## MACHINE LEARNT SOMMELIER

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## **ABSTRACT**

- We analyze what factors go into a great wine
  - Use topic modeling (LDA and NMF)
  - Use classification (Logistic Regression, Bernoulli NB, and Linear SVM)
  - Use regression (Linear, ElasticNet, and Ridge)
- Combine to arrive at criteria for evaluating wines and ratings

## BACKGROUND AND APPROACH

- Much of wine evaluation remains shrouded in mystery
- Look at 130,000 wine reviews from WineEnthusiast
- Much of the literature focuses upon supervised learning
  - Apply latent topic modeling
- Preprocess reviews and encode categorical variables such as origin of wine and variety

## TOPIC MODELING

### Table 1: LDA Topic Modeling of 5 Topics

# Topic 1: Mouth Feel Topic 2: Wine Finish Topic 3: Wine Flavor Topic 4: Wine Notes Topic 5: Fruit Usage Latent Dirichlet Allocation wine fru y it drink acid ripe s the rich y flavor finish palat appl c acid the fru e wine flavor it fru cherri oak y the thi rich cherri palat the black aroma tannin spice red offer note flavor finish aroma fru thi palat plum berri cabernet blend

Table 2: NMF Topic Modeling of 5 Topics

# Topic 1: Aging Process Topic 2: Notes of the Wine Topic 3: Brightness of Wine Topic 4: Scent of Wine Topic 5: Fruit Usage/ Taste Topic 5: Aging Process wine fruit drink s ripe rich thi age the the palate aroma note wh finish nose fresh appl y acid crisp fru fresh bright miner it balanc drink flavor finish thi aroma it oak feel a sweet berri cherri black tannin palat aroma spice red the berri plum

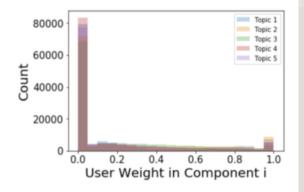


Figure 1: Topic Weighting of LDA

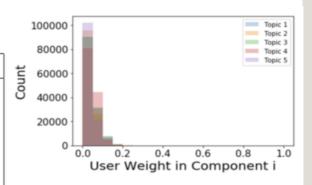


Figure 2: Topic Weighting of NMF

- More even distribution of weights with NMF
- More coherent topics with NMF
- LDA possibly limited by computation power

## **CLASSIFICATION MODELS**

Table 3: Comparison of Classifiers

	Precision	Recall	$F_1$ -score	Support		
Bernoulli Naive Bayes						
False	0.82	0.82	0.82	13,718		
True	0.80	0.79	0.80	12,276		
Linear Support Vector Machine						
False	0.83	0.87	0.85	13,718		
True	0.84	0.80	0.82	12,276		
Logistic Regression						
False	0.83	0.86	0.85	13,718		
True	0.84	0.81	0.82	12,276		

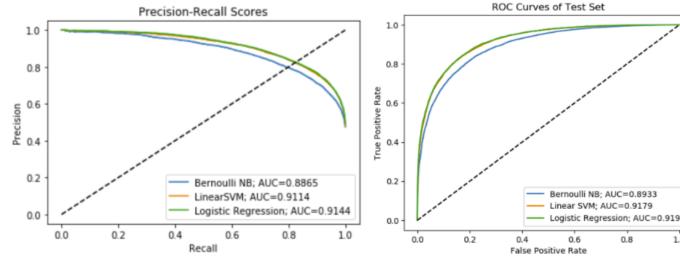


Figure 3: Precision-Recall Scores

Figure 4: Receiver Operating Characteristic Curves

• Linear SVM had best performance for classification task of wines by quality

## REGRESSION MODELS

Feature	Coefficient
country: Argentina	4.118747e+09
country: Peru	3.886923e+09
province: England	8.453873e+08
country: Ukraine	1.868244e+08
taster name: Anne Krebiehl MW	2.764144e+00
province: Wachau	2.416535e+00
province: Puente Alto	2.284224e+00
province: Kumeu	2.269647e+00
province: Kamptal	2.219636e+00
taster name: Matt Kettmann	2.178286e+00
province: Traisental	2.139456e+00
variety: Muscadelle	2.078293e+00
variety: Picolit	2.061431e+00
province: Madeira	1.936232e+00
province: Leithaberg	1.802688e+00
province: Kremstal	1.773534e+00
province: Washington	1.721713e+00
province: California	1.688816e+00
variety: Sangiovese Grosso	1.636819e+00
variety: Sagrantino	1.618324e+00

Table 5: Top 20 Features of Linear Regression by Coefficient

Table 6: Bottom 20 Features of Linear Regression by Coefficient

Feature	Coefficient	
province: Other	-4.118747e+09	
province: Mendoza Province	-4.118747e+09	
province: Ica	-3.886923e+09	
country: England	-8.453873e+08	
province: Ukraine	-1.868244e+08	
variety: Tempranillo Blanco	-4.281550e+00	
variety: Brachetto	-4.115134e+00	
variety: Airen	-4.078972e+00	
province: Molina	-3.743532e+00	
variety: Portuguese Ros	-3.453592e+00	
province: Rio Claro	-3.359180e+00	
province: Greece	-3.034868e+00	
variety: Viura-Chardonnay	-2.956762e+00	
variety: Garnacha-Syrah	-2.738010e+00	
country: Brazil	-2.629350e+00	
province: Bulgaria	-2.545243e+00	
province: Central Valley	-2.494183e+00	
variety: Pinot Noir-Gamay	-2.465141e+00	
variety: Prieto Picudo	-2.421631e+00	
variety: Inzolia	-2.369286e+00	

Table 4: Comparison of Classifiers

Regression Model	Mean Squared Error	Residual Sum of Squares	r-squared
Ridge Regression	6.2980	152,379.097	0.3132
ElasticNet Regression	8.0851	195,617.9242	0.1183
Linear Regression	6.3456	153,532.1311	0.380

- Region of production and variety had largest impacts
- Some bias from small subsamples
- Value of recognized terroir and techniques
- Ridge and Linear had best performance

### REFERENCES

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- [5] Claudia Gonzalez Viejo, Sigfredo Fuentes, Damir D. Torrico, Kate Howell, and Frank R. Dun- shea. Assessment of Beer Quality Based on a Robotic Pourer, Computer Vision, and Machine Learning Algorithms Using Commercial Beers. *Journal of Food Science*, 83(5):1381–1388, 2018.