, from the dataset. After

[9] https://schema.org/ClaimReview

[10] We downloaded the dataset on August 27, 2018. The dataset now contains more than 20,000 fact-checks.

[11] https://www.gossipcop.com/

[12] https://www.washingtonpost.com/

[13] https://www.factcheck.org/

[14] https://www.snopes.com/

	Causation	Change_Position_on_a_Scale	Cause_Change_of_Position_on_a_Scale	Capability	Conditional_Occurrence	Creating	Occupy_Rank	Statement	Taking_Sides	Vote	Ratio	Occupy_Rank_via_Superlatives	Occupy_Rank_via_Ordinal_Numbers	Correlation	Recurring_Action	Recurring_Action_in_Frequency	Comparing_Entities	Comparing_at_Two_Different_Points_in_Time	Uniqueness_of_Trait	Taking_Sides_Consistency
# of FEs	12	25	15	10	3	19	5	20	12	8	4	5	5	2	4	4	5	6	3	4
# of LUs	39	56	26	17	8	1	3	79	18	2	2	12	11	2	1	1	1	1	1	3

Table 3: Descriptive statistics of the corpus of factual-claim specific frames

Taking Sides: Someone has a relatively fixed positive or negative point of view towards an issue. ⇒ [Hillary Clinton $_{\text{COGNIZER}}$] **supported** [North American Free Trade Agreement $_{\text{ISSUE}}$].
Statement: Some entity communicating about a topic. ⇒ [Ronald Reagan $_{\text{SPEAKER}}$] **talked** [about converting the United States to the metric system $_{\text{TOPIC}}$].
Causation: A cause leads to an effect. ⇒ **Due to** [actions by President Barack Obama $_{\text{CAUSE}}$], [the Burger King national headquarters announced this month that they will be pulling their franchises from our military bases $_{\text{EFFECT}}$].
Capability: An entity is able or unable to do something. ⇒ [Former President George W. Bush and former Vice President Dick Cheney $_{\text{ENTITY}}$] are **unable** [to visit Europe $_{\text{EVENT}}$] [due to outstanding warrants $_{\text{CIRCUMSTANCES}}$].
Cause change of position on a scale: An item's position moves along a scale due to some agent or cause. ⇒ [In the last two years $_{\text{TIME}}$], [we $_{\text{AGENT}}$] have **reduced** [the deficit $_{\text{ATTRIBUTE}}$] [by $2.5 trillion $_{\text{DIFFERENCE}}$].
Change position on a scale: An item moves along a scale. ⇒ [Since 2007 $_{\text{TIME}}$], [Texas $_{\text{ITEM}}$] has **gained** [440,000 people $_{\text{DIFFERENCE}}$] while Maryland has lost 20,000.
Creating: A cause leads to an entity being created. ⇒ [In the last 29 months $_{\text{TIME}}$], [our economy $_{\text{CREATOR}}$] has **produced** [about 4.5 million private-sector jobs $_{\text{CREATED\_ENTITY}}$].
Occupy Rank: The location of an entity in a hierarchy with other entities. ⇒ [The U.S. $_{\text{ITEM}}$] only **ranks** [25th $_{\text{RANK}}$] [worldwide $_{\text{COMPARISON\_SET}}$] [on defense spending as a percentage of GDP $_{\text{DIMENSION}}$].
Conditional Occurrence: Something can occur if [a/some] condition(s) [is/are] met. ⇒ [We would create thousands of jobs in Colorado $_{\text{CONSEQUENCE}}$], **if** [the Keystone Pipeline were to be built $_{\text{CONDITIONAL\_EVENT}}$].

Table 4: Existing FrameNet frames related to factual claims

cleaning up the dataset and splitting fact-checks with multiple sentences, we ended up with 6017 fact-checks that we deemed to be high-quality with respect to our task.

4.2. Annotation Process

For each lexical unit in our corpus, we gathered all the sentences containing the lexical unit from the preprocessed 'Share the Facts' dataset. We manually filtered out sentences that did not use a given lexical unit in the same context as the other sentences that they were initially grouped with via by the rudimentary gathering step. We denote this group of sentences that share a lexical unit as S. We took sentences from S and marked syntactic elements in each sentence that corresponded to the frame elements for a given frame. The labels were then vetted by a second person and revisions were made as needed.

