

Beer Reviews



MEET THE TEAM



MARY BOKEN
Chicago, Illinois



SAMI FELLER
Coral Springs, Florida



DAVID LI
Shandong, China



WHATS ON THE MENU

TOPICS AND HIGHLIGHTS

Executive Summary

Introduction

Data Wrangling

Insights & Analytics

Discussion and Conclusion

Beeradvocate



EXECUTIVE SUMMARY

WHAT WE DID

- Found dataset from Kaggle with 1.5 million rows and 13 columns with information on BeerAdvocate user reviews
- Used SQLContext in Pyspark to run queries on dataset and answer initial questions
- Created a recommender system using the Alternating Least Squares (ALS) algorithm from pyspark.ml to predict the ratings for beers which a user has not yet reviewed



INTRODUCTION

MOTIVATION

- Want to chose best possible beer for taste preferences
- Interested in consumer preferences of beer

OVERVIEW

- Used data from reviews on BeerAdvocate, a global beer review platform
- Created recommender system using ALS algorithm

POTENTIAL VALUE

- Reliability - organic means of spreading information
- Inform new market segments
- Partner with breweries, restaraunts and producers

DATA OVERVIEW

- OVER 1.5 MILLION BEER REVIEWS
- SOURCE
[HTTPS://WWW.KAGGLE.COM/RDOUME/BEERREVIEWS?
SELECT=BEER_REVIEWS.CSV](https://www.kaggle.com/rdoUME/BEERREVIEWS?SELECT=BEER_REVIEWS.CSV)

summary	review_aroma	review_appearance	review_overall	review_palate	review_taste
count	1586266	1586266	1586266	1586266	1586266
mean	3.735685565976955	3.84167125816225	3.8156280220341356	3.7437532544982997	3.7929209224682365
stddev	0.6975674474672164	0.6160649705043265	0.7205948113732451	0.682175283752888	0.7319121675111695
min	1.0	0.0	0.0	1.0	1.0
max	5.0	5.0	5.0	5.0	5.0

Beeradvocate®



VARIABLES WE ARE WORKING WITH

brewery_id
brewery_name
review_time
review_overall
review_aroma
review_appearance
filename
beer_style
review_palate
review_tast



