Lecture 27: Case Study

The process



Harvard IACS

CS109A

Pavlos Protopapas, Kevin Rader, and Chris Tanner



ANNOUNCEMENTS

We realize this is a stressful and chaotic time for everyone, please lean on others for support, don't be shy to ask for help or to provide such to others, and be kind to yourself. I'm not just referring to 109 coursework.

Learning Objectives

- Feel prepared for the project
- Gain insights / learn considerations for solving a problem
- Feel prepared tackling the remaining course content / gain confidence!

Agenda

Example project

How prepared do you feel for completing your course project?

DISCLAIMER:

This example project concerns predicting customers' ratings of bourbon (alcoholic drink).

Alcohol is drug. There are state and federal laws that govern the sale, distribution, and consumption of such. In the United States, those who consume alcohol must be at least 21 years of age. In no way am I, or anyone else at IACS or Harvard at large, promoting or encouraging the usage of alcohol. My intention is not to celebrate it. Anyone who chooses to consume alcohol should be of legal age and should do so responsibly. Abusing alcohol has serious, grave effects.

The point of this exercise is purely pedagogical, and it illustrates the wide range of tasks to which one can apply data science and machine learning. That is, I am focusing on a particular interest and demonstrating how it can be used to answer questions that one may be interested in for one's own personal life. You could easily imagine this being used in professional settings, too.

Step 1: formulate questions

1. Are there certain attributes of bourbons that are predictive of good bourbons? (i.e., highly rated by customers)

- Find hidden gems (i.e., should be good but current reviews are absent or unsupportive of such)
- Find over-hyped bourbons (i.e., the reviews seem high but the attributes aren't indicative)
- Are there significant results if we target experts' ratings instead of average customer ratings?

2. Are there certain attributes of bourbons that are predictive of expensive bourbons?

- Find underpriced ones
- Find over-priced ones

Step 1: formulate questions

3. Which bourbons are most similar to each other?

• Which attributes are important for determining similarity? (e.g., does price play a role, or does similarity transcend price?)

Step 1: formulate questions

1. Are there certain attributes of bourbons that are predictive of good bourbons? (i.e., highly rated by customers)

- Find hidden gems (i.e., should be good but current reviews are absent or unsupportive of such)
- Find over-hyped bourbons (i.e., the reviews seem high but the attributes aren't indicative)
- Are there significant results if we target experts' ratings instead of average customer ratings?

I found distiller.com which seems really comprehensive.

It has a community of reviews, an app, and even tries to make personalized recommendations. Surely we can make a better recommendation engine, though!

DISTIL 🌢 E R		ا ٥ د 😬	IN PRO	RECOMMEND	LEARN	BLOG	SIGN IN	REGISTER	۹	* +
ALL SPIRITS	WHISKEY	TEQUILA/MEZCAL	RUM	BRANDY	GIN	VODKA	LIQUEUR	S/BITTERS	OTHER	
							1			

Despite clicking the "whiskey" section, I couldn't find any listing of whiskeys, only an annoying "recent tastes" (from users) sample. If you click one, it would only show a few other related ones.



RECENT TASTES



But, there's a search bar, and if I search for "bourbon", I got tons of search results!

I	DISTIL		٢	JOIN PRO	RECOMMEND	LEARN	BLOG	SIGN IN	REGISTER	۹	
	ALL SPIRITS	WHISKEY	TEQUILA/MEZCAL	RUM	BRANDY	GIN	VODKA	LIQUEUR	S/BITTERS	OTHER	
	SEAR	CH.	• •							C	2
	FILTERING BY 🗸							S	ORT BY DISTIL	LER SCOR	E ~
	HIBIKI 21 YE	EAR		Blended, Japa	n				99 4	.52 ★	
	HIGHLAND	PARK 18 YEAR		Peated Single	Malt, Islands, Scotl	and				10 -	

BOURBON		Q
FILTERING BY V		SORT BY RELEVANCE 🗸
EAGLE RARE 10 YEAR BOURBON	Bourbon, Kentucky, USA	01 4 02 🔶
\bullet	\bullet	ullet
ullet	\bullet	ullet
ullet	\bullet	ullet
WHISKEY CLUB SINGLE BARREL SELECT - TAHWAHBUNGA!!!)		
BARREL BOURBON JAMES BEARD BOURBON CHARITY BARREL PICK #\$407	Bourbon, Kentucky , USA	

Results 1-50 of 2152 Spirits

Top part of page



Bottom part of page

What should we try to extract from each webpage?

