Analysis of Yelp Dataset

In this notebook we will analyze a subset of Yelp's business, reviews and user data. The data was originally obtained from Kaggle but was then uploaded into an s3 bucket.

Part 1: Installation and Initial Setup

First we will validate that everything was setup correctly and do an initial check on current kernel packages.

In [1]:

```
%%info
```

Current session configs: `{'conf': {'spark.pyspark.python': 'python3', 'spark.pyspark.virtualenv.enabled': 'true', 'spark.pyspark.virtualenv.type': 'native', 'spark.pyspark.virtualenv.bin.path': '/usr/bin/virtualenv'}, 'kind': 'pyspark'}`

No active sessions.

In [2]:

```
sc.list_packages() # check kernel packages
```

```
Starting Spark application
```

ID	YARN Application ID	Kind	State	Spark UI	Driver log	Current session?
0	application_1619399119434_0001	pyspark	idle	Link	Link	✔

```
SparkSession available as 'spark'.

Package                    Version
-------------------------- ---------
beautifulsoup4             4.9.1
boto                       2.49.0
click                      7.1.2
jmespath                   0.10.0
joblib                     0.16.0
lxml                       4.5.2
mysqlclient                1.4.2
nltk                       3.5
nose                       1.3.4
numpy                      1.16.5
pip                        9.0.1
py-dateutil                2.2
python37-sagemaker-pyspark 1.4.0
pytz                       2020.1
PyYAML                     5.3.1
regex                      2020.7.14
setuptools                 28.8.0
six                        1.13.0
soupsieve                  1.9.5
tqdm                       4.48.2
wheel                      0.29.0
windmill                   1.6
```

Installing required packages for analysis and visualization

In [3]:

```
sc.install_pypi_package("pandas==1.2.4")
sc.install_pypi_package("matplotlib==3.4.1")
sc.install_pypi_package("seaborn==0.11.1")
sc.install_pypi_package("pyspark==3.1.1")
```

```
Collecting pandas==1.2.4
  Downloading https://files.pythonhosted.org/packages/51/51/48f3fc47c4e2144da2806dfb6629
c4dd1fa3d5a143f9652b141e979a8ca9/pandas-1.2.4-cp37-cp37m-manylinux1_x86_64.whl (9.9MB)
Requirement already satisfied: numpy>=1.16.5 in /usr/local/lib64/python3.7/site-packages
(from pandas==1.2.4)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/site-packages (f
rom pandas==1.2.4)
Collecting python-dateutil>=2.7.3 (from pandas==1.2.4)
  Downloading https://files.pythonhosted.org/packages/d4/70/d60450c3dd48ef87586924207ae8
907090de0b306af2bce5d134d78615cb/python_dateutil-2.8.1-py2.py3-none-any.whl (227kB)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (from
python-dateutil>=2.7.3->pandas==1.2.4)
Installing collected packages: python-dateutil, pandas
Successfully installed pandas-1.2.4 python-dateutil-2.8.1

Collecting matplotlib==3.4.1
  Downloading https://files.pythonhosted.org/packages/ce/63/74c0b6184b6b169b121bb7245881
8ee60a7d7c436d7b1907bd5874188c55/matplotlib-3.4.1-cp37-cp37m-manylinux1_x86_64.whl (10.3
MB)
Requirement already satisfied: numpy>=1.16 in /usr/local/lib64/python3.7/site-packages
(from matplotlib==3.4.1)
Collecting pyparsing>=2.2.1 (from matplotlib==3.4.1)
  Downloading https://files.pythonhosted.org/packages/8a/bb/488841f56197b13700afd5658fc2
79a2025a39e22449b7cf29864669b15d/pyparsing-2.4.7-py2.py3-none-any.whl (67kB)
Requirement already satisfied: python-dateutil>=2.7 in /mnt/tmp/1619401021264-0/lib/pyth
on3.7/site-packages (from matplotlib==3.4.1)
Collecting pillow>=6.2.0 (from matplotlib==3.4.1)
  Downloading https://files.pythonhosted.org/packages/33/34/542152297dcc6c47a9dcb0685eac
6d652d878ed3cea83bf2b23cb988e857/Pillow-8.2.0-cp37-cp37m-manylinux1_x86_64.whl (3.0MB)
Collecting cycler>=0.10 (from matplotlib==3.4.1)
  Downloading https://files.pythonhosted.org/packages/f7/d2/e07d3ebb2bd7af696440ce7e754c
59dd546ffe1bbe732c8ab68b9c834e61/cycler-0.10.0-py2.py3-none-any.whl
Collecting kiwisolver>=1.0.1 (from matplotlib==3.4.1)
  Downloading https://files.pythonhosted.org/packages/d2/46/231de802ade4225b76b96cffe419
cf3ce52bbe92e3b092cf12db7d11c207/kiwisolver-1.3.1-cp37-cp37m-manylinux1_x86_64.whl (1.1M
B)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (from
python-dateutil>=2.7->matplotlib==3.4.1)
Installing collected packages: pyparsing, pillow, cycler, kiwisolver, matplotlib
Successfully installed cycler-0.10.0 kiwisolver-1.3.1 matplotlib-3.4.1 pillow-8.2.0 pypa
rsing-2.4.7

Collecting seaborn==0.11.1
  Downloading https://files.pythonhosted.org/packages/68/ad/6c2406ae175f59ec616714e40897
9b674fe27b9587f79d59a528ddfbcd5b/seaborn-0.11.1-py3-none-any.whl (285kB)
Requirement already satisfied: numpy>=1.15 in /usr/local/lib64/python3.7/site-packages
(from seaborn==0.11.1)
Collecting scipy>=1.0 (from seaborn==0.11.1)
  Downloading https://files.pythonhosted.org/packages/7d/e8/43ffca541d2f208d516296950b25
fe1084b35c2881f4d444c1346ca75815/scipy-1.6.3-cp37-cp37m-manylinux1_x86_64.whl (27.4MB)
Requirement already satisfied: matplotlib>=2.2 in /mnt/tmp/1619401021264-0/lib/python3.
7/site-packages (from seaborn==0.11.1)
Requirement already satisfied: pandas>=0.23 in /mnt/tmp/1619401021264-0/lib/python3.7/si
```

```
te-packages (from seaborn==0.11.1)
Requirement already satisfied: pyparsing>=2.2.1 in /mnt/tmp/1619401021264-0/lib/python3.
7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
Requirement already satisfied: python-dateutil>=2.7 in /mnt/tmp/1619401021264-0/lib/pyth
on3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
Requirement already satisfied: pillow>=6.2.0 in /mnt/tmp/1619401021264-0/lib/python3.7/s
ite-packages (from matplotlib>=2.2->seaborn==0.11.1)
Requirement already satisfied: cycler>=0.10 in /mnt/tmp/1619401021264-0/lib/python3.7/si
te-packages (from matplotlib>=2.2->seaborn==0.11.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /mnt/tmp/1619401021264-0/lib/python
3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/site-packages (f
rom pandas>=0.23->seaborn==0.11.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (from
python-dateutil>=2.7->matplotlib>=2.2->seaborn==0.11.1)
Installing collected packages: scipy, seaborn
Successfully installed scipy-1.6.3 seaborn-0.11.1

Collecting pyspark==3.1.1
  Downloading https://files.pythonhosted.org/packages/45/b0/9d6860891ab14a39d4bddf80ba26
ce51c2f9dc4805e5c6978ac0472c120a/pyspark-3.1.1.tar.gz (212.3MB)
Collecting py4j==0.10.9 (from pyspark==3.1.1)
  Downloading https://files.pythonhosted.org/packages/9e/b6/6a4fb90cd235dc8e265a6a2067f2
a2c99f0d91787f06aca4bcf7c23f3f80/py4j-0.10.9-py2.py3-none-any.whl (198kB)
Building wheels for collected packages: pyspark
  Running setup.py bdist_wheel for pyspark: started
  Running setup.py bdist_wheel for pyspark: finished with status 'done'
  Stored in directory: /var/lib/livy/.cache/pip/wheels/0b/90/c0/01de724414ef122bd05f0565
41fb6a0ecf47c7ca655f8b3c0f
Successfully built pyspark
Installing collected packages: py4j, pyspark
Successfully installed py4j-0.10.9 pyspark-3.1.1
```

In [ ]:

```
```

In [4]:

```
sc.list_packages() # check kernel packages again to verify installation
```

```
Package                    Version
-------------------------- ---------
beautifulsoup4             4.9.1
boto                       2.49.0
click                      7.1.2
cycler                     0.10.0
jmespath                   0.10.0
joblib                     0.16.0
kiwisolver                 1.3.1
lxml                       4.5.2
matplotlib                 3.4.1
mysqlclient                1.4.2
nltk                       3.5
nose                       1.3.4
numpy                      1.16.5
pandas                     1.2.4
Pillow                     8.2.0
pip                        9.0.1
py-dateutil                2.2
py4j                       0.10.9
pyparsing                  2.4.7
pyspark                    3.1.1
python-dateutil            2.8.1
python37-sagemaker-pyspark 1.4.0
```

```
pytz                    2020.1
PyYAML                  5.3.1
regex                   2020.7.14
scipy                   1.6.3
seaborn                 0.11.1
setuptools              28.8.0
six                     1.13.0
soupsieve               1.9.5
tqdm                    4.48.2
wheel                   0.29.0
windmill                1.6
```