Data Wrangling Process



LOADING DATA
INTO SPARK

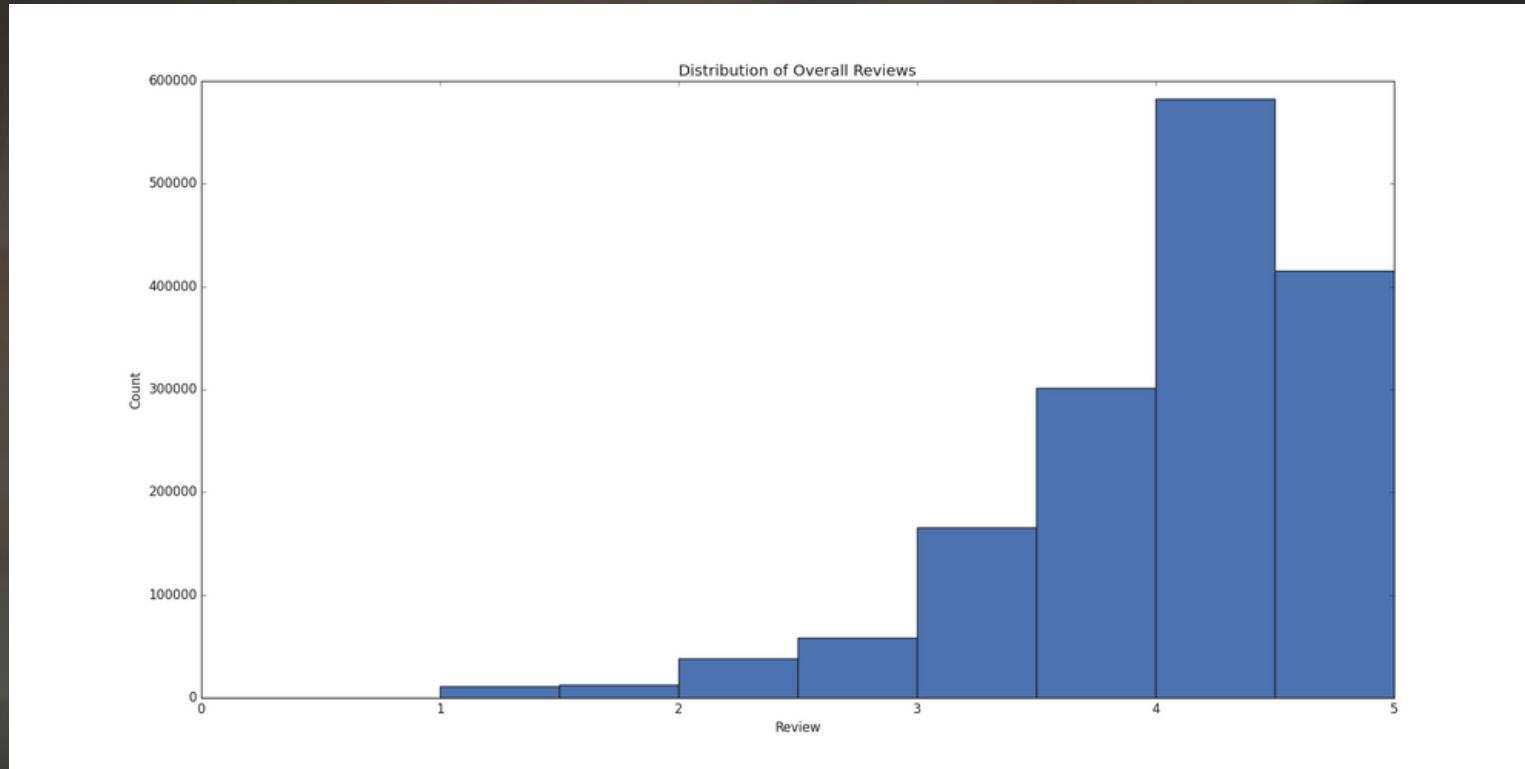
VISUALIZATIONS

QUERIES

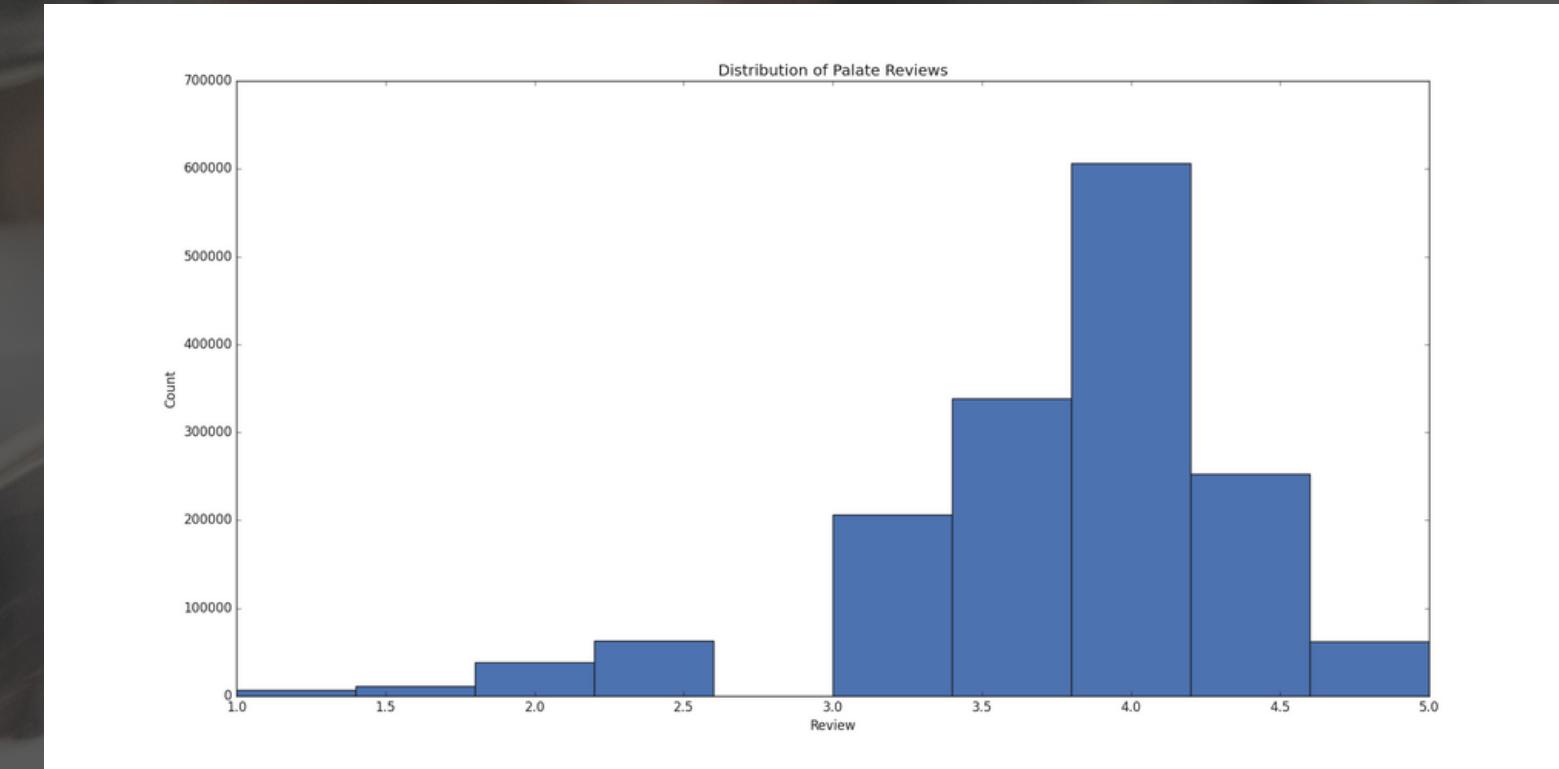
RECOMMENDER
SYSTEM

VISUALIZING OUR DATA - HISTOGRAMS OF REVIEW DATA

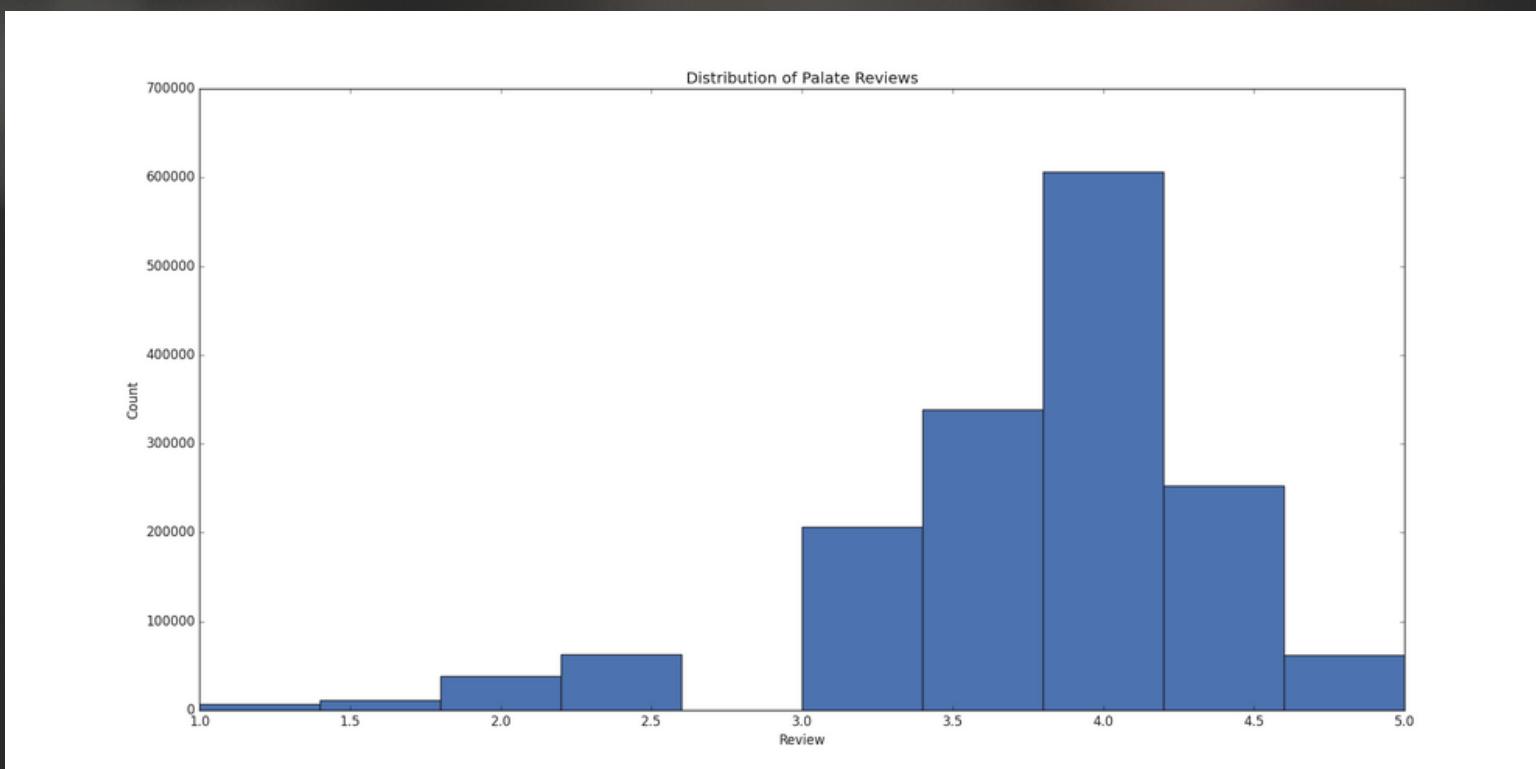
OVERALL



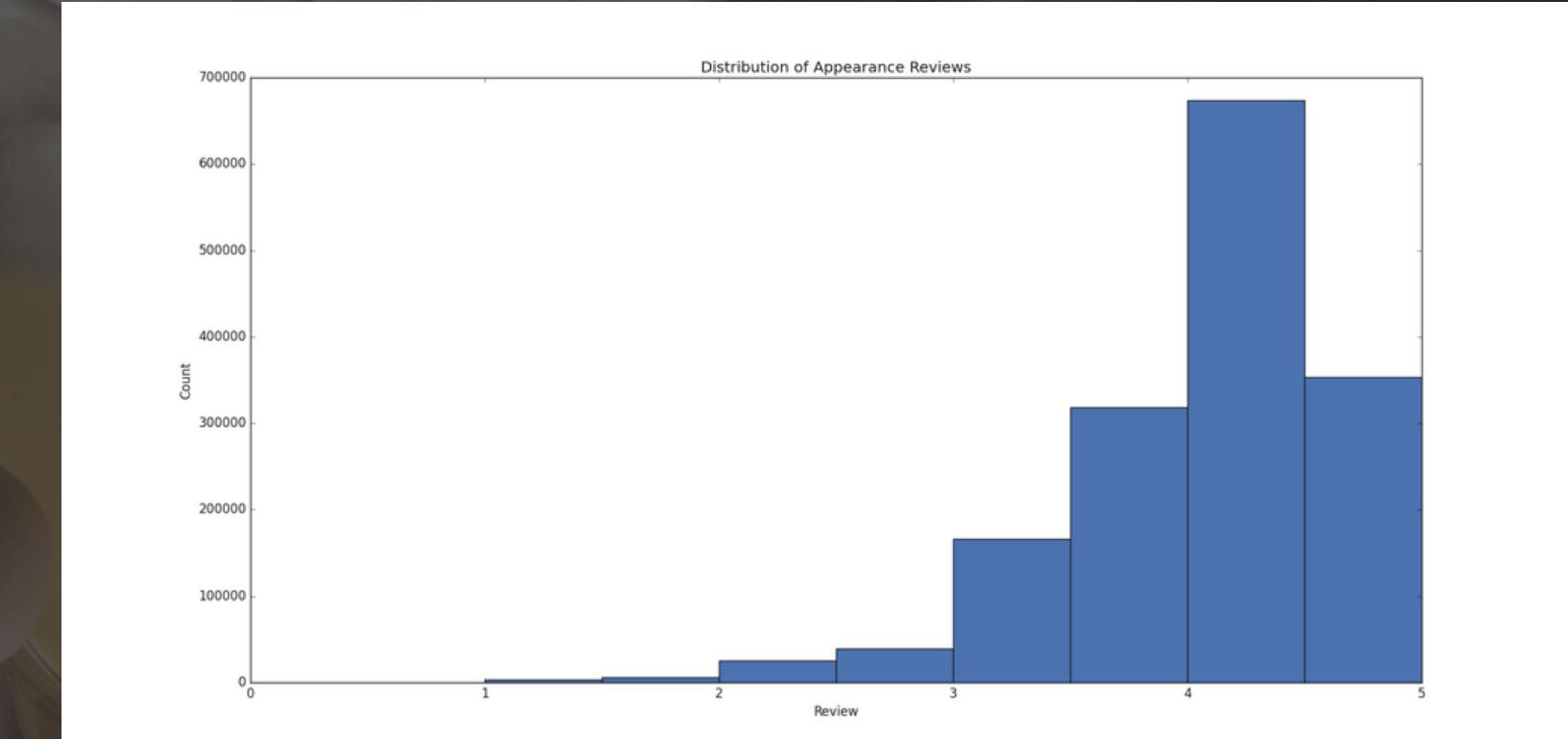
PALATE



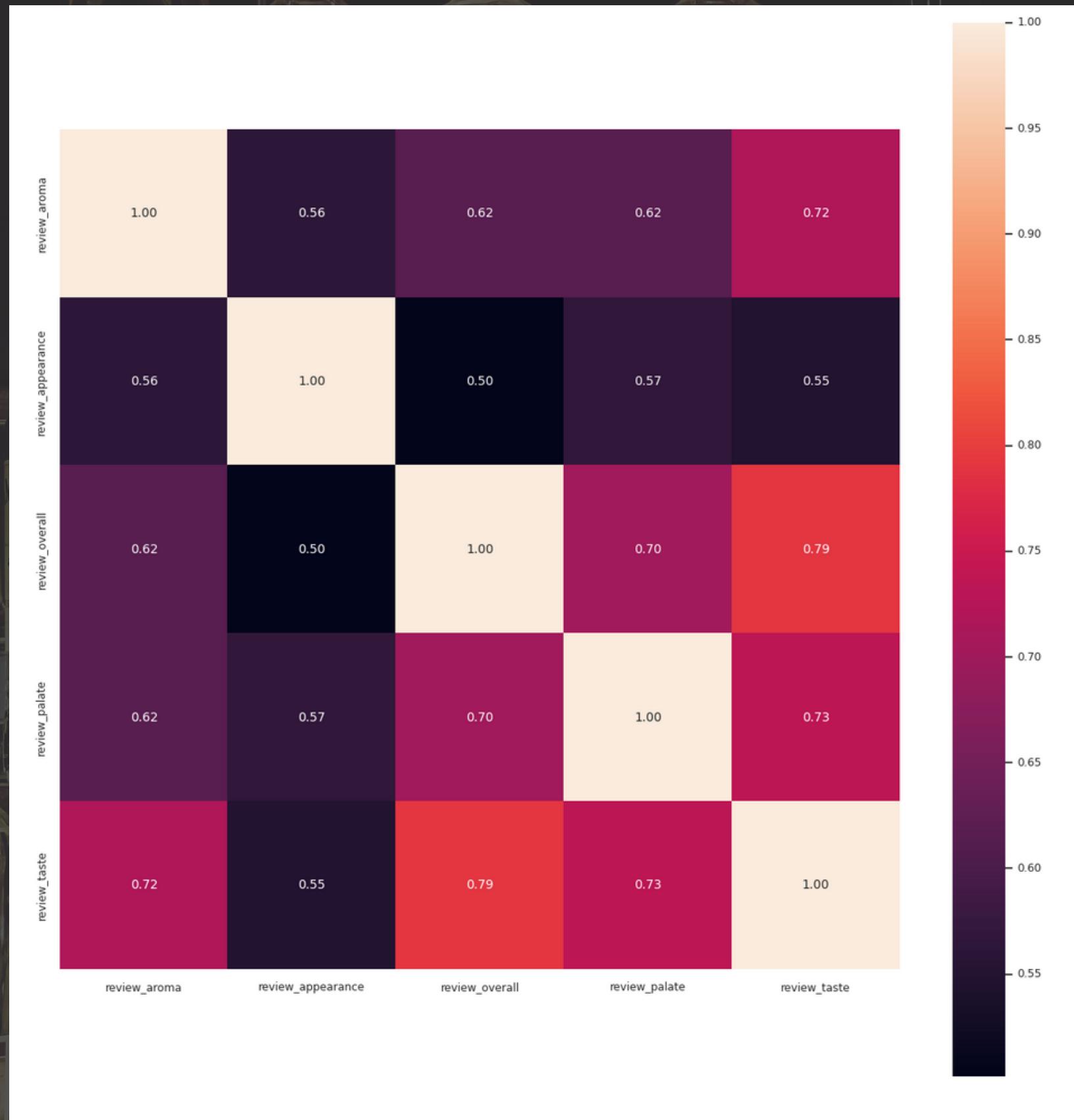
TASTE



APPEARANCE



VISUALIZING OUR DATA - HEATMART FOR CORRELATION AMONG REVIEW TYPES





