

Food Recommendation System

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The Need for Food Recommendation Systems



Culinary Diversity

The increasing variety of food options can overwhelm consumers, making choice difficult.



Personalization Trend

Growing interest in tailored food suggestions based on individual tastes and needs.



Information Overload

In the digital age, users face an abundance of options, necessitating simplified decision-making tools.



Enhanced User Experience

Recommendation systems improve satisfaction by aligning suggestions with personal preferences.





Data Preprocessing: The Foundation

1

Dataset Composition

Four key files: pp_recipes, pp_users, raw_interactions, and raw_recipes, containing comprehensive information on recipes, users, and interactions.

2

Cleaning and Filtering

Removal of irrelevant columns and duplicates. Filtering of users with fewer than 10 interactions to ensure data quality.

3

Data Transformation

Splitting of nutritional information, normalization of columns, and mapping of user and recipe IDs to continuous indices.

4

Matrix Creation

Development of a sparse matrix to efficiently store user ratings and interactions.



Recommendation Techniques

New Users

- Nutrient-Based Recommendations using content based filtering
- Top-Rated Recipes leveraging collaborative filtering

Existing Users

- Personalized Nutrient-Based Recommendations
- Top-Rated Recipes
- Preference-Based Recommendations using collaborative filtering with K-Nearest Neighbors (KNN)





Core Algorithms: The Heart of the System

Content based Filtering (Cosine Similarity)

Measures similarity between items or user profiles by calculating the cosine of the angle between two vectors representing their features.

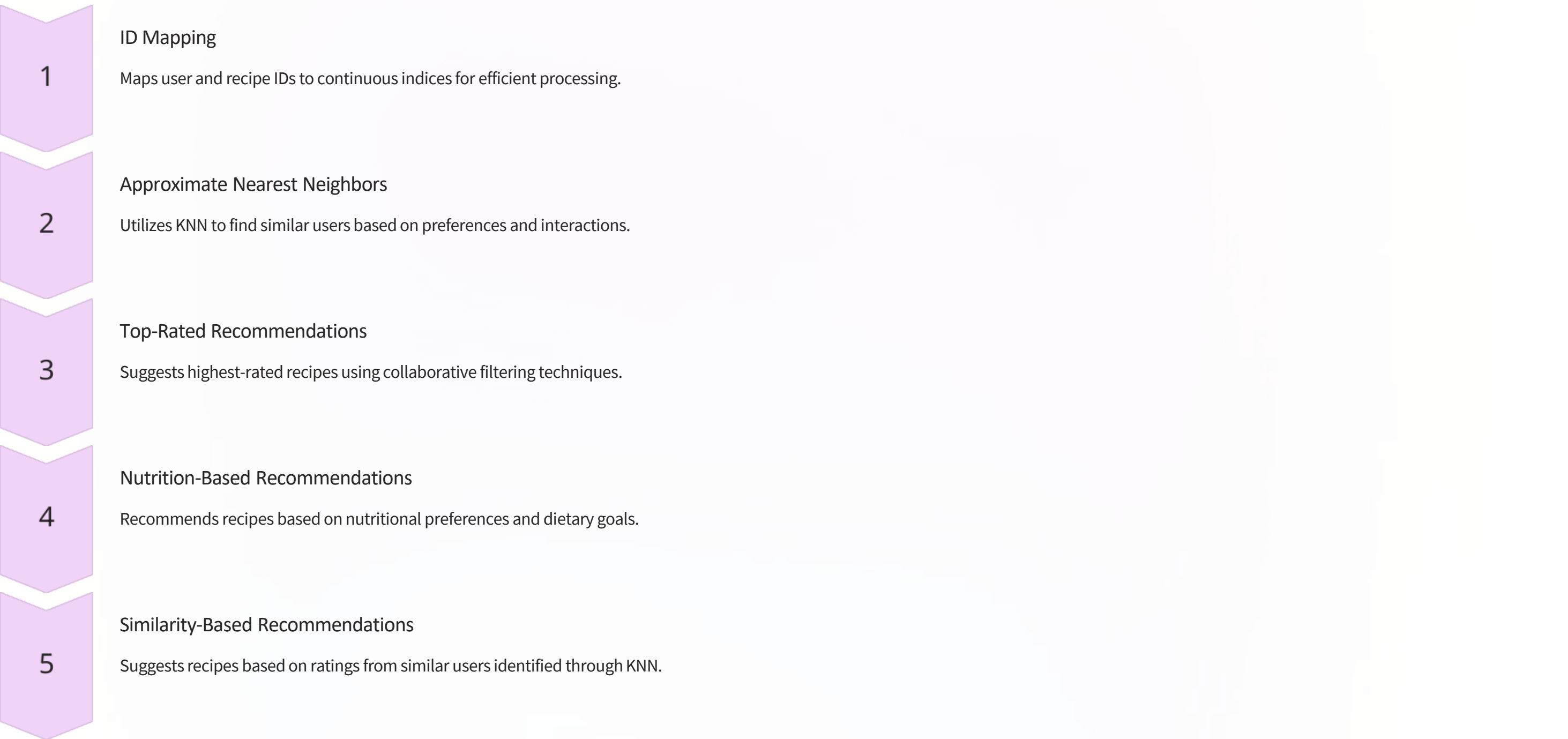
K-Nearest Neighbors (KNN)

