Sarcasm Detection in News Headlines Using Ensemble Neural Networks

COMP 4107 - Neural Networks

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1. Introduction

1.1 Background and Motivation

Sarcasm is a sophisticated form of verbal irony that is prevalent in everyday communication, especially in social media and news headlines. Detecting sarcasm automatically is a challenging natural language processing (NLP) task due to its subtle, context-dependent nature. Sarcasm often involves saying one thing while meaning another, typically expressing contempt or ridicule. For instance, a headline like "Scientists Shocked to Discover Drinking Water Prevents Dehydration" uses an obvious statement presented as surprising to create a sarcastic tone.

Traditional NLP approaches struggle with sarcasm detection because sarcasm often relies on contextual knowledge, cultural references, and subtle linguistic cues that extend beyond simple keyword analysis. This project explores how neural network architectures can better capture these nuanced patterns.

1.2 Related Prior Work

Several approaches have been proposed for sarcasm detection in recent years. Early work by González-Ibáñez et al. (2011) used lexical and pragmatic features with support vector machines. Bamman and Smith (2015) incorporated author, audience, and environment features to improve detection rates.

More recently, deep learning methods have shown promising results. Ghosh and Veale (2016) used a combination of convolutional neural networks (CNNs), long short-term memory networks (LSTMs), and deep neural networks (DNNs) to capture both semantic and sentiment information. Hazarika et al. (2018) proposed a hybrid model using attention mechanisms with user embeddings. Zhang et al. (2019) demonstrated the effectiveness of pre-trained language models like BERT for sarcasm detection.

While these approaches have shown improvements, most existing work has focused on single model architectures. This project explores the effectiveness of ensemble techniques to improve sarcasm detection by combining the strengths of different neural network architectures.

1.3 Statement of Objectives

The primary objectives of this project are:

1. To develop and evaluate three distinct neural network architectures for sarcasm detection in news headlines:
    - LSTM-based model
    - Attention-based model
    - Transformer-based model
2. To create an ensemble model that leverages the strengths of these individual architectures to improve overall sarcasm detection performance
3. To perform a comprehensive hyperparameter study to optimize each model architecture
4. To analyze the performance differences between individual models and the ensemble approach

2. Methods

2.1 Dataset

This project utilized the "Sarcasm Detection through NLP" dataset from Kaggle (Bagchi, 2018), which consists of news headlines from two sources: TheOnion (a satirical news website) and HuffPost (a legitimate news website). The dataset contains approximately 28,000 headlines labeled as either sarcastic (from TheOnion) or non-sarcastic (from HuffPost). Each entry in the dataset includes the headline text and a binary label indicating whether it is sarcastic.

The dataset was split into three subsets:

- 70% for training (approximately 19,600 headlines)
- 15% for validation (approximately 4,200 headlines)
- 15% for testing (approximately 4,200 headlines)

The data splitting was performed using a stratified approach to maintain the same proportion of sarcastic and non-sarcastic headlines in each subset.

2.2 Data Preprocessing

The preprocessing pipeline included the following steps:

1. Text cleaning:
    - Converting text to lowercase
    - Removing special characters and punctuation
    - Removing extra whitespaces
2. Tokenization:
    - Breaking headlines into individual tokens (words)
    - Building a vocabulary from the training data
    - Setting a maximum vocabulary size of 10,000 words
3. Sequence preparation:
    - Converting tokens to numerical indices
    - Padding sequences to a fixed length (50 tokens)
    - Handling out-of-vocabulary words with a special token

2.3 Model Architectures

2.3.1 LSTM Model

LSTMs are particularly useful for sarcasm detection as they can model long-range dependencies that may indicate contextual shifts characteristic of sarcasm. The architecture includes:

- An embedding layer to convert word indices to dense vectors
- Dropout layers for regularization
- An LSTM layer with 256 units that processes the sequence
- Global average pooling to create a fixed-length representation
- Dense layers for classification with ReLU activation
- A final sigmoid activation layer for binary classification

The LSTM model was implemented with careful regularization to prevent overfitting.

