

Deep Learning Based Product Reordering Prediction

Technical Documentation

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Feature Generation

1. Data Integration Process

The feature engineering process begins with merging multiple datasets to create a comprehensive user-product interaction view:

```
python

# Product enrichment with aisle and department information
products = pd.merge(products, aisles, on='aisle_id', how='left')
products = pd.merge(products, departments, on='department_id', how='left')

# Order-product integration with user information
orders_prior = pd.merge(order_products_prior, orders, on='order_id', how='left')
orders_full = pd.merge(orders_prior, products, on='product_id', how='left')
```

2. Feature Categories

2.1 User-Level Features

Generated by aggregating user behavior across all orders:

- `user_total_orders`: Maximum order number per user (indicates user engagement level)
- `user_avg_days_between_orders`: Average days between consecutive orders (ordering frequency pattern)
- `user_days_since_last_order`: Days since the user's most recent order (recency indicator)

python

```
user_features = df.groupby('user_id').agg(  
    user_total_orders=('order_number', 'max'),  
    user_avg_days_between_orders=('days_since_prior_order', 'mean'),  
    user_days_since_last_order=('days_since_prior_order', 'last')  
) .reset_index()
```

2.2 Product-Level Features

Aggregated product popularity metrics across all users:

- **prod_total_orders**: Total times the product was ordered (product popularity)
- **prod_reorders**: Total reorder instances for the product (reorder appeal)
- **prod_reorder_ratio**: Ratio of reorders to total orders (product loyalty metric)

python

```
product_features = df.groupby('product_id').agg(  
    prod_total_orders=('reordered', 'count'),  
    prod_reorders=('reordered', 'sum'),  
    prod_reorder_ratio=('reordered', 'mean')  
) .reset_index()
```

2.3 User-Product Interaction Features

Captures specific user-product relationship dynamics:

- **up_orders**: Number of times specific user ordered this product
- **up_first_order**: Order sequence when user first tried this product
- **up_last_order**: Most recent order sequence for this product
- **up_reorders**: Number of reorder instances for this user-product pair

python

```
user_product_features = df.groupby(['user_id', 'product_id']).agg(  
    up_orders=('order_number', 'count'),  
    up_first_order=('order_number', 'min'),  
    up_last_order=('order_number', 'max'),  
    up_reorders=('reordered', 'sum')  
) .reset_index()
```

2.4 Derived Features

Computed ratios providing normalized interaction metrics:

- **up_order_rate**: User-product order frequency relative to user's total activity
 - Formula: $\text{up_orders} / \text{user_total_orders}$
 - Indicates product importance in user's shopping basket

3. Data Quality and Distribution Analysis

3.1 Missing Value Treatment

- **Primary Gap**: **days_since_prior_order** contains nulls for first-time orders
- **Solution**: Fill missing values with 0, representing new customer baseline

3.2 Skewness Correction

Statistical analysis revealed high skewness in numerical features:

Original Distribution Issues:

- Most features showed significant positive skewness (>2.0)
- High kurtosis indicating extreme outliers
- Non-normal distributions affecting model performance

Log Transformation Applied:

python

```
log_transform_cols = [  
    'up_orders', 'up_first_order', 'up_last_order',  
    'up_reorders', 'up_order_rate', 'user_total_orders',  
    'prod_total_orders', 'prod_reorders'  
]  
  
for col in log_transform_cols:  
    final_features_new[col] = np.log1p(final_features_new[col])
```

Post-Transformation Results:

- Reduced skewness to acceptable ranges (typically <2.0)
- Improved kurtosis values
- Better feature distribution for neural network training

3.3 Categorical Encoding

- **Method**: Label Encoding for categorical variables
- **Variables Encoded**: product_name, aisle, department

- **Rationale:** Maintains ordinal relationships while enabling neural network processing

4. Class Imbalance Handling

Original Distribution:

- Class 0 (No Reorder): ~89%
- Class 1 (Reorder): ~11%

Undersampling Strategy:

- **Method:** RandomUnderSampler
 - **Sampling Ratio:** 0.666 (approximately 2:3 ratio)
 - **Rationale:** Balance classes while preserving sufficient training data
-

Model Architecture

1. Neural Network Design

1.1 Architecture Overview

Deep Feedforward Neural Network with regularization:

```
Input Layer (11 features)
  ↓
Dense Layer 1: 256 neurons + ReLU + BatchNorm + Dropout(0.3)
  ↓
Dense Layer 2: 128 neurons + ReLU + BatchNorm + Dropout(0.25)
  ↓
Dense Layer 3: 64 neurons + ReLU + BatchNorm + Dropout(0.2)
  ↓
Dense Layer 4: 32 neurons + ReLU + BatchNorm + Dropout(0.15)
  ↓
Output Layer: 1 neuron + Sigmoid
```

1.2 Layer-by-Layer Specification

Hidden Layer 1:

- **Neurons:** 256
- **Activation:** ReLU (for non-linearity)
- **BatchNormalization:** Stabilizes training and accelerates convergence
- **Dropout:** 30% (prevents overfitting on complex patterns)

Hidden Layer 2:

- **Neurons:** 128 (progressive reduction)
- **Dropout:** 25% (slightly reduced as network narrows)

Hidden Layer 3:

- **Neurons:** 64
- **Dropout:** 20%

Hidden Layer 4:

- **Neurons:** 32
- **Dropout:** 15% (minimal dropout near output)

Output Layer:

- **Neurons:** 1
- **Activation:** Sigmoid (binary classification probability)

1.3 Training Configuration

Optimizer:

- **Type:** Adam optimizer
- **Learning Rate:** 0.001
- **Rationale:** Adaptive learning rate with momentum for stable convergence

Loss Function:

- **Type:** Binary Cross-Entropy
- **Justification:** Optimal for binary classification problems

Metrics Monitored:

- **Accuracy:** Overall classification performance
- **Precision:** True positive rate among predictions
- **Recall:** True positive rate among actual positives
- **AUC:** Area under ROC curve for threshold-independent evaluation

Regularization Techniques:

1. **Dropout:** Prevents overfitting by randomly deactivating neurons
2. **Batch Normalization:** Reduces internal covariate shift
3. **Early Stopping:** Prevents overfitting by monitoring validation loss

Training Parameters:

- **Batch Size:** 512 (balance between memory efficiency and gradient stability)
- **Maximum Epochs:** 50
- **Early Stopping Patience:** 10 epochs
- **Validation Split:** Separate validation set for unbiased evaluation

2. Data Preprocessing for Model Input

2.1 Feature Scaling

```
python

scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train_numeric)
x_val_scaled = scaler.transform(x_val_numeric)
x_test_scaled = scaler.transform(x_test_numeric)
```

Rationale: Neural networks require normalized inputs for optimal performance

2.2 Train-Validation-Test Split

- **Training:** 70% of undersampled data
 - **Validation:** 10% (for model selection and hyperparameter tuning)
 - **Test:** 20% (for final unbiased evaluation)
 - **Stratification:** Maintains class distribution across splits
-

Evaluation Results

1. Model Performance Metrics

1.1 Classification Performance

Target Achievement:

- **F1-Score Requirement:** >0.65 ✓
- **Actual Performance:** Achieved target on validation data

Key Metrics:

- **Accuracy:** Overall prediction correctness
- **Precision:** Minimizes false positive recommendations
- **Recall:** Captures actual reorder instances
- **F1-Score:** Balanced precision-recall performance
- **ROC-AUC:** Discrimination ability across all thresholds

1.2 Confusion Matrix Analysis

The confusion matrix provides detailed breakdown of:

- **True Positives:** Correctly predicted reorders
- **True Negatives:** Correctly predicted non-reorders
- **False Positives:** Incorrectly predicted reorders (marketing cost)
- **False Negatives:** Missed reorder opportunities (lost revenue)

2. Business Validation Results

2.1 Personalized Product Recommendation

High-Confidence Predictions (Probability > 0.7):

- Identified top products with highest reorder likelihood
- Recommendation accuracy measured for high-probability predictions
- Focus on products with sufficient frequency (>5 occurrences)

Key Insights:

- Products with consistently high reorder probabilities across users
- Correlation between predicted and actual reorder rates
- Recommendation system effectiveness validation

2.2 Inventory Management

Demand Forecasting by Department/Aisle:

- Aggregated reorder predictions for inventory planning
- Comparison of predicted vs. actual demand
- Demand accuracy calculation: $1 - \frac{|predicted - actual|}{actual}$

Performance Metrics:

- Overall demand forecasting accuracy across categories
- Identification of high-demand departments/aisles
- Inventory optimization insights

2.3 Customer Retention Analysis

Churn Risk Assessment:

- Low reorder probability (<0.3) indicates potential churn
- Customer-level aggregation of reorder probabilities

- Churn prediction accuracy validation

Results:

- Percentage of customers identified as high churn risk
- Accuracy of churn risk predictions
- Customer retention strategy insights

2.4 Marketing Optimization

Customer Segmentation by Reorder Intent:

- **High Intent (≥ 0.8):** Upsell opportunities
- **Medium Intent (0.5-0.8):** Nurturing campaigns
- **Low Intent (0.2-0.5):** Re-engagement strategies
- **Very Low Intent (< 0.2):** Win-back campaigns

Segment Performance:

- Actual conversion rates by predicted segment
- Marketing campaign targeting effectiveness
- ROI optimization through segment-specific strategies

3. Model Validation and Robustness

3.1 Generalization Performance

- Consistent performance across training, validation, and test sets
- No significant overfitting observed with regularization techniques
- Stable predictions across different user and product segments

3.2 Feature Importance and Interpretability

- User-product interaction features showed highest predictive power
- Product-level features contributed to general reorder patterns
- User-level features provided personalization context

3.3 Deployment Readiness

Model Artifacts Generated:

- `instacart_model.keras`: Trained neural network model
- `scaler.pkl`: Feature scaling parameters
- Encoder mappings for categorical variables

Production Considerations:

- Consistent preprocessing pipeline
 - Scalable prediction infrastructure via Streamlit interface
 - Real-time prediction capability for individual user-product pairs
-

Business Impact Analysis

1. Revenue Optimization

- **Precision-focused:** Minimize wasted marketing spend on unlikely reorders
- **Recall-balanced:** Capture sufficient reorder opportunities
- **Probability-based:** Enable threshold tuning for different business objectives

2. Operational Efficiency

- **Inventory Planning:** Data-driven demand forecasting
- **Customer Targeting:** Segment-specific marketing strategies
- **Resource Allocation:** Focus on high-value customer-product combinations

3. Strategic Insights

- **Product Portfolio:** Identify high-loyalty vs. trial products
- **Customer Behavior:** Understand reorder patterns and preferences
- **Market Dynamics:** Predict category-level demand trends

This documentation provides comprehensive coverage of the technical implementation, validation results, and business applications of the deep learning-based product reordering prediction system.