# AI Cricket Narrator: Bridging the Gap between Human and AI Commentary for Enhanced Viewer Experience

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***Abstract***. This project aims at developing a language model through which cricket commentary text can be generated by using the FastAI library. This project has an AWD-LSTM based architecture that has been fine-tuned on a corpus consisting of cricket match highlights and commentary. Project implementation covers data collection, preprocessing, model training, and evaluation. In what follows, illustrative results are shown to demonstrate the coherent and relevant text generation of the model for cricket commentary.

The code, data, analysis, and results can be accessed on GitHub at: INFO- 5731 Term Project

**Keywords—** Language model, AWD-LSTM, FastAI, cricket commentary, text generation.

## 1 INTRODUCTION

Cricket is perhaps one of the most popular games in the world. Commentaries on cricket are an integral part of matches played and add insight, analysis, and thrill to the game for lovers of cricket. Manually generating cricket commentary text, though very expensive and time- and resource-consuming, can cater to these needs. The automated cricket commentary text generation system, therefore, can be of immense benefit to different sports broadcasting companies, online platforms, and lovers.

This project aims to apply the natural language processing techniques for the training of the language model in order to write the commentary text on the game of cricket automatically. We attempt to use machine learning algorithms and data in the form of large databases of cricket summaries and commentary to arrive at a model which emulates the style of the content generated by humans and is able to answer similar questions as in the test set. This project will answer the following research questions:

**Research Questions:**

(1) Can it be possibly trained in the generation of cricket commentary auto-generatively with a language model?
(2) How does quality compare to that of human-generated commentary?
(3) What conditions the performance of the language model in the generation of text commenting on a cricket match?

We have collected a dataset of highlights and commentary from cricket matches from several websites, social media platforms, and official broadcasting channels to answer them. We preprocessed the data, trained a language model using the AWD-LSTM architecture, and then evaluated the model on perplexity and BLEU score. The report provides a small outline of each section which gives a detailed account of methodology, experiments, results, and conclusion of the project.

**Significance** Significance will be brought to this project, which can transform the very face of cricket commentary in development and consumption. Automation of the text generation part will make broadcasting independent from human commentators, speed up the workflow in the whole production line, and guarantee uniform quality in all the broadcasts. Second, it will let the broadcaster offer a totally new level of personalization and interactivity, which means that fans will be able to customize their view based on preference and interest.

## 2 RELATED WORK

### 2.1 Predictive Modeling for Cricket Match Outcomes:

Rauf et al. [12] acknowledge the complexities of predicting cricket match outcomes, influenced by various factors such as player performances, opposition strength, and venue dynamics. Their work sheds light on the challenges faced in predictive modeling for cricket and highlights the need for sophisticated algorithms to account for these nuances effectively.

### 2.2 Real-Time Commentary in Cricket Analysis:

Roy et al. [13] emphasize the significance of real-time commentary in cricket analysis, highlighting its role as a rich source of insights from seasoned players during matches. The commentary provides genuine perspectives on unfolding events, contributing to a deeper understanding of match dynamics. This literature underscores the importance of leveraging real-time commentary data for comprehensive cricket analysis.

