burritos

October 22, 2021

1 COGS 108 - Burritos of San Diego

1.1 Permissions

Place an `X` in the appropriate bracket below to specify if you would like your group's project to be made available to the public. (Note that student names will be included (but PIDs will be scraped from any groups who include their PIDs).

- ☒ YES - make available
- ☐ NO - keep private

2 Overview

Mexican food is extremely popular in the United States, even more so in California due to our proximity to Mexico. The burrito is one of the staple foods of Mexican cuisine, and is enjoyed by not only its creators, but by people all around the world. However, this brings up a question: What exactly makes a good burrito? What factors come into play?

Throughout our research, we decided to pursue 3 main dimensions of a burrito: the cost, how much hunger it satisfies, and the quality of the meat in the fillings. With these 3 factors, we set out to find out how much they impact the scores and ratings of a burrito, giving us a hint on what customers value the most in their wrapped meal.

3 Names

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Research Question

What factors can contribute to how good a taco shop's burrito is? Are there any relationships between price, location, proximity to ingredient suppliers, etc.?

3.1 Background & Prior Work

Mexican food is the second most popular cuisine in the United States.(1) Establishments span from fast food joints, to food trucks, to sit-down restaurants. With its close proximity to Mexico and its large Hispanic and Latino population, Southern California is renowned for its Mexican cuisine expertise. San Diego County alone has over 80 Mexican restaurants, specifically ones that sell our target item.(2)

One of the most common orders at a Mexican restaurant is the burrito, a dish consisting of a flour tortilla, which is a thin type of flatbread, wrapped in a tight, cylindrical shape around an assortment of vegetables, cheese, meat, and other ingredients. The internals of a burrito may differ from restaurant to restaurant, but the bulk of taco shops include the basic three: cheese, meat, and salsa. The average cost of a burrito is around $9, but it may vary depending on the type of filling.(3)

As Scott Cole, the primary contributor to our database, says, "Contrary to popular belief, burritos do not merely exist in 3 dimensions. They transcend the physical limitations of space."(2) In order to categorically define a "good" burrito, Cole, along with several San Diegans, established the ten "dimensions" of a burrito: volume, tortilla quality, temperature, meat quality, non-meat filling quality, the ratio between meat and non-meat filling, uniformity, salsa quality, flavor synergy, and tortilla wrap integrity.

References

1. https://www.chefspencil.com/most-popular-ethnic-cuisines-in-america/
2. https://srcole.github.io/100burritos/
3. https://www.forbes.com/sites/priceonomics/2017/04/07/how-much-do-the-ingredients-cost-in-your-favorite-foods/?sh=3e8e9dc011ed

4 Hypothesis

Traffic and customers are important for a store to live, after this project, we should be able to predict whether or not burrito stores are able to make money based on their location. Since price and filling are also important parts for a burrito, we may also find out if there is any relationship between customer satisfaction with their burritos. The majority of burritos consumed in this dataset contain meat, so our primary filling focus will be on meat.

We expect price be the most important part of a burrito store, hunger will be the second one and filling being the third important one for a customer enjoy a specific burrito.

4.1 Dataset

- Dataset Name: Burritos of San Diego
- Link to the dataset: https://docs.google.com/spreadsheets/d/18HkrklYz1bKpDLeL-kaMrGjAhUM6LeJMIACwEljCgaw/edit?usp=sharing
- Number of observations: 424

The data we need would be customers' feedback from yelp and google, with the burrito store's location, how is the surrounding area, the price and suppliers for the burrito, how much and what can I choose to be in my burrito. These data can be accessed through the links provided in the background, and would be organized and analyzed. Having many sets of observations is preferable, and will greatly increase the validity of our data.

Comparing the categories with each other and taking into account certain data will allow us to get a good understanding of our research question.

5 Setup

[1]:
```
import sys
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import patsy
import statsmodels.api as sm
import scipy.stats as stats
from scipy.stats import ttest_ind, chisquare, normaltest
burritos = pd.read_csv("burritodata.csv")
burritos
```

[1]:
```
                    Location        Burrito       Date Neighborhood  \
0          Donato's taco shop     California  1/18/2016      Miramar
1         Oscar's Mexican food    California  1/24/2016   San Marcos
2         Oscar's Mexican food      Carnitas  1/24/2016          NaN
3         Oscar's Mexican food   Carne asada  1/24/2016          NaN
4                Pollos Maria    California  1/27/2016     Carlsbad
..                         …             …         …            …
418  Valentine's Mexican Food      Al Pastor  8/27/2019          NaN
419  Valentine's Mexican Food  Chile Relleno  8/27/2019          NaN
420  Valentine's Mexican Food     California  8/27/2019          NaN
421  Valentine's Mexican Food         Shrimp  8/27/2019          NaN
422  Valentine's Mexican Food    Pollo Asado  8/27/2019          NaN

                     Address  \
0            6780 Miramar Rd
1    225 S Rancho Santa Fe Rd
2                        NaN
3                        NaN
4            3055 Harding St
..                         …
418                      NaN
419                      NaN
420                      NaN
421                      NaN
422                      NaN

                                                   URL  Yelp  Google Chips  \
0                         http://donatostacoshop.net/   3.5     4.2   NaN
1    http://www.yelp.com/biz/oscars-mexican-food-sa…   3.5     3.3   NaN
2                                                  NaN   NaN     NaN   NaN
```

```
3                                        NaN    NaN      NaN    NaN
4                        http://pollosmaria.com/    4.0      3.8      x
..                                          …     …       …     …
418                                      NaN    NaN      NaN    NaN
419                                      NaN    NaN      NaN    NaN
420                                      NaN    NaN      NaN    NaN
421                                      NaN    NaN      NaN    NaN
422                                      NaN    NaN      NaN    NaN

     Cost  …  Nopales  Lobster  Queso  Egg  Mushroom  Bacon  Sushi  Avocado  \
0    6.49  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
1    5.45  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
2    4.85  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
3    5.25  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
4    6.59  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
..    …   …       …        …      …    …         …      …
418  6.00  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
419  6.00  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
420  7.90  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
421  7.90  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN
422  5.50  …      NaN      NaN    NaN  NaN       NaN    NaN    NaN      NaN

     Corn  Zucchini
0     NaN       NaN
1     NaN       NaN
2     NaN       NaN
3     NaN       NaN
4     NaN       NaN
..    …       …
418   NaN       NaN
419   NaN       NaN
420   NaN       NaN
421   NaN       NaN
422   NaN       NaN

[423 rows x 66 columns]
```

6 Data Cleaning

There's some inconsistencies with spelling, so we want to fix that. We also want to fill in the in the NaN cells, since they were left empty if the restaurant had been ordered from previously.