Importing Packages

In [5]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pyspark import *
```

Loading our Data

We load in our data into a dataframe object through spark from our s3 bucket.

In [6]:

```
tot_df = spark.read.json('s3://sta9760-datasets-jay/*.json')
bus_df = spark.read.json('s3://sta9760-datasets-jay/yelp_academic_dataset_business.json
```

Overview of our data

In [7]:

```
#Display Total Columns & Rows & dataframe schema below
print(f'Total Columns: {len(bus_df.dtypes)}')
print(f'Total Rows: {bus_df.count():,}')
bus_df.printSchema()
```

```
Total Columns: 14
Total Rows: 160,585
root
 |-- address: string (nullable = true)
 |-- attributes: struct (nullable = true)
 |    |-- AcceptsInsurance: string (nullable = true)
 |    |-- AgesAllowed: string (nullable = true)
 |    |-- Alcohol: string (nullable = true)
 |    |-- Ambience: string (nullable = true)
 |    |-- BYOB: string (nullable = true)
 |    |-- BYOBCorkage: string (nullable = true)
 |    |-- BestNights: string (nullable = true)
 |    |-- BikeParking: string (nullable = true)
 |    |-- BusinessAcceptsBitcoin: string (nullable = true)
 |    |-- BusinessAcceptsCreditCards: string (nullable = true)
 |    |-- BusinessParking: string (nullable = true)
```

```
 |    |-- ByAppointmentOnly: string (nullable = true)
 |    |-- Caters: string (nullable = true)
 |    |-- CoatCheck: string (nullable = true)
 |    |-- Corkage: string (nullable = true)
 |    |-- DietaryRestrictions: string (nullable = true)
 |    |-- DogsAllowed: string (nullable = true)
 |    |-- DriveThru: string (nullable = true)
 |    |-- GoodForDancing: string (nullable = true)
 |    |-- GoodForKids: string (nullable = true)
 |    |-- GoodForMeal: string (nullable = true)
 |    |-- HairSpecializesIn: string (nullable = true)
 |    |-- HappyHour: string (nullable = true)
 |    |-- HasTV: string (nullable = true)
 |    |-- Music: string (nullable = true)
 |    |-- NoiseLevel: string (nullable = true)
 |    |-- Open24Hours: string (nullable = true)
 |    |-- OutdoorSeating: string (nullable = true)
 |    |-- RestaurantsAttire: string (nullable = true)
 |    |-- RestaurantsCounterService: string (nullable = true)
 |    |-- RestaurantsDelivery: string (nullable = true)
 |    |-- RestaurantsGoodForGroups: string (nullable = true)
 |    |-- RestaurantsPriceRange2: string (nullable = true)
 |    |-- RestaurantsReservations: string (nullable = true)
 |    |-- RestaurantsTableService: string (nullable = true)
 |    |-- RestaurantsTakeOut: string (nullable = true)
 |    |-- Smoking: string (nullable = true)
 |    |-- WheelchairAccessible: string (nullable = true)
 |    |-- WiFi: string (nullable = true)
 |-- business_id: string (nullable = true)
 |-- categories: string (nullable = true)
 |-- city: string (nullable = true)
 |-- hours: struct (nullable = true)
 |    |-- Friday: string (nullable = true)
 |    |-- Monday: string (nullable = true)
 |    |-- Saturday: string (nullable = true)
 |    |-- Sunday: string (nullable = true)
 |    |-- Thursday: string (nullable = true)
 |    |-- Tuesday: string (nullable = true)
 |    |-- Wednesday: string (nullable = true)
 |-- is_open: long (nullable = true)
 |-- latitude: double (nullable = true)
 |-- longitude: double (nullable = true)
 |-- name: string (nullable = true)
 |-- postal_code: string (nullable = true)
 |-- review_count: long (nullable = true)
 |-- stars: double (nullable = true)
 |-- state: string (nullable = true)
```

In [ ]:

Displaying the first 5 rows with columns:

1. business_id
2. name
3. city
4. state
5. stars
6. categories

In [8]:
```
bus_df["business_id", "name", "city", "state","stars", "categories"].show(5)
```

```
+--------------------+--------------------+-----------+-----+-----+--------------------+
|         business_id|                name|       city|state|stars|          categories|
+--------------------+--------------------+-----------+-----+-----+--------------------+
|6iYb2HFDywm3zjuRg...| Oskar Blues Taproom|    Boulder|   CO|  4.0|Gastropubs, Food,...|
|tCbdrRPZA0oiIYSmH...|Flying Elephants ...|   Portland|   OR|  4.0|Salad, Soup, Sand...|
|bvN78flM8NLprQ1a1...|      The Reclaimory|   Portland|   OR|  4.5|Antiques, Fashion...|
|oaepsyvc0J17qwi8c...|         Great Clips|Orange City|   FL|  3.0|Beauty & Spas, Ha...|
|PE9uqAjdw0E4-8mjG...|   Crossfit Terminus|    Atlanta|   GA|  4.0|Gyms, Active Life...|
+--------------------+--------------------+-----------+-----+-----+--------------------+
only showing top 5 rows
```

In [9]:
```
bus_df.select('business_id', 'name', 'city', 'state','stars', 'categories').show(5)
```

```
+--------------------+--------------------+-----------+-----+-----+--------------------+
|         business_id|                name|       city|state|stars|          categories|
+--------------------+--------------------+-----------+-----+-----+--------------------+
|6iYb2HFDywm3zjuRg...| Oskar Blues Taproom|    Boulder|   CO|  4.0|Gastropubs, Food,...|
|tCbdrRPZA0oiIYSmH...|Flying Elephants ...|   Portland|   OR|  4.0|Salad, Soup, Sand...|
|bvN78flM8NLprQ1a1...|      The Reclaimory|   Portland|   OR|  4.5|Antiques, Fashion...|
|oaepsyvc0J17qwi8c...|         Great Clips|Orange City|   FL|  3.0|Beauty & Spas, Ha...|
|PE9uqAjdw0E4-8mjG...|   Crossfit Terminus|    Atlanta|   GA|  4.0|Gyms, Active Life...|
+--------------------+--------------------+-----------+-----+-----+--------------------+
only showing top 5 rows
```

In [ ]:

Part 2. Analyzing Categories

We are interested in finding some information about the different categories in the dataset. Essentially, we have the categories per business as a list - this is useful to quickly see what each business might be represented as.

We would like to find find:

1. How many unique categories are represented in this dataset.
2. How many bunsinesses are categorized as Active Life.
3. What are the top 20 most popular categories available.

Association Table

We need to "break out" these categories from the business ids? One common approach to take is to build an association table mapping a single business id multiple times to each distinct category. For instance, given the following:

business_id	categories
abcd123	a,b,c

We would like to derive something like:

business_id	category
abcd123	a
abcd123	b
abcd123	c

What this does is allow us to then perform a myriad of rollups and other analysis on this association table which can aid us in answering the questions asked above.

Lets first show how our categories currently are

In [10]:
```
bus_df["business_id", "categories"].show(10)
```

```
+--------------------+--------------------+
|         business_id|          categories|
+--------------------+--------------------+
|6iYb2HFDywm3zjuRg...|Gastropubs, Food,...|
|tCbdrRPZA0oiIYSmH...|Salad, Soup, Sand...|
|bvN78flM8NLprQ1a1...|Antiques, Fashion...|
|oaepsyvc0J17qwi8c...|Beauty & Spas, Ha...|
|PE9uqAjdw0E4-8mjG...|Gyms, Active Life...|
|D4JtQNTI4X3Kcbzac...|   Restaurants, Thai|
|t35jsh9YnMtttm69U...|Dentists, Health ...|
|jFYIsSb7r1QeESVUn...|Breakfast & Brunc...|
|N3_Gs3DnX4k9SgpwJ...|Shopping, Jewelry...|
|tXvdYGvlEceDljN8g...|Barbers, Beauty &...|
+--------------------+--------------------+
only showing top 10 rows
```

Now we will try to show the first 5 rows of our association table

In [11]:
```
from pyspark.sql.functions import split, explode, col, desc

# split()--> split DataFrame string Column into multiple columns
# explode()--> used to explode an Array of Array columns to rows on PySpark DataFrame u
#col()-->Returns a Column based on the given column name.
#desc()-->Returns a sort expression based on the descending order of the given column n

split_categories = bus_df.select(bus_df.business_id, explode(split(bus_df.categories, '
split_categories.show(5)
```

```
+--------------------+------------+
|         business_id|    category|
+--------------------+------------+
|6iYb2HFDywm3zjuRg...|  Gastropubs|
|6iYb2HFDywm3zjuRg...|        Food|
|6iYb2HFDywm3zjuRg...|Beer Gardens|
|6iYb2HFDywm3zjuRg...| Restaurants|
|6iYb2HFDywm3zjuRg...|        Bars|
+--------------------+------------+
only showing top 5 rows
```

Total Unique Categories

Finally we can find

1. How many unique categories are represented in this dataset

In [12]:

```
unique_cat = split_categories.select('category').distinct().count()
print('The total number of unique categories in this dataset is: ' + str(unique_cat))
```

```
The total number of unique categories in this dataset is: 1330
```

In [ ]:

Top Categories By Business

We will now try to find the top categories in the dataset by rolling up the categories

Counts of Businesses / Category

So now, let's unroll our distinct count a bit and display the per count value of businesses per category. The expected output should be:

category	count
a	15
b	2
c	45

In [13]:

