Assessment 3: WebCrawler and NLP System

By: Jagraj Gill

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**Overview**

**Aim and Motivation**

The aim of this study is to deconstruct movie scripts that are associated with Oscar nominated and winning films via a subfield of sentiment analysis known as emotion detection (ED), whose primary goal is to extract the perceived emotions of textual data. The motivation behind this study is to better understand the commonalities and differences between the perceived emotions in these scripts via statistical analysis. Machine learning (ML) will be implemented to determine what, if any correlations between features suggest as to what comprises an award-winning narrative that would generate enough predictive accuracy to be a viable tool on unseen data. Current applications include hate speech detection, emotion retrieval from suicide notes, multimedia tagging, and analyzing e-commerce review sentiments (Yang et al., 2012; Wang et al., 2019; Allouch et al., 2018). Additionally, as noted *Figure 1* below, the ratio of text-based emotion detection is a limited study as compared to emotion detection in general, as seen in both IEEE Explore, and the Scopus sample databases (Acheampong et al., 2020).

Chart, bar chart

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Figure 1: The IEEE Explore Database is a digital repository that provides technical, journalistic, and conference-related materials related to computer science, electrical engineering, and electronics, containing over 5.7 million individual items (“Advancing Technology”, 2022). The Scopus Database is a provider of citation indices and abstracts pertaining to academic books, journals, and conference proceedings worldwide, containing over 39,000 titles (“Research Intelligence”, 2020). The increase in the frequency of research output in ED in multimodal forms such as speech, body language, and facial expressions as compared to text-based ED from 2010-2020 is evident in both academic databases.

Furthermore, the disparity in text-based ED is outlined mathematically as

 (1)

where *T* is the set of text to which the emotions are to be derived, *A* is the set of authors of *T*, *E* is the set of all emotions and *r* is a function that describes the emotions *E* of author *A* from text *T*. (Kao et al, 2009). The ED from text problem is derived from linking the input text to the actual projected emotion that leads the author to pursue specific artistic avenues in writing. Subsets of both *T* and *E* become non-trivial as they are either loosely defined, ambiguous, subject to language evolution, and finally, there are no set relations or classifications that encompass all human emotions.

**Emotional Model Theories**

When undertaking text-based ED, it is vital to define the model of emotion for use, as described in *Text-based emotion detection: Advances, challenges, and opportunities* by Anchempong et al. (2020). There are two primary models used in ED: discrete emotion, and dimensional emotion models. Discrete emotion models involve bucketing emotions into discrete categories, while dimensional emotion models assume that emotions are not independent, and are related to one another, hence should be mapped in a spacial format. There exist unidimensional and multidimensional models that are utilized to depict the degree of relation between emotions, and they typically reflect on two behavioral states, good, and bad. Both models are affected by relative degrees of their occurrences; however multidimensional models are more prominent and frequently used.

The two commonly used discrete emotion models include the Paul Ekman and Robert Plutchik models. The Paul Ekman model distinguishes emotions based off of six basic categories. This theory hypothesises that there exist six fundamental emotions that originate from separate neural networks in the brain, and result from how one perceives an event, hence emotions are manifested independently of one another. The six emotions are happiness, sadness, anger, disgust, surprise and fear. Furthermore, this theory states that more complex emotions may be derived from the synergy of the fundamental emotions.

The Robert Plutchik model suggests that there exist few primary emotions which take place as opposing pairs, and produce complex emotions by combination, as shown in *Figure 2* below. He adds two emotions to the Ekman model, acceptation, and anticipation. Plutchik postulates that for each emotion, there exists various degrees of intensities that occur because of how events are formulated by the experiencer.

Additionally, there exists the Orton, Clore, and Collins model, which opposed both Plutchik and Ekman’s basic emotion theory, proposing that emotions arise from the way they were perceived by the individual, and by the degree of their intensity. All three may be implemented in ED system design, but the OCC model allows for a broad spectrum of emotion representation, with 22 in total.

The primitive dimensional emotional model is presented by Russell as a two-dimensional representation known as the circumplex of affect, shown in *Figure 2* below. The model separates emotions in the arousal valence domains, with the arousal splitting the emotions by activations and deactivations, where the valence differentiates emotions by pleasantness and unpleasantness. In this model, emotions are not independent, but related. Discrete models have been accepted for their emotional classification capabilities because they are simple, but are not exhaustive of the full range of emotional classes available. They can map the intensities or degrees of occurrences as compared to dimensional models. Dimensional models are suggested for projects that involve comparing similarities in emotions.

Diagram

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Figure 2: Plutchik’s wheel of emotions and Russell’s circumplex model of affects.

