PROJECT 2: PREDICTING PH

DATA 624 - Predictive Analytics

Group 2

Group Members:

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Contents

Introduction

This project is designed to evaluate production data from a beverage manufacturing company. Our assignment is to predict PH, a Key Performance Indicator (KPI), with a high degree of accuracy through predictive modeling. After thorough examination, we approached this task by splitting the provided data into training and test sets. We evaluated several models on this split and found that **what-ever-worked-best** method yielded the best results.

Each group member worked individually to create their own solution. We built our final submission by collaboratively evaluating and combining each others' approaches. Our introduction should further outline individual responsibilities. For example, **so-and-so** was responsible for **xyz task**.

For replication and grading purposes, we made our code avaliable in the appendix section. This code, along with the provided data, score-set results, and individual contributions, can also be accessed through our group github repository:

- Pretend I'm a working link to R Source Code
- Pretend I'm a working link to Provided Data
- Pretend I'm a working link to Excel Results
- Pretend I'm a working link to Individual Work

1 Data Exploration

The beverage manufacturing production dataset contained 33 columns/variables and 2,571 rows/cases. In our initial review, we found that the response variable, PH, had four missing observations. We choose to drop the complete cases of all observations with null data in the target as they accounted for such a small proportion (< 0.002%) of the observations.

We also identified that 94% of the predictor variables had missing data points. Despite this high occurance, the NA values in the majority of these predictors accounted for less than 1% of the total observations. Only eleven variables were missing more than 1% of data. The table below shows the top variables with the most observations missing:

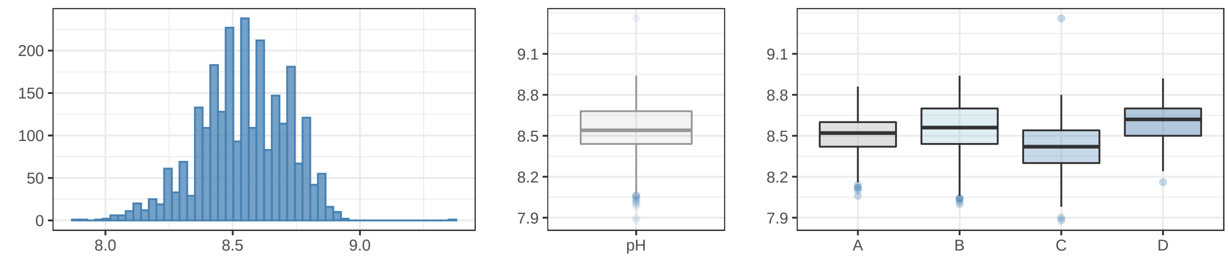
	MFR	BrandCode	FillerSpeed	PCVolume	PSCCO2	FillOunces	PSC	CarbPressure1	HydPressure4	CarbPressure
n	208.0	120.0	54.0	39.0	39.0	38.0	33.0	32.0	28.0	27.0
%	8.1	4.7	2.1	1.5	1.5	1.5	1.3	1.2	1.1	1.1

Response Variable

Understanding the influence pH has on our predictors is key to building an accurate predictive model. pH is a measure of acidity/alkalinity that must conform in a critical range. The value of pH ranges from 0 to 14, where 0 is acidic, 7 is neutral, and 14 is basic.

The plots below show the distribution of `pH` in our data. The histogram shows us this variable follows a somewhat normal pattern and is centered around 8.6. The boxplots also allows us to better visualize the outliers within our target variable. We viewed `pH` (middle) and `pH` by `BrandCode` (right) to examine the differences in distribution and relationship between these variables. Brand D has the highest median `pH` and brand C has the lowest. Brand C also appears to have the largest range in `pH` values.