```
# The counts by category
cat_count = split_categories.groupby("category").count()
cat_count.show()
```

```
+--------------------+-----+
|            category|count|
+--------------------+-----+
|      Dermatologists|  351|
|      Paddleboarding|   67|
|        Aerial Tours|    8|
|         Hobby Shops|  610|
|          Bubble Tea|  779|
|             Embassy|    9|
|             Tanning|  701|
|            Handyman|  507|
|      Aerial Fitness|   13|
|             Falafel|  141|
|        Summer Camps|  308|
|       Outlet Stores|  184|
|     Clothing Rental|   37|
|      Sporting Goods| 1864|
|     Cooking Schools|  114|
|  College Counseling|   20|
|  Lactation Services|   47|
|Ski & Snowboard S...|   55|
|             Museums|  336|
|              Doulas|   52|
```

```
+--------------------+-----+
only showing top 20 rows
```

In [14]:

```
# The top categories based on count
top_cat = cat_count.orderBy(desc('count')).show()
top_cat
```

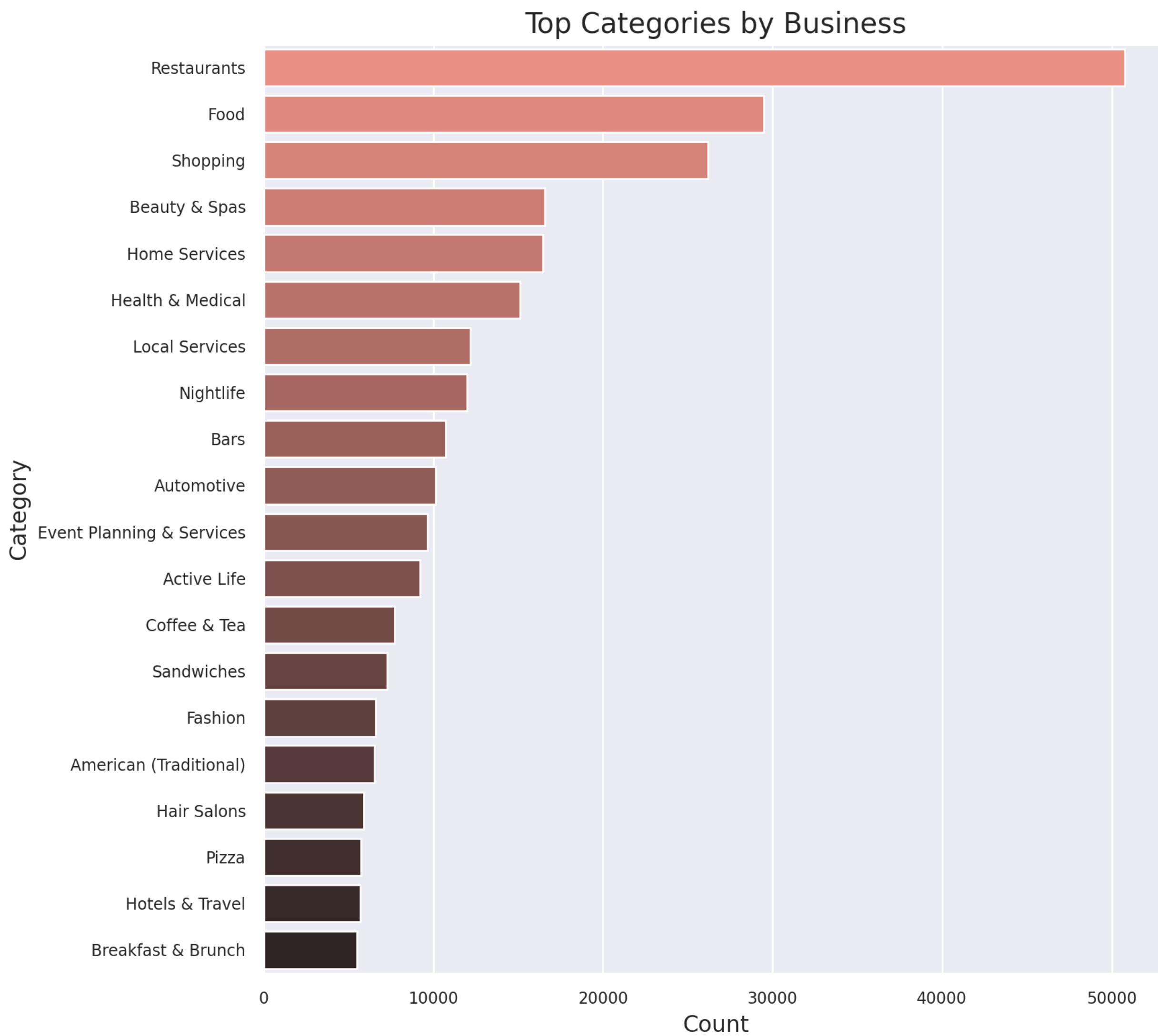
```
+--------------------+-----+
|            category|count|
+--------------------+-----+
|         Restaurants|50763|
|                Food|29469|
|            Shopping|26205|
|       Beauty & Spas|16574|
|       Home Services|16465|
|    Health & Medical|15102|
|      Local Services|12192|
|           Nightlife|11990|
|                Bars|10741|
|          Automotive|10119|
|Event Planning & ...| 9644|
|         Active Life| 9231|
|        Coffee & Tea| 7725|
|          Sandwiches| 7272|
|             Fashion| 6599|
|American (Traditi...| 6541|
|         Hair Salons| 5900|
|               Pizza| 5756|
|     Hotels & Travel| 5703|
|  Breakfast & Brunch| 5505|
+--------------------+-----+
only showing top 20 rows
```

Bar Chart of Top Categories

Before we can plot it is more useful to convert our spark dataframe to a pandas dataframe and then utilize matplotlib/seaborn

In [15]:

```
#Convert and store our Top 20 categories as a pandas dataframe object
top_cat = cat_count.orderBy(desc('count')).limit(20)
top_pdf = top_cat.toPandas()

#Set our seaborn theme and create our plot figure
sns.set_theme()
#palette options: "flare", "pastel", "light:#5A9", "ch:s=.25,rot=-.25 Greens_d", "YlOrB
plt.figure(figsize = (9,8), dpi=200)
axes = sns.barplot(x ='count', y ='category', data = top_pdf, palette="dark:salmon_r")

#Set title and labels
plt.title('Top Categories by Business', fontsize = 15)
plt.xlabel('Count', fontsize = 12)
plt.ylabel('Category', fontsize = 12)

plt.xticks(fontsize = 8.5)
plt.yticks(fontsize = 8.5)

plt.tight_layout()
%matplot plt
```



Part 3. Do Yelp Reviews Skew Negative?

Oftentimes, it is said that the only people who write a written review are those who are extremely dissatisfied or extremely satisfied with the service received.

How true is this really? Let's try and answer this question.

Loading User Data¶

Begin by loading the user data set from S3 and printing schema to determine what data is available.

In [16]:

```
# Load in the review dataset
rev_df = spark.read.json('s3://sta9760-datasets-jay/yelp_academic_dataset_review.json')
rev_df.printSchema()
```

```
root
 |-- business_id: string (nullable = true)
 |-- cool: long (nullable = true)
```

```
 |-- date: string (nullable = true)
 |-- funny: long (nullable = true)
 |-- review_id: string (nullable = true)
 |-- stars: double (nullable = true)
 |-- text: string (nullable = true)
 |-- useful: long (nullable = true)
 |-- user_id: string (nullable = true)
```

Let's begin by listing the business_id and stars columns together for the user reviews data.

In [17]:

```
bus_star = rev_df["business_id", "stars"]
bus_star.show(5)
```

```
+--------------------+-----+
|         business_id|stars|
+--------------------+-----+
|buF9druCkbuXLX526...|  4.0|
|RA4V8pr014UyUbDvI...|  4.0|
|_sS2LBIGNT5NQb6PD...|  5.0|
|0AzLzHfOJgL7ROwhd...|  2.0|
|8zehGz9jnxPqXtOc7...|  4.0|
+--------------------+-----+
only showing top 5 rows
```

Now, let's aggregate along the stars column to get a resultant dataframe that displays average stars per business as accumulated ***by users who took the time to submit a written review.***

In [18]:

```
avg_bus_star = bus_star.groupBy('business_id').mean()
avg_bus_star.show(5)
```

```
+--------------------+-----------------+
|         business_id|       avg(stars)|
+--------------------+-----------------+
|uEUweopM30lHcVxjO...|              3.0|
|wdBrDCbZopowEkIEX...|4.538461538461538|
|L3WCfeVozu5etMhz4...|              4.2|
|bOnsvrz1VkbrZM1jV...|              3.8|
|R0IJhEI-zSJpYT1YN...|3.606060606060606|
+--------------------+-----------------+
only showing top 5 rows
```

Now the fun part - let's join our two dataframes (reviews and business data) by business_id

In [19]:

```
# select required columns from original business dataframe
target = bus_df.select('business_id','stars','name', 'city', 'state')

# join the two data frames based on business_id and stor into merge_df
merge_df =  avg_bus_star.join(target, how='inner',on='business_id')

