



# Labeling Disaster-Related Messages Using Natural Language Processing

# Business Understanding

➔ **Objective:**

- Our goal is to **create a model** that can interpret and label a message using **Natural Language Processing**.
- Messages are either:
  - **direct** (*messages sent from person-to-person*)
  - **news** (*headlines or clippings*)
  - **social** (*social media*)
- In order to simplify the given dataset, I will be working only with **a single label – “aid\_related”**.

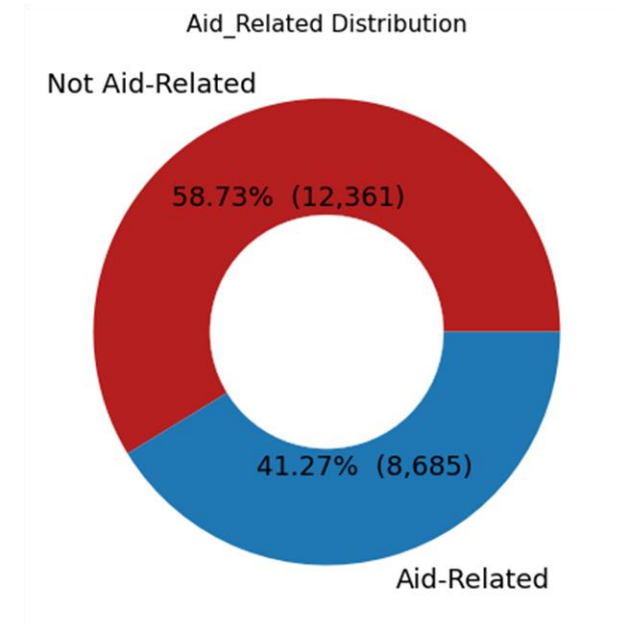
➔ **Success criteria:**

- How well the model finds all the *aid\_related* messages (*Recall*).
- How accurate the model is when it predicts an *aid\_related* message (*Precision*).
- How accurate the model is overall (*Accuracy*).



# Data Understanding

- ▶ The relevant columns of the dataset are **message** and **aid\_related**.
  - ▶ **message** (our predictive data) is a string of text, e.g.:
    - ▶ “Weather update – a cold front from Cuba that could pass over Haiti”
    - ▶ “There’s nothing to eat and water, we starving and thirsty.”
  - ▶ **aid\_related** (our target) is a binary column, i.e.:
    - ▶ Is the message aid related? 1=yes, 0=no.



# Data Understanding

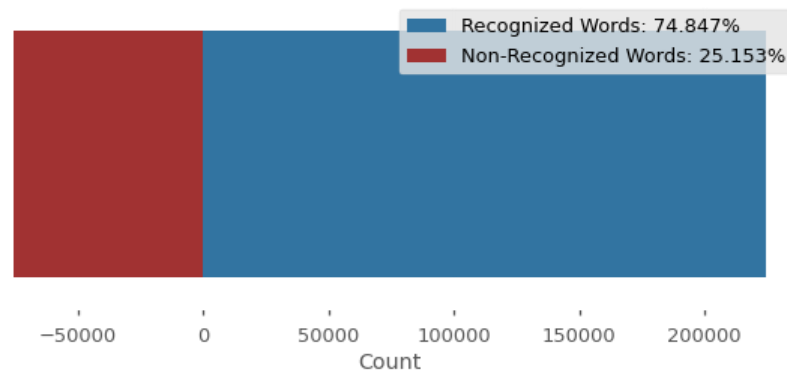
## Non-Aid-Related



## Aid-Related

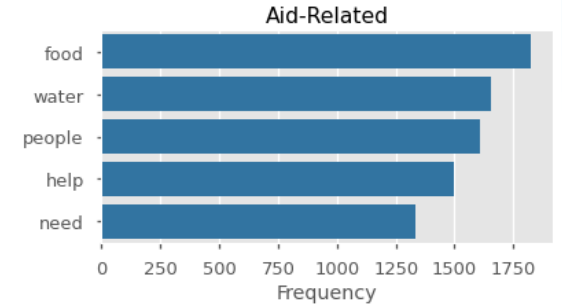
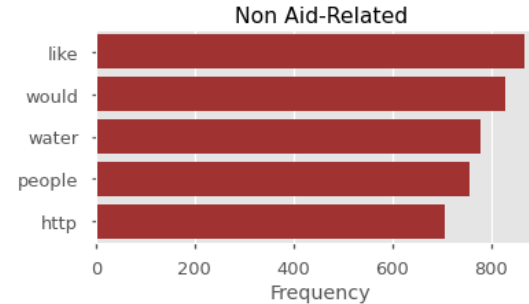