TASTING NOTES

"Eagle Rare 10 Year Bourbon is one of the great bourbon bargains out there, tasting way more expensive than it is. Its complexity starts with fruit flavors of dark cherries, red apples and bananas. Then the spices of cinnamon, clove and allspice kick in. These are rounded by honey, caramel, milk chocolate, vanilla and toasty oak. A rugged leather note rides it off into the sunset."

ADDED BY AMANDA SCHUSTER



FLAVOR PROFILE SWEET & FULL BODIED



```
<div class='flavor-profile'>
<h5>Flavor Profile</h5>
<h3 class='secondary-headline flavors middleweight'>Sweet & amp;
Full Bodied</h3>
<canvas class='js-flavor-profile-chart' data-
flavors='{"smoky":5,"peaty":0,"spicy&q
uot;:30,"herbal":5,"oily":0,"full_bodi
ed":70,"rich":65,"sweet":80,"brin
y":0,"salty":0,"vanilla":40,"tart
":0,"fruity":40,"floral":10}'
height='250' width='900'></canvas>
</div>
```

Do all webpages have this info?

Some are missing graphs?

Missing Age statements?

Missing Customer Reviews?

Missing Expert Scores?

Is it possible to scrape the webpages?



 Download the contents of each search page, while saving each whiskey's URL to a set()

https://distiller.com/search?page=1&term=bourbon



2. Visit each whiskey page, while extracting all the pertinent info that's available

Name Type Cask Location Age ABV % Price Badge # Ratings Customers' Rating Flavor Summary Expert Expert Score Smoky Peaty Spicy Herbal Oily Full-bodied Rich Sweet Briny Salty Vanilla Tart Fruity Floral Review

object object object object object object int64 object int64 object object object object float64 object

City Contraction of the second	EAGLI BOUR BOURBON EAGLE RARE	E RARE BON // rentucky, us dp NOW 14 sell	10 YEAR		
DETAILS			8687 TASTES		
	соммилі 4.02 ★★	TY RATING)		
Eagle Rare 10 Year Bo collection of whiskey distillery. The barrels bottling.	surbon is one of the s. It is made from 10 are hand selected fo	flagship products o) year old bourbon a or quality and consis	f the Buffalo Trace aged at the Kentucky stency before		
AGE	co	ST	ABV		
10 YEAR	\$ \$	\$ \$ \$	45.0		
PRODUCE LEAST 51	EDUI D ANYWHERE I I'& CORN; AGED CONTA CASK NEW, CHARRED	REON N USA; MASH E VIN NEW, CHAR UINERS. TYPE AMERICAN OA	BILL OF AT RRED OAK		
TASTING NOTES					
*Eagle Rare 10 Year Bourbon is one of bargains out there, tasting way more complexity starts with fruit flavors of apples and bananas. Then the spice allspice kick in. These are rounded by chocolate, vanila and toasty oak. A rides it off into the sunset." ADDED BY AMANDA SCHUSTER SCORE 718	of the great bourbor re expensive than it i of dark chernies, red s of cinnamor, clow y honey, caramel, m rugged leather note	n is. Its e and hik s			
FLAVOR PROFILE SWEET & FULL BODIED					

3. Verify it downloaded correctly and that you don't need to change how you obtained the data

How much data? 2,139 search result pages on the site

Downloaded 2,205



Filter by those reviewed by an Expert \rightarrow 701

Filter by those that are bourbons \rightarrow 586

df2 = df2.loc[(df['Type'] == "Bourbon")]

df2['Type'].value_counts()

Bourbon	586
Single Malt	27
Blanded American Whickow	1/
Agod Bum	19
Aged Rum Dested Single Malt	11
Other Whickey	11
Diner whiskey	11
Flavored whiskey	5
GOLA RUM	4
Rhum Agricole Vieux	4
Tequila Reposado	4
Blended	3
American Single Malt	3
Spiced Rum	3
Tequila Añejo	3
Flavored Rum	2
Barrel-Aged Gin	2
Rye	2
Canadian	2
Dark Rum	2
Cachaça	2
Other Brandy	1
Rhum Agricole Éléve Sous Bois	1
Rhum Agricole Blanc	1
Dairy/Egg Liqueurs	1
Silver Rum	1
White	1
Old Tom Gin	1
Other Liqueurs	1

Filter by those that have Customer Rating \rightarrow 585

df2.loc[df2['Customers\' Rating'] == "N/A"]

	Name	Туре	Cask	Location	Age	ABV %	Price	Badge	Ra
1765	Tacoma New West Bourbon	Bourbon	new, charred American oak	Heritage Distilling Co. // Washington, USA	NAS	46	2		
df2 =	df2 lo	ardf2r'	Customer	c\' Patin	a' 1	– "N	/]]		

```
df2 = df2.loc[df2['Customers\' Rating'] != "N/A"]
df2 = df2.astype({'Customers\' Rating' : 'float64'})
```

