Emotional Models: Text Mood Classification

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Abstract. This project explores the classification of emotional states in text using supervised and zero-shot learning approaches. We implement and compare artificial neural networks (ANNs) and transformer-based models to categorize text into six emotion classes. The methodology includes training ANNs for various epochs and evaluating their performance using confusion matrices and accuracy metrics. Additionally, we assess large pre-trained BERT models in a zero-shot setting, in order to draw comparisons between the two approaches. Experimental results demonstrate the effectiveness of both supervised and zero-shot models, with comparative analysis highlighting their strengths and limitations for these sorts of tasks.

Keywords: Emotion Classification · Supervised Learning · Zero-shot Learning · BERT · Artificial Neural Networks

1 Methodology

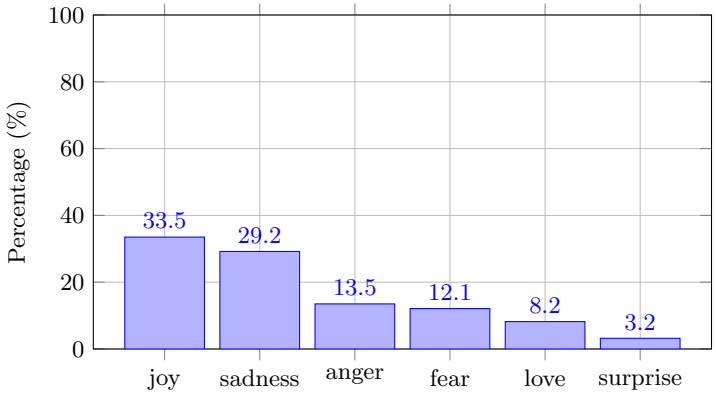
1.1 Dataset

For the purpose of classifying emotional states in text, we utilize the dataset requested in the project statement (HuggingFace's `dair-ai/emotion`[1]), consisting of labeled examples across six emotion categories: sadness, joy, love, anger, fear, and surprise. The characteristics of its split version, which will be used in this project, are as follows:

- **Source:** Social media (Twitter) messages
- **Language:** English
- **Text Length:** 7 → 300 characters
- **Classes:** 6 (sadness, joy, love, anger, fear, surprise)
- **Training Set:** 16000 labeled examples
- **Validation Set:** 2000 labeled examples
- **Test Set:** 2000 labeled examples
- **Total:** 20000 labeled examples

[1] `https://huggingface.co/datasets/dair-ai/emotion`

Fig. 1: Label Distribution in the Dataset



Upon initially looking at the data, a challenge immediately became apparent: class imbalance. Rarer emotions are heavily misrepresented (only 3.2% of examples have a "surprise" label), while simpler, more common emotions which may overlap with others dominate the dataset (the "joy" and "sadness" classes hold a joint 62.7% of the examples). This is an issue because the model can specialize in a subset of the classes and be biased towards them. In this case, completely ignoring "surprise" but getting every other example right would give the model a misleadingly high accuracy of approximately 96.8%. This is one of the reasons why accuracy alone is not a sufficient metric for evaluating model performance in this context, and why confusion matrices and other metrics computed from them (particularly those that measure per-class performance) are very important. This dataset imbalance has other implications as well, specially when comparing two diferent paradigms (supervised learning and zero-shot classification), as each may be affected differently by the lack of data for certain classes. On the one hand we have the ANNs which are directly harmed by the lack of class representation because they learn from the empirical distribution of the data, affecting the decision boundaries they create. On the other hand we have the zero-shot models which dont learn from the data, contrastingly they may be less affected by class imbalance, but their performance may still vary across classes due to the inherent biases in the pre-trained models they rely on.

