

Report

by Yen Mak

Submission date: 11-Feb-2023 10:58PM (UTC-0500)

Submission ID: 2011890716

File name: Time_Series_Based_Text_Summarization.pdf (2.95M)

Word count: 17428

Character count: 88906

TIME SERIES BASED TEXT SUMMARIZATION

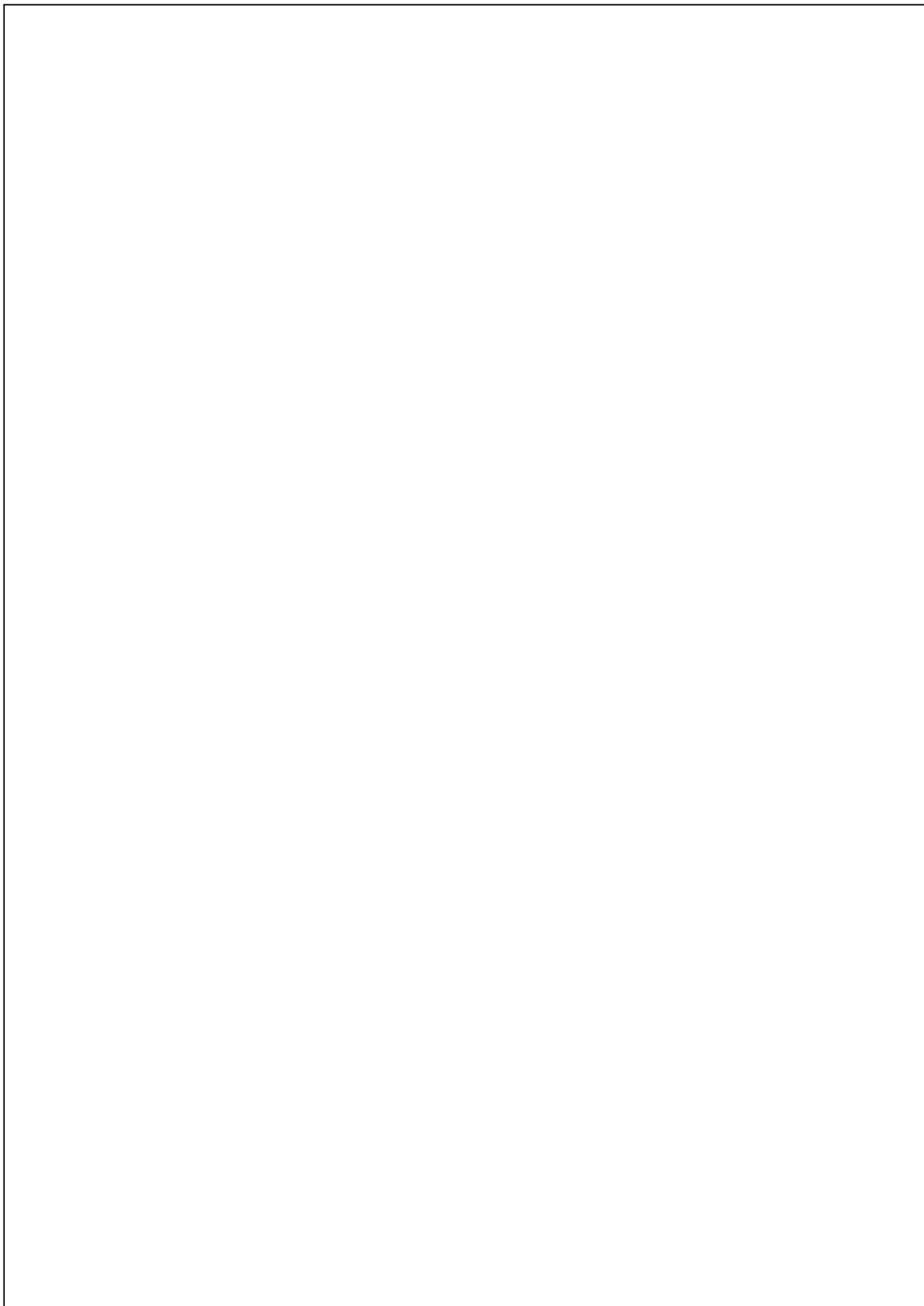
MAK YEN WEI

3

BACHELOR OF COMPUTER SCIENCE (HONS. DATA
SCIENCE)

MULTIMEDIA UNIVERSITY

JANUARY 2023



TIME SERIES BASED TEXT SUMMARIZATION

BY

MAK YEN WEI

³
Bachelor of Computer Science (Hons. Data Science), Multimedia

²
University, Malaysia

THESIS SUBMITTED IN FULFILMENT OF THE

REQUIREMENT FOR THE DEGREE OF

BACHELOR OF COMPUTER SCIENCE (HONS. DATA SCIENCE)

(by Research)

in the

FACULTY OF COMPUTING AND INFORMATICS

MULTIMEDIA UNIVERSITY

MALAYSIA

January 2023

©2023 Universiti Telekom Sdn. Bhd. ALL RIGHTS RESERVED.

Copyright of this report belongs to Universiti Telekom Sdn. Bhd. as qualified by Regulation 7.2 (c) of the Multimedia University Intellectual Property and Commercialisation Policy. No part of this publication may be reproduced, stored in or introduced into a retrieval system, or transmitted in any form or by any means (electronic, mechanical, photocopying, recording, or otherwise), or for any purpose, without the express written permission of Universiti Telekom Sdn. Bhd. Due acknowledgement shall always be made of the use of any material contained in, or derived from, this report.

DECLARATION

I hereby declare that the work has been done by myself and no portion of the work contained in this Thesis has been submitted in support of any application for any other degree or qualification on this or any other university or institution of learning.

Mak Yen Wei

3
Faculty of Computing & Informatics

Multimedia University

Date: 12/02/2023

ACKNOWLEDGEMENTS

I'd like to start by expressing my deepest appreciation to Dr. Goh Hui Ngo, my supervisor, for all of her help during this research, her patience, and her extensive expertise.

3

Additionally, I'd want to express my gratitude to those who have always encouraged and supported me during this endeavour, particularly my family and friends.

ABSTRACT

Finding answers from forums has been one of the most time consuming and tedious tasks for many people. This is because the answers are scattered across the forums and it is very hard to find the relevant answers. This problem particularly shows its face when it comes to software engineering. About 50 percent of searches don't provide enough results, according to Microsoft CEO Satya Nadella. This is especially true in software engineering, where it can be very challenging to zero down on the exact correct solution that solves your problem in such a sophisticated domain. Automatic FAQ Generation, Question Generation, and Answer Retrieval techniques arose over time, however most studies concentrated on broad topics like banking, healthcare, and so on. Therefore, in this work, we attempt to build upon prior research and transfer tried-and-true methods from other fields into the software engineering sphere.

TABLE OF CONTENTS

COPYRIGHT PAGE	ii
DECLARATION	iii
ACKNOWLEDGEMENTS	iv
ABSTRACT	v
TABLE OF CONTENTS	vi
LIST OF TABLES	ix
LIST OF FIGURES	x
CHAPTER 1: INTRODUCTION	1
1.1 Problem Statement	3
1.2 Hypothesis	4
1.3 Objective	4
1.4 Scope	5
CHAPTER 2: LITERATURE REVIEW	6
2.1 FAQ Processing	7
2.1.1 Open Source Forums	9
2.1.2 Neural Networks	10
2.1.3 Context Matching	11
2.1.4 Rankings	13
2.1.5 Semantic Networks	15
2.1.6 Topic Modeling	16
2.2 Stop Words	17
2.3 Sentiment Analysis	20
2.3.1 Granularity	20
2.3.2 Aspect Based	21
2.3.3 Traditional Methods	22
2.3.4 Machine Learning and Deep Learning	22
2.4 Summarization	24
2.4.1 Extractive Summarization	25
2.4.2 Abstractive Summarization	26

2.5 Evaluation Metrics	27
CHAPTER 3: PROPOSED FRAMEWORK	
3.1 Introduction to the framework	28
3.2 Data Collection (Scraping) – 1.0	31
3.3 Inferencing Engine – 2.0	34
3.3.1 Solution A	36
3.3.2 Solution A - Architecture	36
3.3.3 Solution B	55
3.4 Topic Modeling	58
3.5 Real Time Capabilities Issue	59
3.6 FAQs Repository	60
3.7 FAQs Repository - Architecture	60
3.8 FAQs Repository - Approach	61
3.9 FAQs Repository - Database Design	62
3.10 FAQs Repository - System Design	63
3.11 CronJobs - Predictive FAQ Generation System	65
3.12 CronJobs - Predictive FAQ Generation System - Architecture	65
3.13 CronJobs - Predictive FAQ Generation System - Approach	66
CHAPTER 4: PRELIMINARY RESULTS AND DISCUSSION	
4.1 Data Exploration	68
4.1.1 Unique Posts	68
4.1.2 Post Time Distribution	68
4.1.3 Vote Counts Distribution	69
4.2 Post Matching	70
4.2.1 Fuzzy Wuzzy: Partial Ratio and Token Sort Ratio Combined	70
4.3 Preprocessing	72
4.3.1 Evaluate Examples	72
4.3.2 Stopwords Removal	73
4.3.3 Stemming vs Lemmatization	74
4.3.4 Extracting URL	75
4.3.5 Code Blocks Removal	77
4.3.6 HTML Tags Removal	79
4.3.7 Combining all preprocessing techniques	81
4.4 Sentence Scoring	83
4.4.1 Sentence Scoring Results:	85
4.5 Rank Posts: Part 1	86
4.6 Sentiment Analysis	87
4.6.1 Sentiment Analysis Results:	88
4.7 Rank Posts: Part 2	89

4.8 Summarization	89
4.8.1 Summarization Results:	90
4.9 Rank Posts: Part 3	91
4.10 Survey	91
4.10.1 Expert 1	92
4.10.2 Expert 2	92
4.10.3 Expert 3	93
CHAPTER 5: IMPLEMENTATION PLAN	94
5.1 Project Target	95
5.2 Web Application and Framework Hosting	95
43 CHAPTER 6: CONCLUSIONS	97
6.1 Summary	97
6.2 Challenges	97
6.3 Future Work	98
REFERENCES	99
FYP 1 MEETING LOGS	105

LIST OF TABLES

Table 3.1 Special Character	45
-----------------------------	----

LIST OF FIGURES

Figure 2.1 Auto FAQ Gen Architecture by Raazaghi (2015)	8
Figure 2.2 Misconception	13
Figure 3.1 Overall proposed framework	30
Figure 3.2 Stack Exchange API response	32
Figure 3.3 Proposed Inference Engine	35
Figure 3.4 Solution A Architecture	37
Figure 3.5 Unorganized Data	38
Figure 3.6 Organized Data	39
Figure 3.7 GroupedComments Class	42
Figure 3.8 GroupedComments Dictionary Example	43
Figure 3.9 Overall Procedure by Sarica and Luo (2020)	44
Figure 3.10 Solution B Architecture	57
Figure 3.11 FAQ Repository Architecture	61
Figure 3.12 FAQ Database Structure	63
Figure 3.13 CronJobs Architecture	66
Figure 4.1 Post time distribution	69
Figure 4.2 Vote counts distribution	70
Figure 4.3 Partial Ratio and Token Sort Ratio Combined Results	71
Figure 4.4 Spacy Results	72
Figure 4.5 Examples for Evaluation Uses: Example 1	72
Figure 4.6 Examples for Evaluation Uses: Example 2	73
Figure 4.7 Stopwords Removal Results	74
Figure 4.8 Stemming Results	75
Figure 4.9 Lemmatization Results	75
Figure 4.10 Extracting URL Results	76
Figure 4.11 Code Blocks Removal Results	78
Figure 4.12 HTML Tags Removal Results	80
Figure 4.13 Combining all the methods used	82
Figure 4.14 Sentence Scoring Results	85
Figure 4.15 Word Cloud 1st Post Ranking Results	86
Figure 4.16 Sentiment Analysis Results	88
Figure 4.17 Word Cloud 2nd Post Ranking Results	89
Figure 4.18 Summarization Results	90
Figure 4.19 Word Cloud 3rd Post Ranking Results	91
Figure 4.20 Query asked by expert 1	92
Figure 4.21 Feedback from expert 1	92

Figure 4.22 Query asked by expert 2	92
Figure 4.23 Feedback from expert 2	92
Figure 4.24 Query asked by expert 3	93
Figure 4.25 Feedback from expert 3	93
8	
Figure 5.1 Gantt Chart for FYP1	94
Figure 5.2 Gantt Chart for FYP2	95

CHAPTER 1

INTRODUCTION

Google occupies over ninety percent of people's working hours when it comes to software engineering. A large portion of a developer's responsibility is devoted to the removal of errors. Even though it is essential, it might be a tedious waste of time to look through a number of online forums and stack exchanges in order to solve an easy linear equation in Python(Menéndez, 2021).It is not unusual for engineers to explore Stack Overflow for a number of hours in an effort to find an answer that is definite.

It is infamously difficult to address bugs in software due to the vast number of interdependent libraries and packages that are utilised by developers working in a wide variety of programming languages, frameworks, and platforms. Sometimes the problem is caused by a fresh new bug that was included in the most current version of the application. There is also the possibility that a mistake was made in the coding. In rare instances, the problem may also lie inside the local environment of the developer. There might be an infinite number of contributing elements here.

By utilising text processing techniques, ranking approaches, and summarization models, the work of this thesis is to locate the best solution to the problem faced by engineers. With premliminary research, stitching together context from online forums such as stackoverflow with code sharing platforms such as github in order to compile the best possible solution to the problem at hand. This was particularly highlighted in

(Manes & Baysal, 2019).

However, one of the major issue with proposing such framework is the data gathering process. The data is not readily available and hence data scraping is required. To find the best solution, it's beneficial to have as much dataset as possible. Throughout the course of this investigation, a framework to address this issue by using cleverly timed cronjobs to scrape data from online forums as well as a FAQ generation process will be presented.

1.1 Problem Statement

FAQ Generation has been a long history, manually summarizing and cherry picking the best answers to a question was the framework used for decades. The draw-back of this method is that it's time consuming and not scalable(). With the advent of deep learning, the problem of FAQ generation has been addressed by using summarization models. **However the research done in the software engineering area is very limited**, most researches have made effort in the banks, insurance FAQ generation ().

Furthermore, **FAQ Generation on technical forums is a challenging task** as the corpus used will differ from general datasets such as the medical field. The terminologies used differs drastically and hence special care must be taken to ensure the faq generated is accurate. (Sarica & Luo, 2020) (Gerlach, Shi, & Amaral, 2019).

In addition, **keywords used by developers are not always accurate enough to find the best solution**. While google searching does a great job at classifying keywords to finding the matching solution, the same cannot be said for technical forums. Developers are not always able to find the best solution to their problem. (Menéndez, 2021) because the amount of factors that contributes to a problem can be overwhelming.

1.2 Hypothesis

With the advent research gone into summarization, topic modelling, sentiment analysis models. A framework can be developed to address the problem of FAQ generation on technical forums. The framework will be able to generate a FAQ based on the keywords asked by the developer and also be able to rank the best solution to the problem.

1.3 Objective

Through the utilisation of text processing techniques, ranking approaches, and summarization models, providing assistance to developers in their search for answers is worth investigating. An automation towards faq generation in the software engineering domain is the primary aim of this thesis

The project objectives are as follows:

- **To gather** dataset from online forums in the software engineering domain.
- **To propose** a scalable, modular framework for FAQ generation on online forums in the software engineering domain.
- **To evaluate** multiple architectures for FAQ generation.

1.4 Scope

Platform

The stackoverflow forums may be scraped, ranked in terms of their usefulness to the developer's use case, and the top-ranked posts' comments, answers, and responses' comments can be summarised using the framework. As an added bonus, a web app will be built so programmers may use the framework to find the best solution to their problem.

Technologies

- **Web Application:** Python, FastAPI, AWS, ReactJS
- **Scraping:** Selenium
- **Text Processing:** NLTK, Spacy
- **Summarizing:** Tensorflow, Keras

Language

In the context of this thesis, the language used is English. The reason for this is because the majority of the online forums are in English.

CHAPTER 2

LITERATURE REVIEW

The following literature review section highlights the existing work that is related to our research. The work reviewed mostly consists of FAQ Processing and NLP techniques.

One of the caveats of the existing work is that, most of FAQ processing related work are based on the use on non-engineering fields such as the medical field. Likewise, since our research primarily focuses on the software engineering field, we hope to migrate any intuition that we can get from the existing work to our research. Therefore a certain degree of reading has been done in terms of handling technical languages and terminologies.

2.1 FAQ Processing

FAQ retrieval is a crucial task when it comes to question answer pairs rankings (Gupta & Carvalho, 2019). It is a process of retrieving the most relevant questions from a large collection of questions based on a user query. Achieving excellent performance in this task will solve many problems that we've discussed in the previous chapter 1.1.

63 However, most of the traditional methods for FAQ generation are based on the use of extensive manual classification and software engineering (Gupta & Carvalho, 2019), this method takes tremendous amount of time and effort to be done. This was particularly highlighted by (Raazaghi, 2015) (Hu, Yu, & Jiau, 2010) (Henß, Monperrus, & Mezini, 2012) (Razzaghi, Minaee, & Ghorbani, 2016). In addition, the performance of 47 the framework is also affected by the quality of the manual classification and software engineering.

To address the issues brought-up, there are attempts and researches that have done to improve the predecessor. One of the approaches on solving the problem, is to automate the process of FAQ generation using NLP techniques. (Gupta & Carvalho, 2019) has made progress on using deep learning methods such as combining both Deep Matching Networks and Multihop Attention Networks in performing FAQ retrieval. Deep Matching Network also known as (DMN) is a deep learning model that generates 16 a matching scores based of 2 matrices inputs. The matrices are made of the dot product of embeddings of every word of question with every word of answers. While Multihop Attention Networks on the other hand is proven to be effective for reasonings tasks like question answering, which is our focus in this paper (Gupta & Carvalho, 2019). The

network uses multiple "hops" of attention to gather information from a given input and make a prediction. It starts by encoding the input and then uses a decoder network that iteratively attends to different parts of the input, in order to generate an output.

