Craft Beer Segmentation

Making the beers your customers want

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(with thanks to Springboard mentor Max Sop)

Springboard

Capstone Project
(May 2020 Cohort)

What beer would you like?

As the craft beer industry grows so does the choice of craft beers

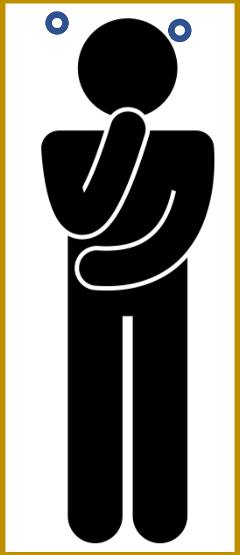
$89bn in 2019 size of craft beer industry in 2019

10.4% forecasted annual growth (accounting for COVID-19 impact to industry) to reach $161bn by 2027

8.9% increase in the number of breweries in US between 2018 and 2019

Identifying the right beer to produce can be a difficult decision for breweries looking to grow

High volume but lower quality



High quality but lower volume

Aim is to identify the beers that consumers both enjoy and drink frequently

Business Problem

Looking to produce new beer in time for Summer launch

Aim

Identify a beer that maintains brewery reputation for high quality beer but that will also have appeal to wider audience

How

Data → EDA → Beer Segmentation → Modelling → Beer Decision

Data

Focused on three main data sources

Reviews

Data on 1.59m beer reviews from 1995 to 2012. Data includes information on:

- Beer and Brewery Name
- Beer Style and ABV
- Profile Name and Review Time
- Five review scores (overall, appearance, aroma, palate, taste)

Beers

Data on 359k beers. Some duplicate information to reviews data but also contains information on:

- Beer Availability
- Beer Retired

Breweries

Data on 50k breweries. Some duplicate information to reviews data but also contains information on:

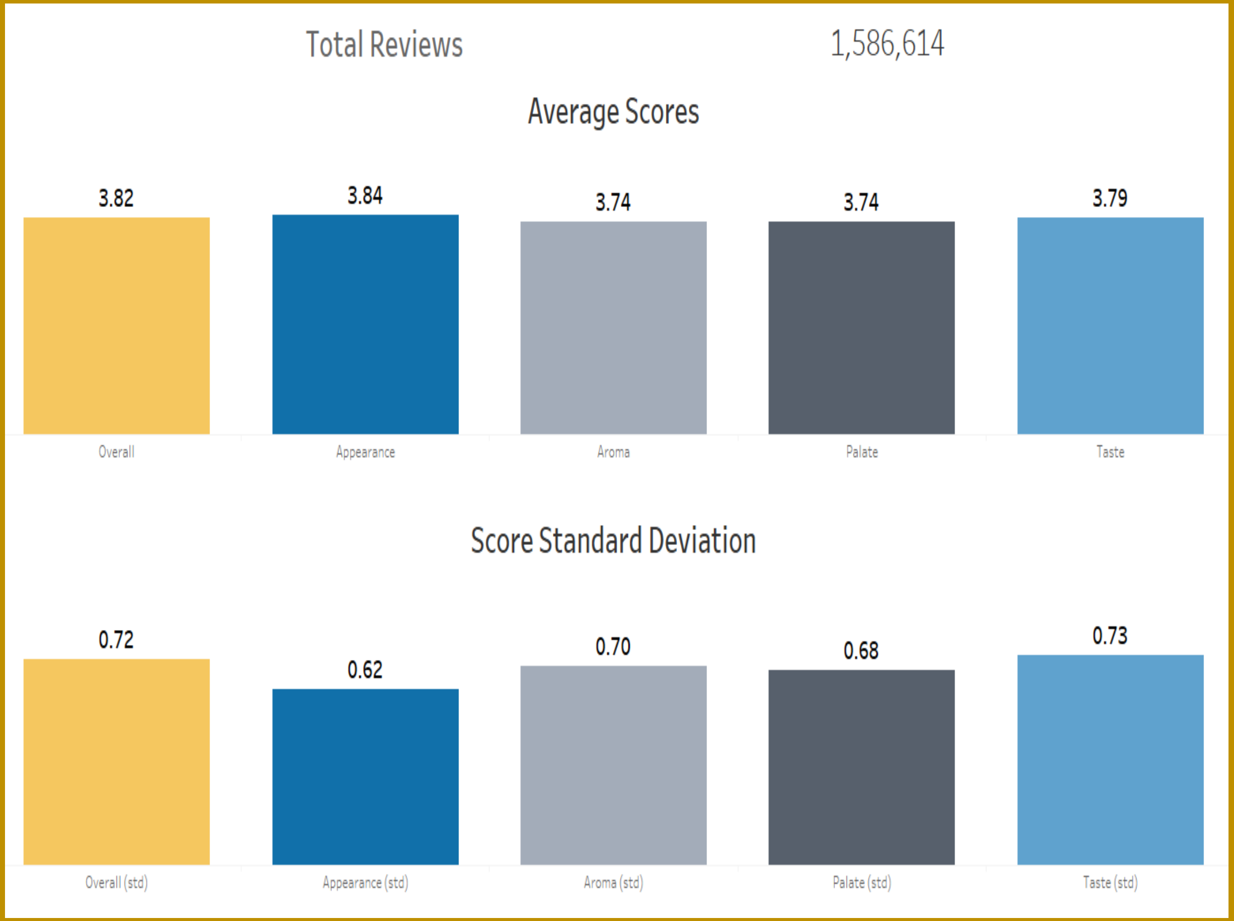
- Brewery Location (city, state, country)
- Brewery Facilities (Bar, Eatery, Beer-to-go, Store)
- Brewery Type (Brewery, Homebrew)

Exploratory Data Analysis

Reviews skewed positive with over 50% of scores being 4 star or higher

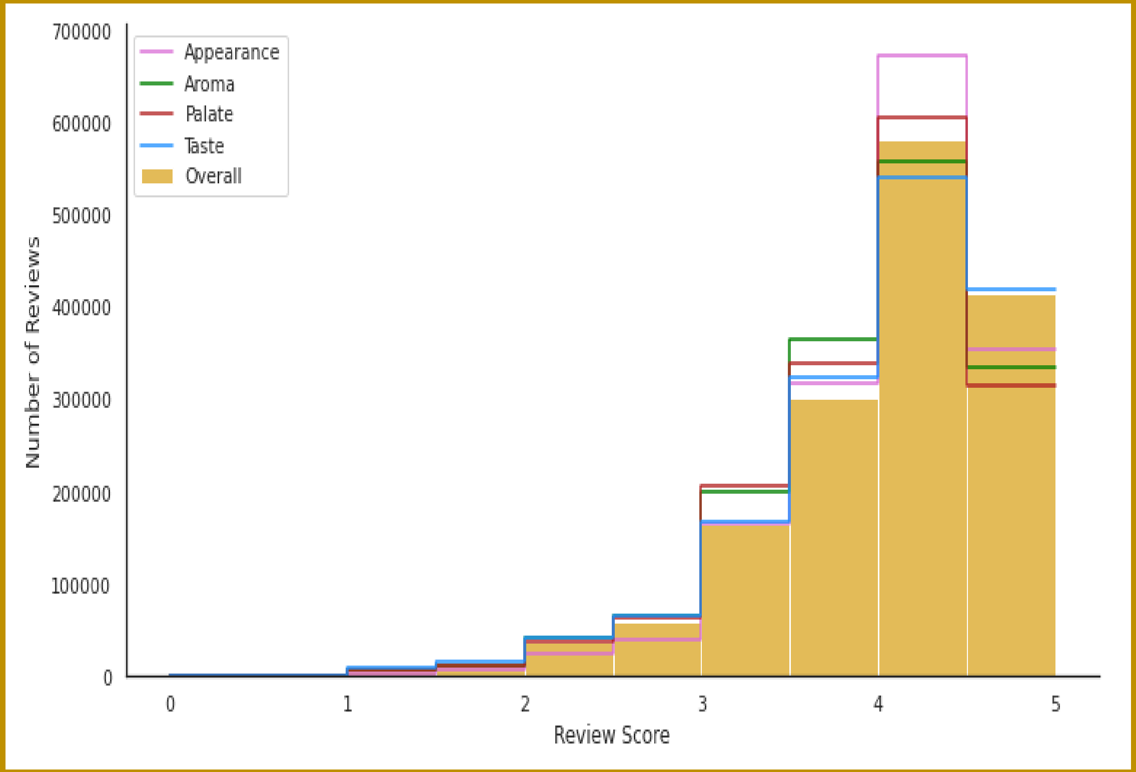
Review Score Average and Standard Deviation

