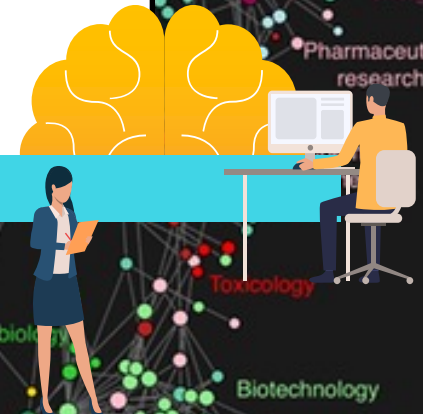




NATURAL LANGUAGE PROCESSING WITH N-GRAM, DEEP LEARNING & spaCy NER



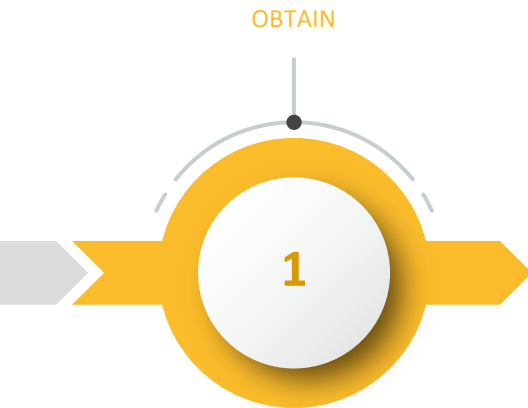
Business Statement

This Kaggle competition challenges data scientists to show how publicly funded data are used to serve science and society.

1. Can NLP find the hidden-in-plain-sight data citations?
2. Can ML find the link between the words used in research articles and the data referenced in the article?

Evidence-Based Policymaking (EBP)

- [Foundations of Evidence-based Policymaking Act \(2016\)](#) requires all federal agencies to show how their data are being used
- Evidence through data is critical if government is to address the many threats facing society: pandemics, climate change, Alzheimer's disease, child hunger, increasing food production, maintaining biodiversity, and addressing many other challenges.
- Automated NLP tool will enable government agencies and researchers to quickly find the information they need:
 - What datasets are being used to solve problems
 - What measures are being generated
 - Which researchers are the experts



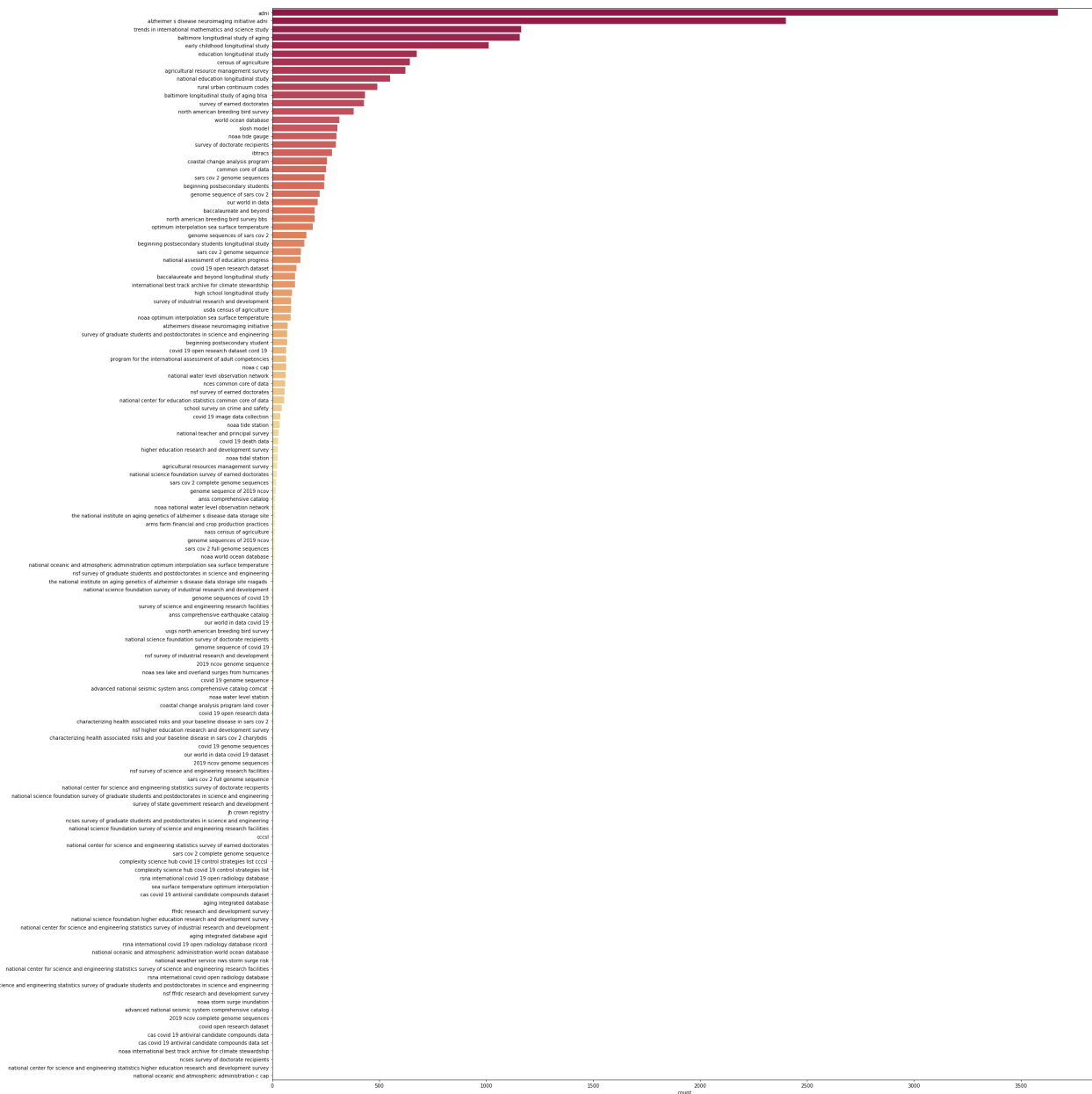
This project uses data from the Kaggle competition sponsored by Coleridge Initiative where scientific publications from numerous research areas are gathered from CHORUS publisher members and other sources

