What does a Data Science project look like?

Client:

My Flower Shop

Ask:

Need to send out a catalog. Would like to know who to send it to.

One translation:

Can we classify people according to whether they're likely to reorder?

Notebook Setup

In [1]:

```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split

sns.set_theme()

%matplotlib inline
```

Read in Data

In [2]:

```
datafile_name = '../data/flowershop_data.csv'
```

In [3]:

```
# print out the first few lines of the datafile, looks like standard csv with a header and dates
!head -5 {datafile_name}

#!more flowershop_data.csv P 5
```

```
lastname,purchase_date,stars,price,favorite_flower

PERKINS,2017-04-08,5,19.599885954165785,iris

ROBINSON,2017-01-01,5,37.98390361682093,

WILLIAMSON,2017-03-20,4,19.339137911467354,carnation

ROBINSON,2017-04-12,5,18.14061575407039,lilac
```

In [4]:

```
# read in data, note the number of rows and columns
df = pd.read_csv('../data/flowershop_data.csv', header=0, parse_dates=True)
print('{:d} rows, {:d} columns'.format(*df.shape))
```

```
1000 rows, 5 columns
```

In [5]:

```
# use head to make sure the data was read correctly
df.head()
```

Out[5]:

	lastname	purchase_date	stars	price	favorite_flower
0	PERKINS	2017-04-08	5	19.599886	iris
1	ROBINSON	2017-01-01	5	37.983904	NaN
2	WILLIAMSON	2017-03-20	4	19.339138	carnation
3	ROBINSON	2017-04-12	5	18.140616	lilac
4	RHODES	2017-03-24	1	22.179522	carnation

Evaluate and Clean Variables

In [6]:

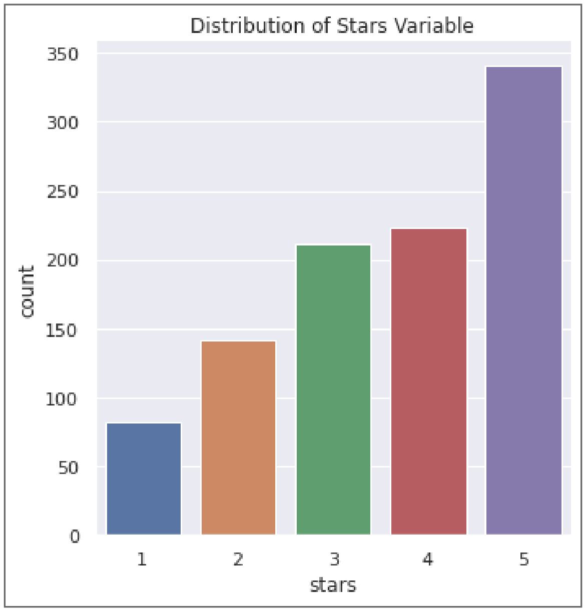
```
# use info to evaluate missing values and datatypes
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   lastname         1000 non-null   object
 1   purchase_date    1000 non-null   object
 2   stars            1000 non-null   int64
 3   price            978 non-null    float64
 4   favorite_flower  822 non-null    object
dtypes: float64(1), int64(1), object(3)
memory usage: 39.2+ KB
```

Evaluate and Clean: Stars

In [7]:

```
# plot histogram for stars
sns.catplot(x='stars',kind='count',data=df);
plt.title('Distribution of Stars Variable');
```



In [8]:

```
# an awful lot of 5s
# get highest name counts
df[df.stars == 5].lastname.value_counts().head()
```

Out[8]:

```
ROBINSON    135
DANIELS       9
CALDWELL      8
JOHNSTON      6
JACOBS        6
Name: lastname, dtype: int64
```

In [9]:

```
# get differences in mean stars by name
robinson_mean = df[df.lastname == 'ROBINSON'].stars.mean()
other_mean = df[df.lastname != 'ROBINSON'].stars.mean()
robinson_mean_diff = robinson_mean - other_mean
print('robinson mean stars: {}'.format(robinson_mean))
print('other mean stars    : {}'.format(other_mean))
print('difference in mean : {}'.format(robinson_mean_diff))
```

```
robinson mean stars: 4.230769230769231
other mean stars    : 3.433080808080808
difference in mean : 0.7976884226884229
```

In [10]:

```
# get counts for names
n_robinson = len(df[df.lastname == 'ROBINSON'])
n_other = len(df) - n_robinson
print('n_robinson: {}'.format(n_robinson))
print('n_other    : {}'.format(n_other))
```

```
n_robinson: 208
n_other    : 792
```

