



COOK YOUR OWN FOOD, ORDER YOUR OWN FOOD

COOK & ORDER ANALYSIS

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Introduction

This report focuses on understanding user behavior, cooking preferences, and order trends by analyzing three distinct datasets: **UserDetails**, **CookingSessions**, and **OrderDetails**. By integrating these datasets, the goal is to uncover valuable insights into user interactions, popular dishes, and demographic factors shaping preferences. The analysis will serve as a foundation for data-driven business decisions, enhancing customer satisfaction and operational efficiency.

Objectives

1. Data Cleaning and Integration

- Ensure data consistency and quality by cleaning and merging the three datasets into a unified format.

2. Relationship Analysis

- Examine the connections between user participation in cooking sessions and their order behaviour.

3. Popular Dish Identification

- Determine the most frequently cooked and ordered dishes, highlighting key preferences.

4. Demographic Behavior Exploration

- Investigate how demographic factors such as age, gender, and location influence cooking and ordering habits.

5. Visualization Development

- Create clear, insightful visualizations to represent trends, patterns, and relationships effectively.

6. Business Recommendations

- Provide actionable recommendations based on the findings to enhance user engagement and business outcomes.

Data Overview:

User Details

- **Age:** Average = 32 years (range 25–42), indicating a diverse age group.
- **Total Orders:** Average = 9 (range 5–15), showing moderate activity levels.

Order Details

- **Amount Spent:** Average = \$11.25 (range \$7–\$15), reflecting affordable pricing.
- **Rating:** High satisfaction with average = 4.3/5.

Session Details

- **Duration:** Average session = 30 mins (range 10–45 mins), showing reasonable engagement.
- **Session Rating:** High user satisfaction, average = 4.5/5.

Data Flow



Data Preprocessing:

Missing Value Imputation:

Use: `.isnull().sum()` to identify missing values in each dataset.

Output:

Imputing Numerical Variables: For the Missing Values in Rating, i have used KNN Imputer to predict and fill missing values. It captures the underlying relationships between features for accurate imputation using the neighbor points.

Standardize Column Names:

Rename 'amount_(usd)' to 'amount' in order_details for uniformity.

Merge Datasets:

Merge user_details with cooking_sessions using user_id.