[2]:
```
# Manually fixing some of the addresses :/
# Difficult to use code, faster to just do it by hand
burritos.loc[burritos.Location == "Valentines Mexican Food", 'Location'] =␣
↪"Valentine's Mexican Food"
```

```
burritos.loc[burritos.Location == "California burritos", 'Location'] =␣
 ↪"California Burritos"
burritos.loc[burritos.Location == "Donato's taco shop", 'Location'] = "Donato's␣
 ↪Taco Shop"
burritos.loc[burritos.Location == "Alberto's 623 N Escondido Blvd, Escondido,␣
 ↪CA 92025", 'Location'] = "Alberto's Mexican Food"
burritos.loc[burritos.Location == "Alberto's Mexican Food", 'Address'] = "623 N␣
 ↪Escondido Blvd, Escondido, CA 92025"
burritos.loc[burritos.Location == "Alberto's Mexican Food", 'Neighborhood'] =␣
 ↪"Escondido"
burritos.loc[burritos.Location == "Taco stand", 'Location'] = "The Taco Stand"
burritos.loc[burritos.Location == "Taco Stand", 'Location'] = "The Taco Stand"
burritos.loc[burritos.Location == "Vallarta express", 'Location'] = "Vallarta␣
 ↪Express"
burritos.loc[burritos.Location == "MXN on Washington", 'Address'] = "719 W␣
 ↪Washington St, San Diego, CA 92103"
burritos.loc[burritos.Location == "Lolita's", 'Location'] = "Lolita's Taco Shop"
burritos.loc[burritos.Location == "Lolita's Taco shop", 'Location'] = "Lolita's␣
 ↪Taco Shop"
burritos.loc[burritos.Location == "Lolita's taco shop", 'Location'] = "Lolita's␣
 ↪Taco Shop"
burritos.loc[burritos.Location == "Los tacos", 'Location'] = "Los Tacos"
burritos.loc[burritos.Location == "Kotija Jr", 'Location'] = "Kotija Jr."

# Filling in the NaNs for multiple orders of the same restaurant
# Creating a dictionary to hold one column for each restaurant
addresses = dict()
neighborhoods = dict()
# urls = dict()
yelp = dict()
google = dict()
# Iterating through DataFrame to fill the dictionaries
for index, row in burritos.iterrows():
    if row['Location'] not in addresses and not pd.isnull(row['Address']):
        addresses[row['Location']] = row['Address']
    if row['Location'] not in neighborhoods and not pd.
 ↪isnull(row['Neighborhood']):
        neighborhoods[row['Location']] = row['Neighborhood']
    # if row['Location'] not in urls and not pd.isnull(row['URL']):
        # urls[row['Location']] = row['URL']
    if row['Location'] not in yelp and not pd.isnull(row['Yelp']):
        yelp[row['Location']] = row['Yelp']
    if row['Location'] not in google and not pd.isnull(row['Google']):
        google[row['Location']] = row['Google']
# Replacing the NaNs to match everything
for key in addresses:
```

```
    burritos.loc[burritos.Location == key, 'Address'] = addresses[key]
for key in neighborhoods:
    burritos.loc[burritos.Location == key, 'Neighborhood'] = neighborhoods[key]
# for key in urls:
    # burritos.loc[burritos.Location == key, 'URL'] = urls[key]
for key in yelp:
    burritos.loc[burritos.Location == key, 'Yelp'] = yelp[key]
for key in google:
    burritos.loc[burritos.Location == key, 'Google'] = google[key]
```

We don't need the chips column or URL column, so it would be best to get rid of them. Likewise, mass and density is sparesely included, so we will drop those as well.

[3]:
```
# Dropping the chips
burritos = burritos.drop(columns=['Chips','URL', 'Mass (g)', 'Density (g/mL)',␣
↪'Unreliable'])
```

The type of filling selection is simply marked by an X. We need to change this to true and false values.

[4]:
```
burritos.update(burritos[['Beef','Pico','Guac','Cheese','Fries','Sour␣
↪cream','Pork','Chicken','Shrimp','Fish','Rice','Beans','Lettuce','Tomato','Bell␣
↪peper','Carrots','Cabbage','Sauce','Salsa','Cilantro','Onion','Taquito','Pineapple','Ham','
↪relleno','Nopales','Lobster','Queso','Egg','Mushroom','Bacon','Sushi','Avocado','Corn','Zuc
↪fillna(False))
burritos.replace(['x','X'], True)
burritos['Volume'].unique()
```

[4]:
```
array([ nan, 0.77, 0.7 , 0.78, 0.96, 0.93, 0.95, 0.81, 0.73, 0.82, 0.88,
       0.65, 0.9 , 0.84, 0.91, 0.85, 0.89, 1.05, 1.01, 1.07, 0.74, 0.83,
       0.75, 0.94, 0.68, 0.57, 0.5 , 0.92, 0.51, 0.79, 0.6 , 1.17, 0.55,
       0.54, 0.87, 0.86, 0.97, 0.72, 0.76, 0.62, 0.64, 0.67, 0.66, 0.69,
       1.  , 0.8 , 0.63, 0.56, 0.59, 1.24, 0.71, 0.58, 1.16, 0.4 , 0.61,
       1.08, 0.41, 0.99, 1.54, 0.47, 1.03, 1.09, 0.98, 0.52, 1.02])
```

We noticed the many of the reviews for burritos did not include the dimensions. Instead of removing them entirely, we created two new data frames, one that has reviews that included dimensions and one that has reviews that excluded dimensions.

[5]:
```
burritos_with_dim = burritos.loc[~burritos['Volume'].isna()]
burritos_without_dim = burritos.loc[burritos['Volume'].isna()]
```

[6]:
```
burritos_with_dim
```

[6]:
```
                    Location       Burrito       Date Neighborhood  \
73         Jorge's Mexicatessen    California  4/24/2016   Encinitas
75               Senor Grubby's    California  4/24/2016    Carlsbad
76               Senor Grubby's        Pastor  4/24/2016    Carlsbad
```

```
78   Mi Asador Mexican & Seafood     California   4/27/2016    Oceanside
79   Mi Asador Mexican & Seafood   El Hawaiiano   4/27/2016    Oceanside
..                           …             …          …            …
418      Valentine's Mexican Food      Al Pastor  8/27/2019     Downtown
419      Valentine's Mexican Food  Chile Relleno  8/27/2019     Downtown
420      Valentine's Mexican Food     California  8/27/2019     Downtown
421      Valentine's Mexican Food         Shrimp  8/27/2019     Downtown
422      Valentine's Mexican Food    Pollo Asado  8/27/2019     Downtown

                     Address  Yelp  Google  Cost  Hunger  Length  …  \
73      267 N El Camino Real   4.0     4.5  5.95     3.5    20.0  …
75   377 Carlsbad Village Dr   4.0     4.1  9.00     2.0    19.0  …
76   377 Carlsbad Village Dr   4.0     4.1  9.00     2.0    18.5  …
78       4750 Oceanside Blvd   4.5     4.4  6.89     3.0    25.0  …
79       4750 Oceanside Blvd   4.5     4.4  6.39     3.0    23.0  …
..                       …   …     …    …      …      …  …
418           1157 Sixth Ave   4.0     4.0  6.00     1.0    17.0  …
419           1157 Sixth Ave   4.0     4.0  6.00     4.0    19.0  …
420           1157 Sixth Ave   4.0     4.0  7.90     3.0    20.0  …
421           1157 Sixth Ave   4.0     4.0  7.90     3.0    22.5  …
422           1157 Sixth Ave   4.0     4.0  5.50     3.5    17.0  …

     Nopales  Lobster  Queso    Egg  Mushroom  Bacon  Sushi  Avocado   Corn  \
73     False    False    0.0  False     False  False  False    False  False
75     False    False    0.0  False     False  False  False    False  False
76     False    False    0.0  False     False  False  False    False  False
78     False    False    0.0  False     False  False  False    False  False
79     False    False    0.0  False     False  False  False    False  False
..       …        …    …    …       …     …    …       …     …
418    False    False    0.0  False     False  False  False    False  False
419    False    False    0.0  False     False  False  False    False  False
420    False    False    0.0  False     False  False  False    False  False
421    False    False    0.0  False     False  False  False    False  False
422    False    False    0.0  False     False  False  False    False  False

     Zucchini
73      False
75      False
76      False
78      False
79      False
..        …
418     False
419     False
420     False
421     False
422     False
```

```
[282 rows x 61 columns]
```