(Raazaghi, 2015) (Jijkoun & de Rijke, 2005) takes an approach where a whole architecture is designed to achieve Auto-Faq-Gen which includes scraping, question construction, a ranking algorithm, and the question generation. The architecture is shown in Figure 2.1.

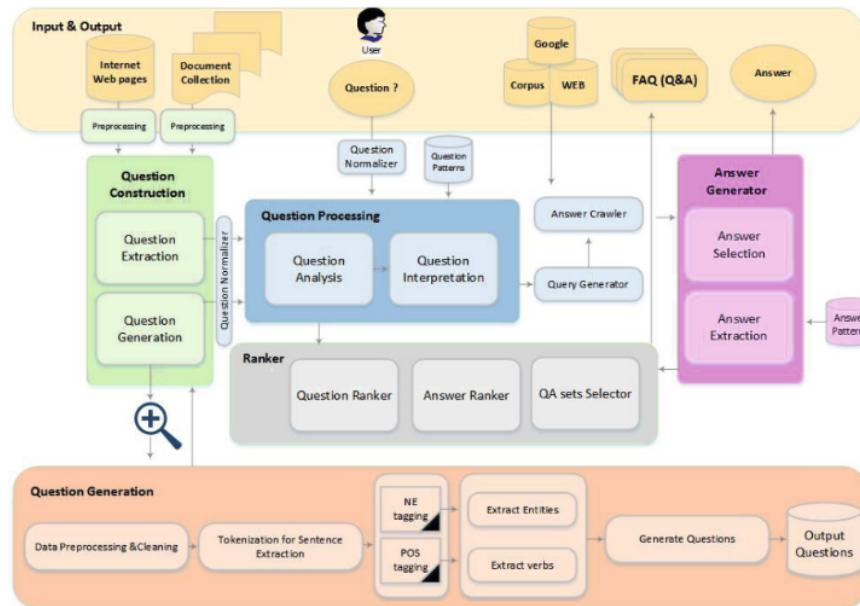


Figure 2.1: Auto FAQ Gen Architecture by Raazaghi (2015)

The architecture presented was shown to be able to make Question and Answer Generation, Question Processing and a Ranker to rank answers.

2.1.1 Open Source Forums

Open source forums are great sources of information for users to find answers to their questions. However, over time, most forums are bloated with a large number of posts, it's always easier if some form of ranking can be performed on these forums to improve user experience.

(Hu et al., 2010) (Makino, Noro, & Iwakura, 2016) has made progress in selecting, weighing, clustering and ranking contextual keywords in order to achieve questions abstraction and ultimately enhance the process of finding questions and related answers in open source forums. The author then proposed the solution to be in a format of semi-automatic FAQ generation.

2.1.2 Neural Networks

Neural Networks are a collection of algorithms modelled after the human brain.

It is a collection of algorithms used to identify patterns. It is able to learn independently by evaluating unstructured material with the capabilities of self-learning and adjusting weights to reach the optimal outcome.

Convolutional neural networks (CNN) and RNN has paved it's way towards text processing tasks for the past decade. In (Duan, Tang, Chen, & Zhou, 2017), CNN

⁷³
was proposed as a method to handle questions generation based on a given passage, it was done in a retrieval based format while RNN was propose to perform questions generation with a generation-based method. Both neural network were able to pull off question pattern prediction, question topic selection, question ranking and lastly question generation. The proposed model is shown to be able to outperform the traditional methods such as MAP or MRR.

2.1.3 Context Matching

Another issue arises, where most of the time, the questions asked by the user might not be easily classified to fit with the existing questions in the FAQ database.

This is because the questions asked by the user might be in a different form or context (Makino et al., 2016). For example, the question asked by the user might be in a different language, or the question asked by the user might be in a different form.

Grammatically, misspellings are another set of issue that we can foresee when it comes to building automated questions answerings, highlighted by (Kothari, Negi, Faruque, Chakaravarthy, & Subramaniam, 2009).

Context Matching is important when it comes to ranking the answers to the user query. The traditional way to score similarity is naive, where the score is calculated by levenshtein distance. (S. Zhang, Hu, & Bian, 2017) However, this method is not effective when it comes to ranking the answers. This is because the levenshtein distance is not able to capture the semantic meaning of the words. Another concept comes to mind which is BOW, the bag of words model, (Zhou, Liu, Liu, Zeng, & Zhao, 2013) highlighted to us where, BOWs similarity matching algorithm can be used on processed text (stop words removal, stemming, etc) to calculate the similarity between the query and the answer, however similarly to levenshtein distance, BOWs is not able to capture the semantic meaning of the words, which will bring false conceptual similarity between the query and the answer.

Word knowledge or Word Embedding is one of the solution to the traditional

⁴⁵
similarity matching algorithm. (Zhou et al., 2013) proposed a method that uses word knowledge to improve the similarity matching algorithm. The model stitch together a knowledge base to a word, which then constructs a knowledge table which consists of the raw words, Hypernyms, Synonyms and Associative concept of words. This solution breaks the traditional similarity matching algorithm, where the similarity is calculated by the semantic meaning of the words, instead of the raw words. (Othman,

Faiz, & Smaïli, 2019) has made progress on proposing a method called "WEKOS

⁸¹
(Word Embedding, Kmeans and COSine based method)". WEKOS (Word Embedding,

Kmeans and COSine) is a new method for question retrieval. The word embeddings

of a question are weighted and averaged to get an overall representation of the ques-

⁵
tion. The continuous word representations are learned in advance using the continuous

⁵
bag-of-words (CBOW) model. (Othman et al., 2019) The cosine similarity is used to

calculate the similarity between the average of the word vectors corresponding to the

question and that of each existing question.

2.1.4 Rankings

Deep Matching Network also known as (DMN) is a deep learning model that generates a matching scores based of 2 matrices inputs. The matrices are made of the dot product of embeddings of every word of question with every word of answers.

16

Multi-hop Attention Network on the other hand is proven to be effective for reasonings tasks like question answering, which is our focus in this paper (Gupta & Carvalho, 2019). The network uses multiple "hops" of attention to gather information from a given input and make a prediction. It starts by encoding the input and then uses a decoder network that iteratively attends to different parts of the input, in order to generate an output.

In order to solve the issue of context misconception between the query and the faq. We can highlight the issue below.

query: I lost my credit card.

the question part of an FAQ: How do I request a new / replacement card?

the answer part of an FAQ: You can request a replacement card by signing in to the online banking and going to the information tab of your account.

Figure 2.2: Misconception

In the above example 2.2, the query only matched with the correct output with 2 characters "I" and "Card", that way, the resulting score will be very low, even though the FAQ is relevant to the query. To counter this issue, the authors of (Makino et al., 2016) proposed a method that predicts if the query corresponds to a FAQ using doc-

ument classifier. The paper begins to highlight that the proposed document classifier uses binary classifiers to classifier each faq to the query. The sentences are broken into unigrams, bigrams to learn the dependency relation between the query and the faq.

2.1.5 Semantic Networks

Automatically Generated Semantic Networks are networks that are generated by machine learning algorithms based on text or other forms of data. These networks are used to represent the relationships and connections between different concepts, entities, or topics in a structured manner, in order to facilitate various NLP or information retrieval tasks, such as classification, summarization, or question answering. They can be thought of as knowledge graphs constructed automatically from text.

Traditionally, QA (Question Answering) are managed using syntactic, semantic methods. However these methods are not practical to perform well on low resource languages like Swahili. Semantic networks can be used to languages like Swahili, where the language generally follows a subject-verb-object structure. (WANJAWA & MUCHEMI, 2020).

2.1.6 Topic Modeling

Topic Modeling is another great way to find Question and Answers Pairings.

Topic modeling is a type of statistical modeling for discovering the abstract "topics" that occur in a collection of documents. It is a frequently used text-mining tool for discovery of hidden semantic structures in a text body. Latent Dirichlet Allocation (LDA) is a popular topic modeling technique that is used to discover topics in a collection of documents. LDA is a generative probabilistic model that assumes each document is a mixture of topics, and each topic is a mixture of words. The model is trained on a corpus of documents, and the topics discovered by the model can be used to label new, unseen documents. (Henß et al., 2012).

An architecture brought up by (Henß et al., 2012) highlights the pipeline on leveraging topic modelling to perform prediction on the question and answer pairings. The pipeline proposed extracts the topics from the corpus, then the topics are used to label the questions and answers, which then extracts answers that closely relates to the topic mined by the model.

2.2 Stop Words

Stop words are words that are filtered out before or after processing of natural language data (text). Though "stop words" usually refers to the most common words in a language, there is no single universal list of stop words used by all natural language processing tools. The stopwords used in technical languages differs from the general stopwords list used by general application such as the NLTK library (Gerlach et al., 2019) (Sarica & Luo, 2020).

The properties of stopwords can be defined as follows (Ladani & Desai, 2020):

- Words used for connecting important words.
- Words that are not important to the meaning of the sentence.
- Words that occurs frequently in the text.

While it might be wise to perform stopwords removal tasks on tasks such as Information Retrieval (IR), classification, it is not advisable to perform stopwords removal on tasks like summarization. (Ladani & Desai, 2020).

(Gerlach et al., 2019) addresses the gap in identifying stopwords for texts in software engineering fields which are not covered by the general stopwords list. The concluded stopwords list is statistically identified and evaluated by experts.

Phrases can be detected by using the algorithm of Mikolov at al (Mikolov,

Sutskever, Chen, Corrado, & Dean, 2013). The algorithm works by finding words that are frequently used together.

40

$$\text{score}(wi, wj) = ((\text{count}(wi * wj) - S)|N| / \text{count}(wi) * \text{count}(wj))$$

15

Term frequency-inverse-document-frequency (TFIDF) is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. Many information retrieval systems use TFIDF as a central tool.

18

TF (Term Frequency) is the number of times a word appears in a document, divided by the total number of words in the document.

$$TF = \frac{\text{Number of times term } t \text{ appears in a document}}{\text{Total number of terms in the document}}$$

20

IDF (Inverse Document Frequency) is the log of the number of the documents in the corpus divided by the number of documents that contain the word w.

$$IDF = \log_e \left(\frac{\text{Total number of documents}}{\text{Number of documents with term } t} \right)$$

34

Term frequency-inverse-document-frequency (TFIDF) is then the product of

TF and IDF.

$$TFIDF = TF * IDF$$

This method particularly favours words that appear many times in a document.

Both of this methods are used to score and rank words in a document, and potentially form a stopwords lists. An interesting fact is that with using the two methods mentioned above, the stopwords list can be generated for a specific domain.

4 2.3 Sentiment Analysis

Sentiment analysis is the process of determining whether a piece of writing is positive, negative, or neutral. It's also known as opinion mining, deriving the opinion or attitude of a speaker. A common use case of sentiment analysis is to discover how people feel about a particular topic. For example, sentiment analysis can be used to discover how people feel about a new movie, or to learn about the general sentiment towards a new product.

While most sentiment analysis work are based of current social medias such as Twitter, Facebook, and Instagram, sentiment analysis can be applied to any text. For instance, (Alqaryouti, Siyam, Monem, & Shaalan, 2019) uses sentiment analysis to further investigate and understand the customers needs and wants for goverment entities.

2.3.1 Grananularity

67
Sentiment analysis can be performed on different levels of granularity. The level of granularity refers to the level of detail at which the sentiment is expressed.

25
There are three levels of granularity: sentence-level, document-level, and aspect-level.

66
Taking into account the level of granularity is important because it affects the type of sentiment analysis that can be performed, and the type of results that can be obtained (Alqaryouti et al., 2019).

2.3.2 Aspect Based

37

Aspect-Based Sentiment Analysis (ABSA) is a subfield of sentiment analysis

that focuses on identifying and extracting opinions towards specific aspects or features of an entity such as a product, a service, or a person. It involves analyzing a piece 39 of text to determine the sentiment expressed towards a particular aspect, rather than the overall sentiment of the text. This type of analysis is useful in understanding the specific opinions and attitudes of customers and users towards a particular product or service, and can be used in a variety of applications such as customer service, market research, and product development (Alqaryouti et al., 2019) (Liu, Chatterjee, Zhou, Lu, & Abusorrah, 2020) (Xue & Li, 2018) (M.Abdelgawad, A.Soliman, I.Taloba, & Farghaly, 2022).

35

The goal of aspect-based sentiment analysis is to identify the sentiment expressed towards a particular aspect of an entity. For example, consider the following sentence:

"The food at this restaurant is great, but the service is terrible."

82

Listing 2.1: Example of Aspect-based Sentiment Analysis

In this sentence, the overall sentiment might be positive, but in actuality the sentiment towards the food is positive, while the sentiment towards the service is negative. Therefore by using Aspect-based sentiment analysis can be used to identify the sentiment towards the food and the service separately. (Alqaryouti et al., 2019) took this intuition and applied it to the government sector. They used the ABSA to identify the

sentiment towards the government services and the government entities.

In our research, we'll be using the ABSA model in the hopes where it'll improve the FAQ Ranker in terms of ranking their sentiment to potentially indicate the quality of the answer.

2.3.3 Traditional Methods

Lexicon and Corpus based approaches are unsupervised learning methods to understand the sentiment of a text.⁸⁶ The lexicon based approach uses a predefined list of words coupled with the annotated polarity values of the word's sentiment. This approach has a major downside where there might be numerous words and expressions that are not included in the lexicons.

Corpus based approach however focuses more in predicting the word to be a prefixer or suffixer of the sentiment word. This approach is more accurate than the lexicon based approach, but it is still not perfect. (Syam Mohan E, 2021)

2.3.4 Machine Learning and Deep Learning⁶²

Multiple researches has proven that machine learning can make promising results in terms of ABSA specifically polarity classification. It was highlighted that attention-based or non attention based LSTM models can be used to achieve promising results (Syam Mohan E, 2021) (Liu et al., 2020)

SVM had received the highest popularity in terms of polarity classification, it was often used with association rules and feature selection such as PCA to achieve promising results⁷¹ (Syam Mohan E, 2021) (Zainuddin, Selamat, & Ibrahim, 2018) (Al-Smadi, Qawasmeh, Al-Ayyoub, Jararweh, & Gupta, 2017)

Convolutional Neural Network were also used to predict polarity of a sentence, there were a handful of attempts in using CNN coupled with Word2Vec that had been proven to be effective (Syam Mohan E, 2021) (Kumar, Pannu, & Malhi, 2020) (Rezaeinia, Rahmani, Ghodsi, & Veisi, 2019) (B. Zhang et al., 2019)

⁸⁰ To learn long term associations and dependencies between texts in a sentence or a document. ⁷⁷ Long Short Term Memory (LSTM) was a popular choice in learning information dependencies across the history of sentences in a document. Multiple attempts had been made to take advantage of LSTM models in building polarity classification models (He, Lee, Ng, & Dahlmeier, 2018) (Ma, Zeng, Peng, Fortino, & Zhang, 2019) (Sindhu et al., 2019)

2.4 Summarization

13 Text summarization is the process of automatically generating a shorter version of a text that preserves the most important information. There are two main types of text summarization: extractive and abstractive. Extractive summarization involves selecting and concatenating important sentences from the original text, while abstractive summarization involves generating new sentences that summarize the meaning of the original text (Sharma & Sharma, 2022) (Nallapati, Zhou, Dos Santos, Gulcehre, & Xiang, 2016).

In contrast to general text summarization, summarizing software engineering related texts differs itself from the general text summarization. The main difference is that the software engineering related texts are often more technical and contain more technical terms, not to mention that at times, processing raw source codes can be a challenge (Moreno & Marcus, 2018).

30 The evaluation metrics used generally is to calculate the compression rate denoted by the ratio of the length of the summary to the length of the original text.(Sharma & Sharma, 2022) The formula is as follows:

$$\text{CompressionRate} = \frac{\text{Length of Summary}}{\text{Length of Original Text}}$$

2.4.1 Extractive Summarization

6 Extractive summarization involves selecting and concatenating important sentences from the original text. The most common approach to extractive summarization is to 4 use a sentence ranking model to rank sentences in the original text, and then select the top ranked sentences to form the summary. The sentence ranking model can be trained 33 using a variety of features, such as the number of named entities in the sentence, the 13 number of words in the sentence which closely relates to TFIDF, the number of words in the sentence that are also in the original text, and the number of words in the sentence that are also in the summary (Sharma & Sharma, 2022).

CN-Summ is one of the notable extractive summarization model that was introduced by (Antiqueira, Oliveira, da F. Costa, & Nunes, 2009). CN-Summ is a neural network based model that uses a graph-like architecture to connect sentences that shared common significant nouns. The model consist preprocesses, a graph construction, and finally selecting the first x sentences as the summarization.

Similarly to using LDA in sentiment analysis (Syam Mohan E, 2021), LDA has also shed light in the field of extractive summarization. (Mashechkin, Petrovskiy, Popov, & Tsarev, 2011) proposed the use of LDA to extractive summarization. The model uses 32 LDA to extract the most important topics in the original text, and then uses the topics to rank sentences in the original text.

2.4.2 Abstractive Summarization

6 Abstractive summarization involves generating new sentences that summarize the meaning of the original text. The most common approach to abstractive summarization 53 is to use a sequence to sequence neural network to generate the summary. A sequence to sequence neural network such as RNN, LSTM is used because they are well-suited for processing sequences of data, such as text. The recurrent connections in RNNs allow them to maintain a hidden state that can capture information from previous steps in the sequence, which is useful for keeping track of contextual information as the 44 model reads the input text. This allows the model to generate a summary that is both concise and semantically relevant to the input text (Sharma & Sharma, 2022).

AMR (Abstract Meaning Representation) was one of the RNN based methods that 25 was introduced by (Banarescu et al., 2013). AMR is a neural network based model 32 produces a single graph to represent time series information in the text to form an abstractive summary.

