MET CS 777

Scalable Emotion Classification for Affective Computing Using Apache Spark

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Contents

Building a Scalable Affective Computing Model

Multi-Label Text Classification with Hybrid Lexical-Dimensional Features

What is affective computing?

The study and development of systems and devices that can recognize, interpret, and respond to human emotions and affective states

Affect: relating to moods, feelings, and attitudes

Motivation

- Affective computing systems will improve Human-Computer Interaction (HCI)
- Traditional sentiment analysis (positive/negative/neutral) lacks granularity for affective computing applications

Research Question

- Can we achieve accurate multi-label emotion classification on large-scale social media text using distributed computing framework?

Technical Challenges

- Inter-rater reliability (Cohen's Kappa) consistency of raters classifying items into mutually exclusive categories more difficult with emotions
- Label imbalance: neutral/positive emotions dominate; negative emotions are rare
- Context dependency: lexical semantics shift with domain and syntax

Theoretical Foundations

History

Emergence of Affective Computing

1972 Ekman's Basic Emotions Theory

- Cross-cultural study of facial expressions → 6 universal emotions, lays the foundation for discrete categorical approaches

1980 Plutchik's Psychoevolutionary Model

- Emotion wheel: 8 primary emotions arranged in opposing pairs; Dyads: Adjacent emotions combine (joy + trust = love)

1995 Picard's "Affective Computing" Paradigm

- Seminal work establishing field: systems that recognize and respond to affect (emotion-aware interfaces improve HCI/UX)

2011 Mohammad's NRC Word-Emotion Lexicon

- Crowdsourced emotion annotations via Mechanical Turk, Enables lexicon-based features for ML pipelines

2020 GoEmotions: Fine-Grained Labeled Corpus

- 58K Reddit comments with 27 emotion labels (extends Ekman/Plutchik)
- Multi-label annotations: captures emotion complexity and co-occurrence
- Developed by Google to understand and classify the nuances of human emotion expressed in text

Theoretical Frameworks

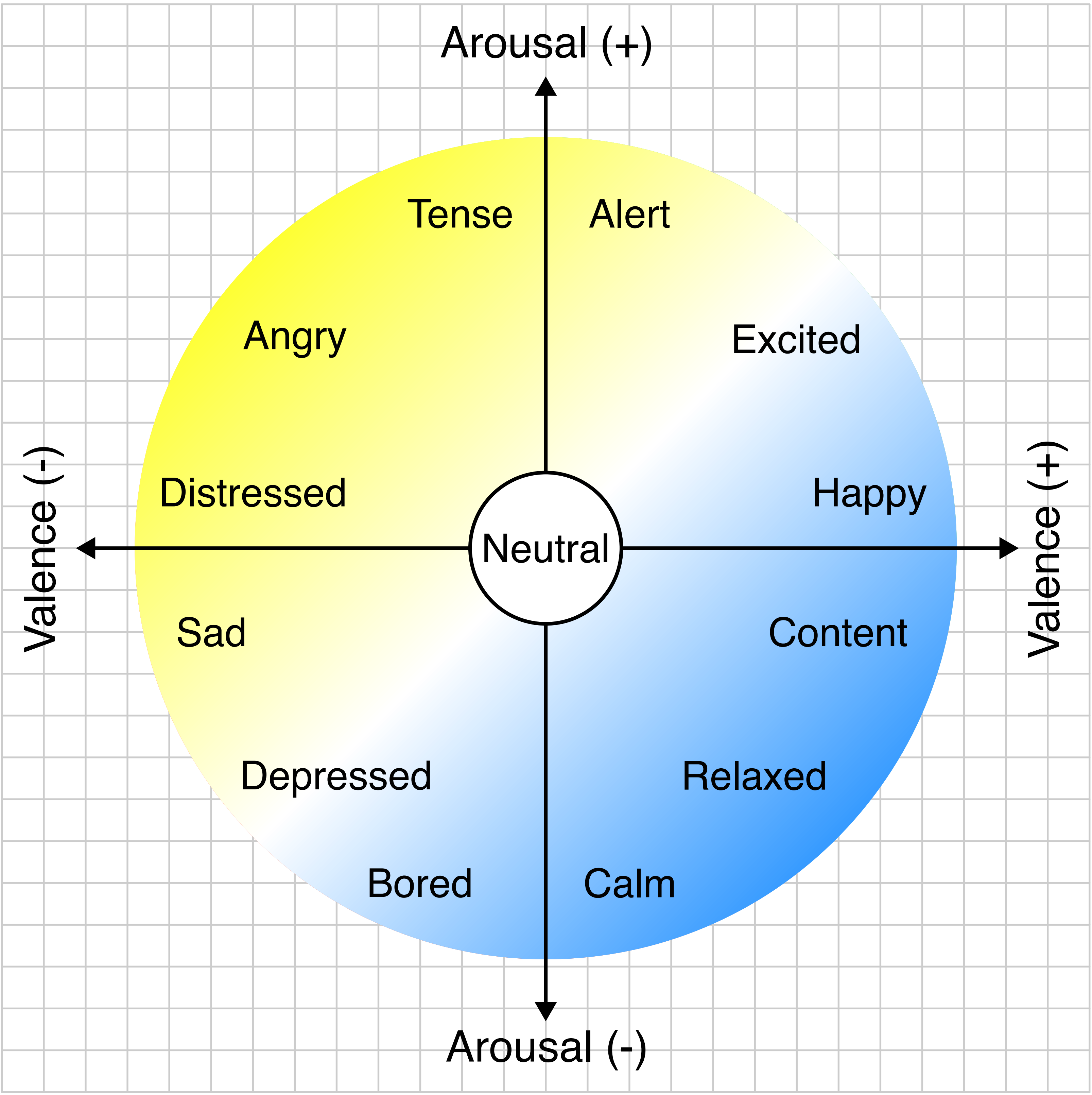
Emotion Taxonomies

Discrete Categorical Models (Ekman, Plutchik)

- Emotions as a finite set of atomic primitives
- Ekman (1972): 6 basic emotions (happiness, sadness, anger, fear, disgust, surprise)
- Plutchik (1980): 8 emotions in opposing dyads (joy-sadness, anger-fear, trust-disgust, anticipation-surprise)

Dimensional Continuous Models (Russell's Circumflex)

- Emotions as coordinates in continuous affective space
- Core dimensions:
  - Valence (V): Pleasantness [-1, +1] (negative ↔ positive)
  - Arousal (A): Activation level [-1, +1] (calm ↔ excited)
  - Dominance (D): Control [-1, +1] (powerless ↔ powerful)
- Example mapping: "Angry" = [-0.6, +0.8, -0.4] (unpleasant, high arousal, low control)



Source: Wikipedia

Sentiment vs. Affect

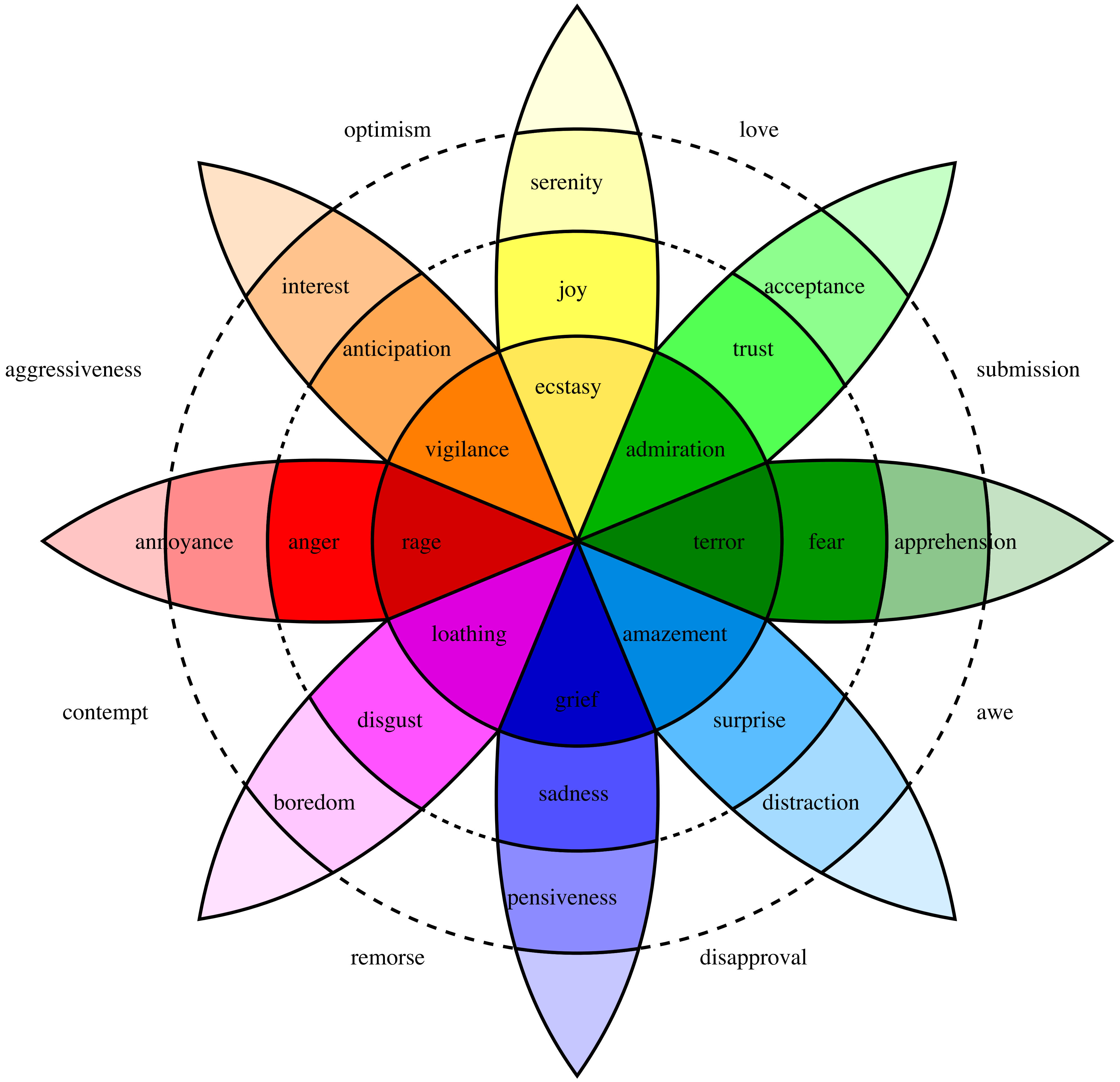
Multi-Label Emotion Classification

Sentiment Analysis

- X → {positive, negative, neutral} single-label classification
- Captures overall evaluative polarity
- Loss of granularity: “I’m furious” and “I’m disappointed” both → negative

Affective Analysis

- X → {0,1}^k where k=8
- Multi-label: each sample can have multiple emotion labels
- Captures emotional complexity: “I’m excited but nervous” → [anticipation:1, fear:1]



Source: Wikipedia

Data Sources

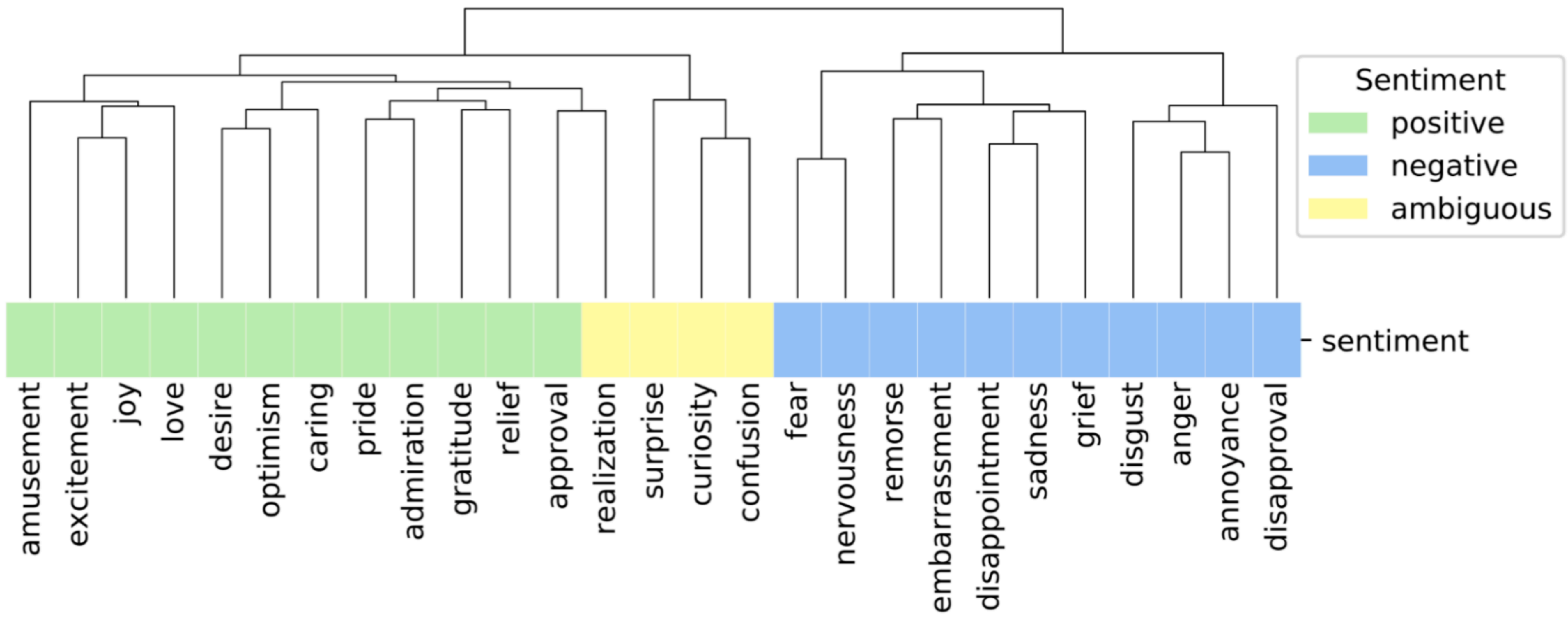
GoEmotions
Dataset Architecture

Corpus Statistics

- Source: Reddit comments (January 2005 - December 2019)
- Size: 58,009 human-annotated instances
- 27 fine-grained emotions + neutral (28 total classes)
- Multi-label: 15.3% of comments have multiple emotion annotations
- Annotators: 3 raters per comment; final label if >= 2 agree (majority vote)

Label Distribution (class imbalance)

- Skewed toward neutral (27.3%) and positive sentiment
- Rare emotions: grief (0.8%), pride (0.9%), relief (1.1%)
- Most frequent: admiration (9.2%), approval (8.1%), neutral (27.3%)



GoEmotions: https://research.google/blog/goemotions-a-dataset-for-fine-grained-emotion-classification/

NRC Word-Emotion Association Lexicon

EmoLex Overview

Lexicon Construction

- Base: 4,454 word-emotion associations
- Annotation: Amazon Mechanical Turk (crowdsourced)
- Schema: binary labels (1/0) for each of 8 Plutchik emotions per word

Feature Extraction for ML Pipeline

- Word-level matching: count words in text matching each emotion category
- Normalized ratios: emotion_count / total_words (controls for length bias)
- Sparse representation: most words map to 0-2 emotions (lexicon coverage ~15% of vocabulary)

Example

- text = “I’m depressed. But happy because I love banana. Please don’t abandon me”
- tokens = [depressed, happy, love, banana, abandon]
- feature vector: [anger: 1, anticipation: 1, disgust: 0, fear: 2, joy: 2, sadness: 2, surprise: 0, trust: 1]
- normalized: [anger: 0.111, anticipation: 0.111, disgust: 0.0, fear: 0.222, joy: 0.222, sadness: 0.222, surprise: 0.0, trust: 0.111]

depressed	anger	1
depressed	anticipation	0
depressed	disgust	0
depressed	fear	1
depressed	joy	0
depressed	negative	1
depressed	positive	0
depressed	sadness	1
depressed	surprise	0
depressed	trust	0

happy	anger	0
happy	anticipation	1
happy	disgust	0
happy	fear	0
happy	joy	1
happy	negative	0
happy	positive	1
happy	sadness	0
happy	surprise	0
happy	trust	1

love	anger	0
love	anticipation	0
love	disgust	0
love	fear	0
love	joy	1
love	negative	0
love	positive	1
love	sadness	0
love	surprise	0
love	trust	0

banana	anger	0
banana	anticipation	0
banana	disgust	0
banana	fear	0
banana	joy	0
banana	negative	0
banana	positive	0
banana	sadness	0
banana	surprise	0
banana	trust	0

abandon	anger	0
abandon	anticipation	0
abandon	disgust	0
abandon	fear	1
abandon	joy	0
abandon	negative	1
abandon	positive	0
abandon	sadness	1
abandon	surprise	0
abandon	trust	0

NRC VAD Lexicon

Valence, Arousal, Dominance

Dimensional Lexicon

- Coverage: 19,970 words
- Annotation: Best-Worst Scaling (BWS) via Mechanical Turk
- Scale: [0, 1] continuous values for each dimension
- Scores in the 0.9 range for Spearman and Pearson correlation with ground truth

Sample Feature Engineering

- text = "I failed the exam. I'm ruined."
- words = [failed, exam, ruined]
- VAD lookups:
  - failed: (V:0.177, A:0.578, D:0.154) - low valence, high stress
  - exam: (V:0.479, A:0.663, D:0.577) - neutral-negative, high arousal
  - ruined: (V:0.135, A:0.564, D:0.194) - very negative, high stress
- Aggregated features:
  - VAD_mean = (0.260, 0.610, 0.308) → negative + stressed + low control
  - VAD_std = (0.156, 0.045, 0.198) → consistent negativity, variable control

fail	0.177	0.578	0.154
exam	0.479	0.663	0.577
ruined	0.135	0.564	0.194

```
text = "I failed the exam. I'm ruined."

def extract_vad_features(text):
    words = re.findall(r'\b[a-z]+\b', text.lower())

valence_sum = 0.177 + 0.479 + 0.125 = 0.781
arousal_sum = 0.578 + 0.663 + 0.588 = 1.829
dominance_sum = 0.154 + 0.577 + 0.192 = 0.923

count = 3 # (failed, exam, ruined)
vad_features = [
    0.781 / 3 = 0.260, # valence (extremely negative)
    1.829 / 3 = 0.610, # arousal (high stress)
    0.923 / 3 = 0.308 # dominance (very low control)
    ]

Text 1: "I'm annoyed by this minor inconvenience"
Text 2: "I'm devastated and utterly destroyed"

# NRC emotion counts might both show:
# - anger: 1
# - sadness: 1
# can't distinguish INTENSITY of negative emotion
```

Technical Approach

Pipeline

Data Preparation

- Load GoEmotions: 58k samples → Spark DataFrame
- Label Mapping: 27 fine-grained → 8 Plutchik emotions (many-to-one hierarchical mapping)
- Stratified Split: 70% train (40,606), 30% test (17,403) preserving label distribution
- Text Cleaning: lowercase, tokenization, URL removal, stop-word removal

Pipeline

Feature Engineering (Multi-Modal Representation)

TF-IDF with n-grams (unigrams + bigrams + trigrams)

- Captures domain-specific vocabulary and rare discriminative terms

Lexicon-Based Emotion Features

- Raw counts and Normalized ratios (length invariance) of NRC emotions
- Captures explicit and interpretable emotion signals

Dimensional Affect Features (VAD)

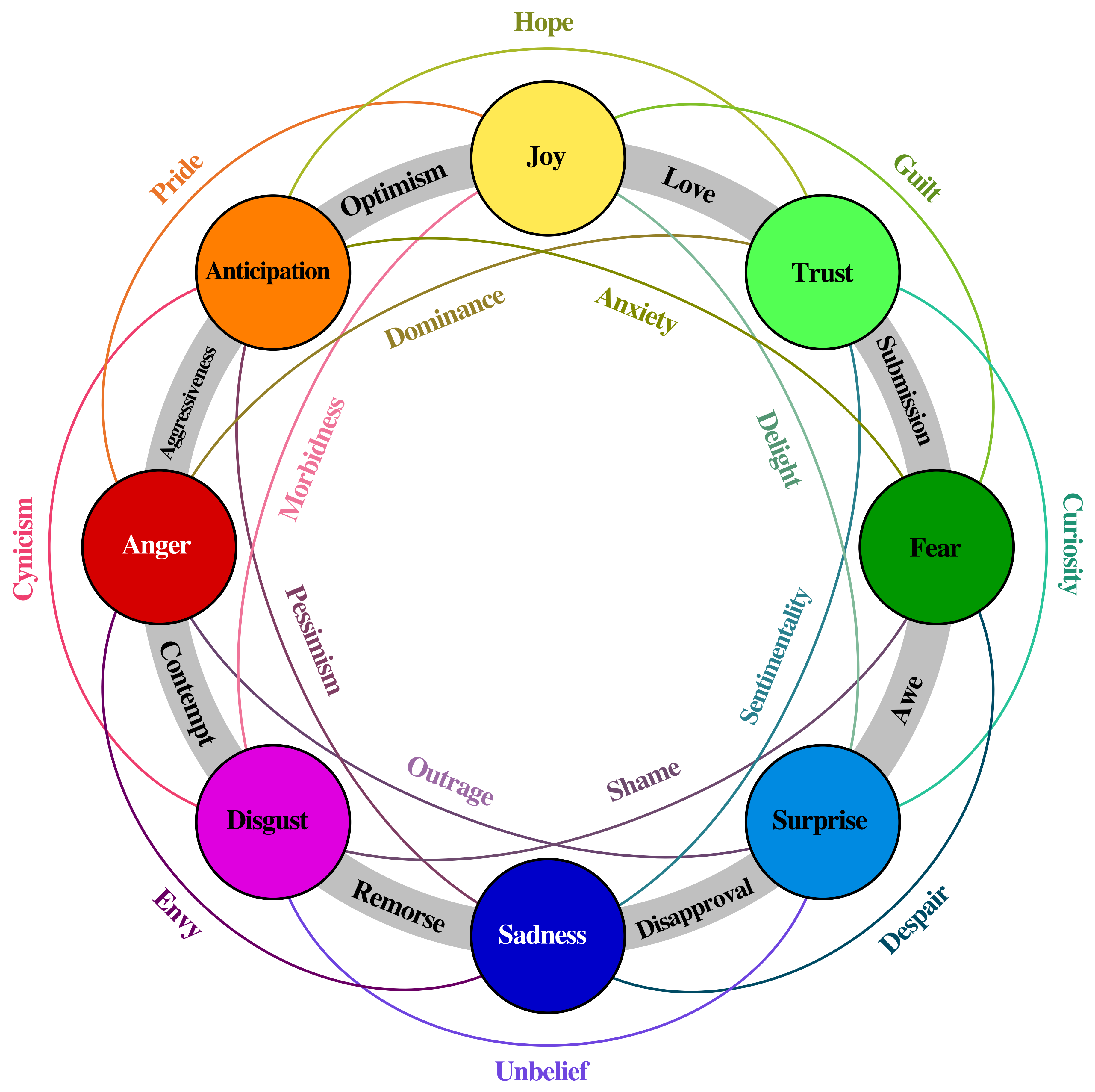
- Aggregates (mean, std and range) of VAD for each word
- Captures emotion intensity and consistency across dimensions

Linguistic Signals

- Length: word_count, char_count
- Punctuation density + emphasis markers: exclamation_ratio, question_ratio, ellipsis_count, CAPS_ratio, repeated_chars (!!!, ???)

Vector Assembly

- Concatenation: x = [TF-IDF ⊕ NRC ⊕ VAD ⊕ Linguistic]



Source: Wikipedia

Pipeline

Model Zoo

Model Training Strategy

- For each emotion $e_i \in$ {joy, trust, fear, surprise, sadness, disgust, anger, anticipation}:
  - Binary labels: $y_i \in \{0, 1\}$
  - Train classifier: $h_i(x) \to [0, 1]$ (probability)
  - Algorithms: Logistic Regression, Linear SVM, Naive Bayes, Random Forest
- Parallelization: 8 independent classifiers trained concurrently

Optimization Techniques

- Broadcast Variables: share NRC/VAD lexicons across executors (avoid data transfer)
- Threshold Tuning: per-emotion optimal thresholds via ROC analysis (maximize F1)
- Ensemble Aggregation: majority voting across 4 algorithms with confidence weighting

Results & Demo

Sample Output and Evaluation Metrics

Key Findings

- Metrics (for the majority vote ensemble)
  - F-1 score: 0.51
  - Precision: 0.51
  - Recall: 0.55
- Positive emotions (joy, trust) achieve 15-20% higher F1
- Logistic Regression - best individual classifier

Demo

- Combines top emotions into a narrative
- E.g., “This demo is awesome” -> “Steady notes of trust lead the narrative, with a uplifting undertone from joy.”


```
{
  "text": "Wow this is amazing. LOVE THIS!!!",
  "predictions": [
    {
      "label": "joy",
      "predicted": true,
      "score": 0.8007311486763947,
      "raw": null,
      "threshold": 0.4
    },
    {
      "label": "trust",
      "predicted": true,
      "score": 0.9170571444419771,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "fear",
      "predicted": false,
      "score": 0.008815574638560714,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "surprise",
      "predicted": true,
      "score": 0.5825290608402673,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "sadness",
      "predicted": false,
      "score": 0.023865459561988243,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "disgust",
      "predicted": false,
      "score": 0.015072881541916815,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "anger",
      "predicted": false,
      "score": 0.04585021930400218,
      "raw": null,
      "threshold": 0.3
    },
    {
      "label": "anticipation",
      "predicted": false,
      "score": 0.05138461374788547,
      "raw": null,
      "threshold": 0.4
    }
  ],
  "positive_labels": [
    "joy",
    "trust",
    "surprise"
  ],
  "top_labels": [
    "trust",
    "joy",
    "surprise",
    "anticipation",
    "anger"
  ],
  "story": "Steady notes of trust lead the narrative (92%), with a uplifting undertone from joy (80%)."
},
```

Applications and Future Directions

Real-World Impact in HCI, Mental Health, and Content Moderation

Emotion-Aware Human-Computer Interaction

- Affectiva (affectiva.com) emotion AI for automotive, media, and market research
  - In-cabin monitoring: Detects driver drowsiness, distraction, and emotional state, used by BMW, Honda, Kia…
- Amazon Alexa Emotion Detection (Patent US10573312B1)
  - Detects frustration in voice to adjust response strategy

Mental Health Monitoring & Crisis Detection

- Crisis Text Line (crisistextline.org) emotion analysis for suicide prevention
  - ML models triage incoming messages by emotional distress level, partners with: Facebook, Instagram for at-risk user detection
- OpenAI Safety Systems (openai.com/safety)
  - ChatGPT detects sensitive conversations (self-harm, crisis), provides crisis resources (988 Suicide & Crisis Lifeline)

Content Moderation at Scale

- Discord's AutoMod (discord.com/safety)
  - Real-time emotion analysis to flag hostile language, includes customizable thresholds for different community standards

Future Research Directions

- Zoom's Emotion AI (Patent 2021) meeting sentiment analysis through multimodal fusion of text + voice + facial expressions
- USC's SimSensei virtual therapist funded by DARPA used microphone, webcam, and depth sensors to track 60 non-verbal behaviors per second, including facial expressions, eye gaze, body posture, and voice intonation

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Q&A