[7]:
```
burritos_without_dim
```

[7]:
```
                   Location      Burrito       Date   Neighborhood  \
0        Donato's Taco Shop   California  1/18/2016        Miramar
1      Oscar's Mexican food   California  1/24/2016     San Marcos
2      Oscar's Mexican food      Carnitas  1/24/2016     San Marcos
3      Oscar's Mexican food  Carne asada  1/24/2016     San Marcos
4              Pollos Maria   California  1/27/2016       Carlsbad
..                      …           …         …            …
378              Taco Villa  Carne asada  8/25/2017            UTC
386      Lolita's Taco Shop   California   1/2/2018    Kearny Mesa
387               El Patron    Breakfast   1/9/2018  National City
388  La Posta de Acapulco   California  1/12/2018      Hillcrest
413             Kotija Jr.   California  8/24/2019        Del Mar

                       Address  Yelp  Google  Cost  Hunger  Length  …  \
0             6780 Miramar Rd   3.5     4.2  6.49     3.0     NaN  …
1       225 S Rancho Santa Fe Rd   3.5     3.3  5.45     3.5     NaN  …
2       225 S Rancho Santa Fe Rd   3.5     3.3  4.85     1.5     NaN  …
3       225 S Rancho Santa Fe Rd   3.5     3.3  5.25     2.0     NaN  …
4             3055 Harding St   4.0     3.8  6.59     4.0     NaN  …
..                        …   …     …    …     …      …   …
378             9500 Gilman Dr   3.5     3.5  6.99     3.5     NaN  …
386  7305 Clairemont Mesa Blvd   4.0     4.4  7.25     4.0     NaN  …
387             5065 Logan Ave   4.5     3.8  4.19     3.0     NaN  …
388             3980 Third Ave   3.5     4.3  7.00     5.0     NaN  …
413    2668 Del Mar Heights Rd   4.0     4.2  8.00     4.0     NaN  …

    Nopales  Lobster  Queso    Egg  Mushroom  Bacon  Sushi  Avocado   Corn  \
0     False    False    0.0  False     False  False  False    False  False
1     False    False    0.0  False     False  False  False    False  False
2     False    False    0.0  False     False  False  False    False  False
3     False    False    0.0  False     False  False  False    False  False
4     False    False    0.0  False     False  False  False    False  False
..      …      …   …    …      …    …   …      …    …
378   False    False    0.0  False     False  False  False    False  False
386   False    False    0.0  False     False  False  False    False  False
387   False    False    0.0      x     False  False  False    False  False
388   False    False    0.0  False     False  False  False    False  False
413   False    False    0.0  False     False  False  False    False  False

    Zucchini
0      False
1      False
```

```
2       False
3       False
4       False
..        ...
378     False
386     False
387     False
388     False
413     False

[141 rows x 61 columns]
```

Finally, we sort the DataFrame by restaurant instead of date.

[8]:
```
burritos = burritos.sort_values(by='Location').reset_index()
burritos_with_dim = burritos_with_dim.sort_values(by='Location').reset_index()
burritos_without_dim = burritos_without_dim.sort_values(by='Location').
 ↪reset_index()
burritos
```

[8]:
```
     index                 Location               Burrito        Date  \
0      148               Albertacos            Carne asada    6/8/2016
1      147               Albertacos            California     6/8/2016
2      131   Alberto's Mexican Food            Carne Asada    5/5/2016
3      383              Burrito Box  Steak with guacamole   12/16/2017
4      362          Burrito Factory      Steak everything     7/13/2017
..     ...                      ...                   ...         ...
418    356         Vallarta Express            Surf & Turf   6/24/2017
419    357         Vallarta Express            California    6/24/2017
420     89         Vallarta Express            California     5/9/2016
421     48         Vallarta Express          Surf and turf   3/21/2016
422     44         Vallarta Express            Quesaburro    3/21/2016

    Neighborhood                              Address  Yelp  Google  \
0     San Marcos              500 W San Marcos Blvd # 103   3.5     3.9
1     San Marcos              500 W San Marcos Blvd # 103   3.5     3.9
2      Escondido  623 N Escondido Blvd, Escondido, CA 92025   NaN     NaN
3       New York                           885 9th Ave   4.0     4.5
4         Austin                     2025 Guadalupe St   4.5     4.8
..           ...                                   ...   ...     ...
418   Clairemont                      4277 Genesee Ave   3.5     4.0
419   Clairemont                      4277 Genesee Ave   3.5     4.0
420   Clairemont                      4277 Genesee Ave   3.5     4.0
421   Clairemont                      4277 Genesee Ave   3.5     4.0
422   Clairemont                      4277 Genesee Ave   3.5     4.0

      Cost  Hunger  ...  Nopales  Lobster  Queso   Egg  Mushroom  Bacon  \
```

```
0      5.25     4.0  …    False    False    0.0  False     False  False
1      5.70     3.5  …    False    False    0.0  False     False  False
2      4.59     4.0  …    False    False    0.0  False     False  False
3     11.50     3.5  …    False    False    0.0  False     False  False
4      7.35     3.5  …    False    False    0.0  False     False  False
..      …      …  …      …      …     …    …       …    …
418    8.55     3.0  …    False    False    0.0  False     False  False
419    7.80     2.5  …    False    False    0.0  False     False  False
420    6.95     4.0  …    False    False    0.0  False     False  False
421    7.65     3.0  …    False    False    0.0  False     False  False
422    6.95     3.5  …    False    False    0.0  False     False  False

     Sushi  Avocado   Corn Zucchini
0    False    False  False    False
1    False    False  False    False
2    False    False  False    False
3    False    False  False    False
4    False    False  False    False
..     …      …    …      …
418  False    False  False    False
419  False    False  False    False
420  False    False  False    False
421  False    False  False    False
422  False    False  False    False

[423 rows x 62 columns]
```

7 Data Analysis & Results

Because our data is comprised of written reviews, the overall scores given for each are subjective and may contribute to some bias. Some variables may be linked to others. We want to see if there are any individual factors that affect a review. We chose to do linear regression because we wanted to find relationships between continuous variables.