4.3. Annotation Tool

We are also making our in-house frame annotation tool[8] available to facilitate annotating sentences with frame semantics. To annotate a corpus of sentences containing different lexical units, this tool[15] requires preparing separate input files of sentences, one for each lexical unit. Once individual files are separately annotated, the annotated files must be merged into a single corpus file. Without automating these repetitive actions, the process would be laborious and time-consuming. To more conveniently annotate

[15] https://framenet.icsi.berkeley.edu/fndrupal/annotation_tool

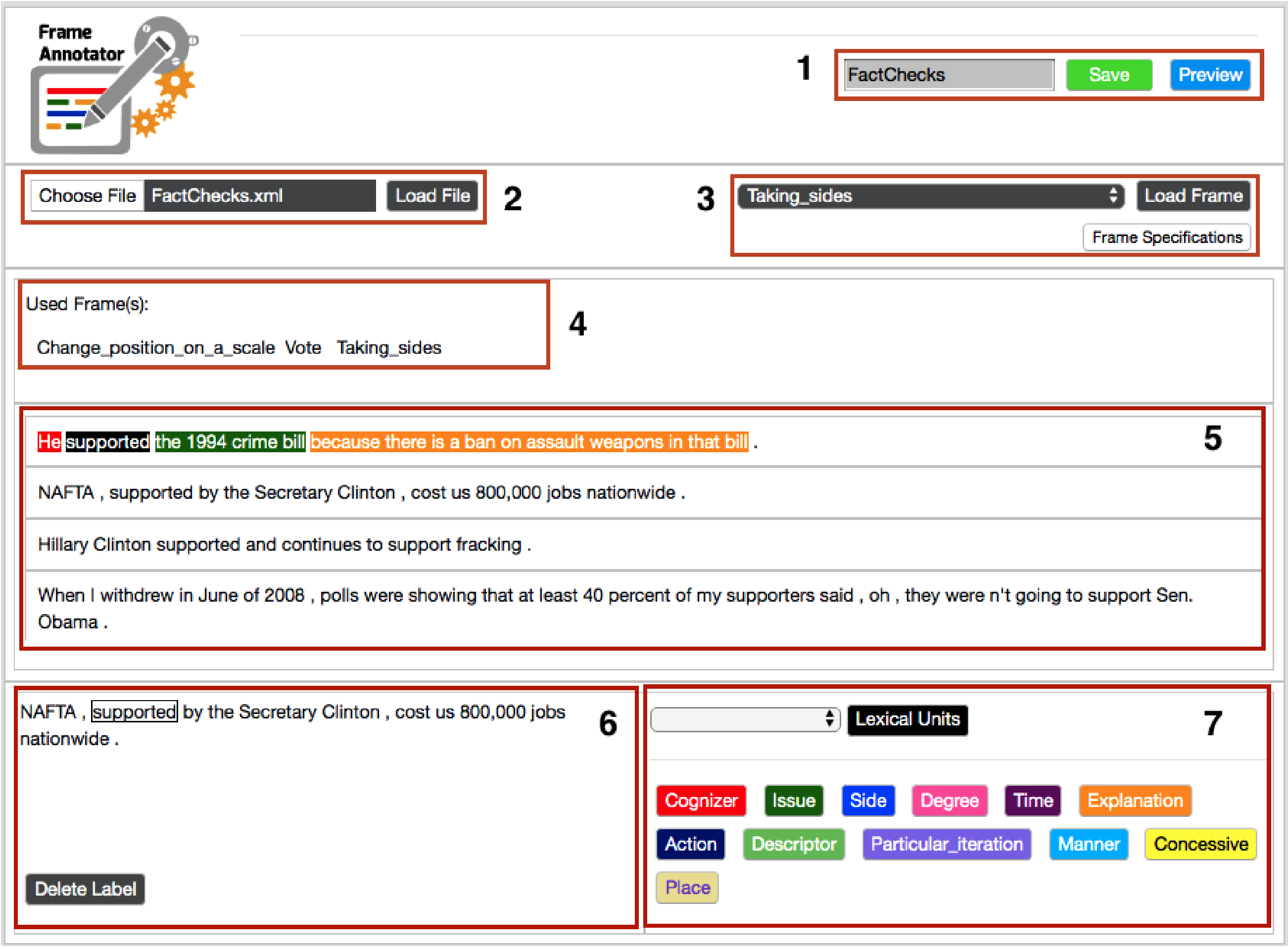

Figure 1: The user interface of *FrameAnnotator*

sentences using our newly created frames, we built a web-application, FrameAnnotator (Roy, 2019),[8] which accepts input sentences that may not have the same lexical unit and does not require additional processing to arrive at a single corpus file.