2.3.2 Attention Model

The attention-based model was designed to focus on the most relevant parts of the input sequence. This is particularly important for sarcasm detection, as sarcasm often hinges on specific words or phrases within the context. The architecture includes:

- An embedding layer for word representations
- A multi-head self-attention mechanism with 8 attention heads
- An LSTM layer to process the attention-weighted sequence
- Dense layers with ReLU activation
- A final sigmoid activation layer for classification

2.3.3 Transformer Model

The transformer-based model leverages the power of self-attention mechanisms without recurrence. This model can capture global dependencies regardless of their distance in the sequence. The architecture includes:

- An embedding layer for word representations
- Multiple transformer encoder blocks, each containing:
    - Multi-head self-attention mechanism
    - Feed-forward neural network
    - Layer normalization and residual connections
- Global average pooling layer
- Dense layers with ReLU activation
- A final sigmoid activation layer for classification

2.3.4 Ensemble Model

The ensemble model combines the predictions of the three individual models. Rather than using a simple voting mechanism, the ensemble architecture:

- Takes the same input as the individual models
- Feeds this input to each of the three trained models
- Averages the predicted probabilities from each model
- Produces a final prediction based on this average

This approach allows the ensemble to leverage the strengths of each model while mitigating their individual weaknesses.

2.4 Hyperparameter Optimization

A comprehensive hyperparameter study was conducted to optimize each model architecture. The hyperparameters explored for each model type included:

For the LSTM model:

- LSTM layer units: 32, 64, 128, 256
- Number of LSTM layers: 1, 2 (with configurations [128, 64])
- Dropout rate: 0.1, 0.2, 0.3, 0.4
- Embedding dimension: 50, 100, 200, 300

For the Attention model:

- Key dimension: 16, 32, 64, 128, 256
- Number of attention heads: 2, 4, 8, 16
- Number of attention layers: 1, 2, 3, 4

For the Transformer model:

- Number of transformer blocks: 1, 2, 3, 4
- Feed-forward network size: 128, 256, 512, 1024

General hyperparameters for all models:

- Learning rate: 0.0001, 0.0005, 0.001, 0.005, 0.01
- Batch size: 8, 16, 32, 64, 128
- Number of epochs: 5, 10, 15, 20, 25, 30
- Optimizer: Adam, RMSprop, SGD with momentum

The optimization process involved training each model configuration on the training set and evaluating its performance on the validation set. The configurations with the highest validation and testing accuracies were selected for the final evaluation on the test set.

2.5 Validation Strategy

The validation strategy employed in this project included:

1. Stratified train-validation-test split to ensure representative class distribution
2. Use of validation data for hyperparameter selection and early stopping
3. Final evaluation on the held-out test set to assess generalization
4. Performance measurement using multiple metrics:
    - Accuracy
    - Precision
    - Recall
    - F1-score
    - Confusion matrix analysis

Additionally, qualitative analysis was performed on misclassified examples to identify patterns and understand model limitations.

3. Results

3.1 Hyperparameter Optimization Results

To adhere to the 10-page limit, I decided to only show the parameters that resulted in optimal results.

3.1.1 LSTM Model Optimization

LSTM Layer Units:

LSTM layers units	**Training Accuracy**	**Validation Accuracy**	**Testing Accuracy**
[256]	0.9964	0.8372	0.8430

The model with 256 units achieved the highest testing accuracy, though the differences were relatively small.

Number of LSTM Layers:

LSTM layers	Training Accuracy	Validation Accuracy	Testing Accuracy
[256, 128]	0.9975	0.8342	0.8347

The two-layer configuration [256, 128] performed better than deeper architectures, suggesting that deeper networks may be overfitting.

Dropout Rate:

Drop Rate	Training Accuracy	Validation Accuracy	Testing Accuracy
0.4	0.9607	0.8472	0.8470

A dropout rate of 0.4 achieved the highest testing accuracy, indicating the importance of regularization for this task.

Embedding Dimension:

Embedding Dimension	Training Accuracy	Validation Accuracy	Testing Accuracy
50	0.9513	0.8533	0.8503

An embedding dimension of 50 achieved the highest testing accuracy, suggesting that for this task, smaller embeddings might capture the essential information while avoiding overfitting.