# remove the business_id column from merged dataframe and show top 5
merge_df.drop('business_id').show(5)
```

```
+------------------+-----+--------------------+----------+-----+
|        avg(stars)|stars|                name|      city|state|
+------------------+-----+--------------------+----------+-----+
|               5.0|  5.0|     CheraBella Salon|   Peabody|   MA|
```

```
|             3.875|  4.0|Mezcal Cantina & ...|  Columbus|   OH|
|3.8666666666666667|  4.0|     Red Table Coffee|    Austin|   TX|
|               5.0|  5.0|           WonderWell|    Austin|   TX|
|             3.375|  3.5|          Avalon Oaks|Wilmington|   MA|
+------------------+-----+--------------------+----------+-----+
only showing top 5 rows
```

In [ ]:

```

```

Compute a new dataframe that calculates what we will call the skew (for lack of a better word) between the avg stars accumulated from written reviews and the actual star rating of a business (ie: the average of stars given by reviewers who wrote an actual review and reviewers who just provided a star rating).

The formula you can use is something like:

(row['avg(stars)'] - row['stars']) / row['stars'] If the skew is negative, we can interpret that to be: reviewers who left a written response were more dissatisfied than normal. If skew is positive, we can interpret that to be: reviewers who left a written response were more satisfied than normal.

Using our merged dataframe we will calculate the skewness of our data and add that as a new colum to merge_df.

In [20]:

```
# First Attempt
merge_df1 = merge_df # create temp dataframe
merge_df1 = merge_df1.withColumnRenamed("avg(stars)","avg_stars") # rename because "avg
merge_df1.registerTempTable('merge_df_table')
skewDF = sqlContext.sql('select *, (avg_stars - stars) / stars as Skew from merge_df_ta
skewDF.show(5)
```

```
+--------------------+------------------+-----+--------------------+----------+-----+---
-----------------+
|         business_id|         avg_stars|stars|                name|      city|state|
Skew|
+--------------------+------------------+-----+--------------------+----------+-----+---
-----------------+
|--JuLhLvq3gyjNnXT...|               5.0|  5.0|     CheraBella Salon|   Peabody|   MA|
0.0|
|--_nBudPOb1lNRgKf...|             3.875|  4.0|Mezcal Cantina & ...|  Columbus|   OH|
-0.03125|
|--kyOk0waSrCDlbSv...|3.8666666666666667|  4.0|     Red Table Coffee|    Austin|   TX|-0.
03333333333333...|
|--z9usx6Fin8P_f0v...|               5.0|  5.0|           WonderWell|    Austin|   TX|
0.0|
|-0qeY1293steyCqYh...|             3.375|  3.5|          Avalon Oaks|Wilmington|   MA|-0.
03571428571428571|
+--------------------+------------------+-----+--------------------+----------+-----+---
-----------------+
only showing top 5 rows
```

In [21]:

```
# Second Attempt to validate
merge_skew = merge_df.withColumn('skew',  (col("avg(stars)") - col("stars")) / col("sta
merge_skew.show(5)
```

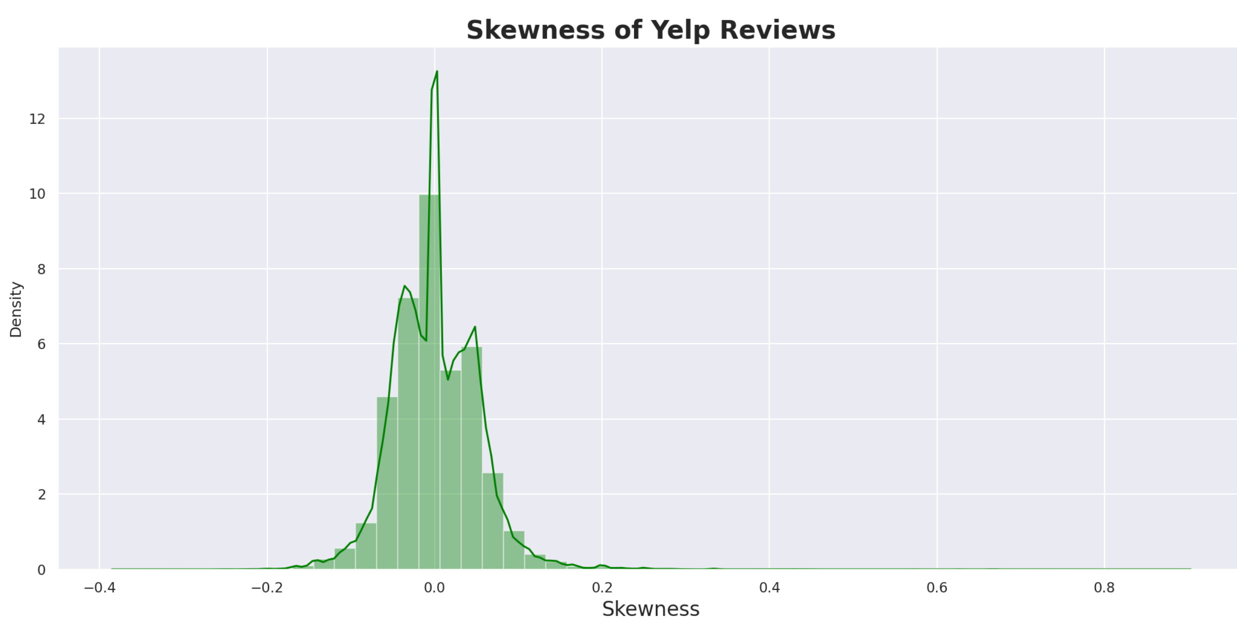
```
+--------------------+-----------------+-----+--------------------+----------+-----+---
-----------------+
|         business_id|       avg(stars)|stars|                name|      city|state|
skew|
+--------------------+-----------------+-----+--------------------+----------+-----+---
-----------------+
|--JuLhLvq3gyjNnXT...|              5.0|  5.0|    CheraBella Salon|   Peabody|   MA|
0.0|
|--_nBudPOb1lNRgKf...|            3.875|  4.0|Mezcal Cantina & ...|  Columbus|   OH|
-0.03125|
|--kyOk0waSrCDlbSv...|3.8666666666666667|  4.0|    Red Table Coffee|    Austin|   TX|-0.
03333333333333...|
|--z9usx6Fin8P_f0v...|              5.0|  5.0|          WonderWell|    Austin|   TX|
0.0|
|-0qeY1293steyCqYh...|            3.375|  3.5|         Avalon Oaks|Wilmington|   MA|-0.
03571428571428571|
+--------------------+-----------------+-----+--------------------+----------+-----+---
-----------------+
only showing top 5 rows
```

And finally, graph it!

First we need to convert it to a pandas dataframe to plot with matplotlib/ seaborn like before.

In [22]:

```
#convert to pandas df
skew_plot = merge_skew.select('skew').toPandas()

#Set our seaborn theme, plot dimensions and plot figure
plt.figure(figsize=(14,7), dpi = 150)
sns.set_theme()
sk_plot = sns.distplot(skew_plot,color='green', kde=True)
plt.title("Skewness of Yelp Reviews", weight='bold', size=20)
sk_plot.set_xlabel('Skewness', size=16)
plt.tight_layout()
%matplot plt
```



Before we make any comments on the graph above we will go a little further and test for normality by also taking into account the kurtosis of the data

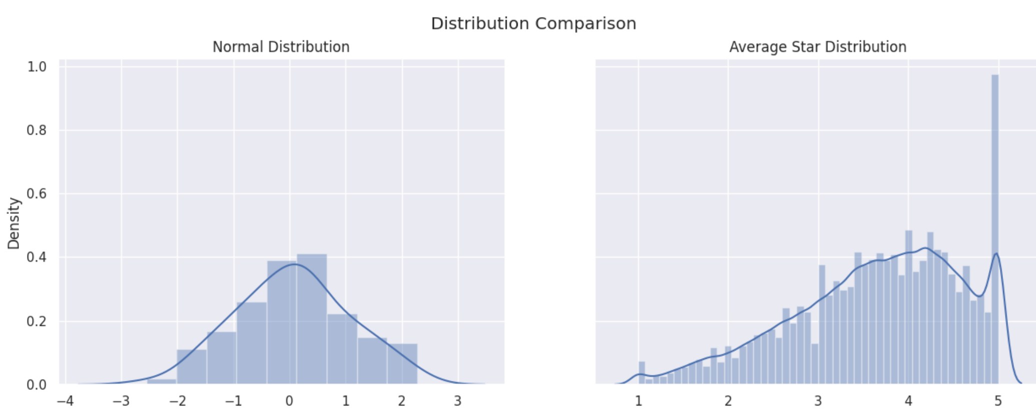
In [23]:

```
# Importing some additional packages
from scipy.stats import kurtosis
from scipy.stats import skew

# Cal mean and variance skew and kurtosis of the average star rating
sk_avg_star = merge_skew.select('avg(stars)').toPandas()
sk_mean = np.mean(sk_avg_star)
sk_var = np.var(sk_avg_star)

print("mean : ", list(sk_mean))
print("var  : ", list(sk_var))
print("skew : ",skew(sk_avg_star))
print("kurt : ",kurtosis(sk_avg_star))
```

```
mean :  [3.6517699800262613]
var  :  [0.8639332056575321]
skew :  [-0.56305766]
kurt :  [-0.29322145]
```

In [24]:

```
# Plotting Normal distribution and distribution of Average Star rating
fig, axes = plt.subplots(1, 2, figsize=(15, 5), sharey=True)
fig.suptitle('Distribution Comparison')
axes[0].set_title('Title of the first chart')