We now explain how to use the annotation tool that we have created with regions marked in Figure 1. First a user uploads sentences in region 2 and selects a frame from region 3. Once sentences have been loaded they appear in region 5. Here, a user can annotate a sentence by simply clicking on a sentence and send it to region 6. When a sentence is populated in region 6, the tool attempts to highlight a potential lexical unit, an example of this can be seen in Figure 1. An annotator can click and drag over a sentence fragment to select it in region 6. When a sentence fragment is selected, the tool highlights the region to provide feedback to the annotator that the system is aware of their selection, once the fragment is highlighted it may be marked by selecting the appropriate frame element in region 7. As frame elements are marked, their respective frames appear in region 4 to provide feedback to the annotator on what frames have been used. To save progress, an annotator may assign a filename and click the “Save” button in region 1. The exported annotations are stored in XML format - thus enabling programs to consume the annotations or annotators to pick up where they left off.

4.4. Annotation Statistics

As we previously mentioned our efforts led to a total of $2,540$ fully annotated sentences with $3,616$ frame annotations. Most sentences, $1,955$, from the set of $2,540$ had only 1 frame associated with them and 478 had two frame instances. The rest of the sentences had between 3 and 10 frame instances with number of sentences decreasing as the number of associated frames increased. In Figure 2 we see a break down of the number and percentage of the corpus composed of annotated sentences by their respective frame instances. Information for the composition of each frame instance is included in Table 8.

5. Potential Uses for the Corpus of Factual-Claim Specific Frames

In this section, we outline some key research areas where the corpus of the factual-claim specific frames can be used.

5.1. Potential Uses in Fact-checking

To understand where we can leverage the corpus of factual-claim specific frames in the fact-checking process, we briefly introduce that process for FactCheck.org, a major fact-checking organization.[16] First, journalists identify “statements of fact” made by people of interest in various

[16] https://www.factcheck.org/our-process/

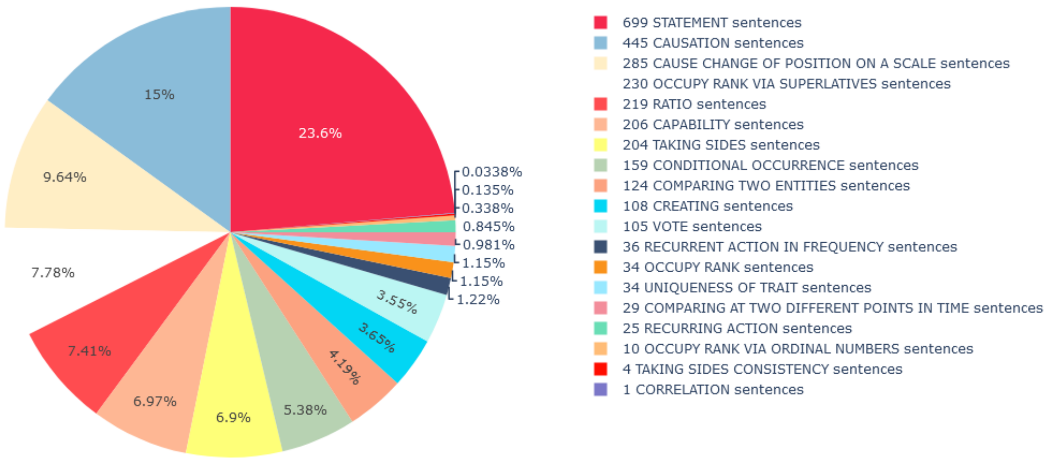

Figure 2: Distribution of annotated sentences by frame instance over corpus

forums. They then research the identified factual claims by considering the speakers' supporting information and various primary sources. Once the independent research is synthesized into a story, that story goes through a rigorous editing process to ensure quality and veracity. This process can be improved by the application of our work in three areas, including 1) identification of "statements of fact", 2) avoiding duplication of work by "matching" repeated "statements of fact" to their corresponding existing fact-checks, and 3) translating them to structured queries that can be verified over a reliable knowledge base.