Identifies nearest neighbors based on similarity metrics, ensuring recommendations are derived from similar users or items.

Collaborative Filtering

Utilizes user behavior and preferences to make recommendations, finding patterns in user-item interactions.

Recommendation Logic: Step-by-Step Process



Evaluation Metrics: Measuring Success

0.9119

MAE

Mean Absolute Error, measuring average magnitude of errors in predictions.

1.3932

RMSE

Root Mean Squared Error, emphasizing larger errors in the model.

0.9322

F1-Score

Harmonic mean of precision and recall, balancing both metrics.

4.37

Mean Rating

Average predicted rating, indicating overall positive recommendations.



Test: Outputs from the Model

Recommendations based on nutritional preferences:

	recipe_id	name	calories	total fat	sugar \
455710	264904	easy caramel frosting	0.005281	0.001571	0.005795
80513	913	ritz mock apple pie iii	0.003735	0.002037	0.003374
194823	81289	chocolate lemonade	0.004060	0.001280	0.003937

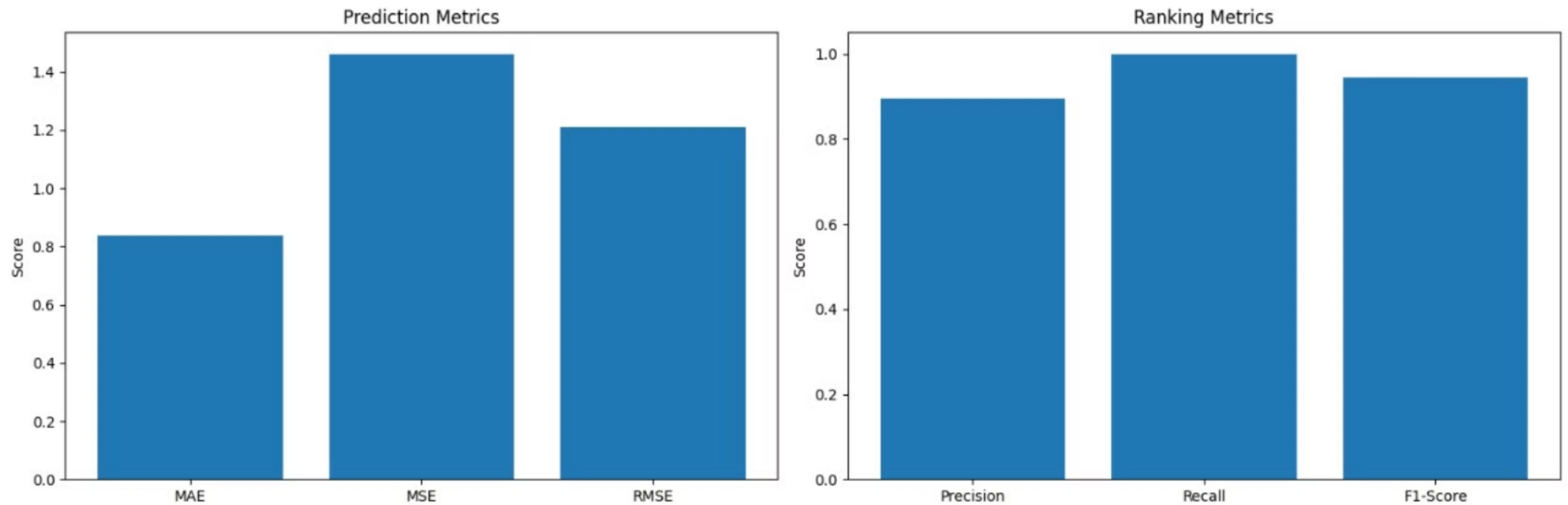
	sodium	protein	saturated fat	average_rating
455710	0.000750	0.001526	0.005195	4.666667
80513	0.001091	0.001832	0.003271	5.000000
194823	0.000784	0.002747	0.002982	4.000000