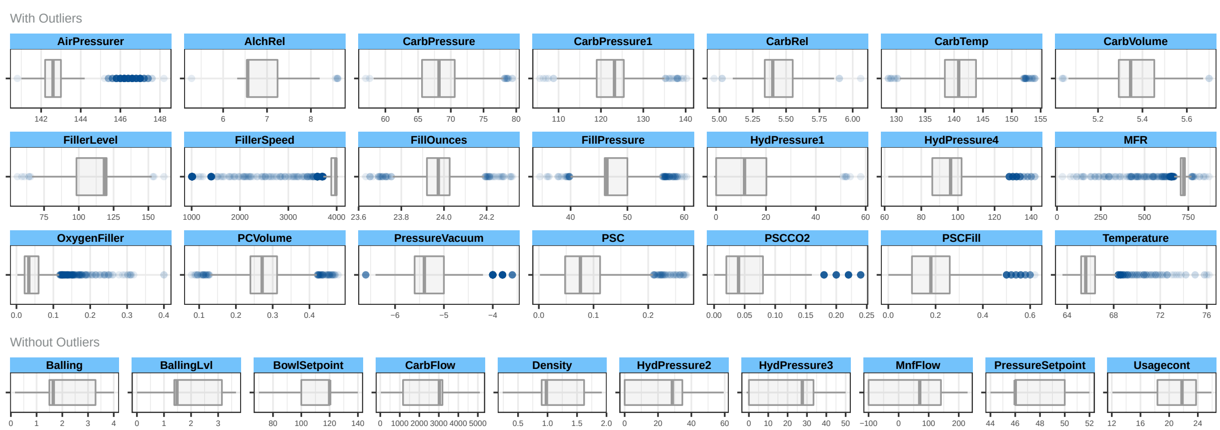
Distribution of Response Variable: pH



Predictor Variables

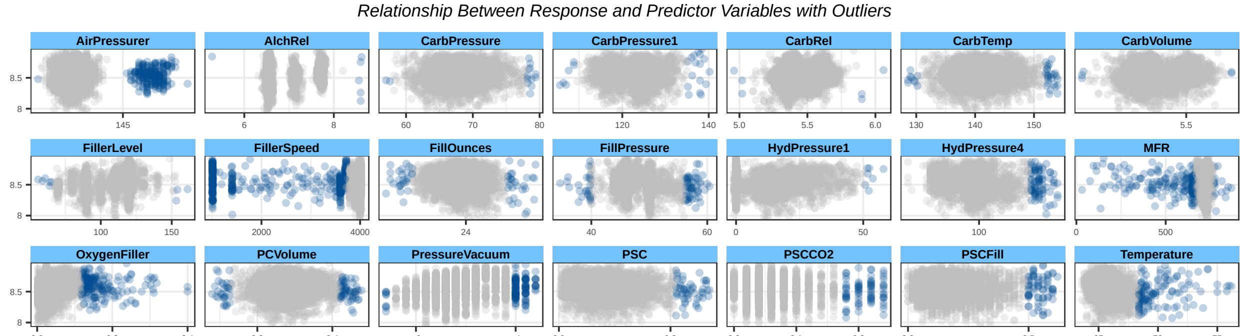
Many of our predictors also contain outliers and have a skewed distribution. The boxplots below help us visualize this spread of our numeric predictor variables.

Box−Plot Distribution of Numeric Predictor Variables



We examined the predictor variables with outliers in a scatterplot against our target, `pH` to better understand predictor and response relationship. The outliers, highlighted in blue, further show which predictors have a heavy-tail distribution. We can also identify many variables with strong outlier patterns, suggesting a high degree of variability within certain measurements.

Relationship Between Response and Predictor Variables with Outliers



pH~Predictor Scatterplots

For example, `AirPressurer` shows one of the more distinct patterns. This variable appears bifurcated with a clear split between normal and extreme values. `MFR` also shows an interesting pattern. The outliers have a weak, negative linear relationship with `pH`, but the non-outliers have no linear relationship and follow a straight, vertical line.

Correlation

9 of our numeric predictor appear heavily related, with correlation values exceeding ± 0.75. The full correlation matrix can be viewed in the appendix section. *Revisit section to add more text*

V1	V2	COR	|	V1	V2	COR
AlchRel	BallingLvl	0.93	|	CarbVolume	AlchRel	0.78
AlchRel	CarbRel	0.84	|	CarbVolume	Density	0.76
Balling	BallingLvl	0.98	|	Density	Balling	0.95
Balling	AlchRel	0.92	|	Density	BallingLvl	0.95
Balling	CarbRel	0.82	|	Density	AlchRel	0.90
CarbPressure	CarbTemp	0.81	|	Density	CarbRel	0.82
CarbRel	BallingLvl	0.84	|	FillerLevel	BowlSetpoint	0.95
CarbVolume	CarbRel	0.79	|	FillerSpeed	MFR	0.93
CarbVolume	Balling	0.78	|	HydPressure2	HydPressure3	0.93
CarbVolume	BallingLvl	0.78	|	MnfFlow	HydPressure3	0.76

Table 1.1: Highly Correlated Predictors

2 Data Preparation

Decision tree and boosted models are robust against the affect of multicollineraty, outliers, and missing values. *Tranformation approaches will vary as we play with model. Visit this section later.*

We divided data using an 80/20 split to create a train and test set. All models will incorporate k-folds cross-validation across 10 folds to protect against overfitting the data.

