Hello everyone,

My name is Yanzhuo Cao, today I will present my project on "Product Satisfaction and Buyback Intention Prediction Based on Review Analysis."

========================= Introduction =====================

Sentiment analysis is crucial for understanding customer feedback on e-commerce platforms. For this project, I used the "Amazon Product Review Dataset" from UC San Diego, which offers a rich source of customer reviews.

Previous research shows the effectiveness of sentiment analysis in identifying customer sentiments from textual data. However, traditional methods often focus on binary classification, which misses the subtleties in numerical ratings, providing deeper insights into customer satisfaction.

To address this, my project aims to refine sentiment analysis for e-commerce by enhancing the predictive accuracy of customer ratings, offering businesses more detailed and actionable insights into consumer preferences and satisfaction drivers.

========================= Problem Description =====================

Let’s move to the problem description and solution part.

Traditional sentiment analysis methods typically rely on binary classification – categorizing reviews as either positive or negative. This oversimplifies the nuanced feedback customers provide, leading to a loss of valuable information. Numerical ratings, like three-star reviews, offer deeper insights compared to one-star or five-star reviews.

========================= Problem Solution =====================

To address the limitations of traditional sentiment analysis, I propose developing advanced models to predict numerical ratings from textual reviews. These models include: Convolutional Neural Networks; Long Short-Term Memory; Transformer models.

========================= Method 1 =====================

Firstly, let’s discussion the Convolutional Neural Networks model.

CNNs capture local patterns in data. The process starts by converting text into numerical vectors using Word2Vec. Convolutional layers identify local patterns, followed by a global max pooling layer to highlight significant features. Dropout regularization prevents overfitting, and dense layers predict numerical ratings. CNNs are effective for analyzing shorter text segments.

========================= Method 2 =====================

Now, let's move on to the second method: Long Short-Term Memory networks, or LSTMs.

LSTMs handle long-term dependencies in sequential data. Text is processed through LSTM layers, maintaining context to understand sentiments. Dropout layers prevent overfitting, and dense layers predict numerical ratings. LSTMs are effective for capturing the flow of sentiments in detailed reviews.

========================= Method 3 =====================

Finally, let's discuss the third method: Transformer models.

Transformers handle long text sequences efficiently. Multi-head attention mechanisms capture global relationships and context, with positional encodings maintaining word order. Transformers process words simultaneously, making them faster and more efficient. Dense layers predict numerical ratings, capturing global context in complex reviews.

========================= Evaluation Metrics and Results =====================

Now that we've covered the methods, let's move on to the evaluation metrics and results.

Key findings include the impact of specific words on review scores. Words like "comfort" and "price" had higher attention weights and were associated with higher scores, indicating positive sentiment, while "material" suggested dissatisfaction.

These findings highlight the models' ability to capture nuances in customer reviews, providing detailed sentiment analysis and consistent improvement over baseline models.

========================= Implications =====================

Next, I will discuss the implications for this project.

For e-commerce businesses, this project enhances understanding of customer feedback, identifying key areas for improvement, and making data-driven decisions to enhance satisfaction and loyalty. Academically, it advances sentiment analysis techniques, demonstrating the effectiveness of advanced models like CNNs, LSTMs, and Transformers in predicting numerical ratings.

========================= Future Work =====================

Looking ahead, there are several avenues for future work and improvements.

Future work includes refining models by fine-tuning Transformer models and experimenting with bidirectional LSTMs. Methodological improvements could involve incorporating unsupervised learning techniques and exploring ensemble methods. Expanding the framework to other domains like healthcare and finance, and developing tools for real-time sentiment analysis on social media platforms, can increase generalizability and utility.

Expanding the dataset and continuously evaluating model performance will ensure relevance and effectiveness. In summary, this project has significant potential for further development and application.

========================= Conclusions =====================

To conclude, my key findings are as follows: LSTM models outperformed other methods in predicting numerical ratings, with a Mean Absolute Error of 1.20 and a Root Mean Square Error of 1.61. Key words like 'comfort,' 'price,' and 'material' were significant in influencing ratings.

These results have important implications for e-commerce, enabling businesses to understand customer feedback more deeply and make data-driven decisions to improve satisfaction and loyalty. Academically, my work advances sentiment analysis techniques and provides a framework adaptable to other domains such as healthcare, finance, and social media.

For future work, I plan to optimize Transformer models and bidirectional LSTMs, incorporate unsupervised learning, and expand our dataset for continuous evaluation and improvement.

Here are my references. And thank you for your attention.