ATSDL is another attempt where the paper introduce a use of combining advantages of extractive and abstractive summazy to form a hybrid model. The model uses a sequence to sequence neural network to generate the summary, and then uses a sentence 31 ranking model to rank the sentences in the summary. The top ranked sentences are then selected to form the final summary (Sharma & Sharma, 2022). A phrase collection model called MOSP was introduced to generate and learn phrase representations and their relationships in a document, the model solves the problem of unusual terms, which abstrative models faced most of the time.

2.5 Evaluation Metrics

Evaluating the success rate of extracting FAQ can be subjective, not all datasets coincide with the same domain. Therefore, a manual evaluation approach are mostly used to evaluate the success rate of a question finding process (Jijkoun & de Rijke, 2005). Manual classification of the questions pairs are carried out and the results are compared with the results of the question finding process.

However there are semi-automated frameworks that can potentially be used to evaluate the success rate of a question finding process. Alternatively, a user feedback framework can be constructed, where a user can provide feedback on the accuracy of the question finding process. The feedback can be used to evaluate the success rate of the question finding process (Raazaghi, 2015).

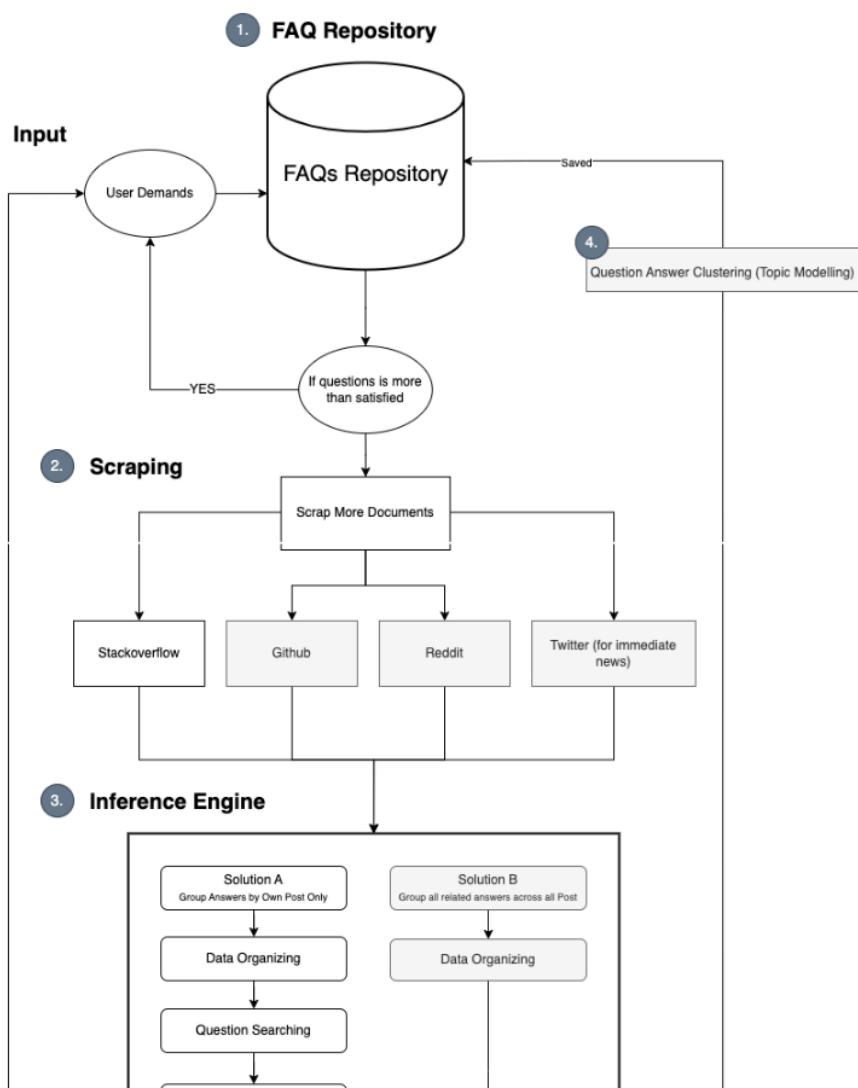
CHAPTER 3

PROPOSED FRAMEWORK

3.1 Introduction to the framework

The following framework, which comprises a series of operations to be done on the data. Figure 3.1 is an illustration of the entire framework.

The pipeline proposed includes all the essential components to comprehensively handle the necessary procedures to solve the problem. The framework was designed to be modular, therefore each component is replaceable with a different implementations if necessary. A distributed design was used in the development of the framework so that it may be utilised on a broad range of computer systems. The framework's ability to readily include more procedures as they become necessary is made possible by the modular nature it possesses.



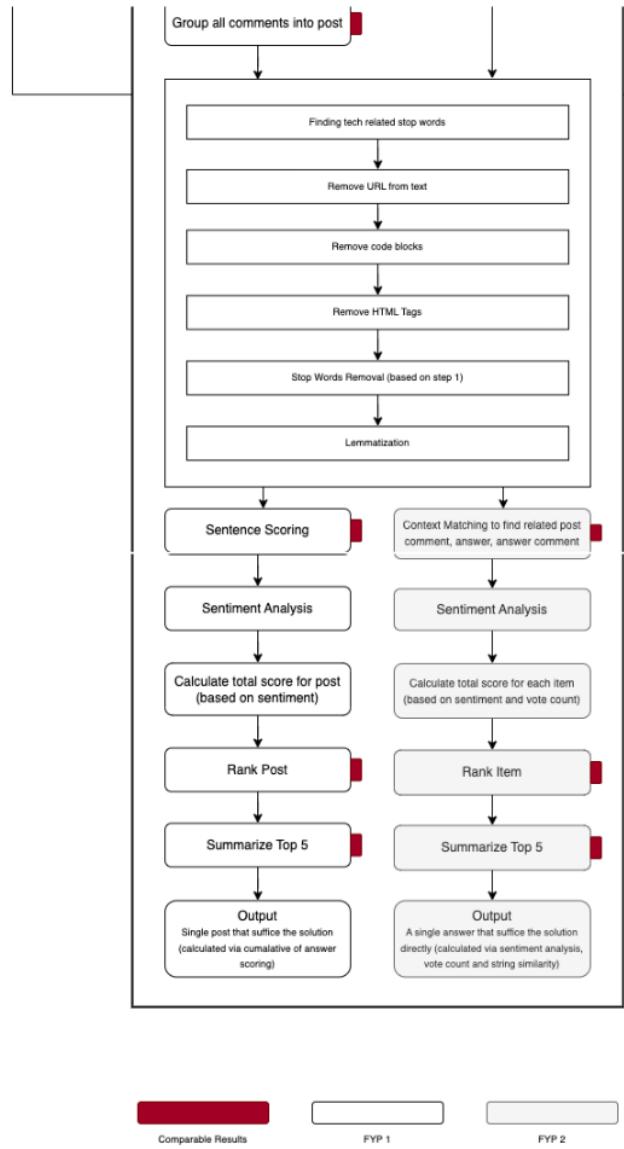


Figure 3.1: Overall proposed framework

Note: The background color of each cell in the framework denotes to:

- **Red - Comparable Results:** Stages where evaluation is done to compare results between each stages.

- White - *FYP 1*: Stages where the main focus is on FYP 1.
- Grey - *FYP 2*: Stages where the main focus is on FYP 2.

3.2 Data Collection (Scraping) – 1.0

According to the suggested framework 3.1, four primary data sources are identified in this work : Stack Overflow, GitHub (Issues), Reddit, and Twitter. Each dataset exhibits different characteristic. The data on Stackoverflow is in the form of questions and answers, but the data on GitHub is in the form of code majority speaking. Reddit data is a forum, whereas Twitter data is more likely to have rapid, real-time updates. In terms of FYP1, Stackoverflow will be our primary data source because it makes it much easier for us to demonstrate whether or not our method works. As a result, the dataset was scraped from stackoverflow.

The stackoverflow api is utilized to locate relevant topics on stackexchange depending on the developer's query. An api token is generated on the user dashboard.

The Stack Exchange API is a RESTful API that allows one to access data from Stack Exchange sites. It is a read-only API, which means that one can only retrieve data from the sites, not modify it. The API is available at api.stackexchange.com/docs.⁶⁹ One can use the API to retrieve data from Stack Exchange sites in a variety of formats, including JSON, XML, and JSONP. We'll be querying the data in JSON format.

Example of a query to the Stack Exchange API:

```
{  
  "tags": [  
    "node.js",  
    "reactjs",  
    "react-hooks"  
  ],  
  "owner": {  
    "account_id": 26363344,  
    "reputation": 9,  
    "user_id": 20019220,  
    "user_type": "registered",  
    "profile_image": "https://lh3.googleusercontent.com/...",  
    "display_name": "George Prethes",  
    "link":  
      "https://stackoverflow.com/users/20019220/george-prethes"  
  },  
  "is_answered": false,  
  "view_count": 27,  
  "answer_count": 3,  
  "score": 0,  
  "last_activity_date": 1674042867,  
  "creation_date": 1674039763,  
  "question_id": 75158231,  
  "content_license": "CC BY-SA 4.0",  
  "link": "https://stackoverflow.com/questions/75158231/..",  
  "title": "React useEffect onSubmit Rendering Post api  
multiple times"  
},
```

Figure 3.2: Stack Exchange API response

Figure 3.2 displays the response from the Stack Exchange API call with a number of useful pieces of data, including the tags, owner, title, link, and many more. In order to automatically scrap the necessary information from the relevant web sites. Selenium is used in this work.

23

Selenium is a free (open source) automated testing suite for web applications across

different browsers and platforms. It is used to automate web applications for testing purposes, but is certainly not limited to just that. Bots that perform web scraping, data mining, load testing, network traffic recording, and screen scraping are all common uses for the tool.

However, there is a problem since most websites nowadays uses anti-bot procedures to block automated programmes. Since the scraper may be blocked from accessing a Cloudflare-protected website, this complicates web scraping.

Therefore, A combination of selenium with the a python package named undetected chromedriver that is created and maintained by *ultrafunkamsterdam*, to properly exploit its potential. This bundle is a selenium wrapper that enables us to utilise selenium without being noticed by the website. The website will deny us access if it discovers that selenium is being used, so knowing this is crucial.

When all of that is complete and in place, scraping on all the posts will be done. The python code is designed to be error fail save, with the bulk of the code wrapped inside try catches blocks, so that if an error does occur, it will not stop the current process. This is critical since we'll be extracting more than 200-300 posts most of the time.

Below is the list of features scraped from stackoverflow. It contains 21 features in total. Post id, Post link, Post Title, Post Body, Post date, Post Votecounts, Comment id, Comment score, Comment username, Comment text, Comment Date Time, Answer id, Answer Text, Answer Body, Answer Date Time, Answer Votecounts, Answer Comment id, Answer Comment Text, Answer Comment Body, Answer Comment Date time, Answer Comment Votecounts,

Because Selenium has a capability called "Find Element," it is quite easy to zero in on all of the components that are of interest. The information is structured in a manner

similar to that of a dictionary, with the post id acting as the key and a list of all objects of interest performing the function of the value. After that, the data with the modifications are saved as a csv file. ⁶⁵ It is important to take note that the CSV file has a separate row for each comment, response, and response comment.

In this work, the scraper scrape articles that include the word "React UseEffect" in order to acquire the necessary data. As a result of this, a.csv file that has 3336 rows and 22 columns is saved and ready for use.

Notably, the web scraper is programmed to run once per day in order to provide us with the most recent data possible. This is necessary since data is always shifting, the framework aims to compile the most up-to-date information possible. In addition to this, the scraper will be housed on a server so that it may expand as the needs of the business dictate.

3.3 Inferencing Engine – 2.0

Figure 3.1 shows the proposed inference engine which will handle the core parts of the system. From preprocessing, sentence scoring, and sentence selection. Every nitty-gritty ⁶⁴ wil be explained in detail in the following sections.

3. Inference Engine

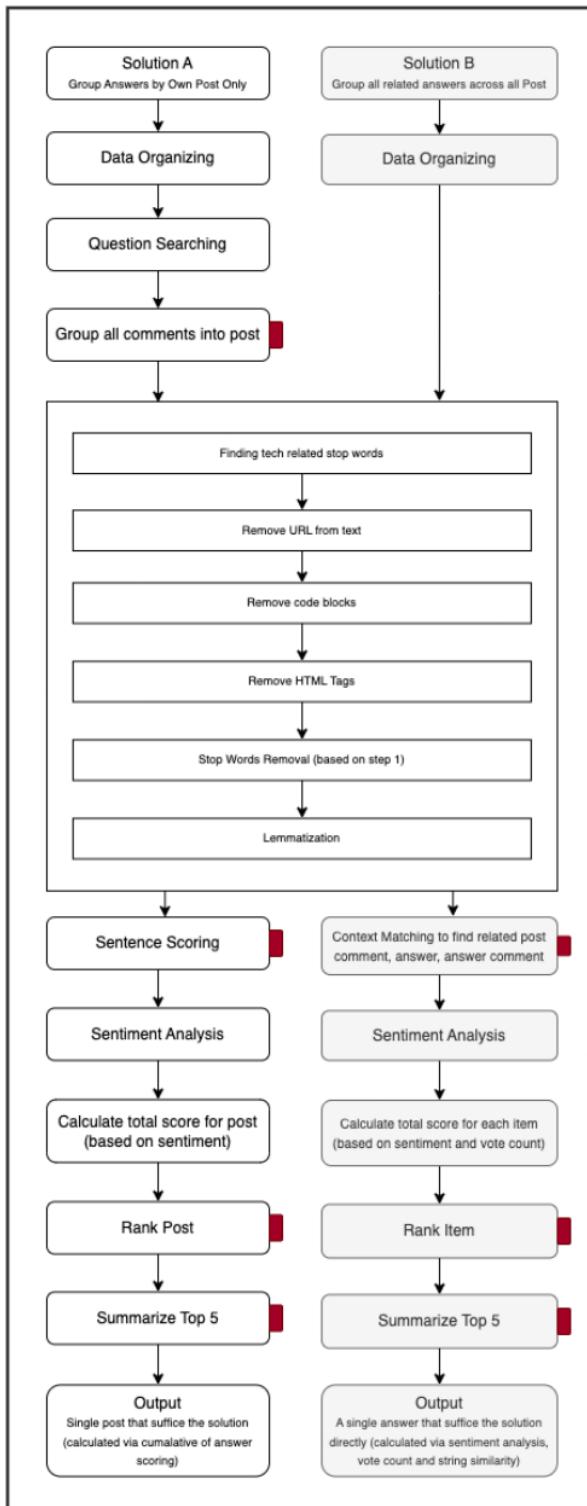


Figure 3.3: Proposed Inference Engine

Note: The background color of each cell in the framework denotes to:

- Red - *Comparable Results*: Stages where evaluation is done to compare results between each stages.
- White - *FYP 1*: Stages where the main focus is on FYP 1.
- Grey - *FYP 2*: Stages where the main focus is on FYP 2.

In the proposed inference engine system, 2 ideas had been proposed to work on the problem, they are named as solution A and solution B. While the work on FYP 1 only focuses on solution A, the work on FYP 2 focuses on testing both solutions, comparing the results and finding the best approach.

3.3.1 Solution A

Post titles are usually short and concise, and they are usually the first thing that people search for when they're looking for a solution to their problem. Therefore, it is intuitive to assume that the title of the post tells us what the post is about. With that being said, all comments and answers should be encapsulated in the post itself, and the post should be viewed as a whole when ranking is performed. This is the idea behind solution A. Essentially, solution A focuses on ranking the posts incorporating the comments and answers into the post itself.

3.3.2 Solution A - Architecture

A close up view of the architecture of solution A can be seen in the following figure 3.4.

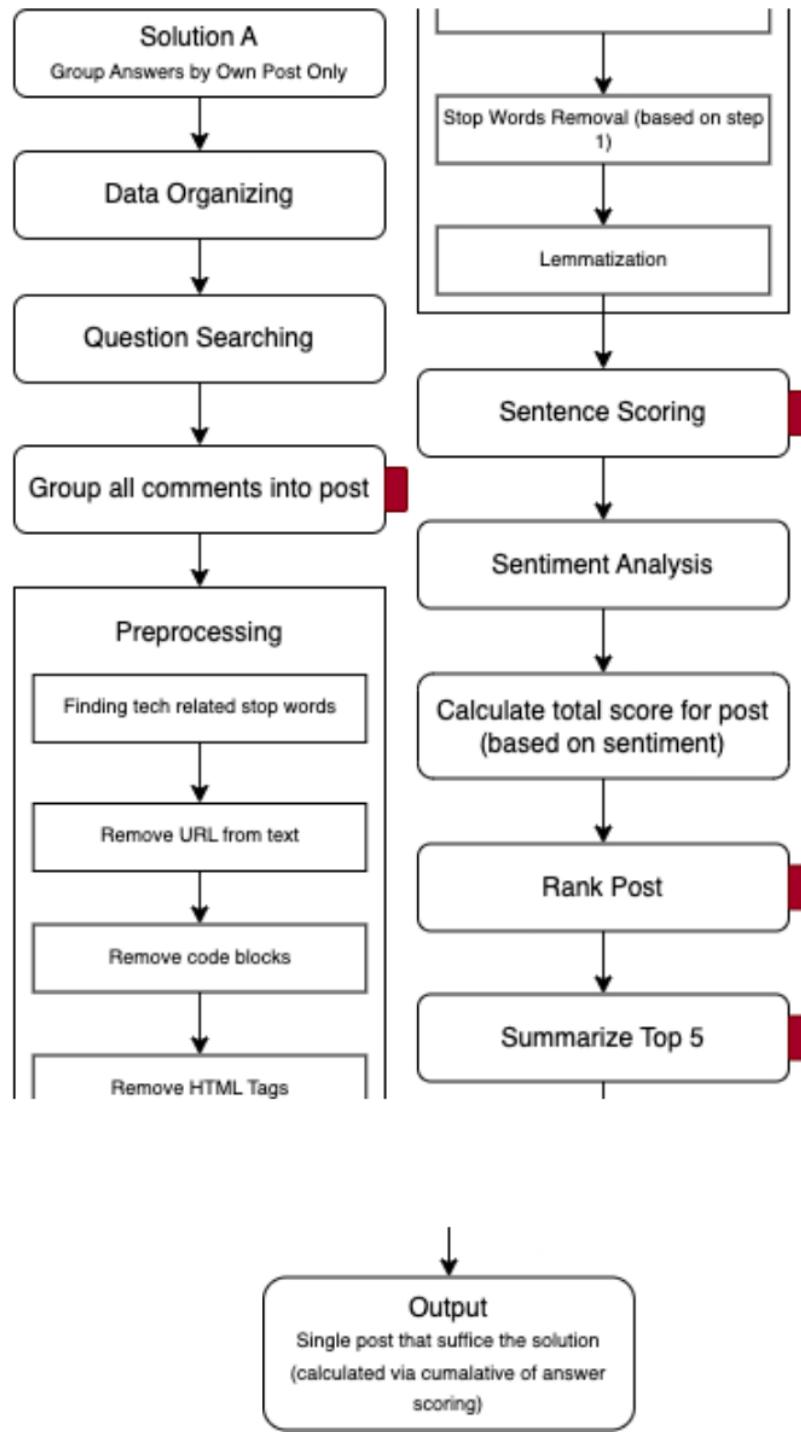


Figure 3.4: Solution A Architecture

3.3.2 (a) Data Organizing

First, The information will be arranged into the appropriate buckets. Posts, comments, answers and answers comments are the four primary types of information that'll be separate apart. The goal here is to facilitate our work with the data. The reason for this is that the data in the csv is not organized in a way that is conducive to our work. The comparison of the data before and after the organization is shown in the following figure.