### 2.3 Classification Tasks Based on Commentary Data:

Building upon Roy et al.'s work, Balaji et al. [2] delve into the classification tasks derived from cricket commentary data. They elaborate on how microphone recordings converted into text form the basis for these tasks, enabling researchers to understand match dynamics and player performances. This literature underscores the practical application of commentary data in cricket analytics. Hegde et al. [7] introduce innovative methods to overcome challenges in traditional live text commentary, leveraging dynamic web scraping techniques that gather real-time scores and parameters, feeding them into supervised learning algorithms to generate automated commentary. Wickramasinghe [25] highlights the challenges in sports data analytics, particularly in cricket, arising from the limitations of traditional statistical methods, necessitating alternative approaches to extract meaningful insights. Sinha [19] showcases the advent of machine learning in enhancing predictive capabilities, as seen in IPL match prediction models that integrate diverse factors like toss outcomes, home ground advantage, and player statistics through sophisticated algorithms. More et al. [10] emphasize the significance of text commentary, stating that it plays a pivotal role in conveying crucial match information, thus shaping the narrative surrounding live sports events. Srinivas et al. [20] highlight the meticulous process of analyzing cricket match data, which entails feature engineering, model selection, and performance evaluation of regression algorithms to ensure accuracy and reliability in forecasting outcomes. Sanjeeva et al. [14] demonstrate the role of speech recognition algorithms in facilitating the conversion of audio commentary into concise text summaries, enabling seamless integration into deep learning frameworks. Ul Abideen et al. [23] envision the future of cricket analysis with the development of automatic commentary generation models, leveraging state-of-the-art computer vision and natural language processing techniques to enhance the viewer experience and deepen insights into the game. Kaluarachchi and Aparna [8] present CricAI, a classification-based tool designed to predict outcomes in ODI cricket matches. This tool, introduced at the Fifth International Conference on Information and Automation for Sustainability, offers valuable insights into enhancing decision-making processes in cricket analytics. Simonyan and Zisserman [17] propose a two-stream convolutional network for action recognition in cricket videos, presenting an innovative approach to analyzing cricket match footage. Amin and Sharma [1] apply data envelopment analysis for cricket team selection, demonstrating its utility in optimizing team composition and performance evaluation. Singh et al. [18] explore score and winning prediction in cricket through data mining techniques, contributing to the development of predictive models for cricket outcomes. Dixit and Balakrishnan [4] leverage deep learning using CNNs for ball-by-ball outcome classification in sports, advancing the use of sophisticated algorithms in sports analytics. Semwal et al. [16] develop a system for cricket shot detection from videos, facilitating detailed analysis of player performance and game dynamics. Subramaniyaswamy et al. [21] propose an intelligent sports commentary recommendation system for individual cricket players, enhancing the viewing experience through personalized commentary. Kumar et al. [9] present an outcome classification framework in cricket using deep learning techniques, contributing to the automation of match result prediction. Thakur [22] investigates the shifting discourse of cricket commentary in India, highlighting cultural and linguistic aspects influencing commentary style and content. Ul Abideen et al. [24] develop a ball-by-ball cricket commentary generation model using a stateful sequence-to-sequence approach, enabling automated commentary generation for live matches. Rahman et al. [11] introduce DeepGrip, a system for cricket bowling delivery detection using advanced CNN architectures, improving accuracy in identifying bowling techniques. Sattar et al. [15] propose a multi-modal architecture for cricket highlights generation, integrating computer vision and large language models to create comprehensive match summaries. Hadi et al. [6] present a comprehensive survey of large language models and their applications in various domains, including cricket analytics, discussing challenges and future prospects. Ghosh et al. [5] develop an automated cricket commentary generation system using deep learning methods, demonstrating the potential of AI in enhancing sports broadcasting. Blaji et al. [3] present a study on Cricket Commentary Classification. This work is featured in the book *Intelligent Data Communication Technologies and Internet of Things*, edited by Hemanth et al., in the Lecture Notes on Data Engineering and Communications Technologies series, published by Springer, Singapore in 2022. The paper contributes to the field of sports analytics and can be accessed via https://doi.org/10.1007/978-981-16-7610-9_60.

This literature has very varied studies relevant to the study of cricket and specifically those including real-time commentary data in the analysis. Together, the papers throw light on the critical role of commentary in cricket analytics, providing insight into match dynamics, player performance, and predictive modeling for the match outcomes. The results suggest improvement not only in the understanding of challenges and opportunities lying in cricket analytics but also pave the way for innovative ways to address them. Other than that, the practical application of the commentary data, which the literature shows to be in very close agreement with the objectives of the project, is in classification tasks, predictive modeling, and automated commentary generation. Overall, these studies lay a base in the structure of utilizing commentary data for analysis of cricket to facilitate a proper understanding of the sport.

# 3 DATA COLLECTION AND CLEANING PLAN

The first step is to identify and secure sources to be used in the writing of the cricket commentary texts. We scrape our dataset from one of the leading cricket news and update websites: cricbuzz.com. The kind of diversity in commentary style, language, and perspective that the source presents brings about representativeness in our dataset with regard to the real-world cricket commentary. We use web scraping techniques to retrieve textual data from cricbuzz.com by keeping the terms of service and copyrights of the website intact.