Since the reviewers included hunger, we want to determine the relationship between hunger and overall ratings of burrito restaurants. The null hypothesis here would be that there is no relationship between hunger and overall ratings.

[9]:
```
outcome1, predictors1 = patsy.dmatrices('Hunger ~ overall', burritos)
model1 = sm.OLS(outcome1, predictors1)
res_1 = model1.fit()
print(res_1.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Hunger   R-squared:                       0.027
Model:                            OLS   Adj. R-squared:                  0.025
```

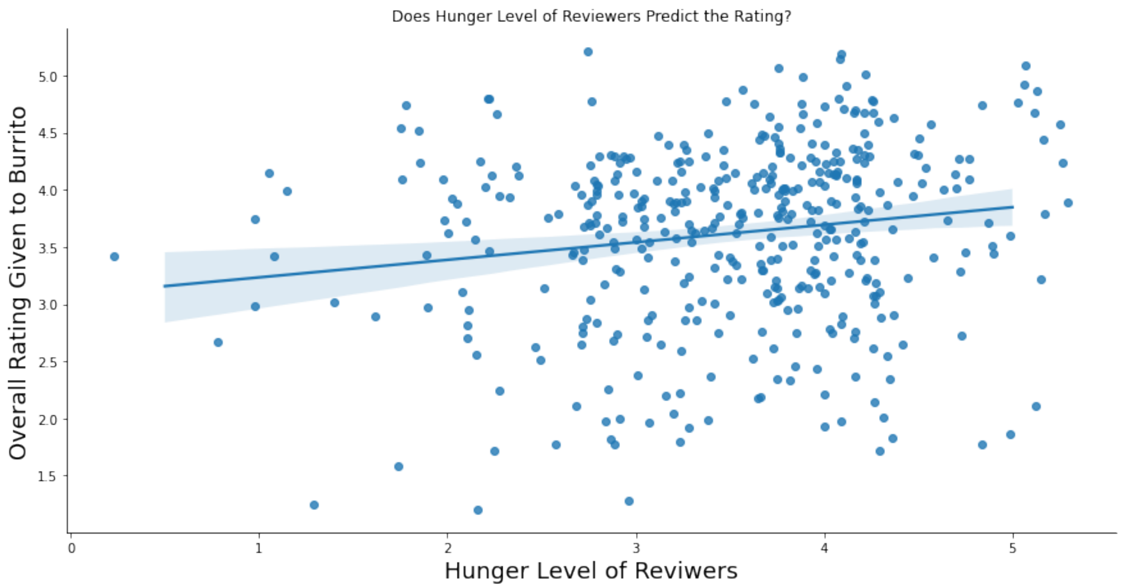
```
Method:                 Least Squares   F-statistic:                     11.65
Date:                Wed, 09 Jun 2021   Prob (F-statistic):           0.000705
Time:                        22:14:53   Log-Likelihood:                -499.83
No. Observations:                 418   AIC:                             1004.
Df Residuals:                     416   BIC:                             1012.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      2.8535      0.192     14.855      0.000       2.476       3.231
overall        0.1775      0.052      3.413      0.001       0.075       0.280
==============================================================================
Omnibus:                       34.581   Durbin-Watson:                   2.036
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               43.020
Skew:                          -0.668   Prob(JB):                     4.55e-10
Kurtosis:                       3.827   Cond. No.                         19.4
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Using an alpha of 0.01, we reject our hypothesis and there is a relationship between hunger levels of our reviewers and overall rating of the burrito they consumed. Here's our plot.

[10]:
```
sns.lmplot(x='Hunger', y='overall',
           data=burritos, fit_reg=True,
           height=6, aspect=2,
           x_jitter=.3, y_jitter=.3)
plt.xlabel('Hunger Level of Reviwers', size=18)
plt.ylabel('Overall Rating Given to Burrito', size=18)
plt.title('Does Hunger Level of Reviewers Predict the Rating?')
```

[10]:
```
Text(0.5, 1.0, 'Does Hunger Level of Reviewers Predict the Rating?')
```



We can also take a look there is a relationship between cost and overall rating. The null hypothesis here would be that there is no relationship between cost and overall rating.

[11]:
```python
outcome2, predictors2 = patsy.dmatrices('Cost ~ overall', burritos)
model2 = sm.OLS(outcome2, predictors2)
res_2 = model2.fit()
print(res_2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Cost   R-squared:                       0.013
Model:                            OLS   Adj. R-squared:                  0.011
Method:                 Least Squares   F-statistic:                     5.450
Date:                Wed, 09 Jun 2021   Prob (F-statistic):             0.0200
Time:                        22:14:54   Log-Likelihood:                -753.94
No. Observations:                 414   AIC:                             1512.
Df Residuals:                     412   BIC:                             1520.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      6.2381      0.363     17.196      0.000       5.525       6.951
overall        0.2293      0.098      2.335      0.020       0.036       0.422
==============================================================================
Omnibus:                      437.523   Durbin-Watson:                   1.642
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            40328.902
Skew:                           4.363   Prob(JB):                         0.00
```

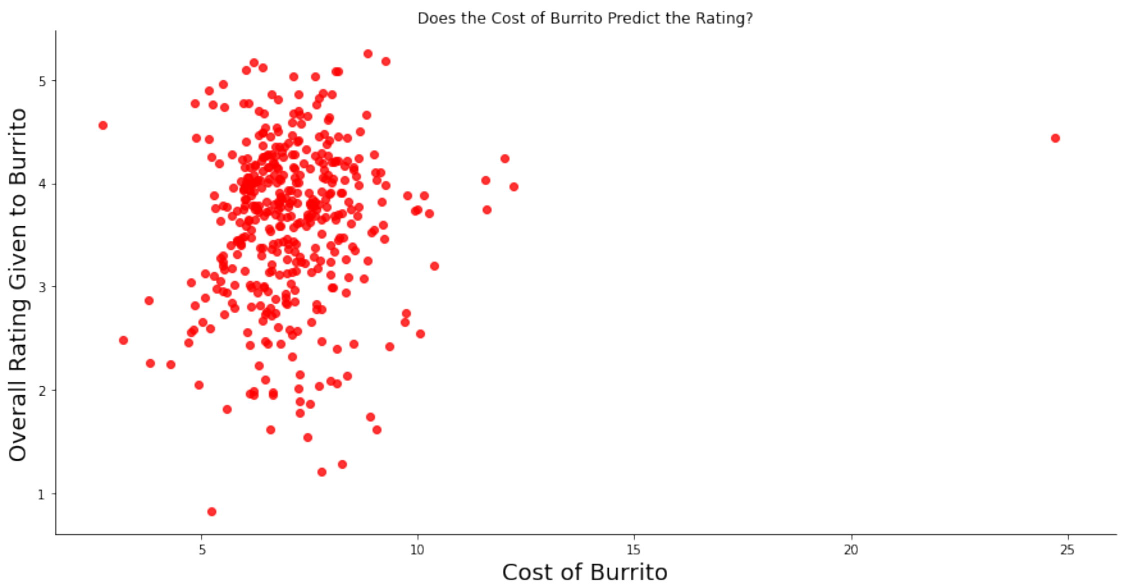
```
Kurtosis:                      50.558   Cond. No.                        19.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Using an alpha level of 0.01, we fail to reject our hypothesis. The cost of the burrito does not significantly predict the overall rating of it. Here's our plot.

[12]:
```
sns.lmplot(x='Cost', y='overall',
           data=burritos, fit_reg=False,
           height=6, aspect=2,
           x_jitter=.3, y_jitter=.3,
           line_kws = {'color': 'red'},
           scatter_kws = {'color': 'red'})
plt.xlabel('Cost of Burrito', size=18)
plt.ylabel('Overall Rating Given to Burrito', size=18)
plt.title('Does the Cost of Burrito Predict the Rating?')
```

[12]:
```
Text(0.5, 1.0, 'Does the Cost of Burrito Predict the Rating?')
```



As we can see, there is a significant outlier on the far right of our data. (Why would someone order a $25 burrito? That's like 3 burritos.) Looking at our graphs, there doesn't seem to be any classifiable distributions in our data regarding cost, hunger levels, and overall rating.

We would also like to see if there is any correlation between our burrito meat and the overall rating given to that specific burrito, as per our hypothesis. The null hypothesis here would be that there is no relationship between meat and overall rating

[13]:
```
outcome3, predictors3 = patsy.dmatrices('Meat ~ overall', burritos)
model3 = sm.OLS(outcome3, predictors3)
res_3 = model3.fit()
print(res_3.summary())
```

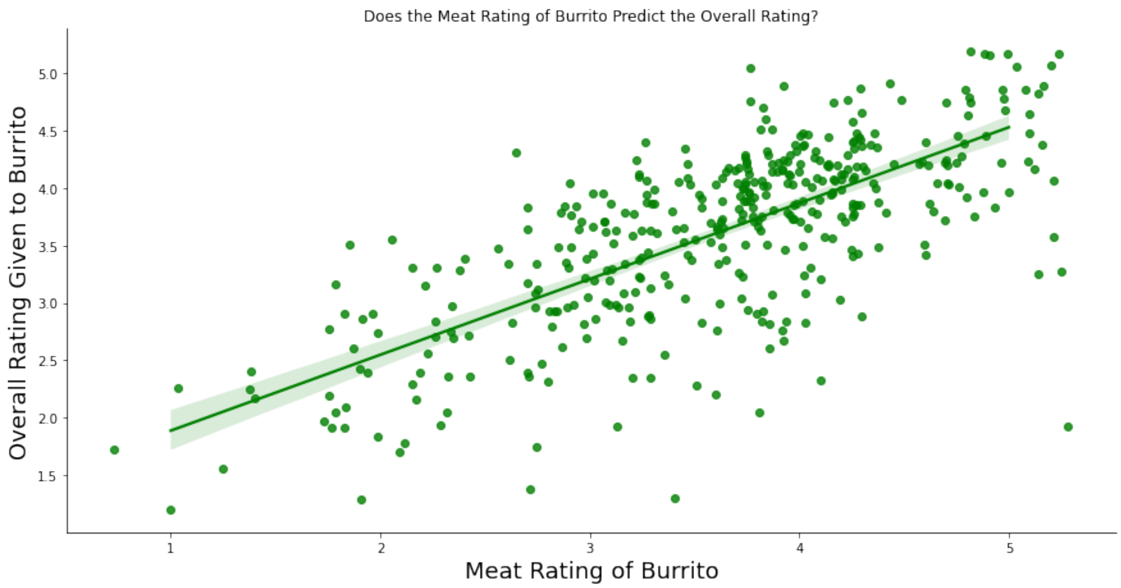
```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   Meat   R-squared:                       0.533
Model:                            OLS   Adj. R-squared:                  0.532
Method:                 Least Squares   F-statistic:                     463.0
Date:                Wed, 09 Jun 2021   Prob (F-statistic):           4.96e-69
Time:                        22:14:54   Log-Likelihood:                -345.68
No. Observations:                 407   AIC:                             695.4
Df Residuals:                     405   BIC:                             703.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.6974      0.139      5.027      0.000       0.425       0.970
overall        0.8080      0.038     21.517      0.000       0.734       0.882
==============================================================================
Omnibus:                       24.511   Durbin-Watson:                   1.850
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               48.730
Skew:                           0.343   Prob(JB):                     2.62e-11
Kurtosis:                       4.550   Cond. No.                         19.5
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

Using an alpha level of 0.01, we reject our hypothesis. There is a relationship between the meat rating the reviewer gave to their burrito and the overall rating they gave to it.

[14]:
```
sns.lmplot(x='Meat', y='overall',
           data=burritos, fit_reg=True,
           height=6, aspect=2,
           x_jitter=.3, y_jitter=.3,
           line_kws = {'color': 'green'},
           scatter_kws = {'color': 'green'})
plt.xlabel('Meat Rating of Burrito', size=18)
plt.ylabel('Overall Rating Given to Burrito', size=18)
plt.title('Does the Meat Rating of Burrito Predict the Overall Rating?')
```

[14]:
```
Text(0.5, 1.0, 'Does the Meat Rating of Burrito Predict the Overall Rating?')
```



Finally, let's take a look at the rankings of restaurants based on the different the different rating categories. Since there are several restaurants that have very few reviews, we will only look at restaurants with 5 or more reviews in the burritos DataFrame. However, for volume ratings, we need to use the burritos_with_dim DataFrame to find restaurants with 5 or more reviews.

[15]:
```
mean_burritos_rating = burritos.groupby('Location').mean()
mean_burritos_rating['NumberOfRestaurants'] = burritos['Location'].
 ↪value_counts()
mean_burritos_rating = mean_burritos_rating.loc[mean_burritos_rating.
 ↪NumberOfRestaurants > 4]
mean_burritos_dim = burritos_with_dim.groupby('Location').mean()
mean_burritos_dim['NumberOfRestaurants'] = burritos_with_dim['Location'].
 ↪value_counts()
mean_burritos_dim = mean_burritos_dim.loc[mean_burritos_dim.NumberOfRestaurants␣
 ↪> 4]
mean_burritos_rating
```

[15]:

Location	index	Yelp	Google	Cost	Hunger \
California Burrito Company	255.200000	3.5	4.4	5.900000	3.200000
California Burritos	189.379310	4.5	4.4	6.317241	3.924483
Cancun Mexican & Seafood	185.166667	4.5	4.1	6.733333	3.716667
El Zarape	179.000000	4.0	4.4	6.775000	3.175000
Lolita's Taco Shop	130.357143	4.0	4.4	7.226923	3.285714
Los Primos Mexican Food	133.666667	3.0	3.7	7.466667	3.375000
Los Tacos	311.000000	NaN	NaN	8.050000	3.241667
Los Tacos 2	361.600000	4.5	5.0	8.740000	3.960000
Lucha Libre North Park	207.500000	3.5	4.3	7.587500	3.489286

