Measuring and Visualizing Short-Term Change in Word Representation and Usage Due to Coronavirus Pandemic on Twitter

First Author
Xinman Liu
xinman.liu@mail.utoronto.ca

Abstract

Linguistic shifts can happen faster on the web or social media, especially during a crisis event. In this paper, we study the short-term semantic change that occurred on Twitter during the coronavirus pandemic. We construct two types of time series for each word based on frequency-based features and contextual semantics respectively. The former measures the concept drift, while the latter captures the representation shift. We find the representation shift is not always equivalent to the concept drift. Also, the words that related to the outbreak, such as lockdown, pandemic, and quarantine, experience more significant semantic change than most of the words. Finally, we also show example visualizations of existing words.

1 Introduction

In recent years, most studies on semantic change concentrate on the historical evolution of language. Some of the most popular corpora are the Google Books Ngram corpus and the Corpus of Contemporary American English (COHA). These corpora usually only contain formal written text and span over several hundreds of years. Thus, the time interval is normally set to decades when experimenting with these corpora. However, short-term semantic change is also worth attention. Short-term semantic change is more useful for natural language preprocessing than long-term semantic change because NLP focuses on the application of computational techniques to modern and contemporary language use (TANG, 2018). Also, studies on semantic changes in social media can help track irregular or innovative activities (Stewart et al., 2017). Language in social media becomes more dynamic compared with the formal language used in books or news. In social media, the meaning shifts are likely to happen at a faster pace, especially when there is a crisis event.

In (Stewart et al., 2017), short-term meaning change and word frequency change during the Russian-Ukraine crisis are jointly analyzed using a corpus containing VKontakte posts. Inspired by (Stewart et al., 2017), instead of the Russian-Ukrainian crisis, the purpose of this work is to study how the meaning and frequency of words change over time in the context of the coronavirus pandemic on Twitter. Specifically, the short-term changes in word contextualized representation (representation shift) will be measured and visualized in contrast with such changes in word frequency (concept drift).

The rest of the paper is structured as follows: Section 2 discusses related work. Section 3 presents the methodology. Section 4 provides details about the experiments, including the dataset used and experiment results. Finally, Section 5 contains the conclusion, the limitations, and future works.

2 Related Work

Previously, most studies focus on long-term semantic shifts. Kulkarni et al. (Kulkarni et al., 2015) investigated the performance of the frequency method, syntactic method, and distributional method on the detection of long-term linguistic change on the Google Books Ngram Corpus. Gulordava et al. (Gulordava and Baroni, 2011) also experimented with the Google Books Ngram Corpus, while they used a word co-occurrence matrix weighted by local mutual information to construct word vectors. Hamilton et al. (Hamilton et al., 2016) utilized three different diachronic embedding methods, positive pointwise mutual information, SVD, and skip-gram with negative sampling, to study the statistical laws of semantic changes - the law of conformity and the law of innovation. However, Dubossarsky et al. (Dubossarsky et al., 2017) reevaluated the laws proposed in (Hamilton et al., 2016) in a control condition and then stated that both the law of conformity and the law of innovation are mostly an artefact of word frequency.

In recent years, more work are done on short-term semantic shifts. (Del Tredici et al., 2019) is the first work that employed a distributional method to analyze different types of short-term shifts in social media data. Both (Del Tredici et al., 2019) and (Noble et al., 2021) investigated the Reddit data. (Del Tredici et al., 2019) focused on a small annotated dataset that only contained a single subreddit. However, the dataset of (Noble et al., 2021) consists of 45 subreddits in total, which is used to study the relationship between the community structure and semantic change. Moreover, even though Kulkarni et al. (Kulkarni et al., 2015) also experimented with Amazon Movie Reviews and Twitter Data trying to detect the short-term meaning shift, they did not provide a detailed analysis of the observed shifts. Marakasova et al. (Marakasova and Neidhardt, 2020) focused on the relationship between the short-term semantic shifts and frequency change in the context of the refugee crisis in Austria from 2015 to 2016. Stewart et al. (Stewart et al., 2017) used both the frequency method and the distributional method to investigate short-term linguistic changes during the Russia-Ukraine crisis from 2014 to 2015. Besides, they predicted the change in meaning based on prior patterns of concept drift and representation shift.

