Transformer-based Architecture Neural Network Approach to Email Message Autocomplete

Mateus Fernando Felismino da Silva Patriota
Advisor: Prof. Dr. Tiago Figueiredo Vieira
Co-advisor: Prof. Dr. Baldoino Fonseca dos Santos Neto

Institute of Computing
Universidade Federal de Alagoas

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Motivation

Studying the area of neural network is of great importance, especially for applications in everyday life and for learning how to improve nowadays algorithms.

- **Recurrent Neural Networks** (RNNs), including Long Short-Term Memory (LSTM) networks have firmly established themselves as state-of-the-art [1];
- In Recent years, the **Transformer** architecture has emerged as a groundbreaking alternative [2];
- Self **attention mechanism** [2];
- Investigate is the **fine-tuning process** of the Transformer-based architecture [3].

Objectives

General Objectives: This project involves the creation of a neural network architecture based on Transformers, **built from the ground up**, with a particular emphasis on improving **email message autocomplete** functionality.

Specific Objectives:

- To design a transformer-based neural network architecture that is able to learn long-range **dependencies in email messages**;
- To pre train and evaluate the proposed architecture on a large dataset of open web texts;
- To fine-tune the proposed architecture on a smaller dataset of user-specific email messages;
- To investigate the effects of different **hyperparameters** on the performance of the fine tuned model.

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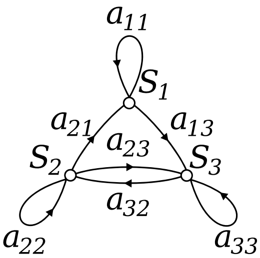
NLP and Machine Learning Approach

- Email auto-completion utilizes AI algorithms, particularly NLP and ML, to predict and suggest sentence completions [4];
- NLP's ability to **understand** and **generate** human language is crucial for efficient auto-complete technology;
- ML algorithms can be trained on extensive text datasets to learn writing styles, common phrases, and patterns;
- The adaptability of AI and its algorithms to user **context, language, and patterns** holds significant potential for the evolution of auto-complete email technology.

Markov Chains

- Markov Chains are probabilistic models that capture the **likelihood** of transitioning from one state to another in a sequence [5].
- May not exhibit the same semantic understanding as NLP-based approaches [6].

Figure: Simple Markov chain graph representation.



Source: Ching (2016) [7].

Generative Pre-trained Transformer 2

- Was introduced in **2019** from OpenAI [8], is a substantial advancement in natural language processing;
- The core idea of **GPT-2** is to predict the next word in a given text based on all the preceding words;
- It also comes with its set of limitations [9].

Bidirectional Encoder Representations from Transformers (BERT)

- BERT employs a **bidirectional transformer architecture**. It is pre-trained using a massive corpus of text data [10];
- It revolutionized natural language processing, it is not without its limitations;
- Computational intensity and large memory requirements, which can make it challenging to deploy in resource-constrained environments [11].

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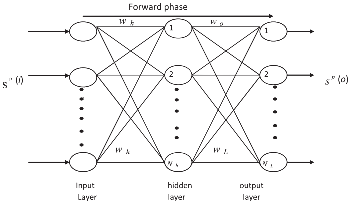
Natural Language Processing (NLP)

- Specialized domain within computer science, artificial intelligence, and linguistics dedicated to investigating the intricacies of automatically generating and comprehending natural human languages.
- In our context, NLP leverages its capabilities to **understand, interpret, and generate** human language to enhance the email composition process [4].
- It can consider the context of the email, the recipient, and the user's writing style to make contextually relevant suggestions.

Neural Networks and Deep Learning

- Inspired by the structure and function of the human brain, which was originated from the simplified mathematical model of **biological neurons** [12].
- The learning process in neural networks involves two main phases: the **forward** pass and the **backward** pass [13].

Figure: Feed-forward neural network.



Source: Hemeida (2020) [14].

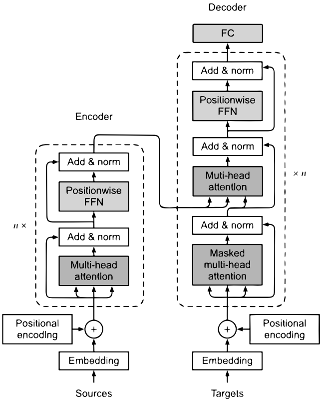
Large Language Model (LLM)

- Advancements in recent years, models like **BERT** [10] and **GPT** [8];
- Can handle NLP tasks, such as **sentiment analysis**, **text classification**, **and machine translation**;
- Considered **unsupervised multitask learners**, as they can learn from vast amounts of text data without the need for task-specific annotations.

Transformer Architecture

- Groundbreaking model architecture introduced in the paper **"Attention is All You Need"** by Vaswani [2];
- Transformer is based on the attention mechanism (self attention);
- Consists of an encoder-decoder structure with **multi-head attention**, enabling the model to weigh the importance of different words or tokens in the input sequence;

Figure: The Transformer - model architecture.



Source: Vaswani 2017 [2], modified.

Attention Mechanism

- Each encoder block consists of two sublayers: **Multi-head** attention and Feedforward network;
- First our model computes the input representation word by word.
- While computing the representation of each word, it relates each word to all other words in the sentence;

Figure: Embeddings for each word.

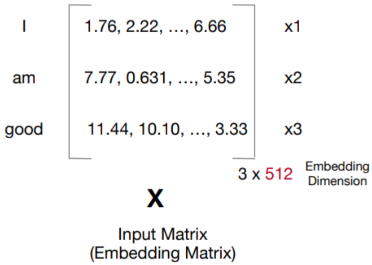
I	x1 = [1.76, 2.22, ..., 6.66]
am	x2 = [7.77, 0.631, ..., 5.35]
good	x3 = [11.44, 10.10, ..., 3.33]

Source: Author.

Attention Mechanism

- We can represent our input sentence using the **input matrix**;
- The dimension of the input matrix will be: **[sentence length x embedding dimension]**;
- Our input matrix dimension will be [3 x 512].

Figure: Embeddings Matrix.



Source: Author.

Attention Mechanism

Attention Function

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

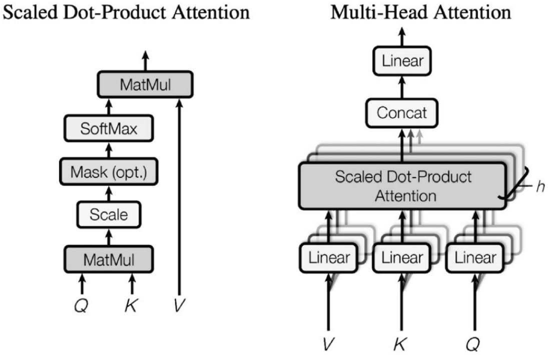
- We can create three new matrices: **Query matrix, Key matrix and Value matrix**.
- The **weight matrices** W^Q, W^K and W^V, are randomly initialized, their optimal values will be learned during training.

The process involves calculating the dot product between the query and each key, dividing the result by the square root of the dimension of the keys (d_k), and then applying a softmax function to obtain the weights assigned to the corresponding values.

Attention Function

$$Attention(Q, K, V) = softmax(\frac{QK^T}{\sqrt{d_k}})V$$

Figure: Left: self-attention. Right: multi-head self-attention.



Source: Vaswani 2017 [2].

Multi-Head Attention

Fundamental component of the Transformer model architecture, introduced by Vaswani et al. [2].

MultiHead Attention

$$MultiHead(Q, K, V) = Concat(head_1, ..., head_h)W^0$$

where:

- $head_i = Attention(QW_i^Q, KW_i^K, VW_i^V)$

- The input is first linearly transformed into three sets of **queries, keys, and values**, with each set associated with a specific **attention head**.
- These transformations are parameterized by weight matrices.
- Each attention head then performs the self-attention process, computing the weights for the given queries and keys, and combining the values.

Residual Connections and Layer Normalization

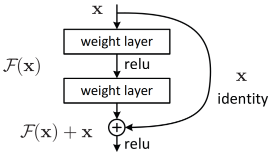
Residual Connection

$$y = F(x) + x$$

where:

- x The input to a specific layer in the network.
- F Represents the transformation applied to the input by the layer.
- y The output of the layer after applying the transformation.

Figure: Residual learning: a building block



Source: Kaiming (2016) [15].

Optimization and Regularization

- These techniques are instrumental in enhancing the **performance and generalization** capabilities of complex models [16];
- Optimization methods are essential for fine-tuning model parameters to **minimize loss** functions and improve predictive accuracy;
- Regularization, on the other hand, helps **mitigate overfitting** by adding penalties to model complexity, thus promoting a balance between fitting the training data and generalizing to unseen data.

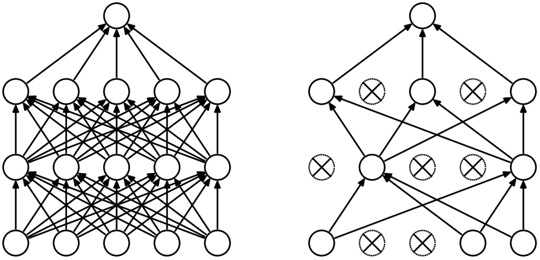
Adam Optimizer

- The Adam optimizer (Adaptive Moment Estimation) and its variant, **AdamW**, represent prominent optimization techniques widely employed in training deep neural networks, adapting learning rates individually for each model parameter, blending stochastic gradient descent (SGD) [17].
- Adam, in particular, maintains **adaptive moving averages** of gradients and squared gradients, facilitating automatic and dynamic learning rate adjustments.

Dropout

- The idea behind dropout is to **randomly drop out** (i.e., set to zero) a fraction of the neurons or units in a neural network during each training iteration.

Figure: Left: A standard neural net with 2 hidden layers. Right: An example of a thinned net produced by applying dropout to the network on the left.



(a) Standard Neural Net

(b) After applying dropout.

Source: Srivastava (2014) [18].

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Hardware

- NVIDIA GeForce RTX 2060 GPU;
- PyTorch/CUDA;
- Total of 9.5 hours of training process.

Hyperparameters

Among the crucial parameters in the Transformer model we can cite:

- Block and Batch Size;
- Learning Rate;
- Weight Decay;
- Embedding Size;
- Model Size;

Model Pre-training

- Training Data and Batching;
- Evaluation Metrics;
  - Loss Function;
  - Perplexity;
  - Hallucination;

Table: Number of characters in each Dataset, used in pre training phase.

Dataset	**Data Size (characteres)**
COCA	13.0M
NOW	13.0M
iWEB	13.0M
OpenWebTextCorpus	19.0M
Enron Email Dataset	12.0M
TOTAL	72.0M

Log Perplexity

$$logPP(W) = \frac{-1}{m} \sum_{i=1}^{m} log_2(P(w_i))$$

where:

w_i i-th word in the test set.

P SoftMax Probabilistic function.

m Token size.

Model Fine-tuning

- The data utilized for the fine-tuning process within the context of email communication was sourced from the **Enron dataset** (16k emails);
- Hyperparameter Updates and **Layer Freezing**;
    - Use less data;
    - Make process more efficient;
    - Prevent overfitting.

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Code Fragment 5.1: GenerativeLanguageModel layers structure. Source: Author; 2023.

```
class GenerativeLanguageModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.token_embd_table = nn.Embedding(vocab_size, n_embd)
        self.position_embd_table = nn.Embedding(block_size, n_embd)
        self.blocks = nn.Sequential(
            *[Block(n_embd, n_head=n_head) for _ in range(n_layer)])
        self.ln_f = nn.LayerNorm(n_embd)
        self.lm_head = nn.Linear(n_embd, vocab_size)

        self.apply(self._init_weights)
```

`GenerativeLanguageModel` class, a pivotal component of our implementation. This class serves as the cornerstone of our generative language model, encapsulating several crucial element.

Results and Discussions

Code Fragment 5.2: Self Attention block layer structure. Source: Author; 2023.

```
class Block(nn.Module):
    def __init__(self, n_embd, n_head):
        super().__init__()
        head_size = n_embd // n_head
        self.sa = MultiHeadAttention(n_head, head_size)
        self.ffwd = FeedFoward(n_embd)
        self.ln1 = nn.LayerNorm(n_embd)
        self.ln2 = nn.LayerNorm(n_embd)

    def forward(self, x):
        x = x + self.sa(self.ln1(x))
        x = x + self.ffwd(self.ln2(x))
        return x
```

The core of the model resides within the `Block` class Layer, where multiple transformer blocks are arranged sequentially to process the input data.

Results and Discussions

Code Fragment 5.3: Self Attention block layer structure. Source: Author; 2023.

```
class FeedFoward(nn.Module):
    def __init__(self, n_embd):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(n_embd, 4 * n_embd),
            nn.SiLU(),
            nn.Linear(4 * n_embd, n_embd),
            nn.Dropout(dropout),
        )

    def forward(self, x):
        return self.net(x)
```

Code Fragment 5.4: Self Attention block layer structure. Source: Author; 2023.

```
class MultiHeadAttention(nn.Module):
    def __init__(self, num_heads, hd_size):
        super().__init__()
        self.heads = nn.ModuleList()
        self.proj = nn.Linear(hd_size)
        self.dropout = nn.Dropout(dropout)

    def forward(self, x):
        out = torch.cat([h(x) for h
            in self.heads], dim=-1)
        out = self.dropout(self.proj(out))
        return out
```

In the left: simple linear layer followed by a non-linearity; Right we have the `MultiHeadAttention` class which take care of the head of self attention set.

GPT-2 as a baseline for hyperparameter comparison [8]

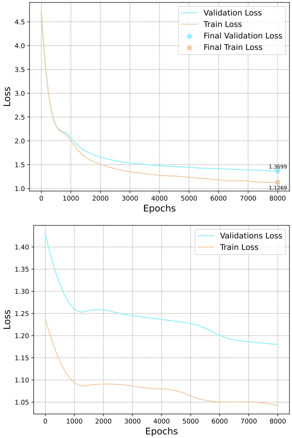
- The parameters were chosen considering the baseline search space and also the limitations faced:

Hyperparams	**Search Space**	**Selected Value**	**Base-line (GPT-2)**
Learning Rate	[0.0001, 0.00001]	0.00001	0.00001
Block Size	[128, 1024]	384	1024
Batch Size	[32, 512]	56	512
Number of Epochs	[6000, 8000]	8000	-
Dropout Rate	[0.1, 0.2]	0.1	0.1
Number of Layers/Heads	[4, 12]	8	12
Embedding dimension	[156, 768]	384	768
Weight Decay	[0.01, 0.000001]	0.000001	0.01
Optimizer	'Adam', 'AdamW'	AdamW	-
Activation function	-	SiLU	GeluNew

Table: Hyperparameter Tuning Results

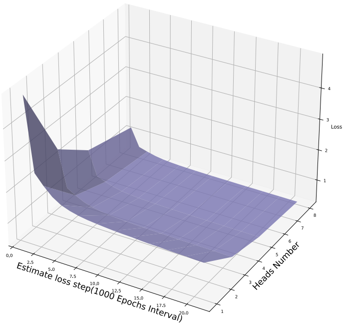
The loss curves demonstrate a consistent **downward trend**, indicating that the model is effectively learning (figure 5.2).
Additionally, another plot the reduction in loss during the fine-tuning phase.

Figure: Loss curves during the pre-training/fine-tuning process.



Results and Discussions

Figure: Loss as a function of epochs for different numbers of heads.



Source: Author, 2023.

One of the main changes tested refers to the amount of attention heads. It was possible to observe the improvement of the model in relation to the number of these.

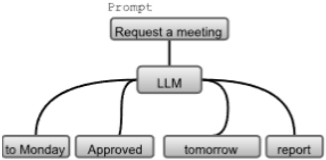


Figure 5.3: Outputs generated by the model given **Request a meeting** text as input.

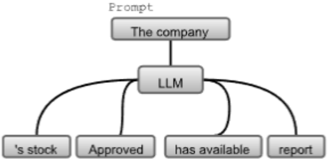


Figure 5.4: Outputs generated by the model given **The company** text as input.

This process showcases the model's proficiency in conjuring fresh and contextually relevant vocabulary, making it a valuable asset in tasks that require adaptive text generation.

Conclusion

The discussed work has endeavored to **develop and explore** an neural network architecture based on Transformers to enhance **email message autocomplete task**.
With the aim of studying the architecture and developing a system with reasonable parameters we've focus on:

- Executed a rigorous **data cleansing** procedure, followed by initial training on a substantial web text corpus;
- Craft a Transformer model capable of effectively capturing intricate **long-range dependencies** inherent in email communications.
- **Fine-tuning** on user-specific email data allowed us to tailor the model to individual preferences;
- Analysis of **hyperparameters** effects on fine-tuning performance.

The approach could deliver a **result satisfactorily** considering the hardware limitations;

Conclusion

Possible future improvements:

- Improve capabilities regarding hardware;
- Apply others **optimization** and **regularization** techniques;
- Incorporation of more extensive and diverse training data;
- Try **another areas** besides the email context.

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