Percent of Recognized English Words

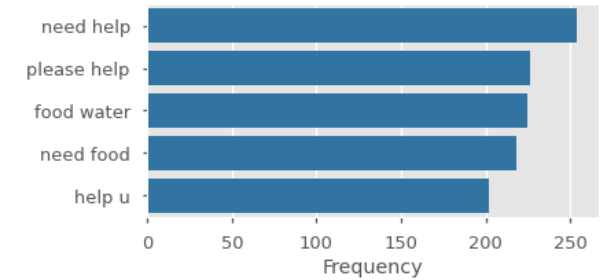
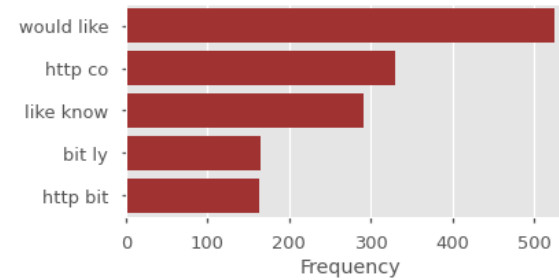


# Data Understanding

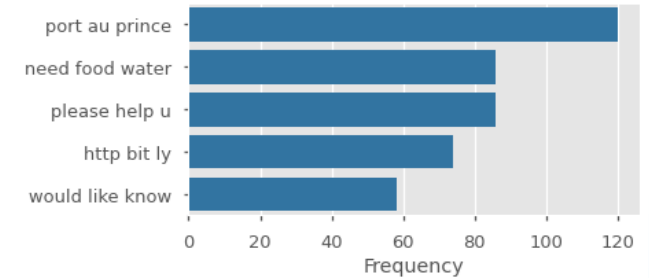
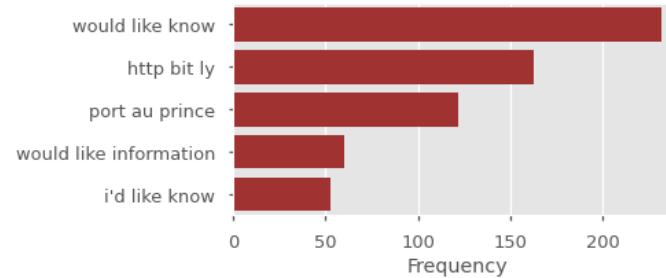
One-word  
sequences



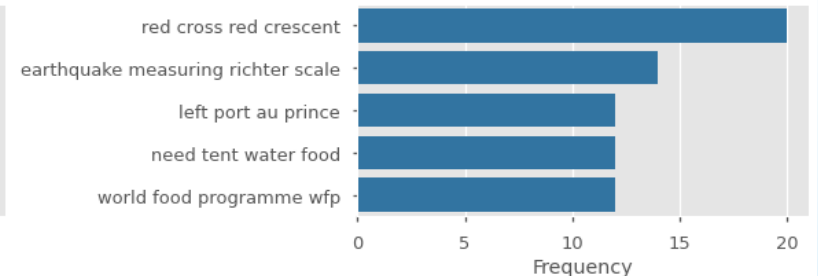
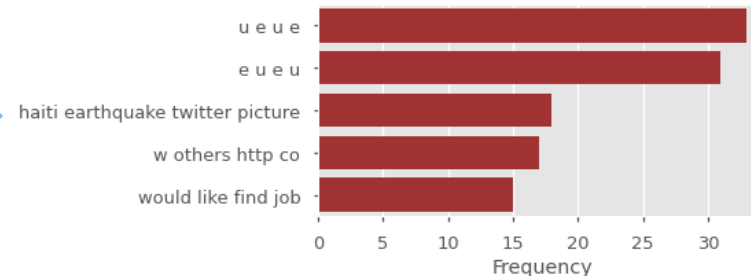
Two-word  
sequences



Three-word  
sequences



Four-word  
sequences







# Data Preparation

- Text Preparation
  - Cleaning abnormalities (unusual html characters),
  - Removing *stop words* ("the", "is", "and") & *punctuation*,
  - Lemmatizing (*feet* -> *foot*; *running* -> *run*)
- Vectorizing
  - Premade Vectorizer - GloVe model (*Global Vectors for Word Representation*)
    - <https://nlp.stanford.edu/projects/glove/>
  - Homemade Vectorizer - Gensim Word2Vec model