# Normal Distribution
sns.set_theme(); np.random.seed(0)
x = np.random.randn(100)
ax1 = sns.distplot(ax=axes[0],x=x)
axes[0].set_title("Normal Distribution")

# Avg Star Rating
ax2 = sns.distplot(ax=axes[1],x=sk_avg_star)
axes[1].set_title("Average Star Distribution")

%matplot plt
```



Discussion: In Statistics and Finance, Skewness is a measure of the asymmetry of the probability distribution of a random variable about its mean.In other words it measures if density to the left of the mean is similar to the density to the right of the mean. Skewness can take on a negative or positive value with a value of 0 indicating perfect symmetry(no skew) while values less than -1 or greater than 1 indicate that the distribution is highly skewed.

On the otherhand Kurtosis refers to the shape of the distribution specifically it is a measure of how "heavy-tailed" or "light-tailed" a distribution is relative to the Normal Distribution. With that in mind we can see that data with high kurtosis have heavier tails indicating outliers while those with low kurtosis tend to have lighter tails and no outliers.

These two values are usually used in tandem to ascertain the "normality" of a dataset. Testing for normality is important because it allows those studying the data to be more careful and precise when choosing what methods and tools to use to best analyze the data. To answer the specific question posed we can see by inspecting our Skewness plot that the Yelp Reviews do indeed tend to skew negative (slightly) which is further confirmed when we calculated the skew and it had a value of `-0.56305766` .This is also further confirmed by our distribution plot of the Average star rating which was left skewed i.e having a long left tail indicating a negative skew in the data. When it comes to Kurtosis we calculated a value of `-0.29322145` which indicated our data had sligtly lighter tails than the normal distribution and was unlikely to contain outliers.

Conclusion: Based on our plot and the calculated values we can say that the Yelp reviews tend to have a negative skew even if only slightly. We can also see that it likely that our data is not normal.

Part 4. Should the Elite be Trusted?

Our final investigation into the Yelp dataset will be trying to ascertain how accurate or close the ratings of the ***elite*** users are to other ***non-elite*** users. We will utilize the **users** dataset and combine it with **business** and or **reviews** dataset and provide atleast one visualization.

In [25]:

```
# Load the user data set
usr_df = spark.read.json('s3://sta9760-datasets-jay/yelp_academic_dataset_user.json')
usr_df.printSchema()
```

```
root
 |-- average_stars: double (nullable = true)
 |-- compliment_cool: long (nullable = true)
 |-- compliment_cute: long (nullable = true)
 |-- compliment_funny: long (nullable = true)
 |-- compliment_hot: long (nullable = true)
 |-- compliment_list: long (nullable = true)
 |-- compliment_more: long (nullable = true)
 |-- compliment_note: long (nullable = true)
 |-- compliment_photos: long (nullable = true)
 |-- compliment_plain: long (nullable = true)
 |-- compliment_profile: long (nullable = true)
 |-- compliment_writer: long (nullable = true)
 |-- cool: long (nullable = true)
 |-- elite: string (nullable = true)
 |-- fans: long (nullable = true)
 |-- friends: string (nullable = true)
 |-- funny: long (nullable = true)
 |-- name: string (nullable = true)
 |-- review_count: long (nullable = true)
 |-- useful: long (nullable = true)
 |-- user_id: string (nullable = true)
 |-- yelping_since: string (nullable = true)
```

Upon seeing the schema lets take a look at the name, elite, review_count, average_stars columns etc.

In [26]:
```
peak = usr_df.select('user_id', 'name', 'elite', 'review_count', 'average_stars','cool'
```

```
+--------------------+---------+--------------------+------------+-------------+-----+--
---+------+----+--------------------+
|             user_id|     name|               elite|review_count|average_stars| cool|fu
nny|useful|fans|       yelping_since|
+--------------------+---------+--------------------+------------+-------------+-----+--
---+------+----+--------------------+
|q_QQ5kBBwlCcbL1s4...|     Jane|2006,2007,2008,20...|        1220|         3.85|11291|10
030| 15038|1357|2005-03-14 20:26:35|
|dIIKEfOgo0KqUfGQv...|     Gabi|2007,2008,2009,20...|        2136|         4.09|18046|10
289| 21272|1025|2007-08-10 19:01:51|
|D6ErcUnFALnCQN4b1...|    Jason|           2010,2011|         119|         3.76|  130|
128|   188|  16|2007-02-07 15:47:53|
|JnPIjvC0cmooNDfsa...|      Kat|2009,2010,2011,20...|         987|         3.77| 4035| 4
722|  7234| 420|2009-02-09 16:14:29|
|37Hc8hr3cw0iHLoPz...|Christine|      2009,2010,2011|         495|         3.72| 1124|
727|  1577|  47|2008-03-03 04:57:05|
+--------------------+---------+--------------------+------------+-------------+-----+--
---+------+----+--------------------+
only showing top 5 rows
```

Elite vs Non-elite %

When it comes to the elite column we see that it seems to be nested over the years for each elite yelper and therefore we need to first create associations tables like we did before. From there we can then separate based on elite status and calculate elite percentages and investigate the "useful" rating to help answer the question of trust.

In [27]:
```
#Splitting the elite column
split_elite = usr_df.select('user_id','name','useful', explode(split(usr_df.elite, ',')
split_elite.show(5)
```

```
+--------------------+----+------+-----+
|             user_id|name|useful|elite|
+--------------------+----+------+-----+
|q_QQ5kBBwlCcbL1s4...|Jane| 15038| 2006|
|q_QQ5kBBwlCcbL1s4...|Jane| 15038| 2007|
|q_QQ5kBBwlCcbL1s4...|Jane| 15038| 2008|
|q_QQ5kBBwlCcbL1s4...|Jane| 15038| 2009|
|q_QQ5kBBwlCcbL1s4...|Jane| 15038| 2010|
+--------------------+----+------+-----+
only showing top 5 rows
```

In [28]:
```
#Display Total Columns & Rows & dataframe schema below
print(f'Total Columns: {len(split_elite.dtypes)}')
print(f'Total Rows: {split_elite.count():,}')
```

```
Total Columns: 4
Total Rows: 2,465,137
```

In [29]:
```
# Do a quick check on elite counts
split_elite.groupBy('elite').count().orderBy('count', ascending=False).show()
```

```
+-----+-------+
|elite|  count|
+-----+-------+
|     |2094043|
|   20|  84038|
| 2019|  47631|
| 2018|  44955|
| 2017|  39659|
| 2016|  32770|
| 2015|  27238|
| 2014|  20856|
| 2013|  18416|
| 2012|  17679|
| 2011|  12832|
| 2010|  10504|
| 2009|   6806|
| 2008|   4091|
| 2007|   2606|
| 2006|   1013|
+-----+-------+
```

In [30]:

```
# Do a quick check on elite useful counts
split_elite.groupBy('elite','useful').count().orderBy('count', ascending=False).show()
```

```
+-----+------+------+
|elite|useful| count|
+-----+------+------+
|     |     0|546528|
|     |     1|274846|
|     |     2|179677|
|     |     3|130621|
|     |     4|101030|
|     |     5| 80836|
|     |     6| 67207|
|     |     7| 56656|
|     |     8| 48912|
|     |     9| 42443|
|     |    10| 37780|
|     |    11| 33161|
|     |    12| 29675|
|     |    13| 26740|
|     |    14| 24020|
|     |    15| 21981|
|     |    16| 19917|
|     |    17| 18408|
|     |    18| 16920|
|     |    19| 15774|
+-----+------+------+
only showing top 20 rows
```

I am interested in first finding what percentage of the data is elite vs non-elite. From the elite count table above we can see that the empty space " " respresents those reviews which were done by non-elite (`2094043` in total) where as the other vals 20, 2019 and so on represent the counts for the number of elite reviews for each year. To find this percentage we need to separate the two.

In [31]:

```
# Filter for elite and non-elite, count and calculate percentage
e_count = split_elite.filter(split_elite.elite != '')
print(f'Total elite: {e_count.count():,}')
```

```
ne_count = split_elite.filter(split_elite.elite == '')
print(f'Total non-elite: {ne_count.count():,}')

e_perc = round((e_count.count()/(e_count.count()+ne_count.count()))*100,2)
ne_perc = round((ne_count.count()/(e_count.count()+ne_count.count()))*100,2)

print("Therefore the dataset contains " + str(e_perc) +"% elites and "+ str(ne_perc) +"

#e_count.toPandas().info() # another way to check count
#e_count.summary().show() # another way to check count
```