Combine the result with order_details using user_id

Standardization

1. Subtract the mean of each feature.
 2. Divide each feature by its standard deviation.
 3. Use StandardScaler
-

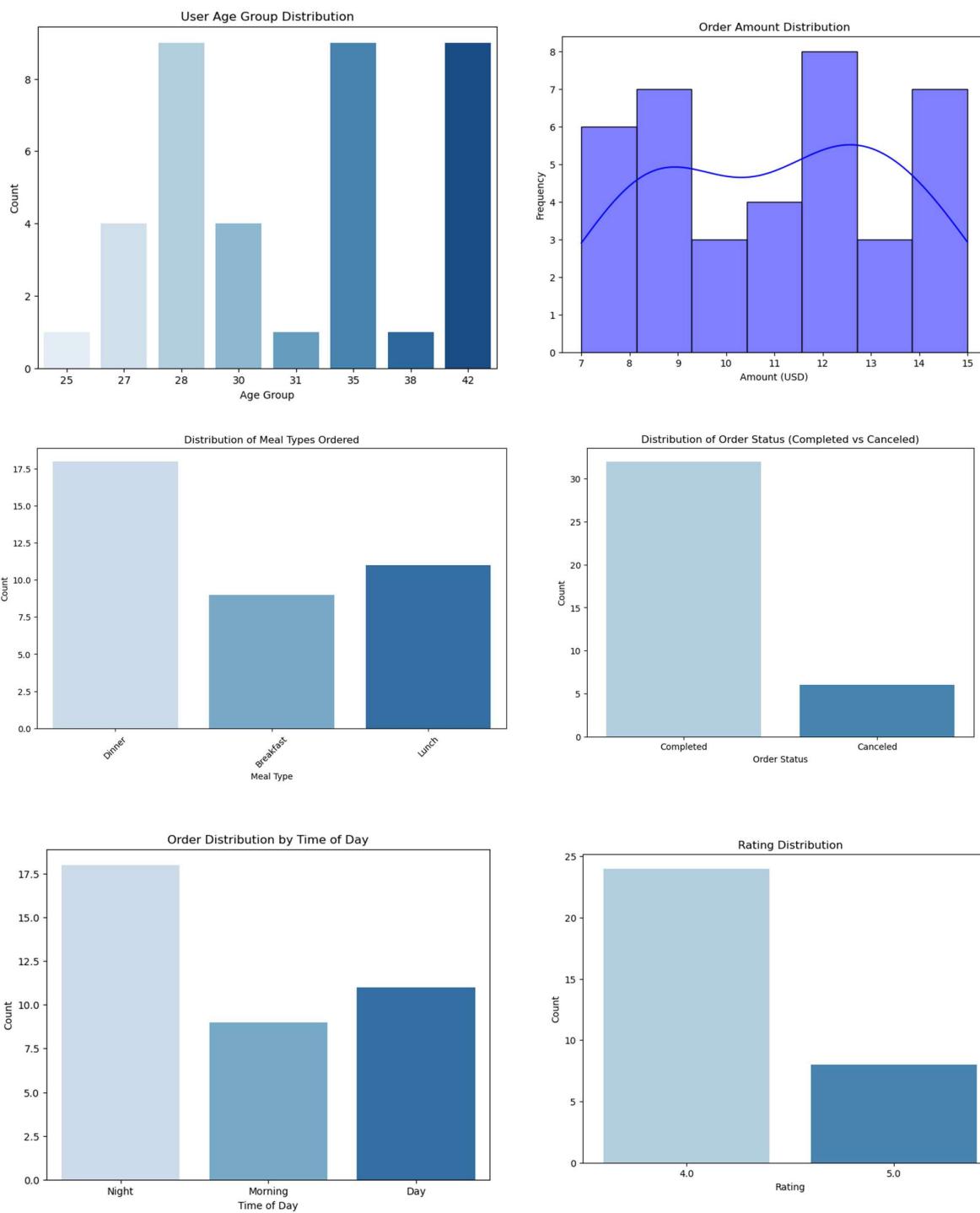
Normalization (if required)

1. Subtract the minimum value of each feature.
 2. Divide by the range (max - min).
 3. Use MinMaxScaler
-

Encoding

1. Apply one-hot encoding using `pd.get_dummies()` or OneHotEncoder to categorical columns
2. Add encoded columns back to the dataset and drop the original categorical columns

Data Distribution



Data Distribution and Business Insights

Interpretation:

 **Key Demographic:** Majority of users are aged **30-35**, a critical segment for targeting. Younger (25-27) and older (36-42) groups are less prevalent.

Introducing **age-specific features** and meal options for younger (25-27) and older (36-42) groups could broaden the customer base and boost inclusivity.

 **Order Amount Trends:** **Bimodal distribution** with peaks at **\$9-10** and **\$12-13**, hinting at two distinct customer types.