By Review Score



Histogram of Review Scores

By Review Score



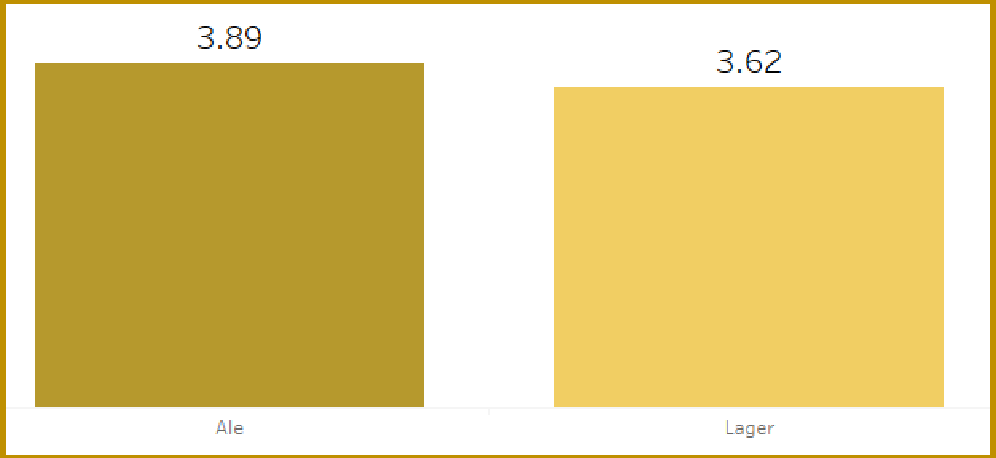
Ales scored better than Lagers

Beer Type

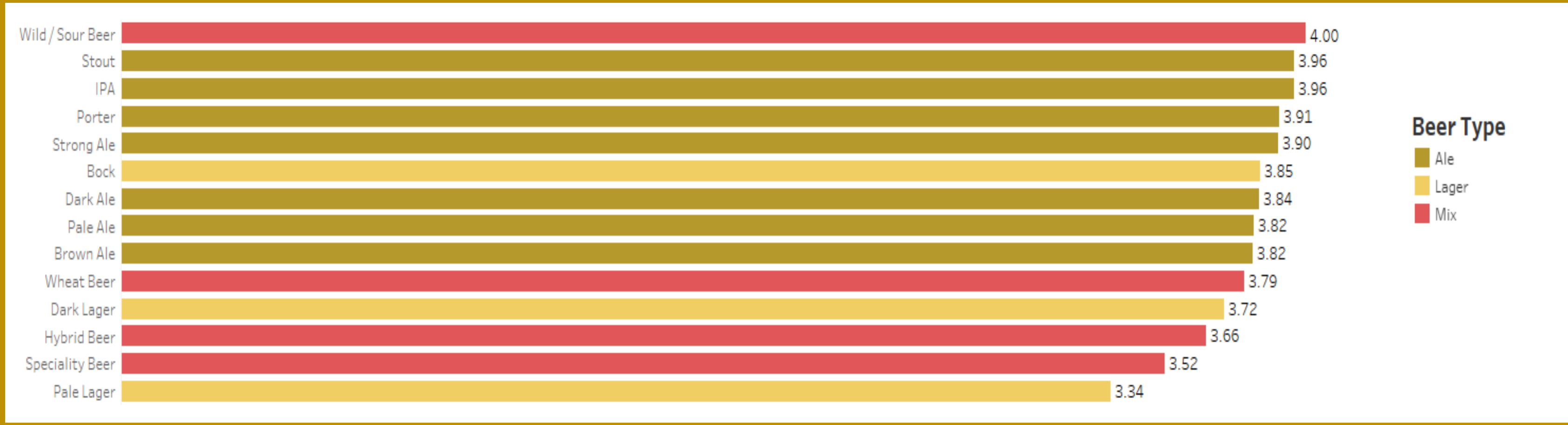
Beer Style

Review Score Average

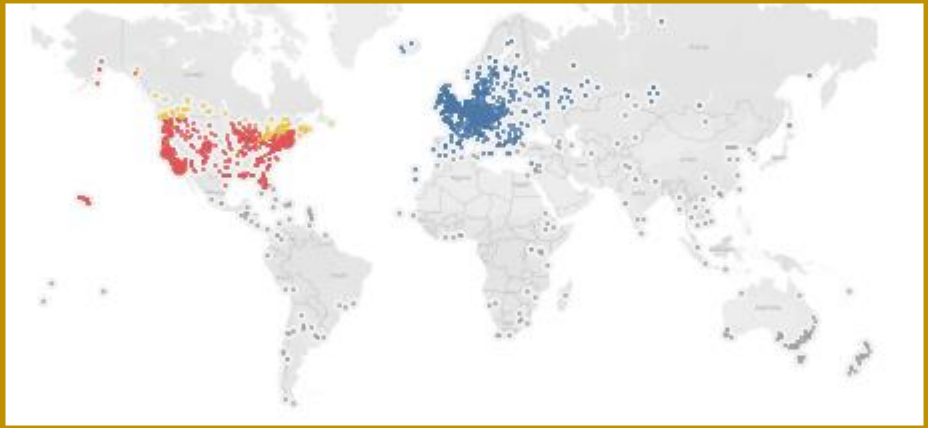
By Beer Type and Beer Sytle



73% reviews related to Ales



European beers score slightly better than American beer

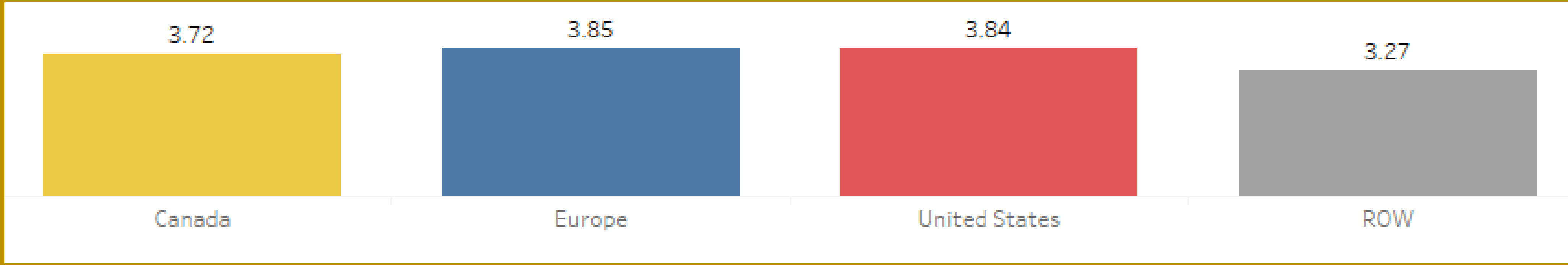


71% reviews related to US brewed beer, with California the most prominent state

23% review related to European brewed beer, with Belgium the most prominent country