INSIGHTS

MODEL-FREE INSIGHTS FROM DATA

Run queries to understand top beers based on volume of rating, top beers based on average score of rating, most popular style of beer, and highest rated style of beer based on average score

MODEL-DRIVEN INSIGHTS

Use collaborative filtering techniques to recommend beers which users have not yet reviewed



RESULTS OF QUERIES

WHICH BEER HAD THE HIGHEST RATING IN DATASET (AT LEAST 1000 REVIEWS)

beer_name	average_rating	num_reviews
Trappist Westvleteren	4.62	1272
Pliny The Elder	4.59	2527
Weihenstephaner H... The Abyss	4.52	1980
Sculpin India Pal... Supplication	4.45	1412
Founders KBS (Ken... Tröegs Nugget Nectar	4.44	1352
Gumballhead	4.43	1053
Bell's Hopslam Ale	4.4	1930
		1954
		1234
		2443



WHICH BREWERY IS MOST POPULAR?

brewery_name	num_reviews
Boston Beer Compa...	39438
Dogfish Head Brewery	33829
Stone Brewing Co.	33053
Sierra Nevada Bre...	28746
Bell's Brewery, Inc.	25189
Rogue Ales	24079
Founders Brewing ...	20000
Victory Brewing C...	19473
Lagunitas Brewing...	16832
Avery Brewing Com...	16105

THE BOSTON BEER COMPANY

WHICH BEER STYLE IS MOST POPULAR?

beer_style	num_reviews
American IPA	117586
American Double / ...	85977
American Pale Ale...	63469
Russian Imperial ...	54129
American Double / ...	50705
American Porter	50477
American Amber / ...	45751
Belgian Strong Da...	37743
Fruit / Vegetable...	33861
American Strong Ale	31945



How the Recommender System Works



INPUTS

User ID - a list of each user
Item Column - list of beer names
Rating Column - overall review each user assigned to each beer



MATRIX REPRESENTATION

	1	2	3	4	5	6
a	+	?	-	-	?	-
b		-		+		+
c	+	+		-	-	-
d			+	+	-	
e	-	-		+	+	



MATRIX FACTORIZATION

Generate latent factors to represent user preferences in a lower dimensionality space