A lot of missing Age statements

we can keep the 'Age' feature for now but be mindful
that it's missing for nearly half of the whiskeys
len(df2.loc[(df2['Age'] == 'NAS') | (df2['Age'] == 'nas') | (df2['Age'] == '')])

378

let's replace all missing values with a reasonable value.
for now, let's use 0 as a placeholder so that we can later swap it out.
df2['Age'] = df2['Age'].replace(['NAS', 'nas', 'N/A',''],'0')

```
# remove the 'Years' part of the text
df2['Age'].replace(to_replace =' [yY]ear[sS]*', value = '', regex = True)
0
                         0
4
                         0
           7 y, 2 m,16 d
12
21
                         0
22
                         0
26
                        17
27
                         0
28
                         0
38
                         6
40
                        17
49
                         0
52
                         0
53
                         0
59
                         0
60
                        10
65
                         0
67
                         0
75
                         0
81
                         0
25
```

```
# manually cleaning up values that otherwise would be a bit impossible to automatically clean
df2['Age'] = df2['Age'].replace(to_replace ='6.*', value = '6', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='(\d+) [Yy].*', value = '\\1', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='4 [Mm]onths', value = '4', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='9 [Mm]onths', value = '9', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='18 - 20 [Mm]onths', value = '1.5', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='32 [Mm]onths', value = '2.67', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='9 [Mm]onths', value = '9', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='9 [Mm]onths', value = '9', regex = True)
df2['Age'] = df2['Age'].replace(to_replace ='9 [Mm]onths', value = '9', regex = True)
```

let's look at all of the items that had an Age
(now that all values have been cleaned-up)
df2.loc[df2['Age'] > '0']['Age']

·		
12	7	
26	17	
38	6	
40	17	
60	10	
97	15	
98	12	
118	12	
119	6	
140	22	
149	3	
154	6	
162	6	
166	11	
188	13	
202	9	
231	17	
236	6	
257	14	
258	6	
df2 -	df2 acture	a(1) and (f)

how many had values?
len(df2.loc[df2['Age'] > 0])

206

<pre>df2['Age'].describe()</pre>					
count	585.000000				
mean	3.776274				
std	6.010627				
min	0.00000				
25%	0.00000				
50%	0.00000				
75%	7.000000				
max	28.000000				
Name:	Age, dtype: float64				

df2['Age'] = df2['Age'].replace(0,7)

df2['Age'].describe()	
------	-------	--------------	--

\mathtt{count}	585.000000
mean	8.311316
std	3.607727
min	0.750000
25%	7.000000
50%	7.000000
75%	7.000000
max	28.000000
Name:	Age, dtype: float64



What's the distribution of the Flavor Summary?

df2['Flavor Summary'].value_counts()

Rich & Full Bodied	54	
Sweet & Rich	40	
Sweet	36	
Vanilla & Sweet	34	
Spicy	33	
Vanilla & Rich	24	
Full Bodied & Rich	20	
Sweet & Vanilla	20	
Spicy & Rich	18	
Vanilla	18	
Vanilla & Full Bodied	17	
Fruity & Sweet	17	
Full Bodied & Spicy	17	
Spicy & Vanilla	16	
Rich & Vanilla	13	
Sweet & Spicy	13	
Rich & Spicy	13	
Full Bodied	11	
Vanilla & Spicy	11	
Full Bodied & Vanilla	10	
Spicy & Sweet	10	
Spicy & Full Bodied	10	

What's the **Badge** feature like?

df2['Badge'].value_counts() 428 RARE 119 Requested By\nElw00t 2 Requested By\njd139 Requested By\ntjbriley Requested By\nBourbon_Obsessed_Lexington Requested By\nCymru-and-the-Ferg Requested By\ndanmeister33 Requested By\nCblake34 Requested By\ndjriebesell Requested By\nandrewls24 Requested By\nspectorjuan Requested By\ncubfancccc Requested By\nsamueljcarlson Requested By\nJFForbes 1 Requested By\nJamesSpears

What's the **Expert** feature like?

df2['Expert'].value_counts()

Jacob Grier	92
Jake Emen	85
Amanda Schuster	76
Stephanie Moreno	66
Rob Morton	62
Keith Allison	26
Colin Howard	23
Sam Davies	21
Nicole Gilbert	17
Distiller Staff	15
Brock Schulte	14
Paul Belbusti	13
Ryan Conklin	12
Jack Robertiello	10
Tim Knittel	10
Katrina Niemisto	8
Dennis Gobis	4

Now that our data is clean, let's explore it. EDA time!