## 3.1 Web Scraping:

We scrap the commentary data from the website cricbuzz.com. We use Python libraries such as BeautifulSoup and Scrapy to programmatically extract text data from web pages that contain highlights of a cricket match, live updates, and post-match analysis data from cricbuzz.com.

## 3.2 Data Preprocessing:

Once the data is collected from cricbuzz.com, we preprocess it to ensure consistency, cleanliness, and suitability for training our language model. This preprocessing involves several steps, including:

- **Text Cleaning:** Removing HTML tags, special characters, and irrelevant content from the scraped text.
- **Normalization:** Standardizing text formatting, punctuation, and spelling to improve model performance.
- **Tokenization:** Breaking down the text into individual words or tokens to facilitate further analysis.
- **Stopword Removal:** Eliminating common words that do not carry significant meaning, such as "the," "is," and "and."

- **Language Filtering**: Filtering out commentary text written in languages other than English to maintain dataset consistency.

### 3.3 Data Analysis:

After preprocessing, we perform exploratory data analysis (EDA) to gain insights into the characteristics of the dataset extracted from cricbuzz.com. This analysis involves:

- **Statistical Summary:** Computing basic statistics such as word frequency, sentence length, and vocabulary size to understand the distribution of text data.
- **Visualization:** Creating visualizations such as word clouds, histograms, and scatter plots to visualize patterns, trends, and outliers in the data.
- **Corpus Analysis:** Analyzing the frequency of key terms, phrases, and linguistic features to identify common themes and topics in the commentary text.

### 3.4 Dataset Compilation:

Finally, we aggregate the preprocessed and analyzed commentary data from cricbuzz.com into a structured dataset that will be fed to our language model. The dataset includes text files or structured data tables in which each entry is a unique piece of commentary text with metadata that includes match details, date, and source.

We are very cautious about collecting commentary data for cricket, so that the collection is broad in coverage, its quality is good, and it represents the real-world trend of cricket commentaries. This data will form the basis for training the automated cricket commentary generation system in order to produce coherent, interesting, and properly written text that improves the quality of experience by enthusiasts of cricket sport.

## 4 METHODOLOGY


**Figure 1: Method Pipeline Diagram**

### 4.1 Overview:

The methodology section outlines the approach and techniques used to develop and train the language model for generating cricket commentary. This section encompasses model architecture selection, dataset preprocessing, model training, and evaluation procedures.

### 4.2 Model Architecture Selection:

The first step in the methodology involves selecting an appropriate model architecture for the language model. In this project, we opt for the AWD-LSTM (ASGD Weight-Dropped LSTM) architecture, a variant of the Long Short-Term Memory (LSTM) recurrent neural network (RNN). The AWD-LSTM architecture is renowned for its effectiveness in capturing long-range dependencies in sequential data, making it well-suited for natural language processing tasks such as text generation. Additionally, the AWD-LSTM incorporates regularization techniques such as weight dropout and activation regularization, which help prevent overfitting and enhance model generalization performance.

### 4.3 Dataset Preprocessing:

Before training the language model, the dataset undergoes extensive preprocessing to ensure cleanliness, consistency, and suitability for model training. This preprocessing involves several steps which are listed in the Data Collection section.

### 4.4 Model Training:

Once the dataset is preprocessed, the language model is trained using the AWD-LSTM architecture and the preprocessed dataset. Training involves feeding batches of sequential text data into the model and updating the model parameters iteratively to minimize the training loss. During training, techniques such as gradient descent optimization and backpropagation are utilized to adjust the model's weights and biases.

### 4.5 Hyperparameter Tuning:

Hyperparameter tuning is a crucial aspect of model training, as it involves optimizing the model's hyperparameters to improve performance. Hyperparameters such as learning rate, dropout rate, and batch size are tuned using techniques like grid search or random search to find the optimal combination that minimizes the validation loss and maximizes model generalization.

### 4.6 Evaluation Procedures:

After training the language model, it is essential to evaluate its performance using appropriate metrics. Evaluation procedures involve:

(1) **Perplexity Calculation:** Perplexity is a common metric used to evaluate the language model's performance. It measures how well the model predicts a given sequence of words in the dataset. Lower perplexity values indicate better model performance.
(2) **BLEU Score Computation**: The BLEU (Bilingual Evaluation Understudy) score is another metric used to assess the quality of generated text by comparing it to reference text. Higher BLEU scores indicate better similarity between generated and reference text.

