COVID-19 Retweet Prediction Report

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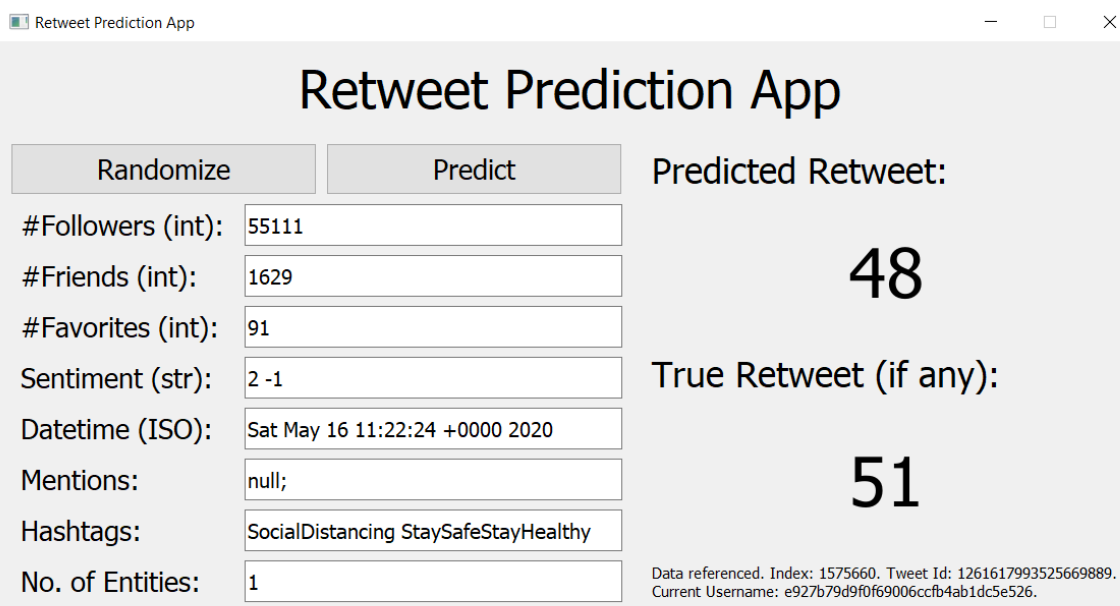
2 Task Description

As COVID-19 impacts our daily routine and changed the norms that we accepted prior to the pandemic, there are some interests in quantifying its impacts on the global stage. One way to measure such impact is to monitor the explosion of activity in social media usage such as Twitter and Youtube, where most people who are not able to move freely, shares their thoughts through such platforms. Twitter in particular, provides a platform that allows the users to post their thoughts in a succint manner and add hashtags or mentions to increase the tweet's exposure on the platform. Our task will thus be to predict the number of retweets a tweet that is COVID-19 related will have using the TweetsCOV-19 dataset.

At the end of this project, we created a Linear Regression Model and an interactive GUI to predict a "ballpark" value of retweet count based on input parameters found in TweetsCOV-19 dataset. Custom values can also be input into the model.



3 Dataset Description

The dataset that is used for this project is obtained from the COVID-19 Retweet Prediction Challenge. For this prediction model, we used Part 2 dataset that can be obtained from this website https://data.gesis.org/tweetscov19/#dataset. This dataset consists of tweets that is COVID-19 related from the month of May 2020.

From the dataset, there are different features for the tweet data that we obtain and the feature description are as follows:

