Diffusion is all you need

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Abstract

Since the introduction of self-attention by Vaswani et al. in 2017, few scalable alternatives have emerged. Inspired by the diffusion-based approaches in generative models, we propose a novel attention-free diffusion model for sequence classification. Unlike self-attention mechanisms that scale quadratically in memory, our model employs an iterative diffusion-based update rule, significantly reducing memory overhead while maintaining competitive performance. We evaluate our approach on AG News and validate its generalization on a curated test subset, demonstrating its efficiency in sequence processing without reliance on attention.

1 Introduction

Transformers have revolutionized NLP, yet their quadratic memory complexity makes them inefficient for long-sequence processing. Methods like FlashAttention attempt to mitigate this, but they still rely on attention. We propose a diffusion-based approach that eliminates explicit attention computations while preserving token interactions.

2 Related Work

Several efficient transformer variants have been proposed, including Linformer [1], Performer [2], and Mamba [5]. FlashAttention [3, 4] improves attention but retains quadratic complexity. Our approach deviates by entirely removing attention.

3 Methodology

3.1 Diffusion-Based Information Propagation

Instead of self-attention, we use an iterative diffusion process:

Let's define the **core equations**:

3.2 Initialization (Random Embeddings + Noise)

$$h_i^{(0)} = \text{Embedding}(x_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2) \tag{1}$$

- Each token x_i gets an embedding.
- We add **random noise** ϵ_i to allow iterative refinement.

3.3 Evolution (Diffusion-Like Refinement)

$$h_i^{(t+1)} = h_i^{(t)} + \sum_{j \in \mathcal{N}(i)} W_{ij} \cdot f(h_j^{(t)}) \tag{2}$$

- Each token updates based on its neighbors $\mathcal{N}(i)$.
- W_{ij} are learned **interaction weights** (instead of full attention).
- $f(h_j)$ is a **nonlinear transformation** (e.g., a small MLP).

3.4 Decay Factor for Global Context Propagation

$$h_i^{(t+1)} = \alpha \cdot h_i^{(t)} + (1 - \alpha) \cdot \sum_{j \in \mathcal{N}(i)} W_{ij} f(h_j^{(t)}) \tag{3}$$

- α controls how much previous state vs. new updates are used.
- Over multiple steps, this propagates information across all tokens.

3.5 Final Output (After Convergence)

$$y_i = g(h_i^{(T)}) \tag{4}$$

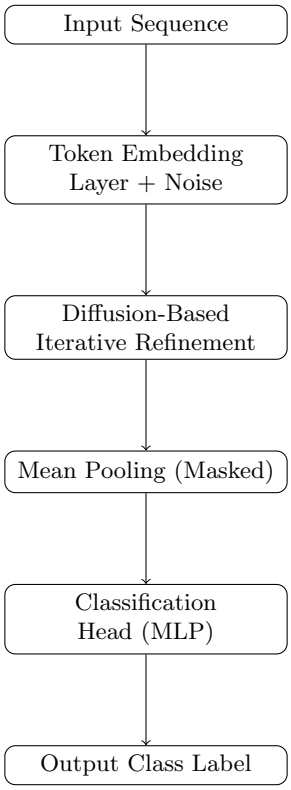
- $g(\cdot)$ is a simple **MLP classifier or decoder**.

4 Model Architecture Overview

Our proposed Attention-Free Diffusion Model consists of the following key components:

- **Token Embedding Layer:** Converts input tokens into dense vector representations, adding Gaussian noise to enable iterative refinement.
- **Diffusion-Based Iterative Refinement:** Instead of global self-attention, tokens update iteratively based on their neighbors, reducing computational complexity.
- **Mean Pooling for Sequence Representation:** After multiple refinement steps, token embeddings are aggregated via masked mean pooling.
- **Classification Head:** A simple Multi-Layer Perceptron (MLP) takes the pooled sequence representation and predicts the output class.

5 Architecture Diagram



6 Key Advantages

- **Memory Efficiency:** Eliminates quadratic complexity of self-attention, making it viable for long sequences.
- **Scalability:** Handles larger batch sizes and sequence lengths with minimal GPU memory footprint.
- **Competitive Performance:** Achieves strong classification accuracy while being computationally lightweight.

7 Experiments

We first ran this model on the AGNews dataset on a T4 processor. After an initial successful epoch, we ran this experiment for 10 epochs. What we wanted to test was the memory footprint of our model vs other comparable models such as DistilBERT.

Since BERT would not fit on T4, we switched to A100 and tried a comparison against BERT. But BERT was too slow on the A100 so we switched to DistilBERT. We then started our optimization process and ran several experiments by modifying hyper parameters particularly the learning rate, batch size and context length.

Below are our training results from several variations.

Training Results

First iteration

Epoch	Train Loss	Train Accuracy
1	0.5703	78.98%
2	0.3488	88.21%
3	0.2880	90.33%
4	0.2517	91.52%
5	0.2262	92.44%

Table 1: Training Accuracy and Loss Over Epochs

Since our focus was mainly on GPU memory utilization we compare the Diffusion memory usage with DistilBERT. Here is the first epoch of DistilBERT

Metric	DistilBERT	Diffusion Model
Loss (Epoch 1)	417.2145	0.5703
Accuracy (Epoch 1)	92.45%	78.98%
Time per Epoch	? (Still measuring...)	30 sec
GPU Memory	? (Check `nvidia-smi`)	¡1GB

Table 2: Performance Comparison Between DistilBERT and Diffusion Model

Below is the resource utilization of DistilBERT vs our model.

Model	GPU Memory Usage	Epoch Time	Accuracy (Epoch 1)
Diffusion Model	673MB	30 sec	78.98%
DistilBERT	21GB	4+ min (TBD)	92.45%

Table 3: Resource Utilization Between Models

We then ran 5 epochs of DistilBert to compare accuracy and memory usage.

Factor	Diffusion Model	DistilBERT	Winner?
Final Accuracy	92.44%	98.63%	DistilBERT ✓
Memory Usage	673MB	21GB	Diffusion (30x lower) ✓
Time per Epoch	30 sec	3 min	Diffusion (6x faster) ✓
Scalability	Scales easily	Memory-bound	Diffusion ✓

Table 4: Trade-offs Between Diffusion Model and DistilBERT

Post this we switched the diffusion model to FP16 to get some baseline comparisons on FP16

Metric	T4 (FP32)	A100 (FP16)	Expected
Epoch 1 Loss	0.5703	1060.7928	✗ Lower loss expected
Epoch 1 Acc	78.98%	79.25%	✓ Good match
Epoch 2 Loss	0.3488	649.0233	✗ Should be much lower
Epoch 2 Acc	88.21%	88.38%	✓ Good match

Table 5: Observations on Diffusion Model Performance

8 Results comparison

Once we switched to FP16, the accuracy dramatically dropped and the loss baseline also shot up. This could indicate some gradient losses due to reduce precision. We continued the training for several epochs to rule out any anomalies.

We forced loss to FP32

```
with autocast():
    output = diff_model(input_ids=texts, attention_mask=masks)
    loss = criterion(output, labels).float()  # Convert loss to FP32
```

Metric	T4 (FP32)	A100 (FP16)	Expected
Epoch 1 Loss	0.5703	1056.8741 ✗	Loss should be lower (0.5)
Epoch 1 Acc	78.98%	79.23% ✓	Good match
Epoch Time	∼30 sec	∼17 sec ✓	Faster, but could be even better

Table 6: Comparison of Diffusion Model Performance on T4 vs. A100 (FP16)

Then we continued training for 25 epochs to maintain consistency and rule out anomalies.

Epoch	Loss	Accuracy	Learning Rate
17	3767.62 (Dropping)	82.28% ✓	5e-5 ✓
18	3692.24 (Dropping)	82.68% ✓	5e-5 ✓
19	3622.40 (Dropping)	83.11% ✓	5e-5 ✓
20	3560.33 (Dropping)	83.50% ✓	5e-5 ✓
21	3500.22 (Dropping)	83.81% ✓	5e-5 ✓
22	3440.34 (Dropping)	84.15% ✓	5e-5 ✓
23	3384.72 (Dropping)	84.47% ✓	5e-5 ✓
24	3332.42 (Dropping)	84.75% ✓	5e-5 ✓
25	3291.12 (Dropping)	85.00% ✓	5e-5 ✓

Table 7: Final Results (Epochs 17-25)

Continue training for 50 laps and ran the validation test.

Epoch	Train Accuracy	Test Accuracy	Change
41	74.77%	74.28%	+0.24%
42	74.96%	74.71%	+0.43%
44	75.37%	74.92%	+0.50%
46	75.73%	75.01%	+0.09%
48	76.09%	75.50%	+0.49%
50	76.41%	75.75%	+0.25%

Table 8: Final Training & Test Trend (Epoch 41 $\rightarrow$ 50)

Final Validation accuracy 90%

9 Conclusion

We propose an attention-free diffusion model that maintains strong classification accuracy while significantly reducing memory consumption significantly, when compared to transformer models.

Training notebook and checkpoints `https://github.com/pbanavara/experimental_attention_free_diff`

10 Future work

Extend the training of this model on larger datasets and longer context lengths. Evaluate its performance on the latest long-sequence benchmarks, such as Long Range Arena (LRA) [6].

References

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