- There are 19,661 publications
- 130 labels

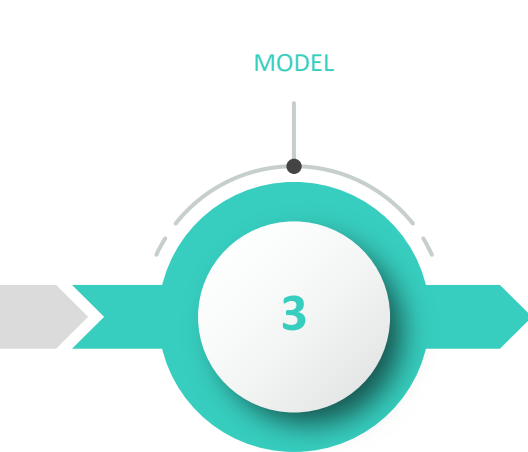
EXPLORE

2

Cleaned Label



Sequence Labeling



N-GRAM CLASSIFIERS



RECURRENT NEURAL NETWORK (RNNs)



CONVOLUTIONAL NEURAL NETWORK (CNNs)



SPACY NER

Data Annotation

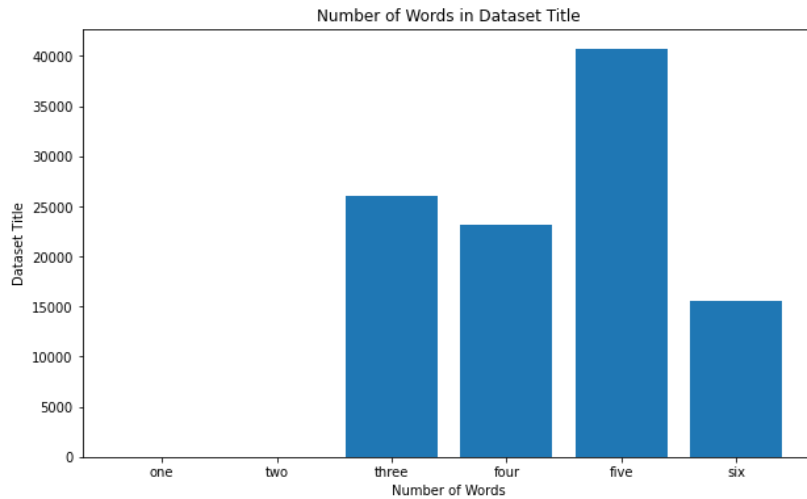
	Sentence	Label
64502	the international community came together to b...	rsna international covid open radiology database
64503	then several 3cl pro ligand complexes are used...	cas covid 19 antiviral candidate compounds dat...
64504	mccs was then applied to carry out the virtual...	cas covid 19 antiviral candidate compounds dat...
64505	section title repurposing cas covid 19 anti...	cas covid 19 antiviral candidate compounds dat...
64506	using this data we applied a variety of machin...	cas covid 19 antiviral candidate compounds dat...
64507	nearly 50 000 substances from the cas covid 19...	cas covid 19 antiviral candidate compounds dat...
64508	the model was then also applied to the cas cov...	cas covid 19 antiviral candidate compounds dat...
64509	using suitable binary classifiers we were able...	cas covid 19 antiviral candidate compounds dat...
64510	after data cleaning and chemical structure sta...	cas covid 19 antiviral candidate compounds dat...
64511	after data cleaning and chemical structure sta...	cas covid 19 antiviral candidate compounds data

	Sentence	Entities
114805	nearly 50 000 substances from the cas covid 19...	{'entities': [(34, 84, 'DATASET']]}
114806	some predicted molecules of these models were ...	{'entities': []}
114807	the model was then also applied to the cas cov...	{'entities': [(39, 89, 'DATASET']]}
114808	the model predicted that 970 of these chemical...	{'entities': []}
114809	using suitable binary classifiers we were able...	{'entities': [(117, 167, 'DATASET']]}
114810	through these screenings we identified many po...	{'entities': []}
114811	after data cleaning and chemical structure sta...	{'entities': [(243, 294, 'DATASET']]}
114812	these searches led to the identification of st...	{'entities': []}
114813	after data cleaning and chemical structure sta...	{'entities': [(243, 290, 'DATASET']]}
114814	these searches led to the identification of st...	{'entities': []}

Sequence Labeling takes a sequence of input instance and learn to predict an optimal sequence of labels.