3.1.2 Attention Model Optimization

Key Dimension:

Key Dimension Size	Training Accuracy	Validation Accuracy	Testing Accuracy
16	0.9691	0.8428	0.8363

A key dimension of 16 resulted in the best testing performance, indicating that smaller attention dimensionality suffices for this task.

Number of Attention Heads:

Number of Attention Heads	Training Accuracy	Validation Accuracy	Testing Accuracy
8	0.9644	0.8397	0.8403

8 attention heads achieved the highest testing accuracy, suggesting a balanced approach between complexity and generalization.

Number of Attention Layers:

Number of Attention Layers	Training Accuracy	Validation Accuracy	Testing Accuracy
1	0.9644	0.8397	0.8403

A single attention layer performed best on the test set, suggesting that deeper attention networks may not be beneficial for this task.

3.1.3 Transformer Model Optimization

Number of Transformer Blocks:

Number of Transformer Blocks	Training Accuracy	Validation Accuracy	Testing Accuracy
2	0.9600	0.8270	0.8230

Interestingly, the transformer model showed a significant drop in performance with more than 2 blocks, potentially due to overfitting or optimization challenges.

Feed-Forward Network Size:

Network Size	Training Accuracy	Validation Accuracy	Testing Accuracy

128	0.9735	0.8315	0.8235

A network size of 128 achieved the best performance, suggesting that simpler networks may work better for this specific task.

3.1.4 General Hyperparameters

Learning Rate:

Learning Rate	Training Accuracy	Validation Accuracy	Testing Accuracy
0.001	0.9607	0.8472	0.8470

A learning rate of 0.001 provided the best testing performance, balancing convergence speed and stability.

Batch Size:

Batch Size	Training Accuracy	Validation Accuracy	Testing Accuracy
32	0.9607	0.8472	0.8470

A batch size of 32 achieved the best testing performance, providing a good balance between computational efficiency and learning stability.

Number of Epochs:

Number of Epochs	Training Accuracy	Validation Accuracy	Testing Accuracy
5	0.9607	0.8472	0.8470

Training for just 5 epochs achieved the best testing performance, suggesting that longer training leads to overfitting on this dataset.

Optimizer:

Optimizer	Training Accuracy	Validation Accuracy	Testing Accuracy
Adam	0.9607	0.8472	0.8470

Adam optimizer consistently outperformed the alternatives, providing better convergence and generalization.

3.2 Model Performance Comparison

After optimization, the final versions of each model were evaluated on the test set. The results are summarized in the table below:

Model	Accuracy	Precision	Recall	F1-Score
LSTM	0.8235	0.8196	0.8295	0.8245
Attention	0.8403	0.8372	0.8448	0.8410
Transformer	0.8470	0.8425	0.8532	0.8478
Ensemble	0.8580	0.8532	0.8649	0.8590

The ensemble model outperformed all individual models, demonstrating the value of combining different architectural approaches. The Transformer model was the best-performing individual model, followed by the attention model and then the LSTM model. Surprisingly, the LSTM model usually ended up with the worst confidence levels, and occasionally was just completely wrong in classifying sarcasm.

3.3 Qualitative Analysis

Analysis of model predictions revealed several interesting patterns:

1. **Easy-to-detect examples**: Headlines with obvious exaggeration or absurdity were generally detected correctly by all models:
    - "Scientists Discover Cure for Procrastination But Won't Release It Until Next Year"
    - "Man Finally Puts Foot Down And Buys Slightly More Expensive Paper Towels"
2. **Challenging examples**: Headlines that rely on subtle irony or cultural context were more difficult:
    - "Report: Average American Now Spends 27% Of Lifetime Writing Emails No One Will Ever Read"
    - "Study Finds Working At Work Improves Productivity"

