

Recipe Recommendation Engine through Collaborative and Content Filtering



Jason Summer
2020

Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

06

Key Takeaways


Google

chicken pot pie recipe

All Videos Images Shopping News More Settings Tools

About 122,000,000 results (0.62 seconds)

Recipes




Classic Chicken Pot Pie

Pillsbury.com

4.5 ★★★★★ (1.9K)
1 hr 5 min

Frozen mixed vegetables, chicken broth, cooked chicken,




Chicken Pot Pie IX

Allrecipes

4.8 ★★★★★ (12K)
1 hr 10 min

Boneless chicken breast, frozen green peas, celery seed, chicken




Favorite Chicken Potpie

Taste of Home

4.8 ★★★★★ (325)
1 hr 15 min

Refrigerated pie crust, potatoes, chicken broth, frozen corn,




Chicken Pot Pie

Food Network

4.9 ★★★★★ (1.1K)
1 hr 55 min

Chicken breasts, heavy cream, carrots, olive oil, chicken bouillon




The Best Classic Chicken Pot Pie Recipe

The Wholesome Dish

5.0 ★★★★★ (165)
50 min

Skinless chicken breast, chicken broth, heavy cream, pie crusts,




Chicken Pot Pie

Delish.com

4.5 ★★★★★ (16)
1 hr 45 min

Skinless chicken breasts, chicken broth, heavy cream,




Chicken Pot Pie

Two Peas & Their Pod

4.8 ★★★★★ (136)
1 hr 25 min

Shredded chicken, chicken broth, heavy cream, carrots, garlic




Healthy Chicken Pot Pie

Well Plated by Erin

5.0 ★★★★★ (97)
1 hr

Dairy free, frozen pearl onions, almond milk, skinless chicken



Delicious Chicken Pot Pie

Food.com

5.0 ★★★★★ (763)
1 hr 45 min

Potato, chicken broth, carrot, pie crusts, celery

Executive Summary

Drive loyalty and user growth of recipe platforms through intelligent recommendations

In the saturated market of recipe aggregation, organizations seeking to grow loyalty and expand their user base should consider machine learning techniques to simplify the customer experience. There is no shortage of quality recipes digitally available. However, simplifying the process to find these recipes and ensuring consistent quality of recipes is key.

The following analysis details how collaborative filtering merged with content filtering can be used to drive loyalty of an existing customer base. Furthermore, it details the effect of a saturated market on usership and how providing optimal first recommendations is crucial for growth.

Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

06

Key Takeaways

Opportunity Overview

Digital recipe aggregators should begin transforming their large networks into measured recommendations



Websites and apps offering recipe libraries today should focus on taking the next step towards data-driven recipe suggestions. These organizations should seek to leverage large user networks for collaborative filtering and recipe descriptions for content filtering. Removing the need for a customer to browse recipes and instead simply trust a suggestion and create a shopping list could result in a key differentiation.

Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

06

Key Takeaways

Data Landscape

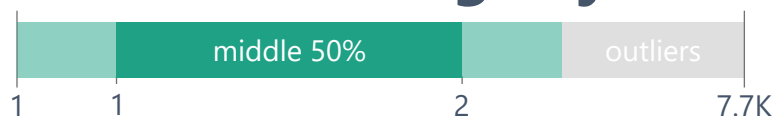
To create an explanatory proof of concept, data from Food.com was sourced via Kaggle.com. The data consist of 200K+ recipes and 1M+ recipe reviews covering 18 years of user interactions and uploads



Rating Submissions

227K unique users rated 231K unique recipes, totaling over 1 million reviews. However, users tend to submit 1-2 ratings and recipes tend to receive 1-4 ratings, indicating very low engagement.

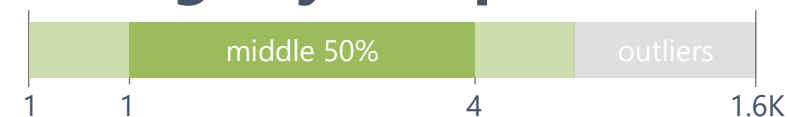
Ratings by User



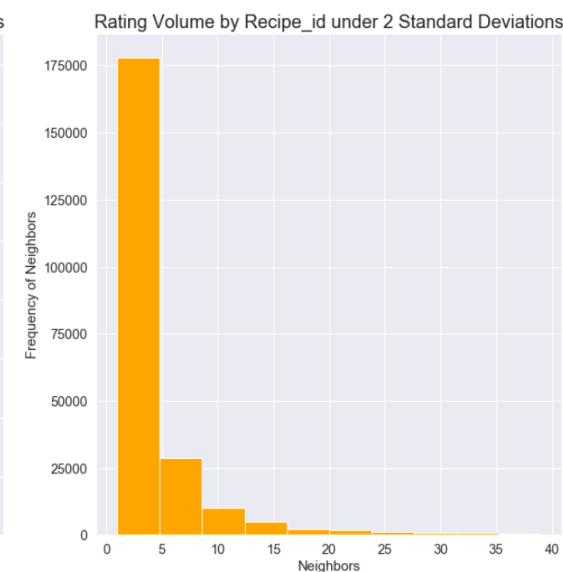
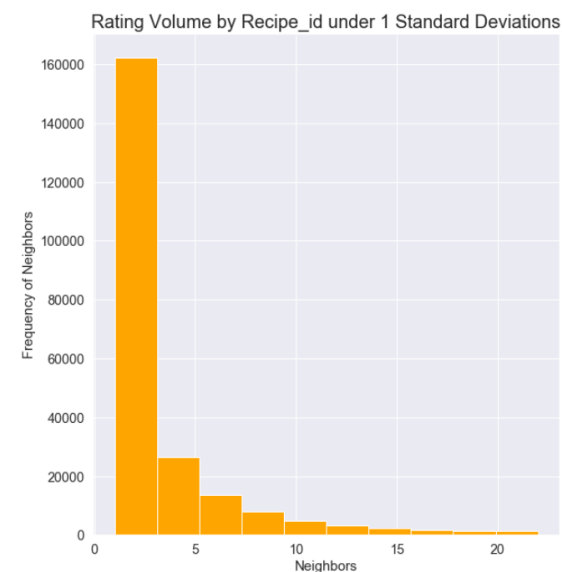
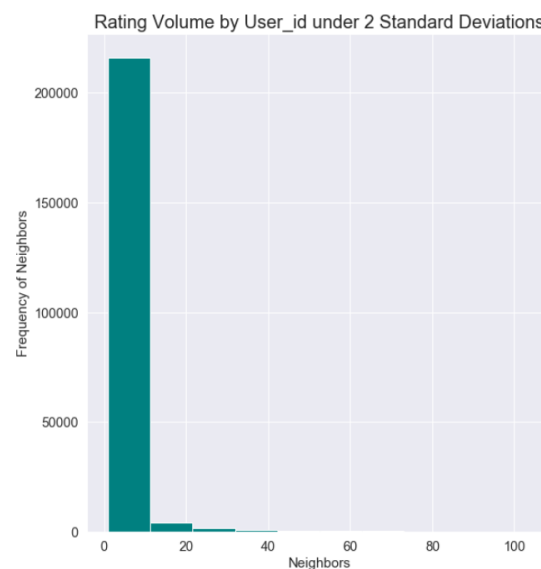
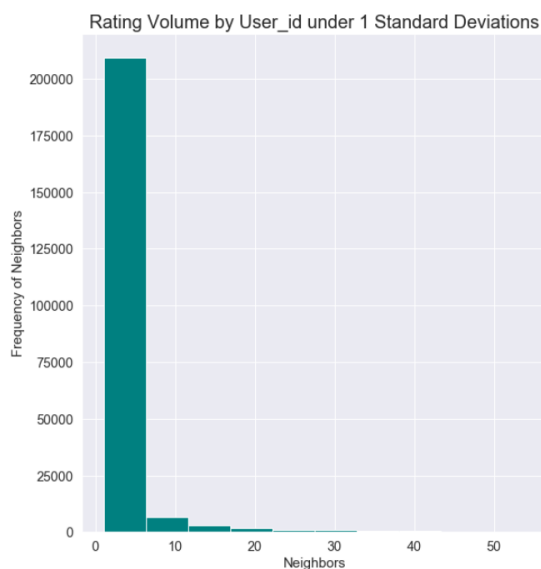
Dataset does not feature any cold start users. Generally users submit 1-2 ratings indicating high possible attrition and low loyalty.