# Data Preparation

Homemade Word Vectors  
Trained on Training Data

```
*****
*                                     *
*                                     *
*****
Most Similar Words:
1.    district
2.    area
3.    tahsil
4.    hill
5.    city
6.    basti
7.    wala
8.    distt
9.    embankment
10.   house

*****
*                                     *
*                                     *
*****
Most Similar Words:
1.    drinking
2.    cloths
3.    toilet
4.    wells
5.    shelter
6.    toilets
7.    latrines
8.    contaminated
9.    rainwater
10.   tablets

*****
*                                     *
*                                     *
*****
Most Similar Words:
1.    families
2.    survivors
3.    those
4.    refugees
5.    children
6.    residents
7.    villagers
8.    victims
9.    persons
10.   students
```

# Modeling Featured Model: **RNN - GloVe**

Try the WebApp on StreamLit here!

Message:

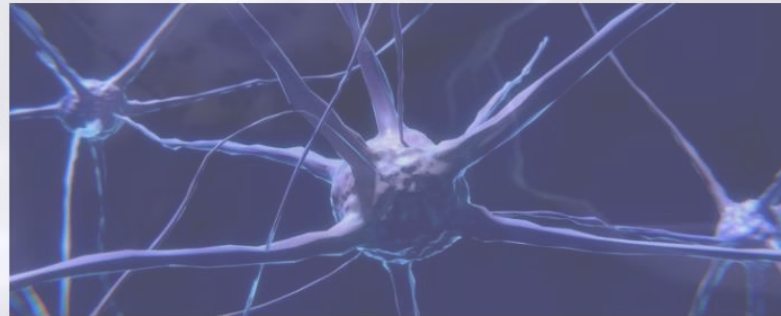
We are out of food and water.

## Disaster Response - Message Identification

This app is designed to show predictions on whether a given text is likely to be **aid-related** or not. A model like this can be used to quickly label a high volume of texts during times when it is important to find messages that are labeled as important.

The model being used is a Recurrent Neural Network built with TensorFlow, using GloVe word embeddings and trained for only 6 epochs.

On unseen text data, 80.67% of **aid-related** messages were found, 80.74% of **aid-related** predictions were correct. The model scored an 82.69% overall accuracy.



Please fill in some text into the left sidebar, then press the button below. (The messages can be any length)

Current text:

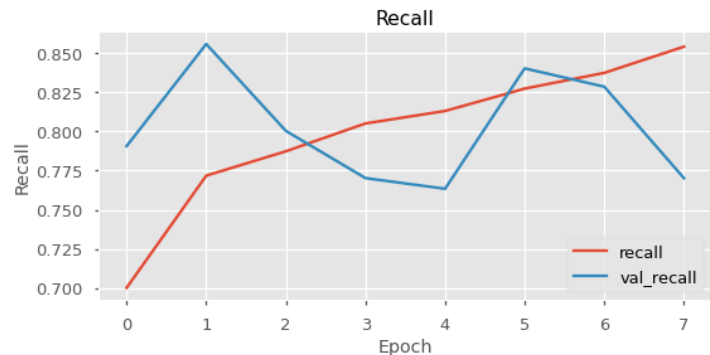
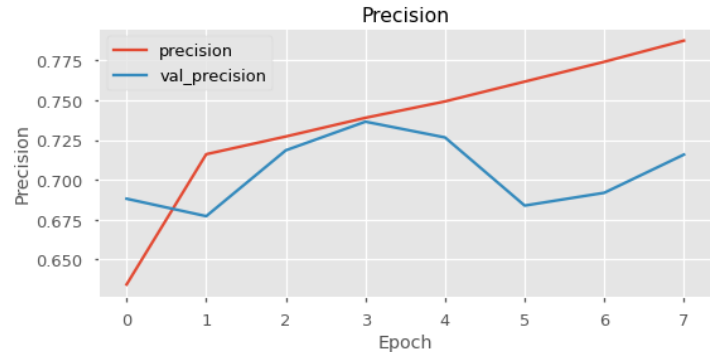
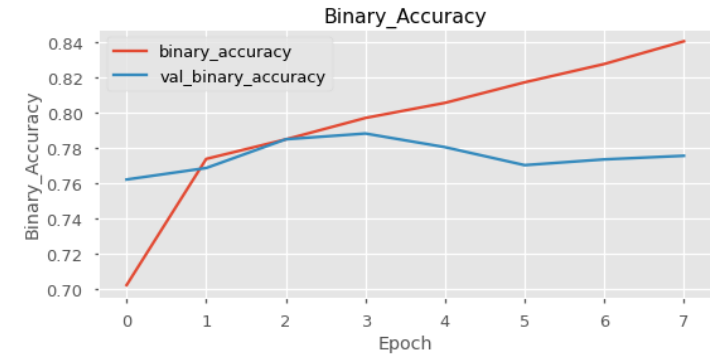
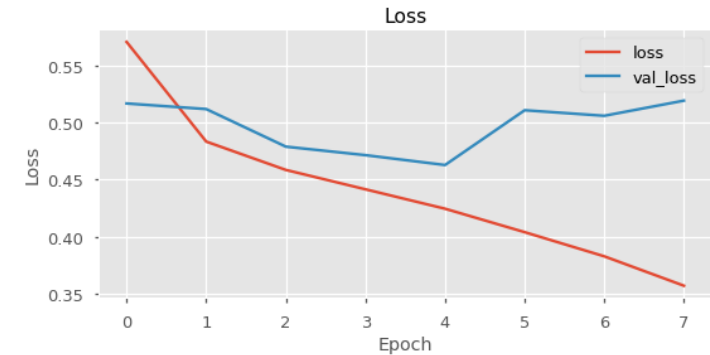
We are out of food and water.