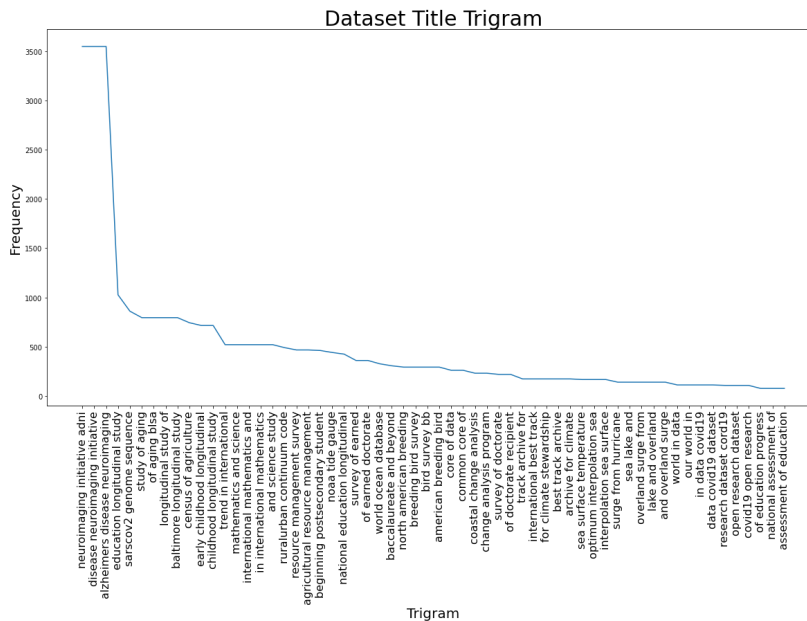
1. Collect a set of representative training sentences that has dataset title in them
2. Label each sentence
3. Train a classifier to predict the labels of each annotated training sentences
4. Test to see if the classifier appropriately output the recognized label

N-Grams



An **n-gram model** is the simplest model that assigns probabilities to sequences of words without considering the word order.

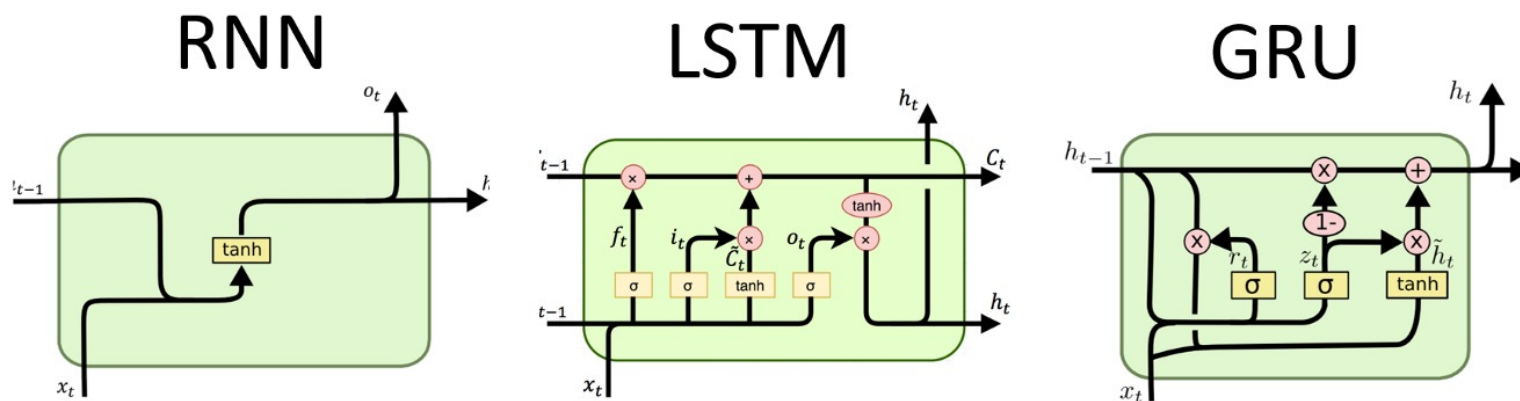
i.e. **dataset title** (3–6-word sequence)



Tri-gram = how often three particular words occurs together

Few common classifiers: random forest, support vector machine (SVM) and naive Bayes.