Review Score Average

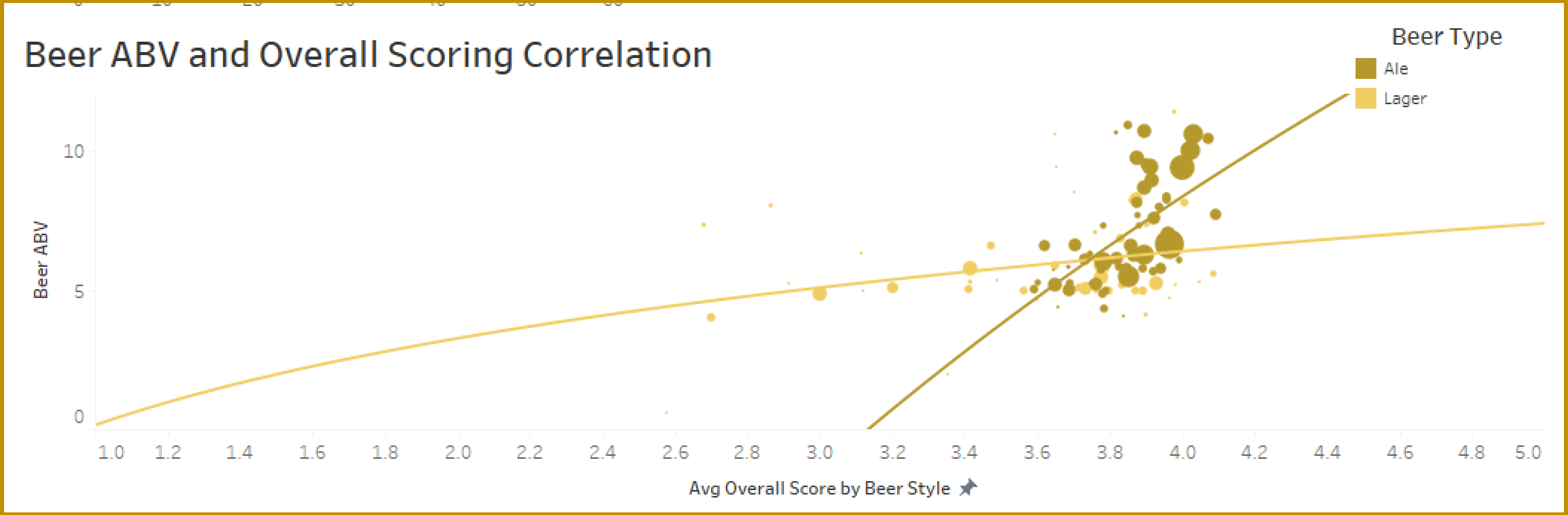
By Brewery Region



Beer ABV is significantly corelated with review score

Beer ABV and Review Score Correlation

By Beer Type



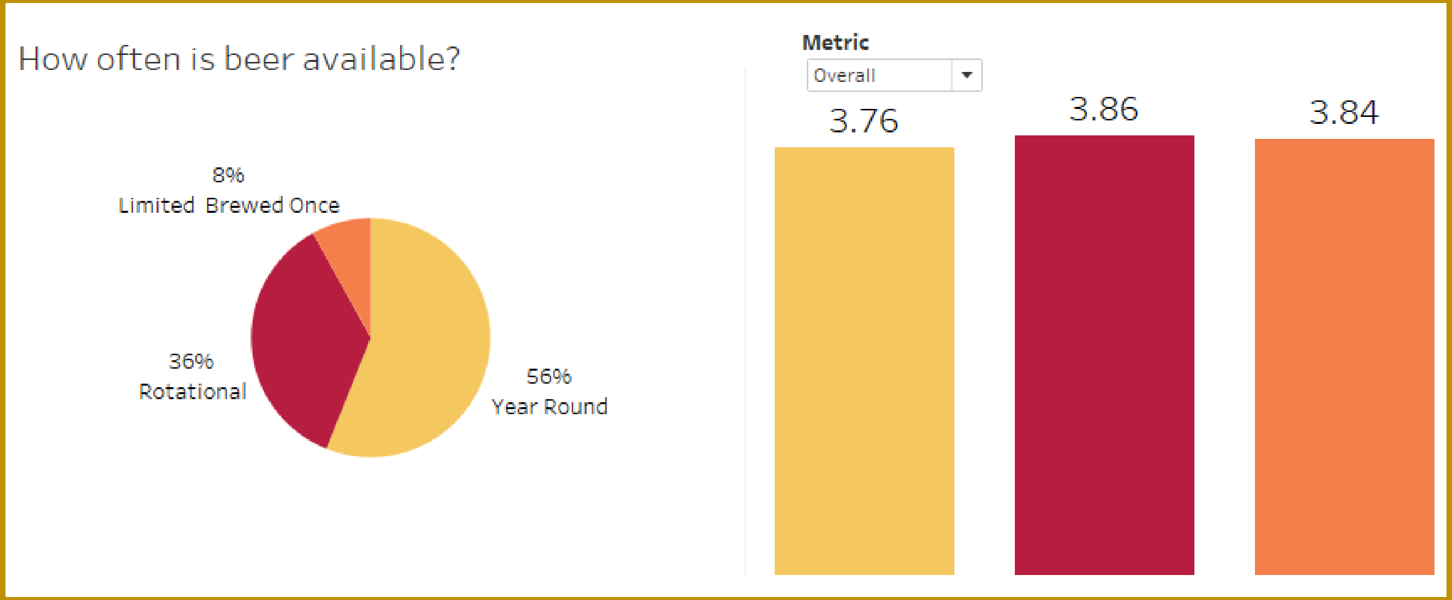
0.31 pearson coefficient

Statistically significant after running permutation test for higher correlation coefficient and achieving a 0.0 p-value

Rotational beers perform better than beers that are available year round

Review Score Average

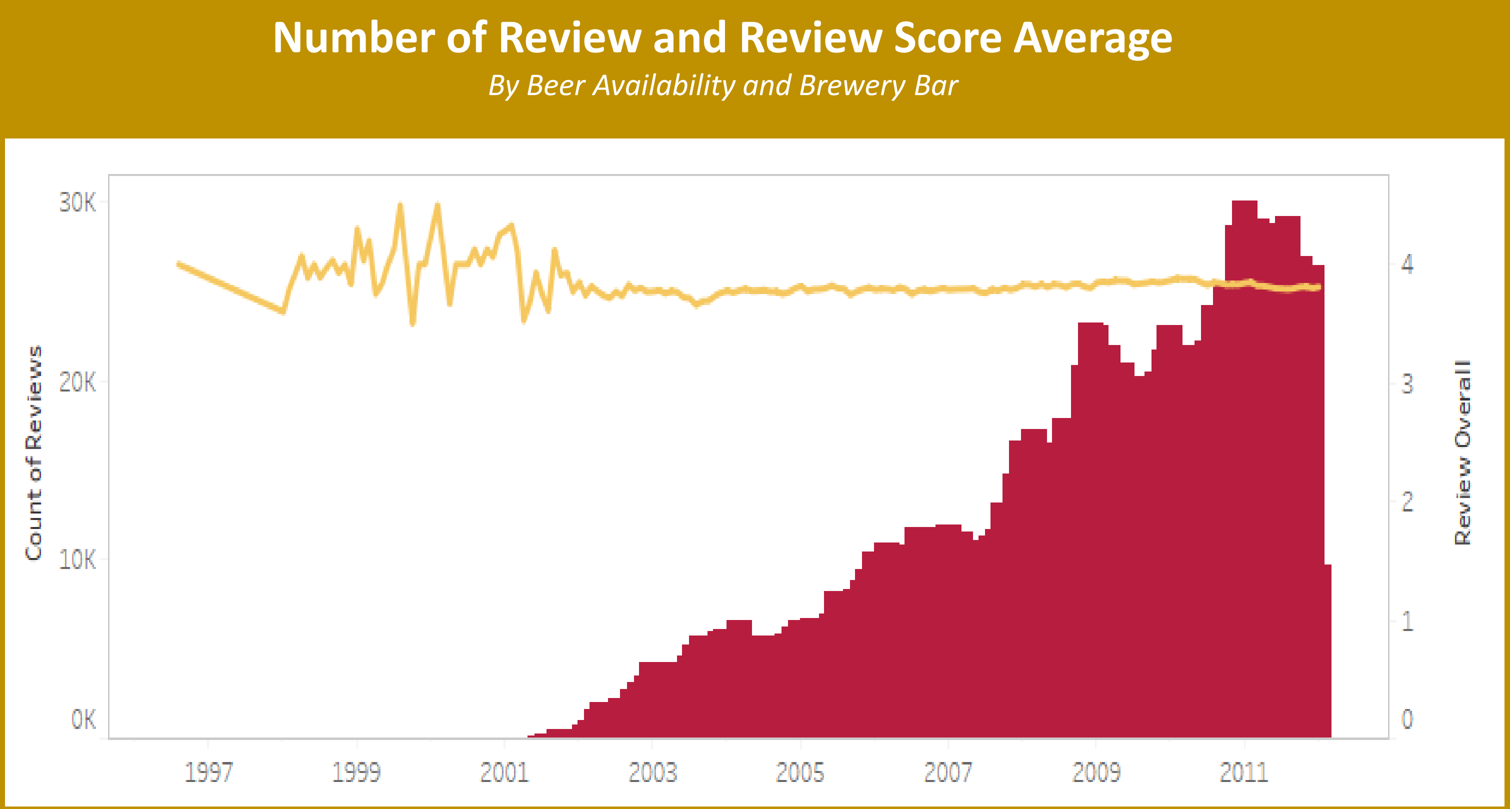
By Beer Availability and Brewery Bar



Rotational beers include all seasonal beers for Spring, Summer, Autumn and Winter – individually only summer beers perform worse