Ratings by Recipe



Ratings by recipe shows less of a long tail but still generally low for most recipes.



Rating Scores

While users generally only submit 1-2 ratings, these ratings seem to generally be between 4 and 5. Evaluating the distribution of common rating submissions shows an obvious tendency to submit positive ratings.

89% of ratings are 4 or higher

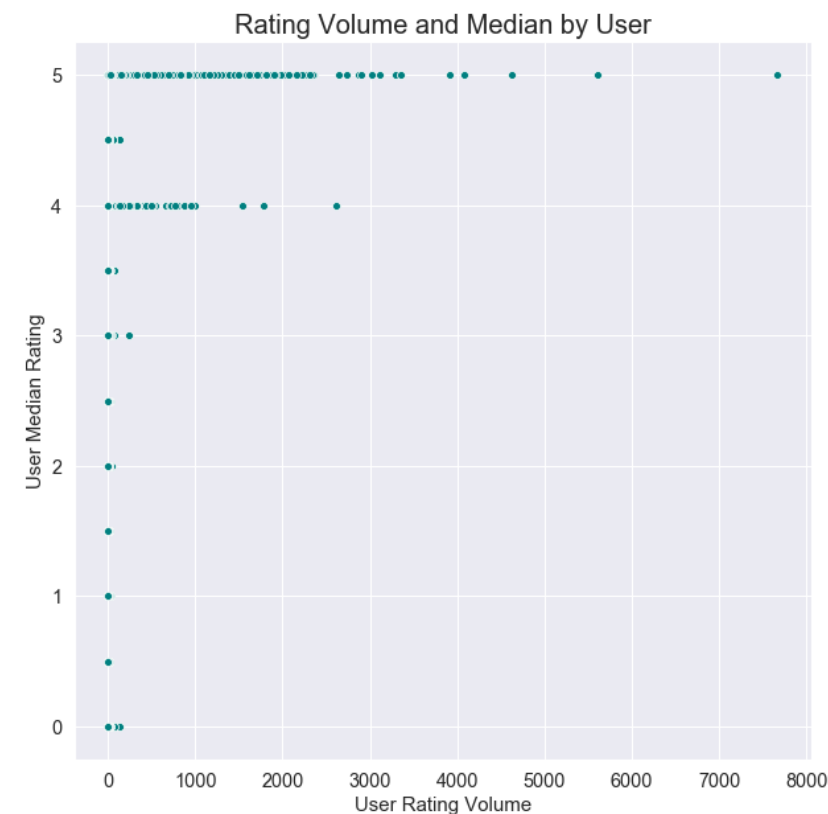
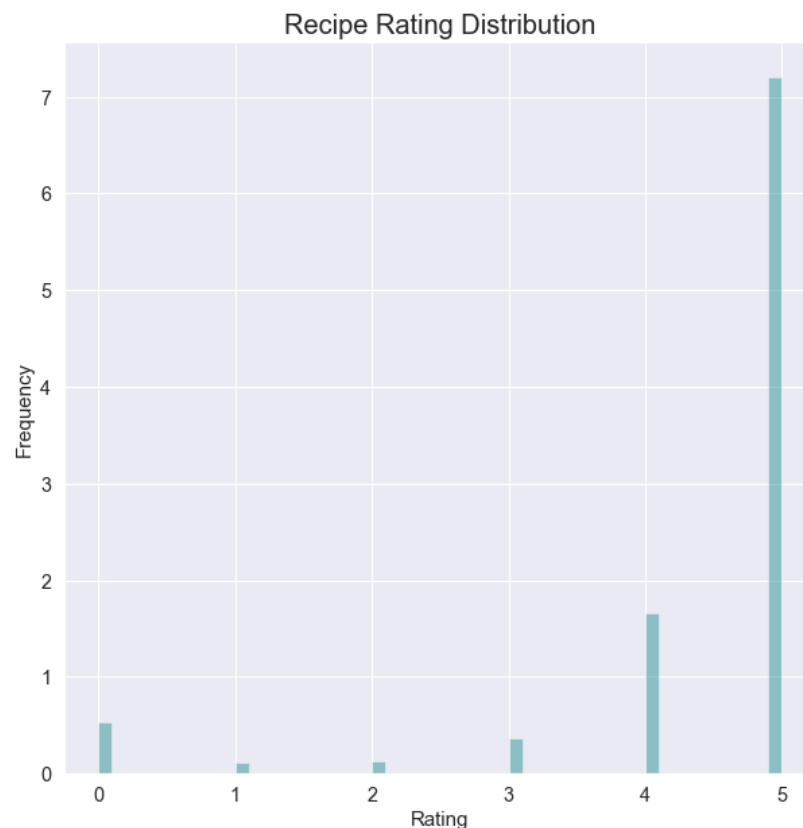


A user's tendency to submit high ratings increases as their rating submissions increase.