Recurrent Neural Networks (RNNs)

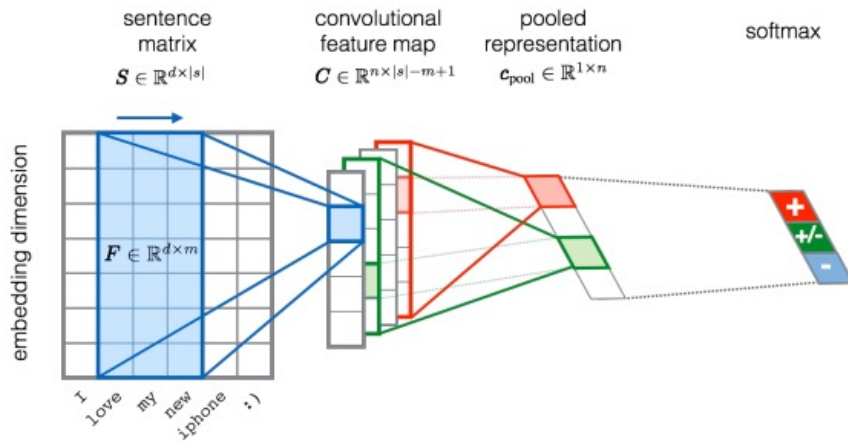


Gated units allow the network to pass or block information from one time step to the other: capable of keeping long-term dependencies effectively while handling the vanishing/exploding gradient problems.

- **Input gate** regulates how much of the new cell state to keep.
- **Forget gate** regulates how much of the existing memory to forget.
- **Output gate** regulates how much of the cell state should be exposed to the next layers of the network.

Convolutional Neural Network (CNNs)

Besides Computer Vision, CNNs can also be applied to NLP. Instead of image pixels, sentences or documents represented as a matrix are the input.



CNNs can identify special pattern of an n -gram in the sentence regardless of their position.

While the RNN computes a weighted combination of all words in the sentence, the CNN extracts the most informative n -grams.

CNNs is much faster than RNNs and much less computationally expensive than n -grams

spaCy Named Entity Recognition

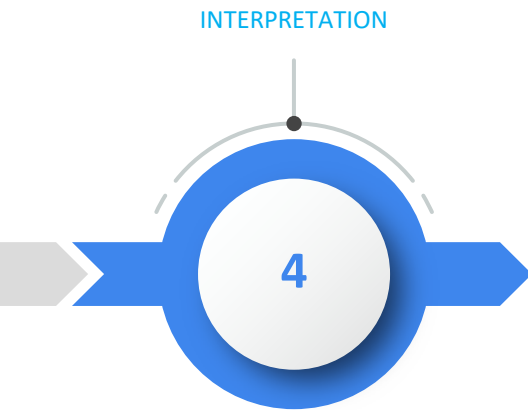
This study used data from the **National Education Longitudinal Study DATASET** (NELS:88) to examine the effects of dual enrollment programs for high school students on college degree attainment.

the international community came together to build the **rsna international covid open radiology database DATASET** record 1 which will be accessible to all investigator to further scientific knowledge and facilitate the development of rapid quantitative assessment tool

spaCy is an open-source library for advanced NLP.

Name Entity Recognition (NER) is used to identify entity **DATASET** mentions in sentences.

Summary of Key Findings



#	Model	Accuracy	CV	Precision	Recall	F1
0	CLF RandomForestClassifier	0.75	0.78	0.44	0.45	0.44
1	CLF Linear Support Vector Machine	0.62	0.62	0.21	0.09	0.11
2	CLF MultinomialNB	0.64	0.62	0.25	0.10	0.12
3	DL GRU	0.83	-	0.29	0.33	0.3
4	DL Bidirectional LSTM	0.83	-	0.28	0.31	0.28
5	DL sep-CNN	0.48	-	0.0	0.01	0.01
6	spaCy NER	0.81	-	-	-	-

- Highly imbalanced dataset
- Number of training samples is not enough
- Missing focus on tweaking the hyper-parameters

Future Work

1st Place Winning Notebook (0.576):

<https://www.kaggle.com/dathudeptrai/biomed-roberta-scibert-base>

<https://www.kaggle.com/suicaokhoailang/submit-gpt-spacy?scriptVersionId=66488765>

- Context Similarity via Deep Metric Learning
 - A shared Bert model for extract Context Embedding and Sequence Tokens Embedding
 - An ArcFace Loss for training Mask/NoMask Embedding
 - A BCE loss for training NER model to detect dataset citation in the input string
- Text extraction model with CLM backbone and beam-search GPT

2nd Place Winning Notebook (0.575):

<https://www.kaggle.com/c/coleridgeinitiative-show-us-the-data/discussion/248296>

- Search for named entities using the Schwartz-Hearst algorithm
 - Filter candidates using a fine-tuned Roberta-base binary classifier
 - Threshold and propagate candidates

Recommendations

1. With supervised learning algorithms, large annotated data for training is required which are expensive and often take a lot of time. Future efforts could be dedicated on providing more effective deep transfer learning models and exploring appropriate data augmentation techniques (He et al., 2020).
2. Most neural models for Sequence Labeling do not scale well because when the size of data grows, the parameters of models increase exponentially, leading to the high complexity of back propagation. There exists need for developing approaches to balance model complexity and scalability (He et al., 2020).
3. Increasing access to confidential data presumed significantly increasing privacy risks. However, the U.S. laws and practices are not currently optimized to support the use of data for evidence building, nor in a manner that best protects privacy. We need to improve data security and privacy protections beyond what exists today (US CEP, 2017).