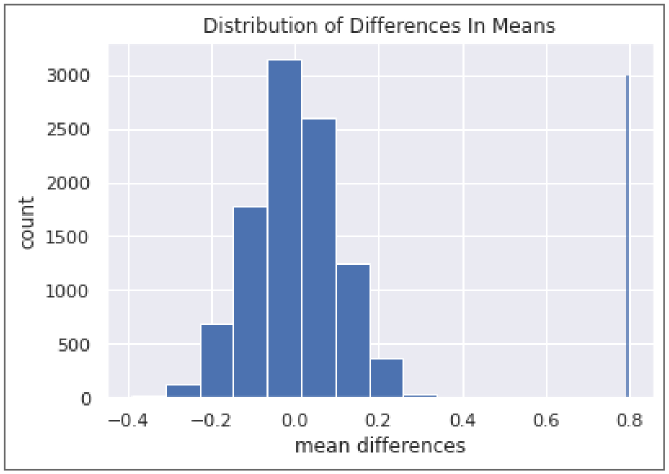
In [11]:

```
# do a permutation test to test for significance of difference

stars = df.stars.values
mean_diffs = []

for i in range(10000):
    perm = np.random.permutation(stars)
    mean_1 = np.mean(perm[:n_robinson])
    mean_2 = np.mean(perm[n_robinson:])
    mean_diffs.append(mean_1-mean_2)

plt.hist(mean_diffs);
plt.vlines(x=robinson_mean_diff, ymin = 0, ymax = 3000);
plt.xlabel('mean differences');
plt.ylabel('count');
plt.title('Distribution of Differences In Means');
```



In [12]:

```
# calculate the p-value
p = sum(np.abs(mean_diffs) >= np.abs(robinson_mean_diff)) / len(mean_diffs)
print(p)
```

```
0.0
```

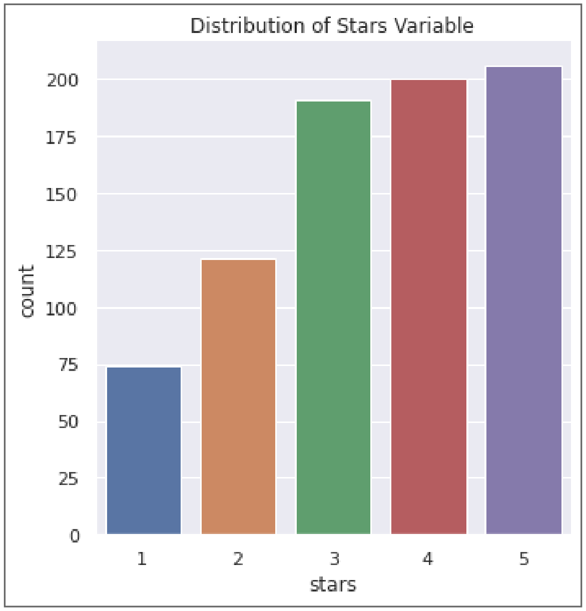
NOTE: Getting rid of the records with lastname ROBINSON as the count of 5 stars from them seems suspiciously high relative to the rest of the sample.

In [13]:

```
# drop rows with lastname ROBINSON
df = df[df.lastname != 'ROBINSON']
```

In [14]:

```
# plot again and notice the change in distiribution
sns.catplot(x='stars', kind='count', data=df);
plt.title('Distribution of Stars Variable');
```



In [15]:

```python
# Reprinting .info(), note we still have missing values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 792 entries, 0 to 998
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   lastname         792 non-null    object 
 1   purchase_date    792 non-null    object 
 2   stars            792 non-null    int64  
 3   price            772 non-null    float64
 4   favorite_flower  654 non-null    object 
dtypes: float64(1), int64(1), object(3)
memory usage: 69.4+ KB
```

Evaluate and Clean Price

In [16]:

```
print(f'proportion of rows with missing price: {sum(df.price.isna()) / len(df):0.3f}')
```

```
proportion of rows with missing price: 0.025
```

In [17]:

