

CAPSTONE PROJECT

SEMANTIC ANALYSIS OF
STARBUCK REVIEW DATASET
USING IBM GRANITE FOR
BETTER REVIEW INTELLIGENCE



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Raw Link Dataset

<https://www.kaggle.com/datasets/harshalhonde/starbucks-reviews-dataset>

Total rows **850**

Name	Location	Date	Rating	Review	Image Links
The reviewer's name, if available.	The location or city associated with the reviewer, if provided.	The date when the review was posted.	The star rating given by the reviewer, ranges from 1 to 5.	The textual content of the review, captures the reviewer's experience and opinions.	Links to images associated with the reviews, if available.

Project Overview

Ideas To Life

About The Project

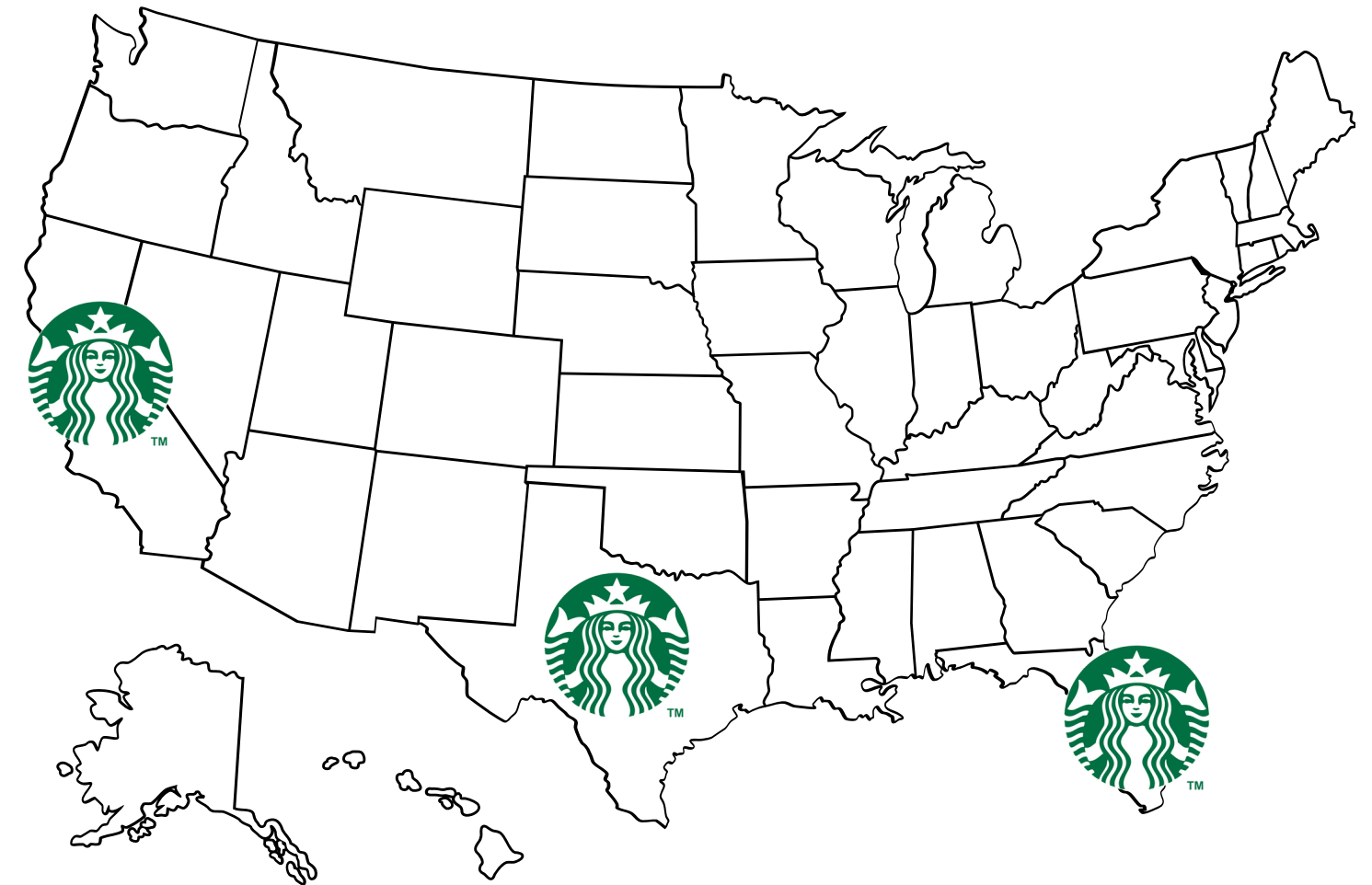
"Customer reviews hold invaluable insights, but their true potential is unlocked when analyzed through the lens of regional behaviors. This project harnesses AI to decode patterns across three key Starbucks markets—California, Florida, and Texas—transforming raw feedback into targeted strategies that enhance customer satisfaction and loyalty.