```
Lupe's Taco Shop             316.833333   3.5     4.5   8.360000  3.733333
Rigoberto's Taco Shop        179.840000   4.0     4.4   6.777083  3.630435
Roberto's Taco Shop Hillcrest 358.000000  4.0     4.2  11.000000  3.600000
Taco Villa                   328.428571   3.5     3.5   6.111667  3.439286
The Taco Stand               130.560000   4.5     4.4   7.645200  3.384000
Tony's Fresh Mexican Food    232.777778   3.0     4.1   7.621111  3.666667
Valentine's Mexican Food     356.388889   4.0     4.0   7.125000  3.222222
Vallarta Express             147.461538   3.5     4.0   7.276923  3.500000

                                Length     Circum    Volume  Tortilla  \
Location
California Burrito Company    19.000000  21.300000  0.686000  3.100000
California Burritos           22.252381  21.457143  0.823333  3.941379
Cancun Mexican & Seafood      19.500000  21.750000  0.735000  4.050000
El Zarape                     17.500000  21.125000  0.620000  3.500000
Lolita's Taco Shop            17.642222  22.913889  0.747778  3.114286
Los Primos Mexican Food       20.214286  21.607143  0.761429  3.333333
Los Tacos                     21.050000  22.600000  0.856000  3.766667
Los Tacos 2                   22.100000  21.400000  0.806000  3.900000
Lucha Libre North Park        18.979167  23.320833  0.827083  3.678571
Lupe's Taco Shop              20.250000  25.500000  1.085000  3.500000
Rigoberto's Taco Shop         22.805882  22.629412  0.933529  3.800000
Roberto's Taco Shop Hillcrest 21.500000  22.100000  0.840000  3.760000
Taco Villa                    18.880952  21.357143  0.687619  3.150000
The Taco Stand                18.627857  23.000000  0.776923  3.840000
Tony's Fresh Mexican Food     21.400000  21.500000  0.786000  3.722222
Valentine's Mexican Food      19.117647  22.517647  0.777647  4.083333
Vallarta Express              20.625000  23.375000  0.895000  2.942308

                                  Temp      Meat  Fillings  Meat:filling  \
Location
California Burrito Company    4.200000  3.300000  2.900000      2.600000
California Burritos           3.544828  4.103448  3.975000      3.991071
Cancun Mexican & Seafood      4.500000  3.833333  3.900000      3.916667
El Zarape                     4.333333  3.750000  3.545000      4.025000
Lolita's Taco Shop            3.450000  3.416667  3.814286      3.491667
Los Primos Mexican Food       3.500000  2.958333  3.250000      2.083333
Los Tacos                     4.250000  4.258333  3.858333      3.825000
Los Tacos 2                   4.375000  3.350000  3.200000      2.700000
Lucha Libre North Park        3.200000  3.612000  3.364286      3.480000
Lupe's Taco Shop              3.833333  3.766667  3.416667      3.083333
Rigoberto's Taco Shop         4.087500  3.873913  3.812000      4.083333
Roberto's Taco Shop Hillcrest 4.080000  3.200000  3.260000      4.000000
Taco Villa                    4.064286  3.711111  3.446429      3.774286
The Taco Stand                3.520000  4.340000  4.040000      3.988000
Tony's Fresh Mexican Food     3.875000  3.125000  3.000000      3.625000
Valentine's Mexican Food      4.205556  4.205882  4.041176      4.161111
```

```
Vallarta Express              3.800000  3.384615  3.384615      3.538462

                              Uniformity   Synergy      Wrap   overall  \
Location
California Burrito Company      3.000000  3.400000  4.600000  3.200000
California Burritos             3.862069  4.089655  4.355172  4.203704
Cancun Mexican & Seafood        3.416667  3.800000  3.916667  4.100000
El Zarape                       3.810000  3.540000  4.700000  3.573333
Lolita's Taco Shop              3.135714  3.567857  4.071429  3.407143
Los Primos Mexican Food         2.863636  2.666667  3.416667  2.758333
Los Tacos                       3.741667  4.225000  4.150000  4.208333
Los Tacos 2                     2.600000  3.340000  3.000000  3.480000
Lucha Libre North Park          3.185714  3.314286  4.014286  3.264286
Lupe's Taco Shop                1.966667  3.316667  3.450000  3.541667
Rigoberto's Taco Shop           3.704000  3.902000  3.860000  3.930000
Roberto's Taco Shop Hillcrest   3.640000  3.400000  4.260000  3.480000
Taco Villa                      3.442857  3.257143  4.014815  3.575000
The Taco Stand                  3.920000  4.292000  4.140000  4.200000
Tony's Fresh Mexican Food       3.666667  3.444444  3.833333  3.405556
Valentine's Mexican Food        3.766667  4.022222  3.694444  4.219444
Vallarta Express                3.292308  3.238462  3.653846  3.553846

                              Queso  NumberOfRestaurants
Location
California Burrito Company      0.0                    5
California Burritos             0.0                   29
Cancun Mexican & Seafood        0.0                    6
El Zarape                       0.0                   10
Lolita's Taco Shop              0.0                   14
Los Primos Mexican Food         0.0                   12
Los Tacos                       0.0                   12
Los Tacos 2                     0.0                    5
Lucha Libre North Park          0.0                   28
Lupe's Taco Shop                0.0                    6
Rigoberto's Taco Shop           0.0                   25
Roberto's Taco Shop Hillcrest   0.0                    5
Taco Villa                      0.0                   28
The Taco Stand                  0.0                   25
Tony's Fresh Mexican Food       0.0                    9
Valentine's Mexican Food        0.0                   18
Vallarta Express                0.0                   13
```

[16]:
```
mean_burritos_dim
```

[16]:
```
                                   index  Yelp  Google      Cost    Hunger  \
Location
California Burrito Company    255.200000   3.5     4.4  5.900000  3.200000
```

```
California Burritos          213.619048   4.5     4.4   6.271429  3.952381
Lolita's Taco Shop           122.666667   4.0     4.4   7.133333  3.077778
Los Primos Mexican Food      154.857143   3.0     3.7   7.014286  3.142857
Los Tacos                    309.100000   NaN     NaN   8.080000  3.290000
Los Tacos 2                  361.600000   4.5     5.0   8.740000  3.960000
Lucha Libre North Park       208.083333   3.5     4.3   7.508333  3.491667
Lupe's Taco Shop             316.833333   3.5     4.5   8.360000  3.733333
Rigoberto's Taco Shop        225.941176   4.0     4.4   6.738235  3.800000
Roberto's Taco Shop Hillcrest 358.000000  4.0     4.2  11.000000  3.600000
Taco Villa                   340.095238   3.5     3.5   6.138000  3.490476
The Taco Stand               176.307692   4.5     4.4   7.695385  3.500000
Tony's Fresh Mexican Food    409.000000   3.0     4.1   8.430000  4.300000
Valentine's Mexican Food     360.470588   4.0     4.0   7.079412  3.205882