This increasing tendency to submit high ratings coupled with generally low engagement highlights key user behavior and opportunity.

A single "poorly selected" recipe can lead to swift user attrition highlighting the need for smart recommendations for new and low usage customers.

There is also an opportunity to drive engagement and loyalty of existing user base through personalized recommendations.



Ratings of 0 were updated to 0.1 for modeling purposes

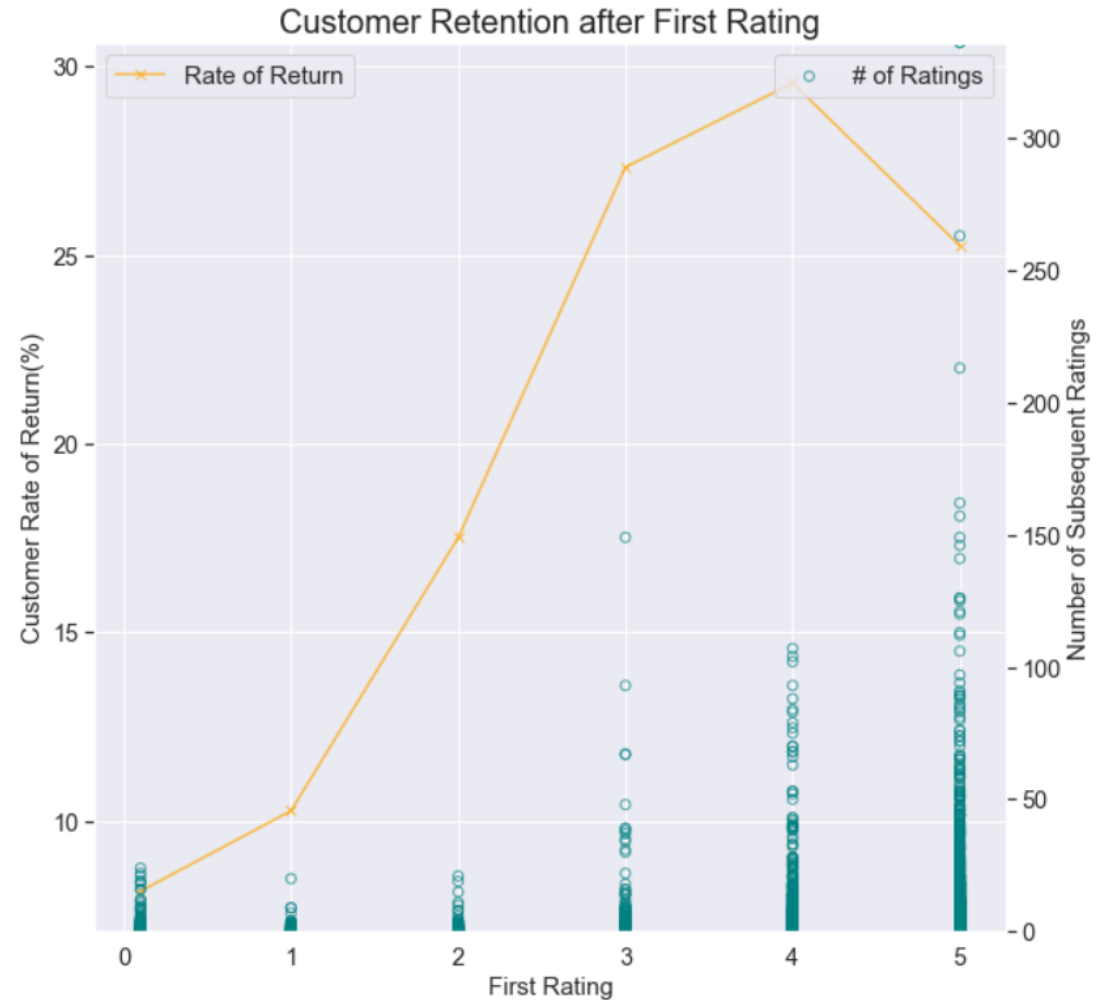
Ratings and Retention

To measure the long-term effect of ratings, rating submissions were cross-referenced with customer rate of return. Comparing the two metrics highlights the importance of high ratings in a market rampant with swift attrition.

24% of customers churn after initial rating

The difference in retention likelihood between a user who submits a rating below 3 compared to those who rate one 3 or above is 15%. A user is more than twice as likely to return after a rating of 3 or more than one below 3.

Furthermore, the higher the initial rating, the more subsequent recipes a user will review in the future, increasing their loyalty and engagement.



Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

06

Key Takeaways

Algorithm Selection

11 algorithms were compared for collaborative filtering and 2 were selected for further tuning and evaluation

The [Surprise library](#) for building and testing recommender systems was selected for this collaborative filtering effort. The specific library was selected due to its similarity to scikit-learn modules and read-to-use prediction algorithms.

The Surprise package offers 11 out of the box algorithms including baseline algorithms, neighborhood-based methods, and matrix factorization approaches. The recipe identifiers, user identifiers and ratings were sampled and used to compare the 11 algorithms.

Algorithm	Mean RMSE	Training Time
SVD ++	1.0533	2.197224
KNN Baseline	1.054044	0.734534
SVD	1.054203	0.990171
Baseline Only	1.054441	0.079275

The top 4 algorithms (shown above) were very similar in their overall root mean squared error. After more precise training time evaluations were conducted, SVD++ was eliminated due to memory limitations. SVD and Baseline Only were selected for further tuning.



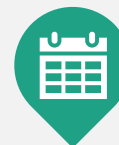
Recipe Identifier



User Identifier



Recipe Rating 0-5



Submission Date



Algorithm Tuning

Using Surprise library's built in cross validation grid search module, the SVD and Baseline Only were tuned using a sample of the ratings data.