Data Imputation

We choose to handle missing data in our predictor variables using multiple imputations. We applied a Multiple Imputation by Chained Equations (MICE) algorthim, which uses sequential regression to fill in the data across all the incomplete cases (including categorical data).

We can also use this same approach to handle outliers (linear model) by setting their value to `NA` and predicticting a value within the expected range.

Pre-Processing

Test the effect of pre-processing methods to maximize the success of our tree and non-tree models. Not currently adding data transformations but may revisit: ie. scale data for PLS.

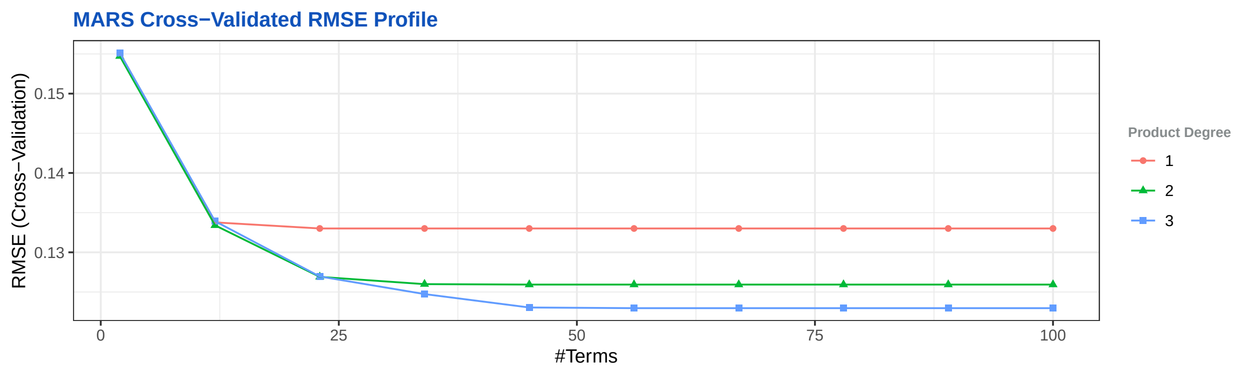
For linear models, we removed the predictor `HydPressure1` as it contained near-zero variance. `HydPressure3`, `Balling`, `BallingLvl`, `FillerSpeed`, `FillerLevel`, and `Density` were also removed due to large absolute correlations with other variables.

3 Predictive Modeling

Only attempted 1 model thus far: MARS. Text explination to come.

MARS Model

Explain text here. Text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text text.



MARS CV RMSE:

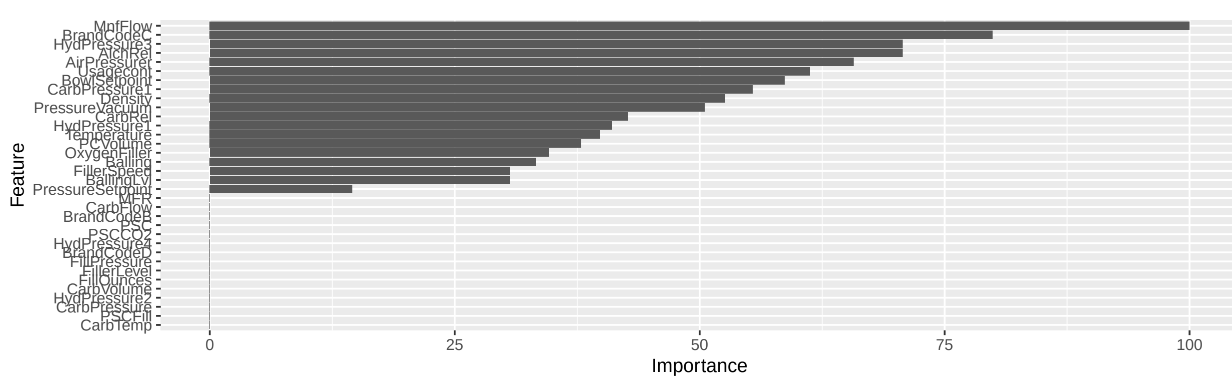
Train Accuracy:

RMSE	Rsquared	MAE
0.1229609	0.5076279	0.0915898

Test Accuracy:

RMSE	Rsquared	MAE
0.1220149	0.4911614	0.0904218

Variable Importance:



Train

Train text.

Test

Test text.

4 Discussion

Eval text. The end.

