

# Multi-Class Text Classification with BERT

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## Task

- **Multi-class text classification** on the 20 Newsgroups dataset  
(20 newsgroup categories)
- **Collect additional data from modern forums**, evaluate and interpret the key findings
- **Add a way for the model to generate a confidence score** indicating how certain it is about its decision
- **Open-world extension:** detect inputs that do *not* belong to any of the 20 known categories

# Dataset: 20 Newsgroups – Overview

Property	Value
Source	SetFit/20_newsgroups
Classes	20 newsgroup categories
Train samples	11 314
Test samples	7 532
Total	18 846

## Category groups

- **Computer (5):** comp.graphics,  
comp.os.ms-windows.misc,  
comp.sys.ibm.pc.hardware,  
comp.sys.mac.hardware, comp.windows.x
- **Recreation (4):** rec.autos, rec.motorcycles,  
rec.sport.baseball, rec.sport.hockey
- **Science (4):** sci.crypt, sci.electronics, sci.med,  
sci.space
- **Politics / Religion (6):** talk.politics.\*,  
alt.atheism, soc.religion.christian
- **Other (1):** misc.forsale

# Dataset – Splits and Statistics

Split	Size	Purpose
Train	11 314	Model training
Validation	3 766	HPO & model selection
Test	3 766	Final held-out evaluation

Metric	Characters	Words
Mean	~1 800	~300
Median	~900	~150
P95	~6 500	~1 100

## Tokenisation coverage (max\_length)

- 128 tokens → ~50 % coverage
  - **256 tokens** → ~75 % coverage ← chosen
  - 512 tokens → ~90 % coverage
- 
- + Manageable training time and computational cost
  - + First 256 tokens are generally sufficient to predict the label
  - Some information loss for very long documents

# Model: ModernBERT

Recent **encoder-only** model by HuggingFace – a modernised version of BERT with multiple architectural improvements for robustness and efficiency.

## BERT → RoBERTa

- Significantly more training data
- No Next Sentence Prediction loss
- Dynamic masking

## RoBERTa → ModernBERT

- Even more training data
- **GeGLU** activation (more robust than GeLU)
- No bias terms except in last linear layer
- **Pre-normalisation** (LayerNorm at the beginning of sub-layers)
- Alternating attention

# Training Strategy

## Layer Freezing

Component	Status
Embedding layer	Frozen
Encoder layers 0–13	Frozen (bottom 50%)
Encoder layers 14–27	Trainable (top 50%)
Classification head	Trainable

Further unfreezing layers significantly increased compute requirements without meaningful accuracy gains.

## Training Configuration

Parameter	Value
Optimiser	AdamW
Epochs	4
Batch size	16 per GPU
Max sequence len	256 tokens
Mixed precision	FP16 (CUDA)
Gradient clipping	max_norm = 1.0
LR scheduler	Linear warmup + decay
Hardware	NVIDIA Tesla T4
Multi-GPU	nn.DataParallel

# Hyperparameter Optimisation

**Method 1:** Hyperparameters from the original ModernBERT paper, theory, and intuition.

## Method 2: Quasi-Random Search (QRS) via Optuna

- Better space coverage than grid or pure random search
- Uses **Quasi-Monte Carlo (QMC)** sampling for low-discrepancy sequences
- More efficient exploration of the hyperparameter landscape

### Search Space

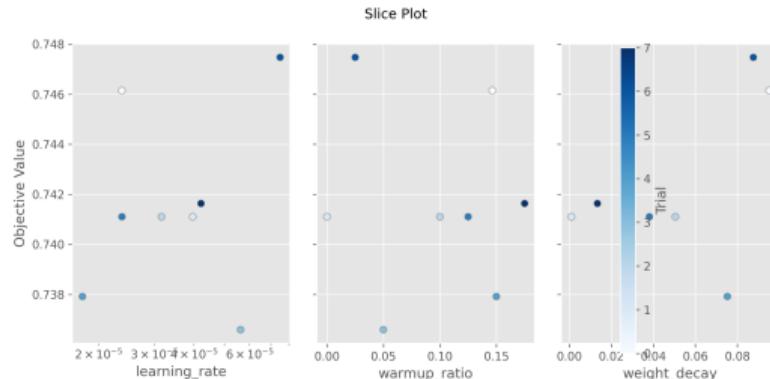
Hyperparameter	Range	Scale
Learning rate	$[10^{-5}, 10^{-4}]$	Log
Weight decay	$[0.001, 0.1]$	Linear
Warmup ratio	$[0.0, 0.2]$	Linear

### Setup

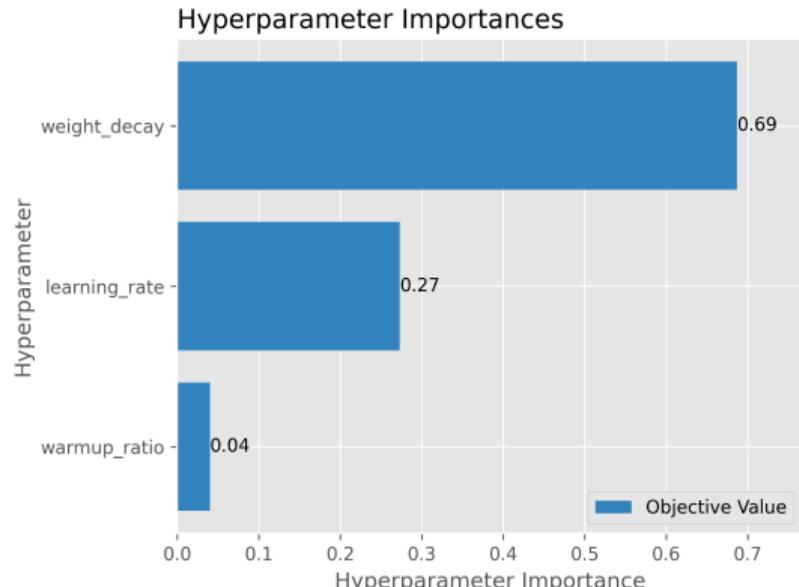
- Objective: **maximise validation accuracy**
- Aggressive memory management (delete non-top-3 checkpoints)
- Optuna visualisations: slice plots & parameter importance

# HPO – Visualisation and Evaluation

## Hyperparameters vs. Loss



## Parameter Importances



## Test-Set Performance

Metric	Top-1	Top-2	Top-3
Accuracy	74.93%	74.35%	73.26%
Macro F1	0.7385	0.7353	0.7246
Weighted F1	0.7486	0.7453	0.7344
Test Loss	1.2554	1.4491	1.6971

# Evaluation on Additional Modern Forum Data

- Collected a few samples for each class using web scrapers and a few samples manually from subReddits.
- Total of **2,000 samples** were collected (100 samples for each class) and stored in `collected_reddit_data.csv`.
- Evaluated the Top-2 model on `collected_reddit_data.csv`.

## Evaluation Results:

- Test Loss: **0.9896**
- Accuracy: **0.7800**

Metric	Test Set	Reddit	Change
Accuracy	0.7435	0.7800	+0.0365
Macro F1	0.7353	0.7700	+0.0347
Weighted F1	0.7453	0.7700	+0.0248

# Key Findings & Interpretation

## Test Set vs. Collected Reddit Data

### 1. Categories with Large Improvements

- rec.autos (+0.293)
- talk.politics.misc (+0.315)
- talk.politics.guns (+0.244)
- sci.electronics (+0.219)
- rec.motorcycles (+0.148)
- sci.space (+0.152)
- rec.sport.baseball (+0.115)
- sci.crypt (+0.100)

### 2. Categories with Moderate Gains

- alt.atheism (+0.060)
- comp.graphics (+0.049)
- comp.sys.mac.hardware (+0.016)

### 3. Categories with Declines

- comp.windows.x (-0.328)
- comp.sys.ibm.pc.hardware (-0.259)
- misc.forsale (-0.230)
- soc.religion.christian (-0.163)
- talk.religion.misc (-0.131)
- comp.os.ms-windows.misc (-0.077)

### 4. Factors Influencing Performance

- Subreddit relevance
- Temporal language shift
- Community norms
- Class imbalance in original data

# Confidence Score & Certainty of the Model

## Maximum Softmax Probability (MSP)

Confidence computed using Softmax:

$$P(y = i) = \frac{e^{z_i}}{\sum_j e^{z_j}}$$

**Confidence score** = Maximum Softmax Probability (MSP)

Evaluated on full test set.

**Results:**

- **Avg Confidence (Correct):** 0.9508
- **Avg Confidence (Incorrect):** 0.6879
- **Correlation (Confidence vs Correctness):** 0.5384

*The model is significantly less confident when it makes a mistake.*

# Confidence Score & Certainty of the Model

## Test-Time Augmentation (TTA) for Uncertainty Estimation

- ① Apply 10 stochastic augmentations to each test sample
- ② Run model inference on each augmented version
- ③ Average predicted probability distributions
- ④ Compute predictive entropy from the averaged probabilities
- ⑤ Compare entropy for correct vs incorrect predictions

### Predictive Entropy Formula

$$H(p) = - \sum_{i=1}^C p_i \log p_i$$

Where  $p_i$  = averaged predicted probability for class  $i$ , and  $C$  = number of classes.  
*Higher  $H(p)$  → higher uncertainty.*

### Results:

- **Avg entropy (Correct):** 0.1424
- **Avg entropy (Incorrect):** 0.9232

# Out-of-Distribution Detection

## Strategy: Maximum Softmax Probability (MSP)

$$\text{score}(x) = \max_k \text{softmax}\left(\frac{\mathbf{z}(x)}{T}\right)_k$$

- If  $\text{score}(x) \geq \tau \rightarrow$  classify as one of the 20 classes (In-Distribution)
- If  $\text{score}(x) < \tau \rightarrow$  reject as “null / other” (Out-of-Distribution)

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Parameter	Effect
Temperature $T$	$T > 1$ : softens probabilities $\rightarrow$ better ID/OOD separation
Threshold $\tau$	Higher $\tau$ : stricter $\rightarrow$ fewer false positives, more false negatives

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# OOD Detection Setup

## In-Distribution (ID)

- **20 Newsgroups test set** (3766 samples)
- Same split used for classification evaluation

## Out-of-Distribution (OOD)

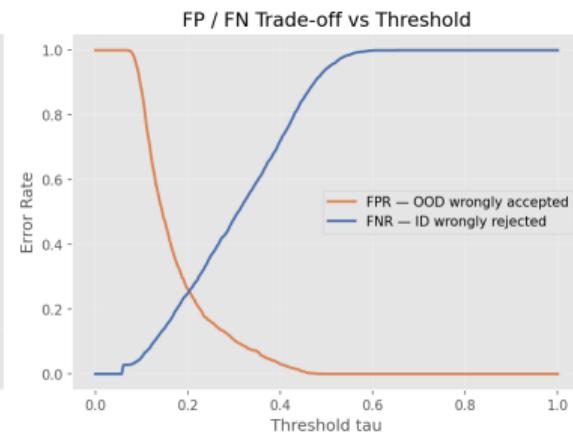
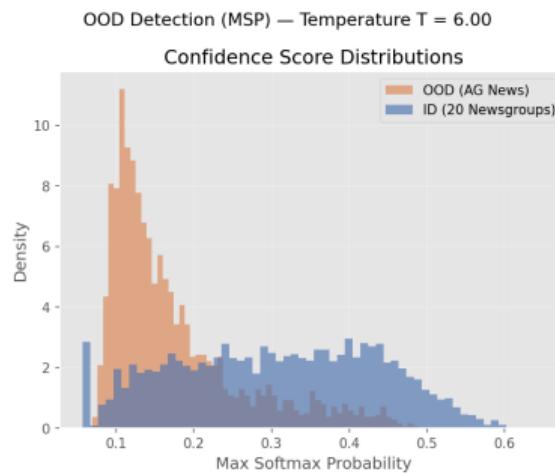
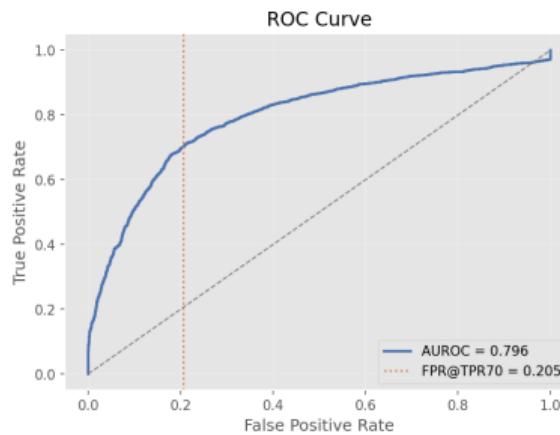
- **AG News** – 4-class news topic classification
- 2 000 randomly sampled test documents
- **Completely different domain** from 20 Newsgroups

## Evaluation Protocol

- ➊ Collect model logits for both ID and OOD data
- ➋ Compute MSP scores at temperatures  $T \in \{6, 7, 8, 9, 10\}$
- ➌ For each  $T$ , report:
  - **AUROC** (Area Under ROC Curve)
  - **AP** (Average Precision)
  - **FPR@TPR70**
- ➍ Per-threshold table: FPR, FNR, retained ID accuracy, % ID kept

# OOD Detection – Diagnostic Visualisations

Three diagnostic plots are generated per temperature:



## 1. ROC Curve

- AUROC summarises discriminative quality
- Annotated with

## 2. Confidence Distributions

- Good detection → well-separated distributions
- OOD should cluster at lower

## 3. FP / FN Trade-off

- Crossing point = balanced operating point
- Select  $\tau$  per application

# OOD Detection – Results & The FP / FN Trade-off

## Temperature Comparison

Temp $T$	AUROC	AP	FPR@TPR70
6.00	0.7961	0.8841	0.2050
7.00	0.7986	0.8860	0.2000
8.00	0.8003	0.8875	0.1970
9.00	0.8016	0.8885	0.1930
<b>10.00</b>	<b>0.8026</b>	<b>0.8893</b>	<b>0.1910</b>

Best at  $T = 10$ : AUROC = 0.8026,  
AP = 0.8893

## Threshold Table ( $T = 6.00$ )

AUROC = 0.7961 AP = 0.8841 FPR@TPR70 = 0.2050

$\tau$	FPR	FNR	ID Acc	% ID
0.10	0.875	0.052	0.785	94.8%
0.20	0.263	0.249	0.874	75.1%
0.30	0.105	0.481	0.942	51.9%
0.40	0.031	0.720	0.974	28.0%
0.50	0.000	0.943	0.991	5.7%

*The optimal operating point depends on tolerance for false positives vs. false negatives.*

# Key Design Decisions

## ① Used ModernBERT Variant of BERT

- Version of BERT that includes multiple small tweaks to make the transformer architecture more robust and efficient

## ② Layer Freezing (50%)

- Faster training, less memory → allows larger batch size
- Minimal accuracy loss: lower layers learn general language features

## ③ Initial Hyperparameters from ModernBERT Architecture

- Seeded tuning process with parameters proven effective in original paper

## ④ Quasi-Random Search (QRS) over Grid/Random

- QMC sampling provides **better coverage** of the search space

## ⑤ Validation Split from Test Set

- Split test 50/50 → separates validation for HPO and final test eval
- Prevents data leakage: HPO decisions never touch the test set

# Pipeline Summary

- ① **Data Loading:** 20 Newsgroups via HuggingFace → Train/Val/Test split
- ② **Tokenisation:** ModernBERT tokenizer, max\_len=256
- ③ **Model Setup:** ModernBERT-Large, 50% layers frozen
- ④ **Hyperparameter Optimisation:** Optuna QRS (LR, weight decay, warmup ratio)
- ⑤ **Model Selection:** Top 3 → evaluate on test set
- ⑥ **OOD Detection:** MSP + Temp. Scaling: ID=20 Newsgroups, OOD=AG News
- ⑦ **Real-World Evaluation:** Evaluate on collected Reddit data, compare & interpret vs test results
- ⑧ **Uncertainty Estimation:** Confidence score & certainty of the model (MSP, TTA)

## Future Work

- More trials of quasi-random search
- Bayesian HPO
- Experiment with other BERT variants

### Lesson Learned

Errors in training pipeline can be very costly when running Optuna Quasi-Random HPO on large transformer models, as each iteration can take hours to run.

# **Thank You!**

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Questions?