Breweries with Bars are also likely to have Eatery and Beer-to-go services (and have similar review profile)

Number of reviews has increased over time but review score has remained consistent



December is month with most reviews

Sunday is day with most reviews

No real change to average review score based on weekly or monthly trends

Beer Clustering / Segmentation

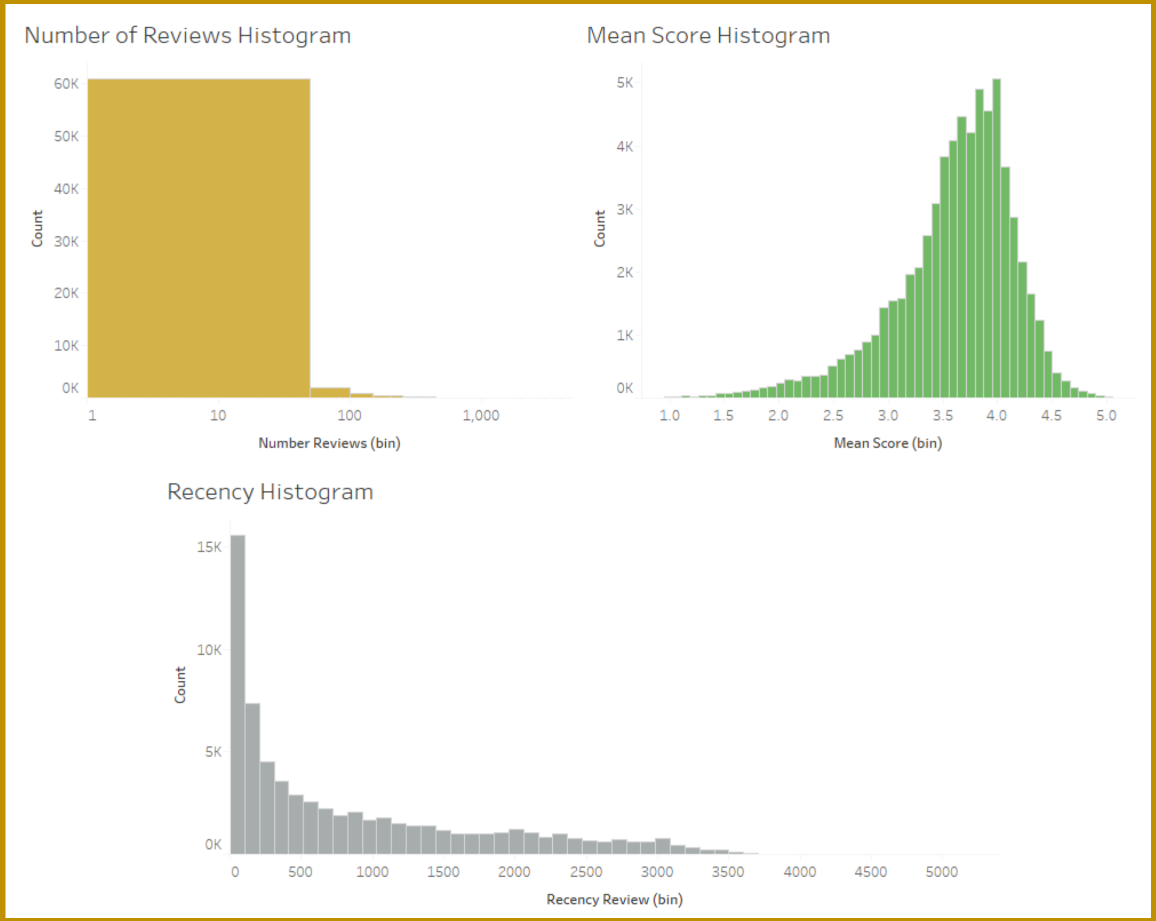
Focus on how beers differed based on three key metrics

1 **Number of Reviews**
Count of reviews for each unique beer

2 **Average Review Score**
Average review score for each unique beer

3 **Recency of Review**
How many days since last review for each unique beer

Histogram of Metrics
By Number of Review, Average Score, and Recency



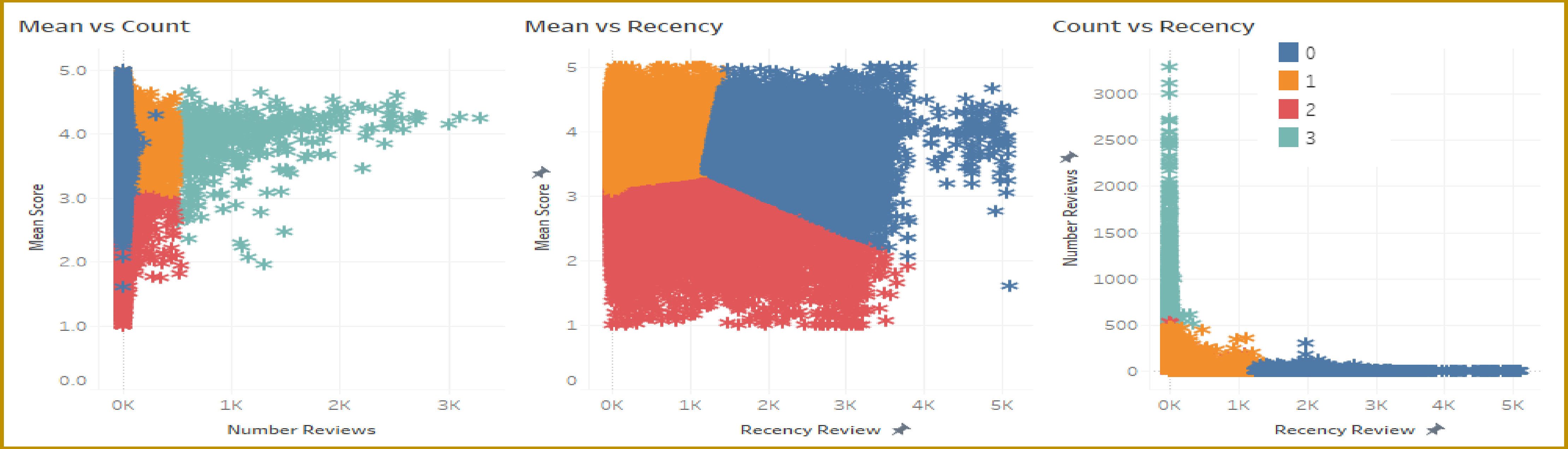
Cluster analysis identified two clusters of interest

Summary of Cluster Performance

	0	1	2	3
Reviews per Beer	3	22	9	933
Mean Score	3.7	3.8	2.7	3.9
Recency of Last Review	2,250	361	814	7
Number of Beers	14,487	38,537	12,394	627

Scatter Plots of Performance

By Cluster



Cluster 3

has all the attributes we are looking for in a beer (high average score, large number of reviews, recently made reviews) but only consists of 627 beers

Cluster 1

has beers with high average scores but number of reviews is a bit lower than would be hoped