Key Objectives:

- Uncover regional sentiment patterns to understand emotional drivers.
- Identify top complaints (e.g., service delays, product consistency, cleanliness gaps).
- Deliver AI-powered action plans tailored to each state's unique customer expectations.

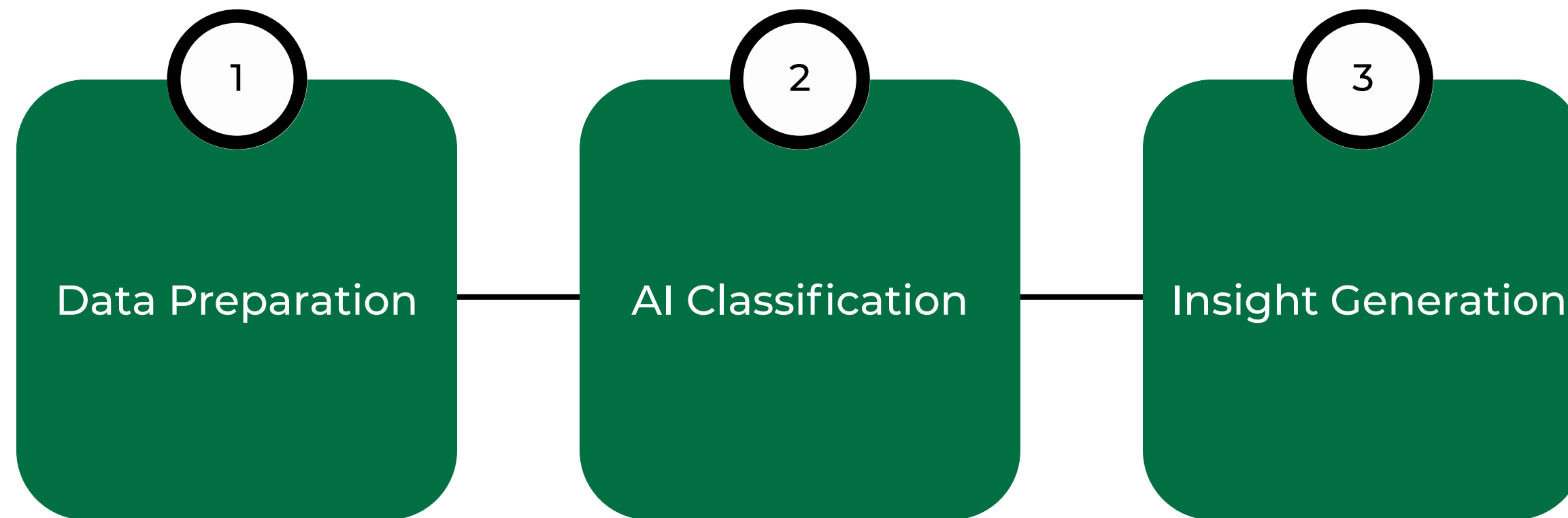
Project Scope:

- 300 reviews (100 per state) sampled for balanced regional representation.
- IBM Granite AI used to enrich data with behavioral context (priority, tolerance, cultural norms).