Essentially the data is organized from this

```
All Columns DF  
Index(['POSTID', 'POSTLINK', 'POSTTITLE', 'POSTBODY', 'POSTDATE',  
       'POSTVOTECOUNTS', 'COMMENTID', 'COMMENTSSCORE', 'COMMENTUSERNAME',  
       'COMMENTTEXT', 'COMMENTDATETIME', 'ANSWERID', 'ANSWERTEXT',  
       'ANSWERBODY', 'ANSWERDATETIME', 'ANSWERVOTECOUNTS', 'ANSWERCMTID',  
       'ANSWERCMTTEXT', 'ANSWERCMTBODY', 'ANSWERCMTDATETIME',  
       'ANSWERCMTVOTECOUNTS', 'TYPE'],  
      dtype='object')
```

Figure 3.5: Unorganized Data

To this:

```

Post DF
Index(['POSTID', 'POSTLINK', 'POSTTITLE', 'POSTBODY', 'POSTDATE',
       'POSTVOTECOUNTS', 'TYPE'],
      dtype='object')

Post Comment DF
Index(['POSTID', 'POSTLINK', 'POSTTITLE', 'POSTBODY', 'POSTDATE',
       'POSTVOTECOUNTS', 'COMMENTID', 'COMMENTSORE', 'COMMENTUSERNAME',
       'COMMENTTEXT', 'COMMENTDATETIME', 'TYPE'],
      dtype='object')

Answer DF
Index(['POSTID', 'POSTTITLE', 'ANSWERID', 'ANSWERTEXT', 'ANSWERBODY',
       'ANSWERDATETIME', 'ANSWERVOTECOUNTS', 'TYPE'],
      dtype='object')

Answer Comment DF
Index(['POSTID', 'POSTTITLE', 'ANSWERID', 'ANSWERCMTID', 'ANSWERCMTTEXT',
       'ANSWERCMBODY', 'ANSWERCMTDATETIME', 'ANSWERCMTVOTECOUNTS', 'TYPE'],
      dtype='object')

```

Figure 3.6: Orginized Data

3.3.2 (b) Matching Posts based on String Similarity

The first step is to match the posts based on string similarity. This is done by using the python package fuzzywuzzy. Fuzzy Wuzzy is a Python library for doing approximate and partial string matching using Levenshtein distance.

There are two methods the work was used in fuzzy wuzzy, partial ratio is the first method, which is used to compare the similarity of two strings. The partial ratio method is a measure of the similarity between two strings, which is used in the fuzzy-wuzzy library. The partial ratio method calculates the ratio of the longest contiguous matching substrings between two strings.

Partial Ratio Flow:

- Split the longer string into all possible substrings of equal length to the shorter string.

- Calculate the ratio of similarity between each substring and the shorter string.
- Return the highest ratio of similarity.

This method can be more effective than other similarity measures, such as the Levenshtein distance, in certain situations where it's important to match substrings rather than individual characters. The partial ratio method can handle differences in the length of the two strings better than the full ratio method, which compares the two strings in their entirety.

The second method is token sort ratio. The token sort ratio method is a measure of the similarity between two strings, which is used in the fuzzywuzzy library. This method splits each string into a list of tokens (i.e., individual words or substrings) and sorts these tokens alphabetically. Then, it calculates the ratio of similarity between the sorted lists of tokens.

Token Sort Ratio Flow:

- Split each string into a list of tokens, using a specified delimiter (e.g., spaces).
- Sort the list of tokens in each string alphabetically.
- Calculate the ratio of similarity between the sorted lists of tokens.

The token sort ratio method is more robust to differences in word order than other similarity measures, such as the Levenshtein distance. For example, the token sort ratio between the strings "apple pear" and "pear apple" would be 100 percent, as the sorted lists of tokens are the same in both strings. This method is particularly useful when comparing strings that represent names or other similar data, where differences in word order can result in significant differences in the similarity of the strings.

In short, partial_ratio checks for longest matching substrings and token_sort_ratio checks for matching tokens after sorting them alphabetically. However, while both methods are robust enough to handle most common cases, they are not contextual and do not take into account the meaning of the strings.

Another string similarity method is then proposed, namely spaCy, which is a free, open-source library for advanced Natural Language Processing (NLP) in Python. It is designed specifically for production use and helps to build applications that process and “understand” large volumes of text.

The notable differences between FuzzyWuzzy and spaCy are:

- FuzzyWuzzy is based on Levenshtein distance, which is a metric for measuring the difference between two sequences. The levenshtein distance between two words is the minimum number of single-character edits (i.e. insertions, deletions or substitutions) required to change one word into the other.
- spaCy is based on word embeddings, which is a type of word representation that allows words with similar meaning to have a similar representation. Word embeddings are a type of word representation that allows words with similar meaning to have a similar representation. It is a distributed representation for the text that is perhaps one of the key breakthroughs for the impressive performance of deep learning methods on challenging natural language processing problems.
- FuzzyWuzzy is faster than spaCy, but spaCy is more accurate.
- FuzzyWuzzy is more suitable for matching short strings, while spaCy is more suitable for matching long strings.

Results are filtered to remain only those that have a score of 50 and above, as the results with a score below 50 are not relevant to the developer requirements. To crown a winner of two of this method in the work, the efficacy of both methods will be examined in the upcoming *chapter 4*.

3.3.2 (c) Group all answers, comments, and answer comments by post_id

The next step is to group all answers, comments, and answer comments by post_id, so this way, all answers, comments, and answer comments can be concatenated into a single dictionary with the post_id as the key, and thus all answers, comments, and answer comments can be viewed as a single entity, and can be compiled to a single string. Viewing everything as a single string is crucial for us as it's way easier to do sentence scoring, sentiment analysis and other NLP tasks on a single string than on a list of strings. For that to happen a class called **GroupedComments** is created, which is responsible for grouping all answers, comments, and answer comments by post_id.

```
class GroupedComments:  
    def __init__(self, title, post, post_comments, answers,  
                 answer_comments):  
        self.title = title  
        self.post = post  
        self.post_comments = post_comments  
        self.answers = answers  
        self.answer_comments = answer_comments
```

Figure 3.7: GroupedComments Class

A simple python script that iterates over the data and groups all answers, comments, and answer comments by post_id. The disctionary can be visualized as follows:

```

"post_id": {
    "title": "title",
    "post": "post",
    "post_comments": "post_comments",
    "answers": "answers",
    "answer_comments": "answer_comments"
}

```

Figure 3.8: GroupedComments Dictionary Example

Since now that the data has been formatted nicely it is very easy for us to track the context of the data and to do further analysis on the data.

3.3.2 (d) Preprocessing - Finding tech related stop words

78
3.3.2 (d) The next step is to find tech related stop words. This is done in order to 49
remove the stop words from the data. Stop words are words that are not important to the data, and they are usually words that are used frequently in the data.

However, finding stop words is a very tedious task, in the previous years, most of the time one would use manually curated stopwords lists to remove stop words from the

56
data (Gerlach et al., 2019), the stop words list can come from a variety of sources, such

54
as a list of stop words from a specific domain, or a list of stop words from a specific language. In our case, we're dealing with a very specific domain, which is the software engineering domain, normal stop words lists are not suitable for our case, as they are not specific to the software engineering domain. Noises in the dataset will be resulted

72
if a normal stop words lists is used to remove stop words from the data.

Stop words list can be found by using a wordcloud to find the most frequent words in the data, and then removing the most frequent words from the data. However, this

method is not very accurate, as it does not take into account the context of the data,

60

and it does not take into account the importance of the words in the data.

(Sarica & Luo, 2020) has made tremendous effort on curating the stopword list for the software engineering domain, they've done it by analyzing the data found in patent documents which mostly describes domains related to software engineering. The notable techniques they've used are minimally described in the Figure 3.9 below. In short, the author of (Sarica & Luo, 2020) had proposed a procedure which carefully picks stopwords from patented documents with using preprocessing techniques, a ranking framework based on terms statistics and finally with an evaluation carried out by experts based on a term-by-term basis. With that being said, the stopwords list curated by them are chosen to be used in this work.

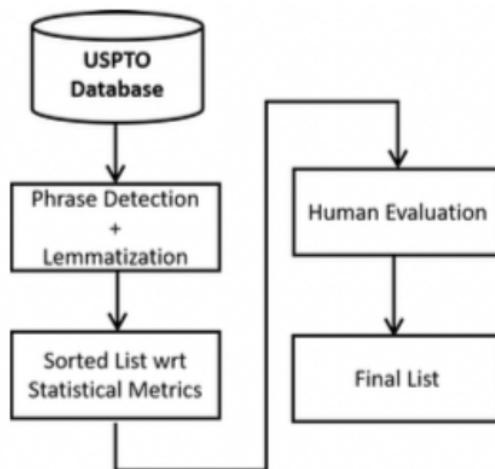


Figure 3.9: Overall Procedure by Sarica and Luo (2020)

3.3.2 (e) Remove Special Characters

The next step is to remove special characters from the data. The data scraped from StackOverflow consists all sorts of special characters, the data is not clean at all. Having special characters in the dataset might cause a lot of unwanted trouble, therefore special characters needed to be treated in our dataset. The table below ?? shows all the special characters that are identified in the dataset.

Case	VoteCount	Dates	All Columns
1	(, License: CC BY-SA 4.0	segFault
2)	(
3	,)	
5	,	,	

Table 3.1: Special Character

3.3.2 (f) Preprocessing - Extract URL from text

It is essential to incorporate URLs into the data, as these may be mined for information on the context of the data. The url can be easily extracted from the data as it is scraped since the data contains HTML tags. The BeautifulSoup package was utilised to access the URLs included inside the data. As a consequence of this, the url can be stored in a separate column of the dataset so that it can be referred to in the future.

In FYP 2, an effort will be made to put in place a framework that can autonomously determine the context relationships between retrieved URLs and extract more information from the URLs that have been obtained. Applying a score framework is one way to determine whether or not the URL in question is relevant to the data. If the scoring

method wasn't implemented, the process of the framework going to each of the urls would take a very significant amount of time.

3.3.2 (g) Preprocessing - Remove code blocks

The framework focuses on removing code blocks next, code blocks are not generally found in normal use cases and are not a huge concern on normal NLP tasks, however, by nature, this work is revolving around stackoverflow, a platform where developers post their questions and answers, and code blocks are a very common occurrence in stackoverflow. Therefore, removing code blocks is a very important step in the preprocessing process to reduce noises in our dataset. Code blocks are usually surrounded by "```" or "~~~" in the data, therefore it's is effortless to identify code blocks in the pipeline and to remove them.

3.3.2 (h) Preprocessing - Remove HTML Tags

HTML Tags are another concerning factors in our work, where the scraping process might have caused some HTML tags to be included in the data. Therefore, special attention is needed to be given to remove the HTML tags. HTML tags are usually surrounded by < and > in the data.

3.3.2 (i) Preprocessing - Stop Words Removal

In the previous step 3.3.2 (d), we've found a list of stop words that are related to the technology domain. The removal is not done on the previous step because the text might contain noisy data. At this current stage, the data has been cleaned and this suggests that the removal of stop words can be done.

3.3.2 (j) Preprocessing - Lemmatization/Stemming

The process of truncating a word to its root or base unit is called stemming or lemmatization.

In the discipline of Natural Language Processing, text normalisation techniques like stemming and lemmatization are employed to get sentences, words, and documents ready for analysis. For instance, the terms "kick" and "kicked" are both forms of the verb "to kick," thus it's possible that you'll want your natural language processing application to recognise this. This is the idea of stripping down many uses of a term to its essential meaning.

Techniques like lemmatization or stemming can be achieved by using the famous Python NLTK package.

However, whether to utilise stemming or lemmatization is a contentious issue. Because stemming is a primitive heuristic procedure that cuts off the ends of words in the aim of reaching this objective properly most of the time, it often involves the removal of derivational affixes.

Lemmatization, on the other hand, is a more complex technique that takes into consideration morphological examination of the words. It does this by the use of a lexicon and morphological analysis of words, with the goal of removing only inflectional ends and returning the base or dictionary form of a word, known as the lemma.

The decision on using stemming or lemmatization will be later defined in chapter 4.

3.3.2 (k) Sentence Scoring

Consequently, all of our sentences should be clean and ready to be scored. The scoring process is done by using the TF-IDF algorithm. The TF-IDF algorithm is a statistical measure that evaluates how relevant a word is to a document in a collection of documents. The algorithm is composed of two terms: the first computes the normalized Term Frequency (TF), to further clarity, the number of times a word appears in a document, divided by the total number of words in that document; the second term is the Inverse Document Frequency (IDF), computed as the logarithm of the number of the documents in the corpus divided by the number of documents where the specific term appears.

The TF-IDF score is the product of these two terms. The TF-IDF score increases proportionally to the number of times a word appears in the document and is offset by the number of documents in the corpus that contain the word, which helps to adjust for the fact that some words appear more frequently in general.

The TF and IDF scores are defined as follows:

$$TF = \frac{\text{Number of times term } t \text{ appears in a document}}{\text{Total number of terms in the document}} \quad (3.1)$$

$$IDF = \log \frac{\text{Total number of documents}}{\text{Number of documents with term } t \text{ in it}} \quad (3.2)$$

At last, The TF-IDF scoring can be simplified into a single formula as shown below:

$$TF-IDF = TF \times IDF \quad (3.3)$$

Each sentences are then scored using the TF-IDF algorithm, the scored are then averaged and the average score is used to rank the associated post. This suggests that the post with the highest score will be the most relevant post to the question.

3.3.2 (l) Sentiment Analysis

Sentiment analysis is the process of determining whether a piece of writing is positive, negative, or neutral. It's also known as opinion mining, deriving the opinion or attitude of a speaker. A common use case of sentiment analysis is to discover how people feel about a particular topic.

Sentiment analysis is usually performed on textual data to help businesses monitor brand and product sentiment in customer feedback, and understand customer needs. It can also be used to gauge the sentiment of the general public to a particular event.

But how does sentiment analysis take place in our framework?

For context, each posts are scored based on the TF-IDF algorithm. The score is then used to rank the post. However the score itself is not telling enough to determine whether the post is useful or not. We've made an assumption that the post with a positive sentiment is more likely to be useful than the post with a negative sentiment. Hence, sentiment analysis is used to determine the sentiment of the post and gives a telling factor of how well "ranked" the post is. Ultimately, it is to add another layer of filtering on the ranking aspect of the framework.

3.3.2 (m) Sentiment Analysis – Model

The sentiment model used in this work is the famous twitter roberta base sentiment analysis model, which has been used over 2 million times this month. It is a RoBERTa base model trained on approximately 124M tweets from January 2018 to December 2021, and finetuned for sentiment analysis with the TweetEval benchmark. The model is able to predict and inference a probability score for each of the 3 classes: positive,

negative, and neutral.

While twitter roberta based sentiment analysis is a normal sentiment analysis model, multiple research has shown in *chapter 2* that aspect-based sentiment analysis is a better approach to sentiment analysis as it is able to identify the sentiment of a specific aspect of a sentence. An aspect-based sentiment analysis approach will be examined in FYP2.

3.3.2 (n) Summarization

Finally as the framework approached to the final cell of the pipeline 3.4, in order to fulfill a better user experience, the engine will then summarize the top 5 sentiment ranked posts.

Summarization is the process of shortening a text document with software, in order to create a summary with the major points of the original document. As the name suggests, it is a technique to reduce the size of the given text while trying to retain the most important information. A summarization is crucial in our framework as it will help the user to understand the post better, faster and easier.

3.3.2 (o) Summarization – Model

The model we've used is the very well known bart large cnn model, which has been used over 1 million times this month. BART model pre-trained on English language, and fine-tuned on CNN Daily Mail. It was introduced in the paper BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation

BART is a transformer encoder-encoder (seq2seq) model with a bidirectional (BERT-like) encoder and an autoregressive (GPT-like) decoder. BART is pre-trained by (1) corrupting text with an arbitrary noising function, and (2) learning a model to reconstruct the original text. BART is particularly effective when fine-tuned for text generation (e.g. summarization, translation) but also works well for comprehension tasks (e.g. text classification, question answering). This particular checkpoint has been fine-tuned on CNN Daily Mail, a large collection of text-summary pairs.

