SentiSenseAI : The Emotion Behind Every Customer Review

Project Overview

In e-commerce, understanding customer sentiment goes beyond simple positive or negative reactions. Our solution employs advanced natural language processing to classify customer reviews into eight distinct emotional categories: Excitement, Satisfaction, Neutral, Confusion, Frustration, Disappointment, Optimism, and Pessimism.

Think of this system as an intelligent reader that understands not just what customers say, but how they feel when they say it. Just as a human can detect excitement in phrases like "absolutely amazing product!" or frustration in "not what I expected at all," our system uses BERT (Bidirectional Encoder Representations from Transformers) to understand these emotional nuances in written reviews.

The solution stands out because it doesn't just classify emotions – it explains its thinking. Imagine asking a friend why they think a customer sounds excited; they might point to specific phrases or expressions that led to their conclusion. Our system does the same, making its decision-making process transparent and understandable.

Key Features:

- Processes both single reviews and large batches through JSON files
- Provides confidence scores, like a measure of how certain the system is about its interpretation
- Explains reasoning by highlighting key phrases that influenced its decision
- Handles reviews of various lengths while maintaining accuracy
- Offers probability distributions across all emotions, showing how strongly each emotion is expressed

The Fine-tuning Approach as a Solution

Standard sentiment analysis often struggles with emotional subtlety – like distinguishing between satisfaction and excitement, or confusion and frustration. It's similar to the difference between a basic language learner who only understands "happy" and "sad," versus a native speaker who can detect subtle emotional tones in conversation.

Our approach of fine-tuning BERT is like teaching an already knowledgeable language expert (pre-trained BERT) to become a specialist in understanding customer emotions. Here's how it works:

1. **Context Understanding**: The model learns how context changes emotional meaning. For example, the word "interesting" could indicate:
    a. **Excitement: "Very interesting design, I love how unique it is!"**
    b. **Confusion: "Interesting sizing, not sure if it fits as expected."**
2. **Pattern Recognition**: The model identifies patterns that humans naturally understand:

   a. **Excitement often comes with exclamation marks and superlatives**
   b. **Confusion typically includes questions and uncertainty words**
   c. **Disappointment often contrasts expectations with reality**
3. **Multi-dimensional Analysis**: Rather than forcing reviews into single categories, the model considers all emotions simultaneously. Like humans, it recognizes that a review might express multiple emotions – perhaps satisfaction with the product quality but frustration with delivery time.

Preparing the training dataset

To create a high-quality emotion classification system, we need training data that accurately captures the nuanced emotions in luxury fashion reviews. This section explains how we combine human expertise with artificial intelligence to create our training dataset, which will be used to teach our BERT model to recognize emotions in product reviews.

Hybrid Approach for Label Generation

Our approach combines human expertise with AI capabilities to create high-quality labelled data. We leverage the Gemini-1.0-pro-001 model's natural language understanding while maintaining human-level accuracy through our seed dataset guidance.

The Seed-and-Scale Method

We employ a novel "seed-and-scale" methodology where 200 manually labelled reviews (Stratified sample) serve as exemplars for the Gemini model. This approach has several key advantages:

1. It maintains consistency with human labelling patterns
2. It provides context-rich examples for the model
3. It allows for quality control through confidence scoring

Stage 1: Seed Dataset Creation

We begin with 200 carefully selected reviews that represent different writing styles, lengths, and ratings. Human experts label these reviews with one of eight emotions: Excitement, Satisfaction, Neutral, Confusion, Frustration, Disappointment, Optimism, or Pessimism. These labelled reviews serve as our "golden standard" examples.

Each review in the seed dataset is manually labelled with one of eight emotions:

- Excitement: High enthusiasm or eagerness
- Satisfaction: Contentment or approval
- Neutral: No strong emotion
- Confusion: Uncertainty or lack of clarity
- Frustration: Annoyance or dissatisfaction

- Disappointment: Strong feeling of sadness
- Optimism: Positive expectations
- Pessimism: Negative expectations

Stage 2: Scaling with Gemini

We use Gemini to expand our labelled dataset to 1,200 reviews, providing sufficient data for BERT fine-tuning. The process employs prompt engineering to ensure consistent and accurate emotion classification. We utilize Gemini-1.0-pro-001, configuring it specifically for emotional analysis in product reviews. The model implementation includes:
Model Parameters:

- Temperature: Default setting for consistent outputs
- Maximum token length: Accommodates full reviews and response format
- Response format: Structured output with emotion, confidence, and reasoning

The model analyses each new review by:

1. Looking at the emotion definitions we've provided
2. Studying our expertly labeled examples
3. Analyzing the new review's language and context
4. Providing its classification along with a confidence score and reasoning

This process is similar to how a human expert would approach the task - first understanding the criteria, looking at examples, then making a reasoned judgment about new cases.

Prompt Engineering

Our prompt structure guides the model with three key components:

1. Emotion Definitions: Clear descriptions of each emotion category
2. Example Reviews: Two randomly selected pre-labelled reviews
3. Classification Format: Structured response template

Quality Assurance

To ensure our training data maintains high quality when scaling from 200 to 1,200 reviews, we implement several safeguards:

1. Confidence Checking: The model assigns a confidence score to each classification. Low-confidence cases are flagged for human review.
2. Reasoning Validation: For each classification, the model must explain its reasoning, helping us verify the logic behind its decisions.

3. Example Guidance: The model always refers to two different human-labelled examples when making its decisions, ensuring consistency with human judgment.

Results and Validation

The final training dataset consists of 1,200 labelled reviews that:

- Maintain consistent emotion definitions across all reviews
- Include confidence scores and reasoning for each classification
- Represent a balanced distribution of different emotions
- Preserve the nuanced understanding needed for luxury fashion context

This carefully prepared dataset provides the foundation for training our BERT model to recognize emotions in product reviews accurately and reliably.

Quality Control Mechanisms

The system implements several quality control measures:

1. Confidence Scoring:
    a. Each classification includes a confidence score (0-1)
    b. Reviews with scores below 0.8 are flagged for review
    c. Default to "Neutral" for uncertain cases
2. Example Selection:
    a. Random sampling of seed examples ensures diverse guidance
    b. Each classification uses two different example reviews
    c. Examples are formatted consistently for model understanding
3. Error Handling:
    a. Robust exception management for API failures
    b. Default classifications for error cases
    c. Continuous logging of classification decisions

Through this carefully designed approach, we successfully scaled our 200 manually labelled reviews to a robust training dataset of 1,200 reviews, maintaining high quality and consistency throughout the process. This dataset forms the foundation for our subsequent BERT fine-tuning phase. This training dataset will be used in the BERT fine-tuning phase, where we'll teach our model to recognize these emotional patterns independently.

BERT Fine-tuning Solution in Detail

Our implementation is like teaching an already smart student to become an expert in a specific subject. We start with BERT's general language understanding and carefully train it to become a specialist in emotional analysis of product reviews.

Model Architecture

We utilize the bert-base-uncased variant with the following configurations:

- Text Processing: Handles up to 256 words per review (about a paragraph)
- Understanding Layer: 768 dimensional space for capturing review meaning
- Emotional Analysis: 12 attention heads examining different aspects of the text
- Decision Layer: Maps understanding to 8 distinct emotions.

Training Process

The model is trained on 1200 carefully picked reviews from Amazon that showcases complex emotions. The training uses three key techniques to ensure reliable results:

1. **Careful Learning Pace**
    a. **Like learning to ride a bike, we start slow (learning rate: 0.00001)**
    b. **We watch for signs of overconfidence (early stopping)**
    c. **We keep track of progress through validation checks**
    d. **Base learning rate: 1e-5**
    e. **Implementation of early stopping to prevent overfitting**
    f. **Monitoring of validation loss for optimal model selection**

1. **Prevention of Memorization**
    a. **Uses dropout (30% randomness) to ensure robust learning**
    b. **Similar to studying different versions of the same concept**
    c. **Helps the model generalize rather than memorize**
    d. **Dropout probability: 0.3**
    e. **Applied to both attention layers and hidden layers**
    f. **Helps prevent over-reliance on specific features**

1. **Performance Monitoring**
    a. **Cross-entropy loss tracking**
    b. **Validation accuracy monitoring**
    c. **Entropy calculation for prediction uncertainty**

Model Optimization Journey: Understanding Epoch Performance and Improvements

Our path to achieving the best model performance was iterative, like a chef perfecting a recipe through multiple attempts. Let's explore how we analysed and improved our model through different training iterations.

Initial Training Attempt

In our first training run, we observed these patterns across epochs:

```
Epoch 1: Training Loss 1.2968, Validation Loss 1.1446
Epoch 2: Training Loss 0.8857, Validation Loss 1.1427
Epoch 3: Training Loss 0.5668, Validation Loss 1.3633
Epoch 4: Training Loss 0.3835, Validation Loss 1.4307
```

This initial attempt revealed a classic overfitting pattern. Think of it like a student who memorizes test answers without understanding the underlying concepts. While the training loss (how well the model performed on known data) kept improving, the validation loss (performance on new data) started deteriorating after epoch 2. This told us we needed to help our model learn more generalizable patterns.

First Improvement: Learning Rate Adjustment

We reduced the learning rate from 2e-5 to 1e-5, similar to asking a student to slow down and take more careful notes. This yielded:

```
Epoch 1: Training Loss 1.4920, Validation Loss 1.2337
Epoch 2: Training Loss 1.0952, Validation Loss 1.1547
Epoch 3: Training Loss 0.8167, Validation Loss 1.1783
Epoch 4: Training Loss 0.6655, Validation Loss 1.1853
```

The results showed more stable learning. The gap between training and validation loss decreased significantly (from ~1.05 to ~0.52 in the final epoch), indicating better generalization. However, we still saw room for improvement in the model's ability to handle complex emotional patterns.

Final Refinement: Adding Dropout Regularization

Our final improvement introduced dropout regularization (30% probability), acting like randomly covering parts of study materials to ensure comprehensive understanding. The results showed:

```
Epoch 1: Training Loss 1.4057, Validation Loss 1.1606
Epoch 2: Training Loss 0.9564, Validation Loss 1.1120
Epoch 3: Training Loss 0.7253, Validation Loss 1.2041
Epoch 4: Training Loss 0.5811, Validation Loss 1.2366
```

This final version achieved our best balance of performance metrics:

- More stable validation accuracy (ranging from 53.59% to 55.47%)
- Smaller fluctuations in validation loss
- Better preservation of model performance across epochs

Key Insights from Our Optimization Process

1. **Early Stopping Implementation** We discovered that our model consistently found its sweet spot around epoch 2. Like knowing when to stop studying to avoid confusion, we implemented early stopping to preserve the model's best performance.
2. **Learning Rate Impact** The slower learning rate (1e-5) proved crucial for stable learning. It's similar to the difference between skimming a text versus reading it carefully – the slower pace allowed for better retention and understanding.
3. **Dropout's Role in Generalization** Adding dropout helped prevent overfitting by forcing the model to develop redundant understanding pathways. This is like ensuring a student understands a concept from multiple angles, not just one perspective.
4. **Performance Metrics Evolution** Each improvement brought us closer to optimal performance:

- Initial model: High variance between training and validation
- Learning rate adjusted: More stable learning but still some overfitting
- Final version with dropout: Best balance of accuracy and generalization

Through these iterations, we achieved a model that not only performs well (validation accuracy >55%) but also demonstrates stable and reliable learning patterns across different types of reviews. The final model shows strong capabilities in:

- Consistent emotion classification across diverse review styles
- Balanced performance between common and rare emotional expressions
- Reliable confidence scoring that correlate well with actual accuracy.

Inference Pipeline

During prediction, the model follows a structured process:

1. **Text Processing**
    a. **Tokenization of input review**
    b. **Padding/truncation to 256 tokens**
    c. **Attention mask generation**
2. **Emotion Classification**
    a. **Forward pass through BERT layers**
    b. **Probability calculation for each emotion**
    c. **Confidence score computation**
3. **Reasoning Generation**
    a. **Identification of influential phrases**
    b. **Template-based explanation generation**
    c. **Confidence-based qualification of results**

The solution achieves a validation accuracy exceeding 55% across eight complex emotional categories, with particularly strong performance in distinguishing between closely related emotions. The model's ability to provide explanations for its decisions makes it particularly valuable for business intelligence and customer experience analysis.

Deployment and Code Structure Guide for SentiSenseAI

Introduction

This section provides a comprehensive overview of the code, deployment, and technical infrastructure of our SentiSenseAI project. We'll explore the key components that bring our sentiment analysis application to life, from the core code files to our deployment strategy.

Streamlit: Our Frontend Framework

We chose Streamlit as our web application framework due to its simplicity and rapid development capabilities. Streamlit allows us to transform our machine learning model into an interactive, user-friendly web interface with minimal web development overhead.

Key Code Files

Our project is composed of several critical files that work together to deliver the sentiment analysis functionality:

1. **app.py**
    a. **The primary Streamlit application file**
    b. **Handles user interface interactions**
    c. **Manages model loading and prediction rendering**
    d. **Provides a seamless user experience for sentiment analysis**
2. **model.py**
    a. **Contains the core machine learning model architecture**
    b. **Implements model loading, preprocessing, and inference logic**
    c. **Defines the backend processing for sentiment predictions**
3. **best_model.safetensors**
    a. **Serialized pre-trained machine learning model**
    b. **Stores the learned model weights and parameters**
    c. **Enables efficient and fast model inference**
4. **requirements.txt**
    a. **Defines all Python package dependencies**
    b. **Ensures consistent environment setup across different development and deployment contexts**

Test Case Implementation

We developed a comprehensive test suite to ensure the reliability and accuracy of our sentiment analysis model:

- Comprehensive test cases covering model inference
- Input validation and error handling tests
- Performance and accuracy benchmarking

GitHub Actions Workflow

Our automated continuous integration workflow (model-testing.yml) provides:

- Automatic test execution on code changes
- Consistent testing environment
- Code quality verification
- Comprehensive test coverage reporting

GitHub Repository

- **Repository Link**: https://github.com/sameersarnad086/SentiSenseAI
- **Access**: Public repository, available for cloning and exploration.

Local Development Setup

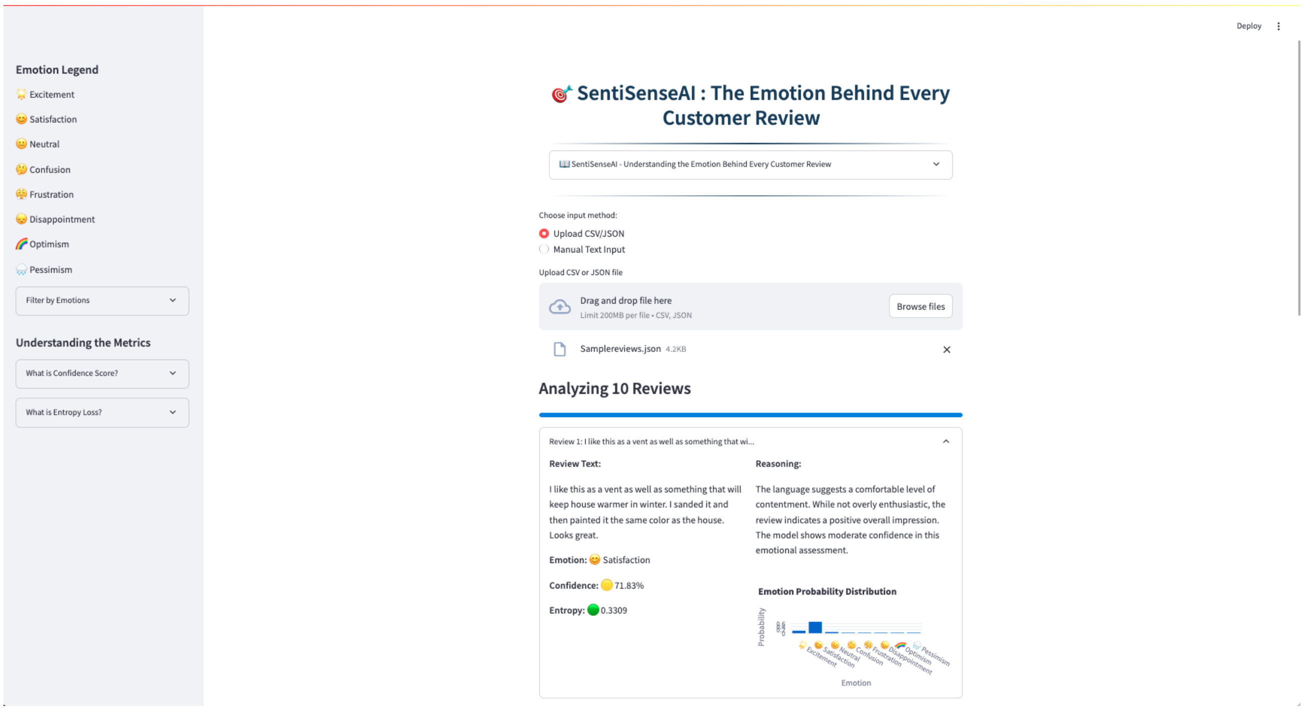
Getting Started

1. Clone the repository
2. Create a virtual environment
3. Install dependencies: pip install -r requirements.txt
4. Launch the Streamlit application: streamlit run app.py

Recommended Environment

- Python 3.9+
- Virtual environment recommended
- Minimum 8GB RAM
- Optional GPU acceleration for improved inference speed

SentiSenseAI: User Interface Guide


Deploy

Emotion Legend

- 🌟 Excitement
- 😊 Satisfaction
- 😐 Neutral
- 🤔 Confusion
- 😤 Frustration
- 😞 Disappointment
- 🌈 Optimism
- 🌧️ Pessimism

Filter by Emotions

Understanding the Metrics

What is Confidence Score?

What is Entropy Loss?

🎯 SentiSenseAI : The Emotion Behind Every Customer Review

📖 SentiSenseAI - Understanding the Emotion Behind Every Customer Review

Choose input method:

[✓ Upload CSV/JSON]

Manual Text Input

Upload CSV or JSON file

Drag and drop file here
Limit 200MB per file • CSV, JSON

Browse files

Samplereviews.json 4.2KB

Analyzing 10 Reviews

Review 1: I like this as a vent as well as something that wi...

Review Text:

I like this as a vent as well as something that will keep house warmer in winter. I sanded it and then painted it the same color as the house. Looks great.

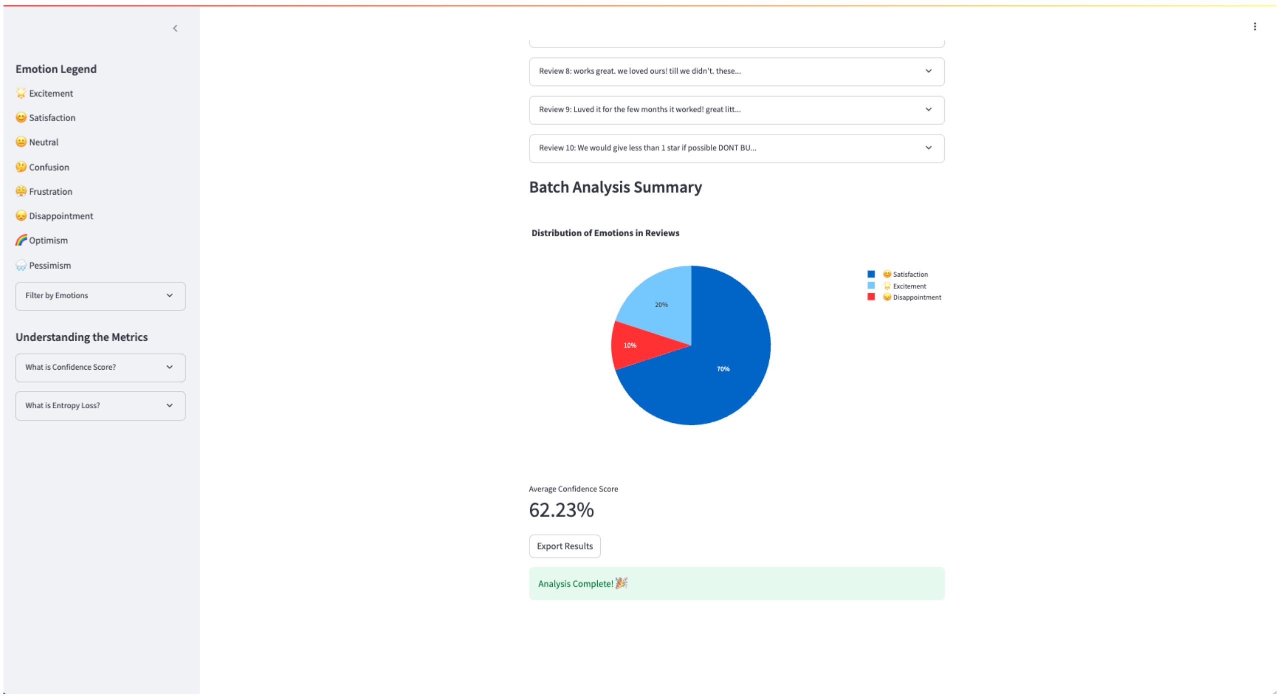
Emotion: 😊 Satisfaction

Confidence: 🟡 71.83%

Entropy: 🟢 0.3309

Reasoning:

The language suggests a comfortable level of contentment. While not overly enthusiastic, the review indicates a positive overall impression. The model shows moderate confidence in this emotional assessment.


Emotion Legend

- 🌟 Excitement
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- 😞 Disappointment
- 🌈 Optimism
- 🌧️ Pessimism

Filter by Emotions

Understanding the Metrics

What is Confidence Score?

What is Entropy Loss?

Review 8: works great. we loved ours! till we didn't. these...

Review 9: Luved it for the few months it worked! great litt...

Review 10: We would give less than 1 star if possible DONT BU...

Batch Analysis Summary

Average Confidence Score

62.23%

Export Results

Analysis Complete! 🎉

Welcome Screen

When you launch SentiSenseAI, you'll see a streamlined interface designed to help you understand the emotions behind customer reviews. The welcome screen features our application name and logo, along with a simple choice: you can either upload multiple reviews or analyze a single review.
Think of this welcome screen as your gateway to emotional intelligence – it's designed to be clean and uncluttered, helping you focus on what matters most: understanding your customer feedback.

Analysis Options

You have two powerful ways to analyze customer emotions:

1. **Upload CSV/JSON Reviews** When you choose this option, you can:
    a. **Drag and drop your file directly onto the upload area**
    b. **Click "Browse files" to select from your computer**
    c. **Use files up to 200MB in size, perfect for large review sets**
    d. **See immediate feedback as your file uploads**
    Your CSV or JSON file should contain customer reviews in a structured format. The system will automatically process all reviews and provide both individual and aggregate analysis.
2. **Manual Text Input** This option lets you:
    a. **Type or paste a single review directly**
    b. **Get immediate analysis of the emotional content**
    c. **Perfect for quick checks or exploring how the system works**

Understanding Your Results

After submitting your reviews, SentiSenseAI provides clear, actionable insights through:

- Individual review cards showing the detected emotion, confidence level, and reasoning
- A probability distribution showing how strongly each emotion was detected
- For batch uploads, a summary pie chart showing the overall emotional distribution
- An average confidence score to help you gauge the reliability of the analysis

Understanding Analysis Metrics

Confidence Score

A percentage-based metric indicating how certain our model is about its emotional prediction for each review. Higher scores suggest stronger, clearer emotional signals in the text.

Entropy Score

A measure of emotional complexity in a review. Lower scores indicate clear, single emotions, while higher scores suggest mixed emotional content.

Working with Multiple Reviews

Batch Analysis Features

- Distribution Visualization: A pie chart showing the proportion of different emotions across all analysed reviews
- Average Confidence Score: A single metric showing the overall prediction confidence across your batch of reviews

Navigation and Export Tools

The left sidebar allows filtering reviews by specific emotions, while the Export Results button lets you download your complete analysis for further use or sharing. This streamlined interface combines powerful analysis with easy navigation, helping you quickly understand the emotional landscape of your customer feedback.