1. Tweet Id: Long. Unique ID for a specific tweet
2. Username: String. Username of the user that published the tweet which is encrypted for privacy.
3. Timestamp: Format (“EEE MMM dd HH:mm:ss Z yyyy”). Specific time and date of the tweet
4. #Followers: Integer. Number of followers of the Twitter user who posted the tweet.
5. #Friends: Integer. Number of friends that the Twitter user who posted the tweet.
6. #Retweets: Integer. Number of retweets that the tweet has obtained and is the label for this project.
7. #Favorites: Integer. Number of favorites for the tweet
8. Entities: String. The entities of the tweet is obtained by aggregating the original text. Every annotated entity will then have its produced score from FEL library. Each entity is separated by char “:” to store the entity in this form “original_text:annotated_entity:score;”. Each entity is separated from another entity by char “;”.Any tweet that has no corresponding entities will be stored as “null;”.
9. Sentiment: String. SentiStrength produces a score for positive (1 to 5) and negative (-1 to -5) sentiment. The two sentiments are splitted by whitespace char ” “. Positive sentiment was stored first and followed by negative sentiment (i.e. ”2 -1”).
10. Mentions: String. Contains mentions and concatenate them with whitespace char ” “. If there is no mention, it is stored as”null;”.
11. Hashtags: String. Contains hashtags and concatenate the hashtags with whitespace char ” “. If there is no hashtag, it is stored as”null;”.
12. URLs: String: Contains URLs and concatenate the URLs using “:-:”. If there is no URL, it is stored as “null;”

[2]:
```
# imports

import logging
import requests
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from gensim.models import Word2Vec

import test
import predict

from model import LinReg2
```

```
c:\users\calvin yusnoveri\appdata\local\programs\python\python36\lib\site-
packages\gensim\similarities\__init__.py:15: UserWarning: The
gensim.similarities.levenshtein submodule is disabled, because the optional
Levenshtein package <https://pypi.org/project/python-Levenshtein/> is
unavailable. Install Levenhstein (e.g. `pip install python-Levenshtein`) to
suppress this warning.
  warnings.warn(msg)
```

[5]:
```python
header = [
    "Tweet Id",
    "Username",
    "Timestamp",
    "#Followers",
    "#Friends",
    "#Retweets",
    "#Favorites",
    "Entities",
    "Sentiment",
    "Mentions",
    "Hashtags",
    "URLs"]

data = pd.read_csv("./data/TweetsCOV19_052020.tsv.gz", compression='gzip',␣
 ↪names=header, sep='\t', quotechar='"')
data.head(5)
```

[5]:
```
              Tweet Id                          Username  \
0  1255980348229529601  fa5fd446e778da0acba3504aeab23da5
1  1255981220640546816  547501e9cc84b8148ae1b8bde04157a4
2  1255981244560683008  840ac60dab55f6b212dc02dcbe5dfbd6
3  1255981472285986816  37c68a001198b5efd4a21e2b68a0c9bc
4  1255981581354905600  8c3620bdfb9d2a1acfdf2412c9b34e06

                        Timestamp  #Followers  #Friends  #Retweets  \
0  Thu Apr 30 22:00:24 +0000 2020       29697     24040          0
1  Thu Apr 30 22:03:52 +0000 2020         799      1278          4
2  Thu Apr 30 22:03:58 +0000 2020         586       378          1
3  Thu Apr 30 22:04:52 +0000 2020         237       168          0
4  Thu Apr 30 22:05:18 +0000 2020         423       427          0

   #Favorites                                          Entities Sentiment  \
0           0                                             null;      1 -1
1           6                                             null;      1 -1
2           2                                             null;      2 -1
3           0                                             null;      1 -1
4           0  i hate u:I_Hate_U:-1.8786140035817729;quaranti…      1 -4
```

```
  Mentions                          Hashtags  \
0    null;  Opinion Next2blowafrica thoughts
1    null;                             null;
2    null;                             null;
3    null;                             null;
4    null;                             null;

                                                URLs
0                                              null;
1                                              null;
2  https://www.bbc.com/news/uk-england-beds-bucks…
3  https://lockdownsceptics.org/2020/04/30/latest…
4                                              null;
```

4 Preprocessing

In order to train our prediction model, we have also done some preprocessing of the features that are available in the dataset. All these changes to the raw features allow us to link these processed features to the final retweet prediction in a more precise manner.