Analysis process

About The Strategy



Data Preparation Plans

Clean and structure raw review data for analysis.

- Loaded the dataset from reviews_data.csv and removed rows with missing reviews or locations.
- Extracted state codes (e.g., CA, FL, TX) from the location column using regex (r'\s*([A-Z]{2})\$').
- Cleaned review text:
 - Preserved negation terms (e.g., "not good" → "not_good").
 - Removed brand mentions ("Starbucks", "SBUX") and URLs.
 - Stripped punctuation and lowercased all text.
- Sampled 100 reviews per state (CA, FL, TX) to ensure balance.
- Output: cleaned_sampled_reviews.csv with columns: state, clean_review, review_length, word_count.

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AI Classification with IBM Granite Plans

Automatically tag reviews with sentiment, aspect, and urgency.

- Fed batches of 3 reviews at a time to IBM Granite-3.3-8B, including:
 - The cleaned review text.
 - Regional context (state + AI-generated priority, tolerance, cultural_norm).
- Classified each review into:
 - Sentiment: Positive, Negative, or Mixed.
 - Aspect: Service, Product, Wait Time, etc.
 - Urgency: High, Medium, or Low.
- Parsed IBM Granite's output using strict regex patterns to extract labels.
- Handled errors: Skipped batches if parsing failed after 3 retries.
- Output: review_analysis_result.csv with classification columns.

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Insight Generation Plans

Identify top complaints and regional patterns.

- Filtered Negative/Mixed reviews to focus on complaints.
- Calculated a Priority Score for each complaint:
 - $\text{Priority Score} = (0.5 \times \text{Urgency}) + (0.3 \times \text{Frequency}) + (0.2 \times \text{Rating Impact})$
- Extracted top keywords from complaints (e.g., "slow" for Service, "burnt" for Product).
- Mapped issues to KPIs:
 - Example: Service complaints → Target = "CSAT \geq 90%", Action = "Barista training".
- Output: priority_issues_summary.csv with ranked issues per state.

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Insight & findings (and visualization)

