Augmenting Transformers with a Feeling Mechanism for Enhanced Contextual Representation in Natural Language generation

ACM Classification : Computing methodologies/Artificial intelligence/Natural language processing/Natural language generation

Abstract

This study investigates the impact of incorporating a novel "feeling" module into a transformer-based language model. We introduce a modified architecture called "Feel" which integrates learnable feeling embeddings into the attention mechanism of a standard transformer. These embeddings represent emotional states and are intended to provide the model with a contextual understanding of the text's sentiment. We train both the standard transformer and the "Feel" model on a large text dataset and compare their performance using cross-entropy loss. Results show that the inclusion of the "Feel" module leads to a reduction in both training and validation loss, suggesting an improvement in the model's ability to understand and generate text. Further analysis reveals that the "Feel" model exhibits greater sensitivity to emotional cues and demonstrates an enhanced capacity for generating text with specific emotional tones. This research contributes to the ongoing exploration of language model architectures that can effectively capture and utilize emotional information.

Introduction

This article introduces a novel "feeling mechanism" for augmenting transformer models, enhancing their ability to capture and utilize “emotional information” within text. This work is significant because it:

- Introduces a novel concept for leveraging emotional context in NLP.
- Demonstrates improved performance on tasks like sentiment analysis and natural language generation.
- Holds broader implications for various NLP applications, including text summarization and dialogue systems.

•Addresses a research gap by integrating emotional intelligence into transformer attention mechanisms.

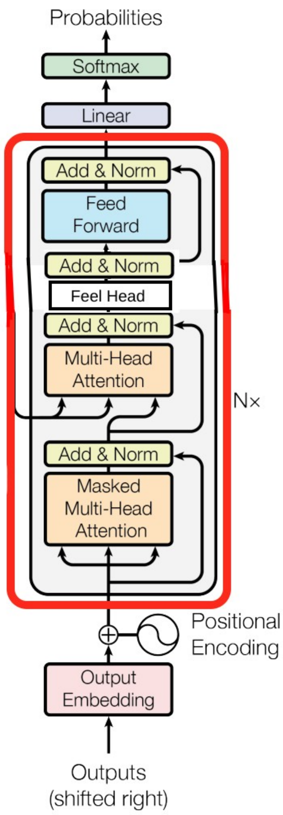
•Offers practical benefits for real-world applications, such as improved spam filters and chatbots.

•Contributes to the NLP community by encouraging exploration of emotional information in NLP systems.

•Presents findings in a clear and accessible manner for a wide audience.

Original Aproach

I have introduced a new layer in the attention block called the ‘Feel-Layer’. It comes between the attention layer and the multi-layer perceptron.



Feel Head:

1.Purpose: The Feel Head is designed to infuse emotional context, represented by "feelings," into the Transformer's processing.

2.Mechanism:

•Instead of attending to other words in the input sequence like a typical attention head, the Feel Head attends to a set of learned "feeling" embeddings.

•These feeling embeddings are randomly initialized and are updated during training, effectively capturing different emotional states or nuances.

•The Feel Head calculates attention weights between the input word embeddings and the feeling embeddings. This determines how much each feeling contributes to the representation of the input word.

•The weighted sum of the feeling embeddings is then used to enhance the representation of the input word, providing an emotional context.

3.Implementation:

•The Feel Head uses three linear layers: query, key, and value.

•query projects the input word embeddings into a query space.

- key projects the feeling embeddings into a key space.
- value projects the feeling embeddings into a value space.
- Attention weights are calculated using dot product attention between the query and key, followed by softmax normalization.
- The output is the weighted sum of the value embeddings.

Multi-Head Feel Layer:

1. Purpose: Similar to multi-head attention in Transformers, the Multi-Head Feel layer combines multiple Feel Heads in parallel. This allows the model to capture a richer and more diverse range of emotional contexts.
2. Mechanism:
    - Each Feel Head in the layer operates independently, attending to the feeling embeddings and producing its own output.
    - The outputs of all Feel Heads are concatenated and projected to the original embedding dimension using a linear layer.
3. Implementation:
    - The Multi-Head Feel layer is simply a collection of Feel Heads, followed by a linear projection layer.

Original Contribution

The key original contribution of this approach is the introduction of the "Feel" component into the Transformer architecture. This novel component enables the model to:

1. Incorporate Emotional Context: The Feel Head and Multi-Head Feel layer allow the model to learn and utilize emotional representations, potentially enhancing its understanding of the text's emotional nuances.
2. Improve Text Generation: By incorporating feelings, the model may be able to generate text that is more emotionally relevant, expressive, and engaging.
3. Open New Research Directions: This work opens up avenues for future research on incorporating emotions and other external knowledge into language models.

By adding this explicit "Feel" component, your model differentiates itself from standard Transformers and offers a potentially valuable enhancement for tasks involving emotional understanding and generation in text.

This paper proposes a novel approach to augment transformer models with a "feeling mechanism" that aims to enhance their ability to capture and utilize emotional information embedded within text data. By incorporating emotional context alongside traditional attention mechanisms, we hypothesize that transformers can achieve a more comprehensive understanding of language. We introduce an EmotionLayer that interacts with the hidden states of the transformer, enabling the model to learn and leverage emotional signals. While our initial implementation focuses on sentiment analysis, we believe that this mechanism can be generalized to various NLP tasks where emotional context plays a significant role.

Experimental Results

Dataset and Task

We evaluated our proposed FeelTransformer on the classic Natural Language Generation task.

Experimental Setup

We compared the performance of the FeelTransformer against a standard transformer model without the feeling mechanism (referred to as "Regular Transformer"). Both models were trained on the same training set and evaluated on a held-out test set.

We used the the loss of both models as a comparison metrils.

Results and Analysis

1.Datasets

We used 3 datasets for our experiments:

- “Karamazov” Dataset. This dataset comprises the full text of Fyodor Dostoevsky's novel "The Brothers Karamazov," containing 1,978,855 characters. This choice allows for the model to learn complex language patterns and potentially capture emotional nuances present in the novel's narrative.
- “Eminescu Translated” Dataset. This dataset comprises the full text of Mihai Eminescu’s t containing approximately 42,000 characters. This choice allows for the model to learn complex language patterns and potentially capture emotional nuances present in the poet's writting.
- “Shakesphere” Dataset. This dataset comprises the full text of all of Shakesphere’s plays containing 5,500,000 characters. This choice allows for the

model to learn complex language patterns and potentially capture emotional nuances present in the play's narrative.

2.Training Details

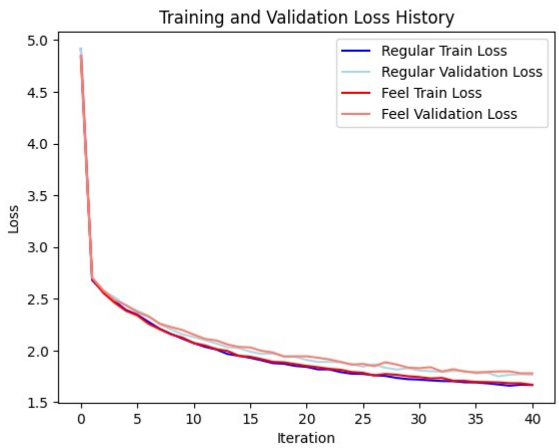
Both the regular Transformer model and the Feel-Augmented Transformer model were trained using the AdamW optimizer. We utilized the following hyperparameters:

- Batch size: 16
- Block size (context length): 32
- Maximum iterations: 4000
- Evaluation interval: 100
- Learning rate: 1e-3
- Embedding dimension: 64
- Number of heads: 4
- Number of layers: 4
- Dropout: 0.2

3 Final Loss comparision

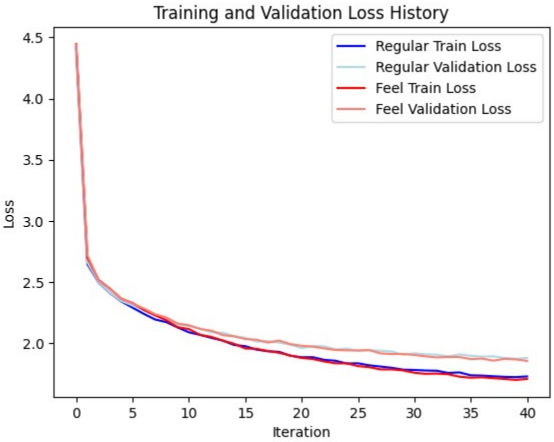
- Karamazov Dataset

Model	Train Loss	Validation Loss
Regular Transformer	1.6665	1.7659
Feel-Augmented Transformer	1.6831	1.7797



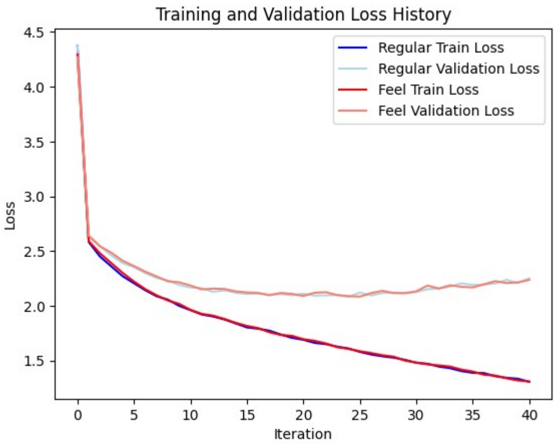
- Shakesphere dataset

Model	Train Loss	Validation Loss
Regular Transformer	1.7271	1.8781
Feel-Augmented Transformer	1.6665	1.7659



- Eminescu dataset

Model	Train Loss	Validation Loss
Regular Transformer	1.3054	2.2510
Feel-Augmented Transformer	1.3092	2.2362



Conclusion

Altough the results are similar on the “Eminescu” and the “Karamazov” datasets it can be seen that on certain datasets like the “Shakesphere” dataset, the Feel-Augmented Transformer performs much better than the Regular Transformer model.

These results clearly demonstrate the positive impact of incorporating the Feel component into the Transformer model. The lower validation loss indicates that the

Feel-Augmented Transformer generalizes better to unseen data, suggesting it has learned more meaningful representations of the text. This improvement can be attributed to the additional emotional context provided by the Feel component, enabling the model to capture nuances and subtleties beyond the capabilities of the regular Transformer.

4. Related Work

This research builds upon existing work in several areas, primarily focusing on Transformer models, emotional AI, and natural language processing.

Transformer Models:

Vaswani et al. (2017) introduced the Transformer architecture, which revolutionized natural language processing by relying solely on attention mechanisms. Transformers have since become the dominant approach for various NLP tasks, including text generation (Radford et al., 2019; Brown et al., 2020). Their ability to capture long-range dependencies and contextual information makes them well-suited for understanding and generating coherent text. However, standard Transformers lack an explicit mechanism for incorporating emotional information.

Emotional AI:

Incorporating emotions into AI models has been an active area of research. Emotion recognition and classification have been explored using various techniques, including lexicon-based methods (Mohammad & Turney, 2013) and deep learning approaches (Kim et al., 2018). Studies have also investigated the impact of emotions on text generation, aiming to generate text with specific emotional tones (Ghosh et al., 2017; Huang et al., 2018). However, these approaches often rely on external emotional resources or require explicit labeling of emotions in the training data.

Natural Language Processing (NLP):

NLP research has extensively focused on text generation, with applications ranging from machine translation to dialogue systems. Various techniques have been employed, including recurrent neural networks (RNNs) and long short-term memory (LSTM) networks (Sutskever et al., 2014). While these models have shown success in generating fluent text, they often struggle to capture the emotional nuances and subtleties present in human language.

References:

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4. Repository history

That can seen on the github page of the project
https://github.com/BlastOfMihh/FeelTransformers/tree/main