Clean Data (Final structure/form of data before it is fed into the model):

1. #Followers: Float. Log transformed: `log_10(x + 1)`
2. #Friends: Float. Log transformed: `log_10(x + 1)`
3. #Favorites: Float. Log transformed: `log_10(x + 1)`
4. Positive (Sentiment): Float. Scaled.
5. Negative (Sentiment): Float. Scaled.
6. Sentiment Disparity: Float. Scaled.
7. No. of Entities: Float. Log transformed: `log_10(x + 1)`
8. Day of Week: Float. One-Hot Vector. (7,) Vector.
9. Time Int: Float. Log transformed: `log_10(x + 1)`
10. Hashtags Embedding: (25,) Vector.
11. Mentions Embedding: (25,) Vector.
12. #Followers Min, Max, Mean: Float. Log transformed: `log_10(x + 1)`
13. #Friends Min, Max, Mean: Float. Log transformed: `log_10(x + 1)`
14. #Retweets Min, Max, Mean: Float. Log transformed: `log_10(x + 1)`
15. #Favorites Min, Max, Mean: Float. Log transformed: `log_10(x + 1)`

In total, the input dimension (first layer) is `8 + 7 + 25 + 25 + 12 = (77, )`.

The target is: #Retweets: Integer. Log transformed: `log_10(x + 1)`

4.1 Hashtags & Mentions

Both Hashtags and Mentions are in the form of list of Strings seperated by whitespace. Thus, in order to create tractable input for the model, embeddings are created for both the Hashtags and Mentions of size `(25, )`.

[19]:
```python
hashtag_embeddings = Word2Vec.load('./data/hashtag_embeddings')
mention_embeddings = Word2Vec.load('./data/mention_embeddings')

hashtags_vocab = hashtag_embeddings.wv.index_to_key
mentions_vocab = mention_embeddings.wv.index_to_key

print(hashtags_vocab[:5]) # example of hashtags key
print(mentions_vocab[:5]) # example of mentions key
```

```
['COVID19', 'coronavirus', 'Covid_19', 'covid19', 'May']
['realDonaldTrump', 'PMOIndia', 'narendramodi', 'jaketapper', 'YouTube']
```

[21]:
```python
hashtags_example = 'COVID19'
mentions_example = 'realDonaldTrump'

print(f"{hashtags_example} -> {hashtags_embeddings.wv[hashtags_example]}")
print(f"{mentions_example} -> {mentions_embeddings.wv[mentions_example]}")
```

```
COVID19 -> [ 0.10622272  0.26996937 -0.46450084  0.10561462 -0.5595082
0.26207525
  0.28835535  0.80339587  0.30626374 -0.13036335  0.8120623  -0.46314418
  0.20126966 -0.9723947  -1.0051426  -0.04809839  0.4593365   0.09532893
 -0.21894015 -0.23557915  0.42107382  0.4622469   0.53460604 -0.589559
  0.6296402 ]
realDonaldTrump -> [ 0.5991303  -0.10410535  0.23690729 -0.23115875 -0.961905
-0.11418784
  0.12405131  0.4196795  -1.493182   -0.20270342  1.2276924  -1.3593616
 -0.19556278  0.27365074  0.32451993  1.9415929  -0.20647514 -0.17526582
 -0.69910485 -1.6436449   1.3161302  -0.17269903 -0.5424232   1.0386076
  1.062889  ]
```

These embeddings are trained over 5 epoch and only considers String symbols that occur at least 200 timex to be relevant. This is done by passing the argument `min_count=200`, when training. The hashtags and mentions vocabularies are saved in: `data`.

Using these embeddings, both Hashtags and Mentions column are iterated over and converted into vectors of size `(25, )`. With these rules: - For those Hashtags/Mentions cells that contain `null`, 0 vector of size 25 is outputted - For those Hashtags/Mentions cells that contain String symbols that occur than less 200 times (hence, not in vocab), they're treated as `null` - For those Hashtags/Mentions cells that contain multiple String symbols, their embedding vectors are summed

4.1.1 Effectiveness of Mentions & Hashtags and their Embeddings

Before attempting to create these embeddings, a quick exploration was done to check the relevance of these Mentions and Hashtags in predicting Retweet score.

