# Comp20008 Project 1 Report

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**Method of retrieving headlines from each article (Task 1)**

Crawling method: This program takes a seed URL as a starting point and crawls for a maximum of 300 distinct pages. The implementation relies on standard Python libraries *requests* and *BeautifulSoup* to make HTTP requests, retrieve and parse data from each website. The data is parsed using a HTML parser. The crawler retains every URL it visits in a list of visited links in order to not repeat any data or fall into an infinite cycle. It searches for additional URLs inside the current page content by searching for *<a>* tags using *BeautifulSoup*'s *findAll()* method; then takes the *href* attributes of the results and joins them with the seed URL to compile new URLs. The crawler appends any unvisited URLs into a to-visit list, before moving on to the next link, continuing until there are no more URLs to visit or the page limit is reached. This is the starting URL: http://comp20008-jh.eng.unimelb.edu.au:9889/main/index.html

Searching for headlines: The program uses *BeautifulSoup*'s *find()* method to find HTML tags where the *id* attribute is *'headline'*. From testing, the crawler retrieved 147 URLs that were directly linked to one another, excluding the initial seed URL, where each URL found contained their own headline. This data is stored inside an article-headline dictionary with the URLs as keys.

Output: The program converts the dictionary of headlines into a *pandas Series* in order to sort the data by URLs. It then produces a CSV file that presents a table of URLs and their corresponding headlines using the *csv* library. In this case, 147 pairs of URL-headline were recorded from the test.

**Method of retrieving teams and highest scores from each article (Task 2)**

Searching for teams: The program opens the *rugby.json* file and uses the standard *json* library to retrieve information about the teams it needs to search for. It does so by iterating through all the *team* attributes of the json file and adding the *name* attribute of each *team* into a regular expression string in the format of:

"(< *team name 1* >|< *team name 2* >| … |< *team name n* >)"

where each < team name > represents a team, i.e. England. This regular expression is used with the *re* library's *search()* method to search for the first occurrence of a team in each article's body segment, ignoring the header segment of the page HTML which provides irrelevant information. This first mentioned team is assumed to be the featured team of the article. If such a team is found, it is put into a featured-team dictionary with the URL of the page as the key.

Searching for match scores: The program searches for match scores using the following regular expression:

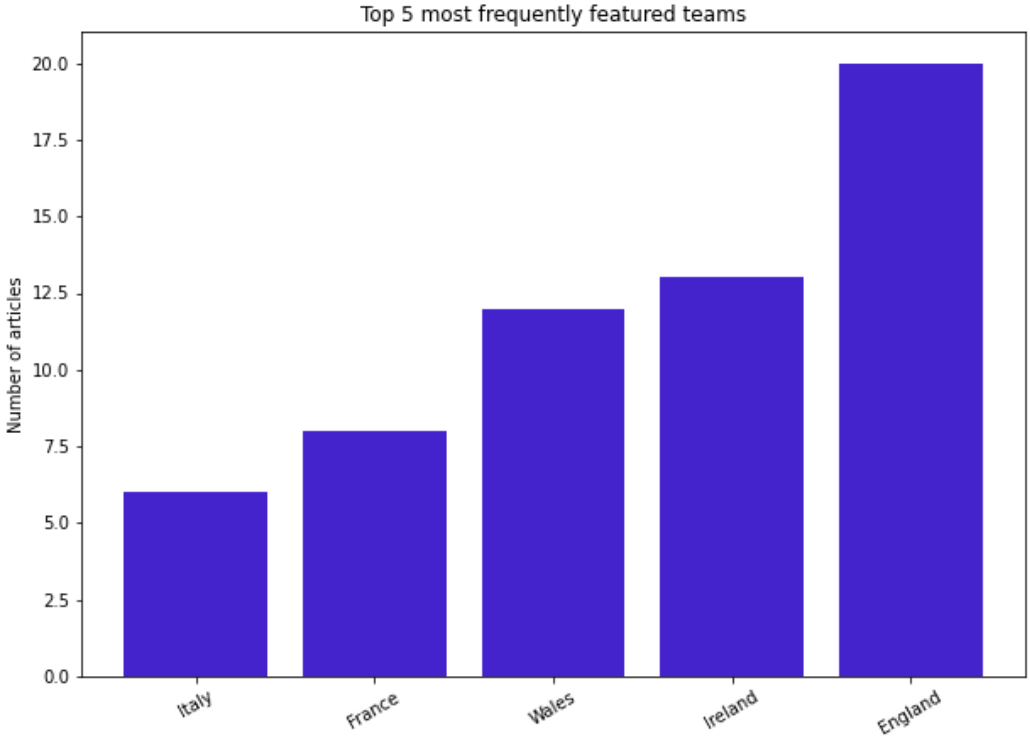
"[0-3]?[0-9]?[0-9]-[0-3]?[0-9]?[0-9]"