Another problem that stands out when analyzing the data is the reliability of its labels. Several of the data points show text-label pairs with a mismatch that is obvious to a human eye, with the most common pattern being lack of context undestanding. For example, texts like *i no longer feel happy to score well* and *i never feel that popular* were both labeled as "joy" due to their use of *happy* and *popular*, words that usually convey positive emotions, even though in these cases their negation is used, causing the overall sentiment to be reversed. Inconsistencies such as these mean that there is a cap to the performance of any model on this dataset, unless it overfits to the noise in the labels (even then, it is not guaranteed that the training and testing sets will have the same types of mismatches). This is shown by Kermani et al.[1] as their attempt at fine-tuning

an extensive model (LLaMA-38B) for this task achieves the best performance out of the tried approaches (including zero-shot classification, which is explored in this project) at 91%.

In order to understand the dataset better, it is important to consider how it was populated. Though no information is provided in the HuggingFace website on this aspect, the GitHub repository containing the data[2] links to a paper by the authors that details the creation process [2] (though the repository and paper do not refer to the same dataset, they are populated in the same manner). The proposed model, CARER, consists of a semi-supervised, graph-based algorithm designed to create contextualized emotion representations that relies on *enriched patterns*, which identify similar text structures across examples to help with classification. However, our manual analysis suggests that while the CARER method aims to account for context, its application in creating this specific dataset may not have fully overcome the challenge of syntactic nuance, leaving a pattern of keyword-emotion association in some entries.

1.2 Experimental Pipeline

The experimental pipeline for this project is illustrated in Figure 1, showcasing the two main approaches: supervised learning using artificial neural networks (ANNs) and zero-shot classification with pre-trained transformer models.

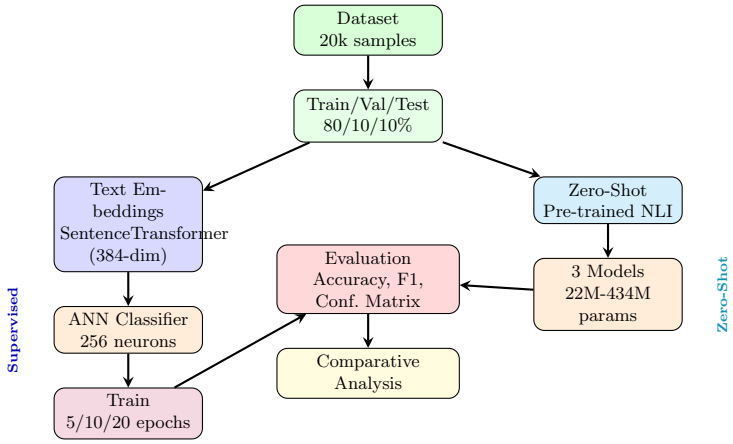


Fig. 1: Experimental pipeline overview: supervised learning (left) trains an ANN on embeddings, while zero-shot (right) uses pre-trained models directly.

[2] `https://github.com/dair-ai/emotion_dataset`

1.3 Implementation

The main goal of this project is to explore and compare supervised and zero-shot learning approaches for emotion classification using a modular and reproducible experimental setup. It is implemented in Python and organized into modular scripts to facilitate experimentation.
The supervised learning pipeline is defined in `supervised.py`, which is an adaptation of the code initially provided with this assignment, where artificial neural networks (ANNs) are constructed and trained using the dataset. The script relies on PyTorch for model definition, training, and evaluation. Training progress and results, including confusion matrices and accuracy metrics, are logged for analysis. The main orchestration of experiments, including data loading, model selection, and evaluation, is handled in `main.py`.
For zero-shot classification, `zero_shot.py` utilizes transformer models from the HuggingFace library, such as BERT. It differs from the previous approach by performing data point classification without explicit training on the dataset labels, instead infering emotions directly from text using pre-trained language representations. The selected models for zero-shot classification aim to cover a range of sizes and capabilities, from large models like BART-large-mnli to more compact ones like DeBERTa-v3-xsmall-zeroshot, allowing for a comparative analysis of performance versus computational efficiency.
The following table summarizes the models evaluated in both supervised and zero-shot settings:

Table 1: Model Specifications and Configurations

Model	**Parameters**	**Training Objective**
Supervised Approach		
ANNClassifier (5 epochs)	98,566	Cross-Entropy Loss
ANNClassifier (10 epochs)	98,566	Cross-Entropy Loss
ANNClassifier (20 epochs)	98,566	Cross-Entropy Loss
Zero-Shot Approach		
BART-large-mnli	406M	NLI (MNLI)
DeBERTa-v3-large-zeroshot	434M	NLI + Zero-shot
DeBERTa-v3-xsmall-zeroshot	22M	NLI + Zero-shot

Supporting modules include `metrics.py`, which provides functions for computing evaluation metrics such as accuracy, F1-score and comparative analysis utilities. Beyond basic metrics, we implement specialized analysis functions in `metrics.py`:

- `compare_supervised_configs`: Tracks the evolution of per-class recall, specificity, and precision across different training epochs (5, 10, 20), identifying

which emotions benefit from longer training and which plateau or degrade (potential overfitting).
- `extract_top_confusions`: Identifies the most frequent misclassification patterns globally, revealing systematic errors (e.g., confusing "love" with "joy", which accounts for 34.6% of "love" misclassifications).
- `analyze_class_mistakes`: Analyzes confusions for individual classes, showing which emotions are most often misclassified as a given target emotion.

Finally, we log all experimental results and configurations using `logs.py` for the consequent analysis and comparison of different models and settings.

2 Results

In this section we seek to analyze and compare the performance of supervised learning models (ANNs) and zero-shot classification models. To do so we start by presenting an overall comparisson and, subsequently, detail each aproach to expose the what's and why's behind the results obtained.

2.1 Overall Performance Comparison

Table 2 presents the test accuracy and macro F1-score for all evaluated models across both supervised and zero-shot paradigms.

Table 2: Overall Performance Comparison (Test Set)

Model	**Accuracy**	**Macro F1**
Supervised Learning		
ANN (5 epochs)	0.6935	0.6055
ANN (10 epochs)	0.7210	0.6358
ANN (20 epochs)	**0.7280**	**0.6495**
Zero-Shot Classification		
BART-large-mnli	0.3765	0.3838
DeBERTa-v3-large	0.7170	0.6417
DeBERTa-v3-xsmall	0.6945	0.6226

The supervised ANN trained for 20 epochs achieves the highest overall performance (72.80% accuracy, 0.6495 macro F1), narrowly outperforming the best zero-shot model, DeBERTa-v3-large (71.70% accuracy, 0.6417 macro F1). The supervised model's advantage is minimal (1.1 percentage points), suggesting that zero-shot approaches can match task-specific training when using appropriately designed models.
However, the huge contrast between DeBERTa variants and BART-large-mnli show that model selection in zero-shot settings is paramount to achieving strong

performance. In this regard, we conducted a thorough research on the training methodologies of each model, which is detailed in Section 2.4.

2.2 Supervised Learning: Training duration

Figure 2 illustrates the evolution of performance metrics across different training configurations.

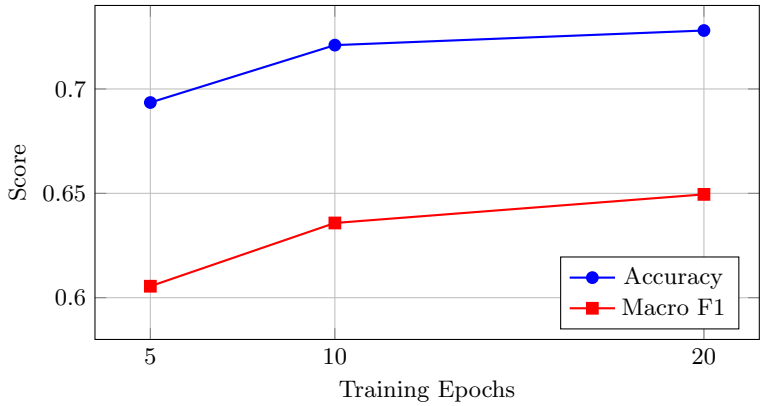


Fig. 2: Performance evolution of supervised ANN across training epochs.

In summary, training for additional epochs yields diminishing returns: the improvement from 5 to 10 epochs is substantial (+2.75 percentage points accuracy, +3.03 pp F1), while further training to 20 epochs provides only marginal gains (+0.70 pp accuracy, +1.37 pp F1). This plateau suggests that the model's capacity to learn from the training data is approaching saturation. Further improvements would likely require architectural changes, regularization techniques to address class imbalance, or data augmentation rather than extended training. Also, the point of using this aproach was showing how a lightweight head on top of embeddings can achieve good results with minimal training, which was accomplished.

2.3 Per-Class Performance Analysis

Table 3 compares per-class F1-scores between the best supervised model (ANN-20) and the best zero-shot model (DeBERTa-v3-large), revealing both approaches' strengths and weaknesses.

Table 3: Per-Class F1-Score Comparison: Supervised vs Zero-Shot

Class	**Support**	**ANN-20**	**DeBERTa-L**	Δ
Sadness	581	0.78	0.76	+0.02
Joy	695	0.77	0.78	-0.01
Anger	275	0.72	0.72	0.00
Fear	224	0.69	0.70	-0.01
Love	159	0.52	0.48	+0.04
Surprise	66	0.42	0.41	+0.01
Macro Avg	–	**0.65**	0.64	+0.01

The two approaches achieve nearly identical performance across all classes, suggesting that pre-trained language understanding can effectively substitute for task-specific training when models are appropriately designed for zero-shot inference.

Both models perform best on high-frequency classes (sadness, joy: F1 > 0.76) and struggle with rare emotions (surprise: F1 ≈ 0.41). This may be caused by two diferent factors: the supervised model's limited exposure to rare classes during training, and the zero-shot model's reliance on general language patterns that may not capture the nuances of ambiguous emotions. The cap on the literature performance for this dataset (around 91% according to Kermani et al. [1]) was achieved through fine-tuning, which enabled the model to learn the dataset's generator's distribution and idiosyncrasies, which is out of scope for this project.

2.4 Zero-Shot Model Comparison: Size vs Performance

The relationship between model size and zero-shot performance is non-trivial, as shown in Table **??**.

Table 4: Zero-Shot Model Size vs Performance Trade-off

Model	**Parameters**	**Accuracy**	**Macro F1**
DeBERTa-v3-xsmall	22M	0.6945	0.6226
BART-large-mnli	406M	0.3765	0.3838
DeBERTa-v3-large	434M	**0.7170**	**0.6417**

The comparison reveals a non-standard relationship between model size and performance. The smallest model (DeBERTa-v3-xsmall, 22M parameters) dramatically outperforms BART-large (406M) by 31.8 percentage points in accuracy, demonstrating that *training data composition matters more than parameter count.*

This performance gap can be attributed to differences in training methodology:

- **DeBERTa-v3-xsmall**: Aggressively trained on human-labeled NLI datasets, including *emotion classification tasks* in its training distribution. This direct exposure to emotion-related data provides strong inductive biases for this specific task.
- **DeBERTa-v3-large**: Trained on a mix of human-labeled and synthetic data, which increases diversity but dilutes task-specific signal. The additional 412M parameters provide only modest gains (+2.25 pp accuracy) over xsmall, suggesting diminishing returns when the training distribution already covers the target task.
- **BART-large**: Trained exclusively on MNLI without emotion-specific data, resulting in poor generalization despite its large capacity.

The xsmall model's competitive performance (69.45%, only 2.25 pp below the large variant) highlights an important practical insight: for emotion classification, a compact model trained on task-relevant data outperforms larger models trained on generic NLI corpora. This suggests that for resource-constrained deployments, DeBERTa-v3-xsmall offers an optimal balance of performance and computational efficiency, particularly when the deployment scenario aligns with its training distribution. However, we can infer that if another task was to be solved, the large variant would likely outperform the small one due to its increased capacity and broader training data, making the performance difference more visible.

2.5 Error Pattern Analysis

Supervised Learning Error Patterns Table 5 presents the most frequent misclassifications for the best supervised model (ANN-20).

Table 5: Top-5 Confusion Patterns: Supervised ANN (20 epochs)

True	Prediction	Count	%
Love	Joy	61	38.4%
Sadness	Joy	74	12.7%
Anger	Joy	31	11.3%
Surprise	Joy	19	28.8%
Surprise	Fear	15	22.7%

The dominant error pattern is over-prediction of "joy", the most frequent class (38.4% of training data). This suggests the model has learned a bias toward the majority class, particularly for related emotions (e.g., i got home feeling hot tired and great labeled as "love" instead of "joy") which is not necessarily wrong, but rather ambiguous. The confusion between Sadness and Joy may seem counterintuitive but, upon closer inspection we find examples such as *i stop feeling guilty* which is labeled as sadness but could be interpreted as joy

depending on context. Similarly, the confusion between Surprise and Fear reflects their semantic proximity.
These patterns reflect genuine semantic overlap rather than pure model failure, as evidenced by similar confusions in zero-shot models (see Section 3.5.2).

Zero-Shot Error Patterns: BART Failure Case BART-large-mnli's catastrophic failure (37.65% accuracy) is explained by extreme prediction bias toward "surprise", as shown in Table 6.

Table 6: Top-5 Confusion Patterns: BART-large-mnli

True Label	Predicted As	Count	% of Class
Joy	Surprise	362	52.1%
Love	Surprise	79	49.7%
Fear	Surprise	110	49.1%
Sadness	Surprise	266	45.8%
Anger	Surprise	125	45.5%

BART predicts "surprise" for approximately 50% of *all* classes, resulting in:

- 86% recall for surprise (57/66 correct predictions)
- Only 6% precision (57 correct out of 999 total "surprise" predictions)

This failure likely stems from the hypothesis template used in zero-shot classification: *"This text expresses surprise"*. BART's pre-training on MNLI may have caused it to assign disproportionately high entailment scores to this specific phrasing, regardless of actual text content. This highlights a critical limitation: zero-shot performance is highly sensitive to hypothesis template design and model-specific biases from pre-training.

Zero-Shot Error Patterns: DeBERTa Models In contrast to BART, DeBERTa models exhibit balanced error distributions similar to supervised approaches, as shown in Table 7.

Table 7: Top-5 Confusion Patterns: DeBERTa-v3-large

True Label	Predicted As	Count	% of Class
Love	Joy	48	30.2%
Love	Sadness	22	13.8%
Surprise	Joy	14	21.2%
Surprise	Sadness	9	13.6%
Fear	Sadness	22	9.8%

DeBERTa's errors mirror those of the supervised model (love → joy, surprise → joy/fear/sadness), indicating these confusions reflect genuine semantic ambiguity rather than model-specific artifacts as proven by the examples on the supervised learning section. The convergence of error patterns between supervised and zero-shot approaches suggests both are capturing similar linguistic regularities in the data.

Notably, the small DeBERTa variant (xsmall) exhibits similar confusion patterns to its larger counterpart, further supporting the conclusion that *training data composition dominates over parameter count*. The xsmall model's inclusion of emotion classification tasks in its training distribution (among 33 human-labeled NLI datasets) likely explains its strong performance despite limited capacity, while the large variant's mixed training approach (human-labeled + synthetic data) provides only marginal improvements for this specific task (although generalization to other tasks benefits from the increased capacity and data diversity).

References

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