5.1.1. Claim Spotting

Claim spotting is a necessary task in the fact-checking process to identify claims worthy of fact-checking from natural language sentences. The task not only consists of identifying claims but also prioritizing them for fact-checking. In recent years, a significant amount of research efforts have been dedicated to the development of claim spotting models. Early models relied on supervised classifiers such as SVM or logistic regression trained on hand-engineered features (Hassan et al., 2015; Patwari et al., 2017; Jaradat et al., 2018). In contrast, recent approaches utilize neural sentence embeddings (Konstantinovskiy et al., 2018; Jimenez and Li, 2018; Hansen et al., 2019; Meng et al., 2020). A number of fact-checking organizations[17][18][19] around the world make use of claim spotting models in their fact-checking efforts to detect claims to check. Claim spotting is one particular task that can benefit from claim specific frames. With factual frames in hand, we can remodel the claim spotting task as identifying and prioritizing claims that have been found to be affiliated with at least one of the 20 frames.

[17] https://fullfact.org/automated

[18] https://team.inria.fr/cedar/contentcheck/

[19] https://reporterslab.org/tech-and-check/

5.1.2. Claim Matching

Given a new factual claim, claim matching is the process of partially or fully matching the claim with supporting or refuting fact-checked claims stored in a repository. In the best-case scenario, a new factual claim is a perfect match with an existing factual claim and a user can be provided with the verdict of the claim's veracity. In other scenarios, we can still leverage fact-checked claims, particularly so when the new claim is partially supported or refuted by existing fact-checked claims.

1. [GOP Rep. Joe Heck of Nevada $_{AGENT}$] **voted** [23 times $_{FREQUENCY}$] [against $_{POSITION}$] [banning terrorists from buying guns. $_{ISSUE}$]

2. [Heck $_{AGENT}$] **voted** [nay $_{POSITION}$] [on tighter gun-control laws. $_{ISSUE}$]

3. [Heck $_{AGENT}$] **voted** [for $_{POSITION}$] [stronger gun-control. $_{ISSUE}$]

Figure 3: A fact-checked claim with similar and opposite factual claims.

The modeling done in this paper can help us address these other scenarios by comparison of the semantics of the claims (i.e. entities, quantities, time intervals, etc.) present in the frame elements for each claim. The similarity or difference in the corresponding frame elements for each claim can be presented to the user to conclude whether the new factual claim is partially similar to or opposite of the previously fact-checked claim. An example of one comparison between similar and opposite claims is provided in Figure 3. The claims in Figure 3 are talking about the same individual and similar issues. Matching the new claims to the fact-checked claim (the first claim in the figure) could provide insight to a user about the veracity of the new claims.

5.1.3. Claim to query translation

Claim-to-query translation is the process of mapping a given input claim to a structured query that can be run on a knowledge base to verify the given claim. The mapping process is not straightforward as it requires understanding: what is being asked, what context it is being asked in, and identifying any key entities and their relationships in order to answer the specific question that is implicitly introduced by the claim. While there are approaches to entity matching, and relationship matching (e.g., SpaCy,[20] TextRazor,[21] etc.) there is still work to be done to correctly map these elements to a structured query that can be applied on a knowledge base. Currently some industrial solutions seem to do this behind the scenes (e.g., Wolfram Alpha[22]). However, these are black-box systems and thus open-source and robust solutions still need to be developed.

In the context of claim-to-query translation, frames can be used to identify the key elements in a claim and how they relate to each other within the context of a given frame. This then enables researchers to create query templates that can directly make use of the parsed frame elements extracted from the claim. These query templates can be general to some extent as they can directly relate to a particular frame. Another possibility would be to have a few query templates per frame depending on how complex of a structure the frame is able to represent. One frame that particularly lends itself to this process is the "Vote" frame. It is easy to envision using public voting records to create a knowledge base and then creating one or a few query templates that can make use of the frame elements (e.g., agent, issue, side, frequency, etc.) from the "Vote" frame in order to verify claims of this nature.

5.2. Other potential use cases

Outside of automated fact-checking, this work has potential use in the areas of browsing and search, the academic study of factual claims and natural language processing tasks.