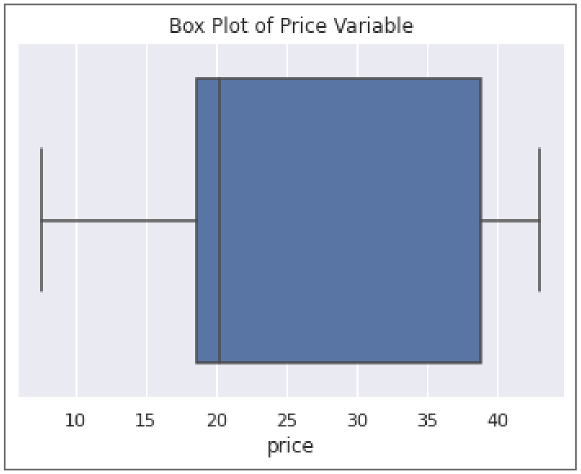
```
# before dealing with missing prices, check distribution
df.price.describe()
```

Out[17]:

```
count    772.000000
mean      23.720669
std       11.154642
min        7.621566
25%       18.596314
50%       20.226653
75%       38.837663
max       42.996317
Name: price, dtype: float64
```

In [18]:

```
sns.boxplot(df.price);
plt.title('Box Plot of Price Variable');
```



In [19]:

```
# create new column encoding missing price
df['price_missing'] = df.price.isna()
print(f'proportion of price missing: {sum(df.price_missing)/len(df):0.3f}')
```

```
proportion of price missing: 0.025
```

In [20]:

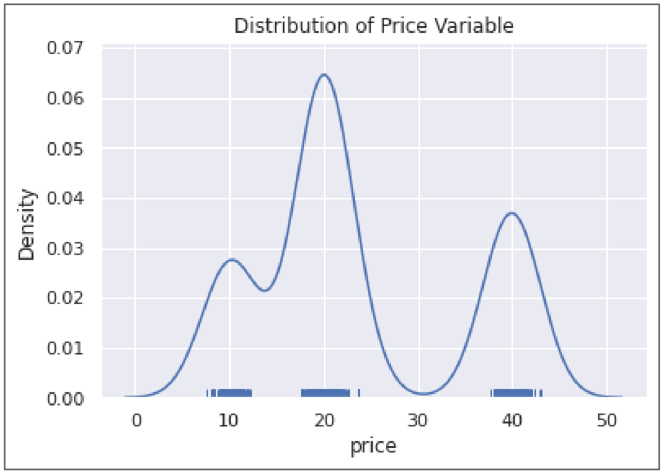
```
# impute missing values with the mean
df.price.fillna(df.price.mean(),inplace=True)
```

In [21]:

```
# check to make sure we're no longer missing data
assert sum(df.price.isna()) == 0
```

In [22]:

```
# plot distribution of price, noting clusters. Depending on model, may want to bin?
sns.distplot(df.price, hist=False, rug=True);
plt.title('Distribution of Price Variable');
```



Evaluate and Clean Favorite_Flower Variable

In [23]:

```
# print out first few values for favorite_flower, noting that it is a categorical variable
df.favorite_flower.head()
```

Out[23]:

```
0         iris
2     carnation
4     carnation
5       gerbera
7       gerbera
Name: favorite_flower, dtype: object
```

In [24]:

```python
# print number of observations of each value
df.favorite_flower.value_counts()
```

Out[24]:

```
rose         106
daffodil      79
carnation     70
gardenia      61
tulip         59
gerbera       44
lilac         44
sunflower     42
orchid        42
jasmine       42
daisy         34
iris          31
Name: favorite_flower, dtype: int64
```

Engineer New Features

In [25]:

```
# create new dataframe for engineered features
dfe = pd.DataFrame()
```

NOTE: our prediction is by family, need to collapse observations

In [26]:

```
# collapse rows
g = df.groupby('lastname')
```

Create Mean Price

In [27]:

```
# get mean price per family
mean_prices = g.price.mean()
mean_prices.head()
```

Out[27]:

```
lastname
ADAMS        38.617753
ALEXANDER    30.106511
ALLEN        26.657993
ALVAREZ      20.676235
ANDERSON     14.653257
Name: price, dtype: float64
```

In [28]:

```
dfe['mean_price'] = mean_prices
```

In [29]:

```
dfe.head()
```

Out[29]:

	mean_price
lastname	
ADAMS	38.617753
ALEXANDER	30.106511
ALLEN	26.657993
ALVAREZ	20.676235
ANDERSON	14.653257

In [30]:

```python
# depending on our model, may want to normalize features

dfe['mean_price_normed'] = (dfe.mean_price.values - dfe.mean_price.mean()) / dfe.mean_price.std()
dfe.mean_price_normed.agg(['mean','std']).round(2)
```