Summarization will be done to each of the top 5 sentiment ranked posts. To clarify,

the summarization summarizes all of the texts from the post, including the post, post comments, answer and lastly answer comments. In addition, the sentences are sorted based on time, this is to ensure that the summarization is in chronological order, where BART will be able to pickup any time series related information about the context of the on-going conversation. Namely, user mentioning each others in the comments section.

3.3.3 Solution B

The first solution focuses on ranking posts, whereby all comments, answers and answers comments are grouped together with the post and is been seen as a whole entity. Closed loop context, is the issue that we'll be addressing in this solution. We'll be explaining the architecture, the issue of solution A in detail, and the approach that we'll be taking to solve the issue.

3.3.3 (a) Solution B - Issue of Solution A

The issue of solution A is the situation – closed loop context, meaning that the ranking of the posts solely depends on the numbers, interactivity and the sentiment of the comments, answers and answers comments of the post.

This is not a serious problem, however there is room for improvement. Jumping on another point of view, let's zoom out from the post context, let's view all of the comments, answers, and answer comments all together from every posts. The argument that we're trying to define here is, is there possibility that the answers from other posts are more relevant to the query than the answers from the post itself? The sole reason where the post that contains the better answers is not ranked is because the title of the post is not relevant to the query.

This is where the second solution comes in. The pipeline uses mostly the same approach as solution A, however we'll be grouping all related answers across all posts and do string similarity, and the rest of the architecture will be more or less similar to solution A.

Note, this is a solution made up with an assumption of the possibility of the answers

from other posts are more relevant to the query than the answers from the post itself.

The actual implementation will be covered in FYP2.

3.3.3 (b) Solution B - Architecture

The architecture of solution B is very similar to solution A, the only difference is that the framework will be grouping all related answers across all posts, The architecture is shown below 3.10

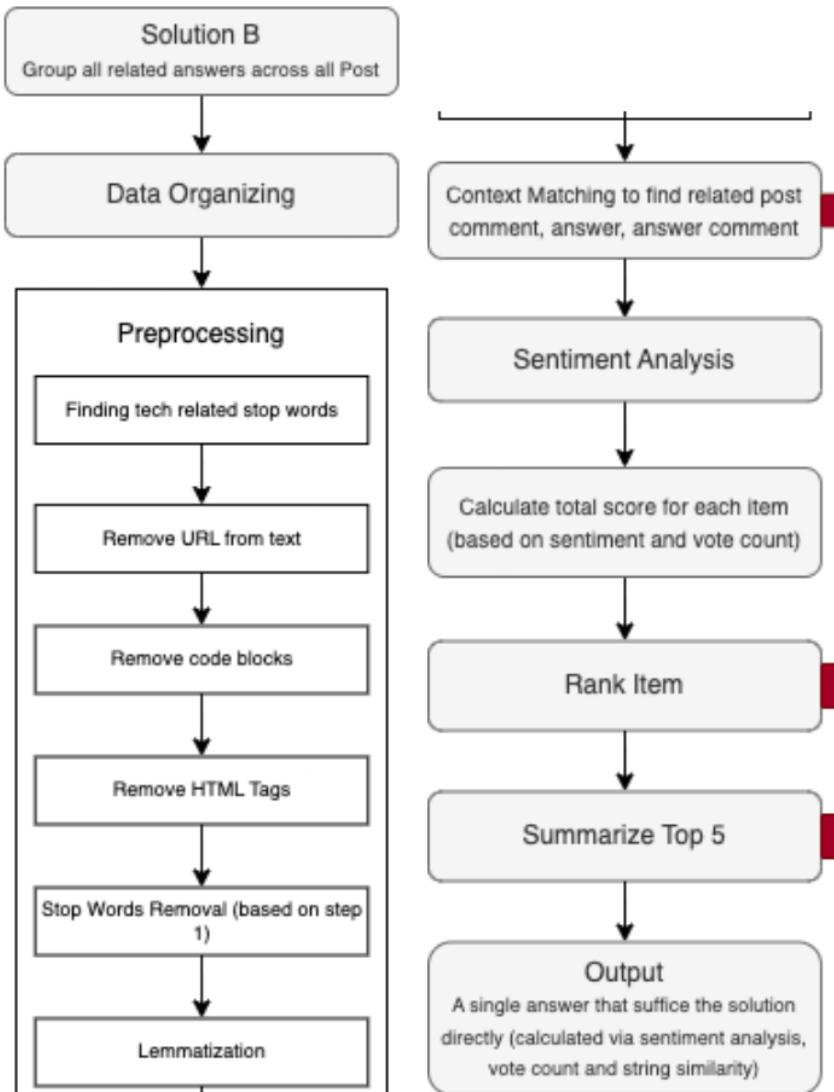


Figure 3.10: Solution B Architecture

3.3.3 (c) Solution B - Approach

The approach is very similar to solution A, the only differentiating factor is that the pipeline not only focuses on an individual post when ranking but on a wider context,

all of the posts, post comments, answer, answer comments. To summarise, all of the comments should be seen as equal no matter the parent post of the comments itself.

Data cleaning ??, organizing 3.3.2 (a), pre-processing 3.3.2 (d) will be done in the same way as solution A. Just that the data will not be grouped by post 3.3.2 (c), but rather by all posts.

This way all comments, answers, answers comments take a part in the ranking process.

This work believe that this is a better framework as it excludes the bias of the post title, and it helps to rank the individual item that are more relevant to the query, eventually leading to a better user experience.

3.4 Topic Modeling

To further improve the framework, topic modelling is the final pieces to the puzzle.

Topic modelling can be used to further mine topics that are hidden in the data, the topic mined can be then used to tag the posts providing extra information when a search is made on our framework.

Topic modeling is a natural language processing technique used to identify and extract the main topics that are discussed in a large collection of text documents. It is a process of automatically discovering the topics that are present in a text corpus by grouping together words that frequently occur together. The resulting topics can then be used for various downstream applications such as text classification, information retrieval, and summarization.

In the context of chatbots like ChatGPT, topic modeling can be used to identify the main topics that are being discussed in a conversation and use that information to generate more relevant and coherent responses. For example, if the conversation is

about a particular news article, the topic model can extract the main topics discussed in the article and use that information to generate a summary or to provide additional information on the same topic.

In FYP2, we hope to port over some of the ideas discussed above to further enhance the framework proposed in this work.

3.5 Real Time Capabilities Issue

One of the big issues for this framework to be generalized is the dataset. The dataset has to be generalized enough to be able to answer any query, that is simply impossible considering the wide range of the technical field.

Real time scraping to populate the dataset is not a good idea as it will be very costly, time consuming, and cpu intensive, as our workers have to scale up to the demand of the users.

Therefore, two solutions are created to solve the problem, the first solution is to build a FAQs repository to store FAQs for further usage, and the second solution is to predict the next faq that will be asked.

3.6 FAQs Repository

With the first solution, a FAQs repository is needed to be built. The FAQs repository will be a collection of questions and answers that are related to the technical field. The way it works is that whenever a user asks a question, the framework will check if the question is in the FAQs repository, if it is, the framework will return the answer from the FAQs repository. If it's not, the framework will then scrap all the related posts from stackoverflow, and do inferencing. The summarized result will be stored in the FAQs repository, and the user or anyone will be able to access the answer from the FAQs repository next time they ask the same question.

3.7 FAQs Repository - Architecture

In the below figure, the architecture of the FAQs repository is presented. The FAQs repository is a database that stores the questions and answers. The database is populated by the system, and the framework will check the database whenever a user asks a question.

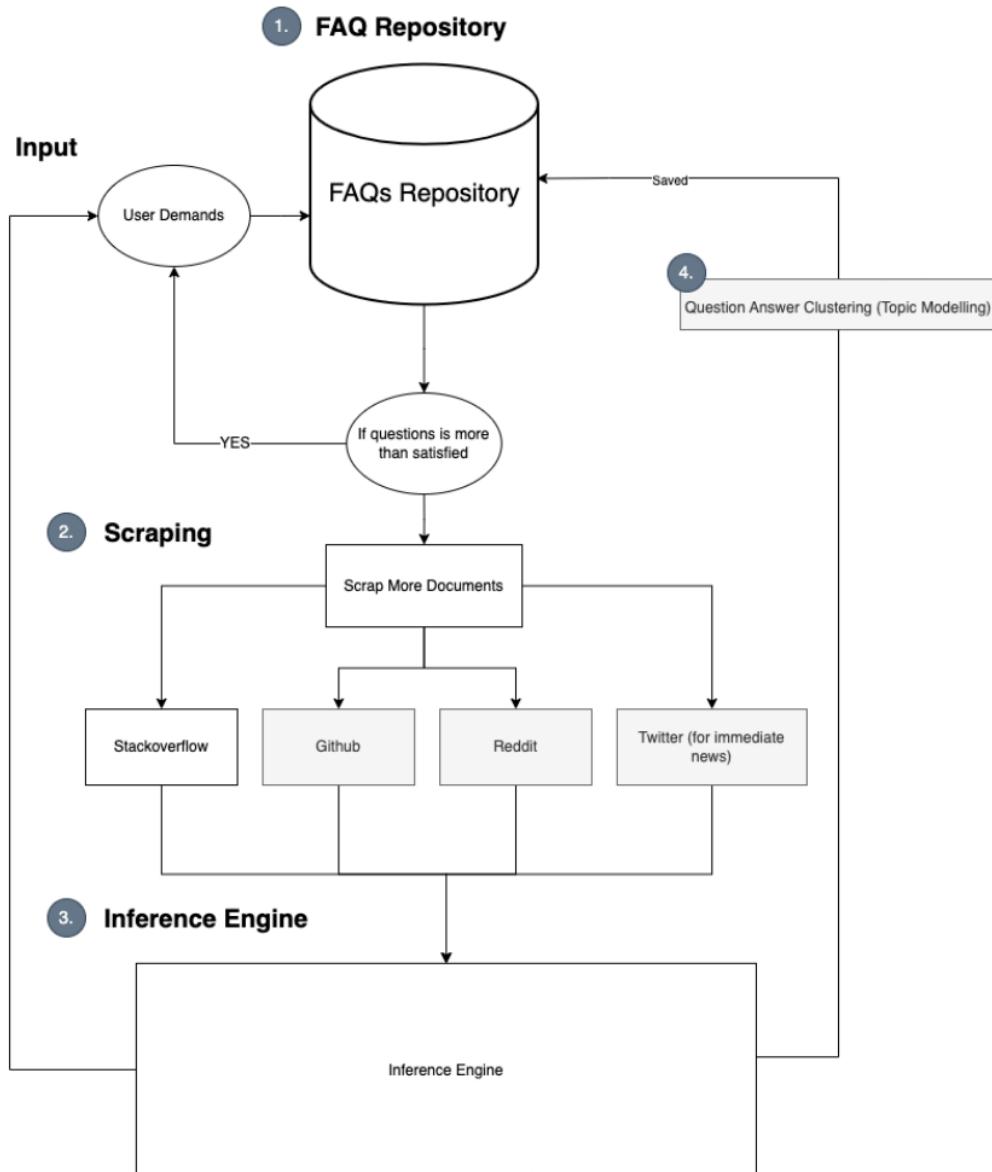


Figure 3.11: FAQ Repository Architecture

3.8 FAQs Repository - Approach

With the above architecture, the framework will be functioning as stated below:

1. The user asks a question
2. The framework will check if the question is in the FAQs repository
3. If the question is in the FAQs repository, the framework will return the answer from the FAQs repository
4. If the question is not in the FAQs repository, the framework will then scrap all the related posts from stackoverflow, and do inferencing
5. The summarized result will be stored in the FAQs repository, and the user or anyone will be able to access the answer from the FAQs repository next time they ask the same question.

With this architecture, the framework ensures that it is not only able to answer the question that is asked before, but also able to answer the question that is not asked before, also it can ensure that the framework will not scrap the same question again and again, as it's already in the FAQs repository.

3.9 FAQs Repository - Database Design

The database of choice is MongoDB, as it's a NoSQL database, and it's very easy to scale up. As a plus point, MongoDB being a NoSQL database gives us the flexibility to store the data in anyway we wanted, and the structure of the data can be altered whenever.

The database will be structured as below:

```

ISent {
    p_score: number;
    n_score: number;
    nu_score: number;
    comparative: number;
    tokens: string[];
    words: string[];
    positive: string[];
    negative: string[];
    neutral: string[];
}

IAns {
    answer: string;
    tags: string[];
    upvotes: number;
    downvotes: number;
    sentiment: ISent;
}

IFaq {
    question: string;
    answer: IAns[];
    tags: string[];
}

```

Figure 3.12: FAQ Database Structure

3.10 FAQs Repository - System Design

The entire backend will be built using NodeJs, as it's a very popular language, and it's very easy to scale. We'll be using a boilerplate created by the author of this thesis, which consists of multi-threading and clustering capabilities. These factors will help us to scale up the framework whenever there's a need to. The boilerplate is available at <https://github.com/Shaunmak1214/cluster-node-auth-sql-boilerplate.git>. A few notable perks that the boilerplate has is that it has a built in authentication system, and it has a built in SQL database, and a whole lot more. All of the important

features of the boilerplate will be listed below:

- Clustering in Node.js
- Server with Express.js
- Database schema and models using Sequelize ORM
- User authentication with JWT
- StandardJs for coding standards and styling
- Request validation using Express-validator
- Morgan and Winston for server side logging
- Swagger for API documentation

To host the backend, AWS EC2 is used, as it's the best cheap option, and it's very easy to scale according to user demands. Amazon Elastic Compute Cloud (Amazon EC2) offers the broadest and deepest compute platform, with over 500 instances and choice of the latest processor, storage, networking, operating system. Lastly to protect the servers from ddos attacks, AWS WAF is used , which is a web application firewall that helps protect a web applications from common web exploits that could affect application availability, compromise security, or consume excessive resources. AWS WAF gives one control over which traffic to allow or block to a web applications by defining customizable web security rules. One can use AWS WAF to create security rules that block common attack patterns, such as SQL injection or cross-site scripting, and rules that filter specific types of traffic. AWS WAF is integrated with AWS Shield, a managed DDoS protection service that safeguards web applications

running on AWS. AWS Shield Standard provides always-on detection and automatic inline mitigations that minimize application downtime and latency, and AWS Shield Advanced provides distributed denial of service (DDoS) attack protection, proactive engagement with AWS support, and usage metrics.

3.11 CronJobs - Predictive FAQ Generation System

While the first solution – FAQ Repository 3.6 is able to solve the problem, there's still a concerning factor. The FAQs repository solution works well if a question is already asked by someone, but what if a question is not asked by anyone before? The framework will not be able to answer the question, and the user will have to wait for the lengthy process for the framework to scrap, process, analyze, rank and summarize the data for the user.

To solve this problem, a cronjob that runs the framework every 24 hours will be implemented, the framework will scrap, process, analyze, rank and summarize the data, and store it in the FAQs repository. This approach, assumes and rightfully predicts the newest, latests tech questions around four of the platforms, Stackoverflow, Reddit, Twitter and Github. The predicted topic is then used to scrap more data from the same platform, and hopefully it suffices the user's needs.

3.12 CronJobs - Predictive FAQ Generation System - Architecture

5. CronJobs

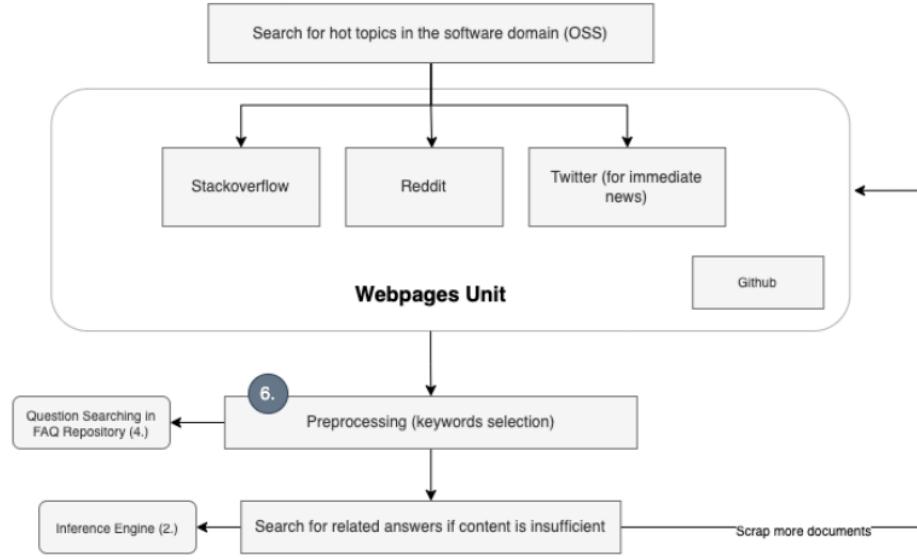


Figure 3.13: CronJobs Architecture

3.13 CronJobs - Predictive FAQ Generation System - Approach

With the above architecture, the framework will be functioning as stated below:

1. The framework will scrap all the posts from stackoverflow, reddit, twitter and github every 24 hours
2. Perform topic modeling on the scrapped data, Extracting keywords
3. If dataset is not sufficient (metrics will be explored), scrap more documents related to the topic.
4. Process, analyze, rank and summarize the data
5. Store the summarized data in the FAQs repository

Which the proposed architecture, the proposed framework will populate itself with the most recent data, and in the hopes where the framework is able to fit with the user's

needs.

CHAPTER 4

PRELIMINARY RESULTS AND DISCUSSION

4.1 Data Exploration

Data exploration refers to the process of analyzing, cleaning, transforming, and modeling data with the goal of discovering valuable insights and understanding the underlying structure of the data. It is an essential step in the data science process and involves visualizing and summarizing data, identifying patterns, outliers and anomalies, and checking for missing or duplicate data. Data exploration helps you get a sense of what your data looks like, identify potential problems, and make informed decisions about how to prepare the data for further analysis. By exploring your data, you can gain insights into the relationships and patterns that exist within the data and gain a better understanding of the problem you are trying to solve.