An initial assumption is that, certain Hashtags or Mentions would correlate in higher Retweet score. But, a quick look of data seems to suggest little correlations as most high Retweet score have `null` Mentions and Hashtags.

[19]:
```python
sorted_by_retweets = data.sort_values(by='#Retweets', ascending=False)
sorted_by_retweets.head(10) # observe that most Mentions and Hashtags are null␣
↪for top #Retweets
```

[19]:
```
                    Tweet Id                          Username  \
1637862  1265465820995411973  0d4d9b3135ab4271ea36f4ebf8e9eae9
1208647  1266553959973445639  c9378a990def5939fb179e034a0d402e
1328169  1258750892448387074  1921c65230cd080c689dc82ea62e6e74
1736035  1263579286201446400  7c4529bc4da01f288b95cd3876b4da47
751238   1266546753182056453  32634ab407c86a56dde59551b3871c42
702118   1259975524581064704  69745f3009b864ba75b7d066ade0adba
1037044  1266738565641371648  71b9c38db144b44e4cbbda75c9fbf272
482286   1267066200049229824  56eb2d106e7611ab8bb76de07af8f318
1812643  1256657625334284292  6b7cc62c18b45d1eee1c34eb375e72a4
1401494  1260237550091935746  6b49e6ca36daebd1048d59b1459026ae

                              Timestamp  #Followers  #Friends  #Retweets  \
1637862  Wed May 27 02:12:17 +0000 2020        3317      3524     257467
1208647  Sat May 30 02:16:10 +0000 2020       18661         0     135818
1328169  Fri May 08 13:29:33 +0000 2020       83320      1753      88667
1736035  Thu May 21 21:15:52 +0000 2020         451       359      82495
751238   Sat May 30 01:47:31 +0000 2020        1545       874      66604
702118   Mon May 11 22:35:48 +0000 2020     6106969       726      63054
1037044  Sat May 30 14:29:43 +0000 2020       45941      4550      61422
482286   Sun May 31 12:11:37 +0000 2020         678       524      61038
1812643  Sat May 02 18:51:40 +0000 2020         778       694      60719
1401494  Tue May 12 15:57:00 +0000 2020        3704      1144      60650

         #Favorites                                          Entities  \
1637862      845579              tear gas:Tear_gas:-1.688018296396458;
1208647      363852                                              null;
1328169      224288  mike pence:Mike_Pence:-0.6712149436851893;ppe:…
1736035      225014                                              null;
751238       193599                 douche:Douche:-2.0041883604919835;
702118       248214                                              null;
1037044      100570                                              null;
482286       101117         quarantine:Quarantine:-2.3096035868012508;
1812643      213614                                              null;
1401494      214508  flatten the curve:Flatten_the_curve:-1.6515462…

        Sentiment Mentions Hashtags   URLs
1637862      1 -1    null;    null;  null;
1208647      1 -3    null;    null;  null;
1328169      1 -1    null;    null;  null;
1736035      1 -1    null;    null;  null;
751238       3 -1    null;    null;  null;
702118       1 -1    null;    null;  null;
```

```
1037044       1 -1    null;    null;  null;
482286        2 -1    null;    null;  null;
1812643       1 -1    null;    null;  null;
1401494       1 -1    null;    null;  null;
```

However, it is believed that there should at least be some value in including these Mentions and Hashtags even though such correlations are weak and not easily discernable. Thus, the embeddings are created regardless of the known weak correlation.

As for the embeddings themselves, based on similarity scores, they seem to be working well. For instance, the embedding are able to recognize `coronavirus` to be similar to `pandemic`, `COVID` and `virus` fairly confidently.

