UNDERSTANDING CUSTOMER FEEDBACK – A SENTIMENT ANALYSIS

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INTRODUCTION

BACKGROUND

- **Company**: Next plc a large clothing retailer
- **Problem statement**:
  - With the rise of digital platforms and social media, customers have become more vocal about their experiences.
  - These feedbacks are usually free text
  - In this study we needed to analyse this text correctly to inform business strategies
- **Data**: 732,621 customer interactions (comments, customer-rated survey scores, agent handling the interaction, etc.)

OBJECTIVE

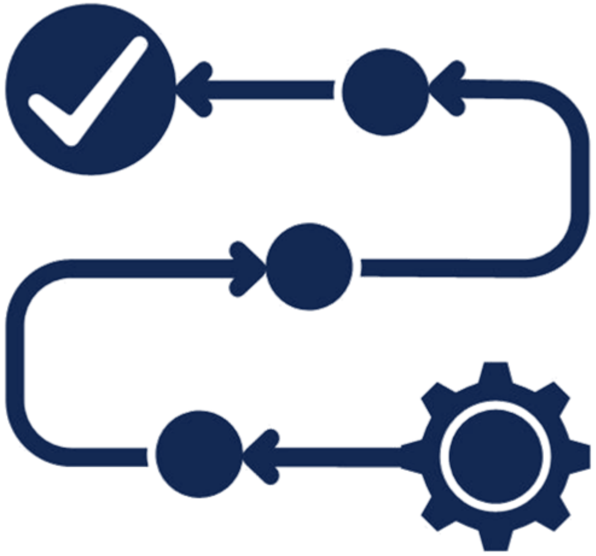
Develop an NLP model for sentiment analysis.

Align sentiments with customer ratings.

Provide actionable insights for enhancing customer service strategies.

SCOPE

- Tailored for NEXT plc customer feedback analysis.
- Primary data collected by NEXT.
- Focused on identifying sentiments associated with specific aspects of the customer experience.
- Does not cover other types of customer feedback analysis, such as the customer segmentation analysis.



METHODOLOGY

DATA COLLECTION & PREPROCESSING

- **Data sources**: Customer feedback from calls, surveys, and chats
- **Preprocessing**:
  - Converting data types
  - Dropping irrelevant columns
  - Handling missing values
  - Text cleaning
  - Expanding abbreviations
  - Tokenization, removing stop words and lemmatization

INITIAL MODELS

Categories	**BERT**	**LSTM**
Full form	Bidirectional encoder representations from transformers	Long short-term memory networks
Architecture	Transformer	Recurrent neural network
Context handling	Bidirectional (both left and right)	Unidirectional (only left)
Training speed	Slow, requires high computational power and memory	Faster than BERT but still slow due to sequential processing
Memory usage	High	Moderate
Strength	Known for high accuracy in NLP tasks, including sentiment analysis.	Effective in handling long-term dependencies in sentences.

FINALIZED MODEL (1 OF 2)

TEXTCNN

- **Purpose**: Adapted from traditional CNNs to work with text data.
- **Architecture**:
  - Embedding layer: Converts input text into dense vector representations using pre-trained embeddings.
  - Convolutional layers: Filters slide over the text to capture n-grams, detecting local dependencies between words.
  - Pooling layer: Max-pooling is used to reduce the dimensionality of the feature maps while preserving the most relevant features.
  - Fully connected layer: Synthesizes features and outputs the sentiment score through linear regression in this study.
- **Advantages**: Computationally efficient and captures local patterns (i.e. effectively identifies key phrases and local interactions in the text)

FINALIZED MODEL (2 OF 2)

GRADIENT BOOSTING

- **Purpose**: Used as a benchmark model for sentiment prediction, offering a simpler, more interpretable alternative to deep learning models.
- **Steps**:
  - Text preprocessing: Applied tokenization, stop word removal, TF-IDF to convert text into numeric feature set.
  - Model: Gradient Boosted Trees Regressor (GBTRegressor) was trained on the same dataset as for TextCNN.
    - Hyperparameters: 1000 boosting rounds, max depth of 3.
  - Evaluation: Done on same text dataset as TextCNN.
    - Predictions were compared using MAE and correlation with customer rating.
- **Advantages**: Interpretable and fast to train