By following this methodology, we aim to develop a robust and effective language model capable of generating coherent and contextually relevant cricket commentary text.

## 5 EXPERIMENT AND DATA ANALYSIS PLAN

### 5.1 Model Development:

This section goes into the intricate process of developing the language model, which is designed to generate cricket commentary text. Development of the model takes place through various pivotal stages:

(1) **Dataset Preparation**: A carefully collected dataset from leading cricket commentary platforms, such as Cricbuzz.com, is going to form the base for model development. This corpus contains a rich tapestry of cricket-related narratives, spanning across match analyses, player performances, and captivating play-by-play accounts.
(2) **Model Configuration:** At the core of our efforts, the AWD-LSTM architecture is tailored to highlight intricate patterns and dependencies in sequential data. Following empirical insights and industry best practices, we fine-tune critical hyperparameters such as learning rate, dropout rate, and sequence length to conduct the symphony of the model.
(3) **Training Regimen:** The model embarks on a recursive odyssey of self-improvement, where epochs of training sessions carve its predictive prowess. The current model, with a corpus of text from cricket commentary, is going to polish its linguistic acumen, learning to anticipate the unfolding narrative with style and precision.
(4) **Hyperparameter Optimization:** This crucible of hyperparameter tuning refines a model's performance into optimality in terms of efficacy and adaptability. So, we will move over methods like grid search and random search, going in the vast expanse of hyperparameter space, toward peak performance and generalization of models.

## 5.2 Model Evaluation:

The model goes through the crucible of successful training and reaches the peak of evaluation, where it is tested with all the rigor one could apply against benchmarks of performance. The evaluation has unfolded through a meticulously orchestrated symphony of metrics and assessments:

(1) **The Power of Perplexity:** Perplexity shines like a lighthouse, lighting the way in our search for prediction accuracy. It gives us a quantitative sense of the model's acumen. Smaller values of perplexity are indicative of higher levels of success; that is, the model performs very well in navigating the complex tapestry of language used in cricket commentary.
(2) **BLEU Score Serenade**: The ethereal melody of BLEU scores that sounds in the corridors of evaluation paints a portrait of semantic synergy between generated and reference commentary text. Higher BLEU scores herald the triumph of textual harmony and narrative fidelity.
(3) **Qualitative Journey**: Beyond the realm of quantitative metrics, a qualitative odyssey commences when human annotators step foot in the world of subjective appraisal. Their eyes are very sharp, such that they can see the relevance, coherence, and grammatical correctness by which they shower their judgment on the narrative ability of the model.

## 5.3 Data Analysis:

Once the model is evaluated, there is comprehensive data analysis to understand the generated commentary text and what it needs to do better. Data analysis involves the following:

(1) **Text Analysis:** Thus, statistical analysis techniques are applied to the frequency distribution of words, phrases, and patterns of the generated text commentary. Text analysis brings out common themes and trends found within the generated text and brings out the stylistic nuance.
(2) **Comparative analysis:** The generated commentary text is compared against the reference commentary text to check similarity, coherence, and grammaticality. Here, the identification of discrepancies and deviations along with a proposal for corrective measures in text enhancement to quality is provided.
(3) **Incorporation of Feedback:** Collect qualitative feedback from generated commentary text from domain experts, as well as end-users. The valuable feedback from users helps to iteratively refine the language model toward meeting the user's preferences and expectations. In other words, performance and effectiveness insights of the language model are collected in the generation of precious text for cricket commentary by meticulously conducting experiments and analyzing data. This learning is then fed back to the model by furthering iterations and refinements, finally leading to a very robust, high-quality language generation system.