PREDICT RATING AND RECOMMEND

Predicts ratings and recommends beers to users based on the highest predicted ratings

RECOMMENDER SYSTEM RESULTS

- ROOT-MEAN-SQUARE ERROR = 0.55
- ON AVERAGE, THE DIFFERENCE BETWEEN THE ACTUAL RATING AND THE PREDICTION IS 0.55 (REVIEW SCALE IS 1 - 5)

review_profilename	review_overall	beer_name	prediction
beertunes	3.0	Pecan Harvest Ale	3.2725961
CortexBomb	5.0	Trois Pistoles	3.8026361
CortexBomb	4.0	Éphémère (Apple)	3.3211913
CortexBomb	5.0	Edition 2004	3.6699762
CortexBomb	4.0	Quelque Chose	3.3831587
CortexBomb	4.5	Unibroue 15	3.629299
beertunes	4.0	Maudite	3.7953036
beertunes	4.0	Raftman	3.623886
BeefyMee	5.0	Samuel Adams Crea...	3.740396
BeefyMee	2.5	Samuel Adams Cher...	2.9721463

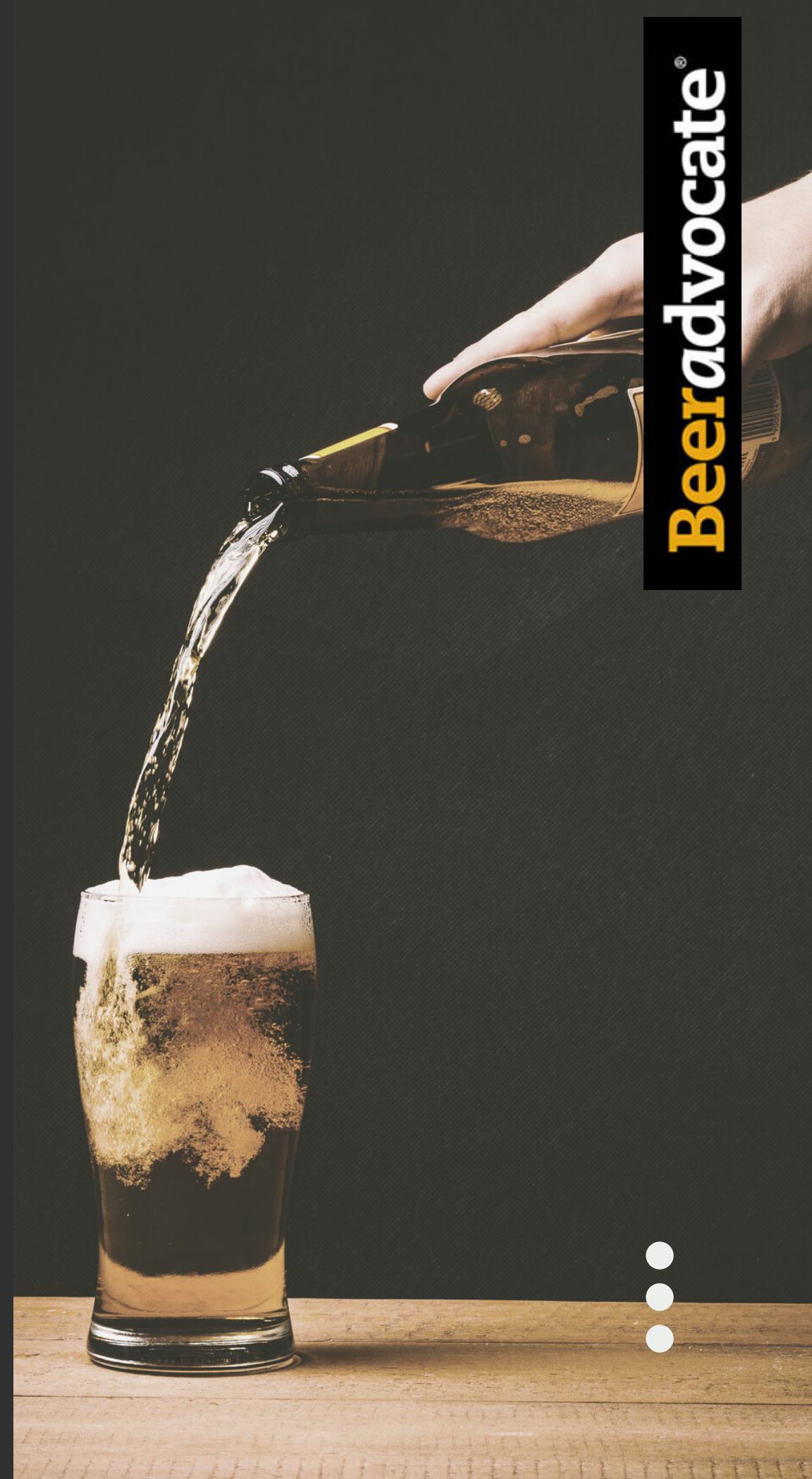
only showing top 10 rows



EXAMPLE RECOMMENDATIONS

RECOMMENDING NEW BEERS FOR USER 1

user_id	rating	brewery_name	beer_name	beer_style
1	5.2295203	Triumph Brewing C...	Snakebite	Fruit / Vegetable...
1	5.1477723	Five Seasons North	Whiskey And Oak B...	Dubbel
1	5.198488	Carter's Brewing	Black Magic Porter	American Porter



REASONS FOR SELECTING APPROACH

EXTREMELY LARGE DATASET

Spark is a memory based data processing framework that is much faster than Hadoop Map Reduce

MODULARITY

Spark offers modules for both SQL queries and machine learning, which were both central to our project

SPARK MLLIB - ALS

ALS algorithm - collaborative filtering to build a recommendation system



GENERALIZABILITY OF INSIGHTS

WHAT WE LEARNED

- THIS TECHNOLOGY IS NOT LIMITED TO THIS TOPIC AND CAN BE USED TO CREATE RECOMMENDATIONS FOR OTHER FOOD AND BEVERAGE INDUSTRIES
