Vivino Emotion–Entropy Analysis Platform

1. Problem Statement

Wine reviews are one of the richest publicly available signals for understanding consumer perception, yet they are largely unstructured, multilingual, emotionally layered, and disconnected from pricing and vintage context. Traditional analysis approaches either:

- Focus on ratings alone (losing emotional nuance), or
- Use simplistic sentiment scores that collapse complex emotional expression into a single polarity.

This creates a blind spot for producers, marketers, and strategists attempting to understand *why* a wine performs differently across vintages, price tiers, or consumer segments.

The goal of this product was to design an end-to-end system that transforms raw wine reviews into **structured emotional, economic, and temporal signals**, enabling quantitative analysis such as entropy measurement and regression modeling.

2. Market & Consumer Context

- The global wine market is valued at **$450B+**, with premium and luxury wines representing one of the fastest-growing segments (IWSR, 2023).
- Platforms like Vivino host **tens of millions of reviews**, acting as de facto consumer research datasets.
- However, wineries and distributors rarely have tooling to convert this qualitative data into **decision-grade analytics**.

Shifting Consumer Behavior

- Recent research shows **Gen Z is drinking significantly less alcohol** than previous generations, prioritizing wellness, moderation, and experience over volume.
- According to **Gallup (2023)** and **IWSR No- and Low-Alcohol Strategic Study (2023)**:
  - Gen Z consumes ~20–30% less alcohol per capita than Millennials at the same age.
  - Premiumization is increasing: fewer drinks, but higher expectations per experience.

This shift makes **emotional clarity, storytelling, and perceived value** more important than ever - especially for vintage-differentiated luxury wines.

3. Product Goals

1. Convert raw, multilingual wine reviews into a **standardized English emotional representation**.
2. Quantify emotional expression using **probability distributions**, not binary sentiment.

3. Measure **emotional entropy** as a proxy for clarity vs confusion in consumer perception.
4. Enable downstream **regression modeling** across price, ratings, entropy, and vintage.
5. Preserve flexibility: allow both **in-app translation** and **external translation workflows**.

4. System Architecture (End-to-End)

Step 1: Review Ingestion

- Reviews are fetched directly from Vivino using a paginated API.
- Each review includes:
  - `review_id` (stable identifier)
  - `review_text`
  - `review_score`
  - `vintage_year`
  - timestamps and metadata

The system supports URLs such as:

- `?year=2018` → filters reviews for a specific vintage
- `?ref=nav-search#all_reviews` → fetches all vintages, enabling later filtering in Excel or analysis

This design intentionally **decouples data collection from experimentation**, allowing analysts to reuse the same dataset across multiple vintages.

Example:

https://www.vivino.com/en/domaine-de-la-romanee-conti-romanee-conti-grand-cru/w/83912

Can be classified as:

1. https://www.vivino.com/en/domaine-de-la-romanee-conti-romanee-conti-grand-cru/w/83912?year=2018
2. `https://www.vivino.com/en/domaine-de-la-romanee-conti-romanee-conti-grand-cru/w/83912?ref=nav-search#all_reviews`

Step 2: Translation Layer

The product supports two translation paths:

A. In-App Translation

- Models supported:
  - NLLB-200 distilled (600M): faster, default
  - M2M100-1.2B: slower, more accurate
- Reviews are:

    - Language-detected
    - Sentence-split
    - Token-budgeted to avoid truncation

Live preview is enabled by default and auto-disabled for large datasets (≥2000 reviews).

B. External Translation Upload

- Users may translate reviews externally (e.g., Google Sheets, enterprise tools)
    - Google sheets has a function: =GOOGLETRANSLATE(L2,"auto","en").
    - Where “auto” detects which language it is and “en” is the english language being translated to
- Uploaded files must include:
    - `translated_reviews` (required)
    - `review_id` (recommended for stable matching)
- **Why `review_id` exists at all?**
    - When you fetch reviews from Vivino, you get **N reviews in some order** and when you translate outside the app, **anything can change**:
        - rows can be re-ordered
        - rows can be deleted
        - rows can be duplicated
        - text can be trimmed, corrected, or re-punctuated

  If that happens, the app still needs a **reliable way to know -** this translated text belongs to *that* original review.

