Sentiment Analysis with Transformers

From Words to Understanding

BSc NLP Module

November 2025

Learning Goals & The Puzzle

After this lecture, you will be able to:

1. Explain why bidirectional context improves sentiment analysis
2. Describe the BERT fine-tuning process for classification tasks
3. Interpret performance metrics and attention patterns
4. Evaluate tradeoffs between traditional ML and transformer approaches
5. Identify when BERT-based sentiment analysis is appropriate

The Puzzle: When "4 out of 5 Correct" Isn't Good Enough

Your startup processes movie reviews daily. You build a BOW+SVM classifier that gets about **4 out of 5 reviews correct**. Investors are thrilled!

But then... users start complaining:

"Great, another boring superhero movie" → Model: POSITIVE → User complaint!

Mystery Question: If we're getting 4 out of 5 right, why are users complaining? Let's investigate...

Clue #1: Why Traditional Methods Fail

Review Text	BOW Predicts	Actual	Why BOW Fails
"Great, another boring movie"	POSITIVE	NEGATIVE	Sees "Great", ignores context
"This is not a bad film"	NEGATIVE	POSITIVE	Sees "bad", ignores "not"
"Absolutely incredible" vs "Somewhat good"	Both POSITIVE	Strong vs Weak	Cannot measure intensity

Pattern Emerges:

- **Sarcasm**: Word polarity reversed by context
- **Negation**: Modifier words change meaning
- **Intensity**: Strength requires understanding relationships

BOW treats words as independent. Context, word order, and relationships matter!

Dead End: Traditional Architectures

Traditional: BOW + SVM

Pipeline:

1. Input: "Great, another boring movie"
2. Word Counts: Great=1, another=1, boring=1, movie=1
3. Feature Vector: [1, 1, 1, 1, ...]
4. SVM Classifier
5. Output: POSITIVE (WRONG!)

Problem: No word order, no context!

Breakthrough: BERT

Pipeline:

1. Input: "Great, another boring movie"
2. Tokenization + [CLS] token
3. Transformer Layers (Bidirectional)

CLS = Sentence Representation

4. Output: NEGATIVE (CORRECT!)

Solution: Understands context!

Structural limitation: BOW/TF-IDF can't capture word order or bidirectional context. BERT can.

Breakthrough: BERT for Sentiment Analysis

Key Insight: Bidirectional context solves our puzzle!

BERT Architecture (High-Level)

- Input: Tokenize with [CLS] token
- Transformer layers (12-24)
- **Bidirectional attention** (key innovation!)

CLS = sentence representation

- Classification head on [CLS]

What "Bidirectional" Means:

When processing *"not very good"*:

- Traditional: left $\rightarrow$ right only
- BERT: $\leftarrow$ left + right $\rightarrow$
- Each word sees **ALL** other words simultaneously

How It Solves Our Puzzle

- Sarcasm: "Great" seen with "boring"
- Negation: "not" modifies "bad"
- Intensity: Measures strength context
- Word order: Fully preserved
- Relationships: Captured by attention

Concrete Example:

"Great, another boring movie"

- "Great" attends to "boring" (reversal!)
- "another" provides sarcastic context
- BERT: Correctly predicts NEGATIVE

Breakthrough: BERT processes words in both directions simultaneously, understanding context like humans do.

The Solution: BERT Fine-Tuning Pipeline

Four-Stage Process:

1. **Stage 1: Pre-trained BERT** (Already done for us!)
   - Trained on Wikipedia + Books (general language)
   - Knows grammar, context, meaning relationships
2. **Stage 2: Add Classifier Head**
   - Linear layer with random initialization
   - 2 outputs: Positive vs Negative
3. **Stage 3: Fine-Tune on Sentiment Data**
   - Train on IMDb reviews (labeled data)
   - Needs only 1000s of examples (not millions!)
4. **Stage 4: Deploy**
   - Apply to new reviews in production
   - Real-time predictions

Key insight: Pre-training gives general understanding, fine-tuning adapts to sentiment task. We don't start from zero!

Checkpoint Quiz

Quick Check: Match the stages to what's learned

1. Pre-trained BERT learns: _____
2. Adding classification head: _____
3. Fine-tuning on IMDb: _____
4. Deployment: _____

Options:

A. General language understanding (context, grammar, meaning)
B. Random initialization for sentiment classification
C. Sentiment-specific patterns from labeled data
D. Apply to new reviews in production

Answers: 1-A, 2-B, 3-C, 4-D. Understanding stages prevents "train from scratch" misconception.

Training Details: Making It Practical

Loss Function (Intuition)

- Cross-entropy loss
- Pushes probability toward correct label
- POSITIVE: maximize $P(\text{pos})$
- NEGATIVE: maximize $P(\text{neg})$
- Gradient descent updates BERT weights

Resource Requirements

- **Data**: Thousands of labeled examples (not millions!)
- **Compute**: Hours on GPU (not weeks)
- **Memory**: Standard GPU RAM
- **Cost**: Affordable on cloud (accessible!)

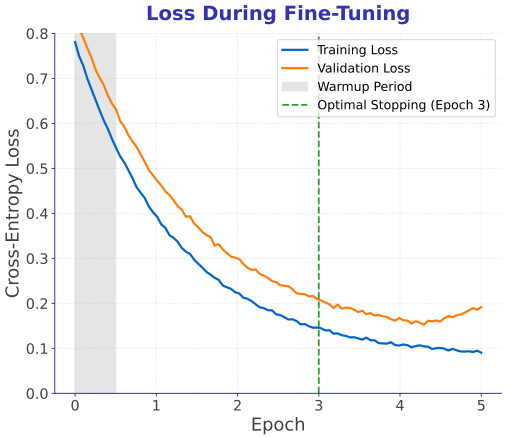
Key Insight

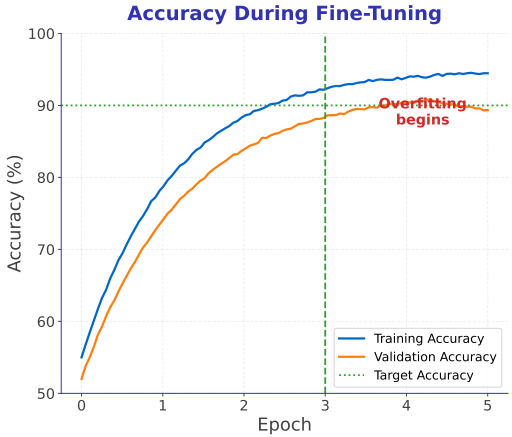
Fine-tuning is efficient because:

- BERT already knows language (pre-training)
- We only teach sentiment patterns (fine-tuning)
- Much faster than training from scratch

Practical reality: BERT fine-tuning is accessible for real projects, not just research labs.

Training Dynamics: Loss and Accuracy Curves





Empirical validation: 3-5 epochs sufficient. Warmup prevents destroying pre-trained weights. Overfitting signals when to stop.

Proof: BERT Solves the Puzzle

Performance Comparison on Sentiment Benchmarks:

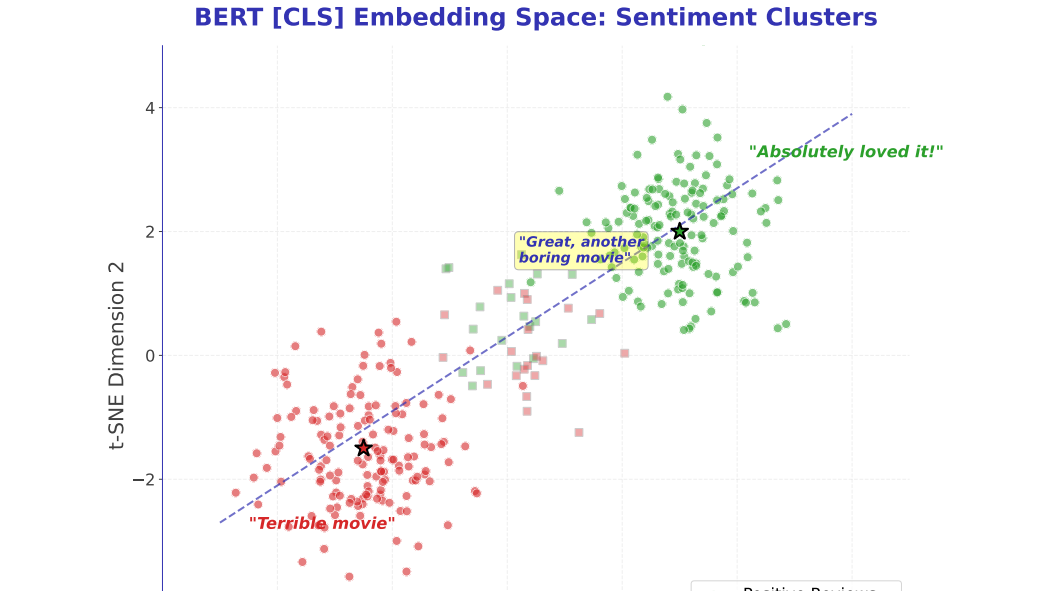
Method	Improvement	Category	Description
BOW + SVM	★	Traditional	Reference baseline
TF-IDF + Logistic	★★	Traditional	Marginal gains
LSTM	★★★	Neural	Notable improvement
BERT-base	★★★★	Transformer	Large gains from context
BERT-large	★★★★★	Transformer	Best-in-class

Key Observations:

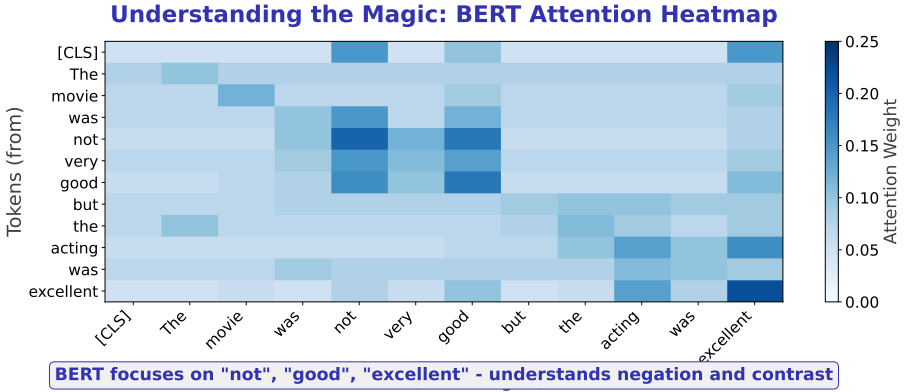
- Traditional methods (★-★★): Limited by bag-of-words assumption
- BERT (★★★★-★★★★★): Substantial improvement from bidirectional context
- Our breakthrough (context understanding) accounts for the jump

Empirical validation: BERT significantly outperforms traditional methods on sentiment benchmarks. Mystery solved!

What BERT Learned: Embedding Space



Understanding the Magic: Attention Visualization



BERT's attention reveals how it solves our puzzle: focusing on critical context words like "not", "good", "excellent".

Wisdom: When to Use BERT vs Traditional Methods

Use BERT When...	Use Traditional (BOW/TF-IDF) When...
Context is critical (sarcasm, negation)	Simple patterns suffice (keyword matching)
You have thousands of labeled examples	Limited data (hundreds of examples)
Accuracy matters more than speed	Need millisecond response times
GPU resources available	CPU-only deployment
Complex language understanding needed	Interpretability critical

Key Tradeoffs:

- **Speed**: BERT inference in seconds vs traditional in milliseconds
- **Data**: BERT needs thousands of examples vs traditional works with hundreds
- **Accuracy**: BERT achieves substantially higher performance (see previous slide)
- **Interpretability**: Traditional models transparent, BERT requires attention analysis

Engineering wisdom: Choose method based on constraints (data, compute, latency) not just "best" performance.

Appendix A1: Cross-Entropy Loss (Mathematical Details)

Binary Cross-Entropy for Sentiment:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$$

Where:

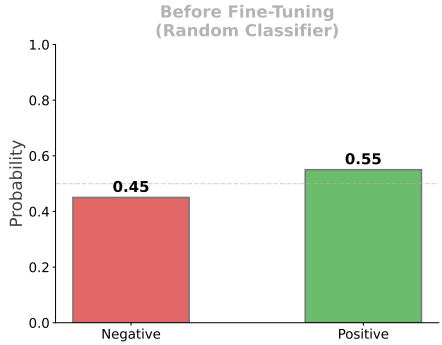
- $y_i \in \{0, 1\}$: True label (0=negative, 1=positive)
- $\hat{y}_i \in [0, 1]$: Predicted probability
- N: Number of training examples

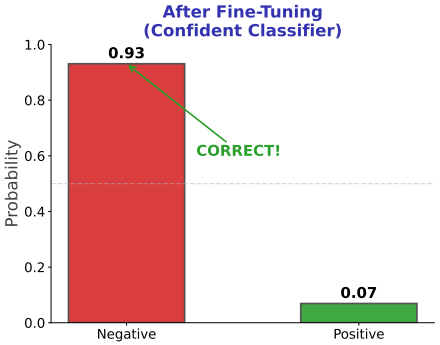
Intuition:

- When $y_i = 1$ (positive): Loss $= -\log(\hat{y}_i)$
  - If $\hat{y}_i = 0.9$ (confident): Loss ≈ 0.05 (small)
  - If $\hat{y}_i = 0.1$ (wrong): Loss ≈ 2.3 (large)
- Gradient descent minimizes loss by adjusting BERT weights
- Optimizer: AdamW with small learning rate (typical for fine-tuning)

Cross-entropy penalizes confident wrong predictions more than unconfident wrong ones.

From Logits to Predictions: Softmax & Cross-Entropy





Softmax Calculation (Worked Example)

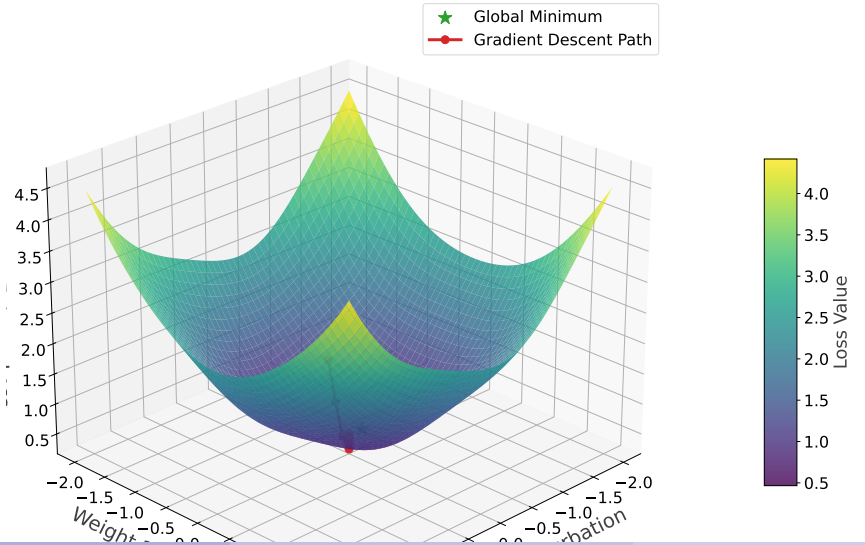
Input: "*Great, another boring movie*"

```
Logits: [2.1, -0.5]

exp(2.1) = 8.17
exp(-0.5) = 0.61
Sum = 8.78
```

Cross-Entropy Loss (Worked Example)

```
Ground Truth: y = [1, 0]  (Negative)
Predicted:    p = [0.93, 0.07]

Loss = -sum(y * log(p))
     = -(1 * log(0.93) + 0 * log(0.07))
     = -(-0.073 + 0)
     = 0.073
```

Loss Landscape: Fine-Tuning BERT for Sentiment



Appendix A2: Optimization & Hyperparameters

AdamW Optimizer:

- Adam with weight decay
- Adaptive learning rates per parameter
- Standard hyperparameters work well for most tasks
- Weight decay prevents overfitting

Learning Rate Schedule:

- **Warmup**: Linear increase from 0 to peak (first portion of training)
- **Decay**: Linear decrease to 0 over remaining steps
- **Peak LR**: Small learning rate (typical for fine-tuning)
- **Why**: Prevents catastrophic forgetting of pre-trained weights

Batch Sizes & Training:

- Batch size: Limited by GPU memory (typically order of magnitude: $\sim$10s)
- Epochs: Few epochs sufficient (typically single digits, more causes overfitting)
- Gradient accumulation if GPU memory limited

Practical Implementation:

- **Hugging Face Transformers**: Provides well-tested default hyperparameters
- `TrainingArguments` class handles learning rate scheduling automatically
- See `transformers.huggingface.co` for documented best practices

Careful hyperparameter tuning prevents destroying pre-trained knowledge while learning sentiment.

Appendix A2b: Attention Score Calculation

Example: "The movie was not very good"

Step 1: Create Query, Key, Value vectors

- Query ("not"): $\mathbf{q} = [0.8, 0.2, -0.1]$
- Key ("good"): $\mathbf{k} = [0.7, 0.3, 0.1]$

Step 2: Compute attention score

$$\text{score}(\text{not}, \text{good}) = \frac{\mathbf{q} \cdot \mathbf{k}}{\sqrt{d_k}} = \frac{0.8 \times 0.7 + 0.2 \times 0.3 + (-0.1) \times 0.1}{\sqrt{3}} = \frac{0.61}{1.73} = 0.35$$

Step 3: Apply softmax (over all keys)

$$\alpha_{\text{not} \to \text{good}} = \frac{e^{0.35}}{e^{0.35} + e^{0.1} + e^{0.2} + \ldots} = 0.18$$

Result: "not" attends to "good" with weight 0.18 — this connection helps BERT understand negation!

Attention scores reveal HOW BERT learns to connect "not" with the word it negates.

Appendix A2c: Stage 1 - Pre-training Deep Dive

Masked Language Model (MLM):

Objective: Predict masked tokens from context

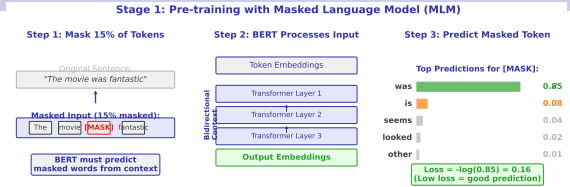
$$\mathcal{L}_{\text{MLM}} = -\mathbb{E}_{x \sim \mathcal{D}} \left[\sum_{i \in \text{masked}} \log P(x_i \mid x_{\setminus i}) \right]$$

Masking Strategy:

- Mask 15% of tokens randomly
- 80% replaced with [MASK]
- 10% replaced with random token
- 10% kept unchanged

Hyperparameters:

- Training corpus: 3.3B words (Wikipedia + BooksCorpus)
- Training time: Several days on TPUs
- Batch size: Thousands of sequences
- Learning rate: Warm-up then decay



Code Example (Simplified):

```
# MLM training loop
for batch in dataloader:
    # Mask 15% of tokens
    masked_inputs = mask_tokens(batch)

    # Forward pass
    outputs = bert(masked_inputs)

    # Loss: predict masked tokens
    loss = cross_entropy(
        outputs[masked_positions],
        original_tokens[masked_positions]
    )

    # Backward pass
    loss.backward()
    optimizer.step()
```

Pre-training teaches BERT general language understanding before task-specific fine-tuning.

Appendix A2d: Stage 2 - Classifier Head Architecture

Architecture Details:

The classifier head is a simple linear layer:

$$z = W^T h_{[CLS]} + b$$

where:

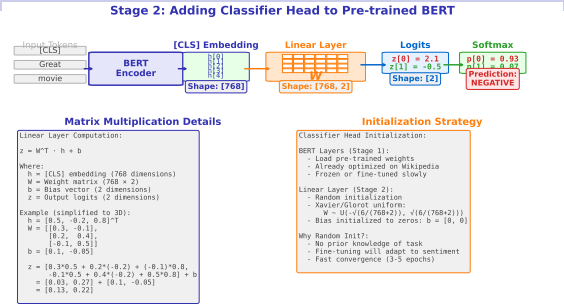
- $h_{[CLS]} \in \mathbb{R}^{768}$ — BERT's [CLS] output
- $W \in \mathbb{R}^{768 \times 2}$ — weight matrix
- $b \in \mathbb{R}^2$ — bias vector
- $z \in \mathbb{R}^2$ — logits (one per class)

Initialization:

- $W \sim \mathcal{U}(-\sqrt{6/(768+2)}, \sqrt{6/(768+2)})$ (Xavier)
- $b = \mathbf{0}$ (zeros)
- Pre-trained BERT weights loaded

Parameters:

- Classifier head: 1,538 parameters
- BERT-base total: 110M parameters
- Ratio: 0.001% new parameters



Code Example:

```
import torch.nn as nn

class BertForSentiment(nn.Module):
    def __init__(self, bert_model):
        super().__init__()
        self.bert = bert_model  # Pre-trained
        self.classifier = nn.Linear(768, 2)
        # Classifier randomly initialized

    def forward(self, input_ids, attention_mask):
        # BERT encoding
        outputs = self.bert(
            input_ids=input_ids,
            attention_mask=attention_mask
```

Appendix A2e: Stage 4 - Deployment & Inference Pipeline

Inference Pipeline:

Step 1: Tokenization (˜1ms)

- WordPiece tokenization
- Add [CLS] and [SEP] tokens
- Convert to input IDs
- Create attention mask

Step 2: Model Forward Pass (˜10-50ms)

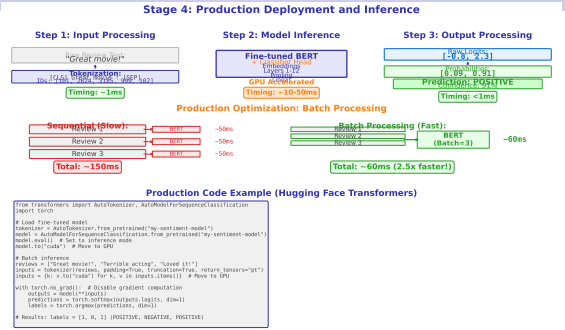
- BERT encoding (12 layers)
- Extract [CLS] representation
- Linear classifier layer
- GPU acceleration critical

Step 3: Post-processing (¡1ms)

- Apply softmax to logits
- Get class probabilities
- Return prediction + confidence

Optimization Strategies:

- **Batching:** Process multiple inputs together (2-3x




```
from transformers import AutoTokenizer, AutoModelForSequenceClassification
import torch

# Load fine-tuned model
tokenizer = AutoTokenizer.from_pretrained("my-sentiment-model")
model = AutoModelForSequenceClassification.from_pretrained("my-sentiment-model")
model.eval()  # Set to inference mode
model.to("cuda")  # Move to GPU

# Batch inference
reviews = ["Great movie!", "Terrible acting", "Loved it!"]
inputs = tokenizer(reviews, padding=True, truncation=True, return_tensors="pt")
inputs = {k: v.to("cuda") for k, v in inputs.items()}  # Move to GPU

with torch.no_grad():  # Disable gradient computation
    outputs = model(**inputs)
    predictions = torch.softmax(outputs.logits, dim=1)
    labels = torch.argmax(predictions, dim=1)

# Results: labels = [1, 0, 1] (POSITIVE, NEGATIVE, POSITIVE)
```

Production Throughput:

- Single GPU (V100): ˜200-500 samples/sec
- With batching (batch=32): ˜1000-2000 samples/sec
- Latency: 10-50ms per prediction (acceptable for most applications)

Appendix A3: Aspect-Based Sentiment Analysis

Problem: Extract sentiment per product aspect
"The phone camera is excellent but battery life is terrible."

- Camera: POSITIVE
- Battery: NEGATIVE

BERT Approach:

1. Identify aspects (camera, battery) via NER or keywords
2. For each aspect:
   - Create input: [CLS] aspect [SEP] sentence [SEP]
   - Fine-tune BERT to predict sentiment for that aspect
   - Use attention to find aspect-relevant words
3. Aggregate aspect sentiments

Applications:

- Product reviews (Amazon, Yelp)
- Survey analysis
- Brand monitoring

Aspect-based extends BERT from document-level to fine-grained sentiment extraction.

Appendix A4: Multi-Label Sentiment Analysis

Problem: Detect multiple emotions per text
"I'm excited about the trip but worried about the cost."

- Joy: HIGH
- Anxiety: MEDIUM
- Anger: LOW

BERT Modifications:

- **Architecture**: Replace softmax with sigmoid activation
- **Output**: K independent probabilities (one per emotion)
- **Loss**: Binary cross-entropy for each label

$$\mathcal{L} = -\frac{1}{K}\sum_{k=1}^{K}[y_k \log(\hat{y}_k) + (1-y_k)\log(1-\hat{y}_k)]$$

- **Threshold**: Predict label if $\hat{y}_k > 0.5$

Applications:

- Emotion detection (Plutchik's wheel)
- Mental health monitoring
- Customer service routing

Multi-label captures emotional complexity beyond simple positive/negative classification.

Appendix A5: Zero-Shot Sentiment with Prompting

Problem: Classify sentiment with NO labeled data

Approach: Use instruction-tuned LLMs (GPT-4, Claude, Llama)

Prompt Template

```
Classify the sentiment of the following review as POSITIVE or NEGATIVE.
Review: ''Great, another boring superhero movie''
Sentiment:
```

Why It Works:

- Pre-trained on massive text (understands sentiment)
- Instruction-tuned to follow prompts
- Can reason about sarcasm, negation, intensity
- No fine-tuning required

Tradeoffs vs BERT Fine-Tuning:

- **Pros**: No labeled data, handles rare cases, flexible
- **Cons**: Slower inference, higher per-query cost, less controllable

Zero-shot useful for prototyping or low-resource scenarios, but fine-tuned BERT better for production.

Appendix A6: Resources & Further Reading

Foundational Papers:

- Devlin et al. (2019). BERT: Pre-training of Deep Bidirectional Transformers. NAACL.
- Liu et al. (2019). RoBERTa: A Robustly Optimized BERT Pretraining Approach. arXiv.
- Sanh et al. (2019). DistilBERT: A distilled version of BERT (smaller, faster).

Practical Tools:

- Hugging Face Transformers: `transformers.huggingface.co`
- Datasets: IMDb, SST-2, Yelp, Twitter Sentiment
- Pre-trained models: BERT, RoBERTa, DistilBERT, ELECTRA

Tutorials:

- Hugging Face Course: `huggingface.co/course`
- Google Colab notebooks (free GPU access)
- Fast.ai NLP course

Advanced Topics:

- Adversarial robustness in sentiment analysis
- Cross-lingual sentiment (multilingual BERT)
- Temporal aspects (sentiment over time)

Start with Hugging Face tutorials for hands-on experience fine-tuning BERT for sentiment analysis.

Appendix A7: Full Mathematical Derivations

Cross-Entropy Gradient (For Backpropagation):

$$\frac{\partial \mathcal{L}}{\partial z_j} = \hat{y}_j - y_j$$

where z_j is the logit for class j. This simple gradient is why cross-entropy works so well!

Softmax Jacobian:

$$\frac{\partial \hat{y}_i}{\partial z_j} = \hat{y}_i(\delta_{ij} - \hat{y}_j)$$

where δ_{ij} is the Kronecker delta (1 if $i = j$, else 0).

Attention Weight Gradient:

$$\frac{\partial \alpha_{ij}}{\partial \mathbf{q}_i} = \alpha_{ij} \left(\mathbf{k}_j - \sum_k \alpha_{ik} \mathbf{k}_k \right) / \sqrt{d_k}$$

BERT Fine-Tuning Update:

$$\theta_{t+1} = \theta_t - \eta \cdot \text{AdamW}(\nabla_\theta \mathcal{L})$$

with small learning rate η and weight decay λ (standard fine-tuning values).

These gradients enable end-to-end training: error signal flows from loss through attention to word embeddings.