A recent paper described a browsing and search system for tweets that may contain factual claims (Majithia et al., 2019). The claim categorization feature of this system leverages our work to train the model responsible for categorizing the factual claims present in tweets. Other systems that aim to add a faceted search interface for users to browse/search for certain types of natural language text may benefit from additional labeled data to train their natural language models on.

Factual claims are studied academically in fields such as social science, journalism and computer science. Some studies, such as (Faasse et al., 2016), analyze the distributions of word tokens across different corpora and derive insight from these distributions–our work may enable the analysis of frame and frame element distributions. This could lead to new findings derived from semantic similarities between corpora as opposed to syntactic similarities.

Many natural language processing tasks can benefit from the usage of frames, some of these tasks include question answering (Shen and Lapata, 2007), information extraction (Moschitti et al., 2003), sentiment analysis (Sharma et al., 2017), and machine translation (Boas, 2002). Our corpus may be leveraged in these tasks as an additional source of data for models to learn from.

6. Conclusions

We present an extension of Berkeley FrameNet that focuses on modeling factual claims. This work can be used to study misinformation, aid in translating claims to structured queries, and aid in fact-checking in several ways. Our work introduces 11 new frames along with 9 existing FrameNet frames that we found to be applicable to our task. We are also releasing $2,540$ fully annotated sentences which we expect to be useful for training machine learning models aimed at tackling fact-checking tasks. Finally, we are providing our annotation tool which should enable researchers to make their own local extensions to FrameNet and facilitate collaboration. We will continue to expand this work in the near future.

7. Acknowledgements

The work is partially supported by NSF grant 1937143, IIS-1719054, and sub-awards from Duke University as part of a grant to the Duke Tech & Check Cooperative from the Knight Foundation and Facebook. Any opinions, findings, and conclusions or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the funding agencies.

[20] https://spacy.io/
[21] https://www.textrazor.com/
[22] https://www.wolframalpha.com/

8. Appendix: Frequencies of Frame Instances in the Corpus of Factual-claim Specific Frames

STATEMENT	acknowledge.v (3), acknowledgment.n, add.v, address.v, admission.n, allegation.n (6), allege.v (4), allow.v, announce.v (19), announcement.n (4), assert.v (4), assertion.n, attest.v (1), aver.v, avow.v, avowal.n, be like.v, caution.n, caution.v, challenge.v, claim.n (18), claim.v (11), comment.n (5), comment.v (3), concession.n, confirm.v (3), conjecture.n, conjecture.v, contend.v, contention.n, declaration.n, declare.v (5), denial.n, describe.v (7), detail.v, exclaim.v, exclamation.n, explain.v (2), gloat.v, explanation.n, hazard.v, insist.v, insistence.n (1), maintain.v, mention.n, mention.v (9), message.n, note.v (2), observe.v (1), pout.v, preach.v, proclaim.v, proclamation.n, profess.v, promulgation.n, pronounce.v, pronouncement.n, proposal.n (32), propose.v (29), proposition.n (7), reaffirm.v (1), recount.v, refute.v (1), reiterate.v (1), relate.v, remark.n, remark.v, report.n (28), report.v (21), say.v (350), smirk.v, speak.v (16), state.v (4), statement.n (11), suggest.v (7), talk.v (21), tell.v (44), venture.v, write.v (18)
CHANGE_POSITION_ON_A_SCALE	accelerated.a, advance.v, balloon.v, climb.v, contract.v, contraction.n, decline.n (5), decline.v, decrease.n (3), decrease.v (2), depressed.a, depression.n, diminish.v (1), dip.v, double.v (10), down.prep (27), drop.v (6), dwindle.v, edge.v, elevated.a, elevation.n, escalation.n, explode.v, explosion.n, fall.n, fall.v (5), fluctuate.v, fluctuation.n, gain.n (3), gain.v (3), grow.v (20), growing.a (2), growth.n (25), hike.n (8), increase.n (77), increase.v (30), increasingly.adv, jump.v (2), lower.v, move.v (2), mushroom.v, plummet.v (2), reach.v (7), rise.n (11), rise.v (13), rocket.v, shift.n, shift.v, skyrocket.v (5), slide.v, soar.v (2), swell.v, swing.v, triple.v (4), tumble.n, tumble.v
CAUSATION	because of.prep (61), because.c (109), bring about.v, bring on.v, bring.v (3), causative.a, cause.n (5), cause.v (17), consequence.n (1), consequent.a, consequential.a, dictate.v, due to.prep (11), for.c, force.v (17), give rise.v, induce.v, lead (to).v (12), leave.v (19), legacy.n (1), make.v (66), mean.v (19), motivate.v, precipitate.v, put.v (41), raise.v, reason.n (16), render.v, responsible.a (11), result (in).v (15), result.n (11), resultant.a, resulting.a (2), see.v, send.v, since.c (4), so.c (31), sway.v, wreak.v
CAUSE_CHANGE_OF_POSITION_ON_A_SCALE	add.v (22), crank.v, curtail.v, cut.n (81), cut.v (61), decrease.v, development.n (10), diminish.v, double.v (10), drop.v, enhance.v, growth.n, increase.v (21), knock down.v, lift.v, lower.v (6), move.v, promote.v, push.n, push.v (6), raise.v, reduce.v (45), reduction.n (14), slash.v (9), step up.v, swell.v
TAKING_SIDES	against.prep (21), back.v (6), backing.n, believe in.v (7), endorse.v (12), for.prep (8), in favor.prep (5), opponent.n (15), oppose.v (19), opposition [act].n (2), opposition [entity].n, part.n, pro.adv (8), side.n (6), side.v (1), support.v (81), supporter.n (15), supportive.a
CAPABILITY	ability.n (6), able.a (24), can.v (153), capability.n, capable.a (4), capacity.n (3), inability.n, incapable.a, incapacity.n, potential.a (3), potential.n (1), power.n (10), powerful.a(4), powerless.a, powerlessness.n, unable.a (2)
CREATING	assemble.v, create.v (62), form.v (7), formation.n, generate.v (7), issuance.n (1), issue.v (11), make.v, produce.v (9), production.n (9), yield.v (2)
CONDITIONAL_OCCURRENCE	as long as.scon (3), assuming.scon, if.scon (154), in case.scon (1), in the event.prep (1), provided.scon, supposing.scon, what if.scon
OCCUPY_RANK	rank.v (12), stand.v, top.a (22)
VOTE	vote.v (105), (a/the) deciding vote.n (5)
UNIQUENESS_OF_TRAIT	the only.a (34)
RECURRING_ACTION	every.prep (25)
OCCUPY_RANK_VIA_ORDINAL_NUMBERS	No. 1.a (10)
OCCUPY_RANK_VIA_SUPERLATIVES	biggest.a (27), fastest.a (4), fewest.a (4), highest.a (61), largest.a (50), longest.a (4), most.adv (53), oldest.a(2), richest.a (2), safest.a (7), smallest.a (1), worst.a (17)
RATIO	percent of. (206), out of. (13)
COMPARING_TWO_ENTITIES	than.sc (124)
COMPARING_AT_TWO_DIFFERENT_POINTS_IN_TIME	than.sc (29)
CORRELATION	every time.adv (1), whenever.c (0)
TAKING_SIDES_CONSISTENCY	change.v (3), flip-flop.v (2), shift.v (1)
RECURRENT_ACTION_IN_FREQUENCY	time.n (36)

9. Bibliographical References

Adair, B., Li, C., Yang, J., and Yu, C. (2019). Automated pop-up fact-checking: Challenges & progress. In *Computation+Journalism Symposium*, pages 1–5.

Allcott, H. and Gentzkow, M. (2017). Social media and fake news in the 2016 election. *Journal of economic perspectives*, 31(2):211–36.

Allcott, H., Gentzkow, M., and Yu, C. (2019). Trends in the diffusion of misinformation on social media. *Research & Politics*, 6(2):2053168019848554.

Arslan, F., Jimenez, D., Caraballo, J., Zhang, G., and Li, C. (2019). Modeling factual claims by frames. In *Proceedings of the 2019 Computation+Journalism Symposium.*

Baker, C. F., Fillmore, C. J., and Lowe, J. B. (1998). The berkeley framenet project. In *ACL*, pages 86–90.

Bennett, L. and Livingston, S. (2018). The disinformation order: Disruptive communication and the decline of democratic institutions. *European Journal of Communication*, 33:122–139.

Berinsky, A. J. (2017). Rumors and health care reform: Experiments in political misinformation. *British Journal of Political Science*, 47(2):241–262.