Hyperparameter tuning of the SVD and Baseline Only algorithms showed minimal improvement. However, optimal values were selected for each.

SVD uses stochastic gradient descent and attempts to characterize the data using fewer dimensions than the raw data. It provides 4 key parameters for tuning.

Hyperparameter	Parameter Description	Value
n_factors	number of latent features used to identify similarities in preferences	25
n_epochs	number of iterations of the stochastic gradient descent used to minimize regularized squared error	30
ir_all	learning rate for all parameters	0.003
reg_all	regularization term for all parameters	0.1

The Baseline algorithm offers two alternative methods to estimate and reduce the regularized squared error of each user and recipe combination. These methods were compared, and the stochastic gradient method performed slightly better than the alternating least squares method.



Recipe Identifier



User Identifier



Recipe Rating 0-5



Submission Date



Prediction Performance

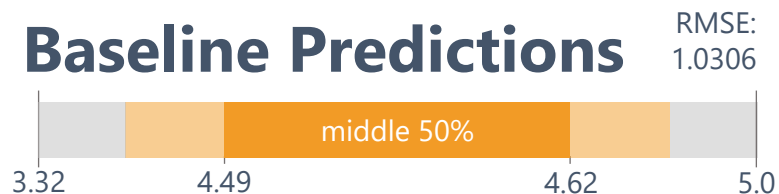
The ratings data were sorted ascending by submission date to allow the model to learn emerging trends.

Each model was trained on the initial 70% of ratings and evaluated on the remaining 30%.

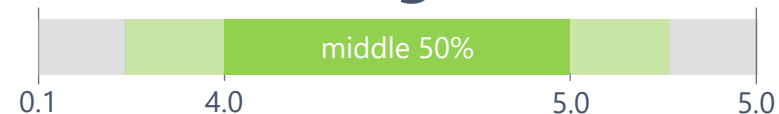
SVD Predictions



Baseline Predictions

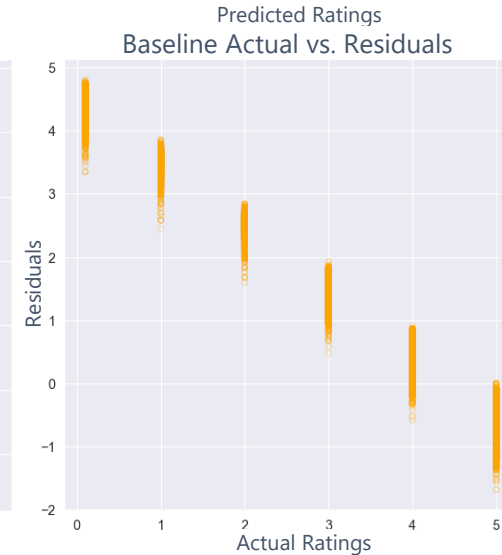
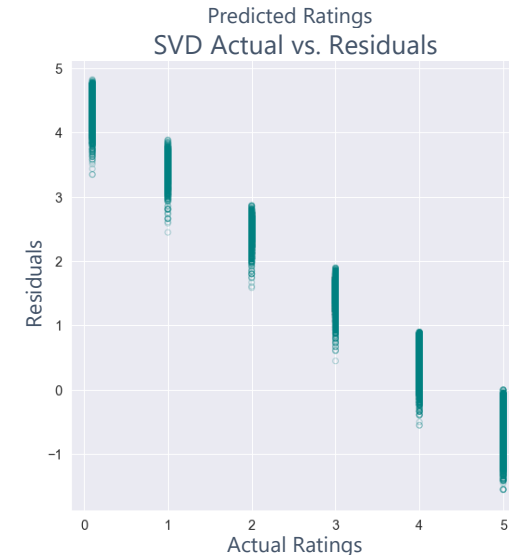
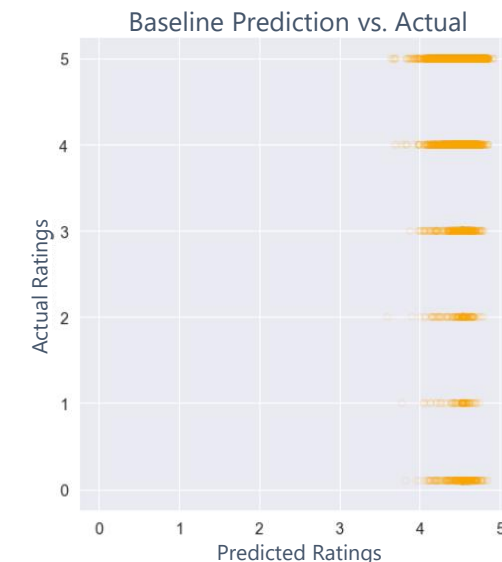
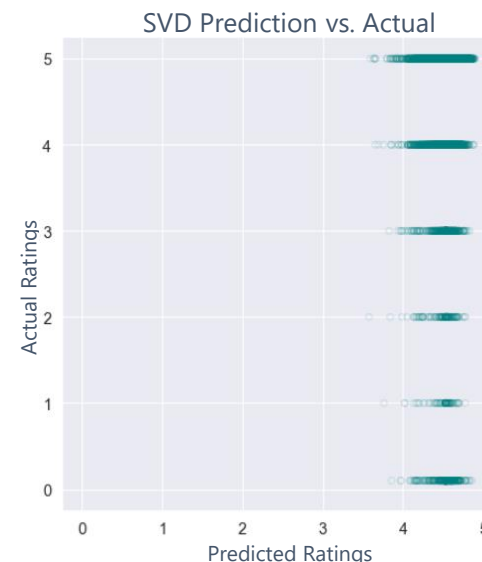


Actual Ratings



Both algorithms perform comparably well with a general error around 1. More interesting however was the apparent effect of imbalanced ratings. Predicted ratings are consistently above 3. As suspected, residuals decrease as actual ratings increase, further highlighting the tendency towards high ratings.

As a comparison, the minority ratings were bootstrapped to create a balanced dataset and the modeling was performed again. The RMSE and variance increased by 1.5x and 29x, respectively. The wider breadth of ratings using the bootstrapped samples confirms the change in behavior due to imbalanced ratings. See Appendix for outputs.