3 Computational Approach

Basically, we adopt the methods proposed in (Stewart et al., 2017). In summary, we will use two different methods to measure the short-term word meaning and usage shifts, which are frequency-based method and distributional method. Our code is available at `https://github.com/Liuxinman/CSC2611Project`.

3.1 Time Series Construction

Frequency-based Method One of the most trivial ways to detect semantic shifts is by looking at the changes in word frequency. The changes in word frequency usually correspond to word gaining or losing senses. Thus, frequency-based methods can be used to capture linguistic shifts (Kulkarni et al., 2015). We construct the two different time series τ_f and τ_{tfidf} of a word w by calculating the probability and the tf-idf score of w over time respectively. These are also called our measures of concept drift. Specifically,

	Mean Pearson Correlation
Similarity	0.643
Relatedness	0.558

Table 1: Results obtained on the similarity and relatedness subsets of WordSim353 dataset. The Pearson correlation is averaged over the model of all time steps.

$$\tau_{f,t} = \frac{count(w,t)}{\sum_{w' \in V} count(w',t)} \tag{1}$$

$$\begin{aligned}\tau_{tfidf,t} &= log(count(w,t)) \\ &\times log(\frac{|P_t|}{|p \in P_t : w \in p|})\end{aligned} \tag{2}$$

where V is the vocabulary, P_t is all posts within the tth time interval. In this work, the time interval ΔT is set to one month.

Distributional Method Besides frequency-based methods only focusing on surface-level features and patterns (Stewart et al., 2017), we also implement distributional methods to learn non-linear, complex features. The distributional method proposed in (Stewart et al., 2017) is adopted. Basically, our goal is to learn a temporal word embedding over vocabulary V and then use it to construct a time series for each word in V.

First of all, we initialize a Word2vec model [1] (Mikolov et al., 2013) with vocabulary V. The Word2vec model is trained with negative sampling. At each timestep t, we iterate over the corpus 5 times in total. At the timestep t_1, we randomly initialize the word embeddings. To make sure the embeddings at different time steps are aligned with each other so that they are directly comparable, we initialize word embeddings at timestep t_i with embeddings at timestep t_{i-1} (Kim et al., 2014). After the training is finished, we test the model's performance on similarity, comparing the model's word similarity scores and word similarity ratings assigned by humans using Pearson correlation. The test dataset used is **WordSim353 - Similarity and Relatedness** (Agirre et

[1]The model is implemented using the Python package Gensim https://pypi.org/project/gensim/

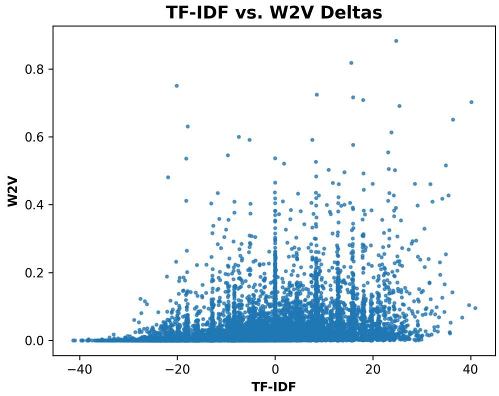


Figure 1: The distribution of concept drift $\Delta\tau_{tfidf}$ versus representation shift $\Delta\tau_e$ for a sample of vocabulary (sample size = 5000).

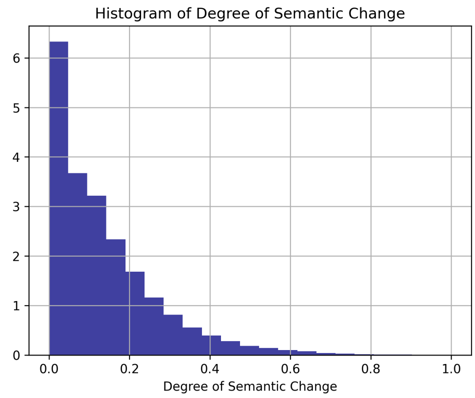


Figure 2: The histogram of degree of semantic change for existing words.

al., 2009). The test performance is shown in Table 1.