```
Total elite: 371,094
Total non-elite: 2,094,043
Therefore the dataset contains 15.05% elites and 84.95% of non-elites.
```

Since there is such large disparity in the percentages between the two categories it doesnt make sense for us to investigate the "fan" counts or the "useful" rating count to make a decision on trust since it is likely the greatest counts will go to the non-elites. Therefore what we can do is focus on the ratings of each group.

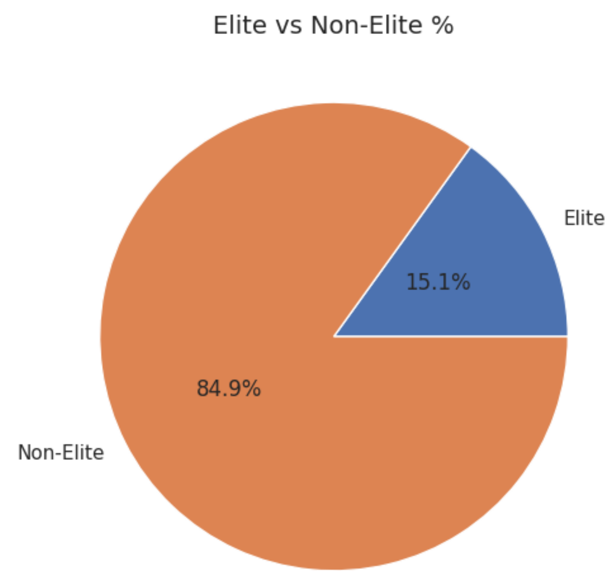
In [32]:

```
# Attempt to create a pyspark dataframe of the percentages for plotting
from pyspark.sql.types import StructType,StructField, StringType, IntegerType
data2 = [("Elite",371094),
    ("Non-Elite",2094043)
  ]

schema = StructType([ \
    StructField("Category",StringType(),True), \
    StructField("Count", IntegerType(), True) \
  ])

perc_df = spark.createDataFrame(data=data2,schema=schema)
#df.printSchema()
perc_df.show(truncate=False)
```

```
+---------+-------+
|Category |Count  |
+---------+-------+
|Elite    |371094 |
|Non-Elite|2094043|
+---------+-------+
```

In [33]:

```
#Convert to pandas and prepare for plot
perc_tem= perc_df.toPandas()
perc_pl = perc_tem.groupby("Category")["Count"].sum()

#set the plot figure and plot pie chart
pie, ax = plt.subplots(figsize=[10,6])
labels = perc_pl.keys()
plt.pie(x=perc_pl, autopct="%.1f%%", labels=labels, pctdistance=0.5)
plt.title("Elite vs Non-Elite %", fontsize=14);
%matplot plt
```



In [ ]:

In [34]:

```
# Use this cell to quickly review the schema for all 3 data sets.
rev_df.printSchema()
usr_df.printSchema()
bus_df.printSchema()
```

```
root
 |-- business_id: string (nullable = true)
 |-- cool: long (nullable = true)
 |-- date: string (nullable = true)
 |-- funny: long (nullable = true)
 |-- review_id: string (nullable = true)
 |-- stars: double (nullable = true)
 |-- text: string (nullable = true)
 |-- useful: long (nullable = true)
 |-- user_id: string (nullable = true)

root
 |-- average_stars: double (nullable = true)
 |-- compliment_cool: long (nullable = true)
 |-- compliment_cute: long (nullable = true)
 |-- compliment_funny: long (nullable = true)
 |-- compliment_hot: long (nullable = true)
 |-- compliment_list: long (nullable = true)
 |-- compliment_more: long (nullable = true)
 |-- compliment_note: long (nullable = true)
 |-- compliment_photos: long (nullable = true)
 |-- compliment_plain: long (nullable = true)
 |-- compliment_profile: long (nullable = true)
 |-- compliment_writer: long (nullable = true)
 |-- cool: long (nullable = true)
 |-- elite: string (nullable = true)
 |-- fans: long (nullable = true)
```

```
 |-- friends: string (nullable = true)
 |-- funny: long (nullable = true)
 |-- name: string (nullable = true)
 |-- review_count: long (nullable = true)
 |-- useful: long (nullable = true)
 |-- user_id: string (nullable = true)
 |-- yelping_since: string (nullable = true)

root
 |-- address: string (nullable = true)
 |-- attributes: struct (nullable = true)
 |    |-- AcceptsInsurance: string (nullable = true)
 |    |-- AgesAllowed: string (nullable = true)
 |    |-- Alcohol: string (nullable = true)
 |    |-- Ambience: string (nullable = true)
 |    |-- BYOB: string (nullable = true)
 |    |-- BYOBCorkage: string (nullable = true)
 |    |-- BestNights: string (nullable = true)
 |    |-- BikeParking: string (nullable = true)
 |    |-- BusinessAcceptsBitcoin: string (nullable = true)
 |    |-- BusinessAcceptsCreditCards: string (nullable = true)
 |    |-- BusinessParking: string (nullable = true)
 |    |-- ByAppointmentOnly: string (nullable = true)
 |    |-- Caters: string (nullable = true)
 |    |-- CoatCheck: string (nullable = true)
 |    |-- Corkage: string (nullable = true)
 |    |-- DietaryRestrictions: string (nullable = true)
 |    |-- DogsAllowed: string (nullable = true)
 |    |-- DriveThru: string (nullable = true)
 |    |-- GoodForDancing: string (nullable = true)
 |    |-- GoodForKids: string (nullable = true)
 |    |-- GoodForMeal: string (nullable = true)
 |    |-- HairSpecializesIn: string (nullable = true)
 |    |-- HappyHour: string (nullable = true)
 |    |-- HasTV: string (nullable = true)
 |    |-- Music: string (nullable = true)
 |    |-- NoiseLevel: string (nullable = true)
 |    |-- Open24Hours: string (nullable = true)
 |    |-- OutdoorSeating: string (nullable = true)
 |    |-- RestaurantsAttire: string (nullable = true)
 |    |-- RestaurantsCounterService: string (nullable = true)
 |    |-- RestaurantsDelivery: string (nullable = true)
 |    |-- RestaurantsGoodForGroups: string (nullable = true)
 |    |-- RestaurantsPriceRange2: string (nullable = true)
 |    |-- RestaurantsReservations: string (nullable = true)
 |    |-- RestaurantsTableService: string (nullable = true)
 |    |-- RestaurantsTakeOut: string (nullable = true)
 |    |-- Smoking: string (nullable = true)
 |    |-- WheelchairAccessible: string (nullable = true)
 |    |-- WiFi: string (nullable = true)
 |-- business_id: string (nullable = true)
 |-- categories: string (nullable = true)
 |-- city: string (nullable = true)
 |-- hours: struct (nullable = true)
 |    |-- Friday: string (nullable = true)
 |    |-- Monday: string (nullable = true)
 |    |-- Saturday: string (nullable = true)
 |    |-- Sunday: string (nullable = true)
 |    |-- Thursday: string (nullable = true)
 |    |-- Tuesday: string (nullable = true)
 |    |-- Wednesday: string (nullable = true)
 |-- is_open: long (nullable = true)
 |-- latitude: double (nullable = true)
 |-- longitude: double (nullable = true)
 |-- name: string (nullable = true)
```

```
 |-- postal_code: string (nullable = true)
 |-- review_count: long (nullable = true)
 |-- stars: double (nullable = true)
 |-- state: string (nullable = true)
```

Joining the datasets

Elite users are not readily identified from the users dataset so we will split them as we did before and compare. But before we can do that it is required that we use at least one other dataset and join it to the users dataset. From reviewing the schemas above we see there isn't one singular id shared amongst them but between 2 datasets at a time case there are shared ids so we will use that to our advantage.

In [35]:

```
# First select useful fields from both dataset while renaming stars to differentiate fr
rev_df1 = rev_df.select('user_id','business_id','stars','date').withColumnRenamed('star
bus_df1 = bus_df.select('business_id', 'stars').withColumnRenamed('stars', 'bus_stars')

# now join review and business dataset
rev_bus_df = rev_df1.join(bus_df1, on = ['business_id'], how = 'inner')
rev_bus_df = rev_bus_df.select('business_id','user_id','rev_stars','bus_stars','date')
print('Review and Business dataset merged')
rev_bus_df.show(5)
```

```
Review and Business dataset merged
+--------------------+--------------------+---------+---------+-------------------+
|         business_id|             user_id|rev_stars|bus_stars|               date|
+--------------------+--------------------+---------+---------+-------------------+
|buF9druCkbuXLX526...|ak0TdVmGKo4pwqdJS...|      4.0|      3.5|2014-10-11 03:34:02|
|RA4V8pr014UyUbDvI...|YoVfDbnISlW0f7abN...|      4.0|      3.0|2015-07-03 20:38:25|
|_sS2LBIGNT5NQb6PD...|eC5evKn1TWDyHCyQA...|      5.0|      5.0|2013-05-28 20:38:06|
|0AzLzHfOJgL7ROwhd...|SFQ1jcnGguO0LYWnb...|      2.0|      3.5|2010-01-08 02:29:15|
|8zehGz9jnxPqXtOc7...|0kA0PAJ8QFMeveQWH...|      4.0|      4.5|2011-07-28 18:05:01|
+--------------------+--------------------+---------+---------+-------------------+
only showing top 5 rows
```

In [36]:

```
# We need to change the date values to make them more readable and easier to plot
from pyspark.sql.functions import to_date, year, mean

rev_bus_df = rev_bus_df.select('business_id', 'user_id','rev_stars','bus_stars',
                               year(to_date(rev_bus_df.date, 'yyyy-MM-dd HH:mm:ss')).alias('y
rev_bus_df.show(5)
```

