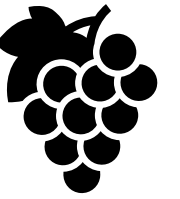


# Wine enthusiast analysis

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# Which vineyard produces the best wine?

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## Best wine

Wine that is given the most points whilst simultaneously being as cheap as possible

## Point to consider

One vineyard that produces the best wine vs a vineyard that consistently produces multiple highly rated wines

## Vineyard that produces best wine

Unoaked at the Pam's Cuties winery

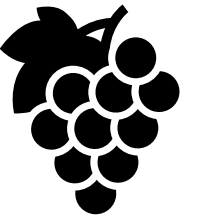
## Vineyard that consistently produces highly rated wines in the top 10 wines

Organic Grapes at the Earth's Harvest winery

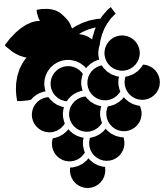
## Methodology

- reorder wines based on points/price
- weight the number of times a vineyard is featured on the top 10 list with its position on the list

# Three wines to recommend



|                     |  |  |   |
|---------------------|--|--|---|
| <b>Title</b>        | Pam's Cuties NV Unoaked Chardonnay (California)  | ManCan NV Fizz Sparkling (California)  | Earth's Harvest 2014 Organic Grapes Chardonnay (California)   |
| <b>Variety</b>      | Chardonnay   | Sparkling Blend  | Chardonnay  |
| <b>Description</b>  | Sweet and fruity, this canned wine feels soft and syrupy, with sugary pear as the primary flavor on the palate. It's a basic white wine in a convenient package. | This sparkling wine is the best of ManCan's three new canned offerings. It has plenty of rich fruit flavors and a buttery note. Lively bubbles settle into the smooth, creamy texture, leaving an overall impression of easygoing enjoyment. | This wine has a deep-gold color, attractive baking-spice and buttered popcorn aromas, appealing apple and pear flavors and medium body. The texture is soft and easy, and the acidity tastes low. |
| <b>Points/Price</b> | 20.75  | 17.4   | 17  |
| <b>Taster</b>       | Jim Gordon   | Jim Gordon   | Jim Gordon  |
| <b>Wine id</b>      | 59507  | 104412   | 37951   |
| <b>Winery</b>       | Pam's Cuties   | ManCan   | Earth's Harvest   |