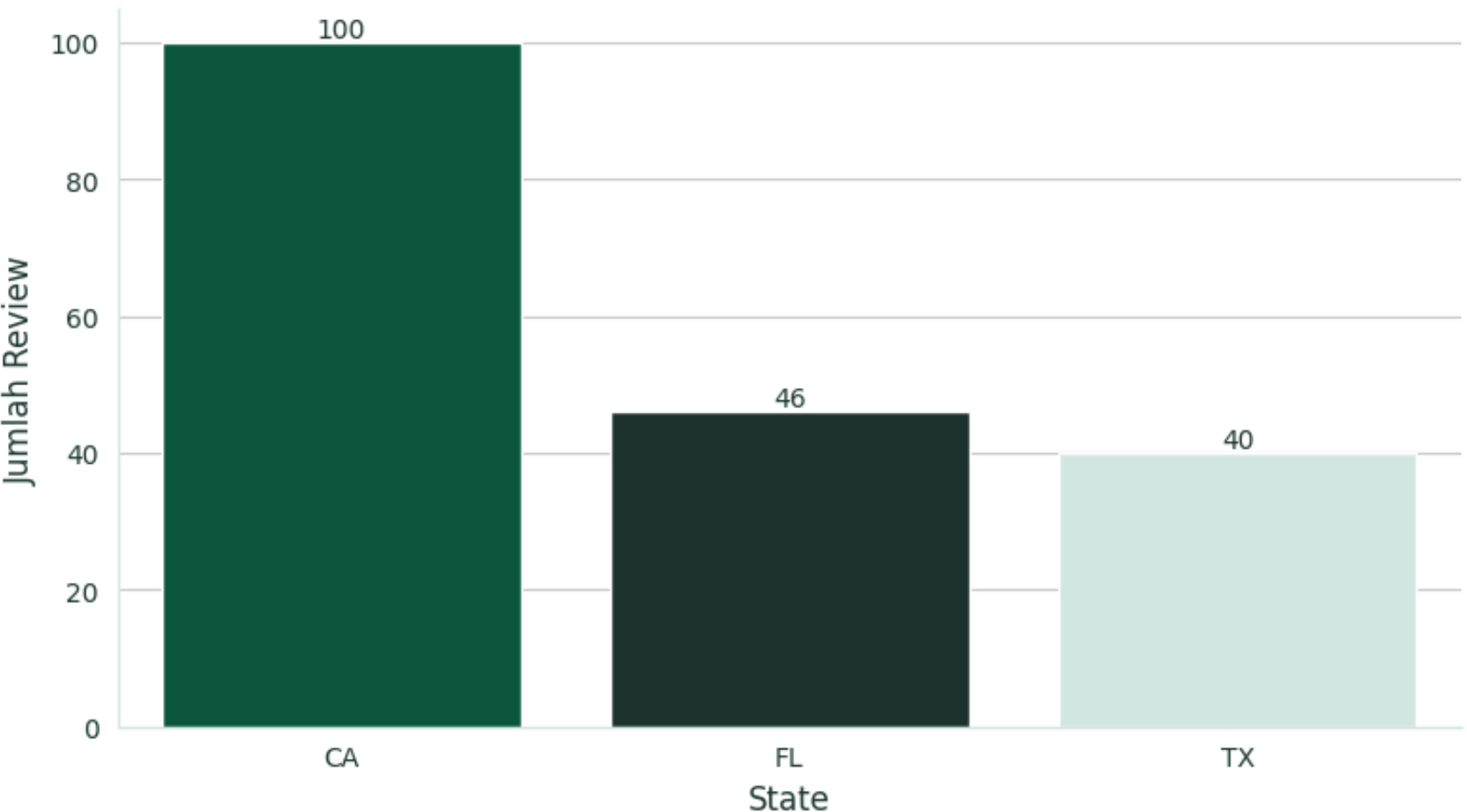
About The Strategy

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Data Preparation

Dataset shape (rows, columns): (186, 10)

