Endterm Report: Natural Language Processing & Large Language Models

Winter in Data Science (WiDS)2025–26

Project: From Word Embeddings to Fine-Tuning BERT

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RepositoryLink:https://github.com/Prash0805/Bridging_Language_and_Personalization

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1. Introduction

1.1 Objective and Scope

The primary objective of this mentorship, conducted under the **Winter in Data Science (WiDS)** program, was to gain a rigorous, ground-up understanding of Modern Natural Language Processing (NLP). The project was structured to traverse the historical and technical evolution of the field, moving from static vector representations (Week 1) to complex, context-aware Transformer architectures (Weeks 2 and 3).

The scope of this report covers the implementation of core algorithms from scratch using Python and PyTorch, verifying their performance on standard benchmarks, and hosting the reproducible code on GitHub.

1.2 The Evolution of NLP

Historically, NLP relied on one-hot encoding, where words were treated as isolated, equidistant symbols. This approach suffered from the "curse of dimensionality" and failed to capture semantic similarity; the vector for "dog" was orthogonal to "puppy".

The first major leap was **Word2Vec**, which introduced "distributed representations," mapping words to dense vectors where similar words clustered together. However, these embeddings remained static—the word "bank" had the same vector in "river bank" and "bank deposit".

The modern era, defined by **BERT (Bidirectional Encoder Representations from Transformers)**, solved this by treating embeddings as dynamic functions of their context. This report documents my journey in implementing these systems as part of the WiDS curriculum.

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2. Week 1: Static Word Embeddings

2.1 Theoretical Foundation: The Skip-Gram Model

In Week 1, I implemented the **Skip-Gram** model. The goal of this model is to predict context words (w_o) given a center word (w_c). The standard Softmax formulation requires summing over the entire vocabulary to calculate probabilities, which is computationally prohibitive (requiring millions of operations per step).

To resolve this, I implemented **Negative Sampling**. This technique reframes the problem as a binary classification task: distinguishing the true context word from K random "noise" words. The noise words are sampled from a distribution raised to the

power of 0.75, which down-weights frequent stop words like "the" or "and" to ensure the model learns from semantically rich data.

2.2 Implementation: Negative Sampling & Loss

A critical part of my implementation was handling the variable-length sequences. I implemented a custom SigmoidBCELoss that masks padding tokens to ensure they do not influence the gradient updates.

Code Implementation: Custom Loss Function The following code demonstrates my implementation of the masked loss function, which is critical for handling batches with variable sequence lengths.

Python

```
class SigmoidBCELoss(nn.Module):
    """
    Binary Cross-Entropy Loss with Masking.
    Effectively ignores padding tokens (0) during backpropagation.
    """
    def __init__(self):
        super(SigmoidBCELoss, self).__init__()

    def forward(self, inputs, target, mask=None):
        # Calculate BCE with Logits (numerically stable)
        out = nn.functional.binary_cross_entropy_with_logits(
            inputs, target, weight=mask, reduction="none")
        # Normalize by the number of valid tokens, not total tokens
        return out.mean(dim=1)
```

Training Output: Using the Penn Tree Bank (PTB) dataset, the model showed consistent convergence over 5 epochs:

Plaintext

```
Epoch 1, Loss 0.481, 41200.8 tokens/sec
Epoch 2, Loss 0.427, 40344.8 tokens/sec
Epoch 3, Loss 0.403, 40631.1 tokens/sec
Epoch 4, Loss 0.380, 40669.7 tokens/sec
Epoch 5, Loss 0.359, 40682.6 tokens/sec
```

2.3 Handling Out-Of-Vocabulary Words: Byte Pair Encoding

Standard Word2Vec fails on unknown words. To address this, I implemented **Byte Pair Encoding (BPE)**. BPE acts as a middle ground between character-level and word-level representations.

The algorithm iteratively finds the most frequent adjacent pair of symbols in the corpus and merges them into a new symbol. This allows the model to handle morphology. For example, the model learns that "er" is a common suffix.

Code Implementation: BPE Merge Step

Python

```
def merge_symbols(max_freq_pair, token_freqs, symbols):
    """Merge the most frequent pair into a new symbol."""
    symbols.append(''.join(max_freq_pair))
    new_token_freqs = dict()
    for token, freq in token_freqs.items():
        # Replace 't a' with 'ta'
        new_token = token.replace(' '.join(max_freq_pair),
                                  ''.join(max_freq_pair))
        new_token_freqs[new_token] = token_freqs[token]
    return new_token_freqs
```

Experimental Output (Subword Merging): My implementation successfully learned to construct the word "faster" from components:

Plaintext

```
Merge #1: ('t', 'a')
Merge #2: ('ta', 'l')
Merge #3: ('tal', 'l')
...
Merge #6: ('fas', 't')
Merge #7: ('e', 'r')
```

2.4 Experiments: Semantic Analogies

To verify the quality of distributed representations, I loaded pre-trained **GloVe** vectors (50-dimensional). I tested the model on vector arithmetic tasks to verify if the geometry of the space captured semantic meaning.

Code Implementation: Analogy Function

Python
```
def get_analogy(token_a, token_b, token_c, embed):
    """Compute analogy: a is to b as c is to ?"""
    vecs = embed[[token_a, token_b, token_c]]
    x = vecs[1] - vecs[0] + vecs[2]
    topk, cos = knn(embed.idx_to_vec, x, 1)
    return embed.idx_to_token[int(topk[0])]
```

Result:

- **Query:** man is to woman as son is to ?
- **Equation:** $Vector(Woman) - Vector(Man) + Vector(Son)$
- **Prediction:** daughter

This confirms that the embedding space successfully captures semantic gender relationships as linear offsets.

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3. Week 2: The BERT Architecture

3.1 From Static to Contextual: The Transformer

In Week 2, I built a BERT model from scratch. Unlike Word2Vec, BERT uses the **Transformer Encoder** architecture. The core innovation is **Self-Attention**, which allows every token to "attend" to every other token in the sequence simultaneously.

My implementation included:

1. **Learnable Positional Embeddings:** Unlike the original Transformer which used fixed sinusoidal functions, BERT learns the position vectors during training.
2. **Multi-Head Attention:** Parallel attention layers to capture different types of relationships (syntactic vs. semantic).

3.2 Implementation: The Encoder Block

Below is the code I wrote for the Transformer Encoder block, encompassing the Self-Attention mechanism and the Feed-Forward Network.

Code Implementation: Encoder Block

Python
```
class EncoderBlock(nn.Module):
    """Transformer Encoder Block implemented from scratch."""
    def __init__(self, num_hiddens, ffn_num_hiddens, num_heads, dropout, **kwargs):
```

```
        super(EncoderBlock, self).__init__(**kwargs)
        # Multi-head attention mechanism
        self.attention = nn.MultiheadAttention(embed_dim=num_hiddens,
                                               num_heads=num_heads,
                                               dropout=dropout,
                                               batch_first=True)
        # Layer Normalization 1
        self.addnorm1 = nn.LayerNorm(num_hiddens)

        # Position-wise Feed-Forward Network
        self.ffn = nn.Sequential(
            nn.Linear(num_hiddens, ffn_num_hiddens),
            nn.ReLU(),
            nn.Dropout(dropout),
            nn.Linear(ffn_num_hiddens, num_hiddens)
        )
        # Layer Normalization 2
        self.addnorm2 = nn.LayerNorm(num_hiddens)

    def forward(self, X, key_padding_mask=None):
        attn_output, _ = self.attention(X, X, X, key_padding_mask=key_padding_mask)
        X = self.addnorm1(X + attn_output) # Residual connection
        ffn_output = self.ffn(X)
        X = self.addnorm2(X + ffn_output)  # Residual connection
        return X
```

3.3 Pretraining Objectives: MLM and NSP

BERT is trained on two tasks simultaneously to achieve deep bidirectional understanding.

Task 1: Masked Language Modeling (MLM)

Standard language models (like GPT) look left-to-right. BERT looks in both directions. To prevent the model from "seeing itself," we mask 15% of the tokens. I implemented the **80-10-10 Rule**:

- 80% of the time, replace with [MASK].
- 10% of the time, replace with a random word.
- 10% of the time, keep the original word.

Task 2: Next Sentence Prediction (NSP)

To understand sentence relationships (crucial for QA tasks), I implemented the NSP head. This binary classifier predicts if Sentence B logically follows Sentence A.

Code Implementation: MLM Data Generation

Python

```
def _replace_mlm_tokens(tokens, candidate_pred_positions, num_mlm_preds, vocab):
    """
    Implements the 80-10-10 masking strategy.
    """
    mlm_input_tokens = [token for token in tokens]
    pred_positions_and_labels = []
    random.shuffle(candidate_pred_positions)

    for mlm_pred_position in candidate_pred_positions:
        if len(pred_positions_and_labels) >= num_mlm_preds:
            break

        if random.random() < 0.8:
            masked_token = '<mask>'
        else:
            if random.random() < 0.5:
                masked_token = tokens[mlm_pred_position] # 10% Original
            else:
                masked_token = random.choice(vocab.idx_to_token) # 10% Random

        mlm_input_tokens[mlm_pred_position] = masked_token
        pred_positions_and_labels.append((mlm_pred_position,
tokens[mlm_pred_position]))

    return mlm_input_tokens, pred_positions_and_labels
```

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4. Week 3: Fine-Tuning for Downstream Tasks

4.1 Task 1: Sentiment Analysis (IMDb)

In the final week, I applied the concepts of Transfer Learning. I fine-tuned a pre-trained bert-base-uncased model on the IMDb movie review dataset. The IMDb dataset is perfectly balanced (25k pos, 25k neg), which negated the need for class-weighting.

Preprocessing: The text was tokenized using the standard BERT tokenizer with truncation=True and max_length=128. This ensures all inputs fit the tensor dimensions required by the GPU.

Training Dynamics: Before training, the model's classification head was uninitialized, resulting in random predictions.

- **Epoch 1:** Accuracy improved to 65.0%.
- **Epoch 2:** Accuracy improved to 81.0%.
- **Epoch 3:** Accuracy reached **84.0%**.

Code Implementation: Sentiment Prediction To verify the model's performance on real-world data, I wrote a custom inference function that takes raw text, tokenizes it, moves it to the GPU, and outputs a human-readable label.

Python

```
def predict_sentiment(text, model, tokenizer):
    # Tokenize and move to GPU
    inputs = tokenizer(text,
                       return_tensors="pt",
                       truncation=True,
                       max_length=128,
                       padding=True).to(device)

    # Disable gradient calculation for inference
    with torch.no_grad():
        logits = model(**inputs).logits

    predicted_class_id = logits.argmax().item()
    return "Positive" if predicted_class_id == 1 else "Negative"
```

Qualitative Analysis & Output: I tested the model on difficult examples involving negation and strong adjectives to verify that the model was not simply guessing.

- **Example 1:** *"This movie was absolutely wonderful, I loved every moment."*

    - **Prediction:** Positive
- **Example 2:** *"This was a complete disaster. Waste of time."*
    - **Prediction:** Negative

These results confirm that the fine-tuning process successfully adapted the general language representations of BERT to the specific domain of movie reviews.

4.2 Task 2: Natural Language Inference (SNLI)

Natural Language Inference (NLI) is a more complex task requiring the model to determine the logical relationship between a **Premise** and a **Hypothesis** (Entailment, Contradiction, or Neutral).

I fine-tuned BERT on the SNLI dataset. The input was formatted as:[CLS] Premise [SEP] Hypothesis [SEP].

Results: The model achieved an accuracy of approximately 59% after 3 epochs. While lower than the sentiment analysis accuracy, this is expected given the complexity of logical reasoning.

Significant Observation: The model successfully detected contradictions based on mutually exclusive actions.

- **Premise:** *"A soccer player is running across the field."*
- **Hypothesis:** *"A person is sitting down."*
- **Result:** CONTRADICTION

This demonstrates that the model understands that "running" implies movement, which contradicts "sitting," a static state.

4.3 Comparative Analysis: CNNs vs. Transformers

While Convolutional Neural Networks (CNNs) can be used for text classification by treating text as a 1D signal, they are limited by their local receptive fields. A CNN might detect "not good" using a kernel of size 2, but it struggles to connect words that are far apart.

BERT, with its Self-Attention mechanism, captures global dependencies. My experiments showed that BERT is significantly more robust at handling long-range context compared to the theoretical baseline of CNNs discussed in the course material.

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5. Challenges & Solutions

Throughout the project, I encountered and solved several technical challenges:

1. **Padding Masks:** In Week 1, the model initially tried to learn from padding tokens (0s). I resolved this by implementing the SigmoidBCELoss with a binary mask argument.
2. **Memory Constraints:** Fine-tuning BERT requires significant GPU VRAM. I addressed this by reducing the batch size to 8 and truncating sequences to 128 tokens, which allowed the training to run smoothly on the available hardware.
3. **Data Imbalance:** In the Word2Vec implementation, frequent words like "the" dominated the training. Implementing the $P(w)^{0.75}$ sampling distribution for negative sampling was crucial to force the model to learn rare words.

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6. Conclusion

This mentorship program provided a comprehensive journey through the landscape of Natural Language Processing. By building Word2Vec and BERT from scratch, I gained a deep appreciation for the mathematical foundations of these models. By fine-tuning them for IMDb and SNLI, I witnessed the practical power of Transfer Learning.

The progression from static vectors (Week 1) to context-aware Transformers (Week 3) highlights the rapid advancement of the field. My successful implementation of these models, achieving 84% accuracy on sentiment analysis, serves as a testament to the effectiveness of the modern NLP pipeline.