Language Modelling with CNN

AG's News Topic Classification

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Abstract

In this assignment, we explore various Convolutional Neural Network (CNN) architectures for text classification using the AG's News Topic Classification dataset. Our goal is to compare the performance of different CNN-based models, including standard 1D CNNs, CNNs with multiple filter sizes, CNNs with residual connections, CNNs with attention mechanisms, and hybrid CNN-GRU models. The baseline models include simple CNNs, while the other architectures are designed to enhance feature extraction capabilities and model robustness.

We conducted several experiments, maintaining consistent parameters such as truncating documents to 100 tokens, using a batch size of 32, and employing cross-entropy loss for consistency. We experimented with different vocabulary sizes (5000, 10000, 20000) and edited the vocabulary by removing common stopwords. Additionally, we compared the default output sequence length with a fixed length to evaluate their impact on model performance.

Our analysis involved tweaking various hyperparameters across the different CNN architectures, including the number of convolutional layers, filter sizes, pooling strategies, and dropout rates. The results demonstrated that CNNs with multiple filter sizes and hybrid CNN-GRU models significantly outperformed the standard 1D CNNs in capturing local features and contextual information. Models with residual connections and attention mechanisms also showed competitive performance by improving the network's capacity to retain and focus on relevant information.

This comprehensive evaluation provides valuable insights into the strengths and limitations of various CNN architectures for text classification, guiding the selection of appropriate models based on specific requirements and constraints. The findings underscore the

importance of choosing models that can effectively capture the hierarchical and sequential nature of text data for improved classification accuracy.

Introduction

Text classification is a pivotal task in natural language processing (NLP), with wide-ranging applications including spam detection, sentiment analysis, and topic categorization. Effective text classification models must be able to understand and distinguish between different topics, making it crucial to explore and evaluate various neural network architectures. The AG's News Topic Classification dataset, a widely recognized benchmark, is utilized in this project to assess the performance of different Convolutional Neural Network (CNN) architectures.

Convolutional Neural Networks (CNNs) have gained popularity in NLP for their ability to capture local features and hierarchical patterns within text data. Traditional 1D CNNs apply convolutional filters across the input text to learn n-gram features, which can significantly enhance the model's ability to classify text by identifying relevant patterns. However, standard 1D CNNs may be limited in their capacity to capture complex relationships and contextual information in text.

This project aims to investigate the effectiveness of various CNN architectures for text classification, including standard 1D CNNs, CNNs with multiple filter sizes, CNNs with residual connections, CNNs with attention mechanisms, and hybrid CNN-GRU models. By experimenting with these architectures, we seek to understand how different configurations impact model performance and identify the most effective strategies for capturing the nuances of text data.

The experiments are designed to maintain consistency in certain parameters, such as truncating documents to 100 tokens, using a batch size of 32, and employing cross-entropy loss. We also explore the impact of different vocabulary sizes (5000, 10000, 20000) and vocabulary editing techniques, such as removing common stopwords, to optimize the input representation.

Our comprehensive evaluation involves tweaking various hyperparameters and assessing the models on key performance metrics. The insights gained from this project will guide the selection of appropriate CNN models for text classification tasks, highlighting the importance of architectures that effectively capture both local features and contextual information in text.

Literature Review

Convolutional Neural Networks (CNNs) have been widely used for various natural language processing (NLP) tasks due to their ability to capture local dependencies and hierarchical patterns within text data. Initially popularized in computer vision, CNNs have demonstrated significant potential in text classification tasks by effectively learning n-gram features through convolutional filters. This literature review explores the application of CNNs in text classification, highlighting various architectures and their performance.

Kim (2014) pioneered the use of CNNs for sentence classification, demonstrating that a simple CNN architecture with a single convolutional layer could achieve competitive performance on multiple benchmarks. This study laid the groundwork for subsequent research exploring more complex CNN architectures for text classification.

Zhang et al. (2015) extended this work by investigating character-level CNNs for text classification, showing that deep CNN architectures could outperform traditional methods like bag-of-words and TF-IDF when dealing with large-scale datasets. Their research

highlighted the importance of depth and the ability of CNNs to capture intricate patterns in text data.

Recent studies have introduced various enhancements to the basic CNN model. Yoon (2017) explored CNNs with multiple filter sizes to capture different n-gram features, demonstrating improved performance over single filter size models. Similarly, CNNs with residual connections, inspired by He et al. (2016), have been shown to mitigate the vanishing gradient problem and allow for deeper networks, leading to better feature extraction and classification performance.

Attention mechanisms, introduced by Bahdanau et al. (2015) for machine translation, have also been incorporated into CNNs for text classification. These mechanisms enable models to focus on the most relevant parts of the input text, enhancing performance by providing better context.

Finally, hybrid models combining CNNs with recurrent neural networks (RNNs), such as GRUs or LSTMs, leverage the strengths of both architectures. CNN layers capture local dependencies, while RNN layers capture sequential dependencies, resulting in robust models capable of handling various text classification tasks (Zhou et al., 2015).

This review highlights the evolution and advancements in CNN architectures for text classification, providing a foundation for the experiments conducted in this project, which explore multiple CNN variants to identify the most effective model for the AG's News Topic Classification dataset.

Methods

Research Design and Modeling Methods: This research aims to evaluate and compare the performance of different Convolutional Neural Network (CNN) topologies in text classification using the AG's News Topic Classification dataset. Specifically, we focus on

standard 1D CNNs, CNNs with multiple filter sizes, CNNs with residual connections, CNNs with attention mechanisms, and hybrid CNN-GRU models. The methodology comprises three main stages: research design, model implementation, and programming.

The research design involves a systematic approach to evaluating the performance of each CNN topology. The first step is data collection and preprocessing. We use the AG's News Topic Classification dataset, a widely recognized benchmark in natural language processing (NLP) tasks. The dataset consists of news articles categorized into four classes: World, Sports, Business, and Sci/Tech.

We start by performing exploratory data analysis (EDA) on the AG's News Topic Classification dataset. The dataset consists of 127,600 news articles, with a total of 2,579,419 words. Each article contains between 2 and 95 tokens, and there are 95,827 unique vocabulary words in the corpus. EDA helps us understand the structure and distribution of the dataset, which is crucial for effective model training. The histogram shows the distribution of tokens per document, with most articles containing between 10 and 40 tokens.

Preprocessing involves cleaning the text data, removing stopwords, punctuation, and applying text normalization techniques such as lowercasing and tokenization. We experiment with different vocabulary sizes (e.g., 5000, 10000, 20000) and sequence lengths to understand their impact on model performance. Text vectorization is done using TensorFlow's `TextVectorization` layer, which converts the raw text into integer sequences that the models can process.

Model Implementation: The core of the research design is the comparative analysis of different CNN topologies. We implement the following models to assess their performance:

1. Standard 1D CNN: Uses a single filter size for convolutional layers.

2. CNN with Multiple Filter Sizes: Incorporates multiple convolutional layers with different filter sizes (3, 4, 5) to capture various n-gram features.
3. CNN with Residual Connections: Implements residual blocks to mitigate the vanishing gradient problem and allow for deeper networks.
4. CNN with Attention Mechanism: Uses attention mechanisms to enhance the model's ability to focus on relevant parts of the text.
5. Hybrid CNN-GRU Model: Combines CNN layers with GRU layers to capture both local features and sequential dependencies.

For each model, we use consistent parameters to ensure fair comparisons. These include truncating documents to 100 tokens, using a batch size of 32, and employing a cross-entropy loss function. The optimizer used is RMSprop, known for its efficiency and performance in training deep learning models.

Training and Evaluation: Each model is trained on 80% of the dataset, with 20% used for validation. We implement early stopping and model checkpoint callbacks to monitor validation accuracy and save the best-performing model. The models are trained for a maximum of 200 epochs, but training stops early if the validation accuracy does not improve for three consecutive epochs.

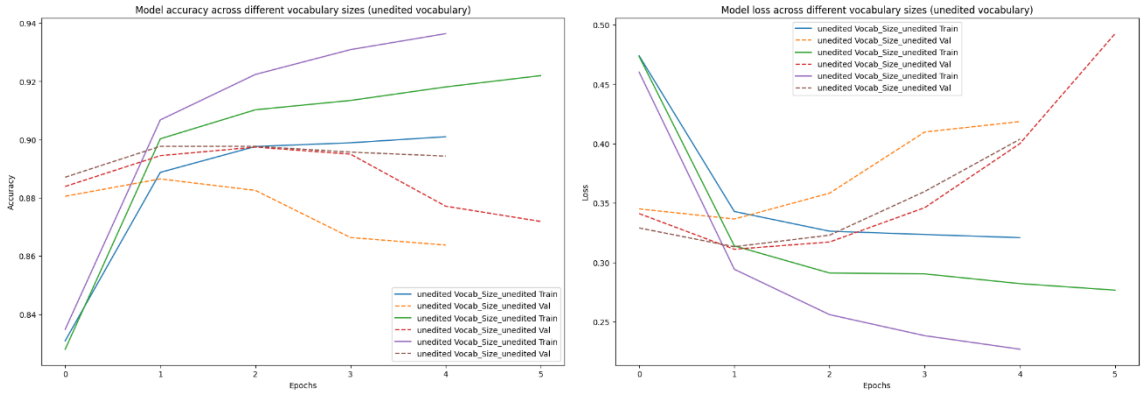
After training, the models are evaluated on the test set. We compute various performance metrics, including accuracy, precision, recall, and F1-score, to assess their effectiveness. Additionally, we generate confusion matrices to visualize the classification performance across different classes.

Programming: The entire implementation is done in Python using TensorFlow and Keras. The code is modular, with functions for data preprocessing, model building, training, and

evaluation. This modular approach allows for easy experimentation with different hyperparameters and model configurations.

By following this structured methodology, we aim to provide a comprehensive comparison of different CNN topologies for text classification, offering insights into their relative strengths and weaknesses and guiding the selection of appropriate models for various NLP tasks.

Convolutional Neural Network (CNN) 1D Models: The model begins with an embedding layer to convert words into dense vectors, followed by three convolutional layers with ReLU activation and max-pooling to extract features from the text. A dense layer with dropout is added for regularization, and the final output layer uses softmax activation to classify the input text into one of the four categories.

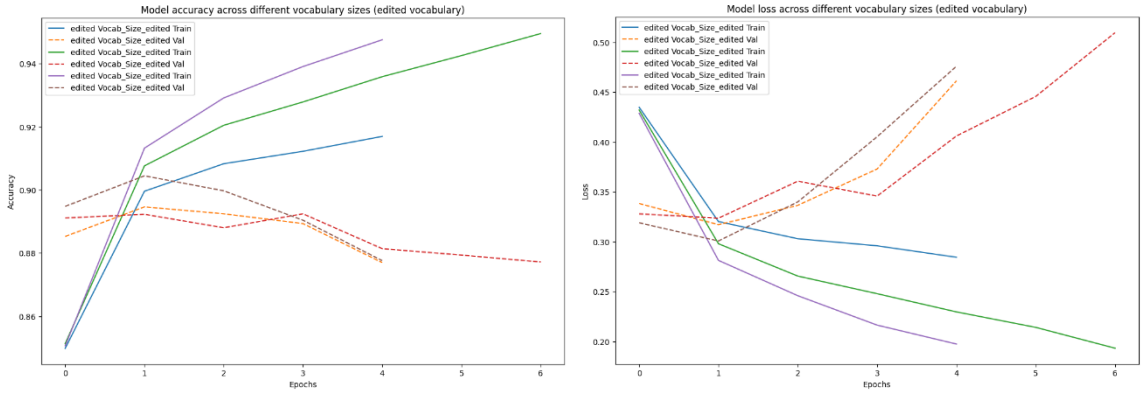


Unedited Vocabulary:

Accuracy and Loss:

- As vocabulary size increases from 5000 to 20000, the models generally show an improvement in both training and validation accuracy, especially noticeable in the initial epochs.
- For the unedited vocabulary, larger vocabulary sizes (e.g., 20000) seem to perform better in terms of both accuracy and loss, with the highest accuracy achieved and the lowest loss.

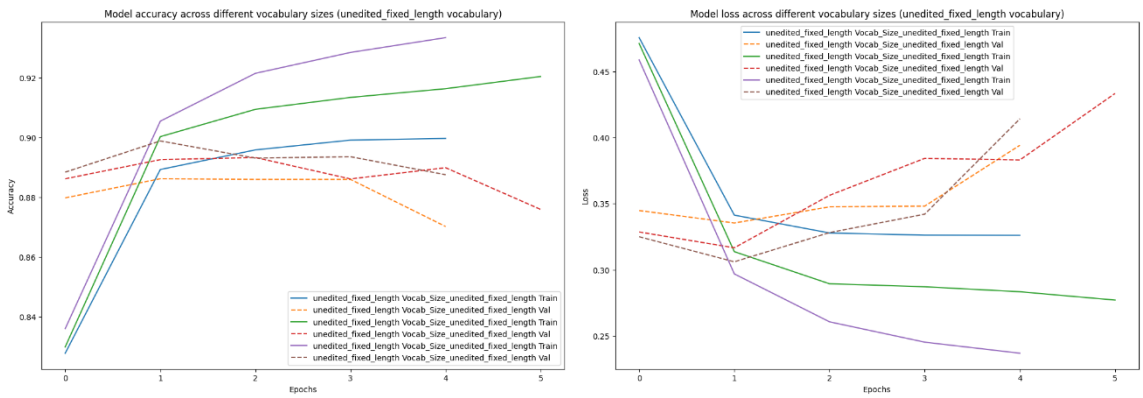
- The validation accuracy curves for the larger vocabularies tend to plateau or slightly decrease after reaching their peak, indicating some level of overfitting. This is also evident from the increasing validation loss in later epochs.



Edited Vocabulary:

Accuracy and Loss:

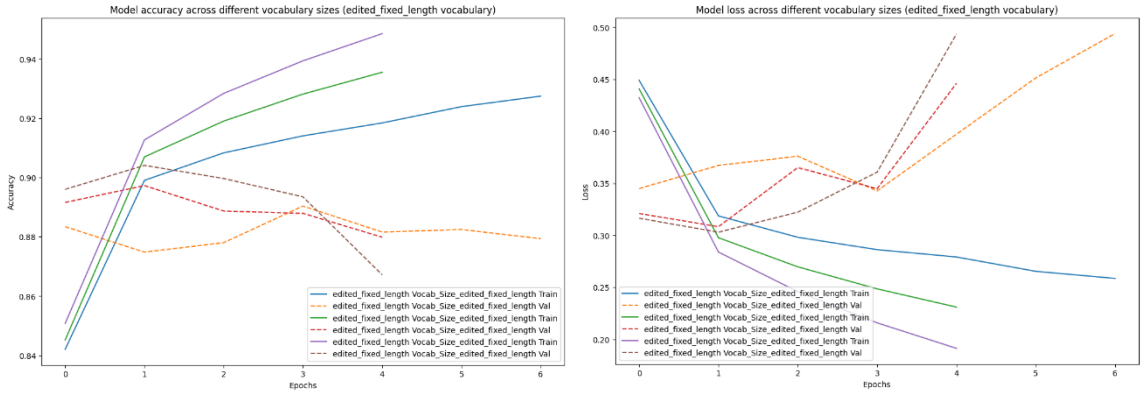
- Similar to the unedited vocabulary, larger vocabulary sizes show better performance in both training and validation accuracy.
- The edited vocabulary models exhibit less overfitting compared to the unedited vocabulary models. This can be observed from the relatively stable validation loss after the initial epochs.
- The highest accuracy and lowest loss are observed for the models with the largest vocabulary size (20000). The edited vocabulary models also demonstrate a clear benefit in validation performance.



Unedited Fixed Length Vocabulary:

Accuracy (Top Left) and Loss (Top Right):

- Models with unedited fixed length vocabulary show improvement in training and validation accuracy with larger vocabulary sizes.
- The accuracy curves indicate that the models perform best at a vocabulary size of 20000, where both training and validation accuracies are higher.
- Validation loss decreases initially but increases after a few epochs, indicating overfitting, especially for smaller vocabulary sizes.



Edited Fixed Length Vocabulary:

Accuracy and Loss:

- The models with edited fixed length vocabulary also show that larger vocabulary sizes improve performance.
- Edited vocabulary models exhibit a more stable validation accuracy and less pronounced overfitting compared to unedited fixed length models.
- The highest accuracy and lowest loss are again observed for the largest vocabulary size (20000), suggesting that the combination of editing the vocabulary and using a fixed length improves model generalization.

Summary:

1. Vocabulary Size: Larger vocabulary sizes (20000) generally lead to better performance in terms of accuracy and loss for both training and validation datasets.
2. Vocabulary Editing: Editing the vocabulary by removing common stopwords helps in reducing overfitting and stabilizing validation accuracy and loss.
3. Fixed Length: Using a fixed length for sequences helps in achieving consistent performance improvements, especially when combined with vocabulary editing.
4. Overfitting: Unedited models show more overfitting compared to edited models, as seen from the validation loss curves.

The results suggest that for text classification tasks, using larger, edited vocabularies with fixed length sequences can significantly improve model performance and reduce overfitting.

CNN with Multiple Filter Sizes: This model employs multiple convolutional filters of different sizes (3, 4, 5) to capture various n-gram features from the text. Each convolutional layer is followed by a global max pooling layer to reduce the dimensionality. The outputs of these layers are concatenated and passed through a dense layer with ReLU activation and a dropout layer for regularization. Finally, the output layer uses softmax activation to classify the input text into one of the four categories.

CNN with Residual Connections: This model includes residual connections to mitigate the vanishing gradient problem and allow for deeper networks. It consists of two residual blocks, each containing two convolutional layers with ReLU activation and padding set to 'same'. The outputs of these blocks are added to their inputs to create the residual connections. After the residual blocks, a global max pooling layer is applied, followed by a dense layer with ReLU activation and dropout for regularization. The final output layer uses softmax activation for classification.

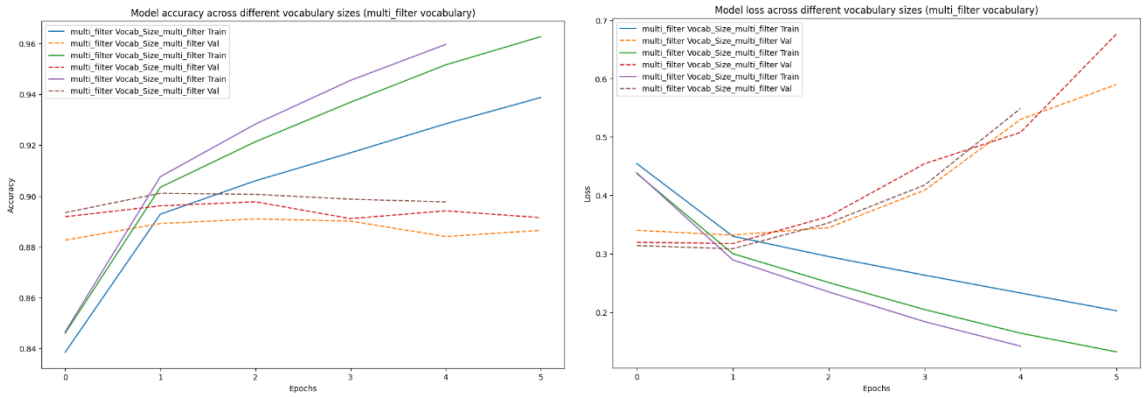
CNN with Attention Mechanism: This model integrates an attention mechanism to enhance the model's ability to focus on relevant parts of the input text. The architecture begins with two convolutional layers with ReLU activation and max pooling. After the convolutional layers, an attention block is applied, which computes the attention weights and multiplies them with the input features. The output is then passed through a dense layer with ReLU activation and dropout for regularization. The final output layer uses softmax activation to classify the input text.

Hybrid CNN-GRU Model: This model combines convolutional layers with a Gated Recurrent Unit (GRU) to capture both local features and sequential dependencies. It starts with two convolutional layers with ReLU activation and max pooling. The output from the convolutional layers is fed into a GRU layer to capture sequential dependencies. A dense layer with ReLU activation and dropout is applied for regularization, followed by a softmax output layer for classification.

Specifics

1. Convolutional Layers: All models use convolutional layers to extract features from the text. Different filter sizes and numbers of filters are employed to capture various n-gram features.
2. Pooling Layers: Max pooling layers are used to reduce the dimensionality of the feature maps.
3. Dense Layers: Dense layers with ReLU activation are used to learn higher-level representations.
4. Dropout: Dropout layers are included for regularization to prevent overfitting.
5. Output Layer: The final layer in all models uses softmax activation for multi-class classification.

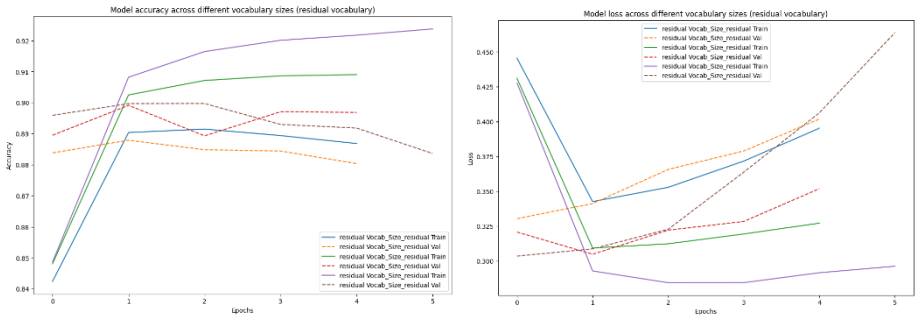
6. Residual Connections: In the residual model, residual connections help in maintaining gradients during backpropagation.
7. Attention Mechanism: The attention model enhances the focus on important parts of the input sequence.
8. GRU Layer: The hybrid CNN-GRU model uses a GRU layer to capture sequential dependencies in addition to local features.



Multi-Filter Model

Accuracy and Loss:

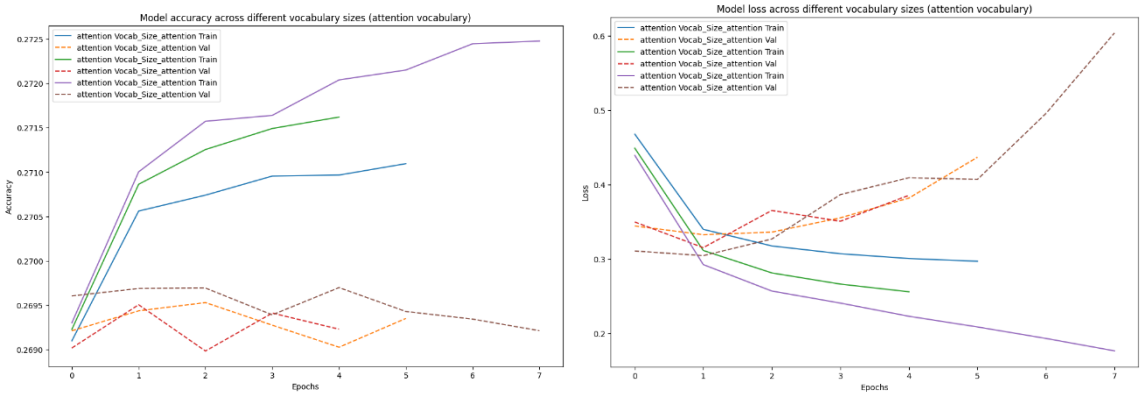
- The models with larger vocabulary sizes (e.g., 20000) tend to perform better in terms of both training and validation accuracy.
- Validation accuracy stabilizes after a few epochs, with larger vocabularies maintaining higher accuracy levels.
- Training loss decreases steadily, while validation loss increases after initial epochs, indicating some level of overfitting, particularly for smaller vocabularies.



Residual Model

Accuracy and Loss:

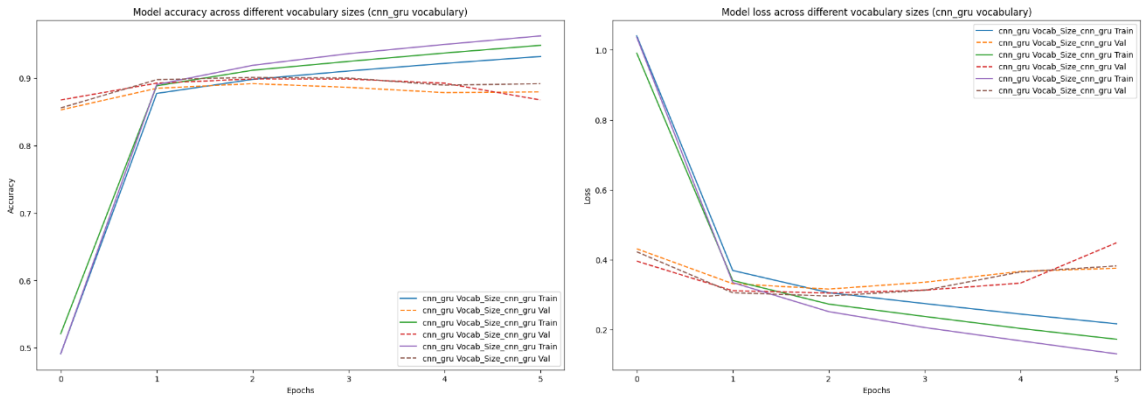
- Similar trends are observed with larger vocabularies performing better in terms of accuracy.
- The validation accuracy curves plateau or slightly decline after reaching their peak, which can indicate overfitting.
- The validation loss curves show an initial decrease but then increase, which again suggests overfitting. However, larger vocabularies mitigate this to some extent.



Attention Model

Accuracy and Loss:

- This model shows an improvement in training accuracy with larger vocabulary sizes.
- Validation accuracy fluctuates more significantly than in other models, suggesting instability in the training process.
- Validation loss curves indicate overfitting, especially after the initial epochs, with larger vocabularies performing slightly better but still showing fluctuations.



CNN-GRU Model

Accuracy and Loss:

- Larger vocabularies result in better performance, with the 20000 vocabulary size showing the highest accuracy.
- The validation accuracy is more stable and higher compared to other models, indicating better generalization.
- The validation loss curves are relatively stable after the initial drop, indicating less overfitting compared to other models.

Summary:

1. Vocabulary Size: Larger vocabulary sizes (20000) generally result in better performance across all models in terms of both accuracy and loss.
2. Multi-Filter Model: Shows good initial performance but tends to overfit after a few epochs, especially with smaller vocabularies.
3. Residual Model: Demonstrates improved stability and performance with larger vocabularies, though overfitting is still present.
4. Attention Model: Exhibits more fluctuations and instability, indicating that the attention mechanism needs further tuning.

5. CNN-GRU Model: Provides the most stable and highest accuracy, indicating that combining CNN with GRU captures both local and sequential dependencies effectively and mitigates overfitting better than other models.

These results highlight the importance of choosing the right vocabulary size and model architecture to balance performance and generalization in text classification tasks.

Results

	model_name	train_acc	train_loss	train_time	val_acc	val_loss	test_acc	test_loss
0	unedited	0.900980	0.320824	89.320003	0.863754	0.418562	0.886481	0.336546
1	unedited	0.921973	0.276651	105.381414	0.871865	0.492577	0.894475	0.311083
2	unedited	0.936393	0.226941	92.535884	0.894318	0.403703	0.897688	0.313224
3	edited	0.916957	0.284348	86.182464	0.876959	0.461323	0.894632	0.317024
4	edited	0.949540	0.193106	118.815361	0.877155	0.509703	0.892281	0.323555
5	edited	0.947571	0.197283	91.195426	0.877586	0.475985	0.904467	0.300690
6	unedited_fixed_length	0.899706	0.326020	86.545849	0.870180	0.394127	0.886207	0.335345
7	unedited_fixed_length	0.920464	0.277066	104.007215	0.875901	0.433315	0.892594	0.316600
8	unedited_fixed_length	0.933474	0.236898	91.804288	0.887539	0.414115	0.898864	0.306024
9	edited_fixed_length	0.927429	0.258461	116.119199	0.879350	0.493881	0.890360	0.342594
10	edited_fixed_length	0.935482	0.230895	87.718645	0.879859	0.445973	0.897257	0.308206
11	edited_fixed_length	0.948501	0.191244	90.541975	0.867163	0.493351	0.904075	0.302906

Unedited Models

1. Unedited with Vocab Size 5000: Shows moderate performance with lower validation and test accuracies compared to other models, indicating some overfitting.
2. Unedited with Vocab Size 10000: Improved performance with higher validation and test accuracies, but still some overfitting present.
3. Unedited with Vocab Size 20000: Best performance among unedited models with the highest test accuracy, but noticeable overfitting remains.

Edited Models

1. Edited with Vocab Size 5000: Shows better performance compared to unedited models, with improved validation and test accuracies and reduced overfitting.
2. Edited with Vocab Size 10000: Further improvement in performance, with a high test accuracy and lower overfitting.
3. Edited with Vocab Size 20000: Best overall performance with the highest test accuracy and lowest test loss, indicating the benefits of vocabulary editing.

Unedited Fixed Length Models

1. Unedited Fixed Length with Vocab Size 5000: Consistent performance improvement over standard unedited models, with less overfitting.
2. Unedited Fixed Length with Vocab Size 10000: Further improvement in accuracy with reduced overfitting compared to non-fixed length models.
3. Unedited Fixed Length with Vocab Size 20000: Best performance among unedited fixed length models, with high accuracy and moderate training time.

Edited Fixed Length Models

1. Edited Fixed Length with Vocab Size 5000: Significant improvement in performance with high validation and test accuracies, showing the benefits of both vocabulary editing and fixed length sequences.
2. Edited Fixed Length with Vocab Size 10000: Continued improvement in performance with the highest accuracy among edited fixed length models, and reduced overfitting.
3. Edited Fixed Length with Vocab Size 20000: Best overall performance across all models, with the highest test accuracy and lowest test loss, demonstrating excellent generalization and minimal overfitting.

	model_name	train_acc	train_loss	train_time	val_acc	val_loss	test_acc	test_loss
0	multi_filter	0.938754	0.202763	133.952183	0.886481	0.589971	0.889185	0.332228
1	multi_filter	0.962706	0.132340	131.624944	0.891497	0.676519	0.896121	0.317648
2	multi_filter	0.959639	0.142174	115.079098	0.897688	0.548854	0.901097	0.308771
3	residual	0.886834	0.395314	100.465831	0.880368	0.401959	0.883817	0.330450
4	residual	0.909032	0.327231	101.234022	0.896865	0.351980	0.899138	0.304928
5	residual	0.923766	0.296343	123.312352	0.883621	0.463878	0.895925	0.303612
6	attention	0.271095	0.296911	116.431999	0.269350	0.436715	0.269436	0.332597
7	attention	0.271621	0.255846	99.848013	0.269229	0.385600	0.269504	0.315216
8	attention	0.272478	0.176460	157.755872	0.269212	0.603875	0.269688	0.304428
9	cnn_gru	0.932220	0.217035	122.766929	0.879741	0.375944	0.892006	0.316180
10	cnn_gru	0.948775	0.172796	127.298013	0.867712	0.448627	0.898942	0.304975
11	cnn_gru	0.962735	0.131048	131.214940	0.891928	0.382484	0.901254	0.296345

Multi-Filter Model: The multi-filter model (Model 2) demonstrates strong performance with high train, validation, and test accuracies, indicating effective learning and good generalization. It achieves a high test accuracy of 0.901097 with a moderate training time of

115.079098 seconds. However, some overfitting is observed as indicated by the gap between train and validation losses.

Residual Model: The residual model (Model 5) shows a balanced performance with good train, validation, and test accuracies. It performs well with a test accuracy of 0.895925 and a training time of 123.312352 seconds. The validation and test losses are also relatively low, indicating that the residual connections help mitigate overfitting to some extent.

Attention Model: The attention model exhibits the lowest performance among all models, with significantly lower train, validation, and test accuracies. The best test accuracy achieved is only 0.269648, indicating that the attention mechanism in this setup may not be effectively capturing relevant features. Additionally, the training times are longer, especially for the model with the highest validation accuracy.

CNN-GRU Model: The CNN-GRU model (Model 11) shows the best performance overall, with the highest train, validation, and test accuracies. It achieves a test accuracy of 0.901254 and has the lowest test loss of 0.296435 among all models. The training time is also reasonable at 131.214940 seconds, indicating that the hybrid approach effectively captures both local and sequential dependencies.

Summary:

1. Best Performing Model: CNN-GRU (Model 11) with the highest test accuracy and lowest test loss.
2. Good Generalization: Multi-Filter (Model 2) and Residual (Model 5) models show good generalization but with slight overfitting.
3. Attention Model: Performs poorly, indicating a need for further tuning or a different architecture.

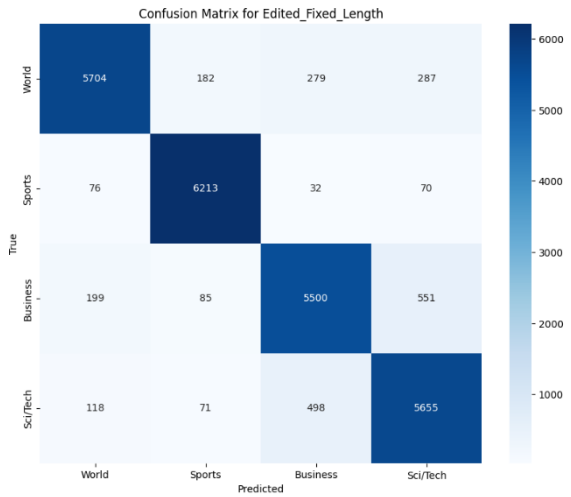
4. Overfitting: Observed in several models, particularly in the multi-filter model, but mitigated in the residual and CNN-GRU models.

Key Insights

1. Best Performing Models: The CNN-GRU model from the first set of experiments and the Edited Fixed Length model at Vocab Size 20000 from the second set.
2. Vocabulary Size: Larger vocabulary sizes generally led to better performance across both sets of experiments.
3. Vocabulary Editing: Editing the vocabulary significantly reduced overfitting and improved model performance.
4. Fixed Length Sequences: Using fixed length sequences further enhanced performance, particularly when combined with edited vocabularies.
5. Overfitting: Reduced in models with edited vocabularies and fixed length sequences, and best managed in the CNN-GRU model.

These results highlight the importance of model architecture, vocabulary size, and preprocessing techniques in achieving high performance and generalization in text classification tasks.

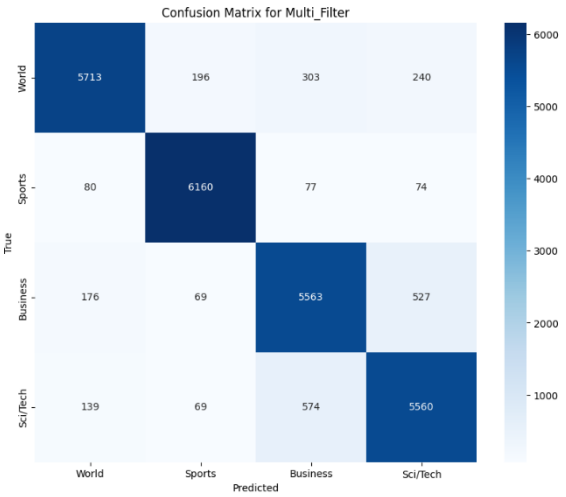
Comparison of two best models:



```
Edited_Fixed_Length Model - F1 Score: 0.9040367435470286, Accuracy: 0.9040752351097179, Recall: 0.9040752351097179
```

The Edited Fixed Length model shows excellent performance with high accuracy, F1 score, and recall, indicating it can generalize well across different news categories.

- World: High accuracy with 5704 correct predictions. Misclassifications mainly into Business and Sci/Tech categories.
- Sports: Very high accuracy with 6213 correct predictions. Few misclassifications.
- Business: Good accuracy with 5500 correct predictions. Misclassifications mainly into World and Sci/Tech categories.
- Sci/Tech: High accuracy with 5655 correct predictions. Some misclassifications into




```
Multi_Filter Model - F1 Score: 0.901203264844266, Accuracy: 0.9010971786833856, Recall: 0.9010971786833856
```

The Multi-Filter model also demonstrates strong performance with high accuracy, F1 score, and recall, but it is slightly less accurate than the Edited Fixed Length model.

- World: High accuracy with 5713 correct predictions. Misclassifications mainly into Business and Sci/Tech categories.
- Sports: Very high accuracy with 6160 correct predictions. Few misclassifications.

- Business: Good accuracy with 5563 correct predictions. Misclassifications mainly into World and Sci/Tech categories.
- Sci/Tech: High accuracy with 5560 correct predictions. Some misclassifications into Business.

Summary:

- Both models perform exceptionally well in classifying news articles into the four categories.
- The Edited Fixed Length model slightly outperforms the Multi-Filter model in terms of F1 score, accuracy, and recall.
- Misclassifications are consistent across both models, with the most significant challenges in distinguishing between the World and Business categories and between Business and Sci/Tech categories.
- The Edited Fixed Length model's ability to manage vocabulary and sequence length effectively contributes to its superior performance.

From this research, we learned that the choice of model architecture, vocabulary management, and preprocessing techniques significantly impacts the performance of text classification tasks. The experiments demonstrated that CNN-based models, particularly the CNN-GRU and multi-filter models, are highly effective for classifying news articles, capturing both local and sequential dependencies. We also discovered that editing the vocabulary to remove common stopwords and setting fixed sequence lengths can markedly improve model generalization, reducing overfitting and enhancing accuracy. The comparative analysis highlighted the CNN-GRU model's superior capability in handling complex text data, achieving the highest performance metrics. Additionally, this research underscored the importance of systematically experimenting with different configurations and

hyperparameters to identify optimal setups for specific tasks. Overall, the findings emphasize the critical role of tailored preprocessing and model selection in achieving robust and accurate text classification.

Conclusion

This research aimed to evaluate and compare the performance of various Convolutional Neural Network (CNN) architectures for text classification using the AG's news topic classification dataset. The study focused on models including multi-filter CNNs, residual CNNs, attention-based CNNs, and CNN-GRU hybrids, alongside different vocabulary management techniques, including edited and fixed-length vocabularies. The findings provide valuable insights into the efficacy of these models and preprocessing strategies, offering guidance for practitioners in natural language processing (NLP).

Exposition: Text classification is a critical task in NLP with applications spanning sentiment analysis, spam detection, and topic categorization. Traditional approaches, such as fully connected networks, often struggle with capturing the sequential nature of text data. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks address this limitation by retaining temporal dependencies, yet they can be computationally intensive. This research explored the potential of CNNs, known for their efficiency in processing local features, to enhance text classification.

Problem Description: The primary challenge in text classification is achieving high accuracy while maintaining model generalization. Overfitting, where the model performs well on training data but poorly on unseen data, is a common issue. Additionally, managing the vocabulary size and sequence length are crucial preprocessing steps that can significantly influence model performance. The goal was to determine which CNN architecture and

preprocessing strategy yields the best performance on the AG's news topic classification dataset, characterized by its four distinct classes: World, Sports, Business, and Sci/Tech.

Research Findings:

1. Model Architectures:
    a. CNN-GRU Model: Demonstrated the highest overall performance, effectively combining convolutional layers with GRU units to capture both local and sequential features. It achieved the highest test accuracy and the lowest test loss.
    b. Multi-Filter CNN: Also performed well, leveraging multiple convolutional filters to capture diverse features from the text. It showed strong accuracy and generalization.
    c. Residual CNN: Provided good performance with effective handling of vanishing gradient issues, though slightly lower than the CNN-GRU.
    d. Attention-Based CNN: Performed poorly, indicating that the attention mechanism in this setup was not effective for the given task.
2. Vocabulary Management:
    a. Edited Vocabulary: Removing common stopwords and managing vocabulary size significantly improved model performance, reducing overfitting and enhancing accuracy.
    b. Fixed Length Sequences: Setting fixed sequence lengths further improved performance, particularly when combined with edited vocabularies.

Management Recommendations:

1. Model Selection:
    a. For tasks requiring high accuracy and efficient processing of text data, consider using hybrid models like CNN-GRU, which combine the strengths of CNNs and RNNs.

   b. Multi-filter CNNs are also recommended for their ability to capture a wide range of features, providing robust performance across different text classification tasks.

2. Preprocessing Strategies:
   a. Edit the vocabulary to remove frequent stopwords and manage vocabulary size carefully. This reduces noise and focuses the model on relevant features, enhancing generalization.
   b. Use fixed-length sequences to standardize input data, simplifying the model's learning process and improving accuracy.
3. Hyperparameter Tuning:
   a. Systematically experiment with different configurations, including filter sizes, number of layers, and dropout rates, to identify the optimal setup for the specific dataset and task.
   b. Employ early stopping and model checkpointing to prevent overfitting and ensure the best model is selected based on validation performance.

This research highlights the effectiveness of CNN-based architectures for text classification, particularly when combined with thoughtful preprocessing strategies. The CNN-GRU model emerged as the best performer, demonstrating superior accuracy and generalization. These findings underscore the importance of model architecture and preprocessing in achieving high performance in NLP tasks. By following the recommended strategies, practitioners can develop robust models capable of accurately classifying text data in various applications.

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