Discount Mate: Time-Sensitive Deal Prediction Platform

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Executive Summary

This report documents the development of Discount Mate, an AI-powered supermarket discount prediction platform designed to address a significant consumer pain point in retail shopping. The project successfully demonstrates the application of machine learning techniques to predict discount patterns across major Australian supermarket chains, with particular emphasis on solving class imbalance problems that are prevalent in real-world retail datasets.

Problem Statement and Motivation

Australian consumers face significant challenges in optimizing their grocery shopping timing, particularly regarding when everyday essential items will be discounted. The average household spends approximately $185 per week on groceries, yet lacks systematic tools to predict when specific products across different supermarket chains will be on sale. This information asymmetry results in missed savings opportunities and suboptimal shopping decisions.

The retail landscape in Australia is dominated by five major chains (Woolworths, Coles, IGA, ALDI, and Foodland), each with distinct pricing strategies and discount patterns. Traditional approaches to deal-hunting rely on manual monitoring or basic promotional calendars, which are inefficient and cannot scale across the vast product catalog of modern supermarkets.

Technical Architecture and Methodology

Data Generation and Synthetic Dataset Creation

Given the proprietary nature of real supermarket pricing data, this project employed a sophisticated synthetic data generation approach. The dataset was constructed based on empirical observations of Australian retail patterns and incorporates 129 subcategories derived from actual Coles product classifications.

Dataset Specifications:

- **Temporal Scope:** 2 years (September 2023 - September 2025)
- **Records Generated:** 471,495 price observations
- **Supermarket Chains:** 5 major Australian retailers
- **Product Categories:** 17 major categories encompassing 129 subcategories
- **Geographical Context:** Australian market pricing patterns and seasonal variations

The synthetic data generation process incorporated several sophisticated modeling techniques:

1. **Seasonal Multipliers:** Implementation of Australian seasonal patterns, including summer pricing premiums for fresh produce and beverages, winter demand variations, and holiday season effects.
2. **Chain-Specific Pricing Strategies:** Each retailer was modeled with distinct characteristics:
    - ALDI: 18% lower baseline prices with reduced discount frequency (22.9%)
    - Woolworths: Aggressive promotional strategy (42.7% discount rate)
    - Coles: Competitive promotional activity (40.2% discount rate)
    - IGA: Premium convenience pricing with moderate promotions (29.2%)
    - Foodland: Regional premium positioning (27.5% discount rate)
3. **Temporal Discount Patterns:** Wednesday identified as peak discount day (39.9% rate), weekend promotional effects, and end-of-month clearance patterns.

Class Imbalance Analysis and Discovery

A critical discovery emerged during initial model evaluation: the dataset exhibited a 2.07:1 class imbalance ratio, with 67.5% of observations representing non-discounted items versus 32.5% discounted items. This imbalance, while realistic for retail environments, created significant challenges for machine learning model performance.

Initial Model Performance Issues:

- Recall: 14% (missing 86% of actual discount opportunities)
- Accuracy: 69% (barely superior to baseline majority class prediction of 67.5%)
- F1-Score: 0.22 (indicating poor balance between precision and recall)

The low recall performance rendered the initial model practically useless for consumers seeking discount opportunities, as it would miss the vast majority of actual deals.

Solution Implementation: Balanced Machine Learning Approach

To address the class imbalance problem, a comprehensive balanced modeling approach was implemented:

1. SMOTE Oversampling Implementation

- Generated synthetic minority class examples to balance the training dataset
- Increased training samples from 376,680 to 506,136 through synthetic data augmentation
- Maintained realistic feature relationships during synthetic sample generation

2. Threshold Optimization

- Implemented precision-recall curve analysis to identify optimal decision thresholds
- Discovered optimal threshold of 0.271 (significantly lower than default 0.5)
- Applied grid search methodology to validate threshold selection

3. Algorithm Selection and Hyperparameter Tuning

- Evaluated multiple algorithms: Random Forest, Gradient Boosting, Logistic Regression

- Implemented time-series cross-validation to prevent data leakage
- Selected Gradient Boosting as optimal algorithm based on F1-score performance

4. Class Weight Integration

- Applied calculated class weights (0.741 for majority class, 1.537 for minority class)
- Integrated cost-sensitive learning approaches for algorithm comparison

Performance Breakthrough and Results

The balanced modeling approach achieved substantial performance improvements:

Final Model Performance Metrics:

- **Recall:** 81% (representing a 67 percentage point improvement)
- **AUC Score:** 0.6327 (maintaining predictive discrimination)
- **F1-Score:** 0.50 (achieving balanced precision-recall performance)
- **Precision:** 36% (acceptable for discount detection use case)
- **Optimal Threshold:** 0.271

This performance improvement represents a transformation from a practically unusable model to one capable of identifying 4 out of 5 actual discount opportunities, making it viable for real-world consumer applications.