- If you don’t use `review_id`, there are only two alternatives:
    1. Match on review_text: This is fragile because:
        - changing a single character breaks the match
        - translations tools often normalize punctuation
        - emojis / accents / whitespace differences cause failures

    2. Match by row order (index): This is actually fine if and only if:
        - you don’t delete rows
        - you don’t re-sort
        - you don’t add rows
        - you don’t filter anything

That’s why I added the **“no header / single column → row-order attach”** path. It works **only when row counts match exactly**. The system enforces explicit matching rules to prevent silent misalignment.

5. Emotion Modeling Strategy

Why Emotion (Not Sentiment)

Wine reviews often express **mixed emotional states**: excitement, nostalgia, disappointment, surprise. Binary or scalar sentiment collapses this complexity.

Two Methods Implemented

Method 1: Softmax-Based (Single Dominant Emotion)

- Extracts raw logits from the model
- Applies softmax across all 11 emotions
- Produces a categorical distribution that sums to 1
- Assumes one dominant emotional intent per review

Pros:

- Fully transparent
- Clean probability simplex

Cons:

- Compresses emotional nuance
- Less expressive for layered reviews

Method 2: Multi-Label (Pipeline-Based)

- Uses HuggingFace pipeline with `return_all_scores=True`
- Applies independent sigmoid activations per emotion
- Allows multiple emotions simultaneously

Chosen Approach: Method 2

Rationale:

- Wine reviews frequently contain emotionally complex signals
- Multi-label representation better matches human expression
- Produces higher-variance signals for entropy and regression

6. Emotional Entropy

Entropy is computed over emotion probability distributions to measure:

- **Low entropy** → emotionally clear, consistent perception
- **High entropy** → emotionally diffuse or conflicting perception

This provides a novel quantitative signal beyond sentiment or rating.

Entropy is calculated per review and averaged across:

- Vintage

- Wine
- Dataset slices

7. Regression Modeling Framework

For a single wine brand, datasets are created per vintage year and analyzed using four linear regression models:

Prices were extracted from two pieces and tested from both Wine-Searcher as well as Vivino:

1. Ridge Vineyards | Monte Bello (MB)
- https://www.vivino.com/en/ridge-vineyards-monte-bello/w/3715?&price_id=33568817
- https://www.wine-searcher.com/find/ridge+monte+bello+santa+cruz+mnt+st+francisco+bay+central+coast+california+usa/1/usa#t5

2. Chateau Montelena | The Montelena Estate Cabernet Sauvignon (ME)
- https://www.vivino.com/en/chateau-montelena-the-montelena-estate-cabernet-sauvignon/w/1376076
- https://www.wine-searcher.com/find/montelena+the+estate+cab+sauv+napa+valley+county+north+coast+california+usa/1/usa

3. Domaine de La Romanée-Conti | Romanée-Conti Grand Cru (DRC)
- https://www.vivino.com/en/domaine-de-la-romanee-conti-romanee-conti-grand-cru/w/83912?ref=nav-search#all_reviews
- https://www.wine-searcher.com/find/dom+de+la+grand+cru+cote+nuit+romanee+conti+vosne+burgundy+france/1/usa?delivery=expedited_shipping%2Cstandard_shipping

Listed price is the price shown by merchants for a given wine and vintage, reflecting **seller-listed or distributor-offered pricing**, not necessarily the final transaction price.

Market price represents an **average market estimate** based on prices from multiple merchants and regions and previously listed prices, intended to reflect the **typical price consumers pay in the market** rather than a single seller's listing.

Model 1

DV: Average Rating
IVs: Listed Price, Entropy (Method 2)
→ Tests whether emotional complexity explains ratings beyond price signals.

Model 2

DV: Listed Price
IVs: Average Rating, Entropy (Method 2)
→ Tests whether pricing reflects perceived quality and emotional richness.

Model 3

DV: Average Rating
IVs: Market Price, Entropy (Method 2)
→ Substitutes market price to control for list-price noise.