```
+--------------------+--------------------+---------+---------+----+
|         business_id|             user_id|rev_stars|bus_stars|year|
+--------------------+--------------------+---------+---------+----+
|buF9druCkbuXLX526...|ak0TdVmGKo4pwqdJS...|      4.0|      3.5|2014|
|RA4V8pr014UyUbDvI...|YoVfDbnISlW0f7abN...|      4.0|      3.0|2015|
|_sS2LBIGNT5NQb6PD...|eC5evKn1TWDyHCyQA...|      5.0|      5.0|2013|
|0AzLzHfOJgL7ROwhd...|SFQ1jcnGguO0LYWnb...|      2.0|      3.5|2010|
|8zehGz9jnxPqXtOc7...|0kA0PAJ8QFMeveQWH...|      4.0|      4.5|2011|
+--------------------+--------------------+---------+---------+----+
only showing top 5 rows
```

In [37]:

```
# Now to join the above dataset with the elite dataset
split_elite1 = split_elite.select('user_id','elite')
```

```
total_df = rev_bus_df.join(split_elite1,on='user_id', how='inner')
print("Total merged dataframe")
total_df.show(5)
```

```
Total merged dataframe
+--------------------+--------------------+---------+---------+----+-----+
|             user_id|         business_id|rev_stars|bus_stars|year|elite|
+--------------------+--------------------+---------+---------+----+-----+
|--1UpCuUDJQbqiuFX...|GgR7kcKykuqXB11fW...|      5.0|      4.5|2018|     |
|--3Bk72HakneTyp3D...|rxNfidGLHtMYyLNeo...|      5.0|      4.5|2017|     |
|--3Hl2oAvTPlq-f7K...|2OaX6XjAoI7VD6jLd...|      2.0|      4.0|2016|     |
|--3Hl2oAvTPlq-f7K...|IfOj3AxPl3Exsd_Yl...|      1.0|      4.0|2016|     |
|--3Hl2oAvTPlq-f7K...|bAuYOa-VuqTOnKzWN...|      2.0|      4.5|2013|     |
+--------------------+--------------------+---------+---------+----+-----+
only showing top 5 rows
```

In [38]:

```
# Split elite and non elite again but now from total_df
elite = total_df.filter(total_df.elite != '')
non_elite = total_df.filter(total_df.elite == '')
print('Elite Data')
elite.show(5)
print('Non-elite Data')
non_elite.show(5)
```

```
Elite Data
+--------------------+--------------------+---------+---------+----+-----+
|             user_id|         business_id|rev_stars|bus_stars|year|elite|
+--------------------+--------------------+---------+---------+----+-----+
|--cd_gA-9Q8gM9P2c...|irdrKokOvuxP_atEj...|      5.0|      4.0|2019| 2019|
|--cd_gA-9Q8gM9P2c...|irdrKokOvuxP_atEj...|      5.0|      4.0|2019|   20|
|--cd_gA-9Q8gM9P2c...|irdrKokOvuxP_atEj...|      5.0|      4.0|2019|   20|
|--cd_gA-9Q8gM9P2c...|y53Y_93Tz90HpefKQ...|      4.0|      3.5|2019| 2019|
|--cd_gA-9Q8gM9P2c...|y53Y_93Tz90HpefKQ...|      4.0|      3.5|2019|   20|
+--------------------+--------------------+---------+---------+----+-----+
only showing top 5 rows

Non-elite Data
+--------------------+--------------------+---------+---------+----+-----+
|             user_id|         business_id|rev_stars|bus_stars|year|elite|
+--------------------+--------------------+---------+---------+----+-----+
|--1UpCuUDJQbqiuFX...|GgR7kcKykuqXB11fW...|      5.0|      4.5|2018|     |
|--3Bk72HakneTyp3D...|rxNfidGLHtMYyLNeo...|      5.0|      4.5|2017|     |
|--3Hl2oAvTPlq-f7K...|bAuYOa-VuqTOnKzWN...|      2.0|      4.5|2013|     |
|--3Hl2oAvTPlq-f7K...|vqQXI-Pxz3izeTUF6...|      5.0|      4.0|2018|     |
|--3Hl2oAvTPlq-f7K...|2OaX6XjAoI7VD6jLd...|      2.0|      4.0|2016|     |
+--------------------+--------------------+---------+---------+----+-----+
only showing top 5 rows
```

Calculating the Average Ratings Over the Years

We can now focus on the ratings of elites and non-elites over the years and see how close or far they are from each other.

In [39]:

```
# Elite
elite_avg_year = elite.groupBy('year').agg(mean('rev_stars'),mean('bus_stars'))
elite_avg_year = elite_avg_year.withColumnRenamed('avg(rev_stars)', 'elite_review_ratin
elite_avg_year = elite_avg_year.withColumnRenamed('avg(bus_stars)', 'elite_bus_ratings'
```

```
print('Elite')
elite_avg_year.show(5)
```

```
Elite
+----+--------------------+------------------+
|year|elite_review_ratings| elite_bus_ratings|
+----+--------------------+------------------+
|2007|  3.7514907966258604| 3.596941862810507|
|2018|  3.9965006580540647| 3.856401355836273|
|2010|   3.722710438013602| 3.647125779594581|
|2011|   3.719965140470805| 3.643982575272907|
|2017|  3.9535886148730306|3.8365759289235255|
+----+--------------------+------------------+
only showing top 5 rows
```

In [40]:

```
# Non-elite
n_elite_avg_year = non_elite.groupBy('year').agg(mean('rev_stars'),mean('bus_stars'))
n_elite_avg_year = n_elite_avg_year.withColumnRenamed('avg(rev_stars)', 'non_elite_revi
n_elite_avg_year = n_elite_avg_year.withColumnRenamed('avg(bus_stars)', 'non_elite_bus_
print('Non-elite')
n_elite_avg_year.show(5)
```

```
Non-elite
+----+------------------------+---------------------+
|year|non_elite_review_ratings|non_elite_bus_ratings|
+----+------------------------+---------------------+
|2007|       3.768732038971052|    3.621486647508236|
|2018|      3.6917618752780923|   3.7610583634869776|
|2010|       3.690827662895443|   3.6660783693622925|
|2011|      3.6600346020761245|   3.6569018045465196|
|2017|       3.698152194184494|    3.745056894041101|
+----+------------------------+---------------------+
only showing top 5 rows
```

Now we can join the two datasets together and plot

In [41]:

```
total_avg = elite_avg_year.join(n_elite_avg_year, on = 'year', how = 'outer')
total_avg = total_avg.sort('year')
total_avg =total_avg.select('year','elite_review_ratings','non_elite_review_ratings','e
total_avg.show()
```

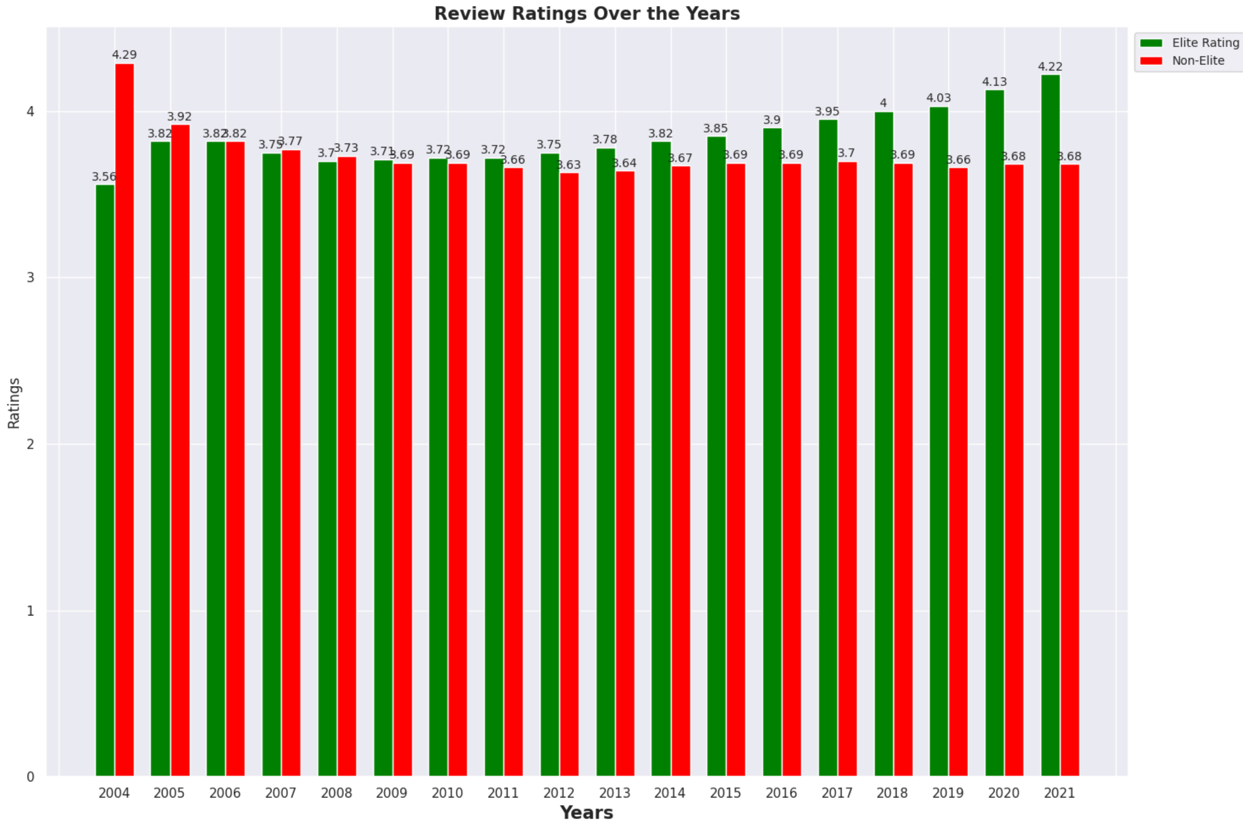
```
+----+--------------------+------------------------+------------------+-----------------
----+
|year|elite_review_ratings|non_elite_review_ratings| elite_bus_ratings|non_elite_bus_rat
ings|
+----+--------------------+------------------------+------------------+-----------------
----+
|2004|   3.562200956937799|       4.285714285714286| 3.647129186602871|    3.73809523809
5238|
|2005|   3.824107464839524|       3.924960753532182| 3.533447529751172|   3.541130298273
1554|
|2006|   3.820479122323329|      3.8203187250996016|3.5702255617616387|     3.6112881806
1089|
|2007|  3.7514907966258604|       3.768732038971052| 3.596941862810507|    3.62148664750
8236|
|2008|  3.6999801379553863|      3.7312761730913775| 3.583479437879616|   3.642368194996
2416|
```