Out[30]:

```
mean    0.0
std     1.0
Name: mean_price_normed, dtype: float64
```

In [31]:

```python
dfe.head()
```

Out[31]:

	mean_price	mean_price_normed
lastname		
ADAMS	38.617753	1.848446
ALEXANDER	30.106511	0.823597
ALLEN	26.657993	0.408357
ALVAREZ	20.676235	-0.311913
ANDERSON	14.653257	-1.037147

In [32]:

```python
# drop the unnormalized variable
dfe.drop('mean_price',axis=1,inplace=True)
```

Create Median Stars

NOTE: Using median to be robust against extreme high or low values

In [33]:

```
g.stars.median().head()
```

Out[33]:

```
lastname
ADAMS        2.5
ALEXANDER    4.5
ALLEN        4.0
ALVAREZ      3.0
ANDERSON     2.0
Name: stars, dtype: float64
```

In [34]:

```
dfe['median_stars'] = g.stars.median()
```

In [35]:

```
dfe.head()
```

Out[35]:

	mean_price_normed	median_stars
lastname		
ADAMS	1.848446	2.5
ALEXANDER	0.823597	4.5
ALLEN	0.408357	4.0
ALVAREZ	-0.311913	3.0
ANDERSON	-1.037147	2.0

In [36]:

```
# again, depending on model, may or may not need to normalize
dfe['median_stars_normed'] = (dfe.median_stars.values / dfe.median_stars.mean()) / dfe.median_stars.std()
dfe.drop('median_stars',axis=1,inplace=True)
```

In [37]:

```
dfe.head()
```

Out[37]:

	mean_price_normed	median_stars_normed
lastname		
ADAMS	1.848446	0.723909
ALEXANDER	0.823597	1.303037
ALLEN	0.408357	1.158255
ALVAREZ	-0.311913	0.868691
ANDERSON	-1.037147	0.579128

Create Favorite Flower Dummies

In [38]:

```
# transform favorite_flower into One Hot Encoding
flower_dummies = pd.get_dummies(df.favorite_flower, prefix='ff')
flower_dummies.head()
```

Out[38]:

	ff_carnation	ff_daffodil	ff_daisy	ff_gardenia	ff_gerbera	ff_iris	ff_jasmine	ff_lilac	ff_orchid	ff_rose	ff_sunflower	ff_tulip
0	0	0	0	0	0	1	0	0	0	0	0	0
2	1	0	0	0	0	0	0	0	0	0	0	0
4	1	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0	0	0
7	0	0	0	0	1	0	0	0	0	0	0	0

In [39]:

```
# add the last name column using index
flower_dummies = df[['lastname']].join(flower_dummies)
flower_dummies.head()
```

Out[39]:

	lastname	ff_carnation	ff_daffodil	ff_daisy	ff_gardenia	ff_gerbera	ff_iris	ff_jasmine	ff_lilac	ff_orchid	ff_rose	ff_sunflower	ff_tulip
0	PERKINS	0	0	0	0	0	1	0	0	0	0	0	0
2	WILLIAMSON	1	0	0	0	0	0	0	0	0	0	0	0
4	RHODES	1	0	0	0	0	0	0	0	0	0	0	0
5	NGUYEN	0	0	0	0	1	0	0	0	0	0	0	0
7	GRAVES	0	0	0	0	1	0	0	0	0	0	0	0

In [40]:

```
# group the flower columns by last name, aggregating by sum
flower_dummies = flower_dummies.groupby('lastname').sum()
```

In [41]:

```
# simplify by transforming count of flower into 0,1
flower_dummies = flower_dummies.applymap(lambda x: int(x > 0))
```

In [42]:

```
# join to our engineered values on lastname
dfe = dfe.join(flower_dummies)
```

In [43]:

```
dfe.head()
```

Out[43]:

lastname	mean_price_normed	median_stars_normed	ff_carnation	ff_daffodil	ff_daisy	ff_gardenia	ff_gerbera	ff_iris	ff_jasmine	ff_lilac	ff_orchid	ff_rose	ff_sunflower	ff_tulip
ADAMS	1.848446	0.723909	0	0	0	0	0	0	0	0	1	0	0	0
ALEXANDER	0.823597	1.303037	0	0	0	0	0	0	0	0	0	0	1	0
ALLEN	0.408357	1.158255	0	0	0	0	0	0	0	0	0	1	0	0
ALVAREZ	-0.311913	0.868691	0	0	0	0	0	0	0	0	1	0	0	0
ANDERSON	-1.037147	0.579128	0	0	1	0	0	0	0	0	0	0	0	0

Create Labels

In [44]:

```
# generate label for repeat customer
labels = df.lastname.value_counts().apply(lambda x: int(x > 1))
```

In [45]:

```
labels.head()
```

Out[45]:

```
DANIELS     1
JACOBS      1
BURKE       1
CALDWELL    1
HUNTER      1
Name: lastname, dtype: int64
```

In [46]:

```python
# join labels to engineered features
labels.name = 'reorder_label'

dfe = dfe.join(labels)

dfe.head()
```

Out[46]:

	mean_price_normed	median_stars_normed	ff_carnation	ff_daffodil	ff_daisy	ff_gardenia	ff_gerbera	ff_iris	ff_jasmine	ff_lilac	ff_orchid	ff_rose	ff_sunflower	ff_tulip	reorder_labe
lastname															
ADAMS	1.848446	0.723909	0	0	0	0	0	0	0	0	1	0	0	0	1
ALEXANDER	0.823597	1.303037	0	0	0	0	0	0	0	0	0	0	1	0	1
ALLEN	0.408357	1.158255	0	0	0	0	0	0	0	0	0	1	0	0	1
ALVAREZ	-0.311913	0.868691	0	0	0	0	0	0	0	0	1	0	0	0	0
ANDERSON	-1.037147	0.579128	0	0	1	0	0	0	0	0	0	0	0	0	1

Train Classifier and Evaluate

In [47]:

```
# get data and label column names
data_cols = dfe.columns[:-1]
label_col = dfe.columns[-1]
```

In [48]:

```
data_cols
```

Out[48]:

```
Index(['mean_price_normed', 'median_stars_normed', 'ff_ca
rnation',
       'ff_daffodil', 'ff_daisy', 'ff_gardenia', 'ff_gerb
era', 'ff_iris',
       'ff_jasmine', 'ff_lilac', 'ff_orchid', 'ff_rose',
'ff_sunflower',
       'ff_tulip'],
      dtype='object')
```

In [49]:

```
label_col
```

Out[49]:

```
'reorder_label'
```

In [50]:

```
# importing here for demonstration
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import train_test_split
```

In [51]:

```
# split into train and test (hold out) sets (using sklearn)
X_train, X_test, y_train, y_test = train_test_split(dfe.loc[:,data_cols],
                                                    dfe.loc[:,label_col],
                                                    test_size=0.2,
                                                    stratify=dfe.loc[:,label_col])
print(f'X_train.shape = {X_train.shape}, y_train.shape = {y_train.shape}')
print(f'X_test.shape = {X_test.shape}, y_train.shape = {y_test.shape}')
```

```
X_train.shape = (201, 14), y_train.shape = (201,)
X_test.shape = (51, 14), y_train.shape = (51,)
```

In [52]:

```
# perform cross validation to tune parameters (not done here)
rf = RandomForestClassifier()
cv_scores = cross_val_score(rf, X_train, y_train, cv=3)
cv_scores
```

Out[52]:

```
array([0.79104478, 0.74626866, 0.70149254])
```

In [53]:

```
print(f'mean cv accuracy: {np.mean(cv_scores):0.2f} +- {np.std(cv_scores)*2:0.2f}')
```

```
mean cv accuracy: 0.75 +- 0.07
```

In [54]:

```
# fit on training data and score on test
rf.fit(X_train,y_train)
print('test set accuracy: {:0.3f}'.format(rf.score(X_test,y_test)))
```

```
test set accuracy: 0.824
```

Which Features are Most Important?

In [55]:

```
for col,fi in sorted(list(zip(data_cols,rf.feature_importances_)),key=lambda x:x[1])[::-1]:
    print(f'{col:20s} : {fi:0.3f}')
```

```
mean_price_normed    : 0.616
median_stars_normed  : 0.197
ff_lilac             : 0.021
ff_rose              : 0.018
ff_gardenia          : 0.017
ff_gerbera           : 0.017
ff_carnation         : 0.017
ff_daisy             : 0.016
ff_sunflower         : 0.015
ff_daffodil          : 0.015
ff_tulip             : 0.014
ff_iris              : 0.013
ff_orchid            : 0.012
ff_jasmine           : 0.012
```

How well could we do just by guessing 1 for everyone?

In [56]:

```
((dfe.loc[:,label_col] == 1).sum() / len(dfe)).round(3)
```

Out[56]:

```
0.71
```