[20]:
```
hashtag_embeddings.wv.most_similar(['coronavirus'])
```

[20]:
```
[('virus', 0.7936981320381165),
 ('pandemic', 0.6945043802261353),
 ('COVID', 0.6876555681228638),
 ('corona', 0.6836724281311035),
 ('mask', 0.6728377342224121),
 ('trump', 0.6640805006027222),
 ('masks', 0.6489465832710266),
 ('covid', 0.6476311087608337),
 ('ClimateChange', 0.6469046473503113),
 ('COVID__19', 0.6411719918251038)]
```

4.2 Timestamp

4.3 Sentiment

4.4 Entities

The entities that are encapsulated in this dataset are aggregated from the original tweet text. This text will then go through a Fast Entity Linker query and find annotated text that can be found and set them as an entity for the text that we pass through. For every entity, it also has its corresponding log-likelihood confidence score which is used as a global threshold for linking.

For this project, we did some preprocessing of the raw entity data from the dataset. With the format of the entities for each tweet data being "original text:annotated text:score;original text:annotated text:score", we will be able to get the number of entities that is found on each tweet. We thus split the entities column data and obtain the length of each entities list to get the number of entities for each tweet.

The column that contains the number of entities for each tweet will then undergo logarithmic transformation of the form `log(x+1)` before they're passed into the model. These log-transformed entity count data will then be used for the training of the prediction model and helps in creating a stronger linkage between the data and the number of retweets.

[12]:
```
entities = data['Entities'].str.split(";")
entity_no = []
```

```python
for ent in entities:
    ent.pop()
    if ent[0]=='null':
        entity_no.append(0)
    else:
        entity_no.append(len(ent))
data['No. of Entities'] = entity_no
# print(len(entities))
data[['Entities','No. of Entities']].head(10)
```

[12]:

	Entities	No. of Entities
0	null;	0
1	null;	0
2	null;	0
3	null;	0
4	i hate u:I_Hate_U:-1.8786140035817729;quaranti…	2
5	god forbid:God_Forbid:-1.2640735877261988;covi…	3
6	beijing:Beijing:-1.4222174822860647;covid 19:C…	3
7	null;	0
8	stealth:Stealth_game:-2.646174787470186;	1
9	quarantine:Quarantine:-2.3096035868012508;	1

5 Model Architecture

We created a simple 2-layer linear regression model to predict the retweet values.

Initially, more layers were used but no significant improvement was observed and to avoid overfitting due to over-parameterized model, the final model only uses 2 simple fully connected layers.

[4]:

```python
# Hyperparameters
input_size = 65
hidden_size = 10
output_size = 1
learningRate = 0.01

model = LinReg2(input_size, hidden_size, output_size)
model
```

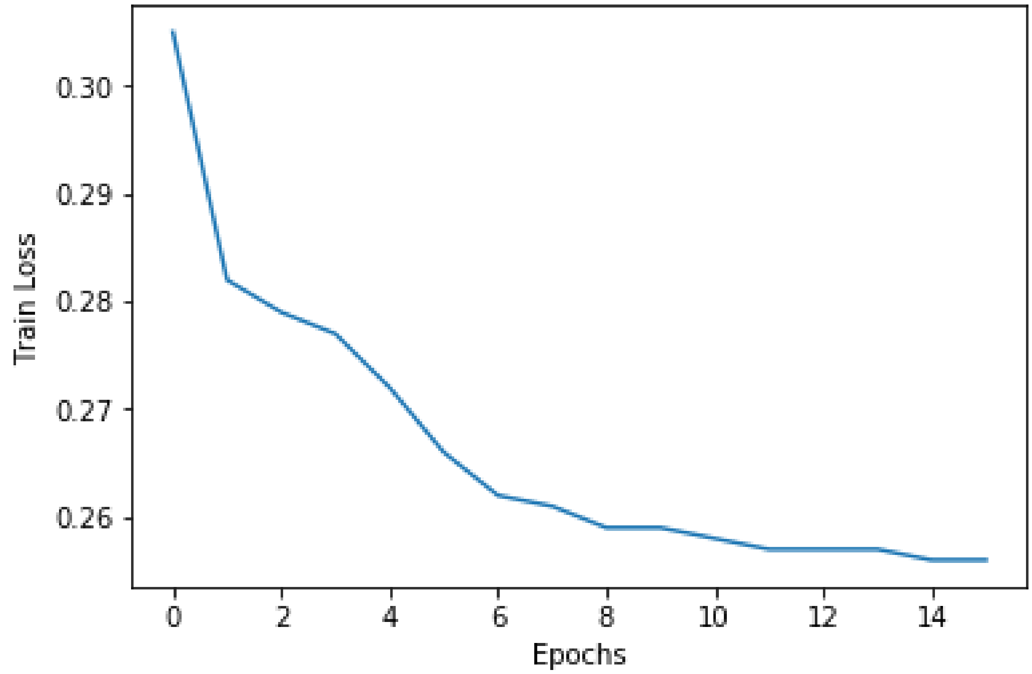
[4]:

```
LinReg2(
  (fc1): Linear(in_features=65, out_features=10, bias=True)
  (relu_h1): ReLU()
  (fc2): Linear(in_features=10, out_features=1, bias=True)
)
```