Boas, H. C. (2002). Bilingual FrameNet dictionaries for machine translation. In *LREC*.

Bovet, A. and Makse, H. A. (2019). Influence of fake news in twitter during the 2016 us presidential election. *Nature Communications*, 10(1).

Faasse, K., Chatman, C. J., and Martin, L. R. (2016). A comparison of language use in pro-and anti-vaccination comments in response to a high profile facebook post. *Vaccine*, 34(47):5808–5814.

Francis, D. and Fact, F. (2016). Herox fact check challenge. https://www.herox.com/factcheck/5-practise-claims. Accessed: 2018-10-25.

Hansen, C., Hansen, C., Alstrup, S., Grue Simonsen, J., and Lioma, C. (2019). Neural check-worthiness ranking with weak supervision: Finding sentences for fact-checking. In *WWW*, pages 994–1000.

Hassan, N., Li, C., and Tremayne, M. (2015). Detecting check-worthy factual claims in presidential debates. In *CIKM*, pages 1835–1838.

Hassan, N., Arslan, F., Li, C., and Tremayne, M. (2017). Toward automated fact-checking: Detecting check-worthy factual claims by claimbuster. In *KDD*, pages 1803–1812.

Jaradat, I., Gencheva, P., Barrón-Cedeño, A., Màrquez, L., and Nakov, P. (2018). ClaimRank: Detecting check-worthy claims in Arabic and English. In *NAACL*, pages 26–30.

Jimenez, D. and Li, C. (2018). An empirical study on identifying sentences with salient factual statements. In *IJCNN*, pages 1–8.

Jo, S., Trummer, I., Yu, W., Wang, X., Yu, C., Liu, D., and Mehta, N. (2019). Verifying text summaries of relational data sets. In *SIGMOD*, pages 299–316.

Konstantinovskiy, L., Price, O., Babakar, M., and Zubiaga, A. (2018). Towards automated factchecking: Developing an annotation schema and benchmark for consistent automated claim detection.

Majithia, S., Arslan, F., Lubal, S., Jimenez, D., Arora, P., Caraballo, J., and Li, C. (2019). ClaimPortal: Integrated monitoring, searching, checking, and analytics of factual claims on twitter. In *ACL: System Demonstrations*, pages 153–158.

Meng, K., Jimenez, D., Arslan, F., Devasier, J. D., Obembe, D., and Li, C. (2020). Gradient-based adversarial training on transformer networks for detecting check-worthy factual claims. *arXiv preprint arXiv:2002.07725.*

Miranda, S. a., Nogueira, D., Mendes, A., Vlachos, A., Secker, A., Garrett, R., Mitchel, J., and Marinho, Z. (2019). Automated fact checking in the news room. In *WWW*, pages 3579–3583.

Moschitti, A., Morarescu, P., and Harabagiu, S. (2003). Open domain information extraction via automatic semantic labeling. In *FLAIRS Conference*, pages 397–401, 01.

Patwari, A., Goldwasser, D., and Bagchi, S. (2017). Tathya: A multi-classifier system for detecting check-worthy statements in political debates. In *CIKM*, pages 2259–2262.

Pennycook, G. and Rand, D. G. (2019). Who falls for fake news? the roles of bullshit receptivity, overclaiming, familiarity, and analytic thinking. *Journal of Personality*.

Roy, S. (2019). Frameannotator - a web-based frame semantic annotation tool. https://rc.library.uta.edu/uta-ir/bitstream/handle/10106/28142/ROY-THESIS-2019.pdf. [Online; accessed 14-November-2019].

Ruppenhofer, J., Ellsworth, M., Petruck, M. R. L., Johnson, C. R., and Scheffczyk, J. (2006). Framenet ii: Extended theory and practice. In *WWW 2006*.

Sharma, R., Somani, A., Kumar, L., and Bhattacharyya, P. (2017). Sentiment intensity ranking among adjectives using sentiment bearing word embeddings. In *EMNLP*, pages 547–552.

Shen, D. and Lapata, M. (2007). Using semantic roles to improve question answering. In *(EMNLP-CoNLL)*, pages 12–21.

Thorne, J. and Vlachos, A. (2017). An extensible framework for verification of numerical claims. In *EACL*, pages 37–40.