# Factors important in determining the overall score of a wine

## Steps to approach this problem

### Step 1:

- Use correlation matrix to understand correlation between different features

### Step 2:

- explore feature importance through Recursive Feature Elimination

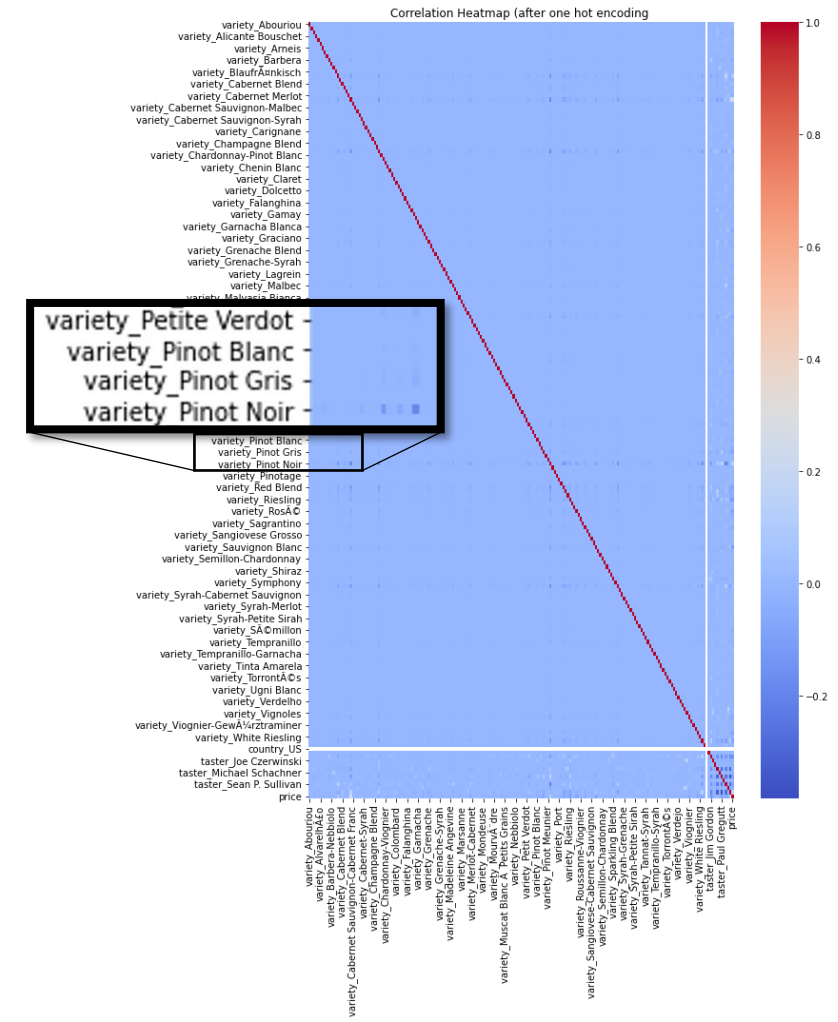
## Correlation Matrix

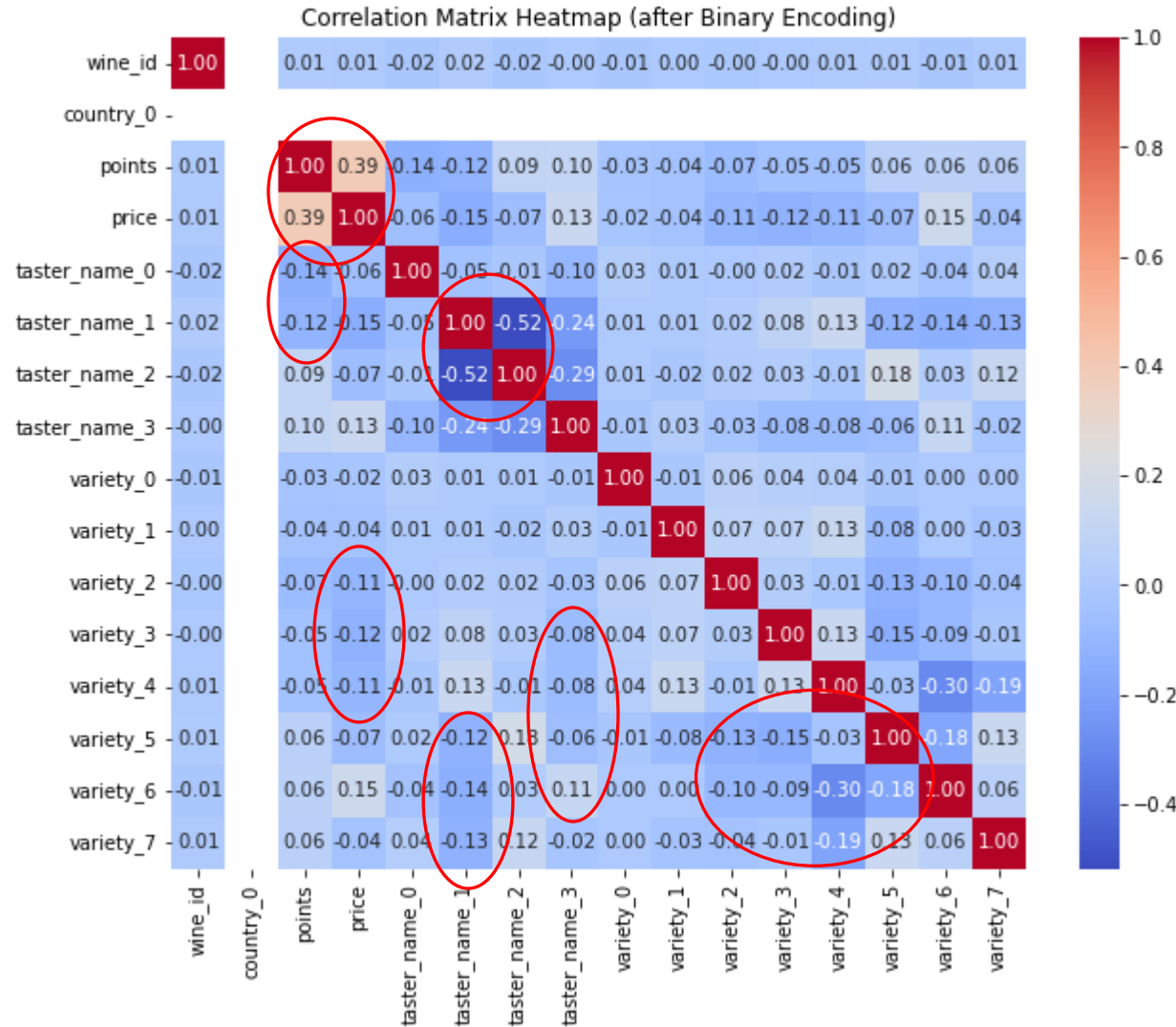
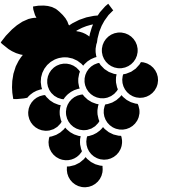
Displays the correlation coefficient between features

