ACML Project Report

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Members:

Nashita Chowdhury (2554397)
Ariella Lewis (2596406)
Liam Brady (2596852)
Chloe Dube (2602515)

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1 Introduction

In this project, we present a Long Short-Term Memory (LSTM) neural network to classify news articles as real or fake based on their textual content. LSTMs, a type of recurrent neural network (RNN), are particularly effective for sequential data tasks due to their ability to capture long range dependencies and contextual information within text. This makes them well-suited for natural language processing tasks such as fake news detection, where meaning often depends on the broader context of sentences and paragraphs.

Our dataset is made up of news articles published between March 31, 2015, and February 19, 2018, with a primary focus on American political content. The volume of articles increases around February 2016, coinciding with the onset of the U.S. presidential primaries, which means there was a likely increase in politically charged information, both real and fabricated.

This report outlines the architecture and implementation of the LSTM model, details the data preprocessing steps, and discusses the strategies used for hyperparameter tuning and model evaluation. Through this approach, we aim to develop a reliable and scalable method for classifying fake news articles using deep learning techniques.

2 The Dataset

2.1 Fake News detection dataset

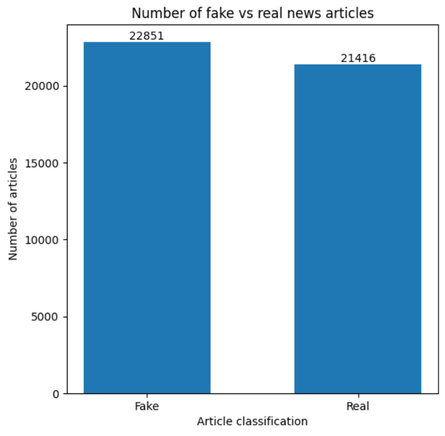
The dataset can be found at: https://www.kaggle.com/datasets/clmentbisaillon/fake-and-real-news-dataset/data .

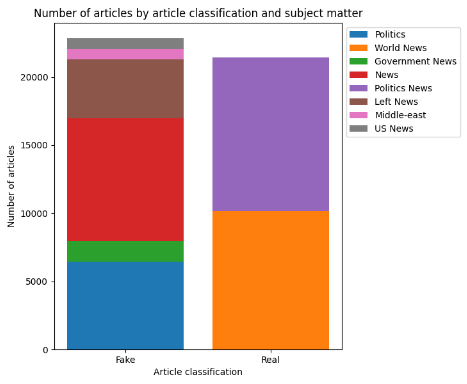
There are two datasets included, we have `Fake.csv` and `True.csv` where the structure is as follows →

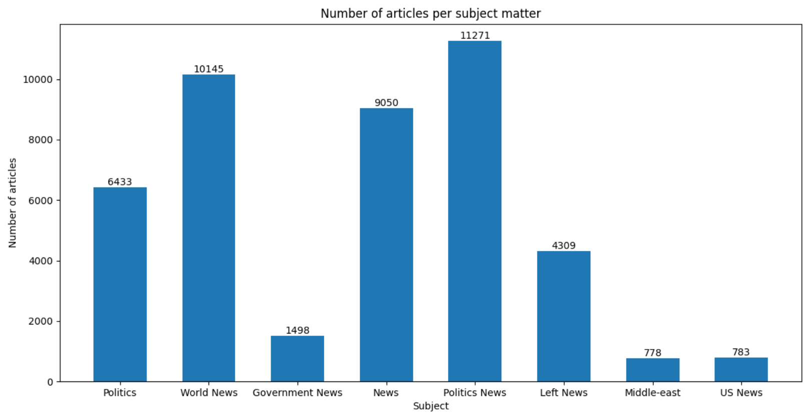
2.2 Structure:

- Dataset separated in two files:
  - Fake.csv (23502 fake news article)
  - True.csv (21417 true news article)
- Dataset columns (features):
  - Title: title of news article
  - Text: body text of news article
  - Subject: subject of news article
  - Date: publish date of news article

The targets for the data are `Fake` and `Real`, thus the classification of the dataset is a binary classification.







2.3 Data management:

To be able to work with the data appropriately, a file `Create_Dataset.py` merges the true and fake datasets and returns the dataset as a merged and shuffled collection, this collection has the null values removed.

