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`

In [1]:
```
sc.install_pypi_package("pandas==1.0.3")
sc.install_pypi_package("matplotlib==3.2.1")
sc.install_pypi_package("seaborn==0.10.0")
```

Starting Spark application

ID	YARN Application ID	Kind	State	Spark UI	Driver log	Current session?
3	application_1619528787164_0004	pyspark	idle			✔

```
SparkSession available as 'spark'.

Collecting pandas==1.0.3
  Using cached pandas-1.0.3-cp36-cp36m-manylinux1_x86_64.whl (10.0 MB)
Collecting python-dateutil>=2.6.1
  Using cached python_dateutil-2.8.1-py2.py3-none-any.whl (227 kB)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib64/python3.6/site-
packages (from pandas==1.0.3) (1.14.5)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/site-pac
kages (from pandas==1.0.3) (2019.3)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/site-package
s (from python-dateutil>=2.6.1->pandas==1.0.3) (1.13.0)
Installing collected packages: python-dateutil, pandas
Successfully installed pandas-1.0.3 python-dateutil-2.8.1

Collecting matplotlib==3.2.1
  Using cached matplotlib-3.2.1-cp36-cp36m-manylinux1_x86_64.whl (12.4 MB)
Collecting pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1
  Using cached pyparsing-2.4.7-py2.py3-none-any.whl (67 kB)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib64/python3.6/site-pa
ckages (from matplotlib==3.2.1) (1.14.5)
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1619537805762-0/
lib/python3.6/site-packages (from matplotlib==3.2.1) (2.8.1)
Collecting kiwisolver>=1.0.1
  Using cached kiwisolver-1.3.1-cp36-cp36m-manylinux1_x86_64.whl (1.1 MB)
Collecting cycler>=0.10
  Using cached cycler-0.10.0-py2.py3-none-any.whl (6.5 kB)
Requirement already satisfied: six in /usr/local/lib/python3.6/site-packages (fr
om cycler>=0.10->matplotlib==3.2.1) (1.13.0)
Installing collected packages: pyparsing, kiwisolver, cycler, matplotlib
Successfully installed cycler-0.10.0 kiwisolver-1.3.1 matplotlib-3.2.1 pyparsing
-2.4.7

Collecting seaborn==0.10.0
  Using cached seaborn-0.10.0-py3-none-any.whl (215 kB)
Collecting scipy>=1.0.1
```

```
  Using cached scipy-1.5.4-cp36-cp36m-manylinux1_x86_64.whl (25.9 MB)
Requirement already satisfied: matplotlib>=2.1.2 in /mnt/tmp/1619537805762-0/lib
64/python3.6/site-packages (from seaborn==0.10.0) (3.2.1)
Requirement already satisfied: pandas>=0.22.0 in /mnt/tmp/1619537805762-0/lib64/
python3.6/site-packages (from seaborn==0.10.0) (1.0.3)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib64/python3.6/site-
packages (from seaborn==0.10.0) (1.14.5)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /mnt/
tmp/1619537805762-0/lib/python3.6/site-packages (from matplotlib>=2.1.2->seaborn
==0.10.0) (2.4.7)
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1619537805762-0/
lib/python3.6/site-packages (from matplotlib>=2.1.2->seaborn==0.10.0) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /mnt/tmp/1619537805762-0/lib
64/python3.6/site-packages (from matplotlib>=2.1.2->seaborn==0.10.0) (1.3.1)
Requirement already satisfied: cycler>=0.10 in /mnt/tmp/1619537805762-0/lib/pyth
on3.6/site-packages (from matplotlib>=2.1.2->seaborn==0.10.0) (0.10.0)
Requirement already satisfied: six in /usr/local/lib/python3.6/site-packages (fr
om cycler>=0.10->matplotlib>=2.1.2->seaborn==0.10.0) (1.13.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/site-pac
kages (from pandas>=0.22.0->seaborn==0.10.0) (2019.3)
Installing collected packages: scipy, seaborn
Successfully installed scipy-1.5.4 seaborn-0.10.0
```

Importing

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

In [2]:

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

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 [3]:

```
biz = spark.read.json('s3://sta9760s2021spark/yelp/yelp_academic_dataset_busines
review = spark.read.json('s3://sta9760s2021spark/yelp/yelp_academic_dataset_revi
user = spark.read.json('s3://sta9760s2021spark/yelp/yelp_academic_dataset_user.j
```

In [4]:

```
biz.show(5)
```

```
+--------------------+--------------------+--------------------+-----------------
---+-----------+--------------------+-------+-------------+---------------+-----
---------------+-----------+------------+-----+-----+
|             address|          attributes|         business_id|          categor
ies|        city|                hours|is_open|     latitude|      longitude|
name|postal_code|review_count|stars|state|
+--------------------+--------------------+--------------------+-----------------
---+-----------+--------------------+-------+-------------+---------------+-----
---------------+-----------+------------+-----+-----+
```

```
|       921 Pearl St|[,, 'beer_and_win...|6iYb2HFDywm3zjuRg...|Gastropubs, Foo
d,...|    Boulder|[11:0-23:0, 11:0-...|       1|   40.0175444|   -105.2833481| Os
kar Blues Taproom|       80302|           86|  4.0|   CO|
|7000 NE Airport Way|[,, u'beer_and_wi...|tCbdrRPZA0oiIYSmH...|Salad, Soup, San
d...|   Portland|[5:0-18:0, 5:0-18...|       1|45.5889058992|-122.5933307507|Flyi
ng Elephants ...|       97218|          126|  4.0|   OR|
| 4720 Hawthorne Ave|[,,,,,,, False,, ...|bvN78flM8NLprQ1a1...|Antiques, Fashio
n...|   Portland|[11:0-18:0,, 11:0...|       1|45.5119069956|-122.6136928797|
The Reclaimory|       97214|           13|  4.5|   OR|
| 2566 Enterprise Rd|[,,,,,,,,, True,,...|oaepsyvc0J17qwi8c...|Beauty & Spas, H
a...|Orange City|                null|       1|   28.9144823|    -81.2959787|
Great Clips|       32763|            8|  3.0|   FL|
|1046 Memorial Dr SE|[,,,,,,,,, True, ...|PE9uqAjdw0E4-8mjG...|Gyms, Active Lif
e...|    Atlanta|[16:0-19:0, 16:0-...|       1|   33.7470274|    -84.3534244|   C
rossfit Terminus|       30316|           14|  4.0|   GA|
+-------------------+--------------------+--------------------+-----------------
---+-----------+--------------------+--------+-------------+---------------+-----
---------------+-----------+------------+-----+-----+
only showing top 5 rows
```

Overview of Data

Display the number of rows and columns in our dataset.

In [5]:
```python
print(f"Number of columns in Business table: {len(biz.columns)}")
print(f"Number of rows in Business table: {biz.count()}")
print(f"Number of columns in User table: {len(user.columns)}")
print(f"Number of rows in User table: {user.count()}")
print(f"Number of columns in Review table: {len(review.columns)}")
print(f"Number of rows in Review table: {review.count()}")
```

```
Number of columns in Business table: 14
Number of rows in Business table: 160585
Number of columns in User table: 22
Number of rows in User table: 2189457
Number of columns in Review table: 9
Number of rows in Review table: 8635403
```

Display the DataFrame schema below.

In [6]:
```python
biz.printSchema()
user.printSchema()
review.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)

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
 |-- 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)
```

Display the first 5 rows with the following columns:

- `business_id`
- `name`
- `city`
- `state`
- `categories`

In [7]:
```
biz.select("business_id","name","city","state","categories").show(5)
```

```
+--------------------+--------------------+-----------+-----+--------------------
-+
|         business_id|                name|       city|state|          categorie
s|
+--------------------+--------------------+-----------+-----+--------------------
-+
|6iYb2HFDywm3zjuRg...| Oskar Blues Taproom|    Boulder|   CO|Gastropubs, Foo
d,...|
|tCbdrRPZA0oiIYSmH...|Flying Elephants ...|   Portland|   OR|Salad, Soup, San
d...|
|bvN78flM8NLprQ1a1...|      The Reclaimory|   Portland|   OR|Antiques, Fashio
n...|
|oaepsyvc0J17qwi8c...|         Great Clips|Orange City|   FL|Beauty & Spas, H
a...|
|PE9uqAjdw0E4-8mjG...|   Crossfit Terminus|    Atlanta|   GA|Gyms, Active Lif
e...|
+--------------------+--------------------+-----------+-----+--------------------
-+
only showing top 5 rows
```

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	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.

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

In [8]:

```
from pyspark.sql.functions import explode,split
```

In [9]:

```
biz_cat = biz.select("business_id","categories")
biz_cat.show(5)
```

```
+--------------------+--------------------+
|         business_id|          categories|
+--------------------+--------------------+
|6iYb2HFDywm3zjuRg...|Gastropubs, Food,...|
|tCbdrRPZA0oiIYSmH...|Salad, Soup, Sand...|
|bvN78flM8NLprQ1a1...|Antiques, Fashion...|
|oaepsyvc0J17qwi8c...|Beauty & Spas, Ha...|
|PE9uqAjdw0E4-8mjG...|Gyms, Active Life...|
+--------------------+--------------------+
only showing top 5 rows
```

Display the first 5 rows of your association table below.

In [10]:

```
biz_cat_exploded = biz_cat.withColumn('categories',explode(split('categories',',',
biz_cat_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 [11]:

```
biz_cat_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
a	15
b	2
c	45

Or something to that effect.

In [12]:

```
biz_cat_exploded.groupby('categories').count().show(20)
```

```
+--------------------+-----+
|          categories|count|
+--------------------+-----+
|      Historical Tours|   78|
|       Dermatologists|  351|
|       Paddleboarding|   67|
|  Mobile Home Dealers|    6|
|     Hot Air Balloons|    8|
```

```
|       Data Recovery|  141|
|       Skating Rinks|   84|
|       Videographers|  110|
|   Pet Waste Removal|   16|
|         Boat Repair|   77|
|              Fondue|   33|
|     Pet Photography|   41|
|             Beaches|   86|
|        Aerial Tours|    8|
|        Contract Law|   12|
|Faith-based Crisi...|    2|
|           Day Spas| 2356|
|        Hobby Shops|  610|
|               Reiki|  277|
|            Honduran|   12|
+--------------------+-----+
only showing top 20 rows
```

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 [13]:

```
biz_cat_sorted = biz_cat_exploded.groupby('categories').count().orderBy('count',
biz_cat_sorted.show(20)
```

```
+--------------------+-----+
|          categories|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
```

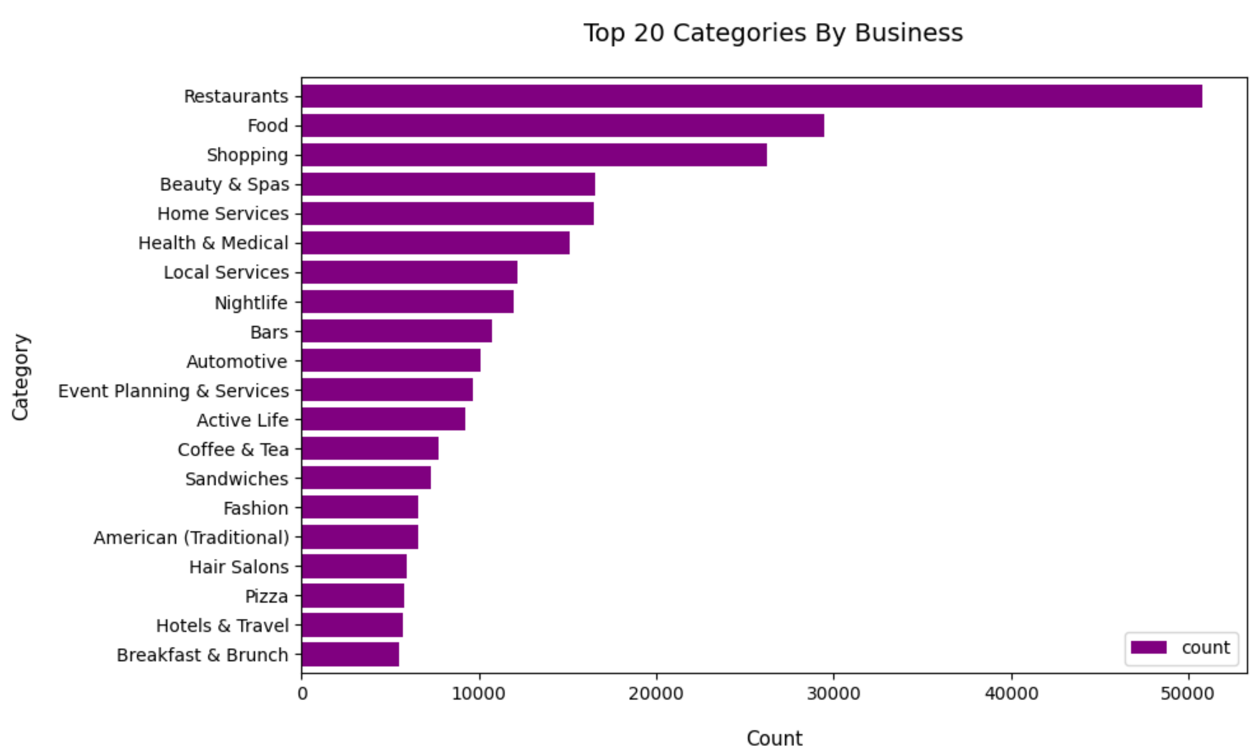
In [14]:

```
bc_top20_df = biz_cat_sorted.limit(20).toPandas()
bc_top20_df
```

```
                   categories  count
0                 Restaurants  50763
1                        Food  29469
2                    Shopping  26205
3               Beauty & Spas  16574
4               Home Services  16465
5            Health & Medical  15102
6              Local Services  12192
7                   Nightlife  11990
8                        Bars  10741
9                  Automotive  10119
10  Event Planning & Services   9644
11                Active Life   9231
12               Coffee & Tea   7725
13                 Sandwiches   7272
14                    Fashion   6599
15     American (Traditional)   6541
16                Hair Salons   5900
17                      Pizza   5756
18             Hotels & Travel   5703
19          Breakfast & Brunch   5505
```

In [15]:

```
ax = bc_top20_df.plot(kind='barh', x='categories', y='count',
            figsize=(10, 6), color = "purple", width = 0.8)
ax.set_xlabel("Count", size=11, labelpad = 15)
ax.set_ylabel("Category", size=11, labelpad = 15)
ax.set_title("Top 20 Categories By Business", size=14,pad = 20)
plt.tight_layout()
plt.gca().invert_yaxis()
%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

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

In [16]:
```
review.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]:
```
review_sub = review.select('business_id','stars')
review_sub.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_stars = review_sub.groupby('business_id').mean()
avg_stars.show(5)
```

```
+--------------------+------------------+
|         business_id|        avg(stars)|
+--------------------+------------------+
|Agq4zoNLSIpT1_ZJb...| 4.388571428571429|
|3ZVgig7uux9jVtEZn...| 4.019120458891013|
```

```
|HXYJIJ7lDhOUjaOvj...| 4.743589743589744|
|uSHEuUnh9d4kabRfs...| 3.686900958466454|
|8oz6JU_1D8PaLDNvq...|4.6521739130434785|
+--------------------+------------------+
only showing top 5 rows
```

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

In [19]:
```
biz_sub = biz.select('business_id', 'name', 'city', 'state', 'stars')
rev_biz = avg_stars.join(biz_sub, biz_sub.business_id == avg_stars.business_id)
```

Let's see a few of these:

In [20]:
```
rev_biz_new = rev_biz.select("name","city","state","avg(stars)","stars")
rev_biz_new.show(5)
```

```
+--------------------+------------+-----+------------------+-----+
|                name|        city|state|        avg(stars)|stars|
+--------------------+------------+-----+------------------+-----+
|             Safeway|   Vancouver|   WA|1.9090909090909092|  2.0|
|Cracker Barrel Ol...|Pickerington|   OH| 2.966292134831461|  3.0|
| Peaceful Restaurant|   Vancouver|   BC|  2.81981981981982|  3.0|
|       ATX Architects|      Austin|   TX|               5.0|  5.0|
|    Evergreen Eatery|      Boston|   MA| 4.524271844660194|  4.5|
+--------------------+------------+-----+------------------+-----+
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 [21]:
```
from pyspark.sql.functions import col
rev_biz2 = rev_biz_new.withColumn("skew",(col("avg(stars)") - col("stars")) / co
skew_df = rev_biz2.select('skew').toPandas()
rev_biz2.show(5)
```

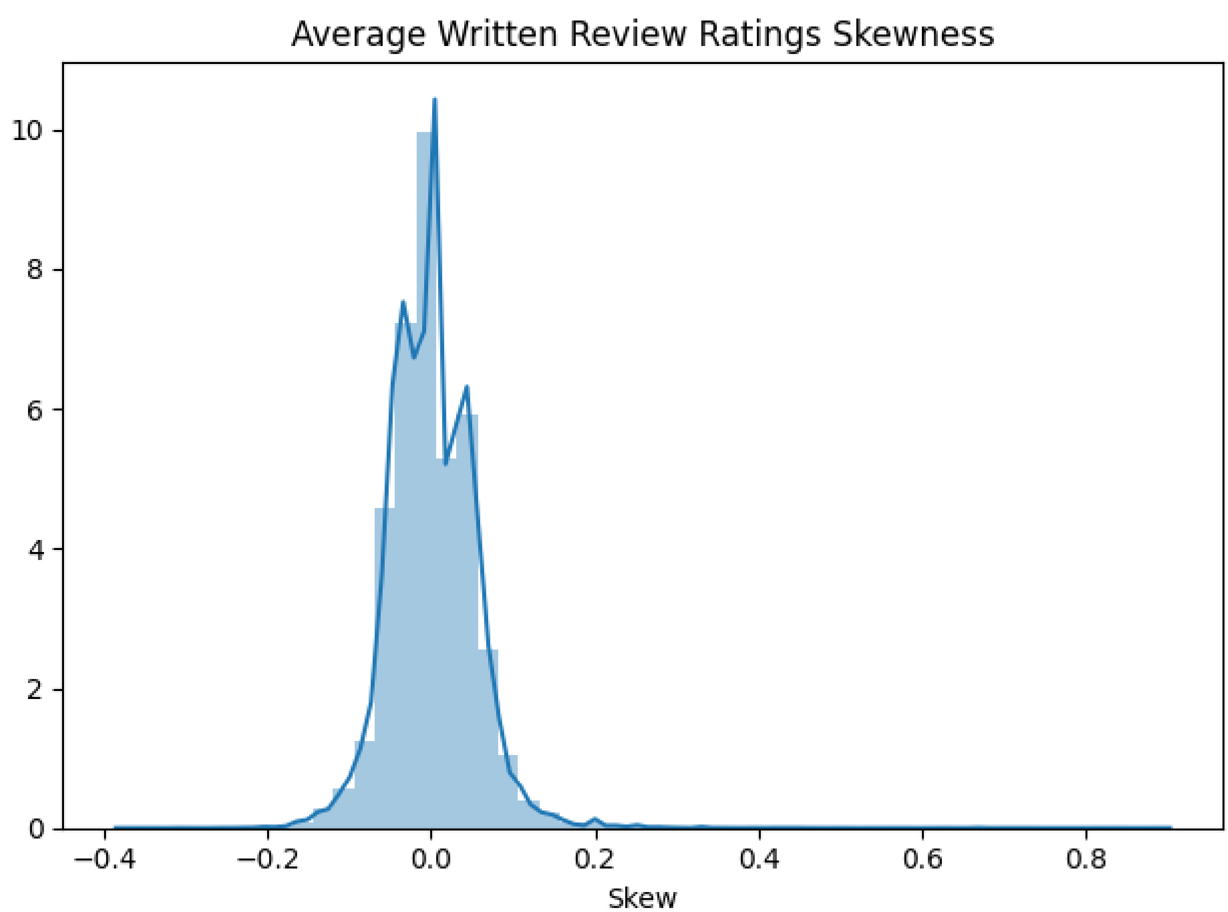
```
+--------------------+------------+-----+------------------+-----+--------------
------+
|                name|        city|state|        avg(stars)|stars|
skew|
+--------------------+------------+-----+------------------+-----+--------------
------+
|             Safeway|   Vancouver|   WA|1.9090909090909092|  2.0|-0.04545454545
```

```
454...|
|Cracker Barrel Ol...|Pickerington|   OH| 2.966292134831461|  3.0|-0.01123595505
617...|
| Peaceful Restaurant|   Vancouver|   BC|  2.81981981981982|  3.0|-0.06006006006
006004|
|      ATX Architects|      Austin|   TX|               5.0|  5.0|
0.0|
|    Evergreen Eatery|      Boston|   MA| 4.524271844660194|  4.5|0.005393743257
820876|
+--------------------+------------+-----+------------------+-----+--------------
------+
only showing top 5 rows
```

And finally, graph it!

In [47]:

```
plt.figure()
sns.distplot(skew_df)
plt.title('Average Written Review Ratings Skewness', fontsize = 12)
plt.xlabel('Skew')
plt.tight_layout()
plt.show()
%matplot plt
```



Yelp written reviews seem to be true to the business ratings. They seem to be a little more positive and satisfied than normal because the distribution is skew to the right slightly. There are some outliers as well as we can see the right tail is long but very slim.

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

Firstly, join the User and the Review table then filter out the non-elite written reviews and ratings. Secondly, join the resultant table with the Business table

In [23]:

```
elite_user = user.select("user_id","elite").filter(user.elite != "")
elite_user.show(5)
```

```
+--------------------+--------------------+
|             user_id|               elite|
+--------------------+--------------------+
|q_QQ5kBBwlCcbL1s4...|2006,2007,2008,20...|
|dIIKEfOgo0KqUfGQv...|2007,2008,2009,20...|
|D6ErcUnFALnCQN4b1...|           2010,2011|
|JnPIjvC0cmooNDfsa...|2009,2010,2011,20...|
|37Hc8hr3cw0iHLoPz...|      2009,2010,2011|
+--------------------+--------------------+
only showing top 5 rows
```

In [24]:

```
elite_review = elite_user.join(review, on = ['user_id'], how = 'left').select("u
elite_review = elite_review.withColumnRenamed('stars',"rev_stars")
elite_review.show(5)
```

```
+--------------------+--------------------+--------------------+---------+
|             user_id|           review_id|         business_id|rev_stars|
+--------------------+--------------------+--------------------+---------+
|-1KKYzibGPyUX-Mwk...|YBhfh-5jUv0IZSQp9...|ROa5tRU4lUn1ffu0H...|      5.0|
|-1KKYzibGPyUX-Mwk...|vN-espiuzK3c0PaOo...|SFqFFIA4Ks2oHfgEA...|      5.0|
|-3i9bhfvrM3F1wsC9...|XkxiFjCzXvHaWSV8F...|H6UPhaA9lVe2w07QC...|      4.0|
|-3i9bhfvrM3F1wsC9...|fg2UnEvhhHx8D6hhr...|wVTbg_ZOjqYwMNTdf...|      4.0|
|-3i9bhfvrM3F1wsC9...|lKQZOJg6nTPGaLifi...|OJqn7poj4dTCpRDDa...|      4.0|
+--------------------+--------------------+--------------------+---------+
only showing top 5 rows
```

In [25]:

```
df = elite_review.join(biz,on = ['business_id'], how = 'left').select("user_id",
df.show(5)
```

```
+--------------------+--------------------+--------------------+---------+-----+
|             user_id|           review_id|         business_id|rev_stars|stars|
+--------------------+--------------------+--------------------+---------+-----+
|-1KKYzibGPyUX-Mwk...|YBhfh-5jUv0IZSQp9...|ROa5tRU4lUn1ffu0H...|      5.0|  4.5|
```

```
|-1KKYzibGPyUX-Mwk...|vN-espiuzK3c0PaOo...|SFqFFIA4Ks2oHfgEA...|       5.0|   4.5|
|-3i9bhfvrM3F1wsC9...|XkxiFjCzXvHaWSV8F...|H6UPhaA9lVe2w07QC...|       4.0|   4.0|
|-3i9bhfvrM3F1wsC9...|lKQZOJg6nTPGaLifi...|OJqn7poj4dTCpRDDa...|       4.0|   4.0|
|-3i9bhfvrM3F1wsC9...|UKKGuKCeHf-iLg89r...|9-gSCzV0UsZuO07m6...|       5.0|   4.0|
+--------------------+--------------------+--------------------+----------+-----+
only showing top 5 rows
```

In [26]:

```
from pyspark.sql.functions import round
```

In [27]:

```
# Calculate and Round the average rating per business from elite users only
df1 = df.select("business_id","rev_stars").groupby("business_id").mean()
df1 = df1.select("business_id",round("avg(rev_stars)",1))
```

In [28]:

```
# Rename the column
df1 = df1.withColumnRenamed("round(avg(rev_stars), 1)","avg_elite_stars")
df1.columns
```

```
['business_id', 'avg_elite_stars']
```

In [29]:

```
# Create a dataframe that includes the business stars and the average elite star
df2 = df1.join(df, on = ['business_id'], how = 'left').select("business_id","sta
df2.show(5)
```

```
+--------------------+-----+---------------+
|         business_id|stars|avg_elite_stars|
+--------------------+-----+---------------+
|-36nnCT71XE0InJXK...|  2.0|            2.0|
|-QOl03c2B22yi_On0...|  3.0|            3.4|
|-VVUUPK0ytYjpJ_S7...|  3.0|            2.8|
|-ZzsPlaAgwO3yt29u...|  5.0|            5.0|
|-gdR559hH89jagbHz...|  4.5|            4.2|
+--------------------+-----+---------------+
only showing top 5 rows
```

In [30]:

```
# Number of businesses that are rated by elite users
df2.count()
```

```
130047
```

In [31]:

```
# Similarly, calculate the "skew", if the skew is positive, elite users have bet
# if the skew is negative, elite users have worse experience than normal
df3 = df2.withColumn("skew",(col("avg_elite_stars") - col("stars")) / col("stars
df4 = df3.select('skew').toPandas()
```

In [32]:

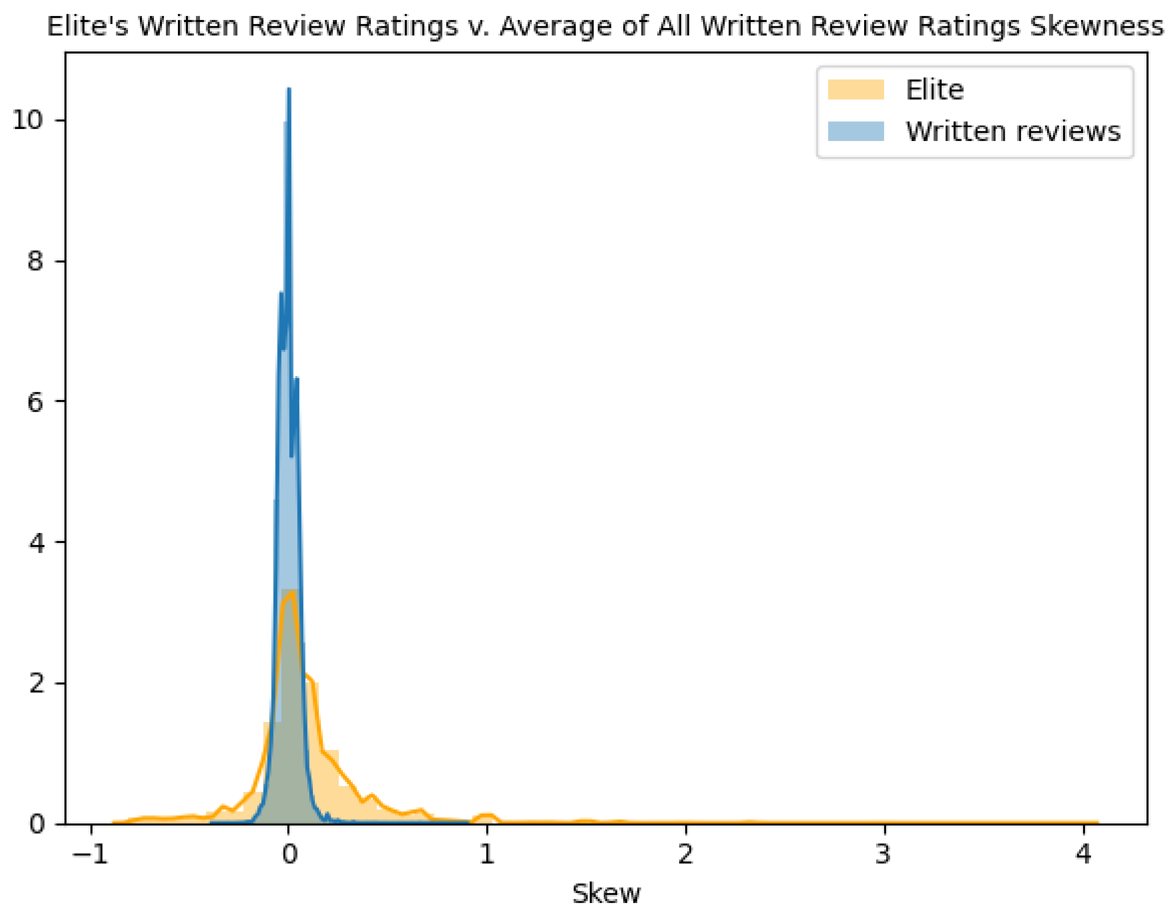
```
df4
```

```
            skew
0       0.000000
1       0.133333
2      -0.066667
3       0.000000
4      -0.066667
...          ...
130042  0.028571
130043  0.050000
130044 -0.033333
130045  0.428571
130046  1.000000

[130047 rows x 1 columns]
```

In [49]:

```
# Plot the skew on top of the skew calculated from all written reviewer to compa
plt.figure()
sns.distplot(df4, color = "orange")
sns.distplot(skew_df)
plt.title("Elite's Written Review Ratings v. Average of All Written Review Ratin
plt.xlabel('Skew')
plt.legend(["Elite","Written reviews"])
plt.tight_layout()
plt.show()
%matplot plt
```



From the distribution plot above, we can see that the ratings from elite users, who also wrote reviews, are closer to the actual business ratings because most skew values are around 0. Therefore, we should trust elite users.

The orange distribution is also right skew due to outliers; however, its right tail is not as flat as the blue distribution, which is the skew between written review ratings and business ratings. Because its right tail is thicker, it implies that most elite users had better experience than normal.