

# Multi-Class Text Classification with BERT

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# Problem Statement

## Task

- **Multi-class text classification** on the 20 Newsgroups dataset  
(20 newsgroup categories)
- **Open-world extension:** detect inputs that do *not* belong to any of the 20 known categories

## Approach

- ① Fine-tune a **pre-trained foundational transformer model** (ModernBERT)
- ② Systematically optimise hyperparameters with **Quasi-Random Search**
- ③ Extend to OOD detection using **Maximum Softmax Probability (MSP)**

# 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
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- + 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

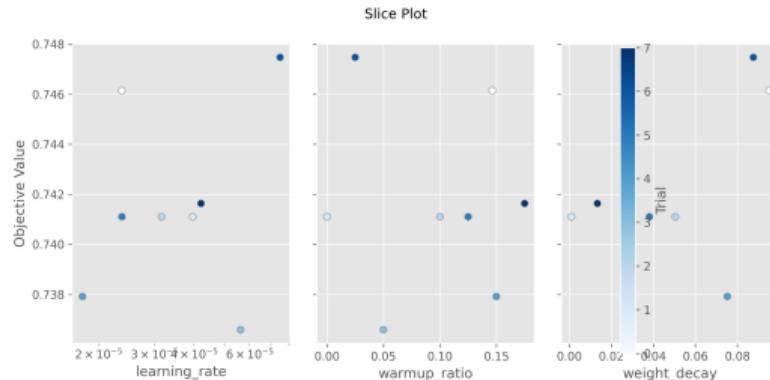
Hyperparameter	Range	Scale
Learning rate	$[10^{-5}, 10^{-4}]$	Log
Weight decay	$[0.001, 0.1]$	Linear
Warmup ratio	$[0.0, 0.2]$	Linear

### Setup

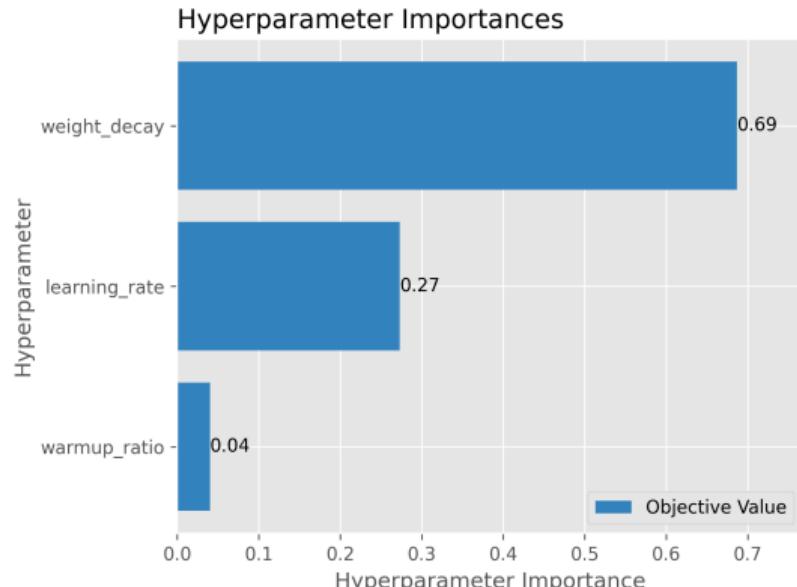
- Objective: **maximise validation accuracy**
- Aggressive memory management (delete non-top-3 checkpoints)
- Optuna visualisations: slice plots & parameter importance

# 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

# 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 – The FP / FN Trade-off

## Understanding the Threshold $\tau$

Direction	Effect	Consequence
$\uparrow \tau$	Stricter	$\downarrow \text{FP} / \uparrow \text{FN}$
$\downarrow \tau$	Looser	$\downarrow \text{FN} / \uparrow \text{FP}$

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

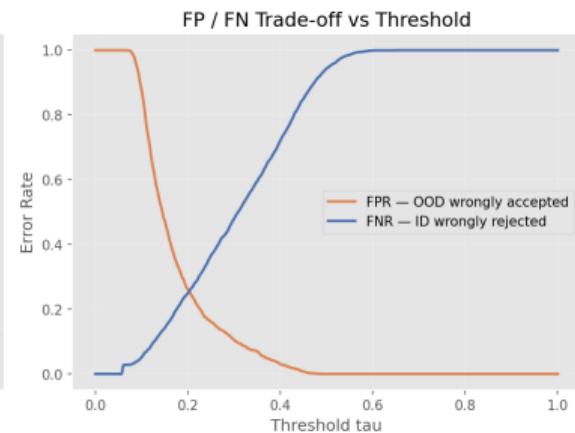
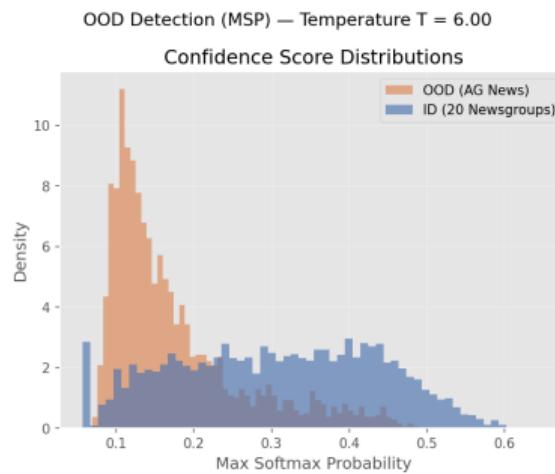
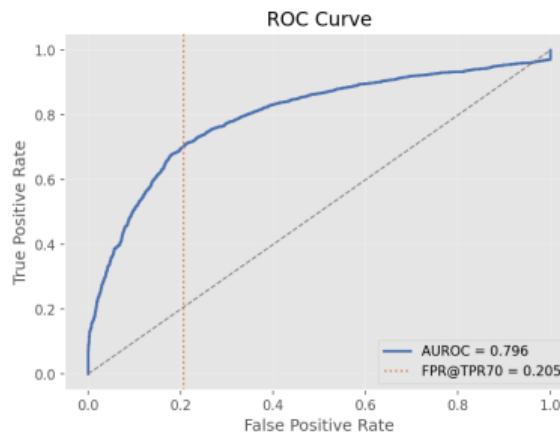
## Threshold Table ( $T = 6.00$ )

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%

# 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

## Results – OOD Temperature Comparison

Temperature $T$	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>

Higher temperatures yield modest improvements across all metrics.

Best performance at  $T = 10$ : AUROC = 0.8026, AP = 0.8893, FPR@TPR70 = 0.1910

# 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 / Validation / 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 + Temperature Scaling) → ID:

# Conclusion

## Summary

- Successfully fine-tuned **ModernBERT-Large** on 20 Newsgroups (20-class classification)
- Systematic **hyperparameter optimisation** with Optuna Quasi-Random Search
- Extended to **OOD detection** using MSP with temperature scaling
- Comprehensive evaluation with AUROC, AP, FPR@TPR70, and threshold analysis

## 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?