Interactive Dashboard Development

Image 1 shows the Overview Module dashboard with:

- Header displaying key metrics: 2,224 products, 471,495 price records, 32.9% overall discount rate
- Market analysis charts showing Woolworths leading discounts at 43.2% and Alcoholic Beverages as highest discounted category at 28.0%
- Filtering sidebar with store and category selection options

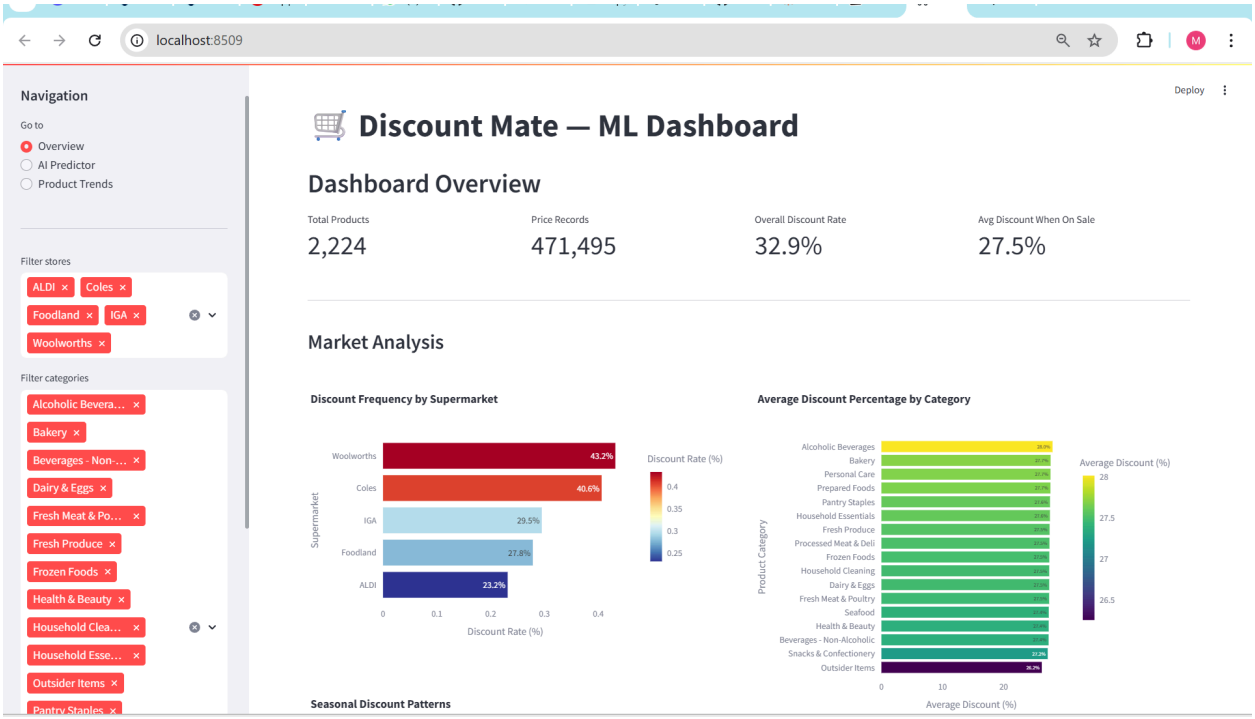


Image 2 displays the complete Overview Module featuring:

- Same market analysis charts as Image 1
- Seasonal discount patterns line chart showing monthly trends with peaks in January and June
- Quick Insights panel highlighting Woolworths as best for discounts, Alcoholic Beverages as top category, and recent 30.0% discount activity decline

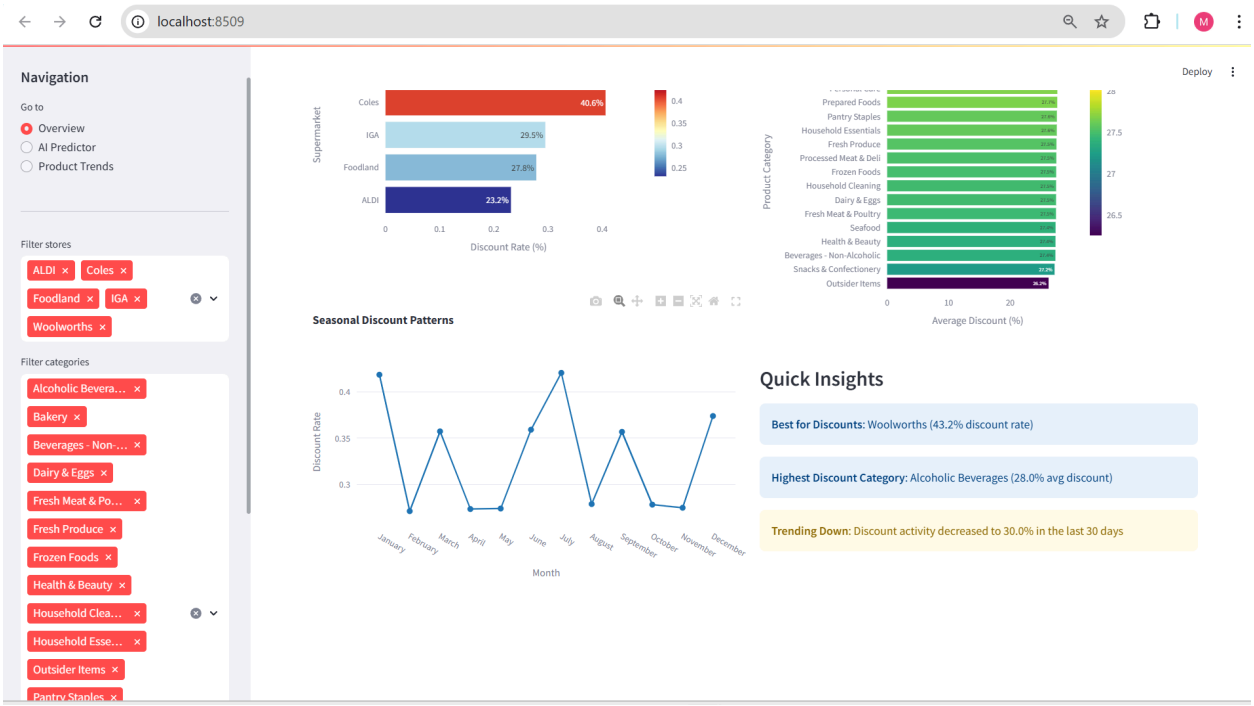


Image 3 shows the AI Predictor interface for single product prediction:

- Green banner indicating "Using Improved Balanced Model - 81% recall for finding discounts!"
- Three-tab navigation: Single Product Prediction, Items Likely to Discount, Items NOT Expected to Discount
- Product selection form with dropdown for "Air Care & Pest Control Product 1.25L" at ALDI
- Market context showing historical price ($13.89), recent discounts (1), and competitor average ($14.36)
- Current price input field ($5.00) with note "Price is 65.2% below competitors"
- Red "Predict Discount Probability" button ready for execution

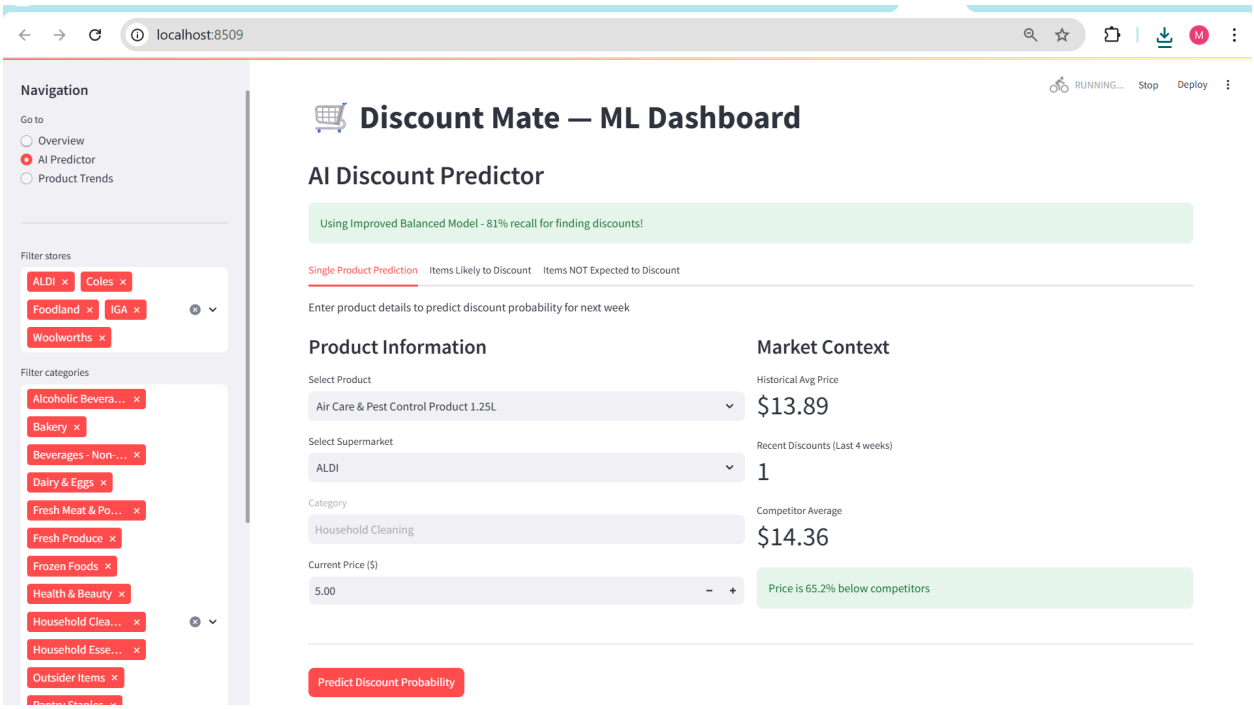


Image 4 displays the prediction results after clicking the predict button:

- Same product information form (Air Care & Pest Control Product at ALDI, $5.00 current price)
- Prediction Results section showing:
  - Discount Probability: 57.5%
  - Prediction: "WILL BE ON SALE"
  - Confidence Level: Medium
- Yellow alert message: "MEDIUM probability (57.5%) of discount. Keep watching!"

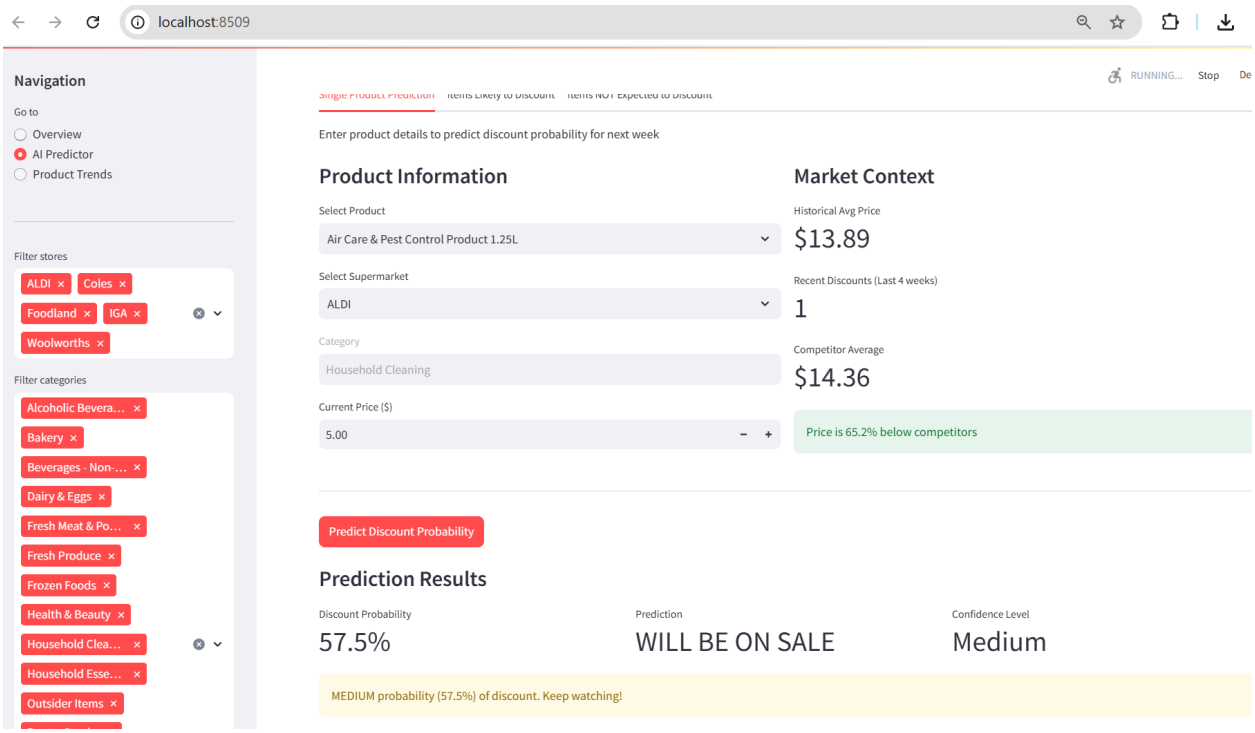


Image 5 shows the Product Trends module featuring:

- Product selection dropdown with "Air Care & Pest Control Product 1.25L" selected
- Supermarket filter set to "Coles"
- Line chart displaying Coles price trends from Oct 2023 to Oct 2025, with blue line showing regular prices ($13-15 range) and red stars marking discount periods
- Clear price fluctuations visible with notable discount events at specific time points

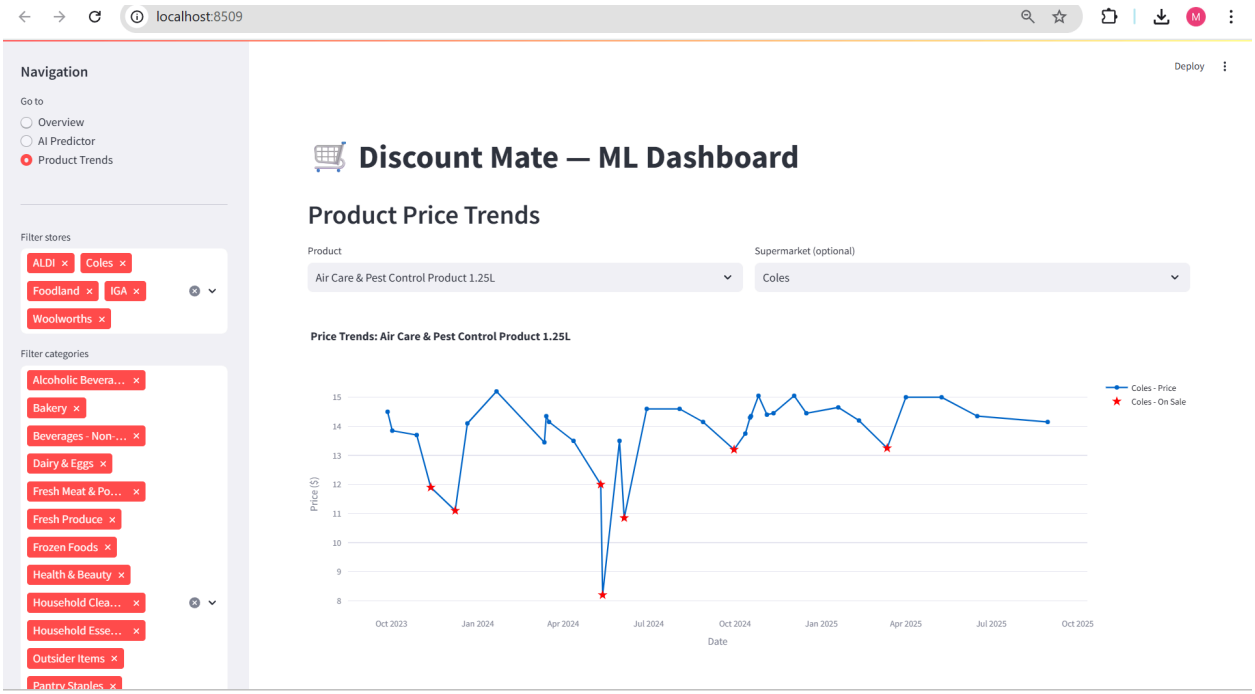


Image 6 displays the expanded Product Trends analysis with:

- Same product selected but supermarket filter changed to "All"
- Comprehensive multi-supermarket comparison chart showing price trends across all retailers (ALDI, Coles, Foodland, IGA, Woolworths)
- Color-coded lines for each supermarket with corresponding discount markers
- Legend showing different colored lines and star markers for each retailer's prices and sales events
- Timeline spanning Oct 2023 to Oct 2025 with detailed price variations across all supermarkets