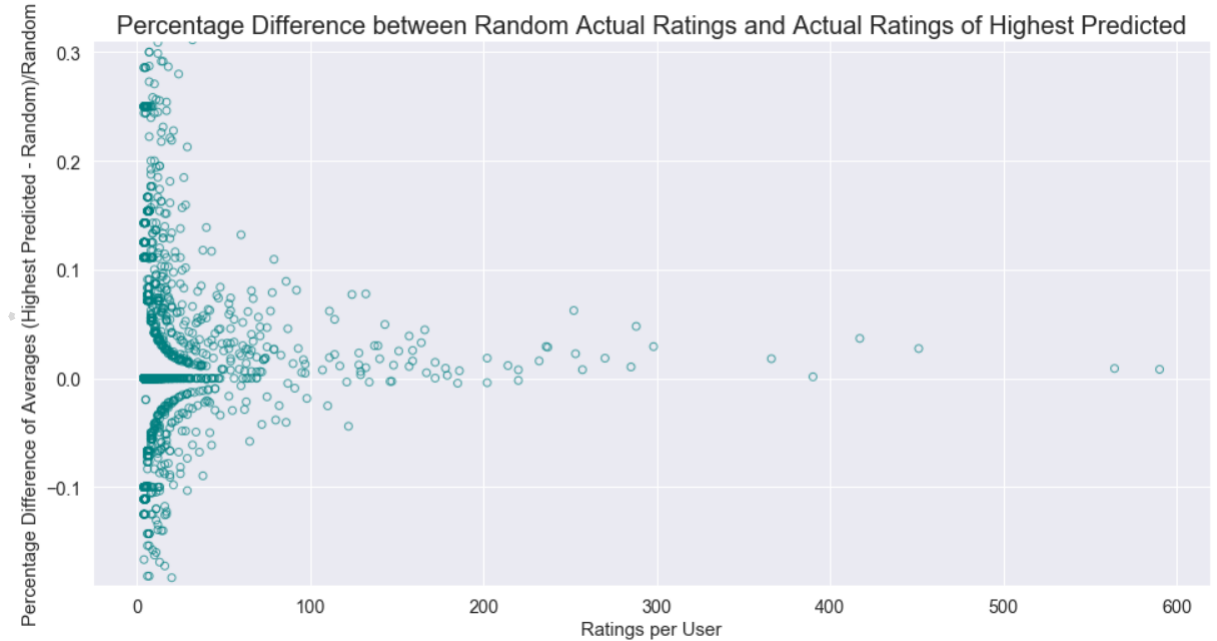
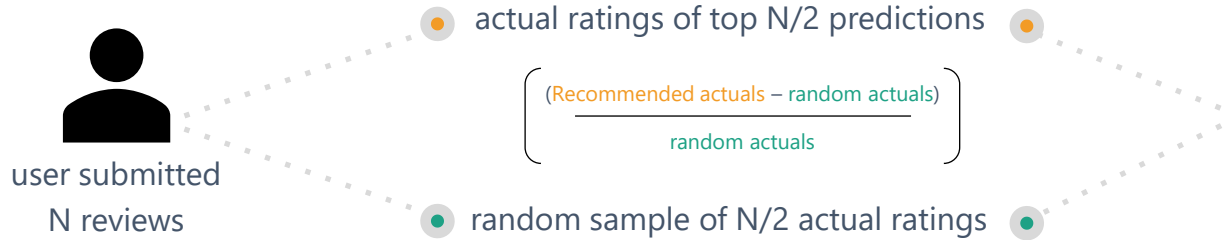


Ratings of 0 were updated to 0.1 for modeling purposes

Prediction Effectiveness

To understand the effectiveness of model recommendations, the actual ratings of each user's top recommended recipes were compared to a random sample of what the user selected without recommendations.

For users in test set with 4 or more ratings, the top half of recommendations for the user, based on predicted rating, were compared to a random selection of what the user selected of equal length



The mean percentage difference above between recommended recipes and those selected by a user without recommendations is 10.9%. Using a random sample of 50,000 ratings from the test set results in an independent t-test p-value of 0.0001 when comparing the recommended actual ratings with the random actuals. Lastly, creating 1,000 bootstrap samples of the percentage difference indicates a 95% confidence interval between 4.6% and 18.6%, indicating the recipes that would be recommended by a model would be rated better than those a user may select without a model.

Y-axis of plot restricted to percent differences between 5th and 95th percentiles
Ratings of 0 were updated to 0.1 for modeling purposes

Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

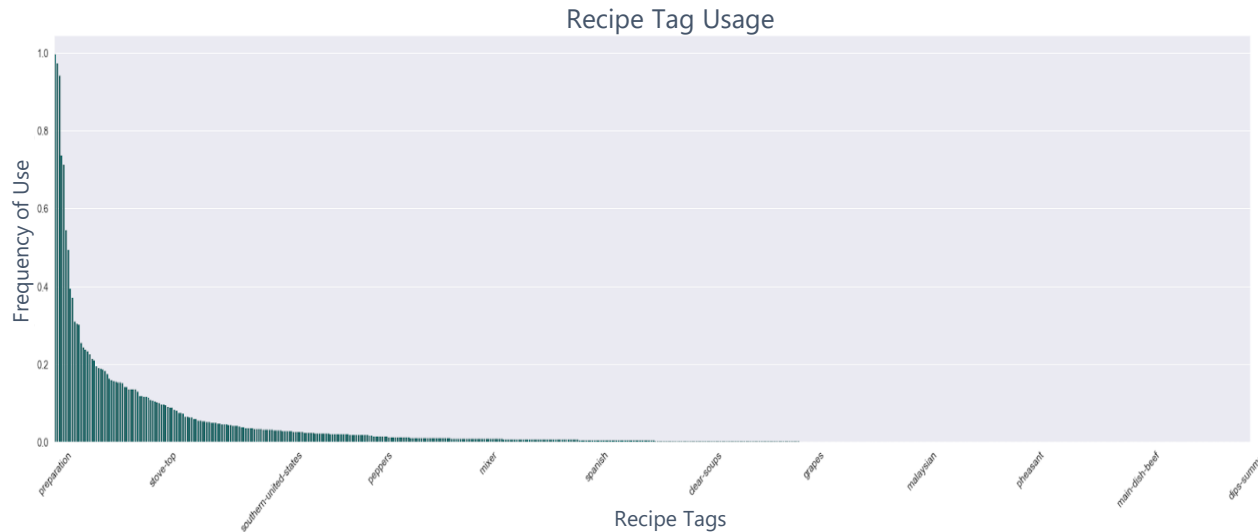
06

Key Takeaways

Recipe Similarity

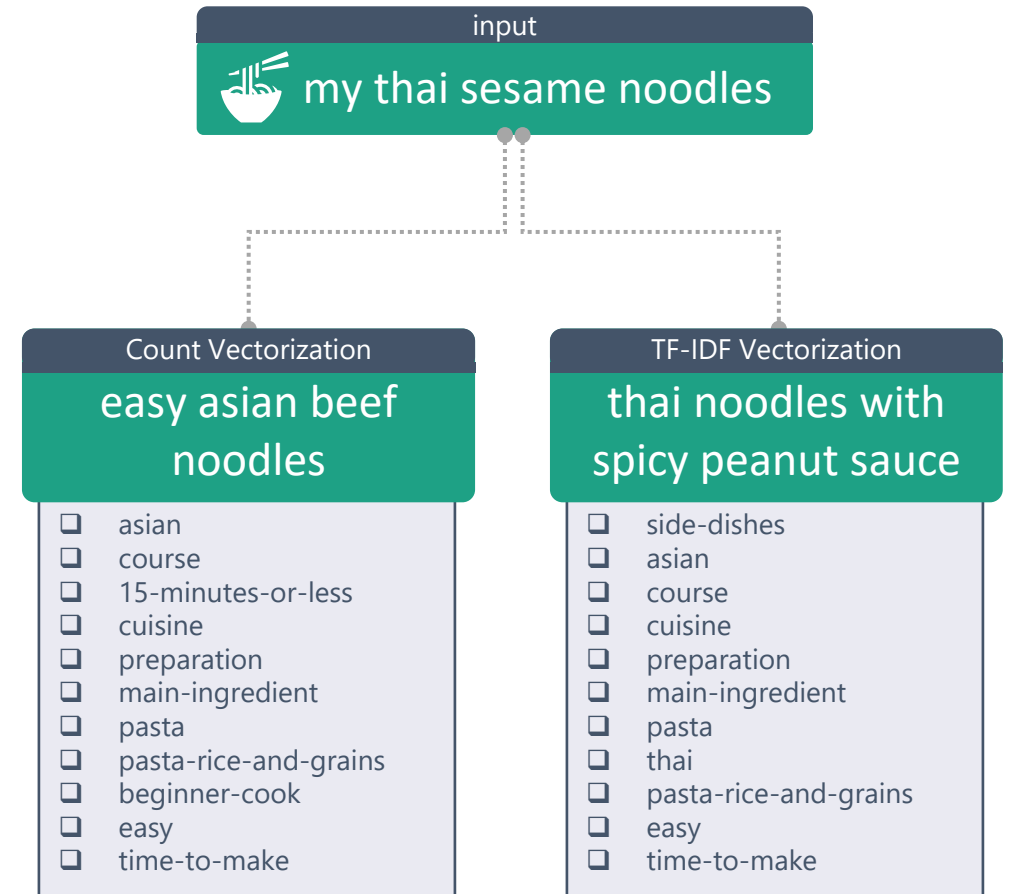
Scikit-Learn TF-IDF and Count Vectorization of recipe tags (i.e. keywords) were used to measure recipe similarities.

552 tags were identified across all recipes



Recipe tags offered a unique comprehensive way to differentiate themes. Tags were not repeated within a single recipe but there were obvious tags serving as noise and an apparent long tail of highly unique tags.

TF-IDF (term frequency-inverse document frequency) offered a unique approach to down weight overly common words. Since words were not repeated within a single recipe's tags, simple binary count vectorization offered a quality baseline as comparison. Tag vectors were then used to calculate cosine similarity values for every pair of recipes, filtering to the most rated recipes.



Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

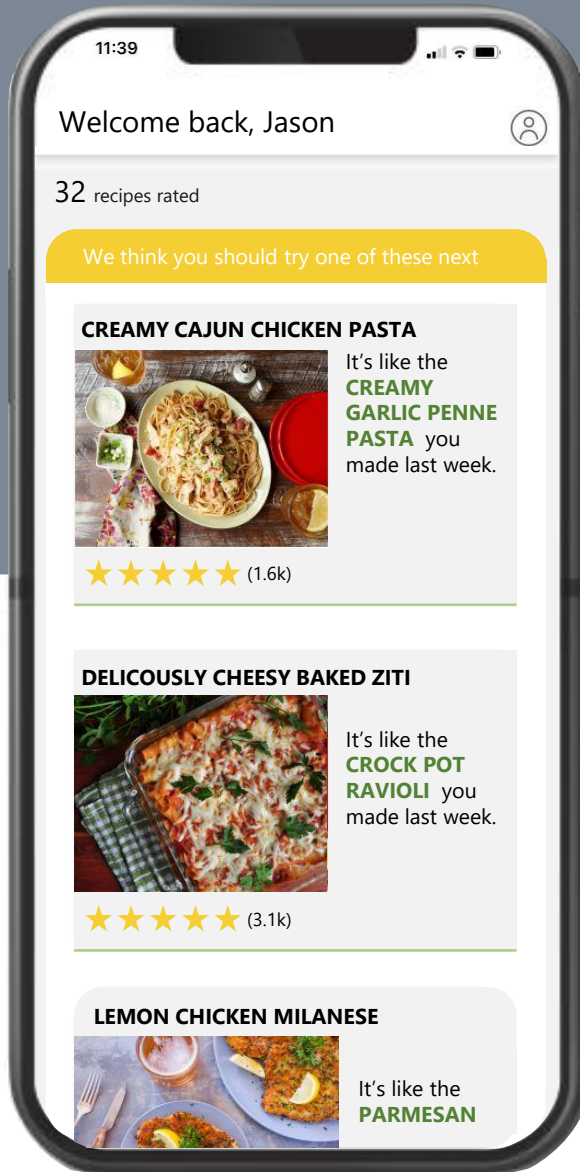
Content Filtering

06

Feature Engineering

06

Key Takeaways



Feature Development

Results from collaborative and content filtering machine learning were functionalized to provide simplified, personalized recommendations in a seamless fashion.