                                Length     Circum    Volume  Tortilla  \
Location
California Burrito Company     19.000000  21.300000  0.686000  3.100000
California Burritos            22.252381  21.457143  0.823333  3.919048
Lolita's Taco Shop             17.642222  22.913889  0.747778  3.200000
Los Primos Mexican Food        20.214286  21.607143  0.761429  3.571429
Los Tacos                      21.050000  22.600000  0.856000  3.670000
Los Tacos 2                    22.100000  21.400000  0.806000  3.900000
Lucha Libre North Park         18.979167  23.320833  0.827083  3.766667
Lupe's Taco Shop               20.250000  25.500000  1.085000  3.500000
Rigoberto's Taco Shop          22.805882  22.629412  0.933529  3.882353
Roberto's Taco Shop Hillcrest  21.500000  22.100000  0.840000  3.760000
Taco Villa                     18.880952  21.357143  0.687619  3.009524
The Taco Stand                 18.400000  23.000000  0.776923  4.000000
Tony's Fresh Mexican Food      21.400000  21.500000  0.786000  4.100000
Valentine's Mexican Food       19.117647  22.517647  0.777647  4.088235

                                  Temp      Meat  Fillings  Meat:filling  \
Location
California Burrito Company     4.200000  3.300000  2.900000      2.600000
California Burritos            3.276190  4.047619  4.014286      3.964286
Lolita's Taco Shop             3.533333  3.312500  3.688889      3.112500
Los Primos Mexican Food        3.214286  2.642857  2.714286      1.642857
Los Tacos                      4.200000  4.210000  3.830000      3.640000
Los Tacos 2                    4.375000  3.350000  3.200000      2.700000
Lucha Libre North Park         3.362500  3.676190  3.429167      3.480952
Lupe's Taco Shop               3.833333  3.766667  3.416667      3.083333
Rigoberto's Taco Shop          4.182353  3.740000  3.752941      4.062500
Roberto's Taco Shop Hillcrest  4.080000  3.200000  3.260000      4.000000
Taco Villa                     3.919048  3.819048  3.380952      3.923810
The Taco Stand                 3.692308  4.346154  4.038462      3.846154
Tony's Fresh Mexican Food      4.500000  3.500000  3.100000      3.750000
Valentine's Mexican Food       4.247059  4.175000  4.043750      4.141176
```

```
                               Uniformity   Synergy      Wrap   overall  \
Location
California Burrito Company       3.000000  3.400000  4.600000  3.200000
California Burritos              3.857143  4.004762  4.157143  4.105000
Lolita's Taco Shop               3.155556  3.250000  3.722222  3.155556
Los Primos Mexican Food          2.416667  2.142857  3.857143  2.271429
Los Tacos                        3.740000  4.220000  4.180000  4.150000
Los Tacos 2                      2.600000  3.340000  3.000000  3.480000
Lucha Libre North Park           3.125000  3.408333  4.016667  3.291667
Lupe's Taco Shop                 1.966667  3.316667  3.450000  3.541667
Rigoberto's Taco Shop            3.829412  3.855882  3.823529  3.894118
Roberto's Taco Shop Hillcrest    3.640000  3.400000  4.260000  3.480000
Taco Villa                       3.400000  3.285714  3.920000  3.695238
The Taco Stand                   4.000000  4.330769  4.076923  4.184615
Tony's Fresh Mexican Food        3.500000  3.500000  4.100000  3.800000
Valentine's Mexican Food         3.723529  4.023529  3.705882  4.191176

                               Queso  NumberOfRestaurants
Location
California Burrito Company       0.0                    5
California Burritos              0.0                   21
Lolita's Taco Shop               0.0                    9
Los Primos Mexican Food          0.0                    7
Los Tacos                        0.0                   10
Los Tacos 2                      0.0                    5
Lucha Libre North Park           0.0                   24
Lupe's Taco Shop                 0.0                    6
Rigoberto's Taco Shop            0.0                   17
Roberto's Taco Shop Hillcrest    0.0                    5
Taco Villa                       0.0                   21
The Taco Stand                   0.0                   13
Tony's Fresh Mexican Food        0.0                    5
Valentine's Mexican Food         0.0                   17
```

[17]:
```
print('Top 5 Restaurant Ratings: Overall')
print(mean_burritos_rating.
 ↪sort_values(by=['overall'],ascending=False)['overall'].head(5))
```

```
Top 5 Restaurant Ratings: Overall
Location
Valentine's Mexican Food    4.219444
Los Tacos                   4.208333
California Burritos         4.203704
The Taco Stand              4.200000
Cancun Mexican & Seafood    4.100000
Name: overall, dtype: float64
```

[18]:
```
print('Top 5 Restaurant Ratings: Volume')
print(mean_burritos_dim.sort_values(by=['Volume'],ascending=False)['Volume'].
↪head(5))
```

```
Top 5 Restaurant Ratings: Volume
Location
Lupe's Taco Shop                1.085000
Rigoberto's Taco Shop           0.933529
Los Tacos                       0.856000
Roberto's Taco Shop Hillcrest   0.840000
Lucha Libre North Park          0.827083
Name: Volume, dtype: float64
```

[19]:
```
print('Top 5 Restaurant Ratings: Tortilla')
print(mean_burritos_rating.
↪sort_values(by=['Tortilla'],ascending=False)['Tortilla'].head(5))
```

```
Top 5 Restaurant Ratings: Tortilla
Location
Valentine's Mexican Food    4.083333
Cancun Mexican & Seafood    4.050000
California Burritos         3.941379
Los Tacos 2                 3.900000
The Taco Stand              3.840000
Name: Tortilla, dtype: float64
```

[20]:
```
print('Top 5 Restaurant Ratings: Temperature')
print(mean_burritos_rating.sort_values(by=['Temp'],ascending=False)['Temp'].
↪head(5))
```

```
Top 5 Restaurant Ratings: Temperature
Location
Cancun Mexican & Seafood    4.500000
Los Tacos 2                 4.375000
El Zarape                   4.333333
Los Tacos                   4.250000
Valentine's Mexican Food    4.205556
Name: Temp, dtype: float64
```

[21]:
```
print('Top 5 Restaurant Ratings: Meat')
print(mean_burritos_rating.sort_values(by=['Meat'],ascending=False)['Meat'].
↪head(5))
```

```
Top 5 Restaurant Ratings: Meat
Location
The Taco Stand              4.340000
Los Tacos                   4.258333
Valentine's Mexican Food    4.205882
```

```
California Burritos         4.103448
Rigoberto's Taco Shop       3.873913
Name: Meat, dtype: float64
```

[22]:
```
print('Top 5 Restaurant Ratings: Non-Meat')
print(mean_burritos_rating.
 ↪sort_values(by=['Fillings'],ascending=False)['Fillings'].head(5))
```