4.1.1 Unique Posts

First we should look at how many unique posts there are. This is important since we want to make sure that we have enough data to work with. After analyzing the data, we can see that there are 660 unique posts. This is a good sign since it means that we have enough data to work with.

4.1.2 Post Time Distribution

In order to analyze the longevity of the current topic on stackoverflow, we will plot the time span distribution of all postings as a whole.

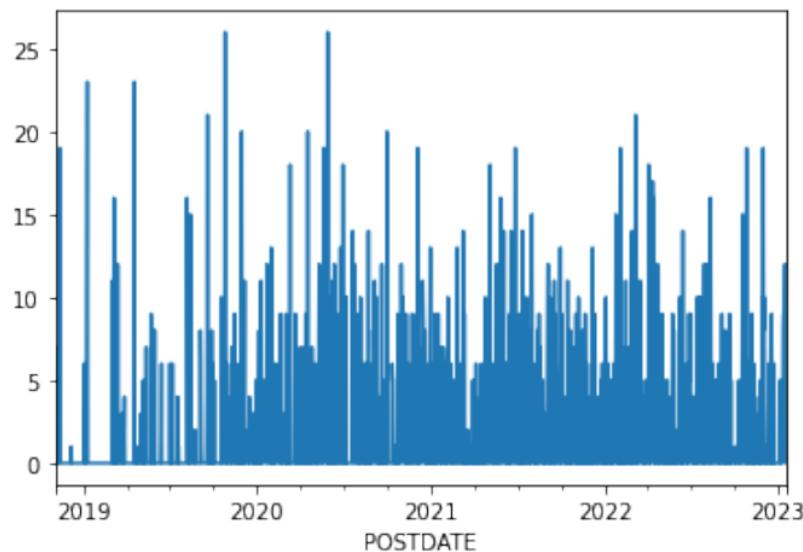


Figure 4.1: Post time distribution

As you can see on the above Figure 4.1, the number of posts per day is pretty constant.

This is a good sign since it means that the number of people using the React UseEffect is still there and therefore it might give us a better result.

4.1.3 Vote Counts Distribution

Next, we will look at the votecounts distribution across all of the dataset as a whole, it is important to note that the votecounts is the number of votes that a post has received, the higher the votecounts, the more popular the post is. We can probably infer that the more popular the post is, the more likely it is to be answered, and the more likely it is to be answered, the more likely it is to be answered correctly.

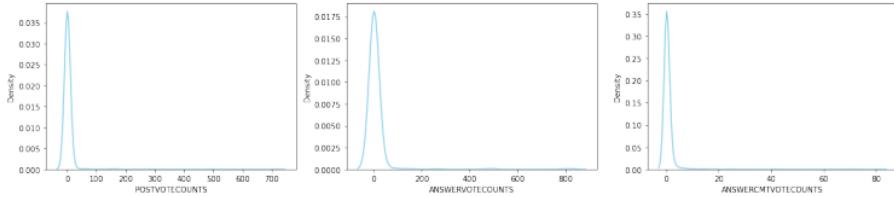


Figure 4.2: Vote counts distribution

As you can tell from the graph in Figure 4.2, the distribution is skewed to the left. This is not a good sign as it means that the majority of the posts have a low votecounts. With that being said, this motivates us to explore more data to be mined from the dataset and facilitate to our work.

4.2 Post Matching

Post Matching is one of the most important part of this work. It is important to note that the post matching is not a trivial task. There are many ways to do it, in the following section we discuss the results that are obtained from 2 different methods that are noted on the "Proposed Framework" section 3.3.2 (b). In the below discussion, we used the query "How to solve useEffect hook rerenders infinitely?" to test and evaluate the performance of the post matching methods, it is important to note the post's title is the only string that is used to match with the query.

4.2.1 Fuzzy Wuzzy: Partial Ratio and Token Sort Ratio Combined

Fuzzy Wuzzy is a python library that provides string matching algorithms. The library provides a simple and efficient way to perform fuzzy string matching tasks, such as finding the similarity ratio between two strings, and finding the closest match for a

given string from a list of potential candidates. A detailed discussion on how partial ratio and token sort ratio differ from each other is further highlighted 3.3.2 (b).

4.2.1 (a) Results:

postId	title	partial_ratio	token_sort_ratio	average
0 73534338	React UseEffect render infinite loop	77	79	78.0
0 64651759	react useEffect hook causes infinite loop	71	71	71.0
0 58557877	React useEffect hook infinity loop	62	75	68.5
0 65558836	React useEffect hook is causing infinite loop	69	68	68.5
0 71835956	React UseEffect hook Issue Rendering an Interval	66	70	68.0
...
0 73334298	React useEffect every 5 seconds with setInterval...	51	50	50.5
0 60524845	React useEffect and clearInterval	45	56	50.5
0 59725069	React useEffect hook register callback with ac...	54	47	50.5
0 70258999	React useEffect() infinite re-render for getti...	46	55	50.5
0 61127662	React useEffect restarting timer	47	54	50.5

112 rows × 5 columns

Figure 4.3: Partial Ratio and Token Sort Ratio Combined Results

Using the partial ratio method combined with token sort ratio, it is able to yield 112 posts title to match with the query.

4.2.1 (b) Spacy Similarity

Spacy is a python library that provides a lot of NLP tools. The library provides a simple and efficient way to perform NLP tasks, such as finding the similarity ratio between two strings, and finding the closest match for a given string from a list of potential candidates. A detailed discussion on how spacy similarity differs from other methods is further highlighted 3.3.2 (b).

4.2.1 (c) Results:

	postid	title	score
0	65404350	How to correctly add event listener to React u...	0.902468
0	70710122	How to use setInterval with react useEffect ho...	0.899317
0	72632981	How to fulfill React useEffect missing depende...	0.871420
0	74609238	How to stop the infinite loop inside this Reac...	0.861767
0	67343507	How to give a boolean indicator to React useEf...	0.833936
...
0	70790681	React useEffect dependency not triggering from...	0.507214
0	72784960	I dont understand why this infinite loop wont ...	0.505654
0	70110116	React useEffect does infinite loop	0.504187
0	71157226	Why is React useeffect not updated when props ...	0.502435
0	73369425	React useEffect invalid hook call	0.500079
195 rows x 3 columns			
195 number of titles found			

Figure 4.4: Spacy Results

A total of 195 posts are matched using the spacy similarity method. Indicating a better matching performance than the fuzzy wuzzy method.

4.3 Proprocessing

4.3.1 Evaluate Examples

4.3.1 (a) Example 1

Imagine if that was a Web Socket and we were scheduling a new heartbeat tick every time we remounted; the server would be very angry at our apps heart palpitations.

Figure 4.5: Examples for Evaluation Uses: Example 1

The text above was used to test and evaluate the following sections 4.3.2 4.3.3

4.3.1 (b) Example 2

```
'\n<p>You have to convert the response to json <a href="https://google.com">Please Look at this link</a> with await <a href="https://google.com">await</a> response.json();\nand then use setState.</p>\n\n<pre class="lang-js s-code-block"><code class="hljs language-javascript"><span class="hljs-title function_">useEffect</span>(<span class="hljs-function">() =&gt;</span> { \n <span class="hljs-variable language_">console</span>.<span class="hljs-title function_">log</span>(<span class="hljs-string">"useEffect TopTen has been called!"</span>); \n <span class="hljs-keyword">const</span> <span class="hljs-title function_">fetchdata</span> = <span class="hljs-keyword">async</span> (<span class="hljs-params"></span>) =&gt; {\\n <span class="hljs-keyword">const</span> response = <span class="hljs-keyword">await</span> api.<span class="hljs-title function_">topTen</span>(); <span class="hljs-comment">// this calls axios(url)</span>\\n <span class="hljs-keyword">const</span> responseData = <span class="hljs-keyword">await</span> response.<span class="hljs-title function_">json</span>();\\n </pre>\\n '
```

Figure 4.6: Examples for Evaluation Uses: Example 2

The text shown is a non-edited scraped html from stackoverflow. It was used to evaluate the following sections 4.3.4 4.3.5 4.3.6

4.3.2 Stopwords Removal

Stopwords are identified as the common words that exists in a language, they are usually removed from the text to give more importance to other words in the text. Stopwords lists can be subjective, stopwords list differ itself from one language to another,

also they are different when treating texts from different domains. A detailed discussion on this domain is further highlighted 3.3.2 (d).

4.3.2 (a) *Results:*

The results after using the stopwords removal is as follows:

Original	Results
Imagine if that was a Web Socket and we were scheduling a new heartbeat tick every time we remounted; the server would be very angry at our apps heart palpitations.	imagine web socket scheduling new heartbeat tick every time remounted; server would angry apps heart palpitations.

Figure 4.7: Stopwords Removal Results

4.3.3 Stemming vs Lemmatization

A comparison of the results of stemming and lemmatization is shown below. Stem-

ming is the process of reducing inflected (or sometimes derived) words to their word stem, base or root form—generally a written word form. Lemmatization is the process of grouping together the inflected forms of a word so they can be analysed as a single item, identified by the word's lemma, or dictionary form. A detailed discussion on this domain is further highlighted 3.3.2 (j).

4.3.3 (a) Stemming Results:

Original	Results
Imagine if that was a Web Socket and we were scheduling a new heartbeat tick every time we remounted; the server would be very angry at our apps heart palpitations.	imagin if that wa a web socket and we were schedul a new heartbeat tick everi time we remount ; the server would be veri angri at our app heart palpit .

Figure 4.8: Stemming Results

4.3.3 (b) Lemmatization Results:

Original	Results
Imagine if that was a Web Socket and we were scheduling a new heartbeat tick every time we remounted; the server would be very angry at our apps heart palpitations.	Imagine if that wa a Web Socket and we were scheduling a new heartbeat tick every time we remounted ; the server would be very angry at our apps heart palpitation .

Figure 4.9: Lemmatization Results

In this work, lemmatization is chosen. Lemmatization has proven to be more effective than stemming if context of the text is taken into consideration.

4.3.4 Extracting URL

4.3.4 (a) Results:

Original	Extracted
<pre>\n<p>You have to convert the response to json Please Look at this link with await await response.json();\nand then use setState.</p>\n\n<pre class="lang-js s-code-block"><code class="hljs language-javascript">useEffect(() =&gt; { \n console.log("useEffect TopTen has been called!"); \n const fetchdata = async () =&gt; { \n const response = await api.topTen(); // this calls axios(url)\n const responseData = await response.json();\n </pre>\n'</pre>	[('https://google.com', 'Please Look at this link'), ('https://google.com', 'await')]

Figure 4.10: Extracting URL Results

The url and the text that is linked to the url is extracted and shown in the results.

4.3.5 Code Blocks Removal

4.3.5 (a) Results:

Original	Results
<pre>\n<p>You have to convert the response to json Please Look at this link with await await response.json();\nand then use setState.</p>\n\n<pre class="lang-js s-code-block"><code class="hljs language-javascript">useEffect(() =&gt; { \n console.log("useEffect TopTen has been called!"); \n const fetchdata = async () =&gt; { \n const response = await api.topTen(); // this calls axios(url)\n const responseData = await response.json();\n </pre>\n ,</pre>	<pre>\n<p>You have to convert the response to json Please Look at this link with await await response.json();\n and then use setState.</p>\n\n<pre class="lang-js s-code-block"></pre>\n ,</pre>

Figure 4.11: Code Blocks Removal Results

In this step, the codeblocks is removed from the original html by detecting the tags and classes used.

4.3.6 HTML Tags Removal

4.3.6 (a) Results:

Original	Results
<pre>'\n<p>You have to convert the response to json Please Look at this link with await await response.json();\nand then use setState.</p>\n\n<pre class="lang-js s-code-block"><code class="hljs language-javascript">useEffect(() =&gt; { \n console.log("useEffect TopTen has been called!"); \n const fetchdata = async () =&gt; { \n const response = await api.topTen(); // this calls axios(url)\n const responseData = await response.json();\n </pre>\n'</pre>	<pre>'\n You have to convert the response to json Please Look at this link with await await response.json();\nand then use setState.\n\nuseEffect() =&gt; { \n console.log("useEffect TopTen has been called!"); \n const fetchdata = async () =&gt; { \n const response = await api.topTen(); // this calls axios(url)\n const responseData = await response.json();\n setLoading(false);\n setTopten(responseData. data); \n setError(responseData. error); \n }; \n\n fetchdata (); \n}, []); \n\n '</pre>

Figure 4.12: HTML Tags Removal Results

In this step, the html tags is removed from the original html by detecting the tags.

4.3.7 Combining all proprocessing techniques

By combining all of the proprocessing techinques used above 4.3.2 4.3.3 4.3.4 4.3.5

4.3.6, an evaluation is made using Example 2 4.3.1 (b)

Original	Results
<pre>'\n<p>You have to convert the response to json Please Look at this link with await await response.json();\nand then use setState.</p>\n\n<pre class="lang-js s-code-block"><code class="hljs language-javascript">useEffect(() =&gt; { \n console.log("useEffect TopTen has been called!"); \n const fetchdata = async () =&gt; { \n const response = await api.topTen(); // this calls axios(url)\n const responseData = await response.json();\n </pre>\n '</pre>	<p>You have to convert the response to json with await response.json();and then use setState.</p>

Figure 4.13: Combining all the methods used

The preprocessing techniques used above has removed the html tags, codeblocks, stopwords, and lemmatized the text. The text is now ready to be used for the following pipeline

4.4 Sentence Scoring

In order to rank sentences in a document, sentence scoring is used in this work, the mechanics used to achieve such scoring is highlighted in 3.3.2 (k). The results of the sentence scoring is shown below:

4.4.1 Sentence Scoring Results:

	title	sentence_scores	sentence_list	avg_score
13	Confusing React useStateEffect hook behaviour	(48.428571428571435)	[State update is asynchronous State is cons...]	48.428571
4	React useStateEffect hook cleanup	(1.99999999999998, 30.428571428571406)	[I doubt, someone may explain that in more com...]	16.214286
15	React useStateEffect hook doesn't clear interval	(16.0)	[this may works for youclearinterv when tim...]	16.000000
21	How can I make this React useStateEffect hook work ...	(2.25, 28.25)	[I tried your first sandbox and printed all th...]	15.250000
10	React useStateEffect hook is causing infinite loop	(14.399999999999999)	[You can pass a dependency array as the last a...]	14.400000
2	React useStateEffect hook	(4.7142857142857135, 4.142857142857142, 27714,..)	[I deleted my answer, I think there were some ...]	12.190476
1	react useStateEffect hook causes infinite loop	(10.333333333333336)	[Not the cause of issue, but what is ?, hook s...]	10.333333
17	componentWillUnmount with React useStateEffect hook	(0.5714285714285714, 14.571428571428573, 12.42,..)	[What is it that you want to do when the compo...]	9.571429
6	React useStateEffect hook dependency array	(13.0, 9.666666666666666, 2.0)	[even if you provide dependency array it will ...]	8.222222
3	Setting hook state inside React useStateEffect hook	(12.333333333333337, 2.333333333333333)	[I dont think you need , also try making a san...]	7.333333
18	React useStateEffect stop infinite loop	(6.0000000000000001, 3.8000000000000007, 12.799,..)	[is a new array on every render, yet the last ...]	6.100000
11	React useStateEffect invalid hook call	(4.5, 3.25, 9.0)	[you cannot use useStateEffect in a function, see t...]	5.563333
19	React useStateEffect hook behaving not like I expected	(7.25, 3.5)	[I deleted my answer, I think there were some ...]	5.375000
0	React useStateEffect hook infinity loop	(3.5714285714285703, 9.571428571428571, 0.1428...	[I dont think the second variation can cause y...]	4.892857
20	React useStateEffect hook loop, dependency problem	(10.666666666666668, 0.16666666666666666, 3.16,..)	[whenever the component is rendered, the depen...	4.750000
5	React useStateEffect hook load onsnapshot condition...	(12.875, 0.25, 2.25, 0.75, 1.125, 24.375, 0.75,..)	[commenting because I dont have time to flesh ...]	4.700000
16	How can I escape React useStateEffect infinite loop?	(0.5, 7.0, 1.5)	[why is in the dependency array for ?, it is i...]	3.000000
9	React useStateEffect fetch hook makes endless calls...	(0.6666666666666666, 0.6666666666666666, ...)	[Objects are compared by reference, not by the...	2.750000
12	React useStateEffect hook toggle issue	(3.5, 1.333333333333333, 0.6666666666666666, ...)	[Don't toggle the class manually Render the ...]	2.666667
7	React useStateEffect hook running infinite loop des...	(0.6666666666666666, 5.0, 1.0)	[If the only changing piece is isAuth then why...]	2.222222
14	componentWillUnmount lifecycle with react use...	(2.0, 1.0)	[yes there is, everything is explained in the ...]	1.500000
8	Using react useStateEffect hook	(0.3333333333333333, 0.3333333333333333, 3.0)	[What do you mean by your loading is not worki...]	1.222222
22	React useStateEffect hook firing every time I click...	0	0.000000	0

Figure 4.14: Sentence Scoring Results

The Figure 4.4.1 angled at 90 degrees, shows the result of the sentence scoring algorithm that we've implemented, the average score of all the sentences on a post are located at the far right of the table. Consequently, the posts are ranked based on the average score column.

4.5 Rank Posts: Part 1

According to the framework proposed in 3.1, the rankings can be evaluated after the sentence scoring is done. The results can be evaluated by using a wordcloud to determine the most important words in selected posts. The wordcloud is shown below:



Figure 4.15: Word Cloud 1st Post Ranking Results

The word cloud generated this round is quite messy, the important keywords are quite a few, this indicates that the ranking framework is not effective enough. This is expected as the ranking framework is still in its early stages.

4.6 Sentiment Analysis

To further rank the sentences, sentiment is another factor that can provide useful pieces of information to rank the sentences, 3.3.2 (l). Note that the list of posts are being filtered in the previous step 4.4, the filtering basically filters out any posts that have a negative or nan score on the previous step.