- ✓ Use collaborative filtering to identify best possible prediction ratings for each user
- ✓ Leverage context filtering to relate to similar recipes from a user's history
- ✓ Intelligently measure recipe popularity and track new user rate of return
- ✓ Generate and adjust automatic grocery list creation from recommendations



Top 10 Recipes For You

Recommend best possible recipes based on similar users



Your Similar Recipes

Contextualize recipe recommendations based on previous experiences



Popular Starter Recipe

Ensure new users receive the best possible recommendations



Add to Grocery List

Integrate recommendations into interactive grocery list

Agenda

01

Executive Summary

02

Opportunity Overview

03

Data Introduction and Analysis

04

Collaborative Filtering

05

Content Filtering

06

Feature Engineering

06

Key Takeaways

A wooden table set with various Mediterranean dishes including hummus, falafel, tabbouleh, and a glass of beer. The image is slightly blurred, creating a warm, inviting atmosphere.

Key Takeaways

A large network of diverse ratings, recipes, and repeat users, may be ripe for collaborative and content filtering recommendations

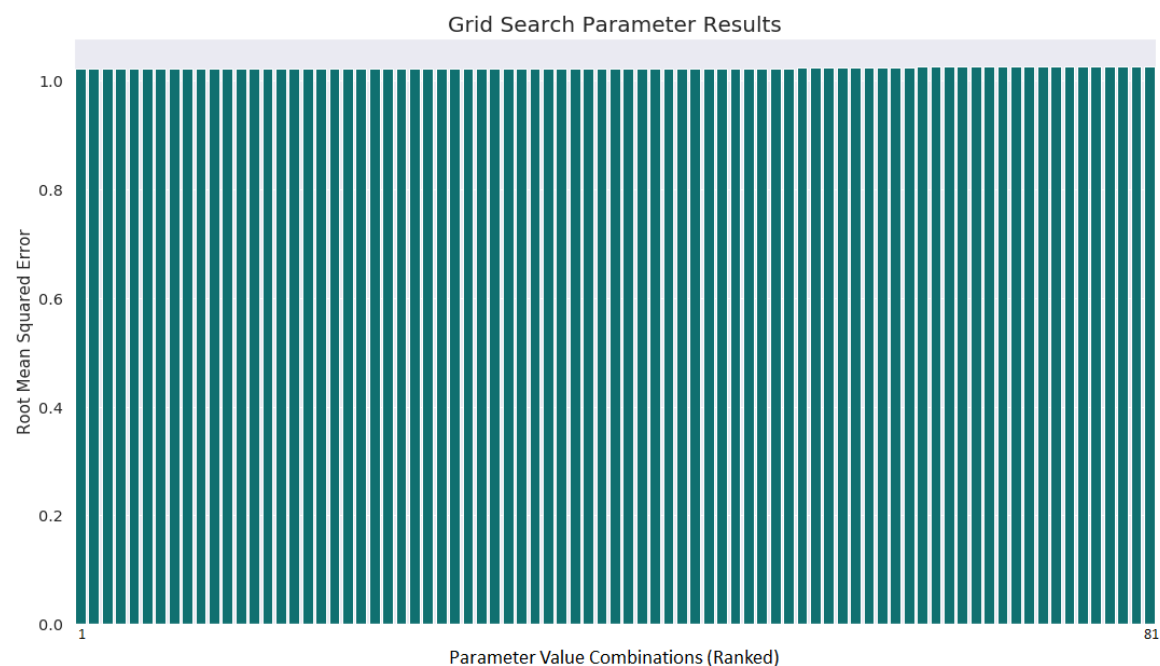
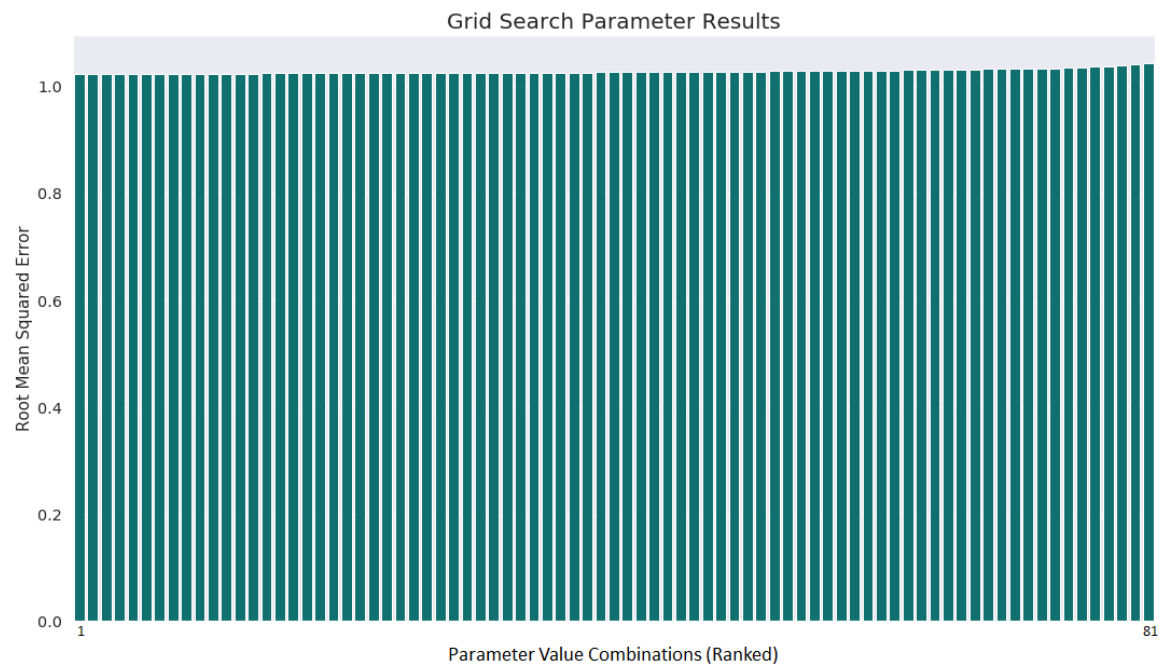
Simplified recommendations from collaborative filtering and association to a user's history through content filtering could be a differentiator for large scale recipe aggregators. An organization should fully understand the distributive nature of their recipe ratings and user frequency to effectively decide if pursuing a collaborative filtering engine is worthwhile.

Additionally, organizations should implement a different strategy based on popularity filters to capture new customers.