Clusters were re-engineered to create target beer group

Summary of Target Beer Performance

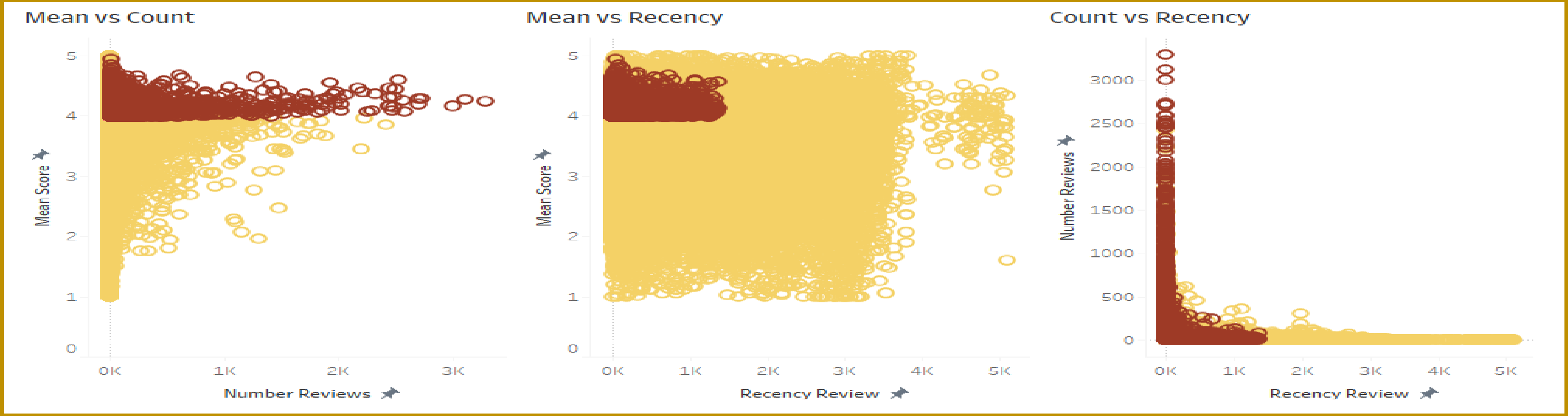
	Target	Other
Reviews per Beer	139	17
Mean Score	4.2	3.6
Recency of Last Review	177	899
Number of Beers	3,851	62,194

Target Beer

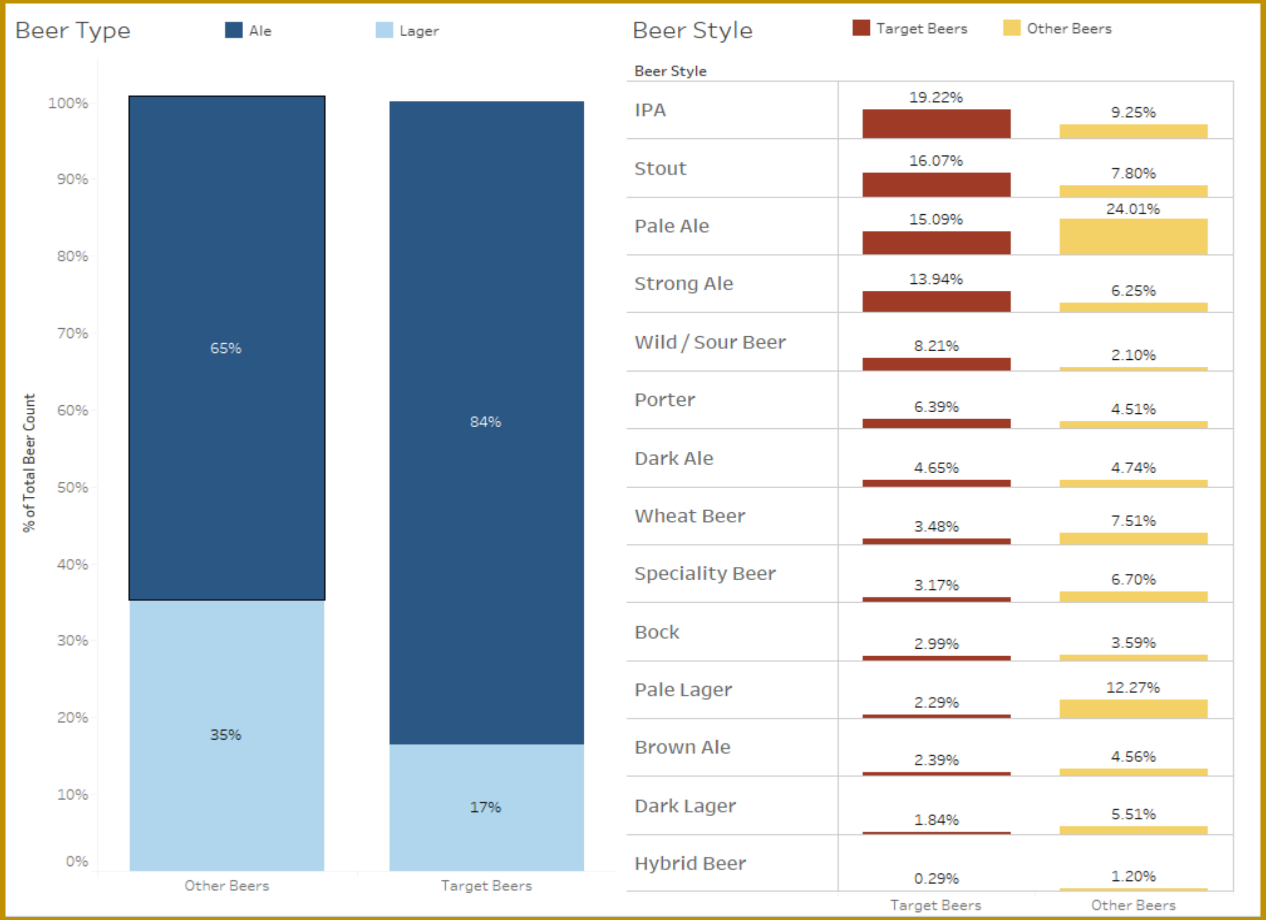
Includes Cluster 1 and 3 but filters on both to only include beers in the 75th percentile for average score (3.98) and number of reviews (11)

Scatter Plots of Performance

By Target



Ales are prominent in our target beer group



19% share increase in ales in target beers vs others

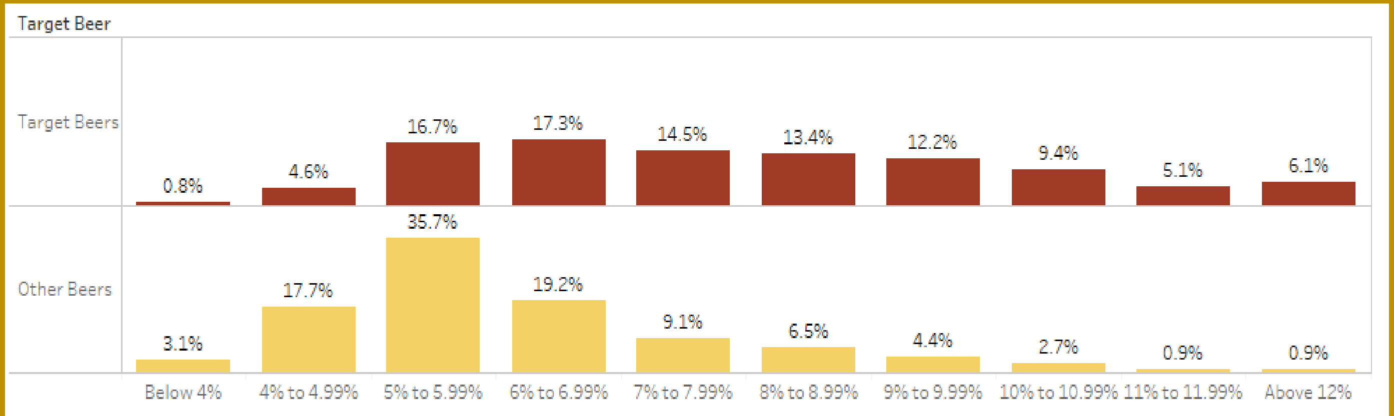
4x the share of Wild / Sour beer in target beers vs other

