Which wine is better ?

B09508009

June 13, 2024

Abstract

- Grape Wine is one of the most complex beverages, with its taste being determined by thousands of factors. Previously, Piyush Bhardwaj et al.(2016) predicted wine quality using machine learning based on physical and chemical properties, finding that good wine indeed has patterns. However, this method is not easily accessible to the general public. Therefore, this report attempts to find features readily available on the market to identify wines widely recognized as good.

Data Understanding

- Xwines is an open dataset. Data were collected from the open web in 2022 and pre-processed for broader free use.
- Includes ratings on a scale from 1 to 5 for 228,000 different types of wines produced in 62 different countries.
- There are over 20 million observations and the following features:

WineID	Vintage	Rating	Date	WineName	Type	Elaborate	Grapes	Harmonize	ABV	Body	Acidity	Country	RegionName	WineryName
136103	1950	4.0	2019-10-14 11:20:52	Lambrusco Emilia	Red	Varietal/100%	['Lambrusco']	['Beef', 'Pasta', 'Lamb', 'Game Meat']	7.5	Full-bodied	High	Italy	Emilia	Riunite

- Source : https://github.com/rogerioxavier/X-Wines

Motivation

- Imagine you are a consumer, and even though the store staff recommend several different wines, you still cannot decide. (You might need to choose one out of five)
- Imagine you open a wine cellar. From the existing 228,000 wines, you need to choose which ones to import.
- Or, you are the owner of a winery and you cannot grasp the preferences of the general public, leading to certain wines always having poor sales.

- Let's start from the perspective of the wine importer and consumer.
- Very obscure at the beginning, we came up with OLS like this:

$$\begin{aligned}\text{Rating} = \beta_0 &+ \beta_1(\text{Type}) + \beta_2(\text{Acidity}) \\ &+ \beta_3(\text{Grapes}) + \beta_4(\text{Body}) \\ &+ \beta_5(\text{Country}) + \beta_6(\text{Vintage}) + \dots\end{aligned}$$

- However, there is more than 10000 unique values in total.
  $\Longrightarrow$ Curse of dimensionality !
- I start to think, how about using stepwise selection or Lasso ?
  - Invalid.
- What about group Lasso?

$$\underset{\beta}{\text{minimize}} \; \|y - X\beta\|_2^2 + \lambda \sum_{g=1}^{G} \|\beta_{Lg}\|_2$$

Sommelier's Knowledge

- In wines industry, each winery usually has its own shifu whose techniques can significantly affect the taste.
- Climate is closely related to the quality of grapes, and different vintages experience different climatic conditions.
- What if we only consider winery$\times$year ? It might be a good proxy of most of the variables.
  - Body, Acidity, ABV...

Updated Model

- Now, the question becomes: In which winery $\times$ year were the best wines produced?

$$\text{Rating} = \sum_i \sum_j \beta_{ij}(\text{winery}_i \times \text{vintage}_j)$$

Data Processing & Cleaning

- For users who rated the same wine multiple times, take the most recent rating.
- Consider red wines first.
- Filter out winery $\times$ Vintage with fewer than 500 ratings.
- For the same wine with ratings from different users, take the average.

Data Exhibition

```
columns_to_group = ['WineID',"Label"]
df =df.groupby(columns_to_group)['Rating'].mean().reset_index()
```

WineID	Label	Rating
168335	Alfredo Roca 2014	3.336207
181668	Wente Vineyards 2014	4.045455
168194	Trapiche 2015	3.579365
174913	Penfolds 2018	3.500000
156421	Matarromera 2016	3.833333

```python
X = sm.add_constant(pd.get_dummies(Label , sparse = True).astype(int))
y = df['Rating']
```

d'Arenberg 2011	d'Arenberg 2012	d'Arenberg 2013	d'Arenberg 2014	d'Arenberg 2015	d'Arenberg 2016
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0	0	0	0
...	...	...	...	...	...

- Size become 64189×5150

Some concern

- There may be some missing controls.
  - Storage conditions of the wine, drinking methods, environment.
- Moreover, system of $X^T\beta = y$ is inconsistent; the solution can only minimize the norm $||X\beta - y||$
  - $\beta = X^{\dagger}y$, where $X^{\dagger}$ is the pseudo-inverse of X

Large Scale Hypothesis Testing

- Among 5150 coefficients, more than 1000 terms are below the significance level of $p = 0.05$.
- The Family-Wise Error Rate (FWER) is $1 - (1 - 0.05)^{1000} = 1$.
  - As wine cellar's owner, you'll have a 100% chance to import the wrong merchandise
- We then apply the idea of Bonferroni correction. The concept is to extract a list of coefficients from the OLS results that are high and significant, hoping that the probability of Type I error for that list is below 5%.

- Pick n, the number of wines you want on your recommendation list.
- We have $(1 - \alpha/n)^n > (1 - \alpha)$, where α is the original significance level.
- For example, take $n = 50$, $\alpha = 0.005$. Then, in this list named "Top 50 Wines", the probability of encountering a misleading recommendation is only 0.5