The background features abstract, organic shapes in light blue and purple. A large, light blue shape is on the left, and a large, purple shape is on the right. The text "THANK YOU" is centered in a bold, teal font, overlapping both shapes.

THANK YOU

The background features abstract organic shapes. On the left, a large, light blue circle is partially visible. On the right, a large, wavy shape transitions from a deep purple at the top to a vibrant blue at the bottom. At the bottom left, there is a smaller, light blue wavy shape.

APPENDIX

Reference

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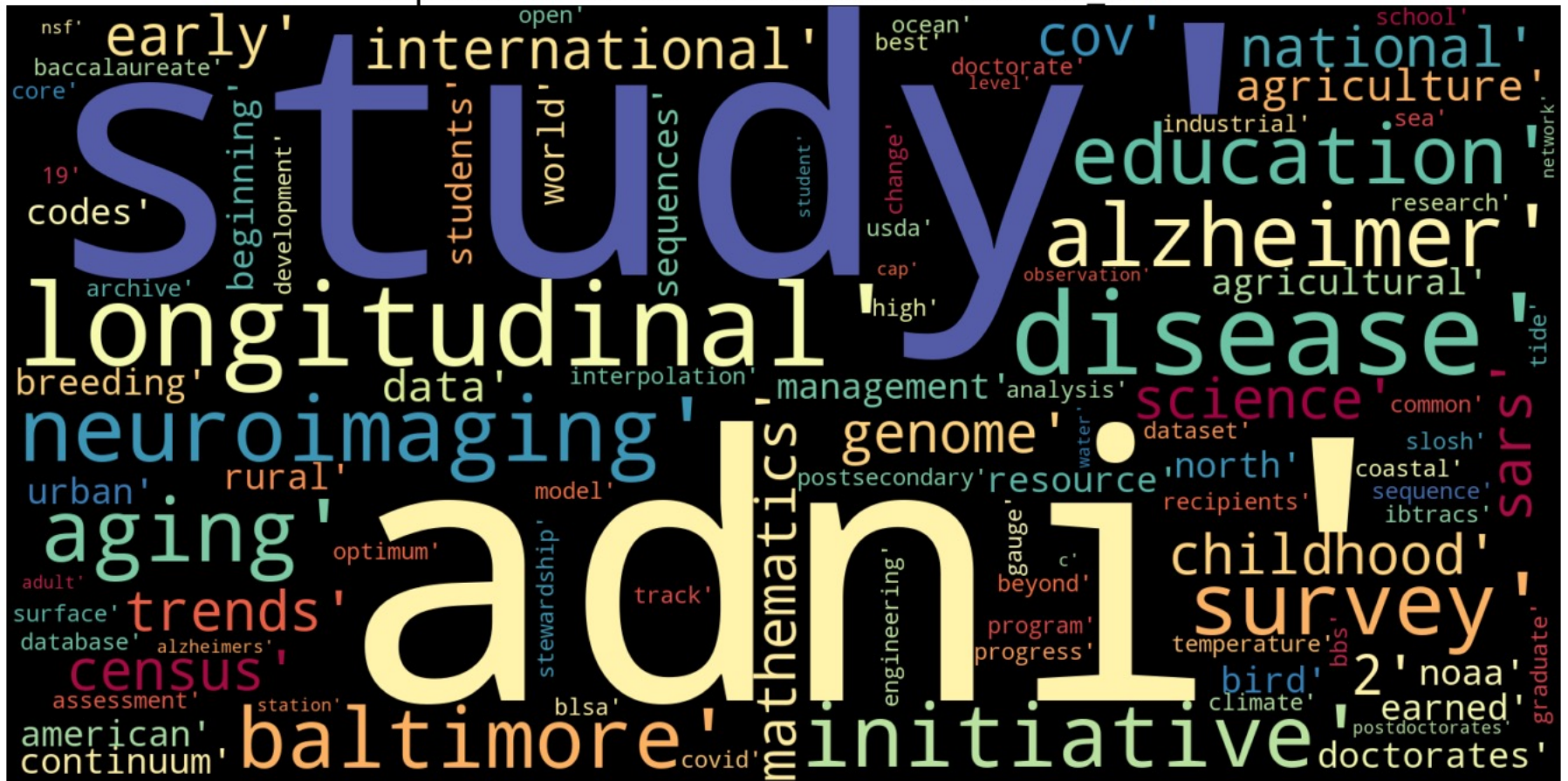
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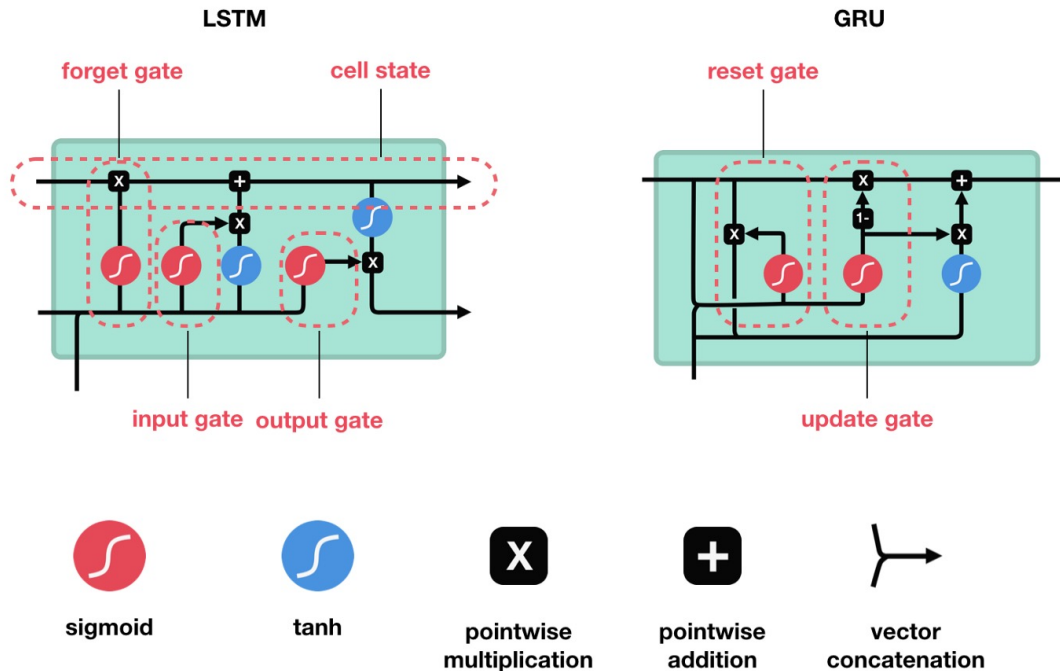
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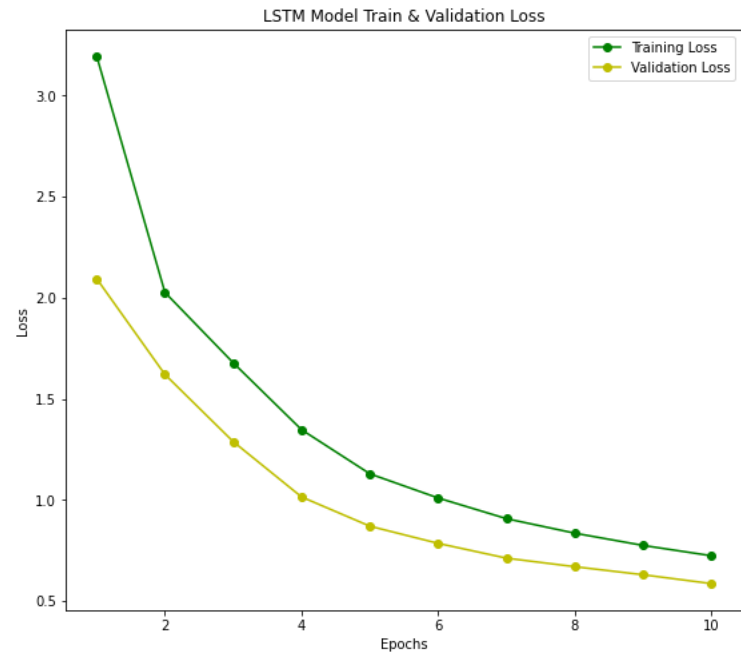
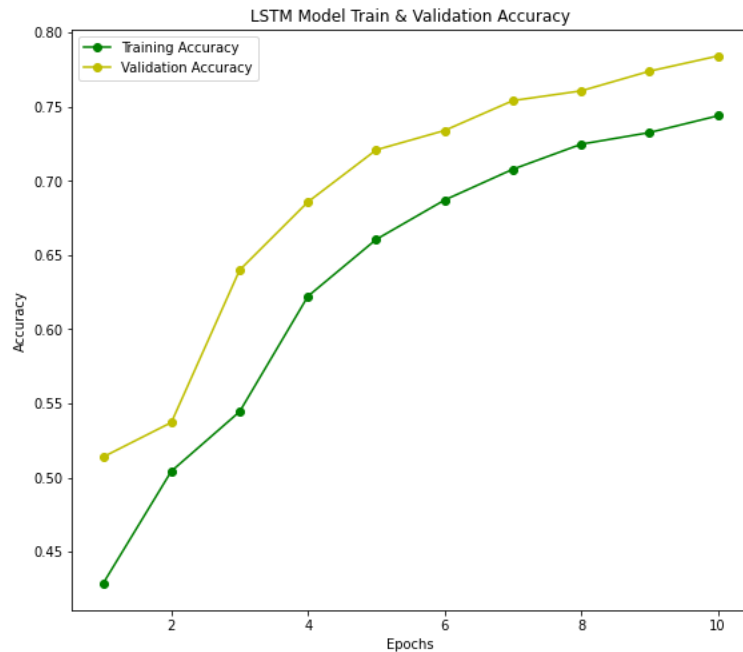
Top 100 Most Common Words in cleaned_label



