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Generalized Abstractive Text Summarization Using Optimized Transformers

Literature Review

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**Acronyms**

|  |  |
| --- | --- |
| AI | Artificial Intelligence. |
| DL | Deep Learning |
| GUI | Graphical user Interface |
| ML | Machine Learning |
| NLP | Natural Language Processing |
| ROUGE | Recall-Oriented Understudy for Gisting Evaluation. |
| BLEU | Continuous-time Recurrent Neural Network. |
| T5 | Deep Learning. |
| BART | Graphics Processing Unit. |
| BERT | Long Short-Term Memory. |
| PEGASUS | Liquid Time-constant. |
| ILP | Machine Learning. |
| LSTM | Symmetric Mean Absolute Product Error. |
| RNN | Mean Absolute Scaled Error. |
| CNN  SEQ2SEQ | Mean Squared Error.  Sequence to Sequence |
| RoBERTa | Robustly Optimized BERT Pre-training Approach |
| GPT-3  REST | Third Generation Generative Pre-Trained Transformer  Representational State Transfer |

# CHAPTER OVERVIEW

In this chapter, the author presents critiques on prior relevant work about the use of abstractive text summarization in the domain of movie review summarization, along with the usage of advanced deep learning approaches such as transformers. Additionally, the author tries to create a generalized model that will handle several other domains in addition, not just to only the movie domain. Finally, the author determines the optimal transformer design that has been improved in order to produce the greatest outcomes by obtaining the optimum set of hyperparameters by model fine-tuning.

# CONCEPT MAP

The concept map illustrates the project scope that will be addressed in this literature review, and the nodes that are highlighted correspond to the project's primary study areas. The concept map was created to ensure that all necessary literature was covered. The concept map can be found in [**Appendix A – Concept Map**](#ConceptMap)**.**

# PROBLEM DOMAIN

The simplicity of selling products or services to customers is growing along with the usage of technology and the internet. Sellers utilize customer feedback to better decide how to improve sales and so attain customer satisfaction (Boorugu, Ramesh and Madhavi, 2019). When it comes to movies, people typically find it quite challenging to quickly determine whether a movie meets their demands by reading the reviews, which may occasionally be very lengthy and time-consuming (Khan et al., 2020).

## **User Reviews**

A user/customer review is typically referred to be written feedback from a customer who has used a product or service. Consumers frequently use user ratings and reviews to drive their purchasing decisions. Because the review data is unstructured, it becomes more challenging for consumers to compare and understand lengthier reviews (Lackermair, Kailer and Kanmaz, 2013).

User and customer reviews are extremely important to major corporations like tourism and hospitality as they constitute the primary engine for the country's economic growth and development. where tourists from over the world may blog about their experiences and share their reviews online in numerous formats (Mukherjee et al., 2020).

## **Corporate Advantage**

It is also known that it costs at least five times as much time and money to acquire a new customer as it does to keep an existing one, so it is important to learn how to foster customer loyalty to the brand, business, or service that is being offered. Customer satisfaction is essential to the survival of corporate industries. Understanding client expectations through their feedback or reviews helps business industries grow and fix faults (Pizam and Ellis, 1999).

On the other hand, companies like Netflix or Amazon Prime can use the movie summaries to help users and understand the watching pattern or their interest. Likewise, the movie-related industries need to allow the customers to quickly scan the summary and quickly decide whether they should be watching it or not (Khan et al., 2020).

## **Text Summarization**

With the massive accumulation of information/data on the internet nowadays, it is extremely difficult to extract relevant information from a large number of textual documents. The goal of text summarizing is to provide a condensed yet meaningful version of a lengthy textual content (Shi et al., 2020).

We all know that text summarization has several uses in a variety of internet-based fields, including search engines that are used for querying and e-commerce sites that utilize sentiment analysis to determine client satisfaction with items (Etemad, Abidi and Chhabra, 2021).

However, in the movie industry, consumers may utilize text summarization to simplify customer reviews of movies, which are often lengthy and time-consuming to read. This enables users to make better decisions when they decide whether or not to watch a certain movie (Khan et al., 2020).

## **3.4 Abstractive and Extractive Techniques**

Generally, text summarization is classified into two which are; abstractive text summarization and extractive text summarization, however the approach for creating a hybrid model for text summarization is possible (Alsaqer and Sasi, 2017). The abstractive text summarization technique aims to produce the sentences on its own and then uses them to provide a coherent summary. Therefore, the summary's content will vary from the original context yet still convey the same idea (Mahajan et al., 2021). Additionally, it is well recognized that a strong abstractive summary encompasses the input's key details and is linguistically fluent (Zhang et al., 2020).

The extractive text summarizing method focuses on picking out key phrases or groups of phrases from the original input content and combining them to produce a concise yet insightful text summary. It is determined which sentences should be included as parts of the summary based on the statistical and linguistic characteristics of the sentences (Gupta and Lehal, 2010). A hybrid system is one that combines various strategies to produce a single system. However, hybrid text summarizing systems do exist, for instance, using a combination of extractive and abstractive summarization can be utilized to generate a hybrid system that uses encoder-decoders (Kirmani et al., 2019; Abolghasemi, Dadkhah and Tohidi, 2022).