6 Results

The following shows the loss curve of the training of the model. It is done over 15 epochs.

[5]:
```
train_losses = np.loadtxt("./data/train_loss_0608-2203.txt", delimiter='\n')
plt.plot(train_losses)
plt.ylabel('Train Loss')
plt.xlabel('Epochs')
plt.show()
```



6.1 Accuracy

To measure the accuracy of the model, we take the log10 of the absolute difference between the prediction and true retweet value + 1. `log10(|y - t| + 1)`

What this essentially means is that we're looking at whether or not the model is able to arrive on a prediction that is within a certain order of magnitude of the actual retweet value instead of whether or not it is able to accurately predict the retweet count. We interpret this as reasonable implementation of what predicting the "ballkpark" figure of a retweet is.

[28]:
```
accuracies = np.loadtxt("./data/accuracy_0608-2059.txt", delimiter='\n')

print(f"""
Min Order of Magnitude Deviation: {np.min(accuracies)}
Mean Order of Magnitude Deviation: {np.mean(accuracies)}
Median Order of Magnitude Deviation: {np.mean(accuracies)}
Max Order of Magnitude Deviation: {np.max(accuracies)}
""")
```

```python
frequency, bins = np.histogram(accuracies, bins=5, range=[0, 5])
accuracies_dist = dict(zip(bins, frequency/len(accuracies) * 100))
accuracies_dist
```

```
Min Order of Magnitude Deviation: 0.0
Mean Order of Magnitude Deviation: 0.4959347980368691
Median Order of Magnitude Deviation: 0.4959347980368691
Max Order of Magnitude Deviation: 4.7193975864238835
```

```
[28]: {0.0: 79.44831353270517,
       1.0: 17.647862094448595,
       2.0: 2.72469495786844,
       3.0: 0.1694901639475946,
       4.0: 0.009639251030194954}
```

As we can see from the result above, the worst deviation is around `4.72` order of magnitude away (difference of `50,000 retweets`). But this extreme deviation is very rare, as a deviation of `4.0+` occurrs less than `0.01%` of the time in the test set.

In fact, the model does pretty well in most cases (`~97%` of cases), as its prediction on `79.4%` of test data lands within `0.0 - 0.99` order of magnitude of the actual tweet (difference of `10 retweet`). Afterwhich, `17.6%` of next portion of test data prediction falls within `1.00 - 1.99` order of magnitude (difference of `100 retweet`).

