In [1]:

Analysis of Yelp Business Intelligence Data

We will analyze a subset of Yelp's business, reviews and user data. This dataset comes to us from Kaggle although we have taken steps to pull this data into a publis s3 bucket: s3://sta9760-yelpdataset/yelp-light/*business.json

Installation and Initial Setup

Begin by installing the necessary libraries that you may need to conduct your analysis. At the very least, you must install pandas and matplotlib

```
sc.install_pypi_package("pandas==1.0.3")
        Starting Spark application
                     YARN Application ID
                                         Kind State Spark UI Driver log Current session?
         2 application_1619538268223_0006 pyspark
                                                idle
                                                        Link
                                                                 Link
        SparkSession available as 'spark'.
        Collecting pandas==1.0.3
          Using cached https://files.pythonhosted.org/packages/4a/6a/94b219b8ea0f2d58016
        9e85ed1edc0163743f55aaeca8a44c2e8fc1e344e/pandas-1.0.3-cp37-cp37m-manylinux1_x86
        Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/site-pac
        kages (from pandas==1.0.3)
        Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib64/python3.7/site-
        packages (from pandas==1.0.3)
        Collecting python-dateutil>=2.6.1 (from pandas==1.0.3)
          Using cached https://files.pythonhosted.org/packages/d4/70/d60450c3dd48ef87586
        924207ae8907090de0b306af2bce5d134d78615cb/python_dateutil-2.8.1-py2.py3-none-an
        y.whl
        Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-package
        s (from python-dateutil>=2.6.1->pandas==1.0.3)
        Installing collected packages: python-dateutil, pandas
        Successfully installed pandas-1.0.3 python-dateutil-2.8.1
In [2]:
         sc.install pypi package("matplotlib==3.2.1")
        Collecting matplotlib==3.2.1
          Using cached https://files.pythonhosted.org/packages/b2/c2/71fcf957710f3ba1f09
        088b35776a799ba7dd95f7c2b195ec800933b276b/matplotlib-3.2.1-cp37-cp37m-manylinux1
         x86 64.whl
        Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1619578930139-0/
        lib/python3.7/site-packages (from matplotlib==3.2.1)
        Collecting pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 (from matplotlib==3.2.1)
          Using cached https://files.pythonhosted.org/packages/8a/bb/488841f56197b13700a
        fd5658fc279a2025a39e22449b7cf29864669b15d/pyparsing-2.4.7-py2.py3-none-any.whl
        Collecting cycler>=0.10 (from matplotlib==3.2.1)
          Using cached https://files.pythonhosted.org/packages/f7/d2/e07d3ebb2bd7af69644
        Oce7e754c59dd546ffe1bbe732c8ab68b9c834e61/cycler-0.10.0-py2.py3-none-any.whl
        Requirement already satisfied: numpy>=1.11 in /usr/local/lib64/python3.7/site-pa
```

ckages (from matplotlib==3.2.1)

Collecting kiwisolver>=1.0.1 (from matplotlib==3.2.1)

Using cached https://files.pythonhosted.org/packages/d2/46/231de802ade4225b76b

```
96cffe419cf3ce52bbe92e3b092cf12db7d11c207/kiwisolver-1.3.1-cp37-cp37m-manylinux1
        x86 64.whl
        Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-package
        s (from python-dateutil>=2.1->matplotlib==3.2.1)
        Installing collected packages: pyparsing, cycler, kiwisolver, matplotlib
        Successfully installed cycler-0.10.0 kiwisolver-1.3.1 matplotlib-3.2.1 pyparsing
        -2.4.7
In [3]:
         sc.install_pypi_package("seaborn==0.11.1")
        Collecting seaborn==0.11.1
          Using cached https://files.pythonhosted.org/packages/68/ad/6c2406ae175f59ec616
        714e408979b674fe27b9587f79d59a528ddfbcd5b/seaborn-0.11.1-py3-none-any.whl
        Requirement already satisfied: numpy>=1.15 in /usr/local/lib64/python3.7/site-pa
        ckages (from seaborn==0.11.1)
        Collecting scipy>=1.0 (from seaborn==0.11.1)
          Using cached https://files.pythonhosted.org/packages/7d/e8/43ffca541d2f208d516
        296950b25fe1084b35c2881f4d444c1346ca75815/scipy-1.6.3-cp37-cp37m-manylinux1 x86
        Requirement already satisfied: matplotlib>=2.2 in /mnt/tmp/1619578930139-0/lib/p
        ython3.7/site-packages (from seaborn==0.11.1)
        Requirement already satisfied: pandas>=0.23 in /mnt/tmp/1619578930139-0/lib/pyth
        on3.7/site-packages (from seaborn==0.11.1)
        Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1619578930139-0/
        lib/python3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
        Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /mnt/
        tmp/1619578930139-0/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn==
        0.11.1)
        Requirement already satisfied: cycler>=0.10 in /mnt/tmp/1619578930139-0/lib/pyth
        on3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
        Requirement already satisfied: kiwisolver>=1.0.1 in /mnt/tmp/1619578930139-0/li
        b/python3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.1)
        Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/site-pac
        kages (from pandas>=0.23->seaborn==0.11.1)
        Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-package
        s (from python-dateutil>=2.1->matplotlib>=2.2->seaborn==0.11.1)
        Installing collected packages: scipy, seaborn
        Successfully installed scipy-1.6.3 seaborn-0.11.1
In [4]:
         sc.install pypi package("bokeh==2.3.1")
        Collecting bokeh == 2.3.1
        Collecting typing-extensions>=3.7.4 (from bokeh==2.3.1)
          Using cached https://files.pythonhosted.org/packages/60/7a/e881b5abb54db0e6e67
        lab088d079c57ce54e8a0la3ca443f56lccadb37e/typing extensions-3.7.4.3-py3-none-an
        Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1619578930139-0/
        lib/python3.7/site-packages (from bokeh==2.3.1)
        Collecting tornado>=5.1 (from bokeh==2.3.1)
          Using cached https://files.pythonhosted.org/packages/bf/fa/2befee379094720b540
        65daa9c6117f3edb7d35f86cde0f50b3a28ecfadf/tornado-6.1-cp37-cp37m-manylinux1 x86
        Collecting pillow>=7.1.0 (from bokeh==2.3.1)
          Using cached https://files.pythonhosted.org/packages/33/34/542152297dcc6c47a9d
        cb0685eac6d652d878ed3cea83bf2b23cb988e857/Pillow-8.2.0-cp37-cp37m-manylinux1 x86
         64.whl
        Collecting packaging>=16.8 (from bokeh==2.3.1)
          Using cached https://files.pythonhosted.org/packages/3e/89/7ea760b4daa42653ece
```

2380531c90f64788d979110a2ab51049d92f408af/packaging-20.9-py2.py3-none-any.whl Requirement already satisfied: numpy>=1.11.3 in /usr/local/lib64/python3.7/site-packages (from bokeh==2.3.1)

Requirement already satisfied: PyYAML>=3.10 in /usr/local/lib64/python3.7/site-p ackages (from bokeh==2.3.1)

Collecting Jinja2>=2.7 (from bokeh==2.3.1)

Using cached https://files.pythonhosted.org/packages/7e/c2/1eece8c95ddbc9b1aeb 64f5783a9e07a286de42191b7204d67b7496ddf35/Jinja2-2.11.3-py2.py3-none-any.whl Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-package s (from python-dateutil>=2.1->bokeh==2.3.1)

Requirement already satisfied: pyparsing>=2.0.2 in /mnt/tmp/1619578930139-0/lib/python3.7/site-packages (from packaging>=16.8->bokeh==2.3.1)

Collecting MarkupSafe>=0.23 (from Jinja2>=2.7->bokeh==2.3.1)

Using cached https://files.pythonhosted.org/packages/98/7b/ff284bd8c80654e471b 769062a9b43cc5d03e7a615048d96f4619df8d420/MarkupSafe-1.1.1-cp37-cp37m-manylinux1 x86 64.whl

Installing collected packages: typing-extensions, tornado, pillow, packaging, MarkupSafe, Jinja2, bokeh

Successfully installed Jinja2-2.11.3 MarkupSafe-1.1.1 bokeh-2.3.1 packaging-20.9 pillow-8.2.0 tornado-6.1 typing-extensions-3.7.4.3

In [5]:

sc.list packages()

Package	Version
beautifulsoup4	4.9.1
bokeh	2.3.1
boto	2.49.0
click	7.1.2
cycler	0.10.0
Jinja2	2.11.3
jmespath	0.10.0
joblib	0.16.0
kiwisolver	1.3.1
lxml	4.5.2
MarkupSafe	1.1.1
matplotlib	3.2.1
mysqlclient	1.4.2
nltk	3.5
nose	1.3.4
numpy	1.16.5
packaging	20.9
pandas	1.0.3
Pillow	8.2.0
pip	9.0.1
py-dateutil	2.2
pyparsing	2.4.7
python-dateutil	2.8.1
<pre>python37-sagemaker-pyspark</pre>	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
tornado	6.1
tqdm	4.48.2
typing-extensions	3.7.4.3
wheel	0.29.0
windmill	1.6

Importing

Now, import the installed packages from the previous block below.

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from bokeh.plotting import figure, output_file, show
```

Loading Data

We are finally ready to load data. Using spark load the data from S3 into a dataframe object that we can manipulate further down in our analysis.

```
In [7]: business_data= spark.read.json('s3://yelp-spark-dataset/yelp_academic_dataset_bu
    review_data=spark.read.json('s3://yelp-spark-dataset/yelp_academic_dataset_revie
    user_data=spark.read.json('s3://yelp-spark-dataset/yelp_academic_dataset_user.js
```

Overview of Data

Display the number of rows and columns in our dataset.

```
In [8]:
         print('Yelp Business Data Set | Rows: '+ str(business_data.count())+' | Columns:
         print('Yelp Review Data Set | Rows: '+ str(review data.count())+ ' | Columns: '+
         print('Yelp User Data Set | Rows: '+ str(user data.count())+' | Columns:'+ str(l
        Yelp Business Data Set | Rows: 160585 | Columns:14
        Yelp Review Data Set | Rows: 8635403 | Columns:9
        Yelp User Data Set | Rows: 2189457 | Columns:22
       Display the DataFrame schema below.
In [9]:
         business data.printSchema()
         review data.printSchema()
         user data.printSchema()
        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)
  -- 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)
```

Display the first 5 rows with the following columns:

- business_id
- name
- city
- state

In [10]:

categories

```
+----+
                        name city|state|stars|
     business id
egories
+----+
|6iYb2HFDywm3zjuRg...| Oskar Blues Taproom| Boulder| CO| 4.0|Gastropubs, F
|tCbdrRPZA0oiIYSmH...|Flying Elephants ...| Portland|
                                      OR 4.0 | Salad, Soup,
Sand...
|bvN78flM8NLprQ1a1...| The Reclaimory| Portland|
                                     OR | 4.5 | Antiques, Fas
hion...
oaepsyvc0J17qwi8c...
                   Great Clips Orange City | FL | 3.0 | Beauty & Spa
s, Ha...
|PE9uqAjdw0E4-8mjG...| Crossfit Terminus| Atlanta| GA| 4.0|Gyms, Active
        _____+
only showing top 5 rows
```

business data.select("business id", "name", "city", "state", "stars", "categories").s

Analyzing Categories

Let's now answer this question: how many unique categories are represented in this dataset?

Essentially, we have the categories per business as a list - this is useful to quickly see what each business might be represented as but it is difficult to easily answer questions such as:

- How many businesses are categorized as Active Life, for instance
- 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	а	
abcd123	b	
abcd123	С	

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.

Implement the code necessary to derive the table described from your original yelp dataframe.

```
In [11]:
    from pyspark.sql.functions import explode, split, trim
    business_data_exploded=business_data.select("business_id","categories")
    business_data_exploded = business_data_exploded.withColumn('categories', explode(
    business_data_exploded = business_data_exploded.withColumn('categories', trim(bu
    #business_data_exploded.columns = business_data_exploded.columns.strip()
    business_data_exploded.count()
```

708968

Display the first 5 rows of your association table below.

```
In [12]: business_data_exploded.show(5)
```

```
+-----+

| business_id| categories|
+-----+

|6iYb2HFDywm3zjuRg...| Gastropubs|
|6iYb2HFDywm3zjuRg...| Food|
|6iYb2HFDywm3zjuRg...| Beer Gardens|
|6iYb2HFDywm3zjuRg...| Restaurants|
|6iYb2HFDywm3zjuRg...| Bars|
```

```
only showing top 5 rows
```

Total Unique Categories

Finally, we are ready to answer the question: what is the total number of unique categories available?

Below, implement the code necessary to calculate this figure.

```
In [13]: business_data_exploded.select('categories').distinct().count()
```

1330

Top Categories By Business

Now let's find the top categories in this dataset by rolling up 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	
а	15	
b	2	
С	45	

Or something to that effect.

```
In [14]: business_data_exploded.groupby('categories').count().show()
```

```
categories count
Dermatologists
Paddleboarding 67
  Aerial Tours
   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
```

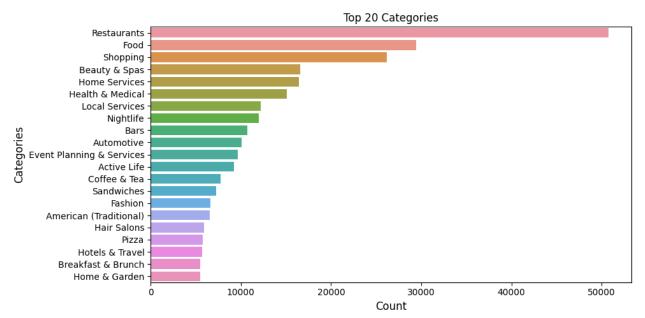
Bar Chart of Top Categories

With this data available, let us now build a barchart of the top 20 categories.

HINT: don't forget about the matplotlib magic!

```
%matplot plt
In [15]: count_business=business_data_exploded.groupby('categories').count().orderBy('cou
In [16]: barchart= count_business.toPandas()
barchart=barchart.head(21)

In [17]: plt.figure(figsize=(10,5))
barchart_viz= sns.barplot(x='count',y='categories',data=barchart)
barchart_viz.set_title('Top 20 Categories')
barchart_viz.set_xlabel( "Count" , size = 12 )
barchart_viz.set_ylabel( "Categories" , size = 12 )
plt.tight_layout()
#plt.show()
%matplot plt
```



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

8635403

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

```
review_data.printSchema()
review_data.count()
```

```
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.

```
star_data=review_data.select("business_id","stars")
star_data.show(5)
```

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**.

```
avg_review_data=star_data.groupby('business_id').mean()
avg_review_data.show()
```

```
business id
uEUweopM301HcVxjO...
wdBrDCbZopowEkIEX... | 4.538461538461538 |
L3WCfeVozu5etMhz4...
                                   4.2
bOnsvrz1VkbrZM1jV...
                                   3.8
R0IJhEI-zSJpYT1YN... | 3.606060606060606
XzXcpPCb8Y5huklEN... 4.66666666666667
yHtuNAlYKtRZniO8O... 4.714285714285714
O BAT rvszHYBNEM6...
E8F17qE y-bhRbkkd... | 4.66666666666667 |
MPzc6QuEjwk3E3jVT...
                                3.3125
dXhuCvyz5nnaboNzp... | 4.392857142857143
deTlQzwpIRfgmAuDa... | 3.7604790419161676 |
VmujhV mpJh1TW3Cx... | 2.7884615384615383 |
bzny-7M JjYHsKuoC... | 4.648648648648648
BnfkEAmvnUyIEUvG3... | 3.979591836734694
jZBhw30QecAQNDtpM...
tI czdTHfsy1ndBwt... | 4.428571428571429 |
4T6yFKDishcRS5k9p... | 4.3333333333333333333
nM6X2lQp5kiVteXBM... | 3.909090909090909
ERI2yvYf9QEN fFOK... | 2.2718446601941746 |
+----+
only showing top 20 rows
```

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

```
bus_data= business_data.select("business_id","name","city","state","stars")
avg_data= avg_review_data.select("business_id","avg(stars)")
all_stars_data = bus_data.join(avg_data, bus_data.business_id == avg_data.busine
```

Let's see a few of these:

```
new_stars_skew=all_stars_data.select("avg(stars)","stars","name","city","state")
new_stars_skew.show(5)
```

+	+	⊦		+ +			
avg(stars)	stars	name	city	state			
5.0		CheraBella Salon		!!!			
3.866666666666667	4.0	Red Table Coffee	Austin	!!!			
5.0	5.0	WonderWell	Austin	TX			
3.375	3.5	Avalon Oaks	Wilmington	MA			
++							
only showing top 5 rows							

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:

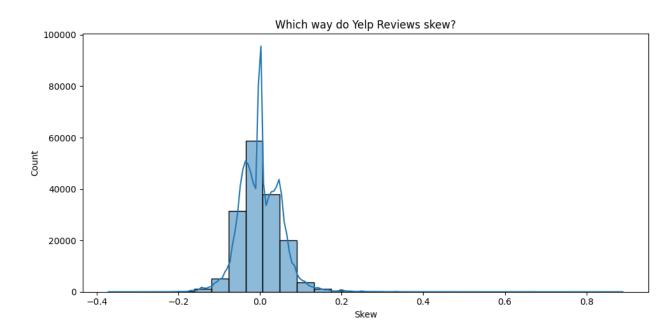
```
(row['avg(stars)'] - row['stars']) / row['stars']
```

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.

```
In [23]:
         new stars skew=new stars skew.withColumn('skew',
                                                 ((new_stars_skew['avg(stars)']-new stars
         new stars skew.show(5)
                                                           city|state|
                 avg(stars)|stars|
                                                 name
                        5.0 | 5.0 |
                                      CheraBella Salon | Peabody |
                                                                    MA
         0.0
                      3.875 | 4.0 | Mezcal Cantina & ... | Columbus |
                                                                           -0.0
         3125
         |3.8666666666666667| 4.0| Red Table Coffee|
                                                                    TX | -0.033333333333333
                                                           Austin
         3...
                                           WonderWell
                        5.0 | 5.0 |
                                                           Austin
         0.0
                      3.375 | 3.5 |
                                          Avalon Oaks | Wilmington |
                                                                    MA | -0.0357142857142
         8571
         only showing top 5 rows
        And finally, graph it!
```

```
new_histplot= new_stars_skew.toPandas()
#new_histplot.head()
plt.figure(figsize=(10,5))
skew_histogram= sns.histplot(data=new_histplot, x='skew',bins=30,kde=True)
skew_histogram.set_title('Which way do Yelp Reviews skew?')
skew_histogram.set_xlabel( "Skew" , size = 10 )
```

```
skew_histogram.set_ylabel( "Count" , size = 10 )
plt.tight_layout()
plt.show()
%matplot plt
```



```
In [25]: print (new_histplot.skew())
```

```
avg(stars) -0.563063
stars -0.541505
skew 0.874749
dtype: float64
```

So, do Yelp (written) Reviews skew negative? Does this analysis actually prove anything? Expound on implications / interpretations of this graph.

```
In [ ]: #The Yelp (written) Review are skewing positively. This shows there is a balance #Therefore it would probably give everyone who uses Yelp a balanced view of diff
```

Should the Elite be Trusted? (Or, some other analysis of your choice)

For the final portion - you have a choice:

- Try and analyze some interesting dimension to this data. The **ONLY** requirement is that you must use the **Users** dataset and join on either the **business* or** reviews** dataset
- Or, you may try and answer the question posed: how accurate or close are the ratings of an "elite" user (check Users table schema) vs the actual business rating.

Feel free to use any and all methodologies at your disposal - only requirement is you must render one visualization in your analysis

4/27/2021

```
Analysis
         user data.printSchema()
In [26]:
         user data.count()
        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)
        2189457
In [27]:
         review data.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)
In [28]:
         df user data=user data.select("user id","average stars","review count")
         df_review_data=review_data.select("user_id","business_id","stars")
         df stars data = df user data.join(df review data, df user data.user id == df rev
         df stars data.show(5)
         df stars data.count()
         +----+
               user id|average stars|review count| business id|stars|
              -----+
                                  2.62 | 12|GgR7kcKykuqXB11fW...| 5.0|
3.67 | 11|rxNfidGLHtMYyLNeo...| 5.0|
         --1UpCuUDJQbqiuFX...
         --3Bk72HakneTyp3D...
                                    2.73
                                                   11|20aX6XjAoI7VD6jLd...| 2.0|
         --3Hl2oAvTPlq-f7K...
                                    2.73|
                                                   11|IfOj3AxPl3Exsd Yl...| 1.0|
         --3Hl2oAvTPlq-f7K...
                                                   11|bAuYOa-VuqTOnKzWN...| 2.0|
         --3Hl2oAvTPlq-f7K...
                                    2.73
```

only showing top 5 rows

4/27/2021

```
Analysis
         8635403
In [29]:
         all_stars_data.printSchema()
         root
          -- name: string (nullable = true)
          -- city: string (nullable = true)
          -- state: string (nullable = true)
          -- stars: double (nullable = true)
          -- business_id: string (nullable = true)
          -- avg(stars): double (nullable = true)
In [30]:
         elite review data=df stars data.select('business id', "average stars")
         elite_review_data=elite_review_data.groupby('business_id').mean()
         elite review data.show()
         elite_review_data.count()
                  business_id|avg(average_stars)|
         |SEHexDtZaL3Gv81aE...| 3.378604651162792|
         B9LGNspzZYVRs5S18... | 3.8768181818181815 |
         XVZDMELcUCdyWjbEz... | 2.8222857142857145 |
          6KGBXOeSJYf9ePdyA... | 3.7497374429223744
          xm4QAhRiwd6Urq6ku...
                                        4.02675
          quL0Dqop3Ni5qcwd2...|3.6404109589041096
          2boQDeHxopolPtJhV... 3.749166666666667
          8e3 PgOlFLeAys6X-... 3.8811111111111111
          08n38tS38iznDwL X... 3.939647887323944
          g8sJbkPtA78h0yNQQ...
          x LapuF4Zkn5lySuA... | 3.2118750000000005 |
         kUV8r9IQ5109XMyjW...|2.867499999999997
          6qlWc-OVhTQfcyVi3... | 4.288823529411765
          dcAzi-fNs05qLl3lw... | 3.3847272727272717
         EvYWMhT0o9M 9NaaI... | 3.1781249999999996 |
         BnBnPjmUeUaMAnbJH... 3.472857142857142
         boF5lsuImrqbuDkuF... | 3.596279069767443 |
         TMxgR8YnOI-0HxrTg...
         |UK5t99N509A12UjUn...| 3.7359333333333333
         ESntdVKBhAdDqERly... 3.7782352941176462
         +----+
         only showing top 20 rows
         160585
In [31]:
         ddf = elite review data.join(all stars data, all stars data. business id == elit
         ddf.show(5)
         ddf.count()
         ---+----+
                                                     city|state|stars|
         |avg(average stars)|
                                           name
                                                                               busines
         s id avg(stars)
                                   ______
```

Peabody

file:///Users/angelaguzman/Desktop/SPRING 2021/CIS:STA9760- Big Data Technologies/Project02/Analysis.html

CheraBella Salon

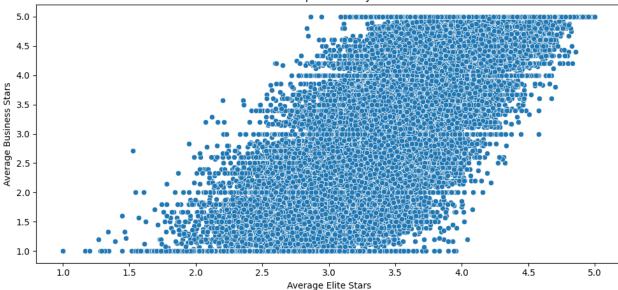
__+___+

3.8949999999999996

MA | 5.0 | -- JuLhLvq3gyjNnX

```
5.0
        T...
                    4.085 | Mezcal Cantina & ... | Columbus |
                                                       OH | 4.0 | -- nBudPOb11NRgK
                       3.875
        |3.65700000000000000 | Red Table Coffee
                                               Austin
                                                       TX
                                                            4.0 | --kyOk0waSrCDlbS
        v...|3.866666666666667|
                                                            5.0 | -- z9usx6Fin8P f0
        4.410714285714286
                                 WonderWell
                                               Austin
                                                       TX
                         5.0
        v...
        3.8206249999999997
                                 Avalon Oaks | Wilmington |
                                                       MA | 3.5 | -0qeY1293steyCqY
        h...
                      3.375
        ____+
        only showing top 5 rows
        160585
In [33]:
        df_correlation=ddf.select("business_id","avg(stars)","avg(average_stars)")
        df correlation.show(2)
        df correlation.count()
        +----+
                business_id|avg(stars)|avg(average_stars)|
            ----+
        |--JuLhLvq3gyjNnXT...| 5.0|
|--_nBudPOb11NRgKf...| 3.875|
                                               3.895
                                              4.085
        +----+
        only showing top 2 rows
        160585
In [43]:
        new scatplot= df correlation.toPandas()
        new scatplot=new scatplot.drop duplicates()
        new scatplot
                        business id avg(stars) avg(average stars)
        0
               --JuLhLvq3gyjNnXT9Q95w 5.000000
                                                3.895000
        1
               -- nBudPOb11NRgKfjLtrw 3.875000
                                                       4.085000
        2
               --kyOk0waSrCDlbSvYtAOw 3.866667
                                                      3.657000
               --z9usx6Fin8P f0vc7DGQ
        3
                                     5.000000
                                                      4.410714
               -0qeY1293steyCqYhqckMA
        4
                                     3.375000
                                                       3.820625
        . . .
                                         . . .
                                     3.092105
        160580 zptEZZLh0iP5PnslDAUbkw
                                                      3.608289
        160581 zvaKvoKVDpgTtKK6Mc1SKw
                                     4.215909
                                                      3.828750
        160582 zwOz6JjjQ0leNlKWhr5Shw
                                     4.789474
                                                      4.196842
        160583 zwT7rrAMgEMA9g8twm7DGg 5.000000
                                                      4.540000
        160584 zzgP0DV4OZfXkPdGNvtANQ
                                     4.200000
                                                      4.142000
        [160585 rows x 3 columns]
In [37]:
        plt.figure(figsize=(10,5))
        scattter plot= sns.scatterplot(data=new scatplot, x="avg(average stars)", y="avg
        scattter plot.set title('The Elite Yelpers v Everyone else')
        scattter plot.set xlabel( "Average Elite Stars" , size = 10 )
        scattter plot.set ylabel( "Average Business Stars" , size = 10 )
        plt.tight_layout()
        plt.show()
        %matplot plt
```





In [45]:

correlation = new_scatplot['avg(stars)']. corr(new_scatplot['avg(average_stars)'
print ('The following is the correlation between Elite Avg Star and Average Star

The following is the correlation between Elite Avg Star and Average Stars: 0.8095213594120078

In []:

Although the graph is too cluttered to make an accurate read of the correlatio #Using the correlation calculation, there is a strong postitive correlation betw #do make a difference in the average rating of a business