2x the share of IPAs, Stouts and Strong Ales in target beers vs other

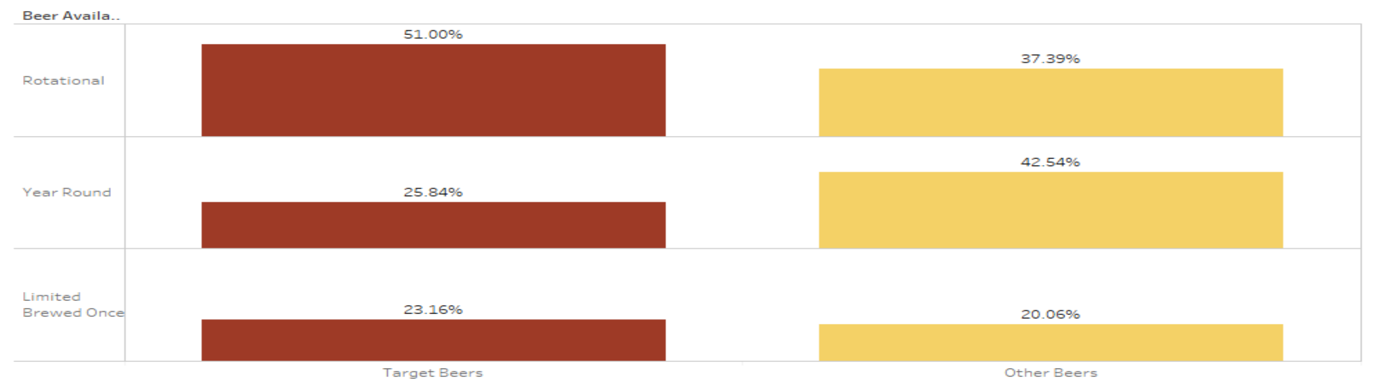
6x the share of Pale Lagers in other beers vs target

Beer ABV is higher in target beers

7% ABV is tipping point where target beer share become more prominent



51% of target beers are rotational, compared to 37% in other beers



Feature Selection and Pre-Processing

EDA identified columns and rows to remove or transform in our dataset

Drop Rows

- NaN values created during merging of dataset can be dropped (more important to keep features)

Drop Columns

- Beer and Brewery name columns
- Beer style (detailed) and Beer retired
- Brewery City, State and Country columns
- Brewery type columns (except Bar)
- Beer-level statistics (number of reviews, average score, recency of review)
- Cluster

Create Binary & Dummy Columns

- Create dummy variables columns for Beer Type, Beer Style, Brewery Region, Brewery Area, and Beer Availability
- Brewery Bar already available as binary column

Why?

Remove high dimension columns where proxy information available (i.e Beer Type or Country Region)

Remove data that was used to generate target definition (i.e. Number of Reviews, Clusters etc)

Remove highly correlated features (i.e. Brewery facilities)

Transform to binary and dummy columns to support modelling

Remove rows that will impact on modelling

Leaving us with our targets and 36 features to split and scale

1 targets

- CLUSTER_TARGET

35 features

- beer_abv
- brewery_bar
- avaiability_Rotational
- avaiability_Year Round
- type_Lager
- style_IPA
- style_Stout
- style_Porter
- style_Pale Ale
- style_Strong Ale
- style_Brown Ale
- style_Dark Ale
- style_Pale Lager
- style_Dark Lager
- style_Hybrid Beer
- style_Speciality Beer
- style_Wild / Sour Beer
- style_Wheat Beer
- region_Europe
- region_USA
- region_ROW
- area_USA
- area_Europe
- area_ROW
- area_Colorado
- area_Michigan
- area_Massachusetts
- area_Wisconsin
- area_Pennsylvania
- area_Oregon
- area_New York
- area_California
- area_Canada
- area_United Kingdom
- area_Germany

Train / Test Split

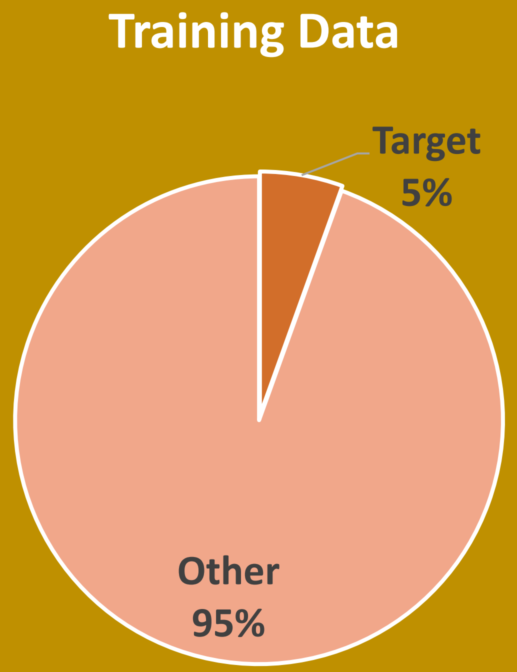
Y = cluster_target
X = Features

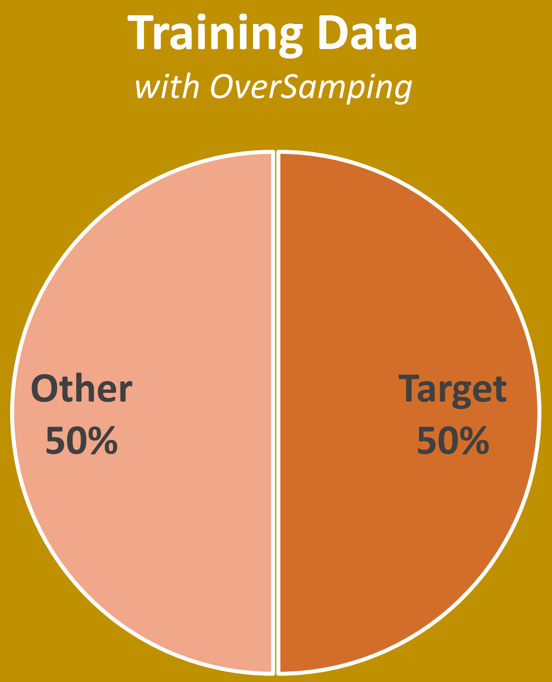
75% / 25% split – Training to Test

Scaling

- Standardization applied to all continuous variables (only Beer ABV)
- Dummy and binary variables are not scaled

Our dataset is imbalanced so we attempted to address this by using Over Sampling





Rebalance our training data using random sampling

Two approaches available

1) Under Sampling: randomly reducing our majority class (other beers) samples
2) Over Sampling: randomly increasing our minority class samples (target beers)

Applied on Over Sampling using imblearn's SMOTE function

- SMOTE generates new samples by interpolation rather than random sampling with RandomOverSampler function