- LEVERAGE SELF-REPORTED INFORMATION AS AN ORGANIC MEANS OF ADVERTISING AND COLLECT ADDITIONAL DEMOGRAPHIC INFORMATION TO GET MORE ROBUST UNDERSTANDING OF CUSTOMERS
- USE TOOL TO PARTNER WITH BREWERIES, RESTAURANTS, PRODUCERS

SWOT Analysis

STRENGTHS

Provides dynamic information on preferences to keep up with how consumers react to trends and new products to generate value of customers and businesses

WEAKNESSES

Data last updated in 2011 so not as up to date as possible and recommender system could be limiting as customer tastes are dynamic with many likes and dislikes

OPPORTUNITIES

Potential partnerships with restaurants, breweries, and beer producers can bring BeerAdvocate additional revenue streams

THREATS

Competitors, change in preferences, first-movers on an alternative recommender system

CONCLUSION

THERE IS CLEAR POTENTIAL VALUE FOR CUSTOMERS LOOKING TO FIND THE PERFECT PRODUCT FOR THEIR TASTE, BUT OUR PROJECT IS UNIQUE BECAUSE THERE IS NOTABLE VALUE FOR SELLERS AS WELL AS THIS IS A FORM OF ORGANIC ADVERTISING FOR EACH BREWERY AND BEER THAT APPEAR IN OUR RECOMMENDER SYSTEM

WORKS CITED

<https://www.kaggle.com/rdoume/beerreviews>
<https://www.beeradvocate.com/user/location/?status=no-location>
<https://towardsdatascience.com/prototyping-a-recommender-system-step-by-step-part-2-alternating-least-square-als-matrix-4a76c58714a1>
<https://towardsdatascience.com/building-a-recommendation-engine-to-recommend-books-in-spark-f09334d47d67>
<https://towardsdatascience.com/intro-to-recommender-system-collaborative-filtering-64a238194a26>
<https://towardsdatascience.com/building-recommendation-system-with-pyspark-using-alternating-least-squares-als-matrix-factorisation-ebelad2e7679>





THANK YOU!
QUESTIONS?
