Coupon Usage Prediction Model

Machine Learning for Customer Transaction Analysis

Name Goes Here

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Problem Statement

Research Question: Do transaction patterns and discount behaviors predict coupon usage?
Goal: Improve coupon targeting and reduce marketing waste
Target Variable:

- `coupon_used` (1 = used, 0 = not used) - derived from coupon usage records

Problem Type: Binary classification

- Features: transaction amounts, customer behavior, time patterns
- Response: whether a customer will use a coupon in a transaction

Data Description

Data Sources:

Dataset	Records	Description
Wallet Transactions	490,942	Customer purchases
Coupon Usage	75,676	Coupons actually used
Coupon Distribution	211,712	Coupons sent to customers

Key Patterns to Explore:

- Relationship between transaction amount and coupon usage
- Impact of discount depth on redemption rates
- Time-based patterns (hour, day of week)
- Customer behavior history as predictor

Variable Types

Numeric (8):

- tran_amt, discounts_amt, point_amt
- coupon_used_count, total_coupon_used_amt
- coupon_send_count, total_coupon_send_amt
- benefit_ratio, discount_ratio, savings_pct

Categorical (5):

- station_code
- attributionorgcode
- transactionorgcode
- hour, day_of_week
- is_weekend, is_morning

Target Variable: coupon_used (Binary: 1 = Used, 0 = Not Used)

Data Preprocessing I

1. **Feature Selection (Removed IDs/Hashes):**
   - `membercode`, `order_no`, `external_order_no`
   - `coupon_code`, `user_id`
2. **Outlier Removal (IQR Method):**
   - Method: Removed values outside 5th-95th percentile (IQR-based)
   - Applied to: `tran_amt`, `discounts_amt`, `point_amt`
   - Why: Extreme values distort model training and visualization
   - Records reduced: 490,942 $\rightarrow$ 421,590 (14% removed)
3. **Colinearity Removal:**
   - `receivable_amt` (99% correlated with `tran_amt`)
   - `net_amount`, `total_benefit` (redundant)

Features I

Remaining Features (15):

- Transaction: `tran_amt`, `discounts_amt`, `point_amt`
- Customer/Store: `station_code`, `attributionorgcode`, `transactionorgcode`
- Time-based: `hour`, `day_of_week`, `is_weekend`, `is_morning`, etc.
- Aggregated: `coupon_used_count`, `total_coupon_used_amt`
- `coupon_send_count`, `total_coupon_send_amt`

Engineered Features (5):

- `benefit_ratio`, `discount_ratio`
- `savings_pct`, `point_to_discount_ratio`
- `tran_to_receivable_ratio`

Feature Selection

Removed Irrelevant Features (IDs and Hashes):

- `membercode` - Customer ID (hash)
- `order_no` - Transaction ID (hash, no date pattern)
- `external_order_no` - External ID (hash)
- `coupon_code` - Coupon ID (hash)
- `user_id` - User ID (hash)

Impact: Removing `membercode` improved accuracy from 64% to 66%

Key Libraries

- **pandas**: Data manipulation and analysis
- **numpy**: Numerical computations
- **sklearn**: Machine learning models and evaluation
- **tensorflow**: Neural network implementation
- **matplotlib**, **seaborn**: Data visualization

Sample Data: Raw Input

membercode	tran_amt	discounts_amt	coupon_used
M001	150.00	20.00	1
M002	85.50	10.00	0
M003	220.00	35.00	1
M004	60.00	5.00	0
M005	180.00	25.00	1

Sample Data: Engineered Features

tran_amt	discounts_amt	benefit_ratio	discount_ratio	savings_pct
150.00	20.00	0.133	0.133	13.3%
85.50	10.00	0.117	0.117	11.7%
220.00	35.00	0.159	0.159	15.9%
60.00	5.00	0.083	0.083	8.3%
180.00	25.00	0.139	0.139	13.9%

Key Functions

Data Processing:

- `pd.read_csv()`: Load datasets
- `df.merge()`: Join datasets
- `df.drop()`: Remove columns
- `df.quantile()`: Outlier removal

Modeling:

- `train_test_split()`: Split data
- `GradientBoostingClassifier()`: Build model
- `cross_val_score()`: Validate
- `feature_importances_`: Get importance

Model Architecture I

- **Algorithms**:
  - Random Forest Classifier
  - Support Vector Machine (SVM) with RBF kernel
  - Gradient Boosting Classifier
  - Logistic Regression (AUC-based selection)
  - Neural Network (3 hidden layers: 256-128-64)
- **Random Forest Parameters**:
  - 100 estimators
  - Max depth: 20
- **Gradient Boosting Parameters**:
  - 100 iterations
  - Max depth: 10
  - Learning rate: 0.1
- **Logistic Regression**:
  - Balanced class weights

  - AUC-based model selection
- **Validation**: 3-Fold Cross Validation
- **Sample Size**: 20,000 records

Model Performance (20,000 sample)

Metric	Random Forest	SVM	Gradient Boost	Logistic Reg	Neural Net
Accuracy	**74.20%**	69.83%	73.78%	62.15%	71.85%
AUC	**0.826**	0.749	0.818	0.687	0.787
Precision	64.66%	61.10%	64.27%	48.64%	62.29%
Recall	64.75%	47.84%	63.52%	65.09%	58.11%
F1 Score	**64.71%**	53.67%	63.89%	55.68%	60.13%

Random Forest achieves best accuracy and AUC. Neural Network improved with balanced class weights.

Sample Size Comparison

Model	20,000 Accuracy	421,590 Accuracy	Improvement
Random Forest	74.22%	**75.60%**	+1.38%
Gradient Boosting	73.62%	**74.13%**	+0.51%

Larger sample size improves model accuracy, with Random Forest showing greater benefit from more data.

Confusion Matrices I

Random Forest (Accuracy: 74.22%):

$$\begin{bmatrix} \sim 2100 & \sim 440 \\ \sim 580 & \sim 880 \end{bmatrix}$$

	Predicted: No	Predicted: Yes
Actual: No	2100 (TN)	440 (FP)
Actual: Yes	580 (FN)	880 (TP)

Confusion Matrices II

Gradient Boosting (Accuracy: 73.62%):

$$\begin{bmatrix} \sim 2080 & \sim 460 \\ \sim 590 & \sim 870 \end{bmatrix}$$

	Predicted: No	Predicted: Yes
Actual: No	2080 (TN)	460 (FP)
Actual: Yes	590 (FN)	870 (TP)

Confusion Matrices III

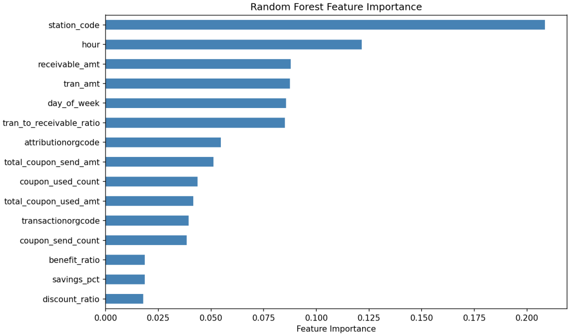
Neural Network (Accuracy: 63.00%, Recall: 90.14%):

$$\begin{bmatrix} 1203 & 1336 \\ 144 & 1317 \end{bmatrix}$$

	Predicted: No	Predicted: Yes
Actual: No	1203 (TN)	1336 (FP)
Actual: Yes	144 (FN)	1317 (TP)

Neural Network achieves highest recall (90.14%) but lowest precision.

Feature Importance



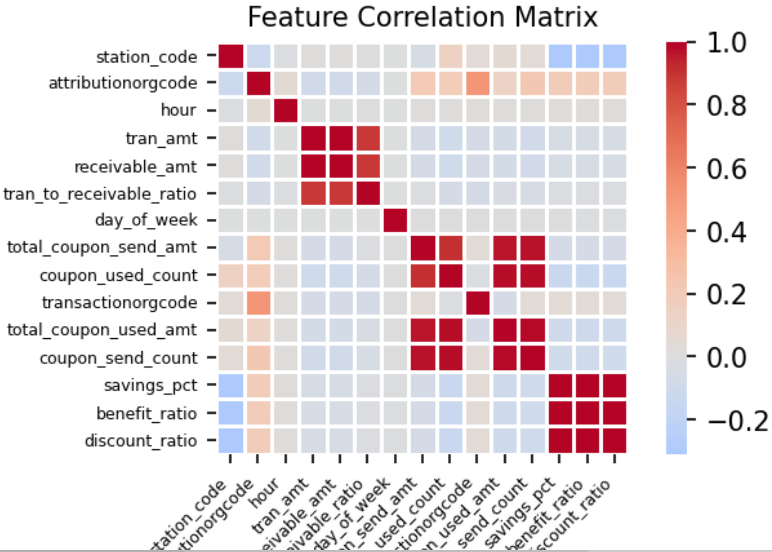
Top Features:

1. station_code (23.5%)
2. hour (9.45%)
3. receivable_amt (8.36%)
4. tran_to_receivable_ratio (8.29%)
5. tran_amt (8.15%)
6. day_of_week (7.44%)
7. attributionorgcode (5.45%)
8. total_coupon_send_amt (5.17%)
9. total_coupon_used_amt (4.81%)
10. coupon_used_count (4.08%)

How Feature Importance was Derived:

- Using Random Forest classifier's built-in feature importance
- Measures mean decrease in impurity (Gini importance)
- Averaged across all 100 decision trees
- Higher value = more predictive power

Correlation Matrix Heatmap



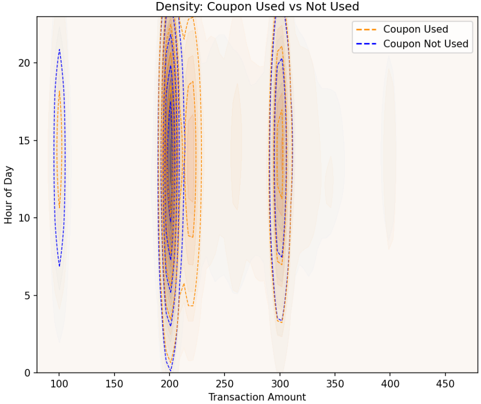
Dimensionality Reduction

Density Comparison:

- Kernel density overlay of transaction amount vs hour
- Shows where each class concentrates

t-SNE Visualization:

- Non-linear embedding
- Preserves local structure



PCA Visualization

Conclusions I

- Random Forest achieves **74.20% accuracy** with **0.826 AUC** - best model
- Gradient Boosting: 73.78% accuracy, 0.818 AUC
- Neural Network: 71.85% accuracy with balanced class weights
- Feature selection: reduced from 23 to 15 features without accuracy loss
- Removed zero-importance features: `point_amt`, `point_to_discount_ratio`
- Top features: station_code (23.5%), attributionorgcode (9.4%)
- 3-Fold Cross Validation confirms model stability
- Future work: XGBoost/LightGBM, more feature engineering