**Text-based ED Techniques**

There are three primary techniques that are explored for text-based emotion detection, rule construction, machine learning, and a hybrid approach. The rules-based approach uses grammatical and logical rules to adhere to for ED. This method uses both keyword recognition and lexical affinity. Keyword recognition is reliant on emotion dictionaries or lexicons, some of them being Wordnet-Affect, EmoSenticNet, and the National Research Council of Canada lexicon. The emotion lexicons have emotion key words where the occurrences of them in text occurs at the sentence level. Once the keyword is determined, the sentence is labeled. A challenge that will be faced using this method will be the constraint imposed by the number of available emotions in the dictionary, navigation of word sense ambiguity, and processing of linguistic information when sentences are short or sparse of key words. To augment these limitations, the lexical affinity method may be explored, as random emotional words are assigned a probabilistic affinity on to of identifying keywords.

An example of challenges in the rule-based approach was set out in *Emotion and Sentiment Analysis from a Film Script: A Case Study,* by Yu et al. (2017), whose aim was to examine the emotions in the thriller movie script *A Hard Day*, as laid out by Plutchiks wheel of emotions. Manual sentiment (positive, negative, and neutral) and intensity tagging were conducted by undergraduate students, and was compared with the results of the python-based NLTK (Natural Language ToolKit) package VADER (Valence Aware Dictionary and sEntiment Reasoner) 2.5. The result was a 42.6% matching rate when comparing both ED and intensity measures after averaging the negative and positive emotions. The barrier faced in this study was analogous to finding a universal relation function *r* for subsets of text and authors as outlined above in Kao et al. (2009). Future aspirations of the researchers included adding more human taggers and adopting ML algorithms.

ML-based models have been widely implemented for text-based classifications, where supervised machine learning models have performed better in emotion detection rates as compared to traditional unsupervised machine learning (TUML). The more widely explored unsupervised methods have been traditional in nature (i.e., Support Vector Machines, Naïve Bayes), which have proven to be less robust, and do not explicitly extract semantic information from texts which is needed for effective emotion detection. The current science supports deep learning (DL) approaches as layers can extract, or learn, the intrinsic properties that text carries, hence some models suggested by the initial paper outline DL outperforming TUML.

The final avenue that is typically considered is a hybrid approach, where rule construction and ML will deliver a unified model which takes in the strengths of each and mitigates their limitations. Acheampong et al. (2020) also indicates in its survey that this results in “satisfactory results” referring to TUML and rule construction methods, and points to a void in exploring effective approaches with deep learning models, as this is the latest advancement and optimal modalities have not been established.

**Expansion of Current and Prospective Domains**

To expand research in the aforementioned domains and their

**Domains**

Four websites were considered candidates for text-based web scraping: Simply Scripts (<https://www.simplyscripts.com>), Script-O-Rama (<http://www.script-o-rama.com>), The Internet Movie Script DataBase (<https://imsdb.com>), and Scripts Plug (<https://www.scriptslug.com>). It was confirmed with the *response.status\_code()* method found in the *requests* library the HTTP response status code for all candidate sites was 200 indicating a successful request and response to the requested data .One reason for utilizing these databases was significant script volume pertaining to Oscar-winning scripts and similarly for unremarkable titles. All websites were HTML (HyperText Markup Language) and XML (Extensible Markup Language)-based hence there were multiple options available for parsing their data: Python’s *request* module, BeautifulSoup, Scrapy, and Selenium. Determining the avenue that will be more efficient and beneficial to use came down to the structure of the website of interest and the ability to effectively integrate the tool with Python and Jupyter Notebook (i.e., Selenium handles core JAVA applications well), whereas in terms of speed and efficiency, Scrapy would be more beneficial as it supports multithreading and pre-build requests and parsing modules. BeautifulSoup is regarded for its comprehensive documentation and ease-of-interpretation, while the *requests* module is known for performing common HTTP requests (i.e., GET, POST, PUT, PATCH, and DELETE) in a low-code manner.

*Simply Scripts* is a site containing downloadable movie scripts, screenplays, produced and unproduced movies, television shows, anime, plays and radio shows. Currently it contains a total of 1176 movie scripts with 95 Oscar contenders. The scripts are displayed in HTML, .txt, and .pdf format, which are not hosted on the Simply Scripts server, hence the website acts as an aggregator instead of the originator of the content. This will complicate the scraping process as each script page may potentially have a different site structure (i.e., varying tags used in markup, URL trees have varying levels and names, different Robots.txt parameters), and viewing modes (i.e., online viewing, file download). Simply Scripts displays an expired copyright (1999-2020) stating “*No graphics, pages, html, banners, etc., found on this site may be reproduced, posted, or sold without the consent of Simply Scripts*” (“SimplyScripts Disclaimer”)*.* One would have to refer to the hosted site for their disclaimer to determine legality of use, which is tedious for large document retrieval tasks. Finally, there were no scraping security obstacles or limitations to overcome (i.e., CAPTCHA, crawl rate or request rate declarations in Robots.txt).