## Implementation

One-hot encoding to convert categorical data into numerical data

Need to explore other options due to too many dimensions



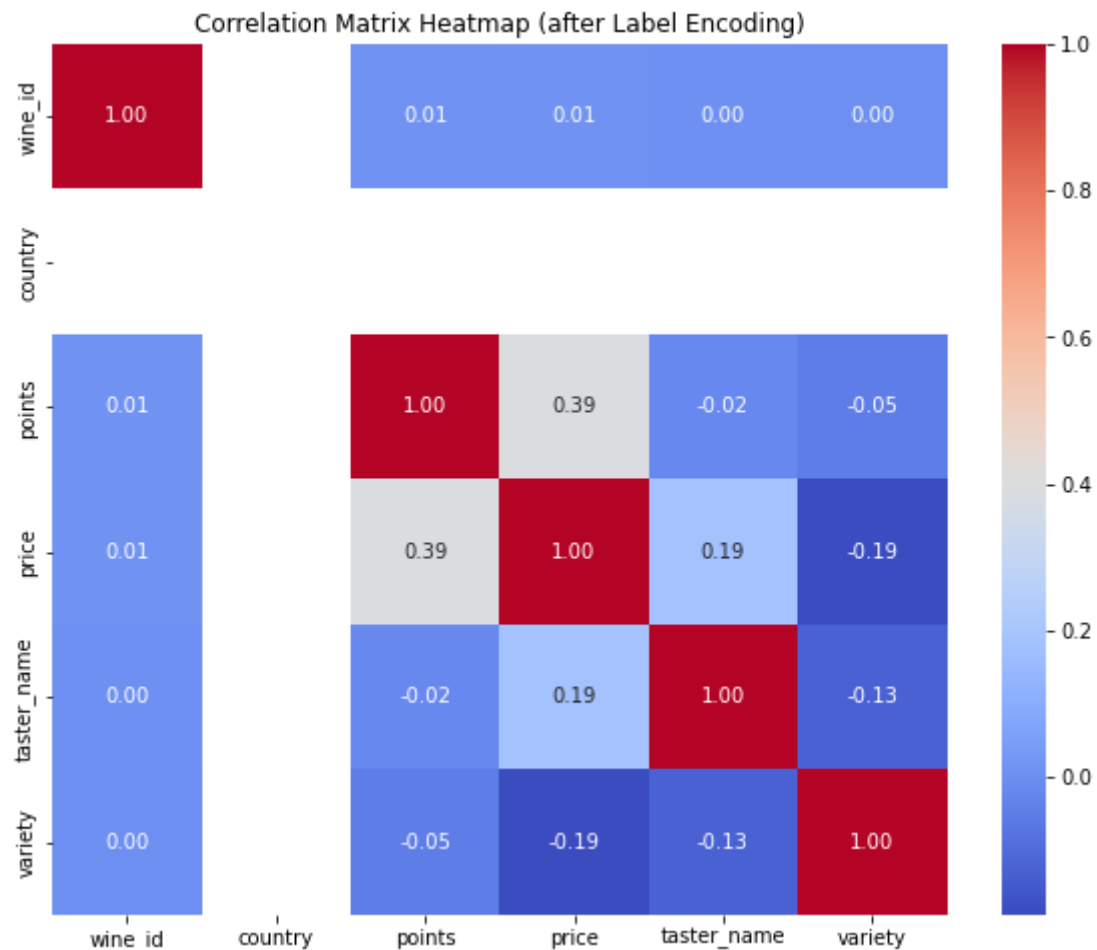
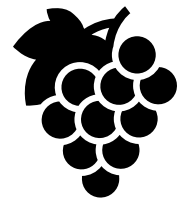