5 Conclusion

sfasdfs

Appendix

Summary Statistics

	vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
BrandCode*	1	2447	2.5	1.0	2.0	2.5	0.0	1.0	4.0	3.0	0.4	-1.1	0.0
CarbVolume	2	2557	5.4	0.1	5.3	5.4	0.1	5.0	5.7	0.7	0.4	-0.5	0.0
FillOunces	3	2529	24.0	0.1	24.0	24.0	0.1	23.6	24.3	0.7	0.0	0.9	0.0
PCVolume	4	2528	0.3	0.1	0.3	0.3	0.1	0.1	0.5	0.4	0.3	0.7	0.0
CarbPressure	5	2540	68.2	3.5	68.2	68.1	3.6	57.0	79.4	22.4	0.2	0.0	0.1
CarbTemp	6	2541	141.1	4.0	140.8	141.0	3.9	128.6	154.0	25.4	0.2	0.2	0.1
PSC	7	2534	0.1	0.0	0.1	0.1	0.0	0.0	0.3	0.3	0.9	0.7	0.0
PSCFill	8	2544	0.2	0.1	0.2	0.2	0.1	0.0	0.6	0.6	0.9	0.8	0.0
PSCCO2	9	2528	0.1	0.0	0.0	0.0	0.0	0.0	0.2	0.2	1.7	3.7	0.0
MnfFlow	10	2567	24.6	119.5	70.2	21.1	161.6	-100.2	229.4	329.6	0.0	-1.9	2.4
CarbPressure1	11	2535	122.6	4.7	123.2	122.5	4.4	105.6	140.2	34.6	0.0	0.1	0.1
FillPressure	12	2549	47.9	3.2	46.4	47.7	2.4	34.6	60.4	25.8	0.5	1.4	0.1
HydPressure1	13	2556	12.5	12.4	11.4	10.9	16.9	-0.8	58.0	58.8	0.8	-0.1	0.2
HydPressure2	14	2552	21.0	16.4	28.6	21.1	13.3	0.0	59.4	59.4	-0.3	-1.6	0.3
HydPressure3	15	2552	20.5	16.0	27.6	20.5	13.8	-1.2	50.0	51.2	-0.3	-1.6	0.3
HydPressure4	16	2539	96.3	13.1	96.0	95.5	11.9	62.0	142.0	80.0	0.6	0.6	0.3
FillerLevel	17	2551	109.3	15.7	118.4	111.0	9.2	55.8	161.2	105.4	-0.8	0.0	0.3
FillerSpeed	18	2513	3688.1	769.6	3982.0	3920.2	47.4	998.0	4030.0	3032.0	-2.9	6.8	15.4
Temperature	19	2555	66.0	1.4	65.6	65.8	0.9	63.6	76.2	12.6	2.4	10.3	0.0
Usagecont	20	2562	21.0	3.0	21.8	21.3	3.2	12.1	25.9	13.8	-0.5	-1.0	0.1
CarbFlow	21	2565	2472.1	1070.4	3030.0	2604.2	323.2	26.0	5104.0	5078.0	-1.0	-0.6	21.1
Density	22	2567	1.2	0.4	1.0	1.2	0.1	0.2	1.9	1.7	0.5	-1.2	0.0
MFR	23	2359	704.0	73.9	724.0	718.2	15.4	31.4	868.6	837.2	-5.1	30.5	1.5
Balling	24	2567	2.2	0.9	1.6	2.1	0.4	0.2	4.0	3.9	0.6	-1.4	0.0
PressureVacuum	25	2567	-5.2	0.6	-5.4	-5.3	0.6	-6.6	-3.6	3.0	0.5	0.0	0.0
PH	26	2567	8.5	0.2	8.5	8.6	0.2	7.9	9.4	1.5	-0.3	0.1	0.0
OxygenFiller	27	2556	0.0	0.0	0.0	0.0	0.0	0.0	0.4	0.4	2.4	8.8	0.0
BowlSetpoint	28	2565	109.3	15.3	120.0	111.4	0.0	70.0	140.0	70.0	-1.0	-0.1	0.3
PressureSetpoint	29	2555	47.6	2.0	46.0	47.6	0.0	44.0	52.0	8.0	0.2	-1.6	0.0
AirPressurer	30	2567	142.8	1.2	142.6	142.6	0.6	140.8	148.2	7.4	2.3	4.7	0.0
AlchRel	31	2560	6.9	0.5	6.6	6.8	0.1	5.3	8.6	3.3	0.9	-0.9	0.0
CarbRel	32	2559	5.4	0.1	5.4	5.4	0.1	5.0	6.1	1.1	0.5	-0.3	0.0
BallingLvl	33	2566	2.1	0.9	1.5	2.0	0.2	0.0	3.7	3.7	0.6	-1.5	0.0

Correlation Matrix