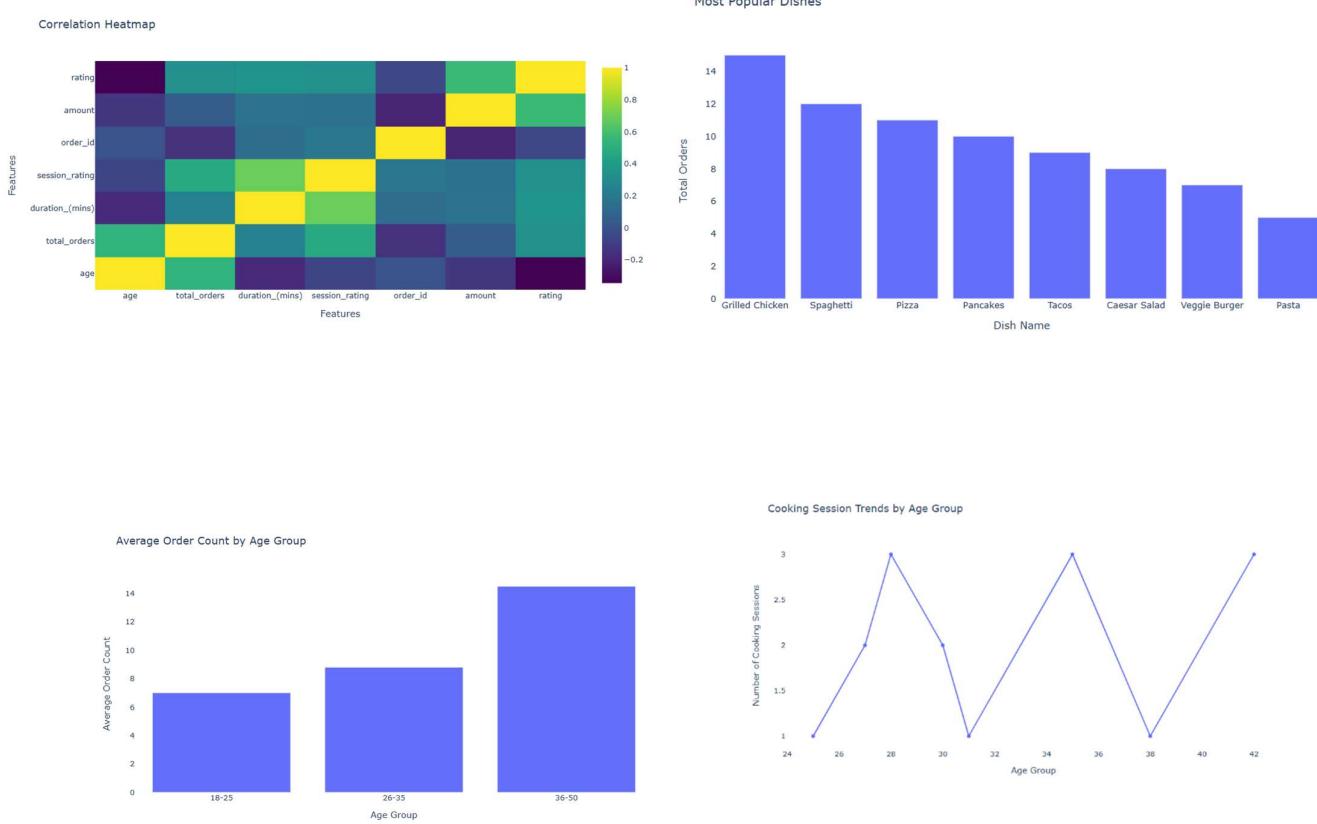
Budget-conscious: Attract with affordable pricing, combo deals, and value packs.

Premium spenders: Appeal with high-quality, exclusive dishes and loyalty programs.

 **Order Cancellations:** While most orders are completed, cancellations are notable. Addressing this could enhance satisfaction and efficiency.

Implement **real-time updates**, **flexible options**, and **follow-up offers** to minimize cancellations and recover lost opportunities.

Exploratory Data Analysis



Interpretation:

Dish Correlations:

- Positive correlations** (GREEN/YELLOW): Certain dishes are often ordered together—great for bundling or combo deals.
- Negative correlations** (RED/PURPLE): Some dish combinations are rare—useful for optimizing menu layout.

⭐ Most Popular Dishes:

- Top Picks:** Grilled Chicken, Spaghetti, and Fries lead the charts!
- Focus inventory, marketing, and promotions around these high-demand items.

👥 Order Count by Age:

- 25-31 age group** places the most orders—key demographic for targeted campaigns.

Comparison Of Dish Made in session increases the Rating of dish order

Summary of order trends after session rating decrease:
order_rating_category dish_similarity count
0 High (>4) False 4
1 High (>4) True 4
2 Low (<=4) False 18
3 Low (<=4) True 12

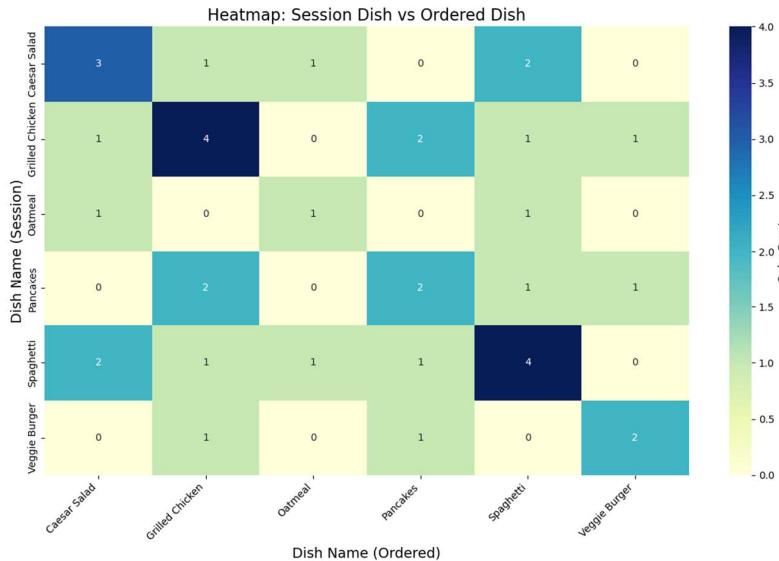
Records where a different dish was ordered:

| user_id | dish_name_x | dish_name_y | session_rating | rating |
|---------|-----------------|-----------------|----------------|--------|
| 1 U001 | Spaghetti | Pancakes | 4.5 | 4.0 |
| 2 U001 | Spaghetti | Grilled Chicken | 4.5 | 5.0 |
| 3 U001 | Pancakes | Spaghetti | 4.2 | 5.0 |
| 5 U001 | Pancakes | Grilled Chicken | 4.2 | 5.0 |
| 6 U001 | Grilled Chicken | Spaghetti | 4.9 | 5.0 |

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| 6 U001 | Grilled Chicken | Spaghetti | 4.9 | 5.0 |



Interpretation:

🍴 Dish Made vs. Dish Ordered:

- **Higher Ratings (🌟 4-5):** When the dish cooked during the session matches the ordered dish.
- **Lower Ratings (⬇️ 4 or less):** When the session dish and ordered dish differ.
- Aligning session dishes with orders boosts satisfaction!

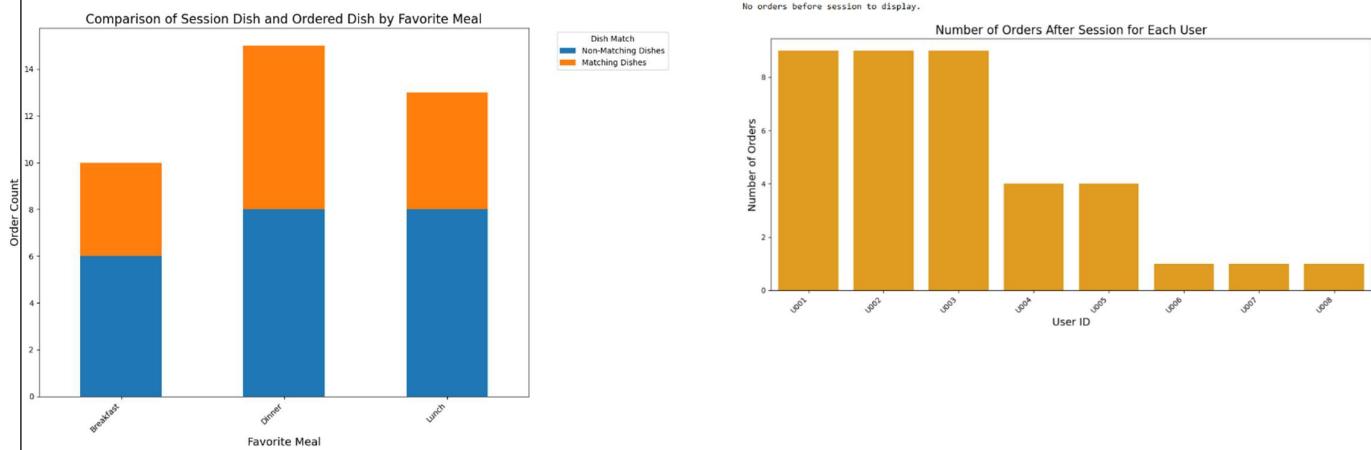
📍 Heatmap: Session vs. Ordered Dish:

- **Diagonal Highlights** (e.g., Spaghetti-Spaghetti): Strong correlations with higher ratings.
- **Off-Diagonal Areas:** Lower correlations and ratings when dishes differ.
- Reinforces the importance of matching session dishes with orders.

📈 Actionable Steps:

- Add **session-to-order reminders** or a seamless way to order dishes cooked in sessions.

Session Dish Cooked Influence



Interpretation:

🍴 Session Dish vs. Ordered Dish (Favorite Meal):

- Strong alignment between session dishes and ordered dishes for **favorite meals** and **usual meals**.
- Matching dishes = **higher satisfaction** and customer happiness!
- Ask Customers Favourite meals in database for future recommendations of sessions

📊 Orders After Cooking Sessions:

- Users cooking their **favorite meal** place **more orders** compared to those cooking usual dishes.
- Positive cooking experiences, especially for favorites, drive **higher engagement** and order frequency.

📈 Actionable Steps:

- Offer **personalized recommendations** for cooking sessions based on user favorites.
- Introduce **session-to-order workflows** to simplify the process of ordering cooked dishes.
- Leverage these insights to refine menus, features, and marketing campaigns to foster loyalty.

Recommendations

For the User: Personalized Meal Recommender

- Use **machine learning** to analyse the user's past orders, cooking sessions, and ratings **to predict their ideal menu choices**
- Seamlessly integrate this into the app's menu so users are guided towards their most satisfying options

Streamlined Session-to-Order Flow

- Optimize the transition from cooking session to placing an order
- Allow users **to easily convert the dish they just cooked into a completed order with one-click**
- Provide **visual cues and nudges** to encourage users to order the dish they just prepared

For the Restaurant: AI-Powered Churn Prediction

- As suggested, leverage machine learning techniques like logistic regression, decision trees, or random forests
- Train models to **predict which customers are at risk of stopping orders** from the restaurant
- Use these predictions to implement proactive retention strategies:
 - Offer **personalized discounts or loyalty rewards to high-risk customers**
 - Encourage users to **cook and order their favourite dishes to boost engagement**

Intelligent Dish Optimization

- Use this data to identify the **most profitable and popular dish combinations** like Grilled Chicken
- Optimize the menu by featuring these **high-performing dish pairings**
- Adjust pricing, promotions, and placement of these top-performing items

Sample Outputs After Recommendations

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🌟 Specials of the Day 🌟

| dish_name_x | session_time | avg_rating | num_orders |
|-----------------|--------------|------------|------------|
| Grilled Chicken | 41.6667 | 4.78889 | 9 |
| Spaghetti | 33.3333 | 4.53333 | 9 |
| Caesar Salad | 21.4286 | 4.31429 | 7 |
| Pancakes | 30 | 4.4 | 6 |
| Veggie Burger | 20 | 4.375 | 4 |

Please choose a dish from the Specials (enter the dish name) or type 'exit' to leave: Spaghetti

🔍 Dish Details for Spaghetti:

| dish_name_x | session_time | avg_rating | num_orders |
|-------------|--------------|------------|------------|
| Spaghetti | 33.3333 | 4.53333 | 9 |

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Thank you for visiting Culinary Upalaince! Come back soon! 🍷