After the word embeddings are constructed, we can construct a time series for each word. Specifically,

$$\tau_{e,t} = \boldsymbol{e}_t(w) \tag{3}$$

3.2 Measuring Semantic Shift

Based on the three different time series we constructed before, we calculate a difference vector for each time series to measure the semantic shift (Stewart et al., 2017):

$$\Delta\tau_f = (\tau_{f,t_2} - \tau_{f,t_1}), ..., (\tau_{f,T-1} - \tau_{f,T}) \tag{4}$$

$$\Delta\tau_{tfidf} = (\tau_{tfidf,t_2} - \tau_{tfidf,t_1}), ..., \\ (\tau_{tfidf,T-1} - \tau_{tfidf,T}) \tag{5}$$

$$\Delta\tau_e = cosDist(\tau_{e,t_2}, \tau_{e,t_1}), ..., \\ cosDist(\tau_{e,T-1}, \tau_{e,T}) \tag{6}$$

3.3 Visualizing Representation Shift

The visualizing method proposed in (Stewart et al., 2017) is adopted. Basically, we first project the high-dimensional embedding of the word w at timestep t into a 2-dimensional space using t-distributed stochastic neighbor embedding (t-SNE) (van der Maaten and Hinton, 2008). For the 5 nearest neighbors of w at timestep t, we also project their embeddings into a 2-dimensional space. We then plot the meaning shift of the word w in the 2D projected space.

4 Results

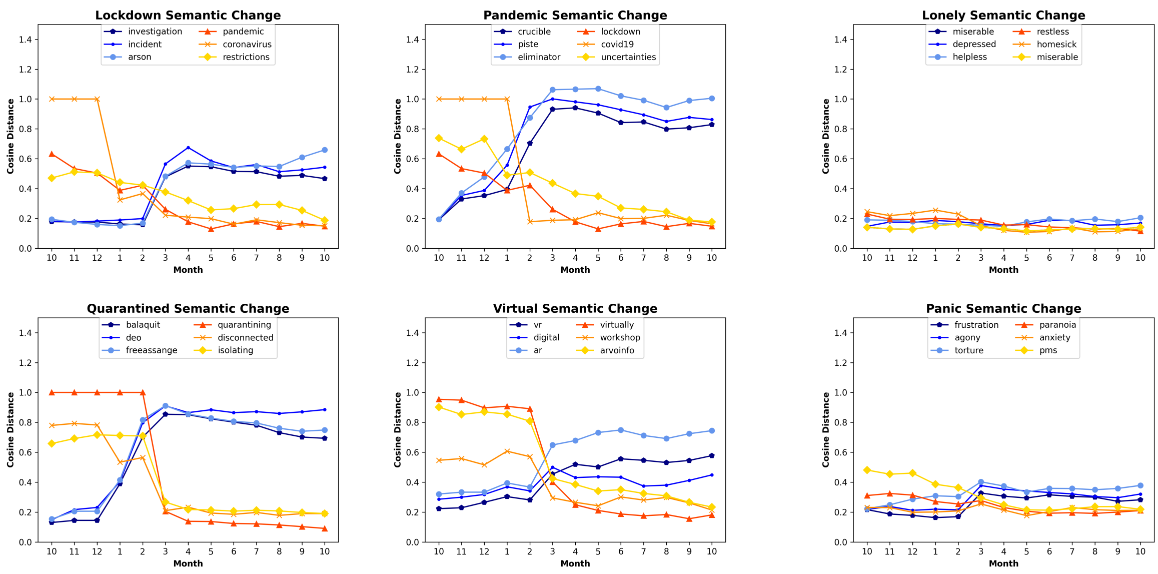
In this section, we present our results in the following order. First, we detail the dataset we used (Section 4.1). Then, we show a detailed comparison between concept drift and representation shift (Section 4.2). Finally, we give example visualizations of semantic change in existing words (Section 4.3).

4.1 Dataset

Since there is no available dataset that contains social media data during the COVID-19 pandemic, we decide to create a dataset using Twitter API[2]. Specifically, tweets in Canada from 2019/10 to 2020/10 are retrieved. The place country of tweets is limited to Canada due to the lack of computing resources and the tweet consumption cap. The time period is set to 2019/10 - 2020/10 because the coronavirus pandemic roughly started from 2020/03. By including tweets before and after the pandemic started, the semantic changes due to the coronavirus pandemic can be better investigated. On Twitter, each tweet is limited to 280 characters and can be posted either publicly or privately. Since we use the full-archive search function, we are only able to access public tweets.