which matches from 1 to 3 digits on each side of a '-'. The scores matched are limited to three digits and a maximum value of 399, given that no rugby match has ever recorded a higher score than this. Therefore, any patterns between 0-0 and 399-399 are considered a score. The above regular expression is used with the *re* library's *findAll()* method to find all the occurrences of a match score in each article. All the scores found are iterated through and the highest overall sum is assumed to be associated with that article. If such a score is found, it is put into a highest-match-score dictionary with the URL of the page as the index.

Output: Using the *pandas* library, the featured-team and highest-match-score dictionaries are converted into *Series*. The program performs an inner join on the three data *Series* produced so

far: article-headlines, featured-teams and highest-match-scores; by merging them into a single *DataFrame* and eliminating records without team or score attributes. The resulting merged table contains records with URLs as indexes and three columns corresponding to headline, team and score. This *DataFrame* is translated into a CSV file using its own *to_csv()* method. From the test, the CSV file produced contained 65 articles out of the original 147 articles, indicating that 82 articles did not feature a team or did not contain a valid match score. The *DataFrame* produced here is used for all further data analyses in tasks 3, 4 and 5; and will be referred to as the 'filtered dataset'.

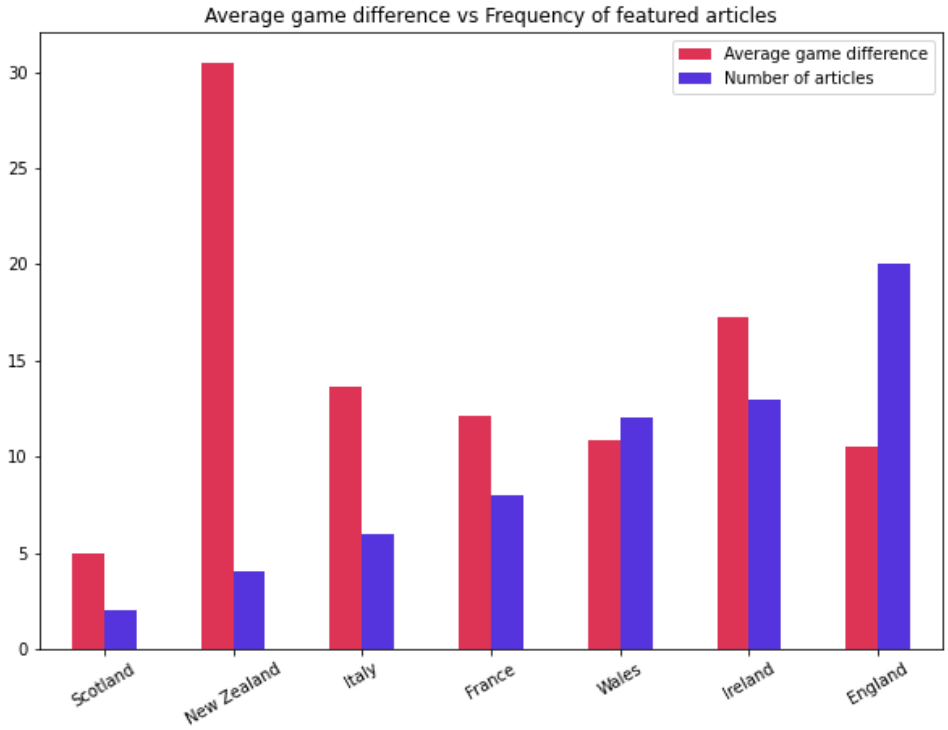
**Analysis of the top 5 most frequently featured teams (Task 4)**
The following graph for task 4 was generated by the program at the time of testing.




The data used: {Italy: 6, France: 8, Wales: 12, Ireland: 13, England: 20}
This data represents the number of times each team is mentioned first in an article. The data is extracted from the filtered dataset and the top five are chosen. The bar chart is chosen to easily visualise the difference in number of articles between different teams.

Analysis: From the graph, England is the most frequently featured team, with 20 out of the 59 articles that the top five teams share belonging to England, a ratio of approximately 1:3. England appears to be featured approximately twice as frequently as the next two countries, and approximately three times as frequently as the bottom two countries in the graph. The average value appears to be Wales with 12 featured articles. Given that the filtered dataset sample of 65 articles is quite small, the data cannot be used to interpret any other information about the news outlet or the teams. It is unknown whether the data is complete, as the crawler would crawl every article that is sequentially linked to the seed URL; however, any articles that are not linked to the 147 articles found would have been missed.