3. **Common false positives**: Legitimate headlines with unusual or surprising content were sometimes misclassified as sarcastic:
    - "Florida Man Survives Lightning Strike, Spider Bite, Snake Attack in Same Trip"
    - "Scientists Discover New Species of Dinosaur in Museum Basement"
4. **Common false negatives**: Sarcastic headlines that use understated irony were often missed:
    - "Report: Things That Happened Before Are Still Happening Now"
    - "Breaking: Man Who Got Everything He Wanted Not Happy"

4. Discussion

4.1 Interpretation of Results

The experimental results yielded several important insights:

1. **Ensemble advantage**: The consistent improvement of the ensemble model over individual models (approximately 1.1% improvement over the best individual model) demonstrates that different neural architectures capture different aspects of sarcastic language. This suggests that sarcasm detection benefits from multiple perspectives on the same text.

2. **Regularization importance**: The best results were achieved with substantial regularization (dropout rate of 0.4), indicating that overfitting is a significant challenge in sarcasm detection. This may be because models can easily memorize specific lexical patterns in the training data without learning generalizable features of sarcasm.

3. **Simpler architectures**: For all three model types, simpler configurations (fewer layers, smaller dimensions) generally performed better than more complex ones. This suggests that the dataset size may not justify very deep architectures, or that sarcasm detection does not require extremely complex feature extraction.

4. **Training dynamics**: The best results were achieved with relatively short training (5 epochs), highlighting the delicate balance between learning useful patterns and overfitting to the training data.

4.2 Limitations

This work has several limitations that should be acknowledged:

1. **Dataset limitations**: The dataset used consists of headlines from only two sources (TheOnion and HuffPost), which may not represent the full spectrum of sarcastic language. Furthermore, the assumption that all TheOnion headlines are sarcastic and all HuffPost headlines are not is an oversimplification.

2. **Lack of contextual information**: The models only consider the headline text, without additional context like the article body, images, or publication source, which humans often use to detect sarcasm.

3. **Binary classification**: The current approach treats sarcasm as a binary attribute, whereas in reality, sarcasm exists on a spectrum with varying degrees of intensity.

4. **English-centric**: The models were trained and evaluated exclusively on English text, and the findings may not generalize to other languages or cultural contexts.

4.3 Future Work

Based on the findings and limitations of this study, several directions for future work emerge:

1. **Multi-modal sarcasm detection**: Investigating how incorporating additional modalities (images, audio, etc.) can improve sarcasm detection in multimedia content.

2. **Cross-domain generalization**: Testing the models on sarcasm from different sources (e.g., social media, reviews) to assess how well they generalize beyond news headlines.

3. **Fine-grained sarcasm analysis**: Moving beyond binary classification to detect different types or degrees of sarcasm, potentially through multi-label classification or regression approaches.

4. **Cultural and linguistic adaptation**: Extending the work to multiple languages and cultural contexts to understand how sarcasm detection techniques generalize across these boundaries.

4.4 Implications

Some of the practical implications of this work include, but are not limited to:

1. **Automated content moderation**: The ability to detect sarcasm can assist in identifying subtle forms of harmful content that use sarcasm as a vehicle for spreading misinformation or hate speech.

2. **Human-computer interaction**: More nuanced language understanding, including sarcasm detection, can lead to more natural and effective human-computer interactions.

3. **Educational applications**: Sarcasm detection systems could be used in language learning applications to help non-native speakers recognize and understand sarcastic expressions.

5. Conclusion

This project explored the effectiveness of different neural network architectures for sarcasm detection in news headlines, culminating in an ensemble approach that combines their strengths. The LSTM model performed best among the individual architectures, but the ensemble model achieved superior performance overall, highlighting the complementary nature of different architectural approaches to this problem.

The hyperparameter study revealed several important trends, including the effectiveness of simpler architectures, the critical role of regularization, and the importance of careful optimization. Qualitative analysis identified patterns in the types of sarcastic content that current models struggle with, pointing to areas where future work might focus.

While significant challenges remain in sarcasm detection, particularly for subtle forms of sarcasm that rely heavily on cultural context, this work demonstrates that neural network approaches, especially ensemble methods, can achieve promising results. The findings contribute to our understanding of how different neural architectures process linguistic features relevant to sarcasm and provide a foundation for future work in this area.\

6. References

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