The market for digital recipe aggregation is saturated; however, providing simplified and optimal recipe recommendations should be considered a prospective solution for customer retention and growth.

Appendix

SVD Grid Search Outputs



Prediction Performance (Balanced Ratings)

The ratings data were sorted ascending by submission date to allow the model to learn emerging trends.
Each model was trained on the initial 70% of ratings and evaluated on the remaining 30%.

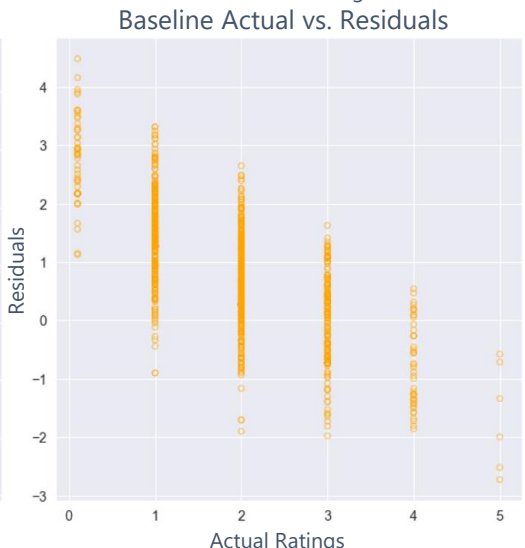
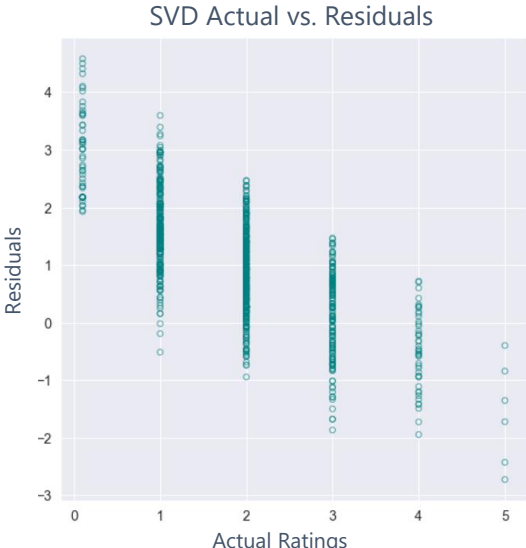
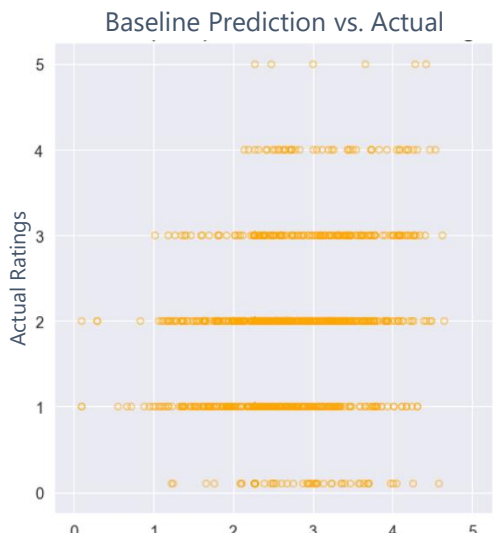
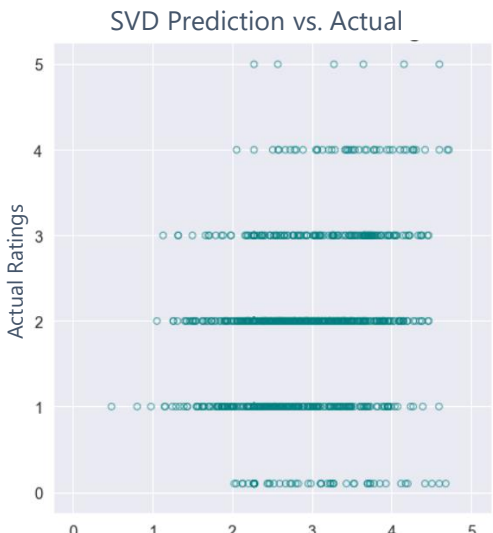
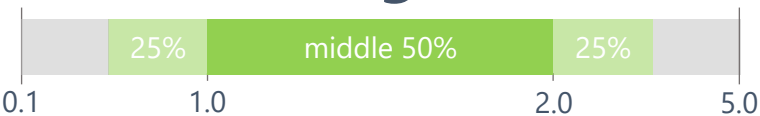
SVD Predictions



Baseline Predictions



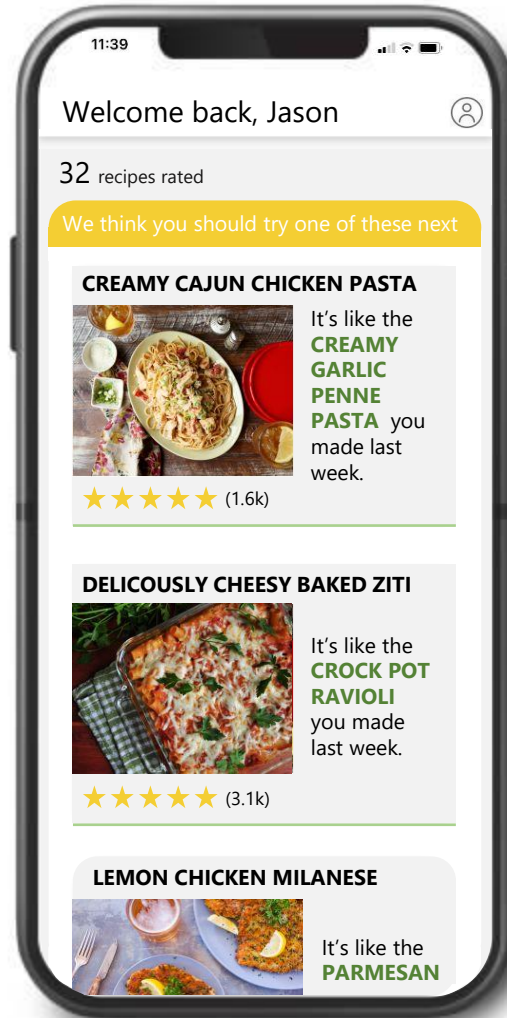
Actual Ratings



Ratings of 0 were updated to 0.1 for modeling purposes

Feature Mockups

Existing User



New User

