Project 38: Understanding Human Emotions and Empathy in Disaster Communication

This project uses CrisisLexT26 dataset. It focuses on human-centric communication signals such as identifying emotions, empathy, concern, and behavioral expressions in crisis tweets. It aims to build models that understand how people feel and react during disasters, rather than just what they report.

Task 1: The first task involves preprocessing the CrisisLexT26 dataset to make it analysis-ready. All tweets will be cleaned by removing URLs, mentions, and emojis, while maintaining punctuation and emotional markers like exclamation marks. Lowercasing and tokenization using BERT tokenizer will ensure uniformity. A detailed text statistics report will highlight average tweet length, vocabulary richness, and noise ratio. This step ensures that emotional and empathetic cues are preserved rather than filtered out.

Task 2: Next, the tweets will be separated by crisis event (e.g., Haiti earthquake, Boston bombing, Alberta floods). Each subset will retain timestamps, allowing event-specific linguistic trend analysis. This stratification helps compare how emotional tone differs between natural and human-induced disasters and lays the foundation for empathy and sentiment contextualization later.

Task 3: In this stage, each tweet's sentiment will be classified as positive, neutral, or negative using two models: VADER (for lexicon-based interpretability), SentiStrength, and RoBERTa-based sentiment analysis (for contextual understanding). The sentiment intensity score will be normalized to highlight crisis peaks, for instance, identifying days where negative sentiment spikes correspond with on-ground impact escalation.

Task 4: Moving beyond polarity, this task maps tweets into Plutchik's eight basic emotions (joy, sadness, fear, anger, surprise, trust, disgust, anticipation). A fine-tuned emotion classification model like GoEmotions-RoBERTa will be used. The output reveals emotional distribution across different crises, for instance, more fear during earthquakes versus more anger during industrial accidents.

Task 5: Empathic language often drives social support in crises. This task trains or fine-tunes a transformer on empathy detection using the Empathic Reactions Dataset as an auxiliary source, applying zero-shot classification on CrisisLexT26 tweets. The goal is to estimate empathy scores identifying compassionate vs. detached tones, to understand the public's collective concern and willingness to help.

Task 6: Empathic tweets tend to use personal pronouns, modal verbs, and direct appeals. This task uses LIWC or spaCy-based linguistic feature extraction to analyze syntactic and stylistic markers. Metrics like lexical diversity, average sentence complexity, and sentiment-bearing adjectives are computed to show how linguistic simplicity rises during emergencies, enhancing accessibility and relatability.

Task 7: Using BERTopic (based on Sentence-BERT embeddings + HDBSCAN clustering), thematic patterns will be extracted from emotionally charged tweets. Topics such as “help requests,” “solidarity,” or “infrastructure loss” are automatically discovered and labeled. Each topic will be annotated with its dominant emotion (from Task 4) to map emotional context to thematic focus.

Task 8: This task aligns tweet timestamps with the progression of each disaster event. A temporal aggregation is performed to visualize emotion transitions — e.g., fear dominating the onset phase, followed by sadness during aftermath. Such temporal emotion trajectories help identify psychological phases of collective response and can inform mental-health-aware early warning systems.

Task 9: Here, engagement metrics (retweets, likes) are statistically correlated with empathy and sentiment scores. Regression models will quantify whether empathetic tweets receive higher engagement and amplification. The hypothesis is that empathetic language acts as a catalyst for virality in humanitarian communication.

Task 10: A transfer learning experiment tests whether a model trained to classify emotion on one disaster generalizes to another. For example, a classifier trained on “flood” events is tested on “earthquake” tweets. The cross-domain F1-score quantifies linguistic variability and universality in emotional expression during crises.

Task 11: Finally, an interactive dashboard will present emotion, empathy, and sentiment trajectories across time and events. Using Plotly or Streamlit, users can explore crisis timelines and observe how empathy evolves alongside sentiment trends. The delivery offers both research insights and a deployable analytical interface for humanitarian organizations.

Task 12: Use appropriate literature to comment on the results and limitations of the data processing pipelines.