**Analysis of Average game difference vs Frequency of featured articles (Task 5)**
The following graph for task 5 was generated by the program at the time of testing:




The data used:
Number of articles: {Scotland: 2, New Zealand: 4, Italy: 6, France: 8, Wales: 12, Ireland: 13, England: 20}
Average game difference (rounded to two decimal places): {Scotland: 5, New Zealand: 30.5, Italy: 13.66, France: 12.13, Wales: 10.83, Ireland: 17.23, England: 10.5}
This data represents the number of times each team is mentioned first in an article, as well as the average game difference of the match scores that are associated with each team. The data is extracted from the filtered dataset and sorted by increasing number of articles. The bar chart is chosen to easily visualise the trend in average game differences.

Analysis: Looking at the graph, there appears to be no linear relationship between the two data vectors. The average game difference value for New Zealand appears to be an outlier, with a much higher value than the rest of the teams. The Pearson correlation coefficient was calculated with a result of -0.1748, showing a small negative correlation between the two data, suggesting that the data for number of articles cannot be used to predict values for average game difference within this sample space. The data's validity is low and will be discussed in the following segment. The reliability of this data is low as match scores can be interpreted in different ways depending on the programmer. Similarly to the number of articles data, the average game difference data may not be complete if there exist articles which are not linked to the 147 articles found. Given each team has at most 20 articles, the sample is too small to be indicative of any conclusions.

**Discussion of the associating the first named team with the first match score**
Associating first named team with first match score: Naturally, news articles often mention the main topic of discussion at the very start of the article as part of the introduction into the topic. Therefore, it is common that if a rugby article is written about a team and a match, these would be mentioned at the beginning of the article. Oftentimes, these pieces of information may also be included in the headline. As a result, it is reasonable to assume that the first named team and the first match score in an article are directly related.

Associating first named team with highest match score: In comparison, the method that was implemented into the crawler is to find the highest match score in the article. Articles can contain information about multiple different matches, which can be located anywhere in the text; thus, there is no logical relationship between the first named team and the highest match score. Several reasons to discuss different match scores within an article include:

- There was another really interesting match that day.
- The article is comparing this match to a similar match.
- The article is giving a suggestion of what the score should have been for this match.
- etc…

Therefore, it is more suitable to associate the first named team with the first match score in preference to the highest match score in the article.

**Two suggested methods for determining whether the first named team won the match**

Method 1: Use the bag of words from the article**:** The program can be configured to scrape all individual words from an article and count how many times each word occurred. This will result in a bag of words being generated for each article. From this data, words can be weighted depending on their positive or negative connotations. By comparing the number of "positive" versus "negative" words, a prediction can be made about whether the team won or lost the match. An advantage of this method is that given the featured team is correctly identified, the outcome should yield substantially valid results as articles often focus on talking about the featured team. A disadvantage of it is the processing, lemmatisation and weighting that is required for each individual word, making the implementation harder. An example where this method does not work well is when an article mentions another match where the result is the opposite of the featured match, giving false indications of performance.

Method 2: Count the number of times the team was mentioned compared to other teams: The program can be configured to scrape all occurrences of a team name in the text and count the number of times each team is mentioned throughout the article. This will result in a table of teams corresponding to their number of appearances in each article. Using this data, the number of times the featured team is mentioned can be compared to the number of times other teams are mentioned. If the ratio leans towards the featured team (i.e. this team is mentioned a substantial amount of times compared to other teams), it can be assumed that this team won the match. An advantage of this method, contrary to method 1, is that it is simple to implement and does not require thorough natural language processing. A disadvantage of it is the invalidity that the results can yield if the articles talk about the featured team for their loss instead of victory. An example where this method does not work well is when an article gives a summary of all the matches in a day, hence mentioning a variety of different teams; this means that the first named team will be mentioned proportionately less, and the match will be considered a loss regardless of the actual outcome.

**Other information to extract from the articles**

The date and time of the match as well as the location where it was played can be sought from scraping the websites. This will give an indication of whether team performance is correlated to time or location of play. Data about the opposing team can also be collected, where a simple strategy would be to find the second mentioned team in the article (different from the first). From this data, it can be determined whether team performance is correlated to the identity of the opposing team. Individual player names can also be collected by scraping through and finding words starting with capital letters that are not locations. This data may give an indication of which players contributed to a win or loss of a team.