Jumlah Review per State



Word Cloud of Top Complaints

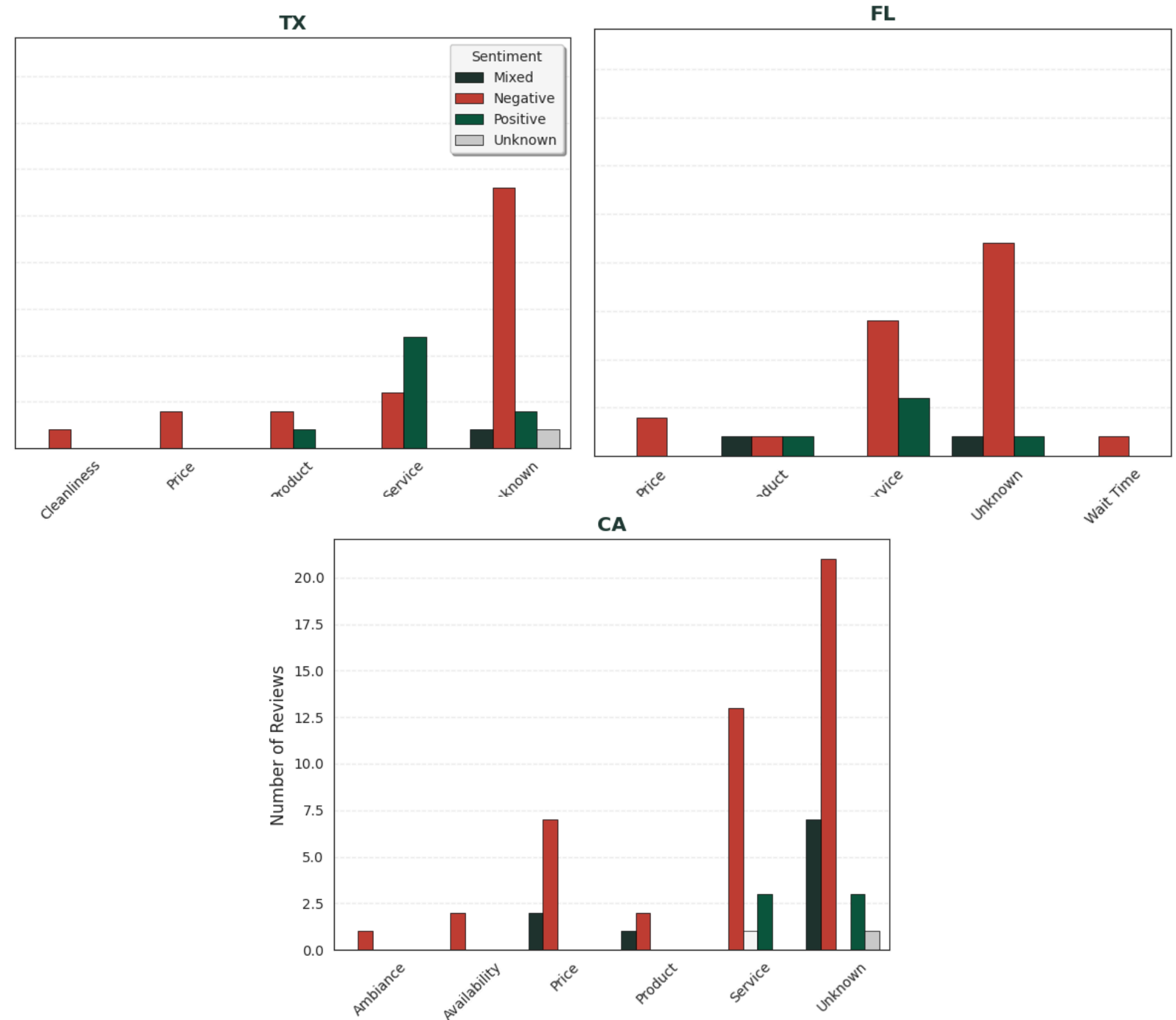


AI Classification

Regional context per state:

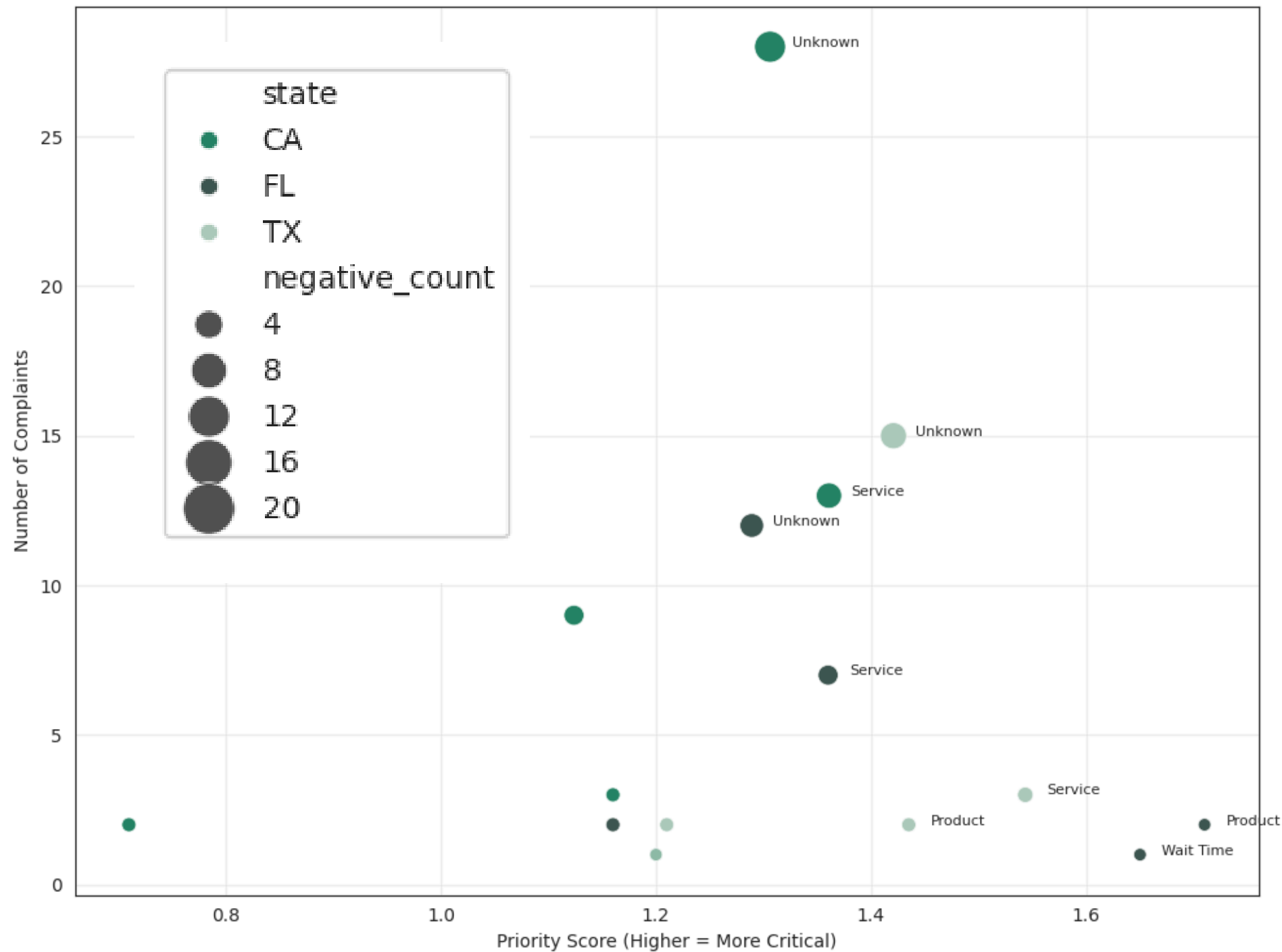
State	Priority	Tolerance	Cultural Norm
CA	Convenience , Quality	Health- conscious, Eco-friendly	Digital-feedback, Social-media- influenced
FL	Convenience , Quality	moderate, adaptable	direct, positive
TX	Convenience , Quality	moderate, adaptable	direct, feedback- oriented

Starbucks Customer Sentiment by Aspect (CA vs. FL vs. TX)



