## **Data Collection and Cleaning Coursework Report**

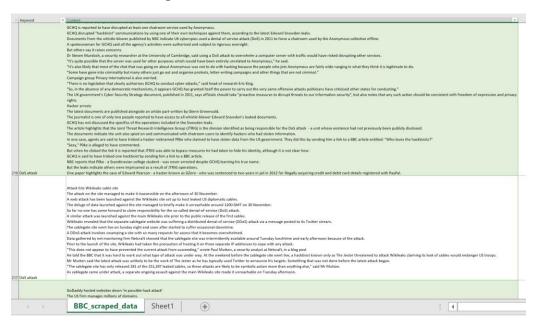
## Problem 1 and 2- requests and web scraping:

For this problem it takes about 2 mins 40 seconds for my program to run.

I decided to code problem 1 and 2 together to increase efficiency, as once I had requested information from webpages it was easy to then store them in a suitable data structure.

After reading in keywords from keywords.xlsx I used the bbc search bar to find article links most relevant to each keyword. I took the first 100 (or as many as were present) relevant articles. I filtered links to make sure they were news articles and were actually links to the bbc website as opposed to a different site. I also filtered scraped articles, ensuring they were relevant by testing if they had the keyword or a variation of it. However, to stop a massive increase in runtime, I stopped filtering for the keyword if my program had scraped 5 pages of articles without finding a relevant one.

I created 5 different functions to scrape all relevant content (including things like figure captions but not links to other parts of the website) from articles of different time periods that had different formats, making sure to preserve the order of text as this was important for my algorithm in problem 3. I used multithreading to increase the speed of my program, as this allowed making requests (the main bottleneck of the program) in parallel. I also used try-except blocks to deal with errors and implement a set number of retries if a request was unsuccessful. I saved article content to a csv file, each row containing the keyword, and article content, including the article title.



## **Problem 3- semantic distance:**

In my python file I have combined the code for problem 3 and 4, as to carry out dimensionality reduction to visualize vectors in 2d tSNE needs access to all the word

vectors created by Word2Vec. Combining code prevents me having to save a large amount of vectors in a file and read this in for problem 4. Together problem 3 and 4 take about 1 min 20 seconds to run.

To calculate semantic distances between keywords I decided to use word embedding with Word2Vec. In word embedding, words are mapped to vectors of real numbers with many dimensions. The Word2Vec python library uses a two layer neural network (1 input, 1 hidden and 1 output layer) to generate word embeddings. Unlike some word embedding approaches (e.g. bag of words and IF-IDF) Word2Vec retains the order of words and context information, and therefore their semantic meaning.

It is worth noting there are other word embeddings (e.g. GloVe) that work in a similar way to Word2Vec. However differences in accuracy vary per dataset, and all are usually very good at capturing semantics. I decided to use Word2Vec due to the large amount of literature pertaining to it, making it easier to understand and use.

To increase the amount of data for the model, I also used requests and beautiful soup to scrape the Wikipedia pages of each of the keywords. Before creating the Word2Vec model I pre-processed the data scraped from the bbc news and wikipedia articles. I convert articles to lowercase and substitute out any characters that aren't letters so I am left with only words. Word2Vec works on single words, so in the next pre-processing step I converted any multiword keywords to single words (e.g. targeted threat -> targeted\_threat) so they are usable in the model. In this step I also convert any plural forms of keywords to singular, so these are also counted in the model (e.g. malicious bots -> malicious\_bot). Finally, I remove stopwords, although Word2Vec down-samples frequent words automatically I did not think stopwords were relevant for finding keyword semantic distance.

I then convert these articles into lists of words and use these to train my Word2Vec model. I decided to use articles instead of individual sentences to train the model, as many articles were not clearly split up into sentences.

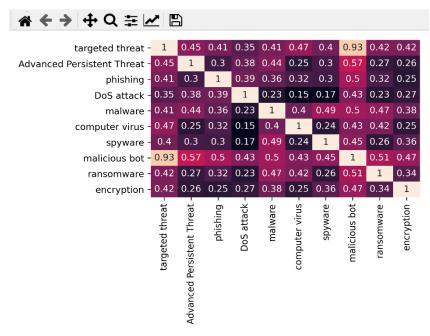
I used the skip-gram architecture in my model, which predicts surrounding context words in a specific window given an input word. Some of the keywords are not common in the articles, and skip-gram works better than CBOW architecture for rare words or phrases. I also use a vector size of 50, as this helps with dimensionality reduction for problem 4.

The Word2Vec model puts words in similar contexts closer to each other in the vector space, words with high semantic similarity will have more similar vectors. I used cosine similarity of keyword vectors (between 0 and 1) to measure how semantically similar they were. Cosine similarity works well even when inputs are of different sizes, it will still be an accurate measure even between keywords that occur at very different rates, unlike Euclidean distance.

This part of the problem takes about 40 seconds to run.

## **Problem 4- visualization:**

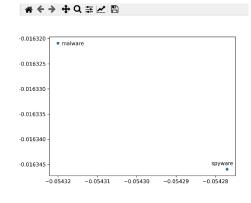
In problem 4, I first used seaborn to plot a heatmap with the cosine similarity of all keywords. This was an easy way to see how closely related all keywords were, with the cosine similarity values between 0 and 1 also on the heatmap:

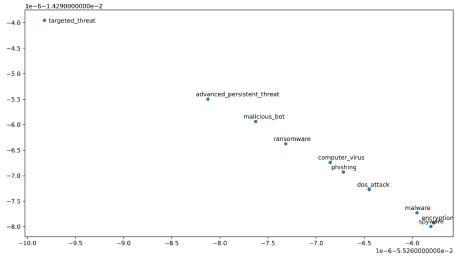


To get a more visual representation of distances between vectors, I carried out

dimensionality reduction with t-SNE. This compresses the 50 dimensional vectors created by the Word2Vec model into 2 dimensional vectors, whilst still keeping similar words close together, and dissimilar words further away. I make sure to set the metric = cosine, as this is the similarity measure I used in problem 3. This will prioritize preserving cosine similarity in the dimension reduction, not Euclidean similarity.

I first plot just 2 keywords to visualize distances on a smaller scale, before then creating a plot with all the keywords:





This part of the problem takes about 40 seconds to run.