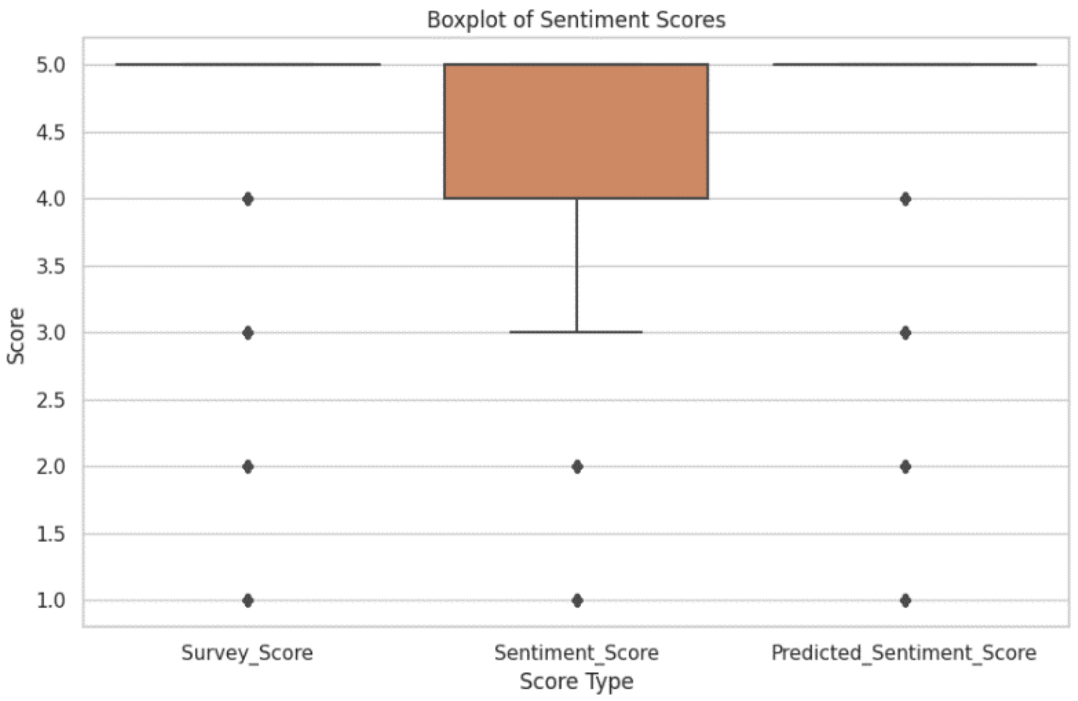
RESULTS

MODEL COMPARISON

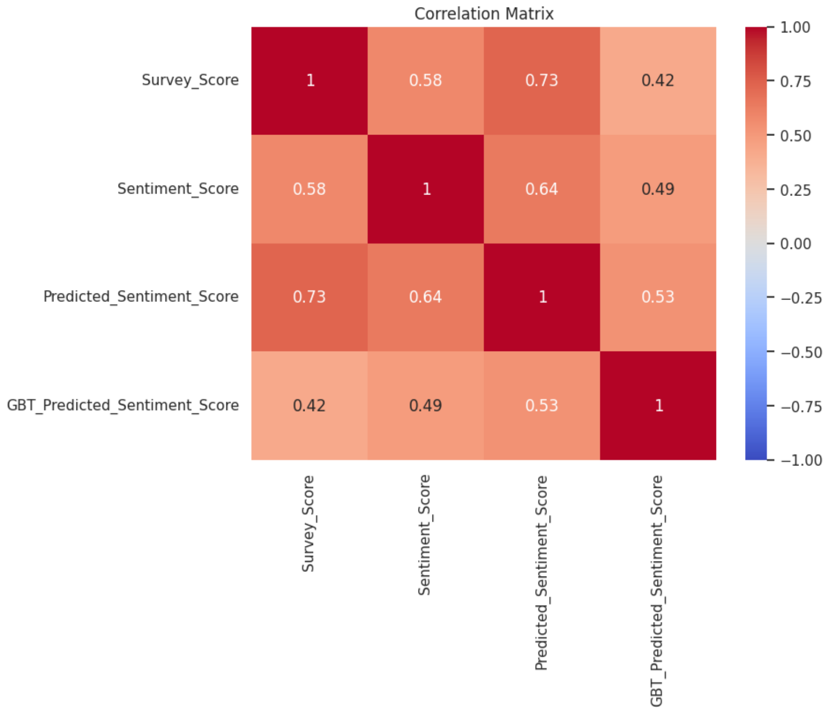
- **BERT**:
  - Accuracy: 8.4% (sample of 1000 records).
  - Training time: Took 70 minutes to process 1000 records, estimated to take 23 days for the full dataset.
- **LSTM**:
  - Accuracy: 8.0% (sample of 1000 records).
  - Training time: Faster than BERT but still significant, estimated to take nearly 3 days to process the entire dataset.
- **TextCNN**:
  - Accuracy: 80%
  - MAE: 0.35
  - Correlation with survey score: 0.73
  - Training time: 70 mins for full dataset.
- **Gradient Boosting**:
  - MAE: 0.57
  - Correlation with survey score: 0.42
  - Training time: 50 mins for full dataset.