Please see Case_Study_PART_1-4.ipynb, which I will make available after the matinee lecture.

Step 4: model the data

1. Are there certain attributes of bourbons that are predictive of good bourbons? (i.e., highly rated by customers)

- Find hidden gems (i.e., should be good but current reviews are absent or unsupportive of such)
- Find over-hyped bourbons (i.e., the reviews seem high but the attributes aren't indicative)
- Are there significant results if we target experts' ratings instead of average customer ratings?

Step 4: model the data

Goal: predict Customers' Ratings

Data: train/dev/test splits

Features to use: ???

Question: which features should we use? Could we use?

Name	object
Туре	object
Cask	object
Location	object
Age	float64
ABV %	float64
Price	int64
# Ratings	int64
Customers' Rating	float64
Flavor Summary	object
Expert	object
Expert Score	int32
Smoky	float64
Peaty	float64
Spicy	float64
Herbal	float64
Oily	float64
Full-bodied	float64
Rich	float64
Sweet	float64
Briny	float64
Salty	float64
Vanilla	float64
Tart	float64
Fruity	float64
Floral	float64
Review	object
Rare	bool

Break-out room time! (Discussion, no coding)

Step 4: model the data

Goal: predict Customers' Ratings

Data: train/dev/test splits

Features to use:

- All 14 flavors
- Age
- ABV %
- Price
- Badge
- Expert Score

Accuracy Metric: MSE

Name	object
Туре	object
Cask	object
Location	object
Age	float64
ABV %	float64
Price	int64
# Ratings	int64
Customers' Rating	float64
Flavor Summary	object
Expert	object
Expert Score	int32
Smoky	float64
Peaty	float64
Spicy	float64
Herbal	float64
Oily	float64
Full-bodied	float64
Rich	float64
Sweet	float64
Briny	float64
Salty	float64
Vanilla	float64
Tart	float64
Fruity	float64
Floral	float64
Review	object
Rare	bool

Step 4: model the data

Model #1: Linear Regression

Question: should we scale our data?

Question: should we use polynomial features?

Please see Case_Study_PART_5.ipynb, which I will make available after the matinee lecture.

Name	object
Туре	object
Cask	object
Location	object
Age	float64
ABV %	float64
Price	int64
# Ratings	int64
Customers' Rating	float64
Flavor Summary	object
Expert	object
Expert Score	int32
Smoky	float64
Peaty	float64
Spicy	float64
Herbal	float64
Oily	float64
Full-bodied	float64
Rich	float64
Sweet	float64
Briny	float64
Salty	float64
Vanilla	float64
Tart	float64
Fruity	float64
Floral	float64
Review	object
Rare	bool

Step 1: formulate questions

1. Are there certain attributes of bourbons that are predictive of good bourbons? (i.e., highly rated by customers)

- Find hidden gems (i.e., should be good but current reviews are absent or unsupportive of such)
- Find over-hyped bourbons (i.e., the reviews seem high but the attributes aren't indicative)
- Are there significant results if we target experts' ratings instead of average customer ratings?

Step 4: model the data

Good, important practices:

- Heavily inspect your data first
- Spend the extra time to clean it
- Start with the most simple models
- If the model seems sensitive to a particular run, use **bootstrapping**
- Inspect results, and allow that to guide your next choices
- Reflect about your modelling choices
- Leverage as much of your data as possible (cross-validation)

Step 4: model the data

Good, important practices:

- When comparing different models, make everything as fair as possible
 - Same data splits
 - Fix all random seeds so your experiments are repeatable
- Look at your worst mistakes. Any patterns to these errors?
- For classification tasks, look at false positives and false negatives
- Do you have any indication that your data is limiting?
 - Clean up data further or get more data?

Step 5: communicate your results

- A long notebooks I provided are only good for exploring and getting work done. By no means is it an attempt to communicate the results
- Think of what would be the easiest, most succinct way to discern:
 - All of your models' results (e.g., heatmap table?).
 - The effectiveness and ineffectiveness of your model
 - Examples of it working / results
- It should be clear and compelling which model we should use (instead of the baseline)
- Review the Visualization lecture for more inspiration

2. Are there certain attributes of bourbons that are predictive of expensive bourbons?

- Find underpriced ones
- Find over-priced ones

Step 1: formulate questions

3. Which bourbons are most similar to each other?

• Which attributes are important for determining similarity? (e.g., does price play a role, or does similarity transcend price?)

Good luck on your projects! You can do it.