## Binary encoding

- Rank number  $k - 1$  in binary
- binary column does not correspond to one specific category but rather a combination of categories
- each category is represented by a combination of bits across multiple columns – difficulties mapping

## Insights

- No correlation for country
- Some tasters have preference for some varieties over others
- Some varieties correlate with price
- Correlation between price and points
- Correlation within varieties as well as within tasters

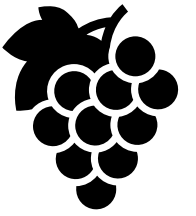


### Label Encoding

- replaces the categorical value with a numeric value between 0 and the number of classes minus 1
- Reduces dimensionality further
- generation of priority issues during model training

### Correlation between:

- price and points
- variety and price
- taster name and price
- taster name and variety



## Step 2

### Recursive Feature Elimination

- RFE is **wrapper** style feature selection algorithm
- Removes the weakest feature per loop until the most important feature is left

### Methodology

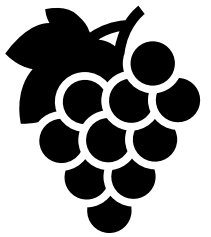
- Pick a classifier and build a model that predicts points rated for the wine
- Measure accuracy for reference
- Implement RFE with a sample
- Increased sample size
- Extrapolate

### Classifier

- Support Vector Machines(SVM) as the main classifier
- Works by implementing a hyperplane to separate data points
- Optimises hyperplane by maximizing distance between hyperplane and nearest datapoint

### Validation metric

- MAE is the weighted sum of difference between predicted value and real value



Sample size = 20% of entire dataset

MAE = 2.0441889539432996

Feature hierarchy based on rankings:

| Feature     | Ranking |
|-------------|---------|
| Taster_name | 1       |
| Price       | 2       |
| Variety     | 3       |
| Country     | 4       |

Sample size = 50% of entire dataset

MAE = 1.9586885164366323

Feature hierarchy based on rankings:

| Feature     | Ranking |
|-------------|---------|
| Taster_name | 1       |
| Price       | 2       |
| Variety     | 3       |
| Country     | 4       |

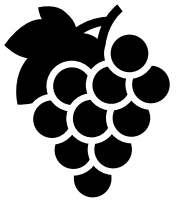
Approximated order of importance for entire data set:

MAE of entire dataset:  
1.9984124492243822

| Feature     | Ranking |
|-------------|---------|
| Taster_name | 1       |
| Price       | 2       |
| Variety     | 3       |
| Country     | 4       |



# Variety of wine for a “dry” and “citrus” flavour



## Methodology

- New data frame with wine that has both ‘dry’ and ‘citrus’ in its description
- Ranking these wines according to points/price ratio
- Same concept as question 1 - weight the number of times a variety is featured on the top 10 list with its position on the list

This gives the variety of wine which fits flavour profile whilst consistently being featured among best wines

Following table displays how the best variety for mentioned condition changes based on how many of the top wines are considered

| No. of top wines considered | Recommended variety |
|-----------------------------|---------------------|
| 5                           | Pinot Grigio        |
| 10                          | Pinot Grigio        |
| 30                          | Riesling            |
| 50                          | Riesling            |