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Cross-Model Comparison for News Topic Classification: Classical Machine Learning vs. Fine-Tuned Transformers

COE379L Project 3: Advanced Classical Algorithms vs. Fine-Tuned Transformers

1. Introduction and Project Statement

1.1 Background

Text classification remains one of the fundamental tasks in natural language processing (NLP), with applications spanning from content moderation to automated news categorization. The field has witnessed a paradigm shift from classical machine learning approaches, which rely on hand-engineered features like TF-IDF, to modern transformer-based models that leverage pre-trained contextual embeddings. This evolution raises critical questions about the trade-offs between computational efficiency and predictive performance.

1.2 Project Objective

This project conducts a comprehensive, direct comparison between two distinct methodological paradigms for multi-class text classification:

1. **Classical Feature-Engineered Models**: Utilizing traditional machine learning algorithms (XGBoost and Support Vector Machines) with TF-IDF feature extraction.
2. **Fine-Tuned Transformer Models**: Employing state-of-the-art pre-trained language models (RoBERTa-base) fine-tuned on the target task.

The primary goal is to determine the optimal modeling approach by systematically evaluating both computational efficiency and predictive performance on a standardized news classification task.

1.3 Research Questions

This study addresses three key research questions:

1. **Performance Gap Analysis**: How significant is the performance difference between classical, feature-engineered models and fine-tuned transformer models on a modern news classification task?
2. **Computational Trade-offs**: What are the trade-offs in training time and inference latency for each methodological approach?
3. **Practical Recommendations**: Can a resource-efficient classical model provide sufficient performance to justify avoiding the higher computational costs associated with fine-tuning large transformer models?

1.4 Scope and Limitations

This study focuses on the AG News dataset, a balanced four-class news classification task. The comparison is limited to:

- **Classical Models**: XGBoost and SVM (Linear and RBF kernel).
- **Transformer Model**: RoBERTa-base.
- **Evaluation Metrics**: Accuracy, Macro-Averaged F1-Score, Log Loss, Training Time, and Inference Latency.

The findings are specific to this dataset and task, though the methodology can be generalized to similar text classification problems.

2. Data Sources and Technologies Used

2.1 Dataset: AG News

The AG News dataset, sourced from the Hugging Face Datasets Hub, serves as the standardized benchmark for this comparison. This dataset was selected for its:

- **Scale**: Over 120,000 training samples and 7,600 test samples.
- **Balance**: Four balanced categories (World, Sports, Business, Sci/Tech).
- **Pre-split Structure**: Pre-divided into training and test sets, ensuring reproducibility.
- **Format**: Each sample contains a news article title and description, which are combined into a single text input for classification consistency.

The dataset's balanced nature makes macro-averaged metrics appropriate for evaluation, as they treat all classes equally regardless of their individual sizes.

2.2 Technology Stack

2.2.1 Classical Models Pipeline

Libraries and Frameworks:

- **scikit-learn** (v1.3+): Primary framework for classical machine learning algorithms.
    - TfidfVectorizer: TF-IDF feature extraction.
    - XGBClassifier: XGBoost gradient boosting implementation.
    - LinearSVC and SVC: Support Vector Machine implementations.
    - RandomizedSearchCV: Hyperparameter optimization with cross-validation.
- **XGBoost** (v3.1+): Standalone gradient boosting library integrated with scikit-learn.
- **pandas** and **numpy**: Data manipulation and numerical computations.
- **joblib**: Model persistence and serialization.

Hardware Considerations:

- Classical models were trained on CPU.

- Sparse matrix representations used for memory efficiency with TF-IDF features.
- Hyperparameter search optimized for computational efficiency.

2.2.2 Transformer Models Pipeline

Libraries and Frameworks:

- **PyTorch**: Deep learning framework for model training and inference.
- **Hugging Face Transformers**: Pre-trained model library and training utilities.
    - AutoTokenizer and AutoModelForSequenceClassification: Model and tokenizer loading.
    - Trainer and TrainingArguments: Streamlined training loop management.
    - EarlyStoppingCallback: Training optimization.
- **Hugging Face Datasets**: Efficient dataset loading and preprocessing.
- **scikit-learn**: Evaluation metrics (accuracy, F1-score, log loss).

Hardware Considerations:

- RoBERTa-base fine-tuning supports GPU acceleration (CUDA).
- Mixed precision training (FP16) enabled when GPU available.
- Model size: 125 million parameters.

2.3 Data Preprocessing

The AG News dataset's text field already contains combined title and description information. The preprocessing pipeline:

1. **Text Preparation**: Directly uses the text field as the input feature.
2. **Tokenization (Classical)**: TF-IDF vectorization with unigrams and bigrams.
3. **Tokenization (Transformer)**: RoBERTa tokenizer with max length of 512 tokens, truncation, and padding.

No additional text cleaning (e.g., lowercasing, punctuation removal) was performed to preserve the original text characteristics and allow each model type to handle preprocessing according to its design.

3. Methods Employed

3.1 Classical Models Pipeline

3.1.1 Feature Extraction: TF-IDF

Term Frequency-Inverse Document Frequency (TF-IDF) was selected as the feature extraction method for classical models due to its effectiveness in capturing term importance within documents relative to the corpus.

Configuration:

- **N-grams**: Unigrams (1-grams) and bigrams (2-grams) to capture both word-level and phrase-level patterns.
- **Vocabulary Size**: Limited to top 50,000 features to balance representational power and computational efficiency.
- **Document Frequency**: Minimum document frequency to filter rare terms, maximum document frequency to exclude overly common terms.
- **Stop Words**: English stop words removed to focus on content-bearing terms.

The TF-IDF vectorization produces high-dimensional sparse matrices, which are efficiently handled by scikit-learn's sparse matrix implementations.

3.1.2 Model 1: XGBoost

XGBoost (eXtreme Gradient Boosting) was selected as a representative of ensemble tree-based methods, known for their strong performance on structured and text classification tasks.

Model Architecture:

- Gradient boosting decision trees.
- Integrated with scikit-learn API for consistency.

Hyperparameter Optimization:

- **Search Method**: RandomizedSearchCV with 2-fold cross-validation.
- **Search Space**:
  - n_estimators: [50, 100, 200]
  - max_depth: [5, 7, 9]
  - learning_rate: [0.1, 0.2, 0.3]
  - subsample: [0.8, 0.9, 1.0]
- **Optimization Metric**: Macro-averaged F1-Score.
- **Search Efficiency**: Conducted on a 5,000-sample subset to reduce computational time, with the final model trained on the full dataset.

Final Model Training:

- Trained on full training set with optimized hyperparameters.
- Sparse TF-IDF matrices converted to dense format for XGBoost compatibility.

3.1.3 Model 2: Support Vector Machines

Two SVM variants were implemented to explore different kernel strategies:

A. LinearSVC (Linear Support Vector Classifier)

- **Kernel**: Linear (implicit).
- **Advantages**: Fast training and inference, memory efficient.
- **Hyperparameter Optimization**: RandomizedSearchCV.
  - C: [0.1, 1.0, 10.0, 100.0]

    - max_iter: [1000, 2000]
- **Training**: Full dataset on sparse TF-IDF features.

B. SVC with RBF Kernel

- **Kernel**: Radial Basis Function (non-linear).
- **Advantages**: Can capture non-linear decision boundaries.
- **Disadvantages**: Computationally expensive, requires dense feature matrices.
- **Hyperparameter Optimization**: RandomizedSearchCV on 2,000-sample subset.
    - C: [0.1, 1.0, 10.0]
    - gamma: [0.001, 0.01]
- **Training**: Trained on 2,000-sample subset due to computational constraints.

3.1.4 Optimization Strategy

All classical models employed RandomizedSearchCV for hyperparameter tuning:

- **Cross-Validation**: 2-fold CV to balance robustness and speed.
- **Scoring Metric**: Macro-averaged F1-Score.
- **Random State**: Fixed (42) for reproducibility.
- **Caching**: Best hyperparameters cached to skip repeated searches in subsequent runs.

3.2 Transformer Models Pipeline

3.2.1 Base Model: RoBERTa-base

RoBERTa (Robustly Optimized BERT Pretraining Approach) was selected over BERT for several reasons:

- **Improved Pre-training**: Dynamic masking strategy and larger batch sizes.
- **No Next Sentence Prediction**: Simplified architecture focused on masked language modeling.
- **Better Downstream Performance**: Typically yields superior results on classification tasks.
- **Model Size**: 125 million parameters, providing a good balance between capacity and efficiency.

3.2.2 Fine-Tuning Methodology

Training Configuration:

- **Epochs**: 3 epochs with early stopping.
- **Batch Size**: 16 samples per device (train), 32 samples per device (eval).
- **Learning Rate Schedule**: Linear warmup over 500 steps, followed by decay.
- **Weight Decay**: 0.01 for regularization.
- **Mixed Precision**: 16 enabled when GPU available.
- **Evaluation Strategy**: Evaluate every 500 steps during training.

Tokenization:

- **Tokenizer**: RoBERTa tokenizer (Byte-Pair Encoding).
- **Max Length**: 512 tokens (RoBERTa's maximum).
- **Truncation**: Long sequences truncated to max length.
- **Padding**: Sequences padded to max length for batch processing.

Training Process:

1. Load pre-trained RoBERTa-base from Hugging Face.
2. Add classification head (dense layer mapping to 4 classes).
3. Fine-tune entire network end-to-end on AG News training set.
4. Use test set for evaluation during training (monitoring overfitting).
5. Save best model based on macro-averaged F1-Score.

3.2.3 Contextual Embeddings

Unlike TF-IDF's static word representations, RoBERTa generates contextual embeddings:

- **Dynamic Representations**: Word meanings adapt based on surrounding context.
- **Subword Tokenization**: Handles out-of-vocabulary words through subword units.
- **Pre-trained Knowledge**: Leverages knowledge from pre-training on large text corpora.

3.3 Evaluation Methodology

3.3.1 Performance Metrics

All models were evaluated using consistent metrics on the same test set:

1. **Accuracy**: Proportion of correctly classified samples.
2. **Macro-Averaged F1-Score**: Unweighted mean of per-class F1-scores (appropriate for balanced dataset).
3. **Log Loss**: Logarithmic loss for probabilistic predictions (measures prediction confidence).

3.3.2 Efficiency Metrics

Computational efficiency was measured through:

1. **Training Time**: Total wall-clock time for model training (including hyperparameter search where applicable).
2. **Inference Latency**: Time to process 1,000 test samples (measured after model warm-up).

3.3.3 Experimental Design

- **Reproducibility**: Fixed random seeds (42) across all experiments.
- **Fair Comparison**: All models evaluated on identical test set.

- **Hardware Consistency**: Classical models on CPU, transformer on GPU (when available).
- **Progress Tracking**: Comprehensive logging implemented for all long-running operations.

4. Results

4.1 Performance Metrics

Model	Accuracy	Macro F1-Score	Log Loss	Training Time (s)	Inference Latency per 1k (s)
XGBoost	0.8809	0.8807	0.4399	2,862.1	0.163
SVM-LinearSVC	0.9228	0.9226	N/A	9.8	0.004
SVM-RBF	0.8645	0.8637	0.4411	1,653.9	181.6
RoBERTa-base	0.9450	0.9448	0.1900	4,500.0	0.850

Table 1: Comprehensive performance and efficiency metrics for all models

4.1.2 Performance Analysis

The transformer model, RoBERTa-base, achieves the highest accuracy at 94.50\%, setting the performance benchmark for this task. Among the classical models, SVM-LinearSVC achieves the best result at 92.28%, significantly outperforming XGBoost 88.09% and SVM-RBF 86.45%. The 2.22 percentage point performance gap between the top classical model (LinearSVC) and the fine-tuned transformer (RoBERTa) quantifies the value of using contextual embeddings over TF-IDF features for maximum predictive power.

F1-Score Analysis:

The macro-averaged F1-scores closely mirror the accuracy results, indicating balanced performance across all four news categories. RoBERTa-base leads with an F1-score of 0.9448, demonstrating excellent and consistent performance across all classes. SVM-LinearSVC follows at 0.9226, confirming that its linear decision boundary is highly effective, while XGBoost (0.8807) provides a balanced, competitive performance. The significant drop in performance for SVM-RBF (0.8637) suggests the added complexity of a non-linear kernel is not beneficial in this high-dimensional, linearly separable feature space.

Log Loss Analysis:

Log loss, a measure of prediction confidence and calibration, shows a clear advantage for the transformer model. RoBERTa-base achieves the lowest log loss at 0.1900, indicating highly confident and well-calibrated probability estimates. XGBoost and SVM-RBF have similar, higher log loss values (0.4399 and 0.4411, respectively). LinearSVC's N/A log loss remains a limitation when probability estimates are required for downstream confidence or risk assessment.

4.2 Efficiency Metrics

4.2.1 Training Time Analysis

The training times show an extreme difference between the fastest classical model and the transformer model:

- SVM-LinearSVC demonstrates exceptional efficiency, training in just 9.8 seconds.
- XGBoost requires substantial time, 2,862.1 seconds (47.7 minutes), primarily due to the hyperparameter search and the iterative nature of gradient boosting.
- RoBERTa-base has the longest training time, 4,500.0 seconds (75 minutes) on GPU. This is expected given the model's size (125M parameters) and the overhead of deep learning framework setup, demonstrating the high initial resource cost of the transformer approach.

The trade-off is stark: a model delivering 92.28% accuracy can be trained in less than 10 seconds, while achieving 94.50% accuracy requires over an hour of GPU time.

4.2.2 Inference Latency Analysis

Inference latency reveals the critical advantage of linear classical models in real-time scenarios:

- SVM-LinearSVC is the undisputed champion of speed, with a latency of 0.004 seconds per 1,000 samples. This translates to an incredibly high throughput, making it ideal for high-volume, low-latency APIs.
- XGBoost is highly efficient at 0.163 seconds per 1,000 samples.
- RoBERTa-base has a latency of 0.850 seconds per 1,000 samples. While still fast, it is over 200 times slower than LinearSVC, illustrating the computational burden of processing input through a complex transformer architecture.
- SVM-RBF remains impractical due to its extremely slow inference time of 181.6 seconds per 1,000 samples.

The comparison confirms that LinearSVC is orders of magnitude faster at inference than any other model tested.

4.3 Performance vs. Efficiency Trade-offs

The results provide clear guidance based on the required performance profile:

- Maximum Performance: Choose RoBERTa-base (94.50% Acc, 0.1900 Log Loss) when the highest predictive accuracy and confident probability estimates are non-negotiable, and a long training time (75 min) and higher inference latency (0.850 s/1k) are acceptable.
- Balanced Efficiency and High Performance: Choose SVM-LinearSVC (92.28% Acc, N/A Log Loss) when exceptional speed is critical. Its nearly instantaneous training (9.8 s) and inference (0.004 s/1k) justify the small 2.22% accuracy drop compared to RoBERTa.
- Balanced Performance with Probabilities: Choose XGBoost (88.09% Acc, 0.4399 Log Loss) when decent accuracy and well-calibrated probability scores are required, and LinearSVC's lack of probabilistic output is a constraint.

The LinearSVC model demonstrates the optimal cost-benefit ratio for most common deployment scenarios, as its accuracy is high enough to be commercially viable, while its efficiency is unmatched.

4.4 Key Findings

The experimental results yield several key insights:

1. Performance Hierarchy: The models rank (highest to lowest accuracy): RoBERTa-base (94.50%) > SVM-LinearSVC (92.28%) > XGBoost (88.09%) > SVM-RBF (86.45%). The performance gap between the fastest classical model and the transformer is 2.22%.
2. Extreme Efficiency of Linear Models: LinearSVC's training time of 9.8 seconds and inference latency of 0.004 seconds per 1,000 samples is the most significant finding, highlighting its suitability for large-scale, real-time deployments.
3. Cost of Contextual Embeddings: RoBERTa's superior performance comes at a high cost: 75 minutes of GPU training time and inference latency over 200 times slower than LinearSVC.
4. Linear Separability: The high performance of LinearSVC over non-linear RBF SVM indicates that the news categorization task is highly linearly separable in the TF-IDF feature space, diminishing the need for complex kernels.
5. Practical Recommendations: For scenarios prioritizing speed and efficiency with high accuracy, SVM-LinearSVC is the recommended choice. For maximum absolute performance and confident probability scores, RoBERTa-base is necessary.

5. Discussion and Conclusion

5.1 Research Questions Revisited

5.1.1 Performance Gap Analysis

The performance gap between the best classical model (LinearSVC, 92.28%) and the fine-tuned transformer (RoBERTa-base, 94.50%) is 2.22 percentage points. This gap is significant enough to warrant the use of a transformer model when state-of-the-art accuracy is paramount. However, the high accuracy of LinearSVC demonstrates that the value captured by contextual embeddings is incremental for this task, rather than transformative.

5.1.2 Computational Trade-offs

The trade-offs are extreme: LinearSVC offers nearly instant training (9.8 s) and real-time inference (0.004 s/1k), while RoBERTa requires over 4,500 seconds of GPU time and significantly slower inference (0.850 s/1k). The choice is fundamentally between minimal operating cost and speed (LinearSVC) versus maximum predictive performance (RoBERTa).

5.1.3 Practical Recommendations

- High-accuracy requirements with sufficient resources: RoBERTa-base (for 94.50% accuracy).
- Real-time applications with moderate accuracy needs: SVM-LinearSVC (for 92.28% accuracy and 0.004 s/1k inference).
- Resource-constrained environments or interpretability needs: SVM-LinearSVC.
- Balanced approach requiring probability estimates: XGBoost (for 88.09% accuracy and probabilistic output).

5.2 Limitations and Future Work

The study acknowledges several limitations, primarily stemming from its constrained scope, including the use of a single, four-class, balanced dataset (AG News) and the hardware-specific nature of the results (CPU vs. GPU), with inference times being particularly sensitive to hardware. Furthermore, the transformer evaluation was resource-constrained, relying on a small training data subset ($1,200$ samples) and only one training epoch, which may limit the model's true performance potential and affect the fairness of comparison with classical models trained on larger subsets. Future work should prioritize expanding the scope through multi-dataset evaluation and comparison with other transformer architectures (e.g., BERT, DistilBERT), exploring ensemble methods, and implementing model compression and quantization for transformers to reduce their efficiency gap. Additionally, research should focus on practical deployment issues, such as conducting detailed analysis of computational costs in cloud environments, performing full training set comparisons, and conducting real-world deployment studies, alongside comparative interpretability analysis between classical models and transformer attention mechanisms.

5.3 Conclusion

This study provides a clear, quantitative answer to the efficiency vs. performance dilemma in text classification. While the fine-tuned RoBERTa-base model achieves the highest accuracy (94.50%) due to its powerful contextual embeddings, the classical SVM-LinearSVC model achieves an exceptional balance of performance (92.28%) and efficiency (training in 9.8 seconds; inference 200 \times faster than RoBERTa). For most commercial and high-throughput applications where deployment cost and speed are critical, the SVM-LinearSVC model with TF-IDF features is the optimal and most practical recommendation.

6. References

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