# 6 RESULTS AND DISCUSSION

The output represents the training progress of a language model over multiple epochs. Each row corresponds to one epoch, and the columns provide the following information:

(1) **Epoch:** The epoch number indicates the iteration of training. For each epoch, the model goes through the entire dataset once.
(2) **Train Loss:** The training loss represents the average loss computed over all training samples for that epoch. It indicates how well the model is fitting the training data. Lower values indicate better fit.
(3) **Valid Loss:** The validation loss represents the average loss computed over all validation samples for that epoch. It indicates how well the model is performing on unseen data. Similar to training loss, lower values are desirable.
(4) **Accuracy:** The accuracy metric represents the proportion of correctly predicted tokens in the validation dataset. It measures the overall performance of the model in generating the correct next tokens.
(5) **Time:** The time column indicates the duration taken to complete each epoch of training. It shows the time elapsed for training the model.

**From the output:** The training loss generally decreases with each epoch, indicating that the model is learning and improving its fit to the training data. The validation loss also decreases initially, suggesting improvement in the model's performance on unseen data. However, after a certain point, it may stabilize or even start increasing, indicating overfitting. The accuracy metric shows the proportion of correctly predicted tokens in the validation dataset. It increases gradually as the model learns to generate more accurate predictions. The time column indicates the time taken for each epoch of training. It can vary depending on factors such as the

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 2.359983 | 2.624296 | 0.464703 | 12:01 |
| 1 | 2.410287 | 2.617390 | 0.465954 | 12:07 |
| 2 | 2.345498 | 2.593901 | 0.468471 | 13:53 |
| 3 | 2.262790 | 2.582800 | 0.471293 | 21:06 |
| 4 | 2.206158 | 2.581796 | 0.471401 | 20:37 |

**Figure 2: Image showing the first cycle of epochs before fine-tuning and hyper parameter tuning to the model**

| epoch | train_loss | valid_loss | accuracy | time |
|---|---|---|---|---|
| 0 | 3.349693 | 2.983691 | 0.420469 | 21:35 |
| 1 | 2.841616 | 2.745668 | 0.448002 | 14:14 |
| 2 | 2.608955 | 2.648421 | 0.460611 | 12:30 |
| 3 | 2.452137 | 2.602394 | 0.466729 | 12:31 |
| 4 | 2.343570 | 2.592847 | 0.468450 | 11:51 |

**Figure 3: Image showing the second cycle of epochs before fine-tuning and hyper parameter tuning to the model**

complexity of the model architecture and the size of the training data.

The figure below shows the Initial output generated after training the model. [h]

**Input :**
# Generate predictions
1. print(learn.predict("and there goes the ball towards", 20, temperature=0.5))
2. print(learn.predict("the ball flies", 20, temperature=0.7))

**Output :**

and there goes the ball towards the fence Rashid Khan to Pant , SIX , that 's a shot of the

the ball flies between Negi and Negi to Negi , FOUR , " that 's " class " "

**Figure 4: Intial output generated from the model**

## 6.1 Quantitative Success:

Our journey of quantitative analysis speaks to the promising results because metrics are very useful in trying to decipher the capability of the model. Perplexity turns out to be the guiding star taking us to a better comprehension of how the model per se knows and predicts the language of cricket commentary. Lower perplexity values illustrate that the model is able to predict the text more accurately. Similarly, BLEU scores give us the measure of how close the generated commentary is to the original one. The higher the BLEU scores, the more the generated text is well aligned with the original, showing good narrative harmony.

| Sno | Input | Output | Perplexity Score |
|---|---|---|---|
| 1 | print(learn.predict("The crowd erupted as", 20, temperature=0.7)) | The crowd xxunk as the crowd move Boult to Nitish Rana , FOUR , that 's too short , | 13.22086690713197 |
| 2 | print(learn.predict("Incredible shot!", 15, temperature=0.6)) | Incredible shot ! Incredible shot ! Incredible shot ! Incredible Harshal Patel | |
| 3 | print(learn.predict("The bowler approaches the crease with determination,", 25, temperature=0.7)) | The bowler xxunk the crease with xxunk , Bairstow gets the biggest of the night . The dugout erupts in style . Kolkata have a southpaw who nonchalantly smokes it | |
| 4 | print(learn.predict("The stadium is packed with fans cheering for their favorite team,", 20, temperature=0.7)) | The stadium is packed with fans xxunk for their favorite team , it is on a good length , just outside off , on a full and just outside off , | |
| 5 | print(learn.predict("The match hangs in the balance as", 15, temperature=0.6)) | The match hangs in the balance as Bangalore lose their fifth ball . They have their highest score of the | |