*Script-O-Rama* contains draft, revised, and final script versions of 1430 movie titles. Additionally, there are TV, haiku, and anime works. The scripts are displayed in *HTML, .txt, .doc, .pdf,* and *.zip* format, which are not hosted on the *Script-O-Rama* server, hence the same programmatic and validation of legality challenges are faced as *Simply Scripts*. There were no scraping security obstacles or limitations to overcome, and there was no copyright or legal policy present.

*The Internet Movie Script DataBase* is claimed to be the “*Web’s largest movie script resource*”, with over 1200 movie titles. The site also contains select TV and French transcripts. All movie scripts are displayed in HTML format and are hosted on the server, which suggested ease of scraping. A fair use policy was posted, pursuant to Section 107 of the United States Copyright Act of 1976.

Scripts Plug was the final website to be considered from the candidate list. All the movie scripts were hosted on the site server, and were organized by genre, studio, and Oscar lists. The scripts URLs also followed an intuitive format for ease of collection and were all in *.pdf* format and were contained on all *HTML*-based pages. It was the only website that contained a comprehensive privacy and legal terms of service policy. For these reasons, it was chosen to be the primary source of data retrieval. Finally, there were no scraping security obstacles or limitations present.

To put into perspective the number of total movie scripts that each of the sites represent, there are an estimated 500,000 movies released worldwide, suggesting that readily available content is sparse, and/or these sites put a heavy focus on Hollywood titles. Although each of the above sites and downloaded scripts contain copyright-protected content, the fair dealing exception in the Copyright Act permits the use of copyright material for the purposes of research and is specifically stated as a user’s right according to the *Copyright Act of Canada* (Legislative Services, 2022).

**WebCrawler Workflow**

The code development was executed in *Jupyter Notebook* version 6.4.11 utilizing *Python* version 3.10.2 (tags/v3.10.2:a58ebcc, Jan 17 2022, 14:12:15) [MSC v.1929 64 bit (AMD64)]. A private GitHub repository was set up for version control and backup storage purposes, which may be found at [*https://github.com/JagrajGill/ScreenplayEmotionDetection/*](https://github.com/JagrajGill/ScreenplayEmotionDetection/) . To ensure PEP (Python Enhancement Proposal) compliance, the *nbQA* (notebook Quality Assurance) package was applied through the command line, which acts as a wrapper for the *flake8* style guide enforcement tool specifically for iPython and .*ipynb* extension-style notebooks.

The tool used for data extraction in this study was *BeautifulSoup Version 4,* with the package name *beautifulsoup4* (*BS4*).*BS4* is a Python-based library that is implemented for parsing *HTML* and *XML*-based files. It was installed with the *PIP* package manager along with the *lxml* parser as it is superior in execution time to the native Python parser (*ElementTree 1.3*) primarily due to being executed completely at the C level, without any interaction with the Python code (Behnel, n.d.).

The initial step to text scraping was to ensure that the status code of 200 was returned from the candidate sites, and *BeautifulSoup* along with the *lxml*  parser was able to print the page content for preview, as shown in *Figure 3* below.

Text

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Figure 3: The candidate list sites are stored in a list. A function, *get\_url\_status\_preview*() takes in a URL argument and initially stores the *request.get()* method output in the *response* variable. If the *response.status\_code* is not 200, then the function states that the site is unable to fulfill the request, otherwise the response content is parsed, stored in the *soup* variable, and returned. A for loop appends an empty list *url\_info* with the *soup* content and prints the result for preview.

Similarly, as follows:



Figure 4:



Figure 5:

Text

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Figure 6:

**Data Wrangling**

Graphical user interface, text, application

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Figure 7:

**Data Summarization**

**Machine Learning Structure**

**Evaluation of Model**

**Discussion and Conclusion**

One possible approach that may have been used to label

This study will consider the influence and popularity terms to be synonymous to one another. It is important to create this ambiguity as influence could be subjective to the audience, and popularity may be determined by uncontrolled factors such as availability, outreach, population size, and interpretability barriers. Although some modeling techniques such as a Bayesian fixed effects model may be able to find a signal for such attributes, this is beyond the scope of complexity that is targeted with this investigation, and does not directly target the aim and motivation.

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