For data pre-processing, we follow the steps in (Stewart et al., 2017). We lowercase the words to avoid problems caused by unusual capitalization habits in social media. When building the vocabulary, we remove all the words whose frequency is less than K = 5 in order to avoid misspelled and rare words. The size of the vocabulary is then 189631. The stop words are removed when calcu-

[2]https://developer.twitter.com/en/docs/twitter-api



(a) (b)

Figure 3: Representation shift measured by the cosine distance between each word and three of its nearest neighbours in the first time interval (2019/10), as well as three of its nearest neighbours in the last time interval (2020/10). Words in figure (a) diverge cleanly from their original meanings, while words in figure (b) do not.

lating the word frequency but are kept when constructing temporal embedding in order to prevent the loss of contextual information in stop words.

4.2 Comparing Concept Drift and Representation Shift

Concept Drift is not equivalent to representation shift. From Figure 4, we notice that an increase in $\Delta\tau_{tfidf}$ is not necessarily associated with an increase in $\Delta\tau_e$ even though they are similar to each other to some extent. A more general picture of the difference between $\Delta\tau_{tfidf}$ and $\Delta\tau_e$ is shown in Figure 1, which displays a distribution of $\Delta\tau_{tfidf}$ versus $\Delta\tau_e$ for a sample of the vocabulary and time steps. We see that even when $\Delta\tau_e$ is close to 0, $\Delta\tau_{tfidf}$ could range from -40 to 40.

	$\Delta\tau_f$	$\Delta\tau_{tfidf}$	$\Delta\tau_e$
$\Delta\tau_f$	1.0	0.895	0.460
$\Delta\tau_{tfidf}$	0.895	1.0	0.426
$\Delta\tau_e$	0.460	0.426	1.0

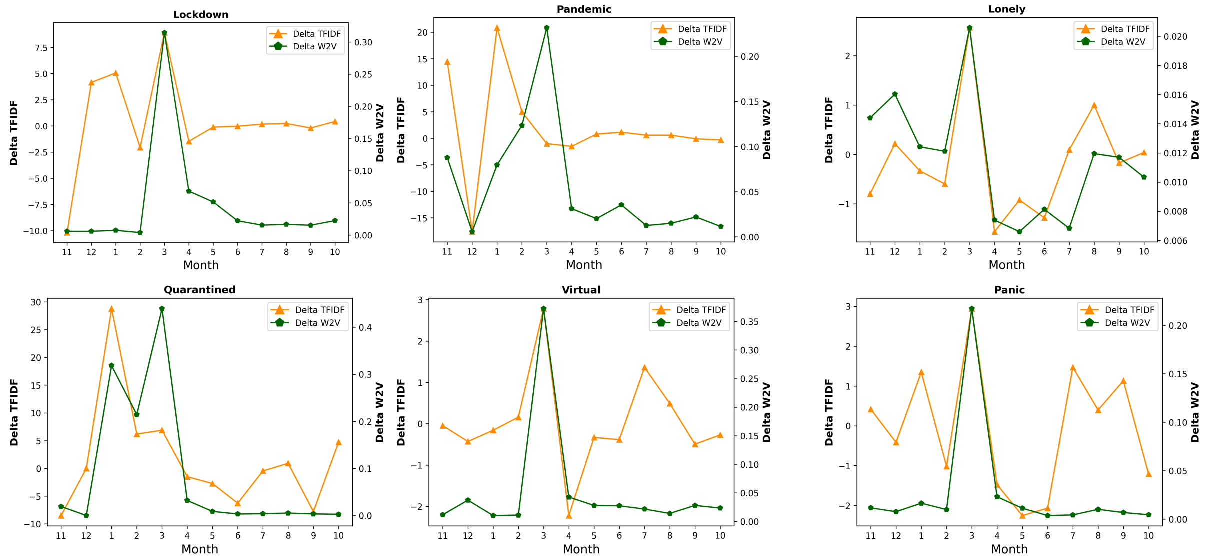
Table 2: The Pearson correlation coefficient between $\Delta\tau_f$, $\Delta\tau_{tfidf}$ and $\Delta\tau_e$ for a sample of vocabulary (sample size = 5000).

Besides, we calculate the Pearson correlation coefficient between $\Delta\tau_f$, $\Delta\tau_{tfidf}$ and $\Delta\tau_e$ for a sample of vocabulary with a sample size 5000 as shown in Table 2. It is not surprising that $\Delta\tau_f$ and $\Delta\tau_{tfidf}$ are highly correlated because the TF-IDF is a feature based on word frequency.