7 Discussion

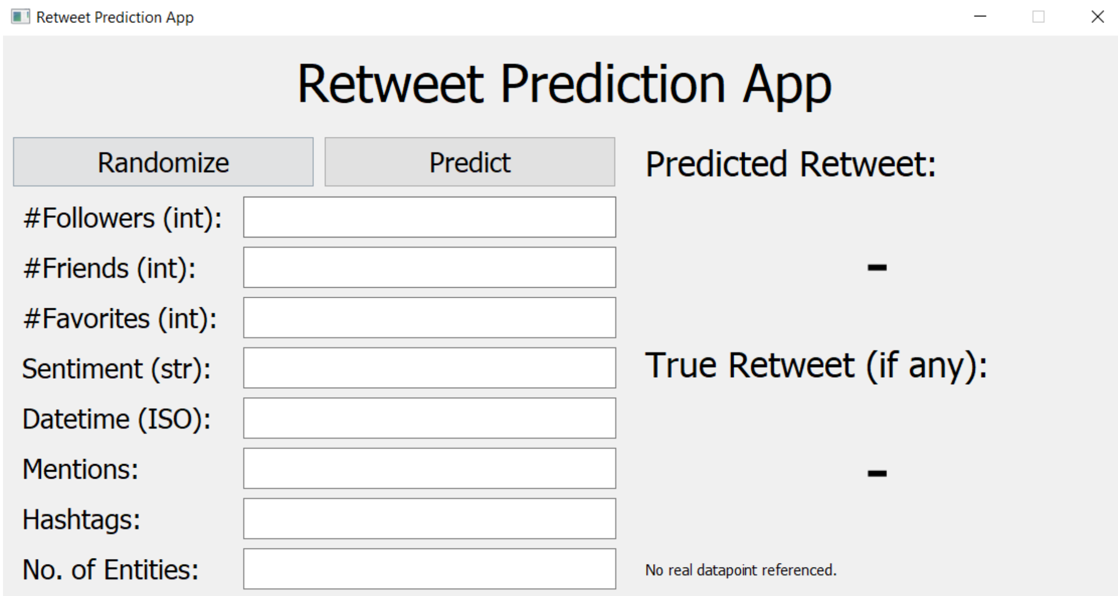
comparing with state of the art.

possible issues. possible improvements

8 GUI

8.1 Running the GUI

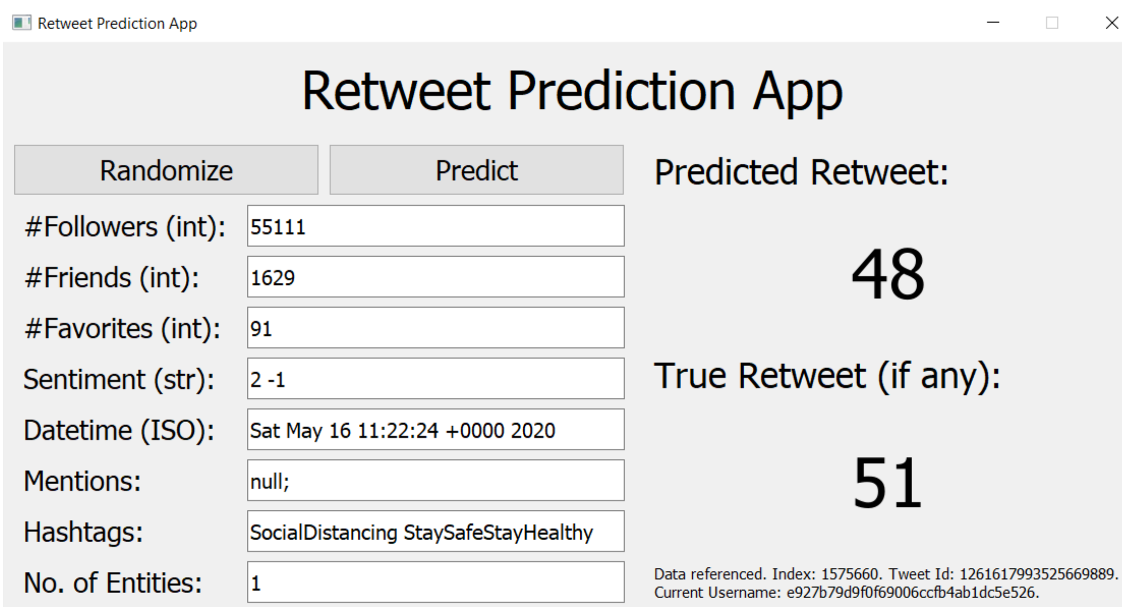
0. Download the dataset called `TweetsCOV19_052020.tsv.gz` and save it in `data` directory. Download from: https://zenodo.org/record/4593502#.YQunN4gzZPY
1. Open command line or terminal and navigate to the project folder.
2. Run `pip install -r requirements.txt`. Ensure that `PyQt5`, `gensim` and `torch` are installed among other things.
3. Navigate to `gui` with `cd gui`
4. Then, run `app.py` with `python app.py` or with your IDLE. Note: `app.py` must be executed from `./gui` NOT `root`!