Recommendations based on top-rated recipes:

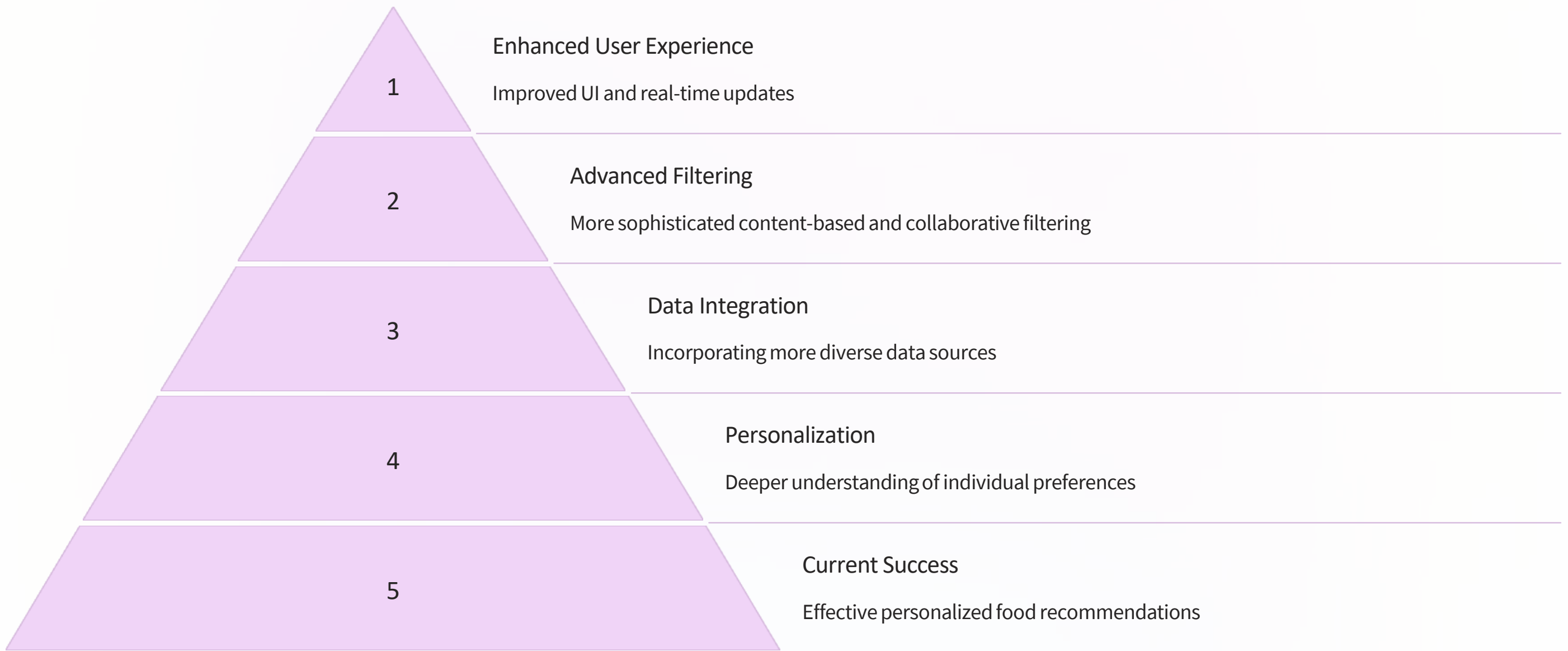
	recipe_id	name	calories	total fat \
17	17387	pizza breadsticks	0.000969	0.000873
6	52077	spicy banana fritters zitumbuwa	0.000275	0.000349
16	68986	apricot mousse	0.000544	0.000233
14	14807	californian apple crunch	0.000664	0.001862
2	27789	ham and swiss in puff pastry	0.000516	0.001455

	sugar	sodium	protein	saturated fat	average_rating
17	0.000014	0.000920	0.003663	0.000770	5.0
6	0.000050	0.000136	0.000916	0.000289	5.0
16	0.000433	0.000375	0.003816	0.000673	5.0
14	0.000229	0.000170	0.000305	0.006349	5.0
2	0.000006	0.000136	0.004731	0.004233	4.0

Results: Insights and Performance



Conclusion and Future Directions



Our Food Recommendation System demonstrates the power of combining content-based and collaborative filtering techniques. As we look to the future, we aim to refine our algorithms, expand our data sources, and create an even more intuitive user experience.