4.3 Visualizations of Semantic Shift in Existing Words

Figure 2 presents a general picture of the degree of semantic change of all existing words. The total number of existing words is 143432. The degree of semantic change here is defined as $cosDist(\tau_{e,t_1}, \tau_{e,T})$. It is interesting to note that only a small portion of words undergo a significant semantic shift. This suggests that the meanings of most words tend to remain relatively stable over time. We also include the rank of the degree of semantic change of some coronavirus-pandemic-related words in Table 3. We can see that these words rank top 30% among all existing words.

Inspired by (Stewart et al., 2017), to better understand how the meanings of existing words evolve over time, we create three types of visualization. The first one is shown in Figure 3. This plot shows the cosine distance from the target word to three of its nearest neighbours in the first time interval (2019/10), as well as three of its near-



(a) (b)

Figure 4: Concept drift $\Delta\tau_{tfidf}$ and representation shift $\Delta\tau_e$ for lockdown, pandemic, quarantined, virtual, panic and lonely. Words in figure (a) experience both significant concept drift and representation shift, while words in figure (b) only experience significant concept drift.

Word	Degree of Change	Rank
quarantine	0.735	439
pandemic	0.704	572
virtual	0.645	1018
quarantined	0.497	3599
lockdown	0.492	3733
outbreak	0.175	41745

Table 3: The degree of semantic change of some coronavirus-pandemic-related words and their ranks.

est neighbours in the last time interval (2020/10). By comparing the distances between the target word and its neighbors in the two time intervals, we can clearly see when the representation shift begins and how significant the shift is. The second is shown in Figure 4. From this plot, we can easily compare the trend of $\Delta\tau_{tfidf}$ and $\Delta\tau_e$. Finally, a t-SNE visualization of the semantic change is also generated using word2vec vectors for each existing word having a significant shift, as illustrated in Figure 5.

For the keywords shown in Figure 3a, we see that the distance between the keyword and its neighbors changes significantly over time, indicating a shift in the word's meaning. Also, from Figure 4a, we notice that both the $\Delta\tau_{tfidf}$ and $\Delta\tau_e$ reach a peak at around March 2020, which is precisely when the coronavirus pandemic started. To illustrate, the word *lockdown* (Figure 3a (top left)) is initially semantically similar to crime-related words like investigation and arson. However, as the coronavirus pandemic begins, the word's representation shifts and it becomes closer to coronavirus-pandemic-related words like coronavirus and restrictions. For the word *pandemic* (Figure 3a (top right)), since the February of 2020, it starts moving towards coronavirus-pandemic-related words, such as covid19 and lockdown. The word *quarantined* (Figure 3a (bottom left)) also shows a clear semantic shift over time. Before the coronavirus pandemic, *quarantined* is related to events like the FreeAssange [3] and the Eduardo Balaquit homicide, indicating that it is typically used in the context of imprisonment. However, after the pandemic begins, it moves closer to words like isolated and disconnected, indicating that it is now more commonly used in the context of self-isolation at home. The Figure 3a bottom right plot shows the semantic shift for the word *virtual*. *Virtual* is previously semantically similar to technology-related words, such as AR and VR, while it starts moving towards words like workshop and event as the coronavirus pandemic be-

[3]https://www.freeassange.net/

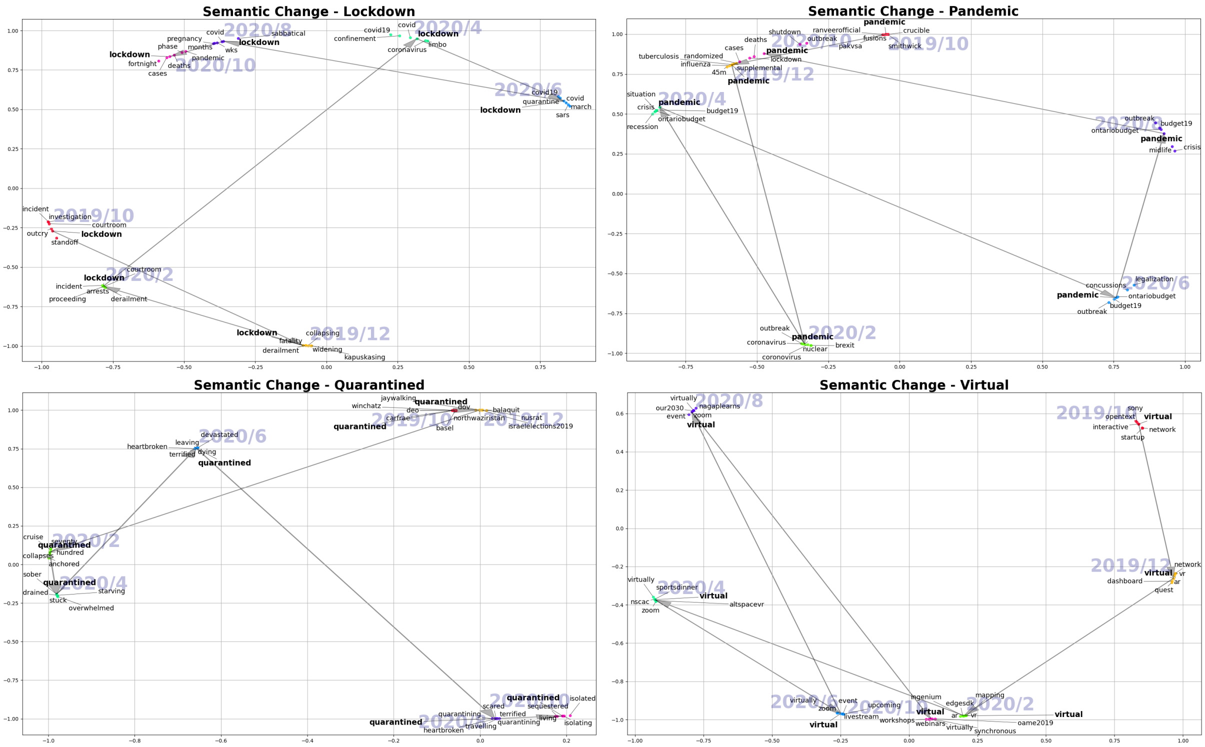


Figure 5: A two-dimensional (t-SNE) projection of word2vec vectors for the words lockdown, pandemic, quarantined, and virtual based on Euclidean distance, showing the semantic trajectories of representation shift with the five most similar words to each word.

gins. We think this can be because most in-person activities are held online instead to prevent the coronavirus spread. Similar trends also emerge in Figure 5.

During the coronavirus pandemic, a mental health crisis is expected due to economic slowdown, physical distancing, and lack of care (Harrigian and Dredze, 2022). Therefore, it is not surprising that the frequency of words like *panic* and *lonely* have increased during the COVID-19 pandemic as shown in Figure 4b, as many people likely experienced feelings of anxiety and isolation during this time. However, it is important to note that an increase in word frequency does not necessarily indicate a change in meaning as discussed in Section 4.2. The meaning of a word is determined by its usage and context, not just its frequency. From Figure 3b, we notice that there is not a clear divergence from the original meaning for both of these two words. Even though the $\Delta\tau_e$ of *panic* and *lonely* also increases in March 2020, it is much less significant compared with the shifts shown in Figure 4a. The words ”panic” and ”lonely” were used in a similar way before and during the pandemic, and therefore their meanings did not change.

5 Conclusion and Future Works

In this paper, we investigate the short-term semantic shifts that happen on Twitter in the context of the coronavirus pandemic. We first contrast concept drift with representation shift and find that they are not always equivalent to each other. Besides, we show that words related to the COVID-19 pandemic, such as lockdown and quarantined, tend to undergo more significant semantic shifts compared to other words. Finally, we give a detailed analysis on how some of these words have changed.

Limitations and Future Works In this work, we only focus on the semantic shifts in existing words. However, it would also be interesting to look into new words like twindemic [4] and anti-masker [5]. The visualization techniques used for existing words could also be useful when understanding the meaning of new words. Moreover,

[4]Twindemic: the dual threat of a severe flu outbreak on top of the COVID-19 pandemic.

[5]Anti-masker: a person who resists wearing a mask to protect themselves and others from infection during a pandemic.

we find that social media language is much noisier compared with the language used in books or news. To improve the quality of pre-processing of the corpus, we think it might be useful to consider tweet syntax and manners. For example, there are many long concatenated words like "quarantinelife" and "changinglivesfromscratch" in the corpus that are likely hashtags. We can detect and ignore all hashtags by removing words starting with a "#". Finally, in section 4.3, we only discussed three words - lockdown, quarantined, and pandemic - that are closely related to the COVID-19 pandemic, and one word - virtual - that is less closely related. In the future, we would like to expand the word set, but it is difficult to define coronavirus-pandemic-related words. A possible solution is to investigate common English words that rank in the top 10% for semantic change during the coronavirus pandemic.

References

[Agirre et al.2009] Eneko Agirre, Enrique Alfonseca, Keith Hall, Jana Kravalova, Marius Paşca, and Aitor Soroa. 2009. A study on similarity and relatedness using distributional and WordNet-based approaches. In *Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, pages 19–27, Boulder, Colorado, June. Association for Computational Linguistics.

[Del Tredici et al.2019] Marco Del Tredici, Raquel Fernández, and Gemma Boleda. 2019. Short-term meaning shift: A distributional exploration. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 2069–2075, Minneapolis, Minnesota, June. Association for Computational Linguistics.

[Dubossarsky et al.2017] Haim Dubossarsky, Daphna Weinshall, and Eitan Grossman. 2017. Outta control: Laws of semantic change and inherent biases in word representation models. In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 1136–1145, Copenhagen, Denmark, September. Association for Computational Linguistics.

[Gulordava and Baroni2011] Kristina Gulordava and Marco Baroni. 2011. A distributional similarity approach to the detection of semantic change in the Google Books ngram corpus. In *Proceedings of the GEMS 2011 Workshop on GEometrical Models of Natural Language Semantics*, pages 67–71, Edinburgh, UK, July. Association for Computational Linguistics.

[Hamilton et al.2016] William L. Hamilton, Jure Leskovec, and Dan Jurafsky. 2016. Diachronic word embeddings reveal statistical laws of semantic change. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1489–1501, Berlin, Germany, August. Association for Computational Linguistics.

[Harrigian and Dredze2022] Keith Harrigian and Mark Dredze. 2022. The problem of semantic shift in longitudinal monitoring of social media: A case study on mental health during the covid-19 pandemic. In *14th ACM Web Science Conference 2022*, WebSci '22, page 208–218, New York, NY, USA. Association for Computing Machinery.

[Kim et al.2014] Yoon Kim, Yi-I Chiu, Kentaro Hanaki, Darshan Hegde, and Slav Petrov. 2014. Temporal analysis of language through neural language models. In *Proceedings of the ACL 2014 Workshop on Language Technologies and Computational Social Science*, pages 61–65, Baltimore, MD, USA, June. Association for Computational Linguistics.

[Kulkarni et al.2015] Vivek Kulkarni, Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. 2015. Statistically significant detection of linguistic change. In *Proceedings of the 24th International Conference on World Wide Web*, WWW '15, page 625–635, Republic and Canton of Geneva, CHE. International World Wide Web Conferences Steering Committee.

[Marakasova and Neidhardt2020] Anna Marakasova and Julia Neidhardt. 2020. Short-term semantic shifts and their relation to frequency change. In *Proceedings of the Probability and Meaning Conference (PaM 2020)*, pages 146–153, Gothenburg, June. Association for Computational Linguistics.

[Mikolov et al.2013] Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013. Distributed representations of words and phrases and their compositionality. In *Proceedings of the 26th International Conference on Neural Information Processing Systems - Volume 2*, NIPS'13, page 3111–3119, Red Hook, NY, USA. Curran Associates Inc.

[Noble et al.2021] Bill Noble, Asad Sayeed, Raquel Fernández, and Staffan Larsson. 2021. Semantic shift in social networks. In *Proceedings of *SEM 2021: The Tenth Joint Conference on Lexical and Computational Semantics*, pages 26–37, Online, August. Association for Computational Linguistics.

[Stewart et al.2017] Ian Stewart, Dustin Arendt, Eric Bell, and Svitlana Volkova. 2017. Measuring, predicting and visualizing short-term change in word representation and usage in vkontakte social network. *Proceedings of the International AAAI Conference on Web and Social Media*, 11(1):672–675, May.

[TANG2018] XURI TANG. 2018. A state-of-the-art of semantic change computation. *Natural Language Engineering*, 24(5):649–676, jun.

[van der Maaten and Hinton2008] Laurens van der Maaten and Geoffrey Hinton. 2008. Visualizing data using t-sne. *Journal of Machine Learning Research*, 9(86):2579–2605.