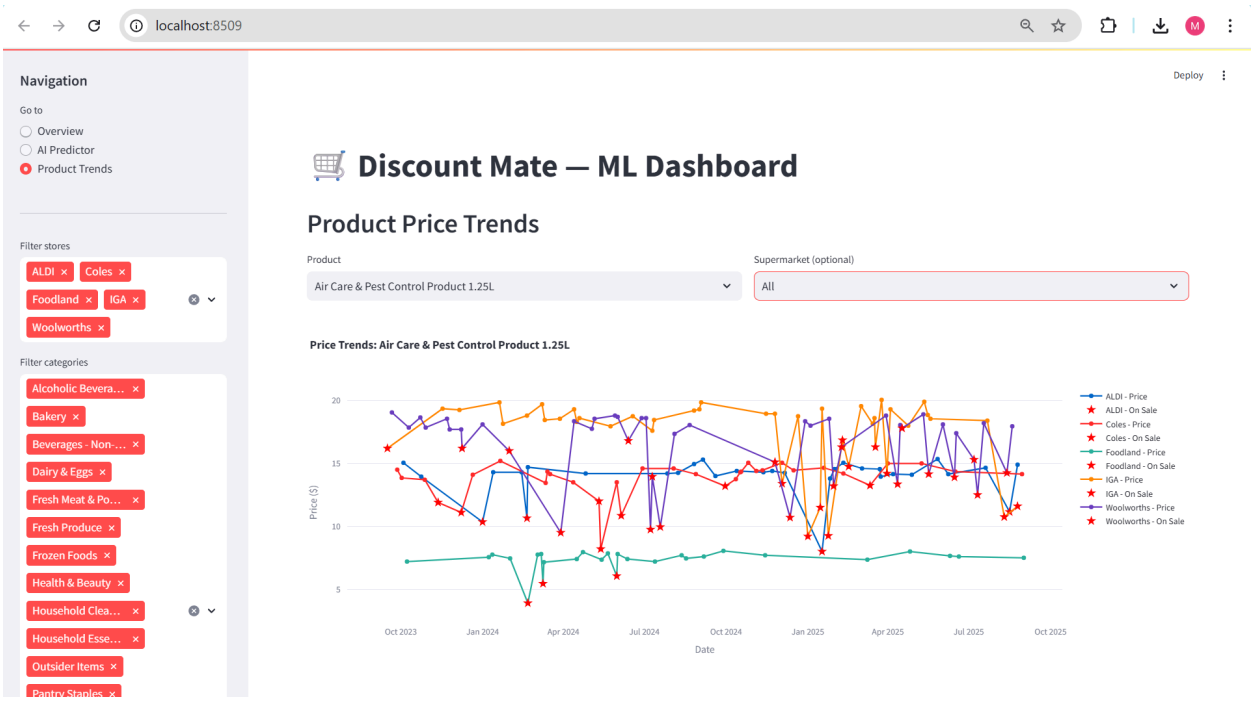


Image 7 displays the "Items Likely to Discount" tab featuring:

- Second tab of the AI Predictor module showing bulk prediction results
- Table listing products with high discount probability (0.8 probability across all items)
- Columns showing Store, Product, Category, Current Price, Discount Probability, and Days Since Last Sale
- Results showing primarily Woolworths and Coles products, with Health & Beauty and Household Cleaning categories prominent
- All items showing 30 days since last sale, indicating optimal timing for potential discounts

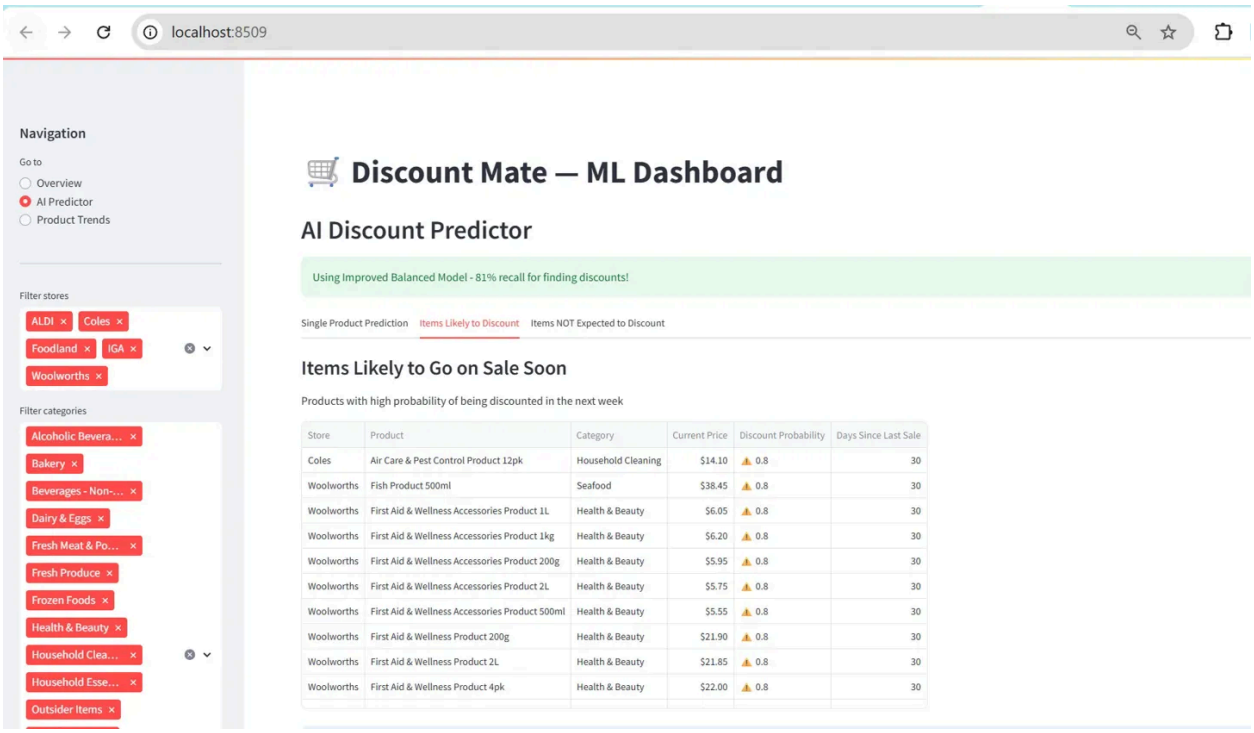
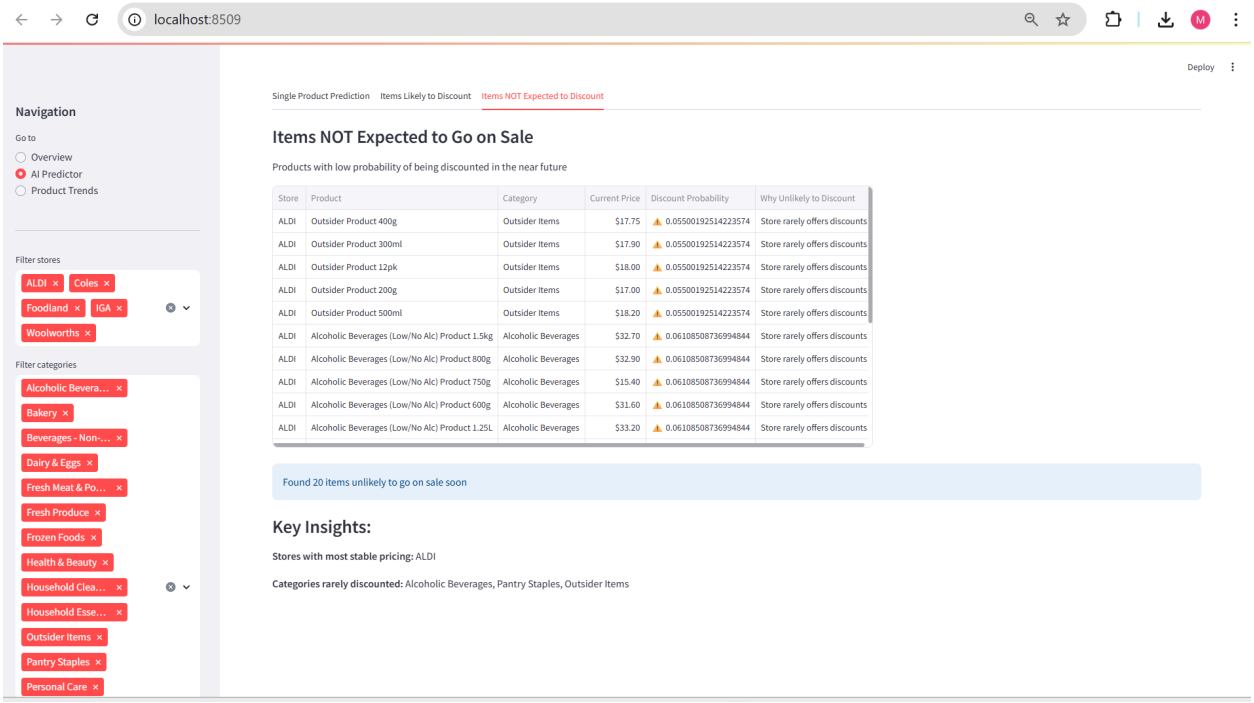