Result

Wine	Coefficient	t-value	P-value
Vega Sicilia 2015	0.931377	3.977395	0.00006976**
Vega Sicilia 2005	0.927762	3.961956	0.00007443**
Silver Oak 2014	0.916108	5.050453	0.00000044****
Vega Sicilia 2000	0.909533	3.884110	0.00010282**
Vega Sicilia 2013	0.909367	3.883401	0.00010312**
Vega Sicilia 2012	0.909832	3.885386	0.00010228**
Vega Sicilia 2006	0.899816	3.842614	0.00012186**
Vega Sicilia 2004	0.895414	3.823813	0.00013154**
Vega Sicilia 2010	0.891497	3.807088	0.00014075**
Vega Sicilia 2007	0.862506	3.683281	0.00023046**
Vega Sicilia 2009	0.870633	3.717990	0.00020100**
Château Margaux 2004	0.872212	3.724734	0.00019570**
Vega Sicilia 2008	0.897957	3.834676	0.00012586**
Vega Sicilia 2011	0.850571	3.632315	0.00028113**
Vega Sicilia 2003	0.854087	3.647331	0.00026521**
Nosotros 2014	0.840403	3.588895	0.00033235**
Pago de Carraovejas 2018	0.828289	4.084297	0.00004427**
Silver Oak 2007	0.827969	4.082718	0.00004457**
Pago de Carraovejas 2009	0.819457	4.517625	0.00000627***
Caymus 2010	0.819157	4.515971	0.00000631***
Caymus 2012	0.808315	4.456195	0.00000836***
Vega Sicilia 2014	0.803720	3.432242	0.00059902*

Winery Aspect

- From the previous OLS results, we found that the vast majority of wineries cannot achieve stable ratings year after year, let alone those that have never made it to the rankings.
- Suppose you are the owner of one of these wineries, and you have no idea how to cater to consumer tastes.
    - Moreover, you cannot imitate previous successes because of the inherent differences caused by climate variations.

Bayes' Theorem

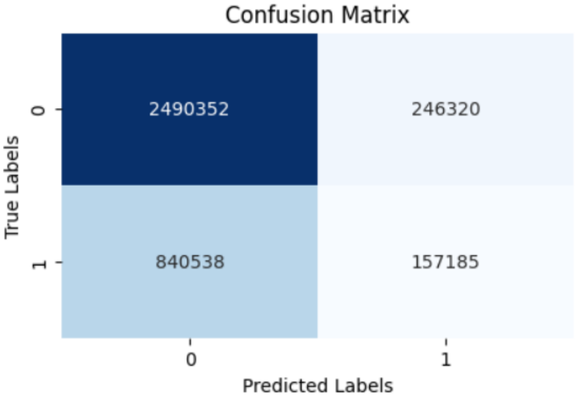
$$P(\text{outcome}|\text{data}) = \frac{P(\text{data}|\text{outcome}) \cdot P(\text{outcome})}{P(\text{data})}$$

- $P(\text{outcome}|\text{data})$: Posterior probability of the outcome given the data.
- $P(\text{data}|\text{outcome})$: Likelihood of the data given the outcome.
- $P(\text{outcome})$: Prior probability of the outcome.
- $P(\text{data})$: Marginal likelihood of the data.

Naive Bayes Classifier

- $\hat{y} = \arg\max_{y_i \in Y} P(y_i | x_1, x_2, \ldots, x_n)$
- $$\arg\max_{y_i \in Y} \frac{P(x_1, x_2, \ldots, x_n | y_i) \times P(y_i)}{P(x_1, x_2, \ldots, x_n)} = \arg\max_{y_i \in Y} \left(\prod_{k=1}^{n} P(x_k | y_i) \right) P(y_i)$$
- X: 'Elaborate', 'Grapes', 'ABV', 'Body', 'Acidity'
- Map ratings to 2 classes: 0 (Rating ≤ 1) and 1 (Rating ≥ 4)

Multinomial NB for red wine



- Not very satisfactory, we expect a higher trace value.

Classification Tree

- $\{(\mathbf{x}_i, y_i) : i = 1, \ldots, N\}\,, \quad \mathbf{x}_i = (x_{i1}, \ldots, x_{ip})$
- $n_L + n_R$ is the number of data in the previous node, a denotes one of the two classes of y.
- Seek the splitting variable j and split point s that minimize the sum of Gini index in each split:

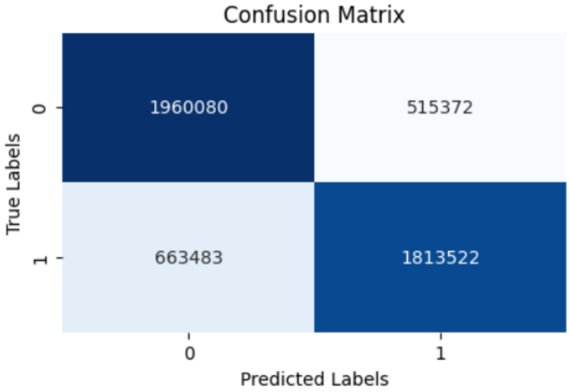
$$\min_{j,s}\left[1 - \left(\left(\frac{a_L}{n_L}\right)^2 + \left(\frac{n_L - a_L}{n_L}\right)^2\right) + 1 - \left(\left(\frac{a_R}{n_R}\right)^2 + \left(\frac{n_R - a_R}{n_R}\right)^2\right)\right]$$

RSCV find Hyperparameter

```
param_dist = {
    'criterion': ['gini', 'entropy'],
    'max_depth': randint(10, 30),
    'min_samples_split': randint(5, 20),
    'min_samples_leaf': randint(2, 10),
}

# Use precision as criteria
random_search = RandomizedSearchCV(clf, param_distributions=param_dist,
n_iter=10, cv=5, scoring='precision')
random_search.fit(X, y)
```

Confusion Matrix of tree



- precision is (0.75 , 0.78)

End

- Code:
  https://github.com/blossmuri/Grape-Wine-Rating-Inference
- Readme: https://muguet-de-mai.notion.site/X-wines-1b7a8220d5d547e3a315a12fa7454a85
- Material : Intel(R) Xeon(R) Gold 6226R*2
  NVIDIA RTX A6000*2