# Movie Synopsis Generation

https://github.com/JiteshJangra/nlp

# Jitesh Kumar (IIT2020224) IIIT Allahabad

## Abstract:

The generation of movie synopses is an essential task in the film industry. The goal is to create a brief summary of the movie that can help potential viewers decide whether they want to watch it or not. This paper presents a literature survey of existing methods for generating movie synopses. We review the state-of-the-art techniques and analyse their strengths and weaknesses. Our survey shows that machine learning-based approaches have achieved promising results in generating high-quality movie synopses.

# INTRODUCTION

Movie synopses provide a quick summary of a movie's plot, theme, and characters. They are often used by movie studios, streaming services, and film reviewers to promote movies and attract audiences. Traditional methods of generating synopses involve manual writing by human experts, which can be time-consuming and expensive. With the advances in natural language processing and machine learning, there has been growing interest in using automated techniques to generate synopses.

In this paper, I present a literature survey of existing methods for generating movie synopses. I analysed the various approaches proposed in the literature, including rule-based methods, template-based methods, and machine learning based methods. We also discuss the evaluation metrics used to assess the quality of the generated synopses.

## Literature Review:

The authors conducted a systematic literature review of text generation using deep neural network models and presented a comprehensive survey of the state-of-the-art techniques.

The authors categorized the existing methods into three main categories:

Recurrent Neural Network (RNN)-based methods,

Transformer-based methods, and

Variational Autoencoder (VAE)-based methods.

RNN-based methods, such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), have been widely used in text generation tasks due to their ability to model sequential data.

The authors reviewed various variants of RNN-based models, including character-level, word-level, and subword-level models, as well as hybrid models that combine RNNs with other deep learning architectures.

Transformer-based methods, such as the popular GPT-2 and BERT models, have also shown promising results in text generation tasks.

These models use self-attention mechanisms to capture longrange dependencies in the input sequence, allowing them to generate coherent and high-quality text.

The authors discussed the strengths and weaknesses of transformerbased models and highlighted the challenges in fine-tuning these models for specific text generation tasks.

VAE-based methods are a relatively new approach to text generation that combine deep neural networks with probabilistic modelling.

These models can generate diverse and creative text by sampling from the latent space of the VAE. The authors reviewed the recent developments in VAE-based text generation and discussed the challenges in training these models on large datasets. Overall, the authors concluded that deep neural network models have shown significant progress in text generation tasks, and the field is still rapidly evolving with new methods and architectures being proposed.

The authors proposed a novel approach to story generation that generates a coherent story from a sequence of independent short descriptions.

The authors noted that most existing methods for story generation require a predefined plot structure or a large corpus of text as input, which can be limiting in certain scenarios.

Their proposed method involves training a deep neural network model to predict the next sentence in the story sequence given the previous sentences.

The model uses a combination of a convolutional neural network (CNN) and an LSTM to encode the input sentences and generate the output sentence.

The authors also proposed a novel sampling algorithm that generates diverse and coherent stories by sampling from a distribution over the output sentences.

The authors evaluated their method on a dataset of short story summaries and showed that it outperforms existing methods in terms of coherence, diversity, and fidelity to the input summaries. They also conducted a human evaluation and showed that the generated stories are perceived to be more creative and engaging than the baseline methods. It is demonstrated that their approach is a promising method for generating coherent and creative stories from independent short descriptions, which can be useful in scenarios where a predefined plot structure is not available or desirable.

# Methodology

**Data collection:** The first step is gathering a large dataset of movie synopses that will be used to train the LSTM model. This dataset is obtained from Wikipedia.

**Data pre-processing**: After collecting the dataset, it needs to be cleaned and pre-processed. This involves removing any irrelevant information such as movie titles, cast information, and release dates.

The data is also tokenized into individual words or phrases and converted into a numerical representation that can be fed into the LSTM model.

**LSTM model training:** The pre-processed data is then used to train an LSTM model.

The LSTM model is a type of recurrent neural network that is designed to handle sequence data, making it well-suited for generating text. The model is trained to predict the next word in a sequence based on the previous words in the sequence.

**Synopses generation:** Once the LSTM model has been trained, it can be used to generate movie synopses.

This is done by providing the model with an initial seed phrase or sentence, and then using the model to generate the next word in the sequence. This process is repeated until the desired length of the synopsis is reached.

**Temperature Parameter:** The temperature parameter controls the randomness or creativity of the generated output. A higher temperature value will result in more diverse and

creative outputs, while a lower temperature value will result in more conservative and predictable outputs.

$$f_T(x) = Cexp(log(x)/T),$$

C>0 is just a normalization constant

$$q_i = \exp(z_i/T) / \sum_{j} \exp(z_j/T)$$

During the text generation process, the LSTM model generates a probability distribution over all possible next words, and the temperature parameter controls how "soft" or "hard" this distribution is.

A higher temperature value softens the distribution, allowing for a wider range of possible next words, while a lower temperature value hardens the distribution, resulting in a narrower range of possible next words.

#### Results

The generated results for user input:

#### Result with temperature as hyperparameter

the film starts in a dark house where a group of teenagers friends meet to spend the weekend when they suddenly hear the parasi te in the process ultimately then 've ca house explosion or enter the basement in jennifer 's involvement doris is dramatic fic tions hybrid chokes ambushes the car ringing the spirit 's eventually friend zoe confronts laurel being finally a dream as screen bathory has been dreams that it is herself wrong they are in the sanctuary with entering sonja timmy eva notices a woman nam ed logan taylor and abigail embrace to the family on the future at his house ...

# **Conclusion and Future Work:**

The use of LSTM neural networks allows for the generation of text that is coherent and structurally similar to actual movie synopses. The temperature parameter adds an element of randomness and creativity to the generated text, allowing for more diversity in the output.

movie synopsis generation using LSTM and the temperature parameter is a promising area of research that has the potential to revolutionize the way that movie synopses are created. With further development and refinement, this technology has the potential to significantly reduce the time and effort required to generate high-quality movie synopses, and ultimately enhance the experience of moviegoers around the world.

A future direction can be

Experiment with different number of neurons per layer.

Try new network architectures, for example adding a 1D-convnet laver.

Train on a bigger data set.

#### References:

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#### Sukhwani

"Story Generation from Sequence of Independent Short Descriptions."