4.6.1 Sentiment Analysis Results:

	title	avg_positive_sentiment	avg_negative_sentiment	avg_neutral_sentiment	sentence_list
0	React useEffect hook does not call after recoil...	0.388867	0.159163	0.451850	[One thing that stands out to me is that you a...]
1	React useEffect hook does not fire when prop d...	0.356100	0.113650	0.530250	[Did you try to pass different photo prop valu...]
2	react useEffect hook triggers only once althou...	0.349400	0.164017	0.486683	[because there is no value change for error &a...]
3	React useEffect hook doesn't clear interval	0.281500	0.159580	0.558860	[this may works for you clearInterval when tim...]
4	How do I fire React useEffect hook only once a...	0.280533	0.047675	0.671700	[Why do you want to update from i? Does the in...]
5	Unexpected behaviour using React useEffect hook	0.242813	0.160796	0.596396	[The line where you have used useState hook, y...]
6	Confusing React useEffect hook behaviour	0.228324	0.098843	0.672843	[1., State update is asynchronous, 2., State ...]
7	react useEffect hook cleanup	0.214458	0.230279	0.555279	[I doubt, someone may explain that in more com...]
8	Loading spinner with react useEffect hook and ...	0.209583	0.219074	0.571343	[Why this statement : "I am using react hook u...]
9	componentWillUnmount lifecycle with react use...	0.207567	0.056167	0.734267	[yes there is, everything is explained in the ...]

Figure 4.16: Sentiment Anlysis Results

The Figure 4.16 angled at 90 degrees, shows the result of the sentiment analysis, the averages of positive, negative, and neutral scores are located at the middle of the table.

The posts are ranked based on the average positive score column.

4.7 Rank Posts: Part 2

The wordcloud is shown below:



Figure 4.17: Word Cloud 2nd Post Ranking Results

The word cloud generated on this section suggests that the important words from the first posts are slightly more exaggerated in the second post. This is a good indication of the effectiveness of the ranking system, because the unrelated posts are removed and the related posts are ranked higher.

4.8 Summarization

The final step is to summarize the top 5 posts ranked by the previous step 4.6. The detailed explanation of the summarization process and the model used is noted in

3.3.2 (n)

4.8.1 Summarization Results:

title	avg_positive_sentiment	avg_negative_sentiment	avg_neutral_sentiment	sentence	Just
0 React useEffect hook does not call after render...	0.3839567	0.1501913	0.453485	[One thing that stands out to me is that you ar...	
1 React useEffect hook does not fire when prop ch...	0.35661	0.19365	0.53925	[Did you try to pass different photo prop val...	
2 react useEffect hook triggers only once although...	0.3494	0.184017	0.486833	[because there is no value change for error & an...	
3 React useEffect hook doesn't clear interval	0.2815	0.15958	0.55986	[This may work for your clearInterval when tim...	
4 How do I fire React useEffect hook only once in ...	0.280633	0.047675	0.6777	[Why do you want to update from 7. Does the in...	Updated is exactly what I needed. What you need...

Figure 4.18: Summarization Results

The Figure 4.18 angled at 90 degrees, shows the result of the summarization implementation, the summary of the top 5 posts are located at the far right of the table.

4.9 Rank Posts: Part 3

The wordcloud is shown below:



Figure 4.19: Word Cloud 3rd Post Ranking Results

The final word cloud gives us a more clearer view on the most important words in the top 5 posts, the words chosen are definitely less noisy than the previous wordclouds.

4.10 Survey

70

The survey is conducted to determine the effectiveness of the system, the survey is conducted on 3 people, 3 of them are experts in the field of "react useeffect" which is the topic of the dataset scraped from stackoverflow. The survey is conducted by asking the experts to come up with the query related to the topic "react useeffect" and to determine if the results of the framework is relevant to the topic of the question and

if they're useful to the experts. The results of the survey is shown below:

4.10.1 Expert 1

The query asked by expert 1 is:

How to fetch data using the useEffect Hook?

Figure 4.20: Query asked by expert 1

Feedback from expert 1:

The result is relevant to the question, but the summarized output is not useful.

Figure 4.21: Feedback from expert 1

4.10.2 Expert 2

The query asked by expert 2 is:

useEffect hook doesn't work!

Figure 4.22: Query asked by expert 2

Feedback from expert 2:

It is able to find the post that are related to my prompt.

Figure 4.23: Feedback from expert 2

4.10.3 Expert 3

The query asked by expert 3 is:

How do i use the Use effect hook with use state.

Figure 4.24: Query asked by expert 3

Feedback from expert 3:

Maybe my query is abit out of context because useState is involved, but surprisingly the framework is able to find the post.

Figure 4.25: Feedback from expert 3

CHAPTER 5

IMPLEMENTATION PLAN

The implementation plan of this work can be divided into two parts, FYP1 and FYP2.

The tasks are then spreaded out into the two parts. Both gantt charts indicate the tasks

and the time frame for each task. The gantt chart for FYP1 is shown in Figure 5.1 and the gantt chart for FYP2 is shown in Figure 5.2.

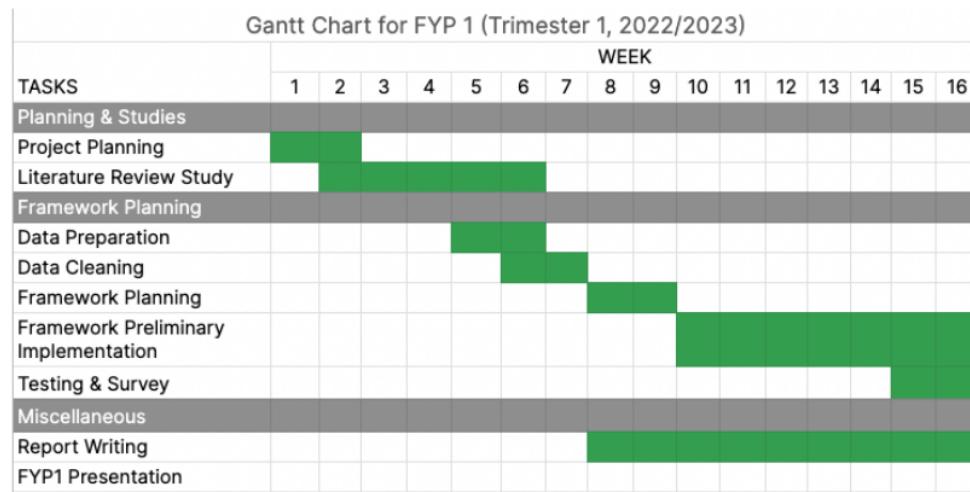


Figure 5.1: Gantt Chart for FYP1

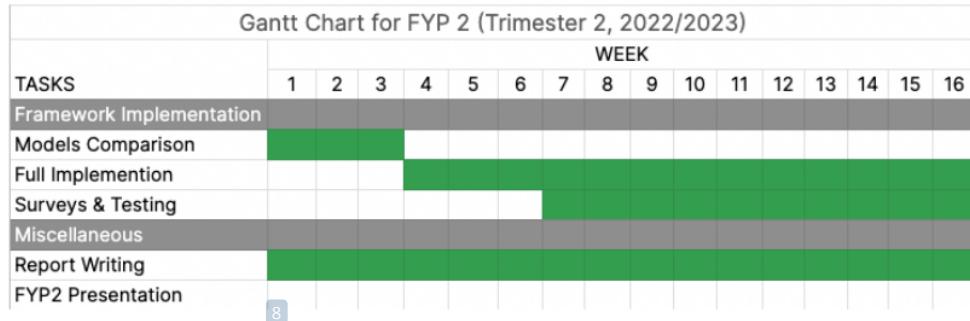


Figure 5.2: Gantt Chart for FYP2

The colored architecture framework also indicates the part of the framework that is being developed in FYP1 or FYP2. The architecture framework is shown in 3.1.

5.1 Project Target

A good amount of research, planning and implementation was done in the FYP 1 phase, the solution A architecture was built and tested. The experiment indicates that there are improvements to be made in order to achieve excellency. Consequently, the FYP 2 phase will be focused on improving the solution A architecture and also implementing the solution B architecture. In addition, Deep learning models should be considered and compared with the current architecture to determine if deep learning models are better. At last, more data sources are also expected to be added to the framework to fully test it's capabilities.

5.2 Web Application and Framework Hosting

A web application written in the "React" framework will be developed to allow users to interact with the framework. While the framework itself will be hosted as an FAST

API server. Both the web application and the framework will be hosted on the cloud platforms, Vercel and AWS respectively to allow public access to the solution.

CONCLUSIONS

6.1 Summary

Over the course of this research, we have scraped, compiled, cleaned, proprocess the dataset. A framework architecture to facilitate the process of finding the related post as an answer to the user prompt has been proposed. The framework is composed of 3 main components: scraping, proprocess and inferencing. 2 inferencing architecture had been proposed in the work, however only the first solution is built and tested with 3 experts that we've identified. One of the important tasks is to find a match of the question asked by the user with the posts in the forum. As of now, all techniques are based of NLP techniques such as FuzzyWuzzy and Spacy which was discussed in 3.3.2 (b) and tested in 4.2, however deep learning models that are discussed in the literature review section 2.1.3 will be tested in the future.

6.2 Challenges

Computation power is one of the main challenges in this work, scraping, sentiment analysis and summarization are computationally expensive tasks. Scraping takes a lot of time as the process is sequential, sentiment analysis and summarization however is slow because the model we're using is expected to be ran on a gpu-enabled machine.

6.3 Future Work

- The results have shown that the summarization of the texts in posts are possible, but the results are not satisfactory. Therefore other summarization algorithms should be tested.
- The framework is slow in general, each process in the pipeline takes time. As planned in the proposed framework an FAQ Repository will be built to store the results of the pipeline. This repository will be used to answer the questions in the future. Therefore the framework should be improved to be able to answer the questions in a reasonable time.
- Solution A is the only architecture we've built and tested in FYP 1, solution B will be built in FYP 2.
- Parallelization of the scraping process is to be explored.
- Possibility of migrating to a fully cloud hosted solution is to be explored.
- Deep learning models for matching posts are to be tested.

REFERENCES

- [1] Alqaryouti, O., Siyam, N., Monem, A., & Shaalan, K. (2019, 11). Aspect-based sentiment analysis using smart government review data. *Applied Computing and Informatics, ahead-of-print*. doi: 10.1016/j.aci.2019.11.003
- [2] Al-Smadi, M., Qawasmeh, O., Al-Ayyoub, M., Jararweh, Y., & Gupta, B. B. (2017). Deep recurrent neural network vs. support vector machine for aspect-based sentiment analysis of arabic hotels' reviews. *J. Comput. Sci.*, 27, 386-393.
- [3] Antiqueira, L., Oliveira, O., da F. Costa, L., & Nunes, M. (2009, 02). A complex network approach to text summarization. *Information Sciences*, 179, 584-599. doi: 10.1016/j.ins.2008.10.032
- [4] Banarescu, L., Bonial, C., Cai, S., Georgescu, M., Griffitt, K., Hermjakob, U., ... Schneider, N. (2013, August). Abstract Meaning Representation for sembanking. In *Proceedings of the 7th linguistic annotation workshop and interoperability with discourse* (pp. 178–186). Sofia, Bulgaria: Association for Computational Linguistics. Retrieved from <https://aclanthology.org/W13-2322>
- [5] Duan, N., Tang, D., Chen, P., & Zhou, M. (2017, September). Question generation for question answering. In *Proceedings of the 2017 conference on empirical methods in natural language processing* (pp. 866–874). Copenhagen, Denmark: Association for Computational Linguistics. Retrieved from <https://aclanthology.org/D17-1090> doi: 10.18653/v1/D17-1090
- [6] Gerlach, M., Shi, H., & Amaral, L. (2019, 12). A universal information theoretic approach to the identification of stopwords. In (Vol. 1). doi: 10.1038/s42256-019-0112-6
- [7] Gupta, S., & Carvalho, V. R. (2019). Faq retrieval using attentive matching. In *Proceedings of the 42nd international acm sigir conference on research and development in information retrieval* (p. 929–932). New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/3331184.3331294> doi: 10.1145/3331184.3331294

- [8] He, R., Lee, W. S., Ng, H. T., & Dahlmeier, D. (2018, July). Exploiting document knowledge for aspect-level sentiment classification. In *Proceedings of the 56th annual meeting of the association for computational linguistics (volume 2: Short papers)* (pp. 579–585). Melbourne, Australia: Association for Computational Linguistics. Retrieved from <https://aclanthology.org/P18-2092>
doi: 10.18653/v1/P18-2092
- [9] Henß, S., Monperrus, M., & Mezini, M. (2012). Semi-automatically extracting faqs to improve accessibility of software development knowledge. In *2012 34th international conference on software engineering (icse)* (p. 793-803). doi: 10.1109/ICSE.2012.6227139
- [10] Hu, W.-C., Yu, D.-F., & Jiau, H. C. (2010). A faq finding process in open source project forums. In *2010 fifth international conference on software engineering advances* (p. 259-264). doi: 10.1109/ICSEA.2010.46
- [11] Jijkoun, V., & de Rijke, M. (2005). Retrieving answers from frequently asked questions pages on the web. In *Proceedings of the 14th acm international conference on information and knowledge management* (p. 76–83). New York, NY, USA: Association for Computing Machinery. Retrieved from <https://doi.org/10.1145/1099554.1099571> doi: 10.1145/1099554.1099571
- [12] Kothari, G., Negi, S., Faruquie, T., Chakaravarthy, V., & Subramaniam, L. (2009, 01). Sms based interface for faq retrieval. In (p. 852-860). doi: 10.3115/1690219.1690266
- [13] Kumar, R., Pannu, H., & Malhi, A. (2020, 04). Aspect-based sentiment analysis using deep networks and stochastic optimization. *Neural Computing and Applications*, 32. doi: 10.1007/s00521-019-04105-z
- [14] Ladani, D. J., & Desai, N. P. (2020). Stopword identification and removal techniques on tc and ir applications: A survey. In *2020 6th international conference on advanced computing and communication systems (icaccs)* (p. 466-472). doi: 10.1109/ICACCS48705.2020.9074166
- [15] Liu, H., Chatterjee, I., Zhou, M., Lu, X. S., & Abusorrah, A. (2020). Aspect-based sentiment anal-

- ysis: A survey of deep learning methods. *IEEE Transactions on Computational Social Systems*, 7(6), 1358-1375. doi: 10.1109/TCSS.2020.3033302
- [16] Ma, X., Zeng, J., Peng, L., Fortino, G., & Zhang, Y. (2019, apr). Modeling multi-aspects within one opinionated sentence simultaneously for aspect-level sentiment analysis. *Future Gener. Comput. Syst.*, 93(C), 304–311. Retrieved from <https://doi.org/10.1016/j.future.2018.10.041> doi: 10.1016/j.future.2018.10.041
- [17] M.Abdelgwad, M., A Soliman, T. H., I.Taloba, A., & Farghaly, M. F. (2022). Arabic aspect based sentiment analysis using bidirectional gru based models. *Journal of King Saud University - Computer and Information Sciences*, 34(9), 6652-6662. Retrieved from <https://www.sciencedirect.com/science/article/pii/S1319157821002482> doi: <https://doi.org/10.1016/j.jksuci.2021.08.030>
- [18] Makino, T., Noro, T., & Iwakura, T. (2016). An faq search method using a document classifier trained with automatically generated training data. In R. Booth & M.-L. Zhang (Eds.), *Pricai 2016: Trends in artificial intelligence* (pp. 295–305). Cham: Springer International Publishing.
- [19] Manes, S. S., & Baysal, O. (2019). How often and what stackoverflow posts do developers reference in their github projects? In *2019 ieee/acm 16th international conference on mining software repositories (msr)* (p. 235-239). doi: 10.1109/MSR.2019.00047
- [20] Mashechkin, I., Petrovskiy, M., Popov, D., & Tsarev, D. (2011, 11). Automatic text summarization using latent semantic analysis. *Programming and Computer Software*, 37, 299-305. doi: 10.1134/S0361768811060041
- [21] Menéndez, H. D. (2021). Software testing or the bugs' nightmare..
- [22] Mikolov, T., Sutskever, I., Chen, K., Corrado, G. S., & Dean, J. (2013). Distributed representations of words and phrases and their compositionality. In C. Burges, L. Bottou, M. Welling, Z. Ghahramani, & K. Weinberger (Eds.), *Advances in neural information processing systems*

- (Vol. 26). Curran Associates, Inc. Retrieved from <https://proceedings.neurips.cc/paper/2013/file/9aa42b31882ec039965f3c4923ce901b-Paper.pdf>
- [23] Moreno, L., & Marcus, A. (2018). Automatic software summarization: The state of the art. In *2018 ieee/acm 40th international conference on software engineering: Companion (icse-companion)* (p. 530-531).
- [24] Nallapati, R., Zhou, B., Dos Santos, C., Gulcehre, C., & Xiang, B. (2016, 02). Abstractive text summarization using sequence-to-sequence rnns and beyond. In (p. 280-290). doi: 10.18653/v1/K16-1028
- [25] Othman, N., Faiz, R., & Smaïli, K. (2019). Enhancing question retrieval in community question answering using word embeddings. *Procedia Computer Science*, 159, 485-494. Retrieved from <https://www.sciencedirect.com/science/article/pii/S1877050919313857> (Knowledge-Based and Intelligent Information Engineering Systems: Proceedings of the 23rd International Conference KES2019) doi: <https://doi.org/10.1016/j.procs.2019.09.203>
- [26] Raazaghi, F. (2015). Auto-faq-gen: Automatic frequently asked questions generation. In D. Barbosa & E. Milios (Eds.), *Advances in artificial intelligence* (pp. 334–337). Cham: Springer International Publishing.
- [27] Razzaghi, F., Minaee, H., & Ghorbani, A. A. (2016). Context free frequently asked questions detection using machine learning techniques. In *2016 ieee/wic/acm international conference on web intelligence (wi)* (p. 558-561). doi: 10.1109/WI.2016.0095
- [28] Rezaeinia, S. M., Rahmani, R., Ghodsi, A., & Veisi, H. (2019). Sentiment analysis based on improved pre-trained word embeddings. *Expert Syst. Appl.*, 117, 139-147.
- [29] Sarica, S., & Luo, J. (2020, 06). Stopwords in technical language processing..
- [30] Sharma, G., & Sharma, D. (2022). Automatic text summarization methods: A comprehensive