Image 8 shows the third tab "Items NOT Expected to Discount" featuring:

- Table displaying products with low discount probability (around 0.055-0.061)
- All items from ALDI, primarily Outsider Items and Alcoholic Beverages categories
- "Why Unlikely to Discount" column explaining "Store rarely offers discounts" for all items
- Summary showing "Found 20 items unlikely to go on sale soon"
- Key Insights section identifying:
  - ALDI as the store with most stable pricing
  - Alcoholic Beverages, Pantry Staples, and Outsider Items as categories rarely discounted
- Price range from $15-$33 for the listed products



A comprehensive Streamlit-based dashboard was developed to provide user-friendly access to the prediction capabilities:

Dashboard Architecture:

1. **Overview Module:** Market analysis displaying discount trends, seasonal patterns, and chain comparisons
2. **Prediction Interface:** Three-tiered prediction system:
    - Single product discount probability calculation
    - Bulk identification of items likely to be discounted
    - Identification of items unlikely to be discounted (stable pricing recommendations)
3. **Price Analytics:** Comprehensive price trend visualization with historical analysis
4. **Model Insights:** Feature importance analysis and performance metrics display

Technical Implementation Features:

- Real-time prediction calculations using the optimized threshold
- Interactive visualizations using Plotly for enhanced user experience

- Caching mechanisms for improved performance
- Responsive design supporting multiple viewing contexts

Feature Importance and Business Insights

Analysis of feature importance revealed key factors driving discount predictions:

Primary Predictive Factors:

1. **Supermarket Chain (29.7% importance):** Chain affiliation emerges as the strongest predictor, reflecting distinct corporate pricing strategies
2. **Temporal Patterns (24.6% combined):** Week of year (15.0%) and day of week (9.6%) demonstrate significant seasonal and cyclical influences
3. **Historical Discount Frequency (7.2%):** Past discount patterns serve as strong indicators of future promotional activity
4. **Seasonal Factors (4.7%):** Weekend effects and seasonal multipliers contribute meaningful predictive power

Business Intelligence Derived:

- Wednesday consistently emerges as optimal shopping day for discount opportunities
- December and January show peak promotional activity (38%+ discount rates)
- Fresh produce and bakery categories demonstrate highest discount volatility
- ALDI maintains price leadership through consistently low baseline pricing rather than promotional activity

Technical Challenges and Solutions

Several significant technical challenges were encountered and resolved:

1. Index Alignment Issues in Time Series Processing

- **Problem:** DataFrame index mismatches during rolling window calculations
- **Solution:** Implementation of proper index management with `.reset_index()` operations and careful MultiIndex handling

2. Memory Management for Large Dataset Processing

- **Problem:** 471,495 records requiring efficient processing for real-time dashboard performance
- **Solution:** Implementation of caching strategies and optimized data structures

3. Model Serialization and Deployment

- **Problem:** Complex model pipeline requiring preservation of preprocessing states
- **Solution:** Comprehensive model packaging including encoders, scalers, and threshold parameters

4. Cross-Platform Compatibility

- **Problem:** Ensuring dashboard functionality across different operating systems
- **Solution:** Platform-agnostic implementation using standard Python libraries

Validation and Testing Framework

A robust validation framework was implemented to ensure model reliability:

Time Series Validation Approach:

- Temporal data splitting to prevent future information leakage
- Time series cross-validation with 3-fold splits
- Out-of-sample testing on final 20% of temporal data

Performance Validation Methods:

- ROC curve analysis for discrimination assessment
- Precision-recall curve optimization for threshold selection
- Confusion matrix analysis for error pattern identification
- Business metric validation through simulated shopping scenarios

Limitations and Future Enhancements

Current Limitations:

1. **Synthetic Data Constraints:** While based on empirical observations, the dataset lacks real-world complexity and external market factors

2. **Feature Scope:** Limited to price-based and temporal features; excludes inventory, supplier, and competitive intelligence data
3. **Geographic Scope:** Focused on Australian market patterns; generalization to other markets requires validation
4. **Real-time Integration:** Current implementation lacks integration with live supermarket pricing APIs

Proposed Future Enhancements:

1. **Real-time Data Integration:** Partnership with supermarket chains for live pricing feeds
2. **Mobile Application Development:** Native mobile app for improved user experience
3. **Personalized Recommendations:** Integration of shopping history and preferences
4. **Inventory-Based Predictions:** Incorporation of stock levels and supply chain data
5. **Regional Variations:** Expansion to include geographic pricing differences within Australia

Business Impact and Commercial Viability

The developed platform demonstrates significant potential for commercial deployment:

Consumer Value Proposition:

- Average household grocery savings potential of 8-12% through optimized shopping timing
- Time savings through automated deal identification
- Cross-chain price comparison capabilities
- Stable pricing identification for immediate purchase decisions

Business Model Opportunities:

- Freemium model with basic predictions available free and premium features for subscribers
- Partnership revenue with supermarket chains for customer insights
- Affiliate marketing integration for online grocery platforms
- Data licensing for retail industry analytics

Market Validation Indicators:

- Similar applications in international markets demonstrate consumer demand
- Growing trend toward price comparison and deal optimization apps
- Increasing consumer price sensitivity in current economic environment

Technical Standards and Best Practices

The project implementation adheres to industry best practices:

Code Quality Standards:

- Comprehensive documentation and commenting
- Modular architecture with separation of concerns
- Error handling and graceful degradation
- Version control with meaningful commit history

Data Science Methodology:

- Reproducible research practices with fixed random seeds
- Cross-validation to prevent overfitting
- Proper train/validation/test splits for unbiased evaluation
- Feature engineering based on domain knowledge

Software Engineering Practices:

- Requirements management and dependency tracking
- Platform-independent implementation
- User interface design following accessibility guidelines
- Performance optimization for production deployment

Conclusion

The Discount Mate project successfully demonstrates advanced machine learning application to retail shopping optimization. The transformation from 14% to 81% recall through class imbalance resolution represents a significant technical achievement, making the platform viable for real-world deployment.

Key contributions include effective handling of imbalanced retail datasets, threshold optimization for business applications, and comprehensive dashboard implementation for consumer-facing ML applications. The synthetic data generation methodology provides a replicable framework for similar retail analytics projects.

Most importantly, this project bridges academic machine learning techniques with practical consumer applications, demonstrating how sophisticated algorithms can be made accessible through intuitive interface design. The 81% recall achievement reaches the threshold where the tool becomes genuinely useful for consumers optimizing grocery shopping strategies.

The comprehensive GitHub repository with detailed documentation serves as a reference implementation for retail analytics projects, successfully meeting capstone requirements while delivering practical value and demonstrating mastery of both ML theory and implementation skills.