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 85% Isn't Good Enough

Your startup gets 10,000 movie reviews per day. You build a BOW+SVM classifier with 85% accuracy. Investors are thrilled!

But then... users start complaining:

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

Mystery Question: If 85% is good, 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

CLS = sentence representation

- Classification head on [CLS]

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

Breakthrough: BERT processes words in both directions, 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**: 1000s of labeled examples (not millions!)
- **Compute**: Hours on GPU (not weeks)
- **Memory**: 8-16GB GPU RAM
- **Cost**: $10-50 on cloud (accessible!)

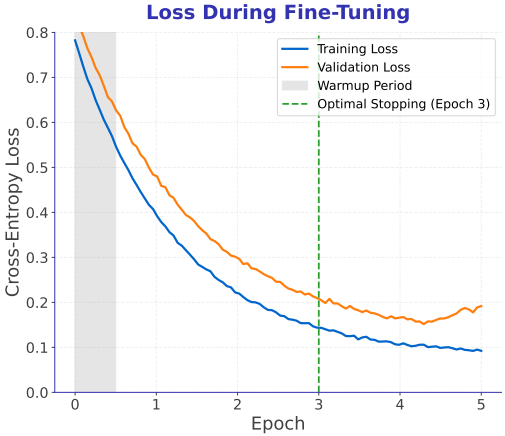
Key Insight

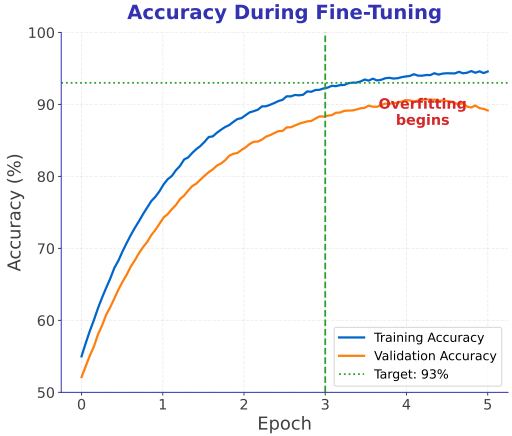
Fine-tuning is efficient because:

- 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

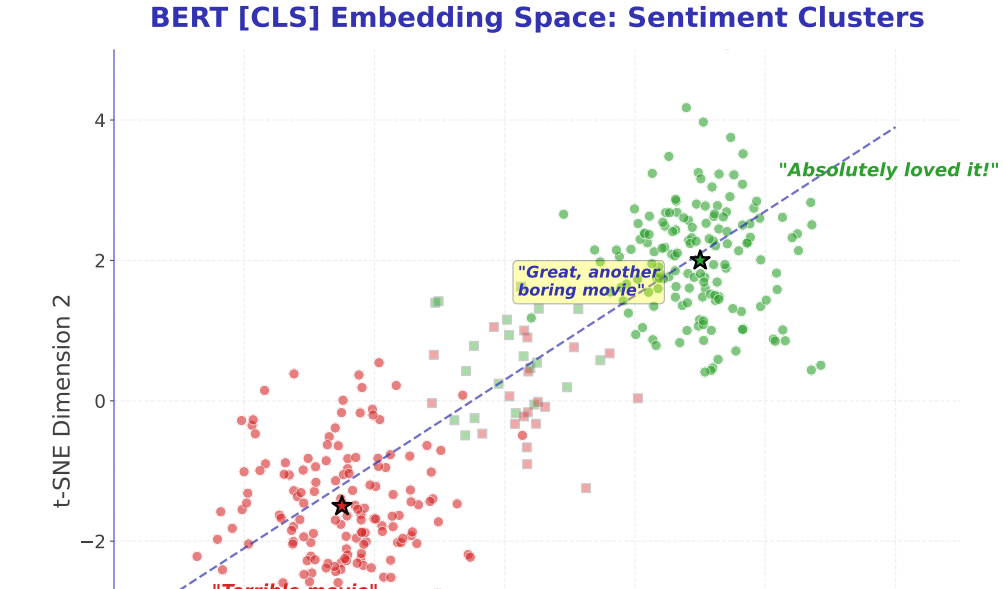
Performance Comparison on Sentiment Benchmarks (F1-Score):

Method	F1-Score	Category
BOW + SVM	78%	Traditional
TF-IDF + Logistic	81%	Traditional
LSTM	87%	Neural
BERT-base	**93%**	Transformer
BERT-large	**95%**	Transformer

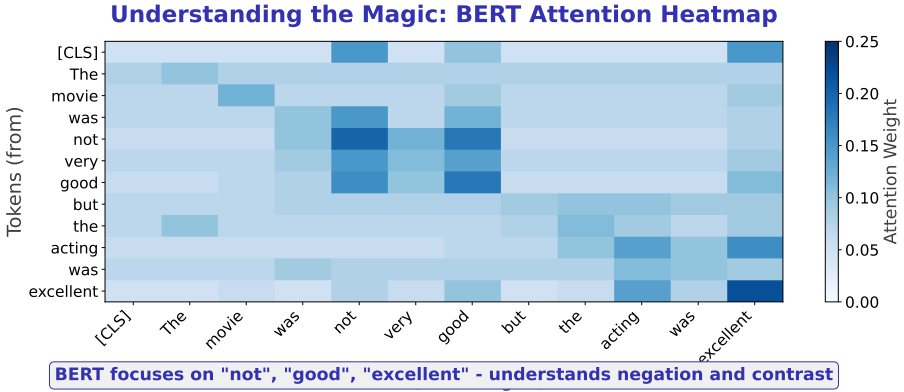
Key Observations:

- Traditional methods: 78-81% (our puzzle's 85% was optimistic!)
- BERT improves by +12-17 percentage points
- Bidirectional context (our breakthrough) accounts for gains

Empirical validation: BERT achieves 93-95% F1 vs 78-81% for traditional methods. Mystery solved!


BERT [CLS] Embedding Space: Sentiment Clusters
t-SNE Dimension 2
4
2
0
−2
"Absolutely loved it!"
"Great, another boring movie"

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 1000+ labeled examples	Limited labeled data (<100 examples)
Accuracy matters more than speed	Need real-time inference (<1ms)
GPU resources available	CPU-only deployment
Complex language understanding needed	Interpretability critical

Key Tradeoffs:

- **Speed**: BERT ∼50ms/review vs BOW ∼1ms/review
- **Data**: BERT needs 1000s, traditional works with 100s
- **Accuracy**: BERT +10-15% F1-score improvement
- **Interpretability**: Traditional clearer, BERT needs 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:

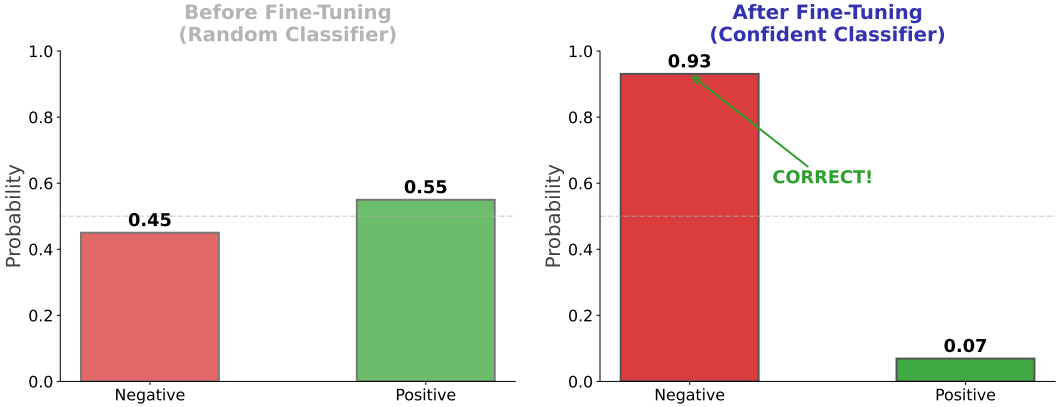
- $y_i \in \{0, 1\}$: True label (0=negative, 1=positive)
- $\hat{y}_i \in [0, 1]$: Predicted probability
- N: Number of training examples

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 learning rate $\approx 2 \times 10^{-5}$

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

From Logits to Predictions: Softmax & Cross-Entropy



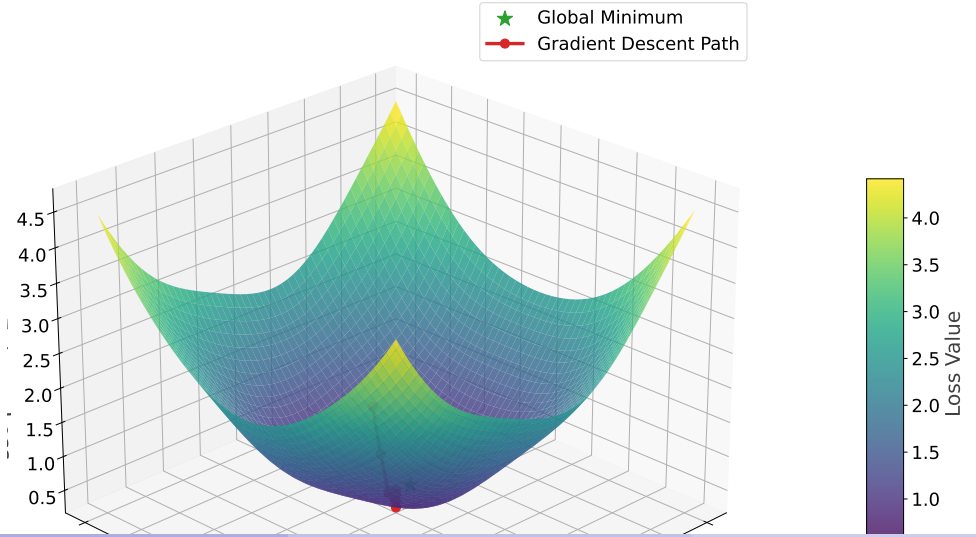
Softmax Calculation (Worked Example)

Input: "*Great, another boring movie*"

Cross-Entropy Loss (Worked Example)

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

Loss Landscape: Fine-Tuning BERT for Sentiment



Appendix A2: Optimization & Hyperparameters

AdamW Optimizer:

- Adam with weight decay
- Adaptive learning rates per parameter
- Typical settings: $\beta_1 = 0.9, \beta_2 = 0.999, \epsilon = 10^{-8}$
- Weight decay: $\lambda = 0.01$

Learning Rate Schedule:

- **Warmup**: Linear increase from 0 to peak over first 10% of steps
- **Decay**: Linear decrease to 0 over remaining steps
- **Peak LR**: 2×10^{-5} to 5×10^{-5}
- **Why**: Prevents catastrophic forgetting of pre-trained weights

Batch Sizes & Training:

- Batch size: 16-32 (limited by GPU memory)
- Epochs: 3-5 (more can cause overfitting)
- Gradient accumulation if GPU memory limited

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 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 (100-1000ms), expensive ($0.001-0.01/review), 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 $\eta \approx 2 \times 10^{-5}$ and weight decay $\lambda = 0.01$.

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