Model 4

DV: Market Price
IVs: Average Rating, Entropy (Method 2)
→ Tests whether emotional complexity influences real market valuation.

Running these models **across vintages** controls for brand effects and isolates temporal shifts in perception.

This allows exploration of:

- Whether emotional ambiguity depresses ratings
- Whether emotionally confusing wines are discounted
- How perception differs across vintages

8. Product Decisions & Trade-offs

- **Review ID Enforcement:** Chosen to prevent silent data corruption during uploads
- **Two Translation Paths:** Flexibility for research vs production robustness
- **Multi-Label Emotions:** Higher complexity, better explanatory power
- **Caching & State Persistence:** Prevents UI resets and re-computation costs

Each decision prioritizes **analytical correctness over convenience**.

9. Outcomes & Impact

- Reduced analysis lead time from **~75 hours to ~5 minutes**
- Enabled repeatable experimentation across vintages
- Revealed measurable links between emotional entropy and ratings
- Created a reusable research platform, not a one-off script

10. Why This Matters

As wine consumption shifts toward **experience-driven, premium-focused buyers**, understanding emotional perception becomes as important as understanding price.

This product demonstrates how unstructured consumer language can be transformed into **decision-grade economic signals**, bridging product analytics, behavioral economics, and AI.

11. Future Extensions

- Consumer segmentation by emotional profiles
- Cross-wine comparative entropy benchmarks
- Time-series tracking of perception drift
- Integration with sales velocity and inventory data

This system is designed not as a dashboard, but as an analytical engine—built to support strategy, not just reporting.

“I built a system that quantifies emotional clarity in consumer language and links it directly to pricing and vintage strategy.”

Define problem statement: *Wine brands rely heavily on* ***ratings and price****, but those don't explain why the same wine performs differently across vintages.Most tools reduce this to* ***star ratings or basic sentiment****, which loses nuance. Reviews contain the answer — but they're:* ● *Unstructured* ● *Multilingual* ● *Emotionally complex* ***Core problem:*** *How do we convert messy consumer language into signals that explain ratings, pricing, and vintage performance?*	***Users & Why This Matters - that answers "Who cares about this?"*** ***Primary users*** ● *Wine producers & brand strategists* ● *Pricing / market analysts* ● *Researchers analyzing consumer perception* **Why now** ● *Wine is a $450B+ market* ● *Gen Z drinks* ***20–30% less alcohol****, but expects higher-quality experiences* ● *Fewer purchases → emotional clarity and storytelling matter more* So understanding how people feel, not just what they rate, becomes strategically *important*.
Solution Overview (Center of board) *"Here's the system I built."* *An end-to-end pipeline that:* 1. *Ingests wine reviews (with ratings + vintage)* 2. *Translates them into English (in-app or external)* 3. *Extracts* ***multi-label emotional probabilities*** 4. *Computes* ***emotional entropy*** 5. *Feeds those signals into regression models with price and ratings* *In short:* **Unstructured text → Emotional probabilities → Entropy → Economic insight**	***Key Product Decisions*** *"The important part is the trade-offs."* ***Decision 1: Emotion vs Sentiment*** ● *Sentiment = too simplistic* ● *Emotion = captures mixed feelings common in wine reviews* *Chose: multi-label emotion modeling* *→ Better reflects human expression* *→ Produces higher-variance signals for analysis* ***Decision 2: Why Emotional Entropy?*** ● *Low entropy → clear, consistent perception* ● *High entropy → confusion or mixed signals* *Entropy becomes a quantitative proxy for clarity vs ambiguity, which ratings alone can't capture.* ***Decision 3: Translation Flexibility + review_id*** ● *Allowed users to translate outside the app (e.g., Google Sheets)* ● *Enforced review_id matching* ***Trade-off:*** *slight friction vs data integrity* *Why: silent misalignment would invalidate all downstream analysis*
Analytics and Validation: "How did we prove this was useful?" : *I validated the system by running vintage-level regressions linking ratings, listed and market price, and emotional entropy, which showed how emotional clarity affects valuation across vintages—while cutting analysis time from ~75 hours to ~5 minutes and turning reviews into a reusable, productized research asset*	