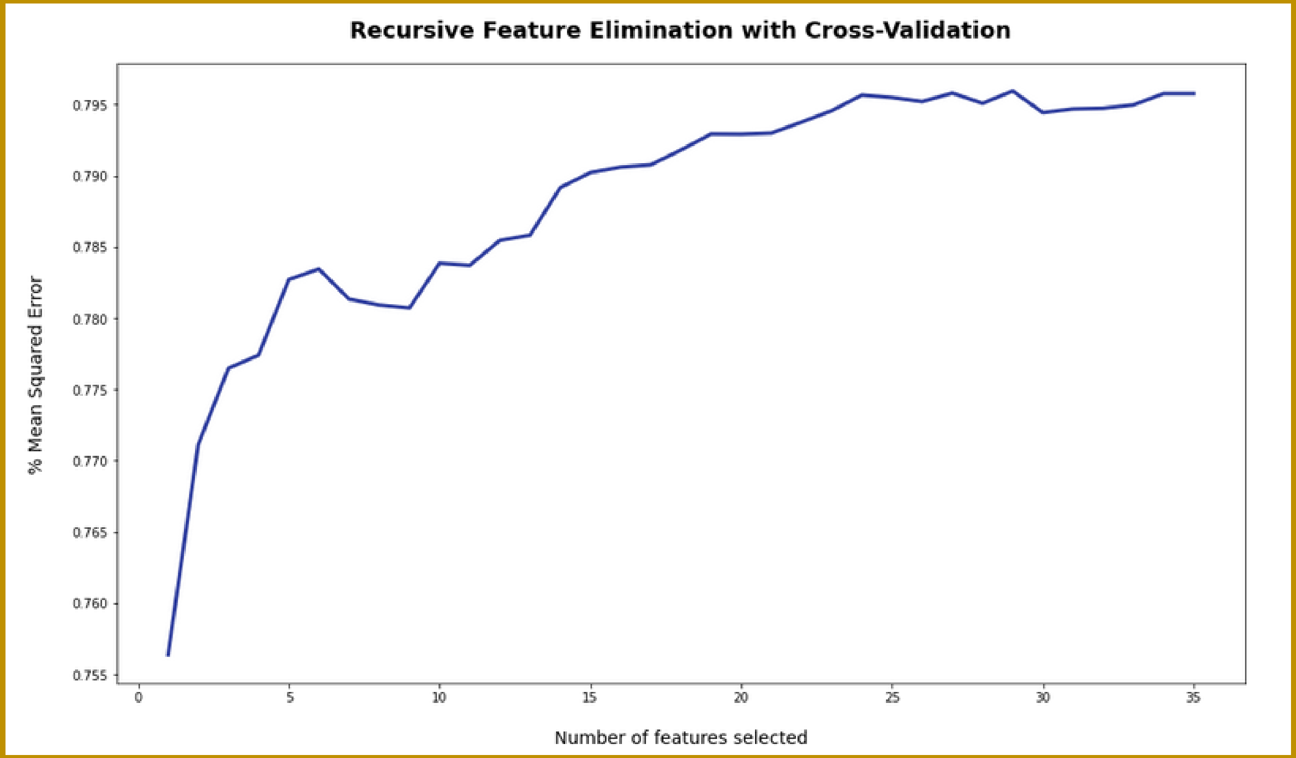
Apply Recursive Feature Elimination to reduce features before modelling

Recursive Feature Elimination with Cross-Validation

Optimal number of features is 29

Drop columns:

- Style_Strong Ale
- Area_United Kingdom
- Style_Wheat Beer
- Area_Canada
- Region_USA
- Area_Germany



Final dataset with 19 features and our target variable

1 targets

- CLUSTER_TARGET

29 features

- beer_abv
- brewery_bar
- avaiability_Rotational
- avaiability_Year Round
- type_Lager
- style_IPA
- style_Stout
- style_Porter
- style_Pale Ale
- style_Brown Ale
- style_Dark Ale
- style_Pale Lager
- style_Dark Lager
- style_Hybrid Beer
- style_Speciality Beer
- style_Wild / Sour Beer
- sregion_Europe
- region_ROW
- area_USA
- area_Europe
- area_ROW
- area_Colorado
- area_Michigan
- area_Massachusetts
- area_Wisconsin
- area_Pennsylvania
- area_Oregon
- area_New York
- area_California

Classification Model

Three classification models were chosen for machine learning

	Model	Description
1	**Logistic Regression**	Logistic regression is a linear model for classification (not regression despite the name). In this model, the probabilities describing the possible outcomes of a single trial are modelled using a logistic function.
2	**Gradient Boosting Classifier**	Gradient Boosting is a generalization of boosting to arbitrary differentiable loss functions. It is an accurate and effective off-the-shelf procedure that can be used for classification problems.
3	**Random Forest Classifier**	A random forest is a meta estimator that fits a number of classifying decision trees on various sub-samples of the dataset and uses averaging to improve the predictive accuracy and control over-fitting.

*** Classification models used as our target variable is binary**

The hyper-parameters for these models were tuned to attempt to find the optimal model

1 Logistic Regression

- C = 0.1
- Penalty = ‘l2’

2 Gradient Boosting Classifier

- learning_rate=0.01
- max_depth=7
- max_features='auto’
- min_samples_leaf=2
- min_samples_split=2
- n_estimators=500

3 Random Forest Classifier

- max_depth=9
- max_features='LOG2’
- min_samples_leaf=20
- min_samples_split=4
- n_estimators=250
- criterion = 'gini'

*** Hyper-parameter tuning completed using RandomizedSearchCV() on sklearn**

Each model was evaluated with five metrics

1	**Accuracy**	Overall performance of model
2	**Precision**	How accurate positive predictions (of target beer) are
3	**Recall**	Coverage of actual positive sample
3	**ROC Curve and AUC**	Relationship between Recall and Specificity
3	**Precision-Recall curve and AUC**	Relationship between Precision and Recall

The models were fitted and evaluated on training data

Model Evaluation on Training Data

By Model & Evaluation Metric

Model	Accuracy	Precision	Recall	ROC-AUC	PR-AUC
Logistic	0.73	0.73	0.72	0.80	0.78
Gradient Boosting	0.86	0.84	0.88	0.93	0.93
Random Forest	0.78	0.77	0.79	0.93	0.93

Gradient Boosting was the best model when applied to all training data

- Highest Accuracy, Precision and Recall
- Same ROC-AUC and PR-AUC as Random Forest

As well as evaluated with cross-validation to understand how performance would generalise

Model Evaluation on Training Data (with 5-fold Cross-Validation)

By Model & Evaluation Metric

Model	Accuracy	Precision	Recall	ROC-AUC	PR-AUC
Logistic	0.73	0.73	0.72	0.80	0.78
Gradient Boosting	0.85	0.84	0.87	0.93	0.93
Random Forest	0.77	0.77	0.77	0.86	0.84

Gradient Boosting was again the best model when 5-fold cross-validation was applied to the training data

- Highest across all metrics
- Random Forest performance declines compared to when applied to full training data
- Logisitc remains similar, showing bias in the model

Models were then fitted to test data and performance declines significantly

Model Evaluation on Test Data

By Model & Evaluation Metric

Model	Accuracy	Precision	Recall	ROC-AUC	PR-AUC
Logistic	0.73	0.13	0.70	0.78	0.19
Gradient Boosting	0.82	0.16	0.54	0.93	0.18
Random Forest	0.76	0.14	0.66	0.78	0.18

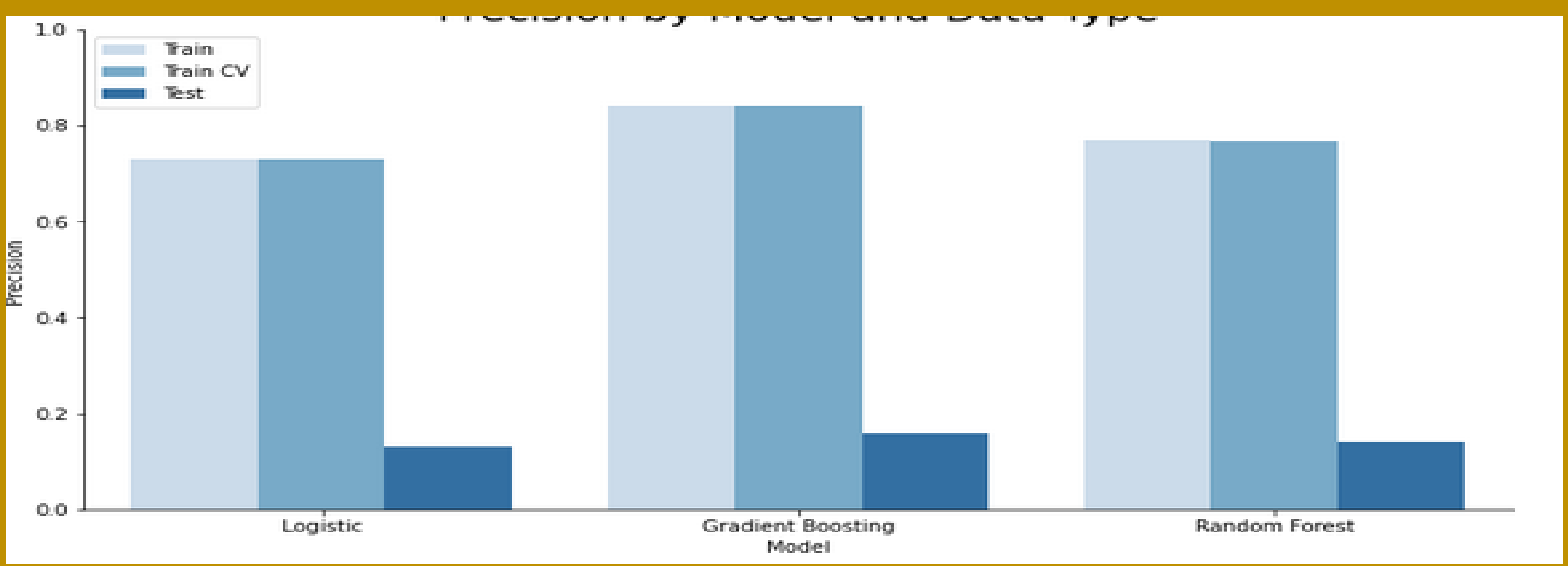
All models see performance decline significantly when applied to test data