[Click here for results.](#)



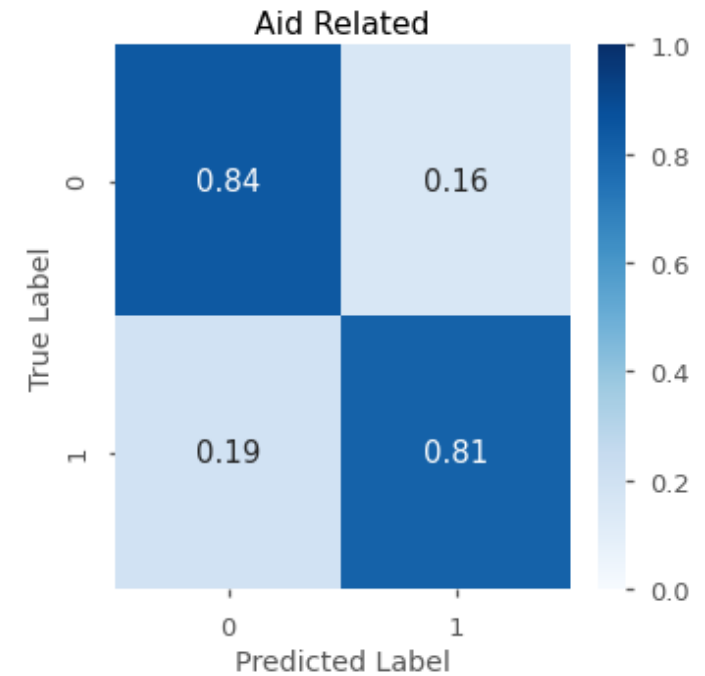
# Modeling Featured Model: RNN - GloVe

	F1	Accuracy	Recall	Precision
<b>RNN_glove</b>	<b>0.807064</b>	<b>0.826862</b>	<b>0.806708</b>	<b>0.80742</b>
multilayer_model_NN_glove	0.77246	0.785261	0.812004	0.736589
SVC_glove	0.769165	0.787639	0.788173	0.751051
simple_model_NN_glove	0.764513	0.771791	0.825243	0.71211
multilayer_model_NN_w2v	0.762413	0.770602	0.819947	0.712423
simple_model_NN_w2v	0.754296	0.773376	0.774934	0.734728
RNN_w2v	0.747631	0.767829	0.766108	0.730025
LOGREG_glove	0.733208	0.718304	0.862312	0.637728
RFC_glove	0.73288	0.76664	0.713151	0.753731
LOGREG_w2v	0.729776	0.751189	0.748455	0.712007
RFC_w2v	0.722543	0.771791	0.661959	0.795334
NB_w2v	0.707668	0.709984	0.781995	0.646244
SVC_w2v	0.707053	0.731775	0.721094	0.693548
NB_glove	0.689233	0.698098	0.745808	0.640637

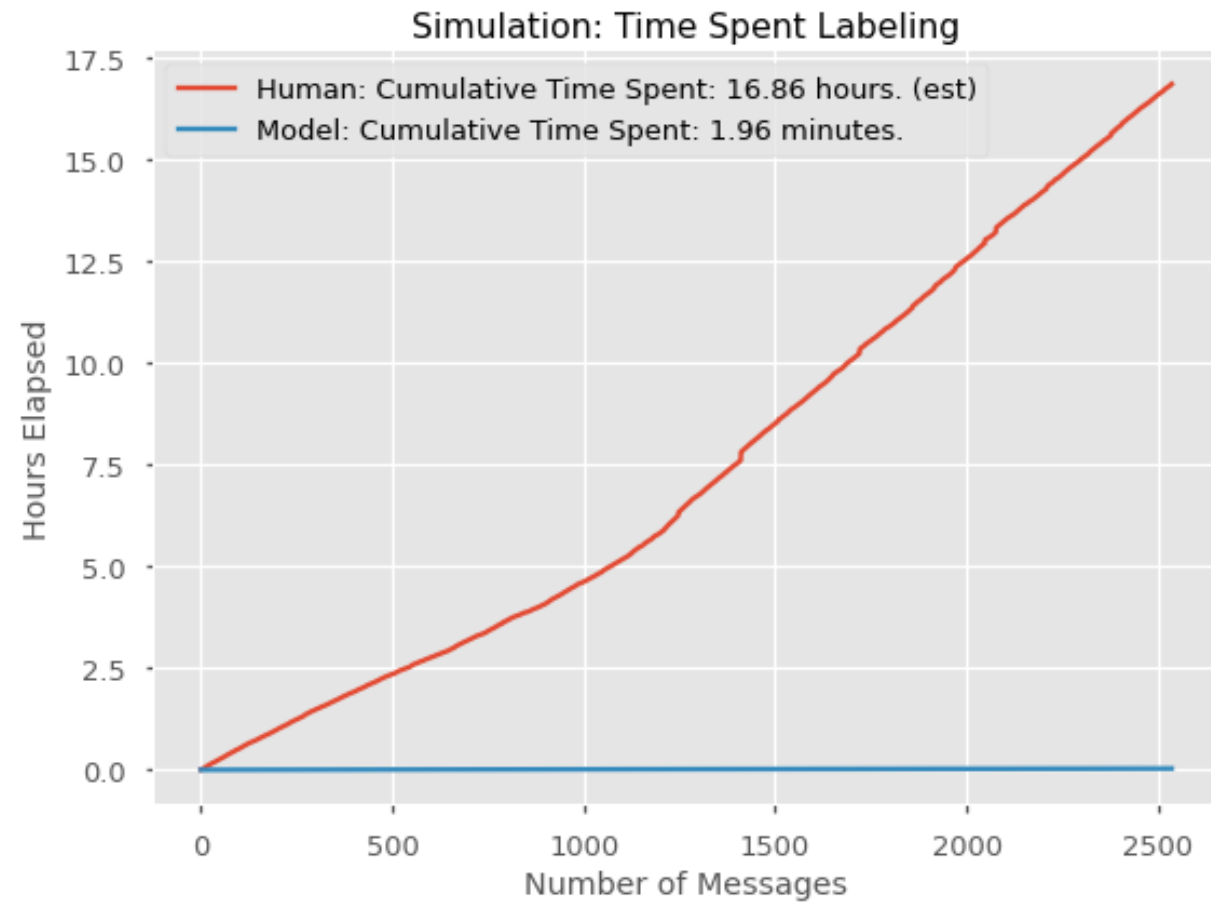


# Evaluation

- Overall, RNN - GloVe (the RNN accompanied by the GloVe embeddings) performed clearly best overall.
- On the test set:
  - 80.67% of `aid-related` messages were found.
  - 80.74% of `aid-related` predictions were correct.
  - 82.69% overall accuracy.



# Evaluation



- This model, if used in the field, would save hours of man-power.
  - With approximately 2500 messages, the model would save approximately 15 hours of time that would have been spent with a human-labeler.

# Model Recommendations

- ▶ If the priority is **overall accuracy, confidence in positive predictions**, and **balance** (F1):
  - ▶ The **Recurrent Neural Network** with GloVe embeddings scored significantly best – 81% of aid-related predictions were correct, and 83% of its overall predictions were correct.
- ▶ If the priority is to **find the most aid-related messages** (at the expense of mislabeling many messages as aid-related):
  - ▶ **Logistic Regression** with the homemade Vectorizer scored the best – finding 86% of all aid-related messages.

	F1	Accuracy	Recall	Precision
RNN_glove	0.807064	0.826862	0.806708	0.80742
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# Future Work

- Include the other 36 target labels to further classify the messages.
  - (Multilabel Classification)
- Add other languages to the model rather than just English translation.
- Continue to explore the complexity of the neural network architecture and create a larger network.





# Thank You!

- Data

- **Appen Datasets**

- <https://appen.com/datasets/combined-disaster-response-data/>

- Flatiron School

- James Irving – DS Instructor