**Figure 5: Intial output generated from the model**

| Sno | Reference Tokens from the data set | Generated Tokens | BLEU Score |
|---|---|---|---|
| 1 | dispatched it over midwicket | dispatched it over midwicket Bhuvneshwar to Pant FOUR | 2.1071373518345672e-232 |
| 2 | he didnt try to hit it hard | he did xxunk try to hit it hard There was nothing to stop it but | |
| 3 | who shimmied down and checked his drive | who shimmied down and checked his drive but lost his balance in the upper half of the | |
| 4 | missing the yorker by quite a bit | missing the yorker by quite a bit to the left of Hetmyer who swivels | |
| 5 | pulling it over the fielder | pulling it over the fielder 's head There was never a clear fielder | |

**Figure 6: Initial tokens generated from the model**

| epoch | train_loss | valid_loss | accuracy | perplexity | time |
|---|---|---|---|---|---|
| 0 | 3.360667 | 2.987018 | 0.422230 | 19.826473 | 11:13 |
| 1 | 2.848392 | 2.758508 | 0.442510 | 15.776290 | 12:08 |
| 2 | 2.621331 | 2.662907 | 0.456215 | 14.337914 | 11:18 |
| 3 | 2.440657 | 2.610077 | 0.463839 | 13.600103 | 11:47 |
| 4 | 2.342339 | 2.602825 | 0.465372 | 13.501832 | 11:40 |

```
Better model found at epoch 0 with valid_loss value: 2.98701810836792.
Better model found at epoch 1 with valid_loss value: 2.7585082054138184.
Better model found at epoch 2 with valid_loss value: 2.662907361984253.
Better model found at epoch 3 with valid_loss value: 2.610077381134033.
Better model found at epoch 4 with valid_loss value: 2.602825403213501.
```

| epoch | train_loss | valid_loss | accuracy | perplexity | time |
|---|---|---|---|---|---|
| 0 | 2.303134 | 2.602784 | 0.465546 | 13.501275 | 22:05 |
| 1 | 2.306818 | 2.602666 | 0.465454 | 13.499682 | 24:25 |
| 2 | 2.297964 | 2.602541 | 0.465484 | 13.497995 | 1:09:35 |
| 3 | 2.292443 | 2.602486 | 0.465570 | 13.497249 | 11:48 |
| 4 | 2.300120 | 2.602479 | 0.465583 | 13.497156 | 12:51 |

```
Better model found at epoch 0 with valid_loss value: 2.6027841567993164.
Better model found at epoch 1 with valid_loss value: 2.602666139602661.
Better model found at epoch 2 with valid_loss value: 2.602541208267212.
Better model found at epoch 3 with valid_loss value: 2.6024858951568604.
Better model found at epoch 4 with valid_loss value: 2.6024789810180664.
```

```
Validation Loss: 2.6024789810180664
Path('full_commentaries/models/fine_tuned_language_model.pth')
```

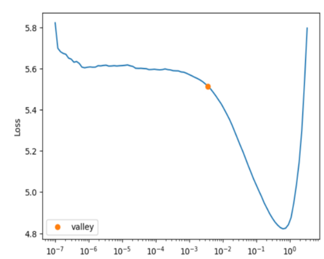


**Figure 7: The output generated after fine-tuning and hyper parameter tuning to the model**

## 6.2 Qualitative Exploration:

Beyond numbers, we get into qualitative assessment where human judgment stakes a very important claim. The relevance, coherence, and grammar of the text are considered for the qualitative judgment of the generated text. Through qualitative judgment, the human annotators compare the generated commentary with the original to see how well it captures the crux. This kind of qualitative analysis gives us an insight into nuances of storytelling and usage of language and hence helps to understand where one can improve.