Opening the GUI may take a while (~3 mins) because it will load the dataset from `data/TweetsCOV19_052020.tsv.gz`. Thus, ensure that this file exist in `data` folder!

8.2 Using the GUI

1. Click `Randomize` Button to randomly load a data from dataset.
2. Click `Predict` Button to predict the retweet.

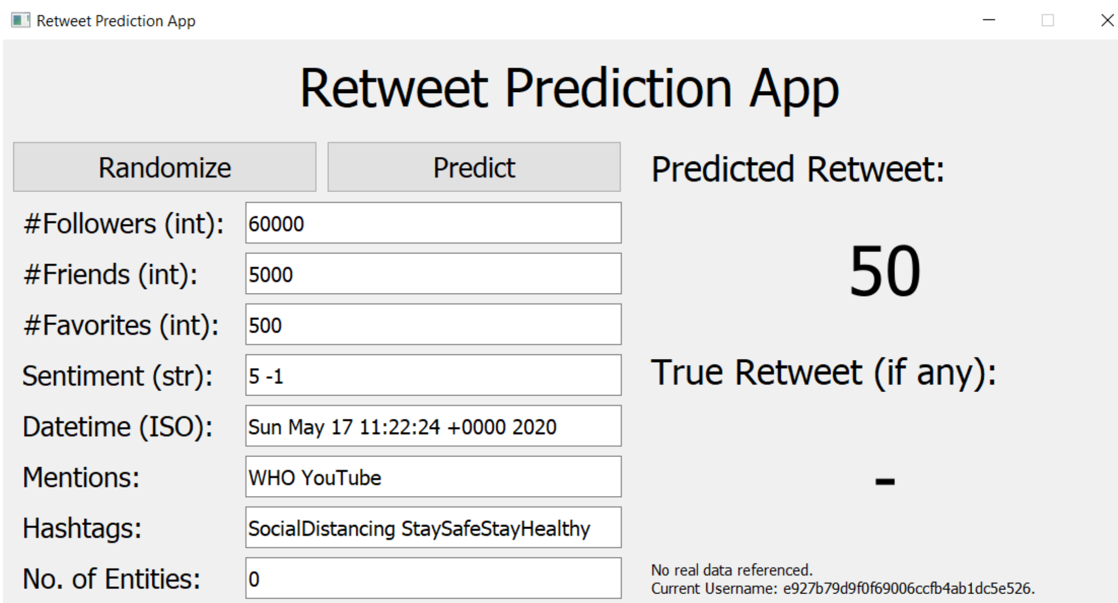


Optionally:

3. Edit the line edits to create your own custom datapoint before predicting. Note: you will still be referencing the previous user. As shown at the `Username` at bottom right hand corner. i.e. the tweet will be treated as though it comes from this user.

Note:

- Fields like `Mentions` and `Hashtags` have their own vocab (consult: `data/hashtags_vocab.txt` and `data/mentions_vocab.txt` for valid values. Random values will just get ignored.
- Each fields have their own format, like the ISO date string. Please follow the format strictly, otherwise it will fail to be parsed.
- Some fields can take in multiple values such as `Mentions` and `Hashtags`, in this case, use white space `" "` to delimit values.



9 Sources

1. Source code: https://github.com/arglux/50021-ai-project
2. Reference papers: