Psychometric Feature Extraction for Mental Health Conversations

An end-to-end AI system that analyzes mental health text and extracts interpretable psychosocial signals to support therapists in message-based telehealth environments.

Project Context

Bridging Technology and Mental Healthcare

Mental health professionals reviewing text-based patient communications need tools to quickly identify concerning patterns. Manual review is time-consuming and may miss subtle indicators. Our system provides automated psychometric feature extraction to assist clinical judgment.

CMPE 255 - Data Mining | Fall 2024 | Final Project

Authors: Varad Poddar, Gowri Preetam G., Samip Niraula, Bala Anbalagan

120K+

Counseling messages analyzed

5 Dimensions

Psychometric features extracted

Multi-Task Psychometric Analysis

Our transformer-based model extracts five key psychometric dimensions from text, providing therapists with contextual cues for patient assessment.

Sentiment Intensity

Range: -1 to 1 (Regression)

Overall emotional valence measuring positive to negative affect in patient communications.

Trauma Indicators

Range: 0 to 7 (Regression)

Linguistic markers suggesting traumatic experiences or post-traumatic stress patterns.

Social Isolation

Range: 0 to 4 (Regression)

Indicators of social disconnection and perceived loneliness in patient narratives.

Support System

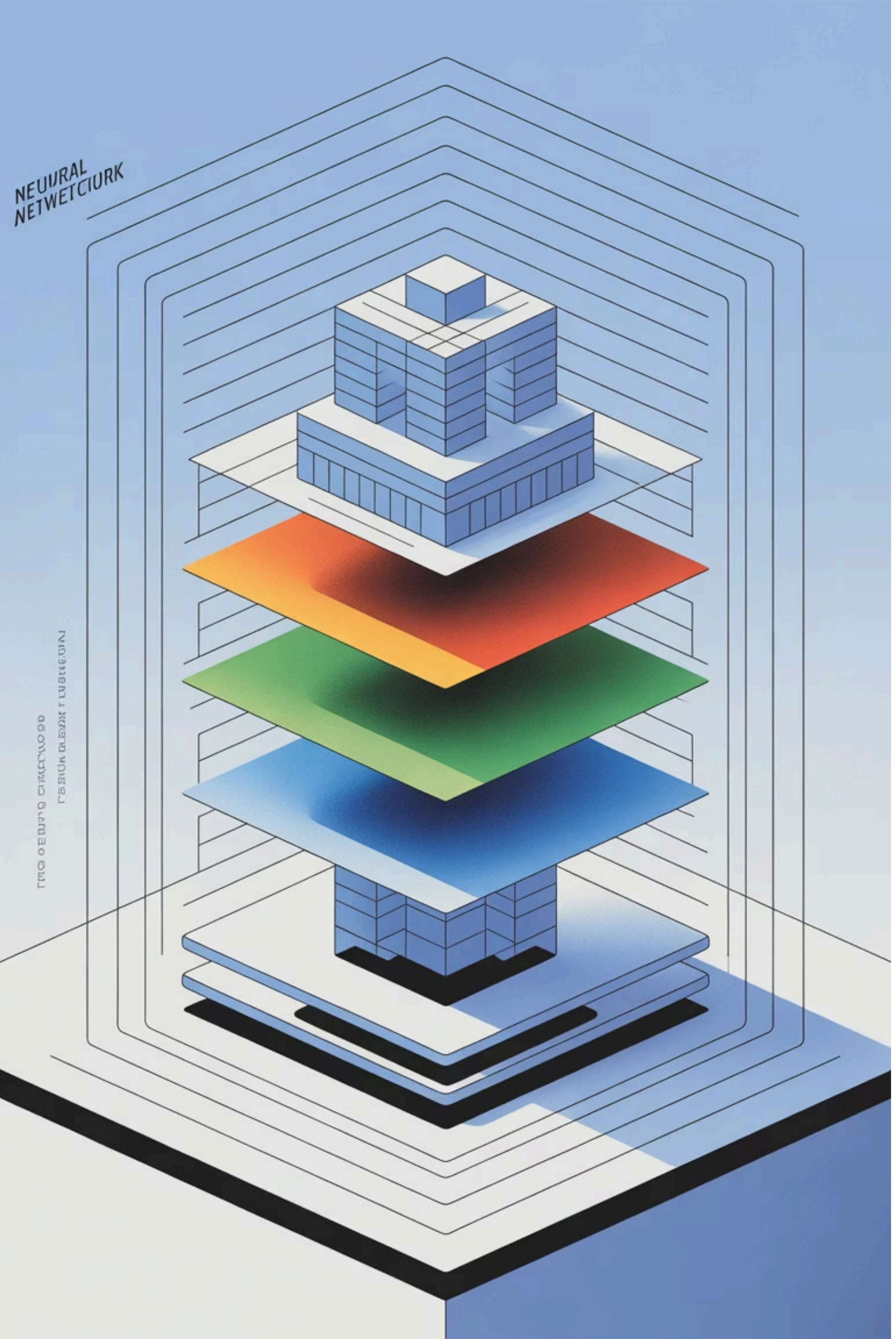
Range: 0 to 1 (Regression)

Perceived availability and strength of social support networks.

Family History

Range: 0-100% (Classification)

Probability of family mental health history mentioned in patient communications.



System Architecture

Model Foundation

- **Backbone:** XLM-RoBERTa Large (1024-dim hidden state)
- **Training Strategy:** Frozen backbone with trainable heads
- **Parameters Trained:** Only 0.5% of total model
- **Multilingual Support:** Built-in cross-lingual capabilities

Multi-Task Design

- Single [CLS] token embedding feeds all heads
- Four regression heads (1024→1 linear layers)
- One classification head with sigmoid activation
- Efficient inference: ~50ms on GPU, ~500ms on CPU

Design Philosophy: Frozen backbone enables efficient training while maintaining state-of-the-art language understanding. Each specialized head learns task-specific patterns from shared representations.

Data Pipeline & CRISP-DM Methodology

Business Understanding

Focus on non-diagnostic psychosocial signals to support clinical decision-making in telehealth.

Data Understanding

EDA on 120K counseling messages: label distribution, target ranges, text length statistics.

Data Preparation

Stratified 70/15/15 splits, tokenization (max_length=256), support scaling, Reddit filtering.

Modeling

Multi-task learning with frozen XLM-RoBERTa, MSE for regression, BCEWithLogits for classification.

Evaluation

R^2/MAE per regression head, F1/AUC for family history, comprehensive visualizations.

Training Data Sources

Primary Dataset

phoenix1803/Mental-Health-LongParas from HuggingFace provides 120,000 counseling-style messages with psychometric annotations. Long-form text averaging 200+ words per message.

Column	Type	Range
sentiment_intensity	float	-0.93 to 0.89
family_history	binary	0 or 1
trauma_indicators	int	0 to 7
social_isolation_score	int	0 to 4
support_system_strength	float	0.0 to 0.04

Pseudo-Labeling Data

Reddit Mental Health Classification dataset with 1.1M posts from mental health subreddits, filtered to ~600K high-quality posts for weak supervision and clustering analysis.

Data Cleaning Pipeline

- Remove survey/YouTube links
- Exclude unrelated subreddits
- Filter texts > 12,000 characters
- Remove spam/solicitations

Model Performance Results

0.62

Sentiment R^2

Strong predictive power for emotional valence (MAE: 0.18)

0.45

Trauma R^2

Moderate correlation for trauma indicators (MAE: 0.89)

0.71

Family History F1

Solid classification performance (AUC: 0.78)

100

Inference Speed

~100ms latency on Vertex AI production endpoint

Validation Set Performance

- Sentiment: R^2=0.62, MAE=0.18 ✅
- Trauma: R^2=0.45, MAE=0.89 ✅
- Isolation: R^2=0.28 ⚠️ Marginal
- Family History: F1=0.71, AUC=0.78 ✅

Clustering Insights

K-Means analysis (K=2, optimal by silhouette score) revealed two distinct narrative archetypes:

- **Cluster 0:** Family-oriented distress narratives
- **Cluster 1:** Individual-focused distress narratives

Production Deployment Pipeline

01

Containerized Training

Docker image with training code pushed to Google Artifact Registry for reproducible model development.

02

Vertex AI Custom Job

GPU-accelerated training (T4/A100) on Vertex AI with automatic artifact storage to Cloud Storage.

03

Model Registry

Trained models uploaded to Vertex AI Model Registry with versioning and metadata tracking.

04

Endpoint Deployment

Auto-scaling endpoints (1-5 replicas) with health checks and traffic splitting for blue-green deployments.

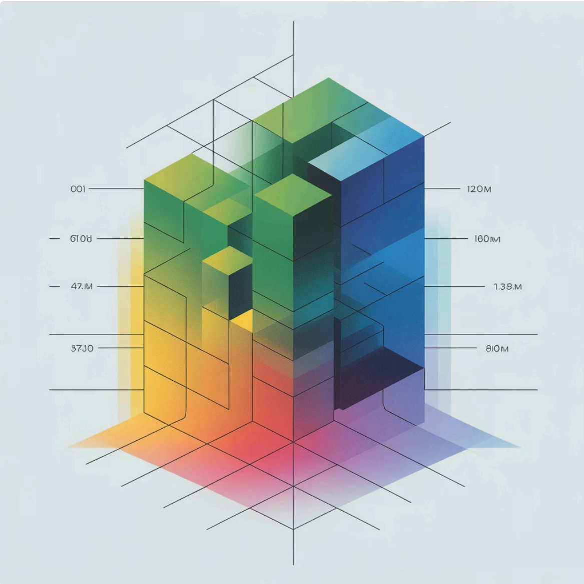
05

Production Serving

REST API integration with Bloom Health telehealth application, serving real-time predictions.

MLOps Excellence: Complete CI/CD pipeline with containerization, GPU training, model versioning, auto-scaling, and production monitoring via Cloud Logging.

Vertex AI Training & Evaluation



Classification Performance

Family history prediction achieved F1=0.71 and AUC=0.78 on validation set, with balanced precision-recall tradeoff.

ROC Analysis

Strong discriminative ability for family history classification with AUC significantly above baseline.

All visualizations generated from Vertex AI Custom Training Job (A100, 5 epochs, Job ID: 3111661388854984704). Training artifacts stored in Cloud Storage and registered in Vertex AI Model Registry.

Deployment & Integration

🚀 FastAPI Service

REST API with `/predict` and `/health` endpoints serving JSON responses.

```
curl -X POST
/predict \
-d '{"text": "feeling
anxious",

"return_all_scores":
true}'
```

🎨 Gradio Interface

Interactive web UI for testing and demonstration with real-time predictions.

```
python
app/gradio_demo.py
```

Launches shareable link with example inputs and visualization.

☁️ Production Endpoint

Region: us-central1

Machine: n1-standard-4

Replicas: 1-5 (auto-scaled)

Latency: ~100ms p50

Docker

Containerized deployment with all dependencies bundled for consistent environments.

Cloud Run

Serverless deployment option with automatic scaling and pay-per-use pricing.

Vertex AI

Production endpoint integrated with Bloom Health telehealth application.