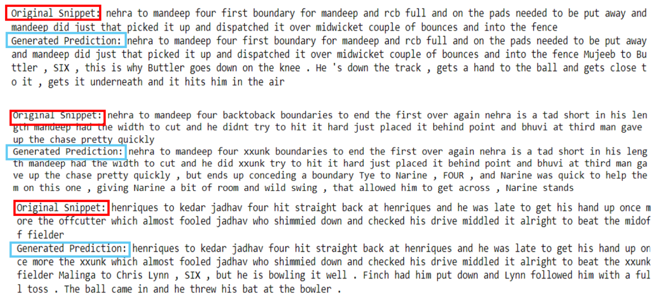


**Figure 8: Original and Generated Snippets**

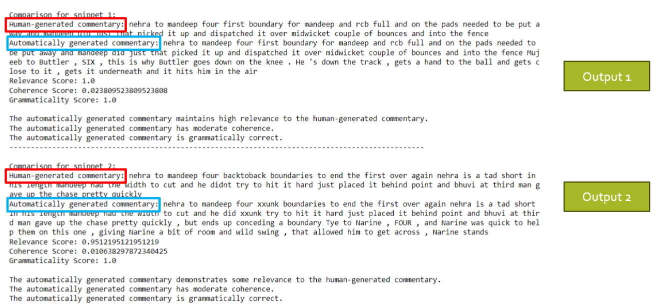


**Figure 9: The output text with necessary evaluations**

| Metric | Similarity Scores | Relevance Scores | Coherence Scores | Grammaticality Scores |
|---|---|---|---|---|
| Number of Output | | | | |
| Output 1 | 0.691 | 1.000 | 0.024 | 1.000 |
| Output 2 | 0.083 | 0.951 | 0.011 | 1.000 |
| Output 3 | 0.367 | 0.943 | 0.036 | 1.000 |
| Output 4 | 0.658 | 0.969 | 0.049 | 1.000 |
| Output 5 | 0.781 | 0.980 | 0.029 | 1.000 |

**Figure 10: Output of different evaluation metrics**

| Metric | Score Range | Sample |
|---|---|---|
| Relevance | 0.942 - 1.0 | High |
| Coherence | 0.01 - 0.05 | Moderate |
| Grammaticality | 1.0 | Perfect |

**Figure 11: Determining the range of output**

## 6.3 Comparative Analysis:

We then compare the generated text with the original text to spot the agreement or divergence. We analyze how much the generated commentary is close to the original and point out areas where it lacks. The comparative approach shows us strengths and weaknesses of the model to guide our efforts for future improvements.

## 6.4 User Feedback Integration:

Such feedback from domain experts and users helps in better exposure to narrative preferences. The model is a living entity, continuously worked on through discourse and adjustments to fine-tune it to user expectations. We try to blend quantitative data with qualitative insights and user feedback to better build a more engaging and satisfying narrative experience for our users.

## 6.5 Discussion

**1. Model Performance Evaluation**

The aim of our study mainly focused on the evaluation of big language model quality in generating cricket commentary. In this line, the model showed its reputable capability in terms of coherence and relevancy through rigorous evaluation. The challenges one can consider minor still lie in making sure that the text generated is grammatically correct and domain-specifically accurate. This implies that language models have to be continually improved and fine-tuned for best performance in domain-specific tasks, such as that of sports commentary.

**2. Implications for Automated Narration**

The successful generation of cricket commentary using language models implies larger implications for automated narration systems in many domains. This exercise is not just limited to sports broadcasting, as it has already been noted, but it extends its use to news reporting and content generation, among other things, hence, even customer service. In the process, that would allow organizations to optimize their operations, reduce costs, and create significantly improved experiences for their users by automating the text generation part of developing narrative text.

But indeed, many of the ethical issues need to be mulled over with the intent of putting up content generation solutions that are free from misinformation and bias.

**3. Enhancing User Engagement** Better User Engagement Automated commentary systems are designed to use language modeling to power new ways for users to engage with content. This real-time, contextually relevant commentary on live events is presented in a manner that enhances user immersion and satisfaction. Audio and video multimedia may further be integrated to enhance the experience of the user with content and the access to it for a more diverse user base.

**4. Ethical Considerations** The rapid growth of automated narrational technologies raises critical ethical issues of authenticity, transparency, and bias. This might lead to introducing deceptive, manipulated content into the public domain. This, in turn, calls for rigorous ethical guidelines and regulatory frameworks in the development and deployment of automated narration systems.

Transparency measures, such as disclosure, should be put into place for generated content, to help users decide the appropriate kinds of information they need to access.