```
Top 5 Restaurant Ratings: Non-Meat
Location
Valentine's Mexican Food    4.041176
The Taco Stand              4.040000
California Burritos         3.975000
Cancun Mexican & Seafood    3.900000
Los Tacos                   3.858333
Name: Fillings, dtype: float64
```

[23]:
```
print('Top 5 Restaurant Ratings: Meat to Filling Ratio')
print(mean_burritos_rating.sort_values(by=['Meat:
 ↪filling'],ascending=False)['Meat:filling'].head(5))
```

```
Top 5 Restaurant Ratings: Meat to Filling Ratio
Location
Valentine's Mexican Food         4.161111
Rigoberto's Taco Shop            4.083333
El Zarape                        4.025000
Roberto's Taco Shop Hillcrest    4.000000
California Burritos              3.991071
Name: Meat:filling, dtype: float64
```

[24]:
```
print('Top 5 Restaurant Ratings: Uniformity')
print(mean_burritos_rating.
 ↪sort_values(by=['Uniformity'],ascending=False)['Uniformity'].head(5))
```

```
Top 5 Restaurant Ratings: Uniformity
Location
The Taco Stand              3.920000
California Burritos         3.862069
El Zarape                   3.810000
Valentine's Mexican Food    3.766667
Los Tacos                   3.741667
Name: Uniformity, dtype: float64
```

Since there are empty Salsa cells (now filled with False values), presumably because the reviewer ordered a burrito without salsa, we will rank the salsa based on the rows have salsa rated.

[25]:
```
# For some reason, pd could not calculate the mean of the Salsa column. We␣
 ↪couldn't figure out exactly why,
```

```
# and calling burritos['Salsa'].unique() only showed floats, but the dtype was␣
↪still an object.
# This function basically forces everything to be a float, and then we take the␣
↪average Salsa rating over
# each restaurant.
def to_float(x):
    return float(x)
salsa_burritos = burritos.loc[burritos['Salsa'] != False]
salsa_burritos = salsa_burritos[['Location', 'Salsa']]
salsa_burritos['Salsa'] = salsa_burritos['Salsa'].apply(to_float)
salsa_burritos['Salsa'].dtype
mean_burritos_salsa = salsa_burritos.groupby('Location').mean()
mean_burritos_salsa['NumberOfRestaurants'] = salsa_burritos['Location'].
↪value_counts()
mean_burritos_salsa = mean_burritos_salsa.loc[mean_burritos_salsa.
↪NumberOfRestaurants > 4]
print('Top 5 Restaurant Ratings: Salsa')
print(mean_burritos_salsa.sort_values(by=['Salsa'],ascending=False)['Salsa'].
↪head(5))
```

```
Top 5 Restaurant Ratings: Salsa
Location
Lucha Libre North Park      3.925926
Los Tacos                   3.875000
The Taco Stand              3.848000
Valentine's Mexican Food    3.750000
California Burritos         3.550000
Name: Salsa, dtype: float64
```

[26]:
```
print('Top 5 Restaurant Ratings: Filling Synergy')
print(mean_burritos_rating.
↪sort_values(by=['Synergy'],ascending=False)['Synergy'].head(5))
```

```
Top 5 Restaurant Ratings: Filling Synergy
Location
The Taco Stand              4.292000
Los Tacos                   4.225000
California Burritos         4.089655
Valentine's Mexican Food    4.022222
Rigoberto's Taco Shop       3.902000
Name: Synergy, dtype: float64
```

[27]:
```
print('Top 5 Restaurant Ratings: Wrap Integrity')
print(mean_burritos_rating.sort_values(by=['Wrap'],ascending=False)['Wrap'].
↪head(5))
```

```
Top 5 Restaurant Ratings: Wrap Integrity
```

```
Location
El Zarape                        4.700000
California Burrito Company       4.600000
California Burritos              4.355172
Roberto's Taco Shop Hillcrest    4.260000
Los Tacos                        4.150000
Name: Wrap, dtype: float64
```

8 Ethics & Privacy

The data set we are using is provided by a data scientist on a public Github repository. The data is publicly available and free, so there shouldn't be any problems with using or accessing it. Fundamentally, this data is very subjective because it deals with taste. However, we believe that there are steps taken to reduce the impact of subjectivity. Since we do not know the people who reviewed the burritos, we cannot evaluate how impartial they are or what biases they may have. It is possible that there are some group wide biases that significantly affect the data. If we come across what appears to be bias during our analysis, we will work together to understand and work around it. If necessary, we will contact the teaching staff to ask for advice. If we cannot do anything to resolve the issue, we will make sure that it is clear that we are aware of the issue and what it may imply during the communication of our analysis.

We do not anticipate that our analysis will raise any controversy or that it will violate privacy. This is because the data does not contain any information that can actually be used to identify people involved and the subject matter is not considered offensive or sensitive. Some possible outcomes of our analysis is that some burrito locations will gain popularity while others lose popularity, or that burrito restaurants will use our findings to improve their offerings.

9 Conclusion & Discussion

Overall, the analysis gave us a good idea of what factors influence a burrito's rating, and what people look and value for in the meal. Our hypothesis was mostly proven by the dataset, although not completely what we expected.

As we can see in our data analysis, there is some relationship between people's hunger level with the overall rating of the burrito. When people experience a higher hunger level, they seem to provide their burrito a higher rating. This is what we predicted, but the relationship seems lower than we expected. They say "hunger is the best spice", but as it turns out there are a lot more factors to consider as well. A closer relationship can be found between the meat rating of burrito and the overall rating of the burrito. This is also what we expected, since the meat is usually considered the "main" part of a burrito. It would make sense that the quality of the meat dictates customer satisfaction. Furthermore, We did not see a relationship between cost of burrito and overall rating of the burrito. This can be attributed to most burritos being at an average price of $8-$9, so price doesn't really have a big impact on whether or not the burrito is good. It is good to note here that an increase in price also corresponds to higher expectations of the burrito. For example, there was an outlier of a burrito costing $25 (lobster burrito). If one were to spend that much money on a burrito, their expectations will be fairly high. This could impact ratings and create bias since the customer already has high (or low, depending on price) of the burrito. People are subjective to the rating, the result might be biased, so we also provide some ratings for burrito stores within different categories(overall, volume, tortilla, temperature, meat, non-meat, meat to Filling Ratio and uniformity).

There were some limitations to the project, mainly, our dataset. Since the dataset is a contribution by many people, there may be different ratings and biases for each individual. For example, one person may rate a fish burrito higher because they like seafood, while another rates it lower because they dislike it. In addition, the dataset could be considered small, compared to a large dataset of thousands of values. This work provides an insight into what people value in a burrito. This could prove useful to both the restaurant and the customers. The restaurants would know where to place more value in their burritos, and customers would be able to know which restaurants have high ratings, and decide where to eat at.

10 Team Contributions

-Ethan Tao: Hypothesis, Background, Dataset

-Haaris Waleh: Dataset, EDA

-Sean Li: Dataset, EDA

-Han Zhang: EDA, Conclusion