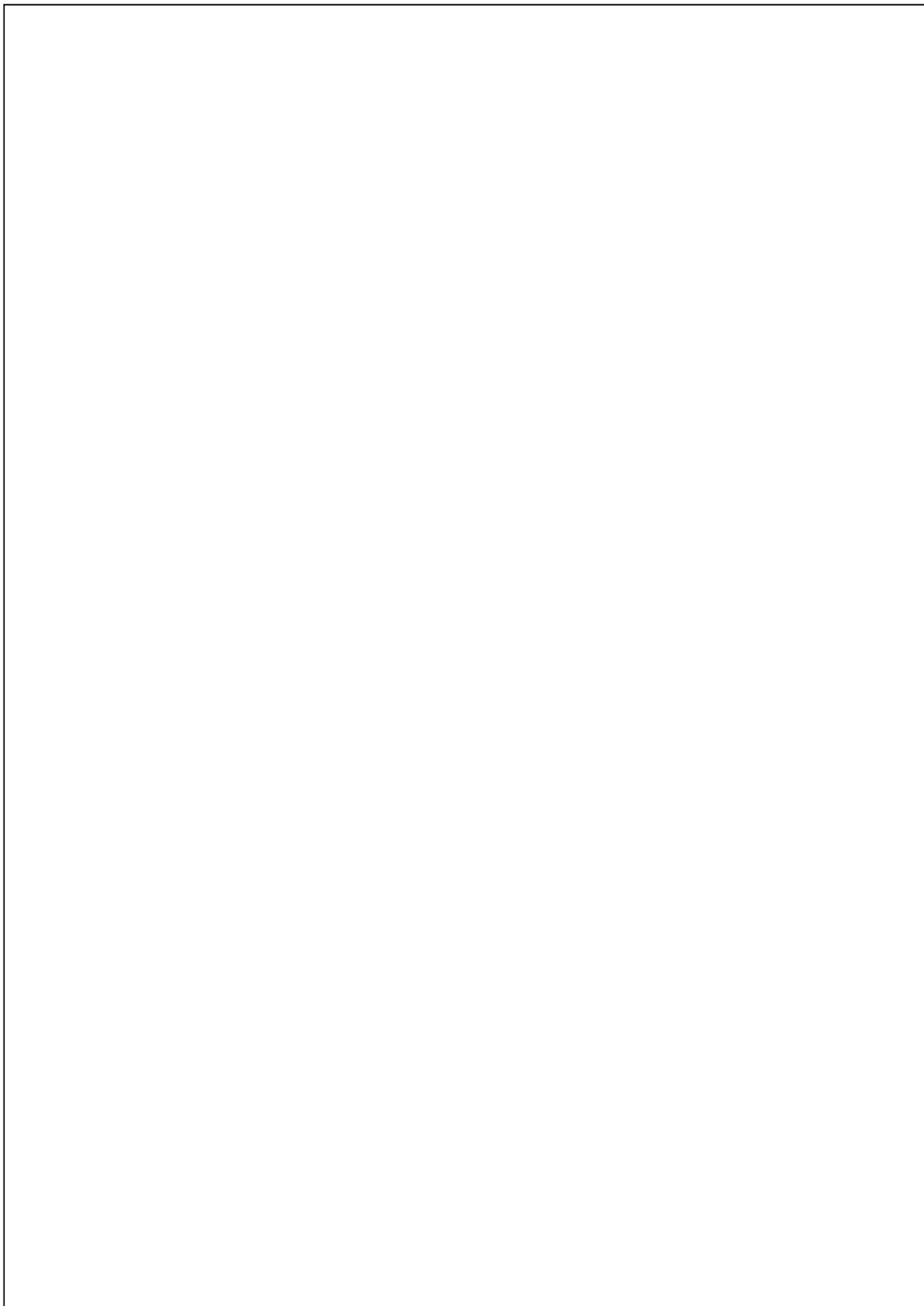
- review. *SN Computer Science*, 4(1), 33. Retrieved from <https://doi.org/10.1007/s42979-022-01446-w> doi: 10.1007/s42979-022-01446-w
- [31] Sindhu, I., Daudpota, S. M., Badar, K., Bakhtyar, M., Baber, J., & Nurunnabi, M. (2019). Aspect-based opinion mining on student's feedback for faculty teaching performance evaluation. *IEEE Access*, 7, 108729-108741.
- [32] Syam Mohan E, R. S. (2021). Survey on aspect based sentiment analysis using machine learning techniques. *European Journal of Molecular and Clinical Medicine*, 7(10), 1664-1684. Retrieved from https://ejmcm.com/article_6773.html
- [33] WANJAWA, B., & MUCHEMI, L. (2020). Question answering using automatically generated semantic networks – the case of swahili questions. In *2020 ist-africa conference (ist-africa)* (p. 1-8).
- [34] Xue, W., & Li, T. (2018, July). Aspect based sentiment analysis with gated convolutional networks. In *Proceedings of the 56th annual meeting of the association for computational linguistics (volume 1: Long papers)* (pp. 2514–2523). Melbourne, Australia: Association for Computational Linguistics. Retrieved from <https://aclanthology.org/P18-1234> doi: 10.18653/v1/P18-1234
- [35] Zainuddin, N., Selamat, A., & Ibrahim, R. (2018). Hybrid sentiment classification on twitter aspect-based sentiment analysis. *Applied Intelligence*, 48, 1218-1232.
- [36] Zhang, B., Xu, X., Li, X., Chen, X., Ye, Y., & Wang, Z. (2019, sep). Sentiment analysis through critic learning for optimizing convolutional neural networks with rules. *Neurocomput.*, 356(C), 21–30. Retrieved from <https://doi.org/10.1016/j.neucom.2019.04.038> doi: 10.1016/j.neucom.2019.04.038
- [37] Zhang, S., Hu, Y., & Bian, G. (2017). Research on string similarity algorithm based on levenshtein distance. In *2017 ieee 2nd advanced information technology, electronic and automation control*

conference (iaeac) (p. 2247-2251). doi: 10.1109/IAEAC.2017.8054419

- [38] Zhou, G., Liu, Y., Liu, F., Zeng, D., & Zhao, J. (2013, 01). Improving question retrieval in community question answering using world knowledge. *IJCAI International Joint Conference on Artificial Intelligence*, 2239-2245.

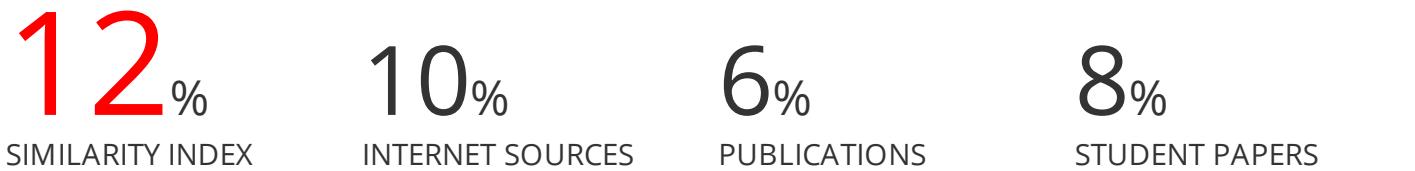
FYP 1 MEETING LOGS

The following pages include the 6 meeting logs for FYP 1.



Report

ORIGINALITY REPORT



PRIMARY SOURCES

1	fossies.org Internet Source	2%
2	v1.overleaf.com Internet Source	1 %
3	Submitted to Multimedia University Student Paper	<1 %
4	medium.com Internet Source	<1 %
5	hal.archives-ouvertes.fr Internet Source	<1 %
6	Submitted to AlHussein Technical University Student Paper	<1 %
7	Submitted to Harrisburg University of Science and Technology Student Paper	<1 %
8	Submitted to Taylor's Education Group Student Paper	<1 %
9	github-wiki-see.page Internet Source	<1 %

10	Submitted to De Montfort University Student Paper	<1 %
11	www.csharp-console-examples.com Internet Source	<1 %
12	Qihao Bao, Jia Zhang, Xiaoyi Duan, Rahul Ramachandran et al. "A Fine-Grained API Link Prediction Approach Supporting Mashup Recommendation", 2017 IEEE International Conference on Web Services (ICWS), 2017 Publication	<1 %
13	dokumen.tips Internet Source	<1 %
14	thealphaedge.github.io Internet Source	<1 %
15	link.springer.com Internet Source	<1 %
16	vitordecarvalho.github.io Internet Source	<1 %
17	www.ess.washington.edu Internet Source	<1 %
18	bibliotecadigital.fgv.br Internet Source	<1 %
19	researchrepository.wvu.edu Internet Source	<1 %
	www2.sis.pitt.edu	

20	Internet Source	<1 %
21	Fahri Yetim. "Chapter 8 User-adapted hypertext explanations", Springer Science and Business Media LLC, 1993 Publication	<1 %
22	Submitted to Universiti Malaysia Pahang Student Paper	<1 %
23	www.slideshare.net Internet Source	<1 %
24	Submitted to Imperial College of Science, Technology and Medicine Student Paper	<1 %
25	www.statmt.org Internet Source	<1 %
26	gist.github.com Internet Source	<1 %
27	Charles V. Trappey, Amy J.C. Trappey, Sam C.-C. Lin. "Intelligent trademark similarity analysis of image, spelling, and phonetic features using machine learning methodologies", Advanced Engineering Informatics, 2020 Publication	<1 %
28	dokumen.pub Internet Source	<1 %

29	www.researchgate.net Internet Source	<1 %
30	Submitted to Datta Meghe College of Engineering Student Paper	<1 %
31	Submitted to Polytechnic of Turin Student Paper	<1 %
32	Wafaa S. El-Kassas, Cherif R. Salama, Ahmed A. Rafea, Hoda K. Mohamed. "Automatic Text Summarization: A Comprehensive Survey", Expert Systems with Applications, 2020 Publication	<1 %
33	docplayer.net Internet Source	<1 %
34	towardsdatascience.com Internet Source	<1 %
35	Submitted to Erasmus University of Rotterdam Student Paper	<1 %
36	Submitted to The University of the South Pacific Student Paper	<1 %
37	Submitted to University of Leeds Student Paper	<1 %
38	ir.unimas.my Internet Source	<1 %

39	pyralead.com Internet Source	<1 %
40	Submitted to The University of Manchester Student Paper	<1 %
41	Submitted to VIT University Student Paper	<1 %
42	docshare.tips Internet Source	<1 %
43	studentsrepo.um.edu.my Internet Source	<1 %
44	Ayham Alomari, Norisma Idris, Aznul Qalid Md Sabri, Izzat Alsmadi. "Deep Reinforcement and Transfer Learning for Abstractive Text Summarization: A Review", Computer Speech & Language, 2021 Publication	<1 %
45	Bambang Dwi Wijanarko, Yaya Heryadi, Hapnes Toba, Widodo Budiharto. "Question generation model based on key-phrase, context-free grammar, and Bloom's taxonomy", Education and Information Technologies, 2020 Publication	<1 %
46	Jiangfeng Zeng, Xiao Ma, Ke Zhou. "Enhancing Attention-based LSTM with Position Context	<1 %

for Aspect-level Sentiment Classification", IEEE Access, 2019

Publication

47	aclweb.org	<1 %
48	citeseerx.ist.psu.edu	<1 %
49	coek.info	<1 %
50	core.ac.uk	<1 %
51	id.123dok.com	<1 %
52	www.coursehero.com	<1 %
53	"Chinese Computational Linguistics", Springer Science and Business Media LLC, 2020	<1 %
54	Himat Shah, Mohammad Rezaei, Pasi Fränti. "DOM-based keyword extraction from web pages", Proceedings of the International Conference on Artificial Intelligence, Information Processing and Cloud Computing - AIIPCC '19, 2019	<1 %
	d-nb.info	

55	Internet Source	<1 %
56	gifftutoring.org Internet Source	<1 %
57	research.gold.ac.uk Internet Source	<1 %
58	scholarworks.umass.edu Internet Source	<1 %
59	slidelegend.com Internet Source	<1 %
60	vdoc.pub Internet Source	<1 %
61	"Computational Science and Its Applications – ICCSA 2021", Springer Science and Business Media LLC, 2021 Publication	<1 %
62	"Deep Learning-Based Approaches for Sentiment Analysis", Springer Science and Business Media LLC, 2020 Publication	<1 %
63	"Natural Language Processing and Chinese Computing", Springer Science and Business Media LLC, 2020 Publication	<1 %

- 64 "Perspectives on Content-Based Multimedia Systems", Springer Science and Business Media LLC, 2002 **<1 %**
Publication
-
- 65 "Semantic Keyword-Based Search on Structured Data Sources", Springer Science and Business Media LLC, 2018 **<1 %**
Publication
-
- 66 "Trends and Advances in Information Systems and Technologies", Springer Nature, 2018 **<1 %**
Publication
-
- 67 Chaithra V. D. "Hybrid approach: naive bayes and sentiment VADER for analyzing sentiment of mobile unboxing video comments", International Journal of Electrical and Computer Engineering (IJECE), 2019 **<1 %**
Publication
-
- 68 Hamed Asgari, Behrooz Masoumi, Omid Sojoodi Sheijani. "Automatic text summarization based on multi-agent particle swarm optimization", 2014 Iranian Conference on Intelligent Systems (ICIS), 2014 **<1 %**
Publication
-
- 69 Johan Vos, Stephen Chin, Weiqi Gao, James Weaver, Dean Iverson. "Chapter 7 Connecting to Enterprise Services", Springer Science and Business Media LLC, 2018 **<1 %**
Publication
-

70	ebin.pub Internet Source	<1 %
71	fdocuments.in Internet Source	<1 %
72	insightsociety.org Internet Source	<1 %
73	ipfs.io Internet Source	<1 %
74	theses.gla.ac.uk Internet Source	<1 %
75	umkeprints.umk.edu.my Internet Source	<1 %
76	www.mdpi.com Internet Source	<1 %
77	"Chinese Computational Linguistics and Natural Language Processing Based on Naturally Annotated Big Data", Springer Science and Business Media LLC, 2017 Publication	<1 %
78	"Emerging Research in Computing, Information, Communication and Applications", Springer Science and Business Media LLC, 2018 Publication	<1 %
79	"Handbook of Chemoinformatics", Wiley, 2003 Publication	

<1 %

-
- 80 "Knowledge Science, Engineering and Management", Springer Science and Business Media LLC, 2018 <1 %
Publication
-
- 81 Nouha Othman, Rim Faiz, Kamel Smaïli. "Enhancing Question Retrieval in Community Question Answering Using Word Embeddings", Procedia Computer Science, 2019 <1 %
Publication
-
- 82 P. K. Thulasi, K Usha. "Aspect polarity recognition of movie and product reviews in Malayalam", 2016 International Conference on Next Generation Intelligent Systems (ICNGIS), 2016 <1 %
Publication
-
- 83 hdl.handle.net <1 %
Internet Source
-
- 84 "Information Retrieval", Springer Science and Business Media LLC, 2018 <1 %
Publication
-
- 85 "Natural Language Processing and Chinese Computing", Springer Science and Business Media LLC, 2018 <1 %
Publication
-

86

Bilal Chandio, Asadullah Shaikh, Maheen Bakhtyar, Mesfer Alrizq, Junaid Baber, Adel Sulaiman, Adel Rajab, Waheed Noor.

<1 %

"Sentiment Analysis of Roman Urdu on E-Commerce Reviews Using Machine Learning", Computer Modeling in Engineering & Sciences, 2022

Publication

Exclude quotes On

Exclude matches Off

Exclude bibliography On

Report

PAGE 1

PAGE 2

PAGE 3

PAGE 4

PAGE 5

PAGE 6

PAGE 7

PAGE 8

PAGE 9

PAGE 10

PAGE 11

PAGE 12

PAGE 13

PAGE 14

PAGE 15

PAGE 16

PAGE 17

PAGE 18

PAGE 19

PAGE 20

PAGE 21

PAGE 22

PAGE 23

PAGE 24

PAGE 25

PAGE 26

PAGE 27

PAGE 28

PAGE 29

PAGE 30

PAGE 31

PAGE 32

PAGE 33

PAGE 34

PAGE 35

PAGE 36

PAGE 37

PAGE 38

PAGE 39

PAGE 40

PAGE 41

PAGE 42

PAGE 43

PAGE 44

PAGE 45

PAGE 46

PAGE 47

PAGE 48

PAGE 49

PAGE 50

PAGE 51

PAGE 52

PAGE 53

PAGE 54

PAGE 55

PAGE 56

PAGE 57

PAGE 58

PAGE 59

PAGE 60

PAGE 61

PAGE 62

PAGE 63

PAGE 64

PAGE 65

PAGE 66

PAGE 67

PAGE 68

PAGE 69

PAGE 70

PAGE 71

PAGE 72

PAGE 73

PAGE 74

PAGE 75

PAGE 76

PAGE 77

PAGE 78

PAGE 79

PAGE 80

PAGE 81

PAGE 82

PAGE 83

PAGE 84

PAGE 85

PAGE 86

PAGE 87

PAGE 88

PAGE 89

PAGE 90

PAGE 91

PAGE 92

PAGE 93

PAGE 94

PAGE 95

PAGE 96

PAGE 97

PAGE 98

PAGE 99

PAGE 100

PAGE 101

PAGE 102

PAGE 103

PAGE 104

PAGE 105

PAGE 106

PAGE 107

PAGE 108

PAGE 109

PAGE 110

PAGE 111

PAGE 112

PAGE 113

PAGE 114

PAGE 115

PAGE 116

PAGE 117

PAGE 118

PAGE 119