Bidirectional LSTM vs. GRU

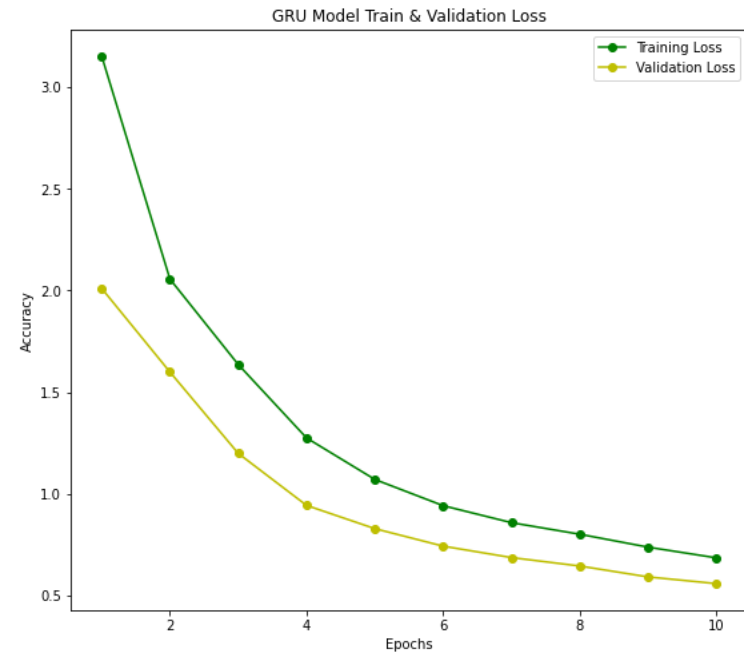
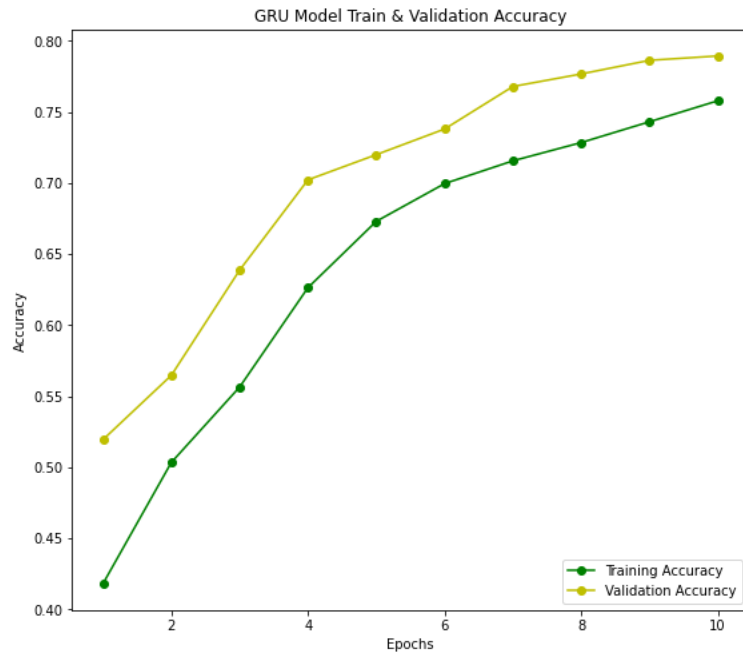


- GRU has two gates (reset and update gates) whereas an LSTM has three gates (input, output and forget gates)
- LSTM remember longer sequences than GRU
- GRU is simpler and trains faster than LSTM