- Fall in precision across all models is massive concern – as this highlights that model is doing a poor job of classifying our target beers on new data
- Decline in Recall also shows that model is incorrectly classifying target beers as non-target more often
- Models do not generalise well

Precision decline on test data means models are not accurately predicting our target beer

Precision Score Evaluation

By Model & Data Tye



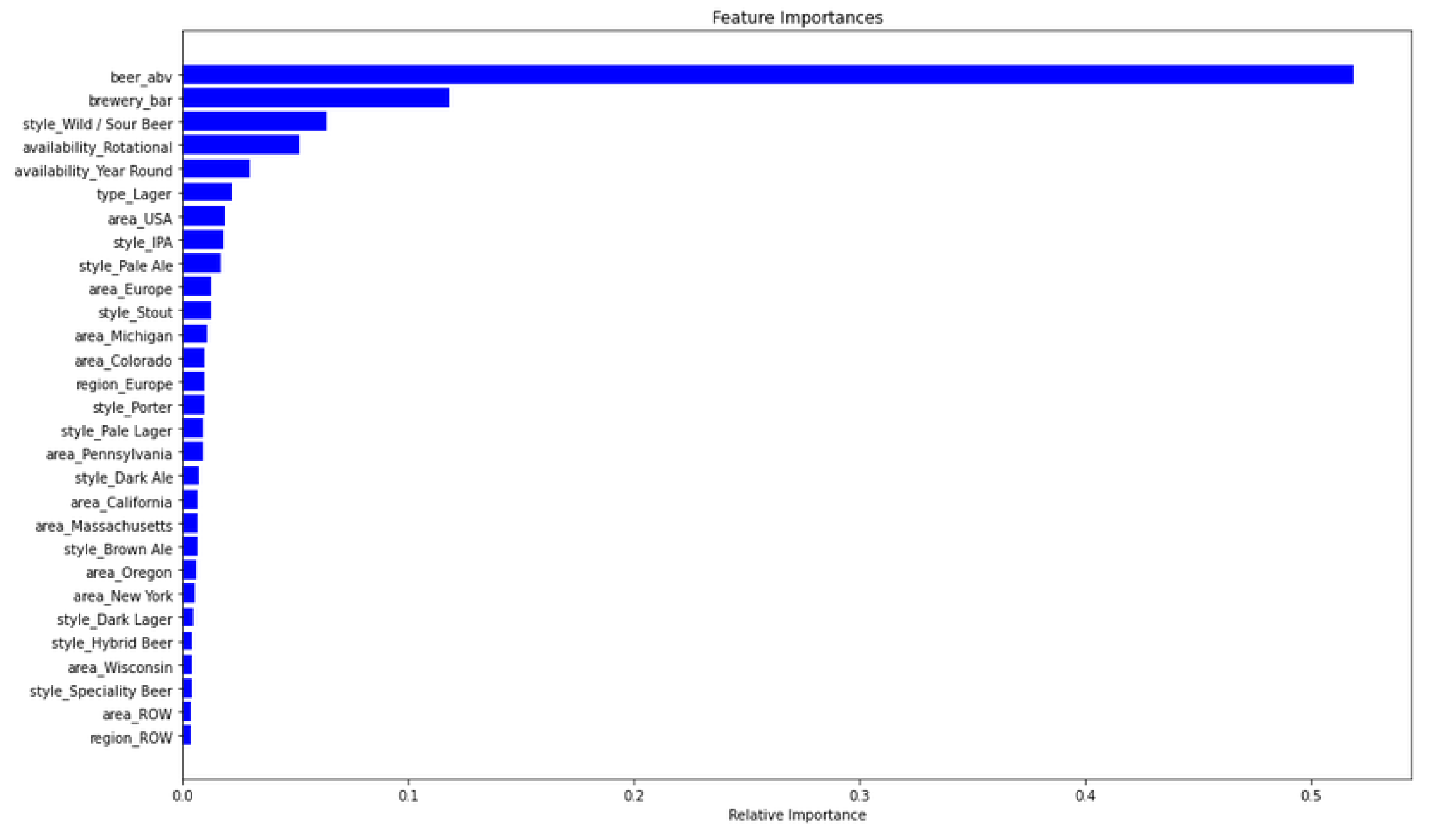
	Logistic	Gradient Boosting	Random Forest
Training	0.73	0.84	0.77
Training (with CV)*	0.73	0.84	0.77
Test	0.13	0.16	0.14

Feature importance suggest that Beer ABV is most important

- Beer ABV is main feature across all models
- Wild / Sour Beer most important beer style feature across all models, followed by Brewery with Bar
- Brewery Locations not adding as much value to model

Feature Importance (on Gradient Boosting Model)

By Feature



Conclusion

Conclusion

Pros

- EDA
  - Clear picture of what beers and breweries perform best in our review dataset
  - Clustering used to segment beers into relevant groups based on quality, volume and recency metrics
- Modelling
  - Provides some information on the importance of certain features

Cons

- Modelling
  - Imbalanced data causing problems
  - Low precision / recall on test data
  - Needs to be refined before supporting overall decision making

Beer Recommendation – Seasonal Wild Ale

Rotational

As model still needs to be fined tuned to make more reliable predictions for our target beer, a sensible approach would be to release a small batch seasonal beer. Rotational beers generated higher review scores and a high feature importance in all models. This approach would allow the brewery produce release a beer at lower risk and allow it to gauge customer response to beer before making decision to produce at larger scale

High ABV

All our analysis has shown that beer with higher Beer ABV review better – be it average review score, significance testing of the corelation coefficient, or it being the most important feature in our models. The new beer being produce should look to have an ABV of greater than at least 7%.

Ale

Ales perform much better than lagers and this is shown throughout our EDA and modelling. Producing an Ale is more likely to receive positive reviews.

Wild Beer

Wild / Sour beers are the top performing beers in our dataset. This is shown through it having the highest rating in our review dataset, as well as being one of the top 5 feature importance in our model.

Next Steps

How to Improve

New techniques for handling imbalanced data

- SMOTE approach used for this analysis but other UnderSampling or other approaches to be considered
- Different train / test splits may support better generalisation

New data

- Additional features to support modelling (ingredients, sales data) would help enrich model
  - Current model is limited to beer style, brewery location, and beer availability – reducing the number of variables related to these fields and increasing in relation other categories would help enrich our model
- More reviews would help increase size of minority class – in conjunction with techniques outlined above

Re-engineer data / metrics

- Look at beer performance by Year / Month to add time relevant data to your model and also increase the number of rows in beer-level dataset
- Instead of looking at overall review score, look at particular attribute (i.e. taste)
- Use previous review data to predict future review data
- Segment using only metrics instead of three

Reframe question

- Focus solely on volume of reviews and develop model to see how quality impacts on this using five scoring metrics (appearance, aroma, palate, taste, overall)
  - This analysis would not provide brewery with exact beer to produce but give steer on what attributes of beer matter most to consume
- Use clustering on all five review metrics to see what groups this suggest and then look to see how these translate back to existing labelled data for beer styles
  - Identify new style that is popular but not yet being promoted

Archive

Data Flow Diagram