*Table 1: Comparison of Text Summarization Techniques*

|  |  |
| --- | --- |
| **Abstractive** | **Extractive** |
| Paraphrases content like humans do, meaning it creates its own context (Mahajan et al., 2021) | Doesn’t create its own context but uses the best possible phrases from the original document (Gupta and Lehal, 2010) |
| A vast number of datasets are available to experiment working in this domain. | Capable of visualizing sentence scores and investigating gradient-based ways to calculating the contribution of each input token to score prediction (Pai, 2014) |
| There is a probability of creating information which may be faulty or that gives a different in meaning compared to the original text. | There is a possibility that the combined sentences made from the extracted sentences will contain errors. |

## **3.5 NLP with Deep Learning**

## NLP is a method for computers to intelligently and effectively analyze, comprehend, and derive meaning from human language, as opposed to other approaches that only focus on the interactions between human language and computers. Deep learning techniques are increasingly being used in the field of AI compared to traditional machine learning approaches due to their success rates in handling difficult high computing learning tasks (Lopez and Kalita, 2017; Mahajan et al., 2021).

In today's NLP, machine learning is prominent, but for the most part it only involves numerically optimizing the weights of characteristics and representations that have been created by humans. Deep learning aims to investigate how computers can utilize data to create features and representations suitable for challenging interpretation tasks (Socher, Bengio and Manning, 2012).

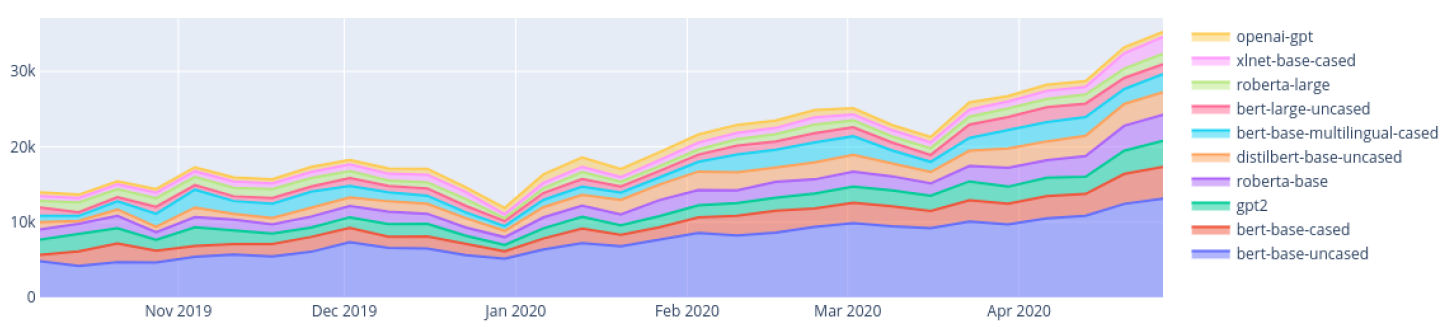
## **3.6 Transformers**

Open-source library Transformers contains modern transformer architectures that have been thoroughly developed and are integrated by a common API. Pretraining has enabled the efficient use of this capacity for a wide range of activities, and these designs have permitted the construction of higher-capacity models. Transformers are designed to be easy for practitioners, expandable for researchers, and quick and reliable in industrial deployments (Wolf et al., 2020).

It has been demonstrated that the modern generation of pre-trained language models based on transformers is rather competent at identifying syntactic signals like noun modifiers, possessive pronouns, prepositions, or co-referents, as well as semantic cues like entities and relations (Brasoveanu and Andonie, 2020).

Hugging Face Hub offers a variety of transformer designs, including BERT, GPT2, T5, PEGASUS, and many others. The figure below represents the daily average for unique downloads of the pretrained transformer model architectures between Oct 2019 to May 2020 (Wolf et al., 2020).

*Figure 3.1 – Transformer Architecture Downloads Rate (Wolf et al., 2020).*



(Etemad, Abidi and Chhabra, 2021) research compares various other researchers approaches taken in order to perform abstractive text summarization, these techniques includes the use of transformers and other neural network approaches such as CNN and LSTM RNN networks. The research comparison table below only includes the approaches of transformers used taken abstractive text summarization.

*Table 3.1 – Comparison table for abstractive text summarization using transformers (Etemad, Abidi and Chhabra, 2021).*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Researcher | Year | Type of model | Rouge 1 | Rouge 2 | Rouge L | Dataset |
| Haoyu Zhang et al. | 2019 | Transformer with BERT | 41.71 | 19.49 | 38.79 | CNN-Daily Mail |
| Andrew Hoang et al | 2019 | Transformer | 39.01  36.73  40.87 | 17.87  14.93  28.59 | 36.17  29.66  37.62 | CNN Daily Mail  Xsum  Newsroom |
| Kaiqiang Song et al. | 2019 | Transformer | 40.89  45.93 | 19.11  24.14 | 37.60  42.51 | Gigaword,  Newsroom |
| Mike Lewis et al. | 2019 | BART | 44.16  45.14 | 21.28  22.27 | 40.90  37.25 | CNN Daily Mail  Xsum |
| Itsumi Saito et al. | 2020 | RoBERTa Base | 45.80  45.42 | 22.53  22.13 | 42.48  36.92 | CNN Daily Mail  Xsum |
| Beliz Gunel et al. | 2020 | Transformer XL | 34.273 | 13.018 | 32.048 | CNN Daily Mail |
| Colin Raffel et al. | - | T5 | 43*.*52 | 21*.*55 | 40*.*69 | CNN Daily Mail |

## **3.7 Hyperparameter Tuning**

# about hyper parameter tuning and how its important

# hyperparameter to be tuned which parameters has the most contribution towards the model performance

# hyperparameter framework

## **3.8 Generalization**

# about generalization

# how is it important

3.9 Proposed architecture for the generalized text summarization system

# EXISTING WORK

# TECHNOLOGICAL REVIEW

# EVALUATION APPROACHES

# CHAPTER SUMMARY

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# APPENDIX A – CONCEPT MAP