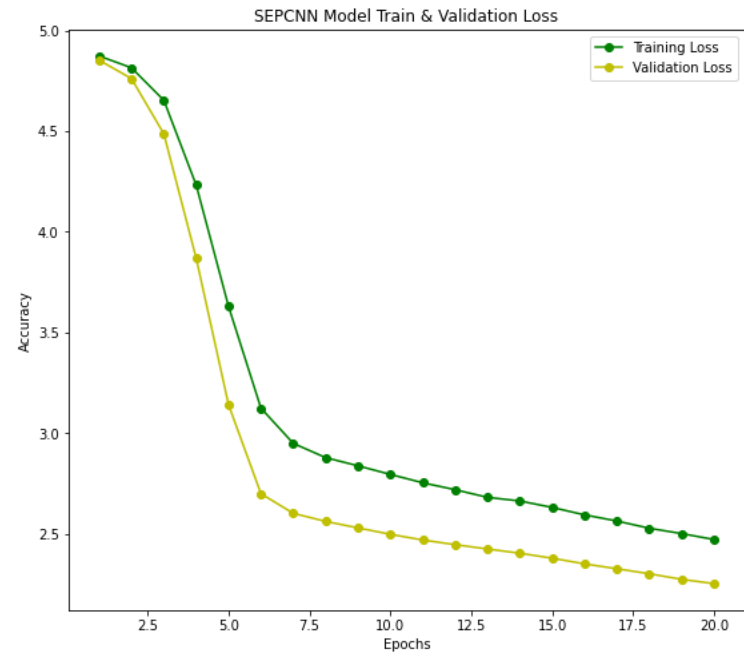
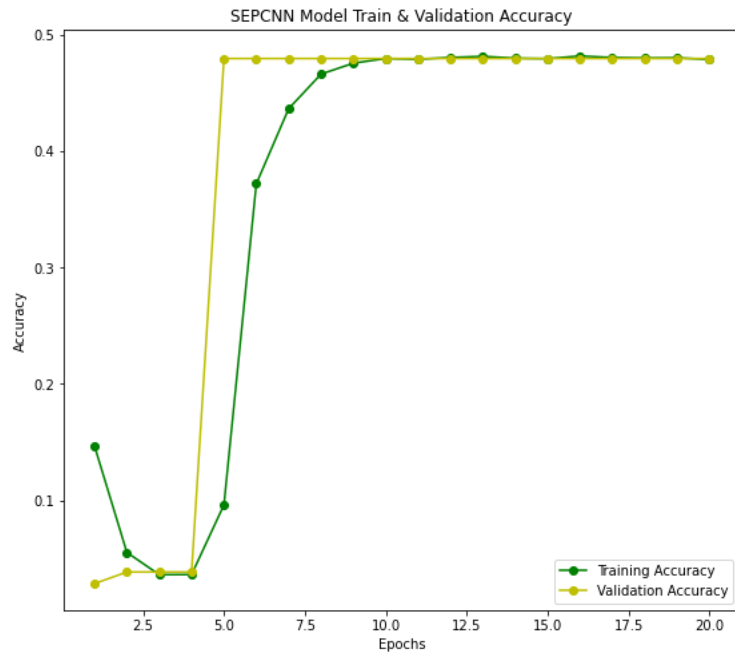
1613/1613 [=====] – 346s 215ms/step – loss:
 0.3470 – acc: 0.8369
 Train loss & accuracy: [0.34700754284858704, 0.8368695378303528]

404/404 [=====] – 88s 218ms/step – loss:
 0.3859 – acc: 0.8283
 Test loss & accuracy: [0.3859459459781647, 0.8282570242881775]



1613/1613 [=====] – 437s 271ms/step – loss:
 0.5258 – acc: 0.7959
 Train loss & accuracy: [0.5257872343063354, 0.7959076762199402]

404/404 [=====] – 109s 269ms/step – loss:
 0.5597 – acc: 0.7894
 Test loss & accuracy: [0.5597025156021118, 0.7893512845039368]



1613/1613 [=====] – 24s 15ms/step – loss:
 2.3333 – acc: 0.4805
 Train loss & accuracy: [2.333292007446289, 0.4804975986480713]

404/404 [=====] – 6s 15ms/step – loss:
 2.3373 – acc: 0.4797
 Test loss & accuracy: [2.3373019695281982, 0.4796558916568756]

```
cleaned label: {'adni', 'alzheimer s disease neuroimaging initiative  
adni '}  
RandomForestClassifier_label: {'adni'}  
MultinomialNB_label: {'adni'}  
SGDClassifier_label: {'adni'}  
lstm label: {'adni'}  
gru label: {'adni'}  
sepcnn label: {'adni'}  
spacy label: adni
```

```
cleaned label: {'common core of data', 'trends in international  
mathematics and science study', 'nces common core of data'}  
RandomForestClassifier_label: {'adni', 'common core of data',  
'census of agriculture', 'trends in international mathematics and  
science study', 'ibtracs', 'program for the international assessment  
of adult competencies', 'baccalaureate and beyond'}  
MultinomialNB_label: {'beginning postsecondary student', 'adni',  
'trends in international mathematics and science study', 'early  
childhood longitudinal study'}  
SGDClassifier_label: {'common core of data', 'adni', 'trends in  
international mathematics and science study'}  
lstm label: {'adni'}  
gru label: {'our world in data'}  
sepcnn label: {'adni'}  
spacy label: trends in international mathematics and science study
```

```
cleaned label: {'slosh model', 'noaa storm surge inundation', 'sea  
lake and overland surges from hurricanes'}  
RandomForestClassifier_label: {'noaa tide gauge', 'slosh model',  
'adni', 'ibtracs', 'noaa storm surge inundation'}  
MultinomialNB_label: {'slosh model', 'adni'}  
SGDClassifier_label: {'adni'}  
lstm label: {'ibtracs'}  
gru label: {'ibtracs'}  
sepcnn label: {'adni'}  
spacy label: slosh model
```

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cleaned label: {'rural urban continuum codes'}  
RandomForestClassifier_label: {'adni', 'census of agriculture',  
'rural urban continuum codes', 'ibtracs'}  
MultinomialNB_label: {'adni', 'rural urban continuum codes'}  
SGDClassifier_label: {'adni', 'rural urban continuum codes'}  
lstm label: {'adni'}  
gru label: {'adni'}  
sepcnn label: {'adni'}  
spacy label: rural urban continuum codes
```