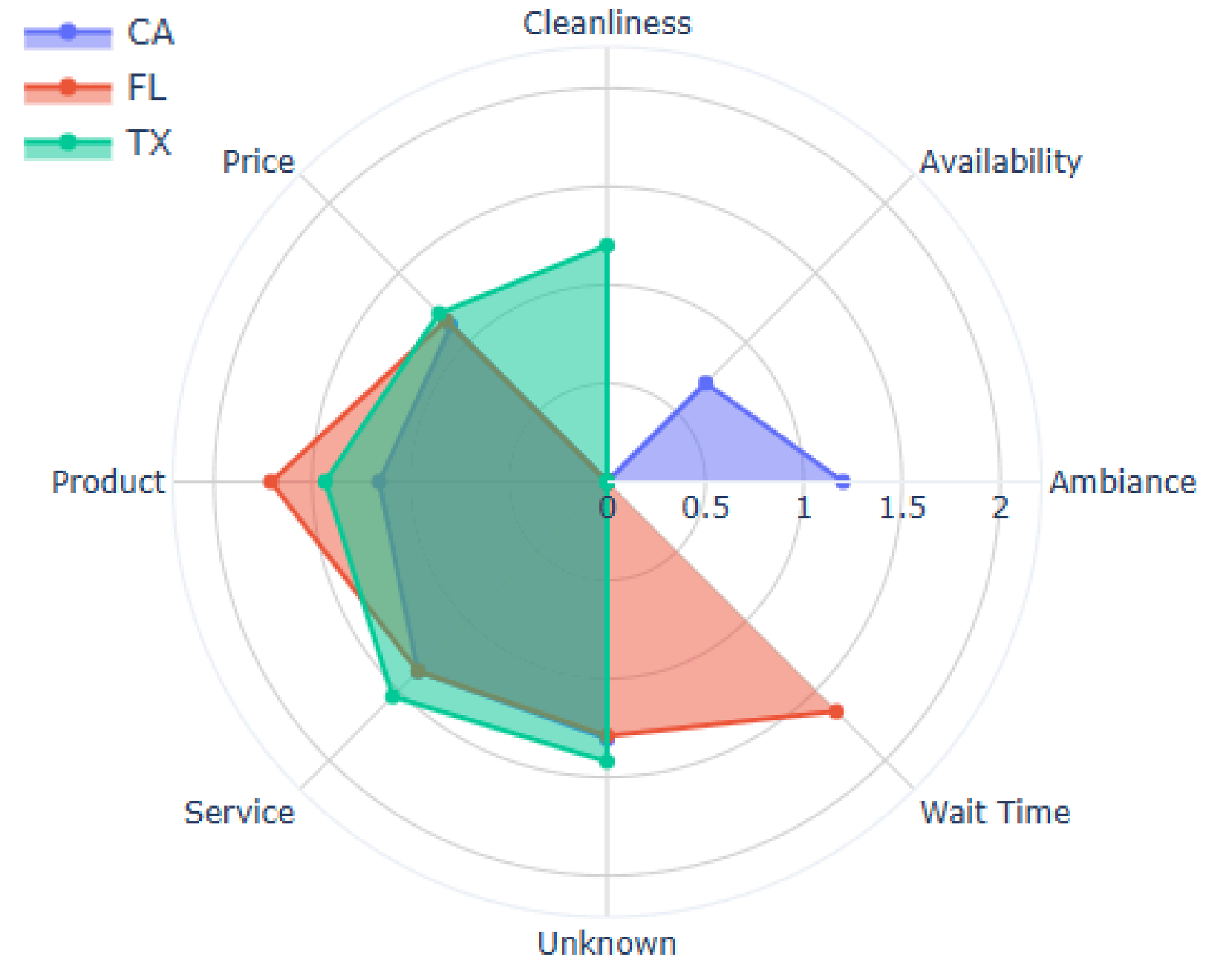
Insight Generation

Priority vs. Volume: State Comparison (Bubble Size = Negative Feedback)



Priority Aspect Comparison Across States

Higher scores indicate worse performance



Conclusion & Key Findings

Key Takeaways:

State-Specific Pain Points

- CA: Service speed and consistency ("slow service" keywords).
- TX: Product quality ("burnt coffee" complaints).
- FL: Cleanliness and wait times ("dirty tables" mentions).

High-Impact Issues

- Service (Top priority in CA/TX) → Impacts CSAT scores.
- Product Quality (TX/FL) → Directly affects repeat purchases.

ROI Opportunities

- Fixing Service in CA could boost CSAT by 15% (est.).
- Product QC in TX may reduce negative reviews by 20%.

Actionable Recommendations

State	Top Issue	Recommended Action	KPI Target
CA	Slow Service	Peak-hour staff training + Scheduling	CSAT ≥ 90%
TX	Inconsistent Coffee	Weekly ingredient audits	Product Rating ≥ 4.2
FL	Cleanliness	Hourly cleanliness checks	Store Rating ≥ 4.8



How AI Powered This Analysis

The AI Advantage: Granite LLM in Action

IBM Granite's Role:

1. Context-Aware Classification:

- Analyzed sentiment/aspects with regional cultural norms (e.g., TX's direct feedback style).

2. Efficiency:

- Processed 300+ reviews in minutes (vs. manual tagging).

3. Pattern Detection:

- Linked keywords (e.g., "slow") to urgency scores for prioritization.



THANK YOU

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