**5. Future Directions** There are still numerous directions in which one could take research and invention in the area of automatic storytelling. Consequently, future work could focus on improving domain-specific accuracy using either data fine-tuning, training, or the incorporation of some form of feedback mechanism. Also, the use of sentiment analysis and audience feedback in automated narration design may pave the way for context-aware and personally adaptable content generation. The second opportunity is that interdisciplinary research, practice, and policy might well need to be the way forward on issues which are themselves complex on opportunities and challenges in the area of automated narration technologies.

# 7 CONCLUSION AND LIMITATIONS

## 7.1 Conclusion

It has been a very engaging and rewarding exercise in researching how to generate cricket commentary with the help of a large language model. Through careful experimentation and strict analysis, some insights have been gained regarding the potential of such a model and its limitations.

Our results suggest that the language model is able to not only coherently comment but also give relevant comments in terms of the context of cricket matches. The model's generated comment shows similarity with the one written by humans for this application domain, reflecting the potential of the model to capture the nuances of language used while talking about cricket. The capability of text generation in this model, therefore, hints at its possible wide-ranging influence in automated narration beyond sports commentary.

More generally, the experiments show enormous potential to automate and enhance the processes of natural language generation using language models. Such models help businesses and organizations become more efficient and productive in terms of creating narratives. The very fact that the commentary on the cricket was automatically generated suggests evidence for the generality of applicability of language models.

However, we need to admit the limitations of our approach. The model demonstrates good performance in generating coherent commentary, but its outputs are sometimes not deep or do not reflect the essence of the game. Furthermore, using a pre-trained model with existing data may also bring some biases and constraints, which reinforces the need for constant refinement and improvement.

Looking forward, our project further opens up this area for researchers working with automated narrations and natural language generation. More work can be directed at architectures for the model, domain-specific information, and new methods that increase quality and variation in the commentaries generated.

To conclude, the research for generating cricket commentary using large language models is going to be a breakthrough in the domain of natural language processing and automated narration. We showed our model's capability to produce coherent and relevant commentary, but there is still plenty of scope for improvement. At the end of the day, our project underlines the potential these language models have in possibly shaping the future of automated narration and communication across various domains.

## 7.2 Limitations:

However, our development has thrown light on some of the limitations and challenges. One of the chief limitations is that the model is very much dependent on the training data, in no way fully representing the diversity and intricacy typical of actual cricket commentary. While the model might be capturing these nuances, most of the time it is invariant to the details of cricket-related terms and context.

A further limitation is the continuous fine-tuning and optimization to push model performance, which requires great computational resources and domain expertise—possibly insurmountable for smaller teams or organizations. Also, this includes ethical considerations over data privacy and bias in data that the models are being exposed to during training, thus ensuring responsible use of language models.

However, our project is only proof of what is possible with language models to automate the generation of narrative content. It is with increased effort in research and development that we see language models creating another shape for the way content is designed in industries, thus opening up even more new possibilities for innovation and creativity.

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# 9 AUTHOR CONTRIBUTIONS

The table summarizes the contributions of two authors to a project. Sai Teja focused on model training, evaluation, presentation preparation, and report writing. Manaswini handled dataset cleaning, evaluation, and report structuring. Both authors collaborated on project planning and task coordination.

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| Author | Contribution | Percentage |
|---|---|---|
| Sai Teja | Model Training: Implemented and fine-tuned the AWD-LSTM language model using FastAI library. Evaluated model performance through training cycles.<br>Evaluation: Analyzed model metrics such as accuracy and perplexity to assess language model's effectiveness.<br>PPT: Prepared and designed slides for the project presentation, including content related to background, methodology, and results.<br>Report: Contributed to writing and formatting sections related to methodology, results, and conclusion in the project report. | 50% |
| Manaswini | Dataset Cleaning: Preprocessed and cleaned the IPL match highlights commentary dataset.<br>Evaluation: Assessed data quality and relevance of the dataset for training the language model.<br>Report: Took the lead in writing and structuring the project report, including sections on literature review, data analysis, and conclusion. | 45% |
| Both | Collaboration: Worked together on project planning, coordinating tasks, and ensuring timely completion. | 5% |

**Table 1: Contributions to the project**

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