TEXTCNN PERFORMANCE (1 OF 2)

- Predicted score distribution

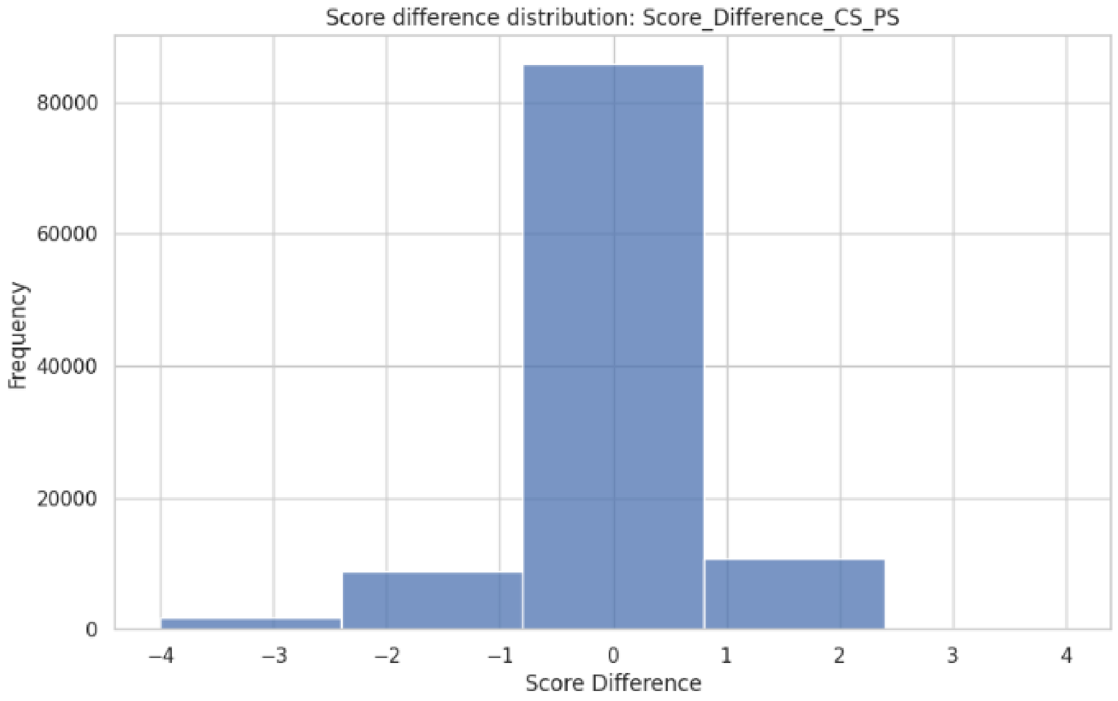


- Correlation matrix

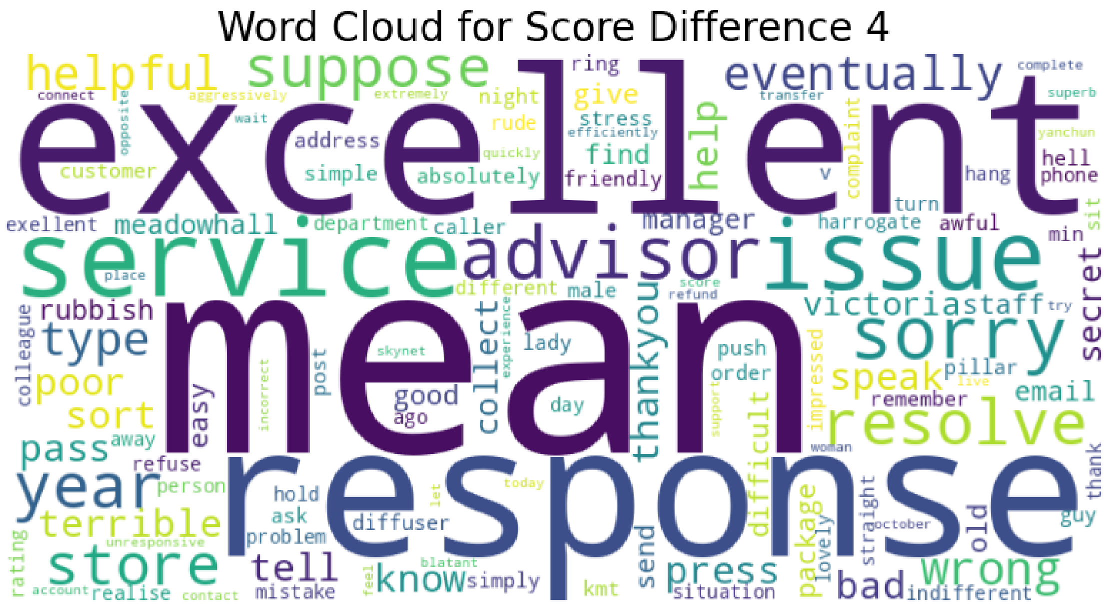


TEXTCNN PERFORMANCE (2 OF 2)

- Score difference distribution

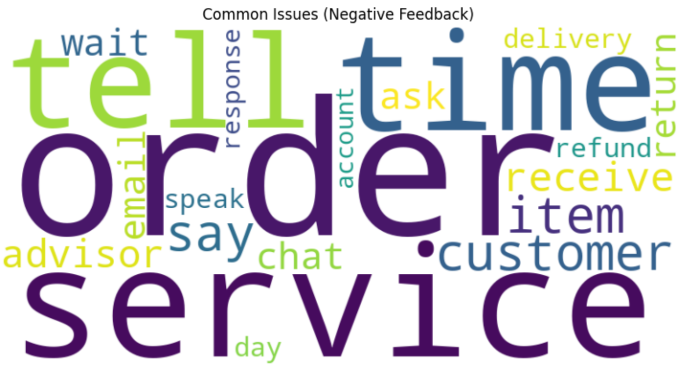


- Extreme misclassification



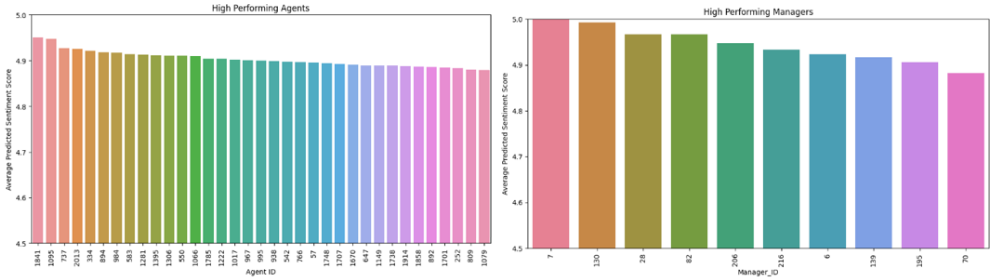
ACTIONABLE INSIGHTS

- Common issues

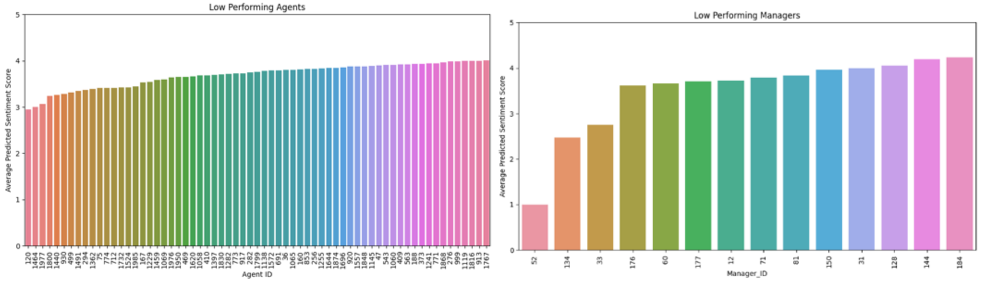


- Areas of excellence

- High performers



- Low performers



CONCLUSION

RECOMMENDATIONS AND FUTURE WORK

Recommendations:

- Adopt TextCNN Model for large-scale sentiment analysis.
- Refine customer rating system for clarity (e.g., 5-star scale).
- Use insights for targeted agent/manager/department improvements.

Future Work:

- Enhance sentiment analysis with advanced models
- Sentiment analysis across different languages
- Investigate the impact of sentiment on customer retention
- Analyse factors leading to high and low performance