Additionally, the features in the dataset were seperated into dependant and independant features so that it can be determined which features rely on others to be classified in the model.

3 Preprocessing

To prepare the data for training a text classification model, we applied a series of Natural Language Processing preprocessing steps. These steps were implemented in Python using the NLTK library and were designed to reduce noise, standardize the text, remove unnecessary variation and convert raw language into embeddings (the real-valued vectors consumed by the LSTM).

3.1 Preprocessing pipeline:

1. Dataset Construction and Removing Duplicates:

- Combined Fake.csv and True.csv datasets into `Create_Dataset`, added binary labels (0 = fake, 1=real).
- Removed rows with empty text and removed duplicate articles.
- Shuffled the resulting dataset.
- Originally, we had 44 898 articles, after removing 6252 duplicates and 631 empty-text rows, we ended up with 38 646 articles.

2. Lowercasing and Data Cleaning:

In Preprocessing.py, all text was converted to lowercase. Special characters, punctuation, and non-alphabetic symbols were removed via regex.

3. Sentence and Word Tokenization:

Articles were split into individual sentences, and each sentence was further tokenized into words using NLTK's word_tokenize function.

4. Stopword Removal:

Common English stopwords (e.g., “the”, “and”, “in”) were removed to eliminate low-value words.

5. Lemmatization:

Remaining words were lemmatized to reduce each word to its base form (e.g., “running” becomes “run”).

6. Special Tokens and Length Limitation:

We added an end of sentence token to each sentence. This helped the model recognize where sentences began and ended. Each article was then condensed to a maximum length of 256 tokens. This was done to ensure that all inputs were the same length and to avoid exceeding memory constraints.

7. Vocabulary Filtering:

We built a vocabulary from the cleaned tokens, keeping only tokens that occurred at least 3 times in the training dataset. Words not in the vocabulary were replaced with an `<unk>` (unknown) token.

8. Padding:

All token sequences were padded so that every article was the same length. This was necessary for batch processing and consistent input dimensions for the LSTM.

We used NLTK for linguistic preprocessing (tokenization, stopword removal, and lemmatization) In addition to these steps, we implemented efficient data storage. The final encoded dataset and vocabulary were saved as .pkl files in the Pickled_data folder to keep file sizes small and avoid exceeding GitHub's 100MB commit limit. Human-readable .txt files—containing the unprocessed text, vocabulary, and encoded sequences—were saved in a Readables folder, which is excluded from version control. These preprocessing steps not only standardized and cleaned the text but also contributed to noise reduction, dimensionality control (through a filtered vocabulary), and semantic consistency (via lemmatization). As a result, the model was able to train more efficiently and generalize better to unseen data.

3.2 Data Splitting

The dataset was split using SKlearn into:

- 60% training set – for model learning.
- 20% validation set – for hyperparameter tuning and model selection.
- 20% test set – for final performance evaluation.

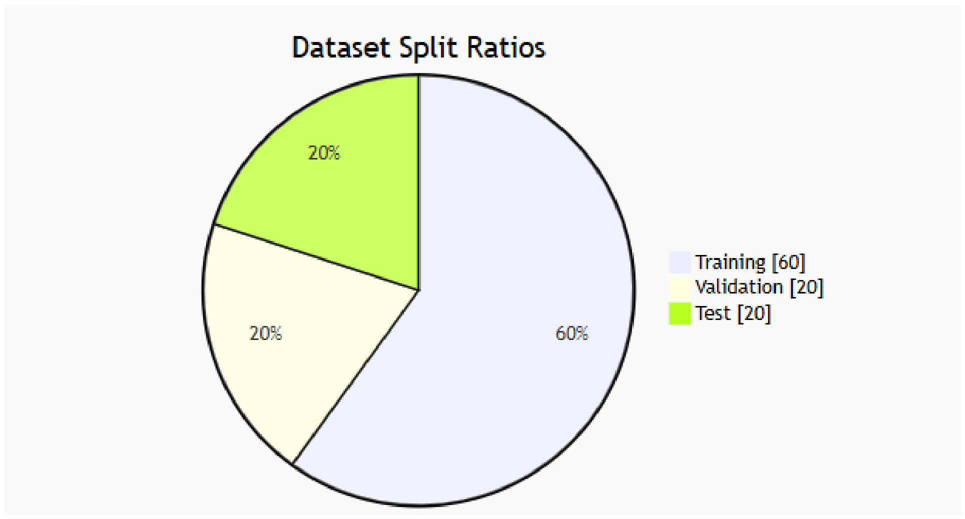


Figure 1: alt text

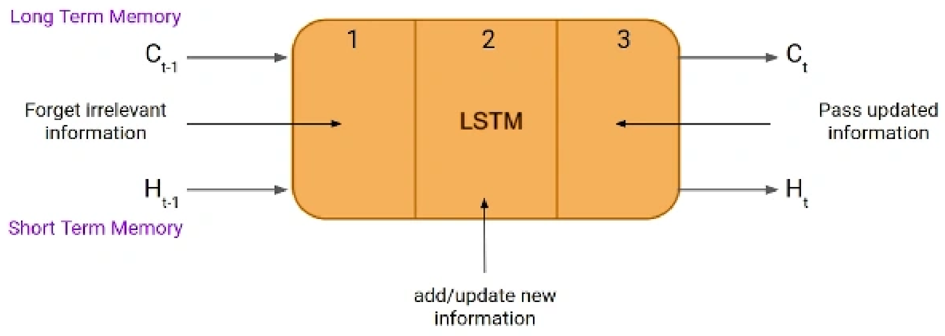
4 Long Short Term Memory (LSTM)

4.1 LSTM Defined

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN). LSTMs can capture long-term dependencies in sequential data making them ideal for tasks like language translation, speech recognition and time series forecasting (GeeksforGeeks, 2019).

LSTMs can hold memory for a significant amount of time so that it is possible for the model to learn any long-term dependencies. It does this via the use of a `hidden state` to keep a short-term memory of previous inputs as well as a `cell state` which keeps long-term memory of previous inputs.

The general structure is as follows:



(saxena, 2021)

- Part 1 (Forget Gate): chooses whether the information coming from the previous timestamp is to be remembered or is irrelevant and can be forgotten.
- Part 2 (Input Gate): the cell tries to learn new information from the input to this cell.
- Part 3 (Output Gate): the cell passes the updated information from the current timestamp to the next timestamp.

This one cycle of LSTM is considered a single-time step.

The cell state will carry all the information about the data as well as the timestamps.

Finally the LSTM computations are done in the following way: Computation in a LSTM is done by first concatenating the current input `x(t)` with the previous short-term memory `h(t - 1)` to get `x(t)h(t - 1)` and then computing

- Forget gate: $f(t) = \sigma([x(t), h(t-1)]W_f + b_f)$
- Input gate: $i(t) = \sigma([x(t), h(t-1)]W_i + b_i)$
- Candidate memory: $\tilde{c}(t) = \tanh([x(t), h(t-1)]W_c + b_c)$
- Output gate: $o(t) = \sigma([x(t), h(t-1)]W_o + b_o)$

The above vectors are then combined as follows: - $c(t) = f(t) \odot c(t-1) + i(t) \odot \tilde{c}(t)$
- $h(t) = o(t) \odot \tanh(c(t))$ where represents pointwise multiplication of vectors

4.2 Reasoning for choice of LSTM

Most machine learning models often rely on fixed-size input vectors and may fail to capture the nuanced dependencies that exist across time steps in a sequence. Whereas, Long Short-Term Memory (LSTM) networks are specifically designed to handle sequential data, making them appropriate for text classification tasks such as fake news detection.

The memory and gating features allow LSTMs to selectively retain or discard information over long sequences, enabling the model to learn both short-term and long-term dependencies within the text. This means that, LSTMs can understand context over multiple words and sentences which is an essential capability when dealing with politically based or convoluted language that often appears in fake news content.

Considering our dataset, we have the task of identifying whether excerpts of text can be classified as fake or genuine news articles. LSTMs are relevant in this case in that they have feedback connections, allowing them to process entire sequences of data, not just individual data points. This makes them highly effective in understanding and predicting patterns in sequential data like text and speech (saxena, 2021).

Given these strengths, building an LSTM model for the binary classification seemed an appropriate choice.

4.3 LSTM Implementation

4.3.1 Hyperparameters to consider:

Hyperparameter	Value
Max Seq Length	256
LSTM Hidden Units	128
Batch Size	16
Learn Rate	0.001
Epochs	15 - 20
Embedding Dimension	128
Optimizer	Adam
Loss	Binary Cross-Entropy
No. of LSTM layers	2
Dropout	0.5
Weight Decay	1e-5

4.3.1.0.1 Further explanation

- **Max Seq Length**: The number of words, tokens, allowed in each input sample.
- **LSTM Hidden Units** : The number of hidden state dimensions in each LSTM cell, how much memory each LSTM unit has.
- **Batch Size** : The number of training examples the model sees before updating weights.
- **Learn Rate**: A changing value that determines how much the model will tune its hyperparameters and the rate at which it will learn, it starts at 0.001, and will change as the model learns.
- **Epochs**: One full pass through the entire training dataset.

- **Embedding dimension**: The size of the vector space each word is mapped into.
  - The embedding layer converts words or phrases into a dense vector space, meaning that each word is represented as a vector of real numbers (Yadav, 2024).
- **Optimizer**: The algorithm used to update weights in the neural network during training.

- **Loss**: The function the model tries to minimize, so it measures the difference between predicted and actual outputs.

- **No. of LSTM layers**: How many LSTM layers are stacked, in our binary classification case it is better limited to 1.
- **Droput** - Dropout is a regularization method where input and recurrent connections to LSTM units are probabilistically excluded from activation and weight updates while training a network. This has the effect of reducing overfitting and improving model performance (Brownlee, 2017)
- **Weight Decay** -

4.3.2 Evaluation Metrics

- **Metrics**: Evaluation criteria during training and testing. E.g `accuracy` for training, `F1, precision, and recall` for evaluation.

Metric	Formula	Purpose
Accuracy	$\frac{TP+TN}{Total}$	Measures overall prediction correctness
Precision	$\frac{TP}{TP+FP}$	Controls false positives
Recall	$\frac{TP}{TP+FN}$	Controls false negatives
F1-Score	$2 \times \frac{P \times R}{P+R}$	Harmonic mean of precision and recall

4.3.2.0.1 These values are used to compute the confusion matrix:

- **TP**: True Positives
- **TN**: True Negatives
- **FP**: False Positives
- **FN**: False Negatives

4.3.3 General algorithm:

The general algorithm is as follows:

```
sequence_len = N

for i in range (0,sequence_len):

    # at initial step intialize h(t-1) and c(t-1) randomly

    if i==0:
        ht_1 = random ()
        ct_1 = random ()

    else:
        ht_1 = h_t
        ct_1 = c_t

    f_t = sigmoid ( matrix_mul(Wf, xt) +matrix_mul(Uf, ht_1) +bf)
    i_t = sigmoid ( matrix_mul(Wi, xt) +matrix_mul(Ui, ht_1) +bi)
    o_t = sigmoid ( matrix_mul(Wo, xt) +matrix_mul(Uo, ht_1) +bo)
    cp_t = tanh   ( matrix_mul(Wc, xt) +matrix_mul(Uc, ht_1) +bc)

    c_t  = element_wise_mul(f_t, ct_1) + element_wise_mul(i_t, cp_t)
    h_t  = element_wise_mul(o_t, tanh(c_t))
```

The next section will explore the Python libraries and frameworks used to implement the LSTM appropriately for the dataset.

5 Python Libraries, Frameworks and packages.

5.1 Pytorch

The model and data pre-processing are implemented using `PyTorch` as an aspect, PyTorch is an open source machine learning (ML) framework based on the Python programming language and the Torch library (Yasar, 2022).

5.1.1 How PyTorch was used :

(Pytorch.org, 2024)

- `Create_Datasets.py`
  - Imported the function `random_split(...)` from `torch.utils.data`, this functon is used to randomly split the dataset into non-overlapping new datasets of given lengths, namely into validation, test and training datasets.
- `LSTM.py`
  - Imported `torch.nn` as `nn` and used the following functions:
    * `nn.Embedding(...)`
    * `nn.LSTM(...)`
    * `nn.Linear(...)`
  - `nn.Embedding(...)`, used to make vectors of the words/tokens from the articles, so the model can map words or tokens to learnable vector representations.
  - `nn.LSTM(...)`, initializes a multi-layer LSTM Long Short-Term Memory network to process the sequential data.
  - `nn.Linear(...)`, creates a linear layer to map the output of an LSTM or any hidden layer to the desired output size, typically the number of classes or target values.
- `Train.py`
  - Imported `torch`, `torch.nn` as `nn`, `import torch.optim as optim` and `torch.utils.data import DataLoader, TensorDataset`
  - `torch` used by...
  - `torch.nn` used `nn.CrossEntropyLoss()` to initialize a cross-entropy loss function.
  - `torch.optim` initliazes the optimizer... (subject to change)
  - `torch.utils.data` made use of `TensorDataset` creates a PyTorch TensorDataset, to wrap the torch.Tensor objects (inputs and labels) into a dataset so they can be accessed together

one sample at a time, later the samples are to be loaded into `DataLoader`.

- To use PyTorch to make an LSTM model the following steps are taken:
  - `import torch`
  - `import torch.nn`

It is particulary relevant to our chosen `LSTM` model because

5.2 Natural Language Toolkit (NLTK)

- Tokenization
  NLTK's tokenization functions were employed at two levels:
  - **Sentence Tokenization**: `sent_tokenize()` splits documents into sentences

  - **Word Tokenization**: `word_tokenize()` splits sentences into words
- Stopword Removal
  - Used NLTK's English stopwords list (`stopwords.words('english')`) to filter common words.
- Lemmatization
  - NLTK's `WordNetLemmatizer` reduced words to their base forms (lemmas).
- NLTK Data Downloads
  Downloaded these NLTK data packages:
  - `stopwords`

  - `wordnet` (for lemmatization)

  - `punkt` (for tokenization)
- Preprocessing Pipeline

5.2.0.1 Text Cleaning Steps

1. **Case Normalization**: Convert text to lowercase

2. **Special Character Removal**: Regex removes non-alphabetic chars

3. **Stopword Removal**: Filters common stopwords

4. **Lemmatization**: Reduces words to base forms

5. **Special Tokens**: Adds `<eos>` markers

- Vocabulary Construction
  1. Built vocabulary from words appearing ≥ times (`MIN_VOCAB_FREQ`)

  2. Included special tokens:

  – `<pad>` (padding)

  – `<eos>` (end-of-sentence)

  – `<unk>` (unknown words)
- Data Encoding
  1. Encoded text using vocabulary indices

  2. Handled unknown words with `<unk>`

  3. Padded/truncated to fixed length (`MAX_ARTICLE_LEN`)

5.3 Scikit-learn

Scikit-learn's module was integrated to evaluate the performance of an LSTM model for fake news classification.

- Performance Metrics

```
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix
)
```

- The dataset splitting strategy using scikit-learn `train_test_split` function to create training, validation, and test sets for model development.

```
from sklearn.model_selection import train_test_split

def Split_Dataset(dataset):
    """Splits dataset into training (60%), validation (20%), and test (20%) sets
```

```
Args:
    dataset: Pandas DataFrame containing text and label columns

Returns:
    Tuple of (training_data, validation_data, test_data)
"""
# First split: 60% training, 40% temp holdout
training_data, temp_data = train_test_split(
    dataset,
    test_size=0.4,
    random_state=42,
    stratify=dataset['label']
)

# Second split: 50/50 split of temp data → 20% validation, 20% test
validation_data, test_data = train_test_split(
    temp_data,
    test_size=0.5,
    random_state=42,
    stratify=temp_data['label']
)

return training_data, validation_data, test_data
```

5.3.0.0.1 Key Features

- Maintains original class distribution using stratify parameter which is important for imbalanced datasets.Ensures representative samples of both classes ('Fake'/'Real') in all splits.
- Reproducible Splits
  - Fixed `random_state=42` guarantees:
    - Same splits across different runs
    - Consistent model evaluation

6 References

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