```
|2009|   3.706608980078526|       3.69283741009512|3.6168725103262123|    3.65518810557
4304|
|2010|   3.722710438013602|      3.690827662895443| 3.647125779594581|   3.666078369362
2925|
|2011|   3.719965140470805|     3.6600346020761245| 3.643982575272907|   3.656901804546
5196|
|2012|   3.750420578112367|      3.630444437590599| 3.671183305571814|    3.65556549363
1064|
|2013|  3.7769064803232513|      3.635523458159917| 3.699754659335319|    3.66918135885
4246|
|2014|  3.8163350496895725|     3.6727432666313846|3.7385984150191764|      3.684429219
1724|
|2015|  3.8547568918137385|     3.6858769527287483|3.7705544824666513|   3.698077985167
1515|
|2016|  3.8970136566901443|      3.694521203068598|3.8028075867475057|    3.72129282050
2742|
|2017|  3.9535886148730306|      3.698152194184494|3.8365759289235255|    3.74505689404
1101|
|2018|  3.9965006580540647|     3.6917618752780923| 3.856401355836273|   3.761058363486
9776|
|2019|   4.033233447628779|     3.6554335736074575| 3.889140131456137|   3.775836463810
1245|
|2020|   4.132207048433037|      3.675654903500546|3.9433981982735196|    3.81402369619
7456|
|2021|    4.22028970723248|     3.6773052631578946| 4.007765479955116|               3.
8168|
+----+--------------------+-----------------------+------------------+-----------------
----+
```

In [ ]:

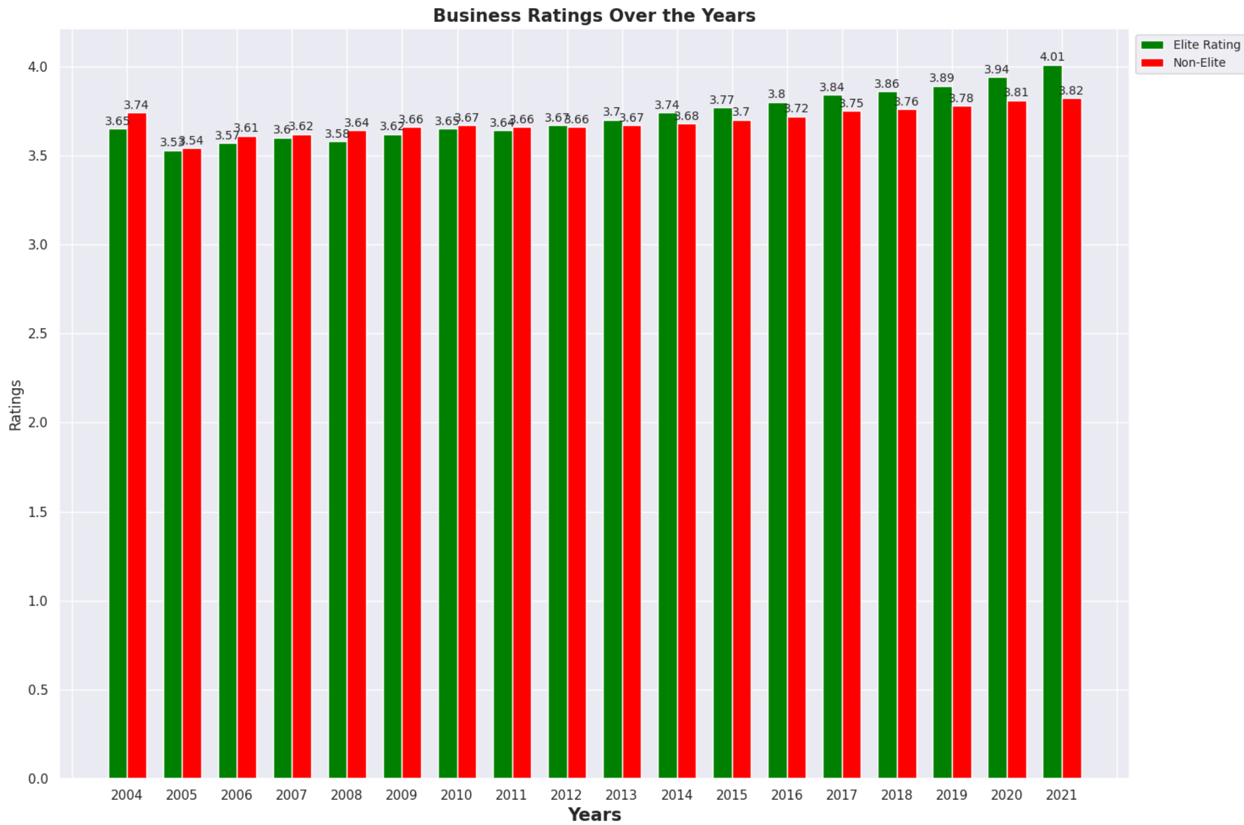
In [42]:

```python
# Plotting Review Stars
import matplotlib.ticker as plticker
avg_plot = total_avg.toPandas()
avg_plot = round(avg_plot,2)
labels = avg_plot.year
x = np.arange(len(labels)) # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(15, 10), dpi=100)
rects1 = ax.bar(x - width/2,avg_plot.elite_review_ratings,width,color='green', label='E
rects2 = ax.bar(x + width/2,avg_plot.non_elite_review_ratings,width,color='red', label=

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Ratings')
ax.set_xlabel('Years',weight='bold', size=15)
ax.set_title('Review Ratings Over the Years',weight='bold', size=15)
ax.set_xticks(x)
ax.set_xticklabels(labels,rotation=0,ha='center')
ax.legend( bbox_to_anchor=(1, 1), loc='upper left', fontsize=10)
ax.bar_label(rects1, padding=1,fontsize=10)
ax.bar_label(rects2, padding=1,fontsize=10)

loc = plticker.MultipleLocator(base=1) # this locator puts ticks at regular intervals
ax.xaxis.set_major_locator(loc)

fig.tight_layout()
%matplot plt
```



In [43]:

```
# Plotting Business Stars
import matplotlib.ticker as plticker
labels = avg_plot.year
x = np.arange(len(labels)) # the label locations
width = 0.35  # the width of the bars

fig, ax = plt.subplots(figsize=(15, 10), dpi=100)
rects1 = ax.bar(x - width/2,avg_plot.elite_bus_ratings,width,color='green', label='Elit
rects2 = ax.bar(x + width/2,avg_plot.non_elite_bus_ratings,width,color='red', label='No

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Ratings')
ax.set_xlabel('Years',weight='bold', size=15)
ax.set_title('Business Ratings Over the Years',weight='bold', size=15)
ax.set_xticks(x)
ax.set_xticklabels(labels,rotation=0,ha='center')
ax.legend( bbox_to_anchor=(1, 1), loc='upper left', fontsize=10)
ax.bar_label(rects1, padding=1,fontsize=10)
ax.bar_label(rects2, padding=1,fontsize=10)

loc = plticker.MultipleLocator(base=1) # this locator puts ticks at regular intervals
ax.xaxis.set_major_locator(loc)

fig.tight_layout()
%matplot plt
```



Should the elites be trusted?

Despite the analysis done above, it is still a hard question to answer. We saw that based on just counts alone, there is a much higher percentage of non-elite reviewers(85%) than there are elite reviewers(15%). This made it so that review tags such as being voted "useful", "cool" or "funny" couldnt be used in terms of counts to address if elite reviews are found more useful than non-elites.

When Looking at the average rating across reviews and business we can see from the plot that there are some similarities. The years of greatest difference between elite and non-elite are 2004 and 2021 also on average the elites tend to give better ratings than non-elites across both plots. Generally, their ratings tend to be close year by year and this is very interesting when considering the fact that non-elites count is more than tripple that of the elites.

If we were to really dig deeper we would need to draw an equal sample size from each group and then conduct an ANOVA test after determining independence between the samples. Ideally the ANOVA could indicate to us if there is a statistical difference between the two groups. In other words an ANOVA could give us an idea of which group, the elites or non-elites, is providing better or more useful reviews and thereby which group should be trusted more.

Another interesting analysis that could be made would be trying to predict what are the top features that likely determine what makes a person become an elite yelp reviewer. Would it be the number of reviews, number of fans, funny/cool upvotes, years on yelp? It could be any one or a combination of these and that could be a whole other project.

In [ ]: