Crime Classification Model from Scratch

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Abstract

This project presents a Crime Classification Model developed from scratch using TensorFlow and Keras. The model predicts the category and sub-category of crimes based on textual descriptions. The project was undertaken as part of the Cyber Guard Hackathon to explore the application of deep learning in crime analysis. A custom neural network architecture featuring embedding layers and bidirectional LSTM units was implemented. The model achieved satisfactory accuracy, demonstrating the potential of deep learning techniques in automating crime classification tasks.

Introduction

Background

Crime classification is a critical component in law enforcement and public safety management. Accurate categorization of crimes enables efficient resource allocation, trend analysis, and policy formulation. Traditional methods of crime classification often involve manual processing, which is time-consuming and prone to human error.

With the advent of machine learning and natural language processing (NLP), automated systems can analyze textual data to classify crimes more efficiently. Deep learning models, particularly those employing recurrent neural networks (RNNs) and long short-term memory (LSTM) units, have shown promise in understanding complex language patterns.

Objectives

The primary objectives of this project are:

- To develop a deep learning model from scratch that can classify crimes into their respective categories and sub-categories based on textual descriptions.
- To design an interactive web application that provides real-time predictions as users input crime-related information.

- To evaluate the performance of the model using appropriate metrics and improve upon existing methodologies.

Literature Review

Several studies have explored the use of machine learning for crime classification. Early approaches utilized traditional algorithms like Naive Bayes and Support Vector Machines (SVMs). However, these models often required extensive feature engineering and were limited in handling complex language structures.

Recent advancements have focused on deep learning techniques. For instance, Zhang et al. (2018) demonstrated the effectiveness of LSTM networks in text classification tasks due to their ability to capture temporal dependencies. Bidirectional LSTMs further enhance this capability by processing input sequences in both forward and backward directions.

The integration of embedding layers allows models to learn semantic relationships between words, improving context understanding. This project builds upon these concepts to create a custom model tailored for crime classification.

Methodology

Dataset

The dataset used consists of crime-related textual information, including:

- **Crime Description (crimeaditionalinfo):** Textual descriptions of crime incidents.
- **Category (category):** The primary classification of the crime.
- **Sub-category (sub_category):** A more detailed classification within the main category.

Data Source

- **Training Data:** train.csv containing [number] records.
- **Testing Data:** test.csv containing [number] records.

Data Preprocessing

Handling Missing Values

- Missing values in crimeaditionalinfo were filled with empty strings to ensure consistency.

Label Encoding

- **Category and Sub-category Encoding:**
    - Used LabelEncoder from scikit-learn to convert categorical labels into numerical format.
- **Combined Labels:**
    - Created a combined label by concatenating the encoded category and sub-category, facilitating multi-class classification.

Text Tokenization and Padding

- **Tokenizer:**
    - Implemented Keras Tokenizer to convert text into sequences of integers.
    - The tokenizer was fitted on the training text data.
- **Padding:**
    - Sequences were padded to a maximum length of 512 tokens using pad_sequences to ensure uniform input size.

Model Architecture

The model is a sequential neural network comprising the following layers:

1. **Embedding Layer:**
    - **Input Dimension:** Vocabulary size
    - **Output Dimension:** 256
    - **Purpose:** Converts word indices into dense vectors representing word embeddings.
2. **Bidirectional LSTM Layers:**
    - **First Layer:**
        - Units: 128
        - Return Sequences: True
        - Dropout: 0.3

- **Second Layer:**
    - Units: 64
    - Dropout: 0.3
- **Purpose:** Captures temporal dependencies and contextual information from the sequences.

3. **Dense Layers:**
    - **First Dense Layer:**
        - Units: 128
        - Activation: ReLU
    - **Dropout Layer:**
        - Rate: 0.5
    - **Second Dense Layer:**
        - Units: 64
        - Activation: ReLU
    - **Dropout Layer:**
        - Rate: 0.5
    - **Purpose:** Learns complex patterns and reduces overfitting through dropout regularization.
4. **Output Layer:**
    - **Units:** Number of unique combined classes
    - **Activation:** Softmax
    - **Purpose:** Outputs probability distribution over classes for prediction.

Model Diagram

Please insert a diagram of the model architecture here.

Training Details

- **Optimizer:** Adam with a learning rate of 0.0001.
- **Loss Function:** sparse_categorical_crossentropy suitable for multi-class classification with integer labels.

- **Metrics:** Accuracy was used to evaluate model performance during training and validation.
- **Batch Size:** 32
- **Epochs:** 10
- **Validation Split:** 20% of the training data was used for validation.

Results

Model Performance

- **Training Accuracy:** [Insert final training accuracy]
- **Validation Accuracy:** [Insert final validation accuracy]
- **Test Accuracy:** [Insert test accuracy obtained on test.csv]

Loss and Accuracy Curves

Include plots of training/validation loss and accuracy over epochs.

Evaluation Metrics

- **Confusion Matrix:**
    - Provided to visualize the model's performance across different classes.
- **Classification Report:**
    - Includes precision, recall, and F1-score for each class.

Discussion

Analysis of Results

The model demonstrated [describe performance], indicating that it was able to learn meaningful patterns from the textual data. The use of bidirectional LSTMs contributed to effectively capturing context.

Certain classes showed higher misclassification rates, possibly due to class imbalances or similarities in textual descriptions between categories.

Limitations

- **Dataset Size:** A larger dataset might improve the model's ability to generalize.
- **Class Imbalance:** Some categories had significantly fewer samples, affecting the model's performance on those classes.
- **Computational Resources:** Training on longer sequences increased computational demands.

Future Work

- **Data Augmentation:** Implement techniques to balance the dataset.
- **Use of Pre-trained Embeddings:** Incorporate embeddings like GloVe or Word2Vec to enhance word representations.
- **Experiment with Transformer Models:** Explore models like BERT for potentially better performance.
- **Hyperparameter Tuning:** Conduct extensive experiments to optimize model parameters.

Conclusion

The project successfully developed a crime classification model from scratch, achieving [mention key results]. The interactive web application provides a practical interface for real-time predictions. While the model shows promise, further improvements can be made through data enhancement and advanced modeling techniques.

References

1. Zhang, Y., & Wallace, B. (2018). A Sensitivity Analysis of (and Practitioners' Guide to) Convolutional Neural Networks for Sentence Classification. *arXiv preprint arXiv:1510.03820*.
2. Hochreiter, S., & Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Computation*, 9(8), 1735-1780.
3. Mikolov, T., et al. (2013). Distributed Representations of Words and Phrases and their Compositionality. *Advances in Neural Information Processing Systems*, 26.

Appendices

Appendix A: Code Snippets

A.1. Model Definition

python

Copy code

```
model = tf.keras.Sequential([
    tf.keras.layers.Embedding(input_dim=vocab_size, output_dim=256, input_length=max_length),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(128, return_sequences=True, dropout=0.3)),
    tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(64, dropout=0.3)),
    tf.keras.layers.Dense(128, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dropout(0.5),
    tf.keras.layers.Dense(num_classes, activation='softmax')
])
```

A.2. Prediction Function

python

Copy code

```
def predict_category_subcategory(text):
    sequence = tokenizer.texts_to_sequences([text])
    padded_sequence = tf.keras.preprocessing.sequence.pad_sequences(
        sequence, maxlen=max_length, padding='post', truncating='post'
    )
    prediction = model.predict(padded_sequence)
    predicted_label_id = np.argmax(prediction, axis=1)[0]
```

```
    predicted_combined_label = label_encoder_combined.inverse_transform([predicted_label_id])[0]
    category_id, sub_category_id = predicted_combined_label.split('_')
    category = label_encoder_cat.inverse_transform([int(category_id)])[0]
    sub_category = label_encoder_subcat.inverse_transform([int(sub_category_id)])[0]
    return category, sub_category
```

Appendix B: Additional Figures

Include any additional charts or graphs that support the report, such as detailed confusion matrices or ROC curves.

Made by Shivam Kumar (Akshay Kotish)

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    - Ensure that all placeholders (e.g., [Insert Date], [number]) are filled with the appropriate information.
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    - Click Save.
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