Analysis of Yelp Business Intelligence Data

Project 2 by Sofia Shur

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://cis9760-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]:
```
%%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.install_pypi_package("pandas==1.0.3")
sc.install_pypi_package("matplotlib==3.2.1")
sc.install_pypi_package("scipy==1.7.1")
sc.install_pypi_package("seaborn==0.11.2")
```

▸ Spark Job Progress

```
Starting Spark application
```

ID	YARN Application ID	Kind	State	
4	application_1651346511111_0005	pyspark	idle	Link (http://ip-172-3 2.compute.internal:20888/proxy/application_16513

```
SparkSession available as 'spark'.

Collecting pandas==1.0.3
  Using cached https://files.pythonhosted.org/packages/4a/6a/94b219b8ea0f2d
580169e85ed1edc0163743f55aaeca8a44c2e8fc1e344e/pandas-1.0.3-cp37-cp37m-many
linux1_x86_64.whl (https://files.pythonhosted.org/packages/4a/6a/94b219b8ea
0f2d580169e85ed1edc0163743f55aaeca8a44c2e8fc1e344e/pandas-1.0.3-cp37-cp37m-
manylinux1_x86_64.whl)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/sit
e-packages (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/36/7a/87837f39d0296e
723bb9b62bbb257d0355c7f6128853c78955f57342a56d/python_dateutil-2.8.2-py2.py
3-none-any.whl (https://files.pythonhosted.org/packages/36/7a/87837f39d0296
e723bb9b62bbb257d0355c7f6128853c78955f57342a56d/python_dateutil-2.8.2-py2.p
y3-none-any.whl)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-pa
ckages (from python-dateutil>=2.6.1->pandas==1.0.3)
Installing collected packages: python-dateutil, pandas
Successfully installed pandas-1.0.3 python-dateutil-2.8.2

Collecting matplotlib==3.2.1
  Using cached https://files.pythonhosted.org/packages/b2/c2/71fcf957710f3b
a1f09088b35776a799ba7dd95f7c2b195ec800933b276b/matplotlib-3.2.1-cp37-cp37m-
manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/b2/c2/71fcf9
57710f3ba1f09088b35776a799ba7dd95f7c2b195ec800933b276b/matplotlib-3.2.1-cp3
7-cp37m-manylinux1_x86_64.whl)
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/16513616853
29-0/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/d9/41/d9cfb441058980
5cd787f8a82cddd13142d9bf7449d12adf2d05a4a7d633/pyparsing-3.0.8-py3-none-an
y.whl (https://files.pythonhosted.org/packages/d9/41/d9cfb4410589805cd787f8
a82cddd13142d9bf7449d12adf2d05a4a7d633/pyparsing-3.0.8-py3-none-any.whl)
Collecting cycler>=0.10 (from matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/5c/f9/695d6bedebd747
```

```
e5eb0fe8fad57b72fdf25411273a39791cde838d5a8f51/cycler-0.11.0-py3-none-any.w
hl (https://files.pythonhosted.org/packages/5c/f9/695d6bedebd747e5eb0fe8fad
57b72fdf25411273a39791cde838d5a8f51/cycler-0.11.0-py3-none-any.whl)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib64/python3.7/si
te-packages (from matplotlib==3.2.1)
Collecting kiwisolver>=1.0.1 (from matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/51/50/9a9a94afa26c50
fc5d9127272737806990aa698c7a1c220b8e5075e70304/kiwisolver-1.4.2-cp37-cp37m-
manylinux_2_5_x86_64.manylinux1_x86_64.whl (https://files.pythonhosted.org/
packages/51/50/9a9a94afa26c50fc5d9127272737806990aa698c7a1c220b8e5075e7030
4/kiwisolver-1.4.2-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.whl)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-pa
ckages (from python-dateutil>=2.1->matplotlib==3.2.1)
Collecting typing-extensions; python_version < "3.8" (from kiwisolver>=1.0.
1->matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/75/e1/932e06004039dd
670c9d5e1df0cd606bf46e29a28e65d5bb28e894ea29c9/typing_extensions-4.2.0-py3-
none-any.whl (https://files.pythonhosted.org/packages/75/e1/932e06004039dd6
70c9d5e1df0cd606bf46e29a28e65d5bb28e894ea29c9/typing_extensions-4.2.0-py3-n
one-any.whl)
Installing collected packages: pyparsing, cycler, typing-extensions, kiwiso
lver, matplotlib
Successfully installed cycler-0.11.0 kiwisolver-1.4.2 matplotlib-3.2.1 pypa
rsing-3.0.8 typing-extensions-4.2.0

Collecting scipy==1.7.1
  Using cached https://files.pythonhosted.org/packages/b5/6b/8bc0b61ebf824f
8c3979a31368bbe38dd247590049a994ab0ed077cb56dc/scipy-1.7.1-cp37-cp37m-manyl
inux_2_5_x86_64.manylinux1_x86_64.whl (https://files.pythonhosted.org/packa
ges/b5/6b/8bc0b61ebf824f8c3979a31368bbe38dd247590049a994ab0ed077cb56dc/scip
y-1.7.1-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.whl)
Requirement already satisfied: numpy<1.23.0,>=1.16.5 in /usr/local/lib64/py
thon3.7/site-packages (from scipy==1.7.1)
Installing collected packages: scipy
Successfully installed scipy-1.7.1

Collecting seaborn==0.11.2
  Using cached https://files.pythonhosted.org/packages/10/5b/0479d7d845b5ba
410ca702ffcd7f2cd95a14a4dfff1fde2637802b258b9b/seaborn-0.11.2-py3-none-any.
whl (https://files.pythonhosted.org/packages/10/5b/0479d7d845b5ba410ca702ff
cd7f2cd95a14a4dfff1fde2637802b258b9b/seaborn-0.11.2-py3-none-any.whl)
Requirement already satisfied: numpy>=1.15 in /usr/local/lib64/python3.7/si
te-packages (from seaborn==0.11.2)
Requirement already satisfied: scipy>=1.0 in /mnt/tmp/1651361685329-0/lib/p
ython3.7/site-packages (from seaborn==0.11.2)
Requirement already satisfied: matplotlib>=2.2 in /mnt/tmp/1651361685329-0/
lib/python3.7/site-packages (from seaborn==0.11.2)
Requirement already satisfied: pandas>=0.23 in /mnt/tmp/1651361685329-0/li
b/python3.7/site-packages (from seaborn==0.11.2)
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/16513616853
29-0/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.2)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
 /mnt/tmp/1651361685329-0/lib/python3.7/site-packages (from matplotlib>=2.2
->seaborn==0.11.2)
Requirement already satisfied: cycler>=0.10 in /mnt/tmp/1651361685329-0/li
b/python3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.2)
Requirement already satisfied: kiwisolver>=1.0.1 in /mnt/tmp/1651361685329-
```

```
0/lib/python3.7/site-packages (from matplotlib>=2.2->seaborn==0.11.2)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/sit
e-packages (from pandas>=0.23->seaborn==0.11.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-pa
ckages (from python-dateutil>=2.1->matplotlib>=2.2->seaborn==0.11.2)
Requirement already satisfied: typing-extensions; python_version < "3.8" in
/mnt/tmp/1651361685329-0/lib/python3.7/site-packages (from kiwisolver>=1.0.
1->matplotlib>=2.2->seaborn==0.11.2)
Installing collected packages: seaborn
Successfully installed seaborn-0.11.2
```

Importing

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

In [3]:

```
%matplotlib inline
```

In [4]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sb
import scipy as scp
```

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 [5]:

```
business = spark.read.json('s3://project02-data/yelp_academic_dataset_busines
```

▸ Spark Job Progress

In [6]:
```
business.show(5)
```

▸ Spark Job Progress

```
+--------------------+--------------------+--------------------+-----------
---------+------------+--------------------+-------+----------+-----------
-+--------------------+-----------+------------+-----+-----+
|             address|          attributes|         business_id|          c
ategories|        city|               hours|is_open|  latitude|   longitud
e|                name|postal_code|review_count|stars|state|
+--------------------+--------------------+--------------------+-----------
---------+------------+--------------------+-------+----------+-----------
-+--------------------+-----------+------------+-----+-----+
|1616 Chapala St, ...|[,,,,,,,,,,,, True...|Pns2l4eNsfO8kk83d...|Doctors, Tr
aditio...|Santa Barbara|                null|      0|34.4266787|-119.711196
8|Abby Rappoport, L...|      93101|           7|  5.0|   CA|
|87 Grasso Plaza S...|[,,,,,,,,,, True,,...|mpf3x-BjTdTEA3yCZ...|Shipping Ce
nters,...|       Affton|[8:0-18:30, 0:0-0...|      1| 38.551126|  -90.33569
5|       The UPS Store|      63123|          15|  3.0|   MO|
|5255 E Broadway Blvd|[,,,,,,,, True,, T...|tUFrWirKiKi_TAnsV...|Department 
Stores...|       Tucson|[8:0-23:0, 8:0-22...|      0| 32.223236| -110.88045
2|              Target|      85711|          22|  3.5|   AZ|
|         935 Race St|[,, u'none',,,,, ...|MTSW4McQd7CbVtyjq...|Restaurant
s, Food...| Philadelphia|[7:0-21:0, 7:0-20...|      1|39.9555052| -75.15556
41|  St Honore Pastries|      19107|          80|  4.0|   PA|
|       101 Walnut St|[,,,,,,,, True,, T...|mWMc6_wTdE0EUBKIG...|Brewpubs, B
reweri...|   Green Lane|[12:0-22:0,, 12:0...|      1|40.3381827| -75.471658
5|Perkiomen Valley ...|      18054|          13|  4.5|   PA|
+--------------------+--------------------+--------------------+-----------
---------+------------+--------------------+-------+----------+-----------
-+--------------------+-----------+------------+-----+-----+
only showing top 5 rows
```

Overview of Data

Display the number of rows and columns in our dataset.

In [7]:
```
print(f"Number of rows in the Business table: {business.count():,}")
print(f"Number of columns in the Business table: {len(business.dtypes)}")
```

▸ Spark Job Progress

```
Number of rows in the Business table: 150,346
Number of columns in the Business table: 14
```

Display the DataFrame schema below.

In [8]:
```
business.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)
```

Display the first 5 rows with the following columns:

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

In [9]:
```
business.select("business_id", "name", "city", "state", "categories").show(5)
```

▸ Spark Job Progress

```
+--------------------+--------------------+------------+-----+------------
--------+
|         business_id|                name|        city|state|          ca
tegories|
+--------------------+--------------------+------------+-----+------------
--------+
|Pns2l4eNsfO8kk83d...|Abby Rappoport, L...|Santa Barbara|   CA|Doctors, Tra
ditio...|
|mpf3x-BjTdTEA3yCZ...|       The UPS Store|      Affton|   MO|Shipping Cen
ters,...|
|tUFrWirKiKi_TAnsV...|              Target|      Tucson|   AZ|Department S
tores...|
|MTSW4McQd7CbVtyjq...|  St Honore Pastries| Philadelphia|   PA|Restaurants,
Food...|
|mWMc6_wTdE0EUBKIG...|Perkiomen Valley ...|  Green Lane|   PA|Brewpubs, Br
eweri...|
+--------------------+--------------------+------------+-----+------------
--------+
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 [10]:
```
# Install the necessary libraries here
from pyspark.sql.functions import explode, split
```

In [11]:
```
dt = business.select("business_id", "categories")
dt.show(5)
```

▸ Spark Job Progress

```
+--------------------+--------------------+
|         business_id|          categories|
+--------------------+--------------------+
|Pns2l4eNsfO8kk83d...|Doctors, Traditio...|
|mpf3x-BjTdTEA3yCZ...|Shipping Centers,...|
|tUFrWirKiKi_TAnsV...|Department Stores...|
|MTSW4McQd7CbVtyjq...|Restaurants, Food...|
|mWMc6_wTdE0EUBKIG...|Brewpubs, Breweri...|
+--------------------+--------------------+
only showing top 5 rows
```

In [12]:
```
business_category = dt.withColumn('category',explode(split('categories',", "))

business_category= business_category.drop("categories")
```

Display the first 5 rows of your association table below.

In [13]:
```
business_category.show(5)
```

▸ Spark Job Progress

```
+--------------------+--------------------+
|         business_id|            category|
+--------------------+--------------------+
|Pns2l4eNsfO8kk83d...|             Doctors|
|Pns2l4eNsfO8kk83d...|Traditional Chine...|
|Pns2l4eNsfO8kk83d...|Naturopathic/Holi...|
|Pns2l4eNsfO8kk83d...|         Acupuncture|
|Pns2l4eNsfO8kk83d...|    Health & Medical|
+--------------------+--------------------+
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 [14]:
```
from pyspark.sql.functions import countDistinct
business_category.select(countDistinct("category")).collect()[0][0]
```

▸ Spark Job Progress

```
1311
```

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

category	count
b	2
c	45

Or something to that effect.

In [15]:

```
from pyspark.sql.functions import count, col
dt2 = business_category.groupBy("category")
dt2.count().show()
```

▸ Spark Job Progress

```
+--------------------+-----+
|            category|count|
+--------------------+-----+
|      Dermatologists|  336|
|      Paddleboarding|   98|
|        Aerial Tours|   12|
|Faith-based Crisi...|    1|
|         Hobby Shops|  552|
|          Bubble Tea|  477|
|            Handyman|  356|
|             Tanning|  667|
|      Aerial Fitness|   19|
|             Falafel|  103|
|        Summer Camps|  232|
|       Outlet Stores|  182|
|     Clothing Rental|   37|
|      Sporting Goods| 1662|
|     Cooking Schools|   76|
|  Lactation Services|   27|
|Ski & Snowboard S...|   40|
|             Museums|  413|
|              Doulas|   31|
|     Baseball Fields|   14|
+--------------------+-----+
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
```

If you want, you can also use seaborn library

In [16]:
```
top_cat = dt2.count().sort("count", ascending = False)
top_cat.show()
```

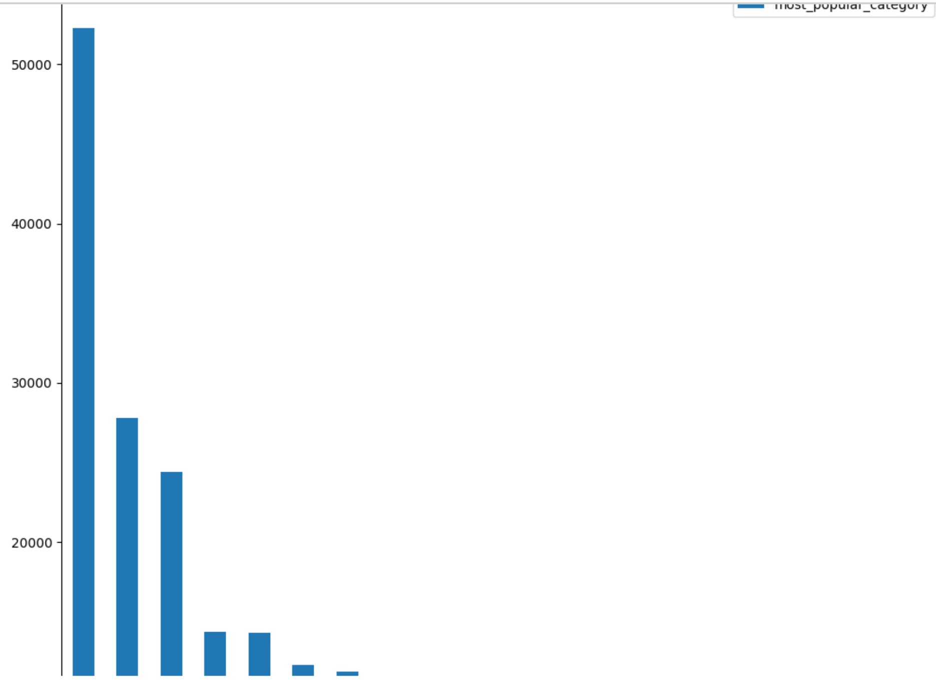
▸ Spark Job Progress

```
+--------------------+-----+
|            category|count|
+--------------------+-----+
|         Restaurants|52268|
|                Food|27781|
|            Shopping|24395|
|       Home Services|14356|
|       Beauty & Spas|14292|
|           Nightlife|12281|
|    Health & Medical|11890|
|      Local Services|11198|
|                Bars|11065|
|          Automotive|10773|
|Event Planning & ...| 9895|
|          Sandwiches| 8366|
|American (Traditi...| 8139|
|         Active Life| 7687|
|               Pizza| 7093|
|         Coffee & Tea| 6703|
|           Fast Food| 6472|
|   Breakfast & Brunch| 6239|
|      American (New)| 6097|
|     Hotels & Travel| 5857|
+--------------------+-----+
only showing top 20 rows
```

In [17]:
```
business_category.createOrReplaceTempView('Top_20')
sqldf = spark.sql(

'''
SELECT `category`, COUNT ( `category`) as most_popular_category FROM Top_20
GROUP BY `category`
ORDER BY most_popular_category DESC
LIMIT 20
'''
)
```

In [18]:
```
sqldf.toPandas().plot(kind ='bar', x ='category', figsize =(12,12))
%matplot plt
```



Loading User Data

Begin by loading the user data set from S3 and printing schema to determine what data is available. `s3://cis9760-yelpdataset/yelp-light/*review.json`

In [19]:
```
review = spark.read.json('s3://project02-data/yelp_academic_dataset_review.js
```

▸ Spark Job Progress

In [20]:
```
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 [21]:
```
user_review = review.select("business_id", "stars")
user_review.show(5)
```

▸ Spark Job Progress

```
+--------------------+-----+
|         business_id|stars|
+--------------------+-----+
|XQfwVwDr-v0ZS3_Cb...|  3.0|
|7ATYjTIgM3jUlt4UM...|  5.0|
|YjUWPpI6HXG530lwP...|  3.0|
|kxX2SOes4o-D3ZQBk...|  5.0|
|e4Vwtrqf-wpJfwesg...|  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 [22]:
```
#to check if our data has users that did not write a review.
print(f"Submitted written review: {review.filter(review.text.isNotNull()).cou
print(f"No written review submitted: {review.filter(review.text.isNull()).cou
```

▸ Spark Job Progress

```
Submitted written review: 6,990,280
No written review submitted: 0
```

In [23]:
```
avg_star = user_review.groupBy("business_id").avg("stars")
avg_star.show(5)
```

▸ Spark Job Progress

```
+--------------------+------------------+
|         business_id|        avg(stars)|
+--------------------+------------------+
|HSzSGdcNaU7heQe0N...|3.3333333333333335|
|skW4boArIApRw9DXK...|2.3947368421052633|
|zJErbOQMKX-MwHs_u...|2.9279279279279278|
|I0053JmJ5DEFUWSJ8...|2.3956043956043955|
|wS-SWAa_yaJAw6fJm...| 3.357142857142857|
+--------------------+------------------+
only showing top 5 rows
```

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

In [24]:
```
bus = business.select("business_id", "name", "city", "state", "stars")
rev = avg_star.select("business_id", "avg(stars)")
combined = bus.join(rev, bus.business_id == rev.business_id)
comb = combined.drop("business_id")
```

Let's see a few of these:

In [25]:
```
comb=comb.select("name", "city", "state", "avg(stars)","stars")
comb.show(5)
```

▸ Spark Job Progress

```
+--------------------+------------+-----+------------------+-----+
|                name|        city|state|        avg(stars)|stars|
+--------------------+------------+-----+------------------+-----+
|Philadelphia Marr...|Philadelphia|   PA|2.9279279279279278|  3.0|
|Gaetano's of West...| West Berlin|   NJ|2.8823529411764706|  3.0|
|Gillane's Bar & G...|     Ardmore|   PA|3.3333333333333335|  3.0|
|Champps Penn's La...|Philadelphia|   PA|2.3947368421052633|  2.5|
|Golden Corral Buf...|      Tucson|   AZ|2.3956043956043955|  2.5|
+--------------------+------------+-----+------------------+-----+
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 [26]:
```
comb = comb.withColumn('skew', ( comb['avg(stars)'] - comb['stars'] ) / comb[
```

In [27]:
```
comb.show(5)
```

▸ Spark Job Progress

```
+--------------------+-----------+-----+------------------+-----+---------
-----------+
|                name|       city|state|        avg(stars)|stars|
skew|
+--------------------+-----------+-----+------------------+-----+---------
-----------+
|Gillane's Bar & G...|    Ardmore|   PA|3.3333333333333335|  3.0| 0.111111
11111111116|
|Champps Penn's La...|Philadelphia|   PA|2.3947368421052633|  2.5|-0.042105
26315789469|
|Philadelphia Marr...|Philadelphia|   PA|2.9279279279279278|  3.0|-0.024024
02402402...|
|Golden Corral Buf...|     Tucson|   AZ|2.3956043956043955|  2.5|-0.041758
24175824179|
|  Swiss Watch Center|      Tampa|   FL| 3.357142857142857|  3.5|-0.040816
32653061223|
+--------------------+-----------+-----+------------------+-----+---------
-----------+
only showing top 5 rows
```

In [28]:
```
pdf = comb.select("skew")
pdf = pdf.toPandas()
pdf
```

▸ Spark Job Progress

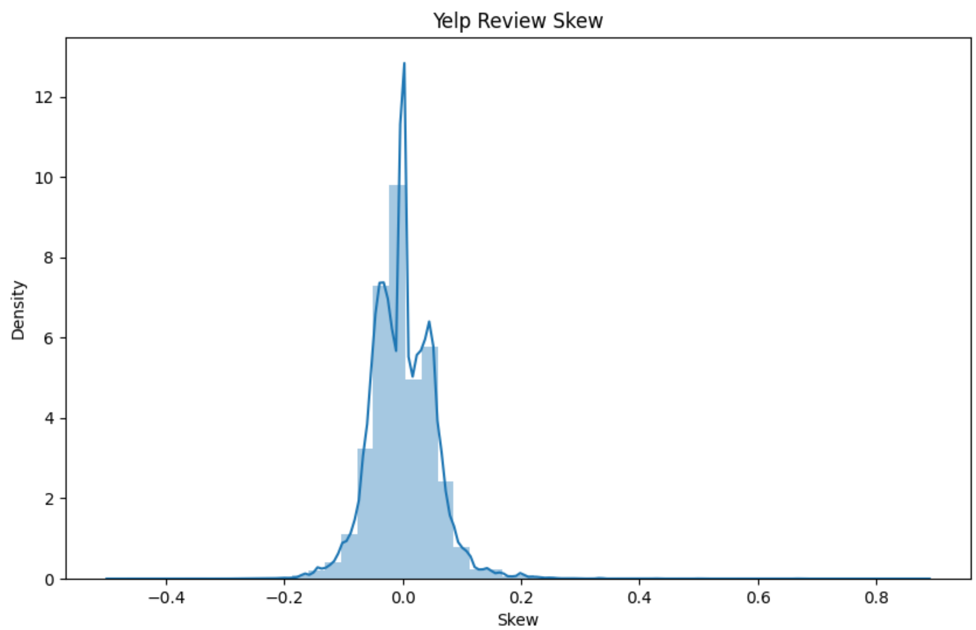
```
            skew
0      -0.024024
1      -0.039216
2       0.111111
3      -0.042105
4      -0.041758
...          ...
150341  0.000000
150342  0.000000
150343 -0.166667
150344  0.000000
150345  0.010101

[150346 rows x 1 columns]
```

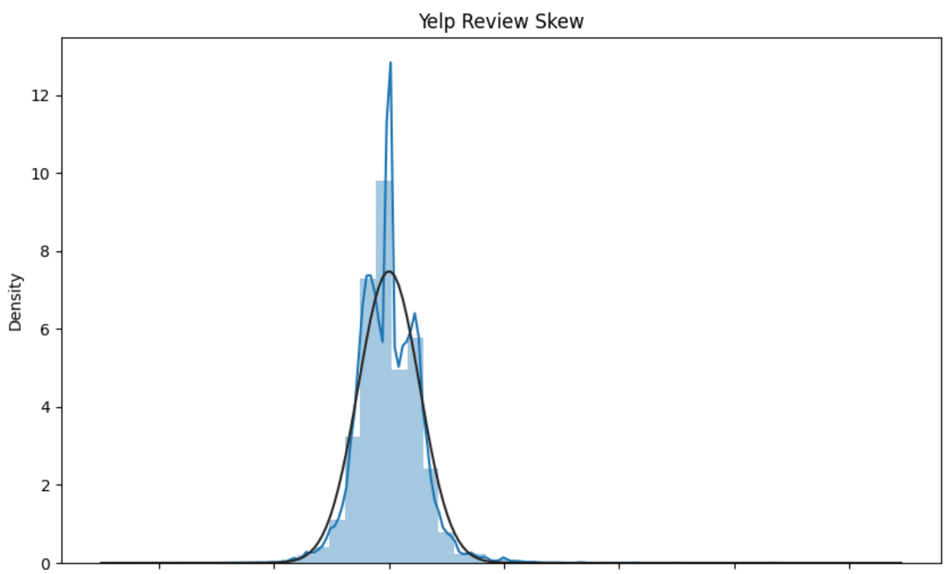
And finally, graph it!

In [29]:

```
plt.figure(figsize =(10,6))
from scipy.stats import norm
sb.distplot(pdf, axlabel='Skew', kde=True).set(title='Yelp Review Skew')
%matplot plt
```



In [30]:
```
#To check against normal distribution
plt.figure(figsize=(10,6))
from scipy.stats import norm
sb.distplot(pdf, axlabel='Skew', fit = norm, kde=True).set(title='Yelp Review
%matplot plt
```



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

ANSWER:

Yes, Yelp reviews skew negative.The distribution of written reviews/skew curve (in blue) is non-symmetric comparing to the bell-shaped curve (in black) for symmetric distribution. The plot of the Skew distribution does not have a well-defined center of data distribution that implies to a satisfaction rate differences between reviewers who wrote an actual review and reviewers who just provided a star rating. It is "skewed left" which means that reviewers who wrote an actual review are generally more pessimistic as compared to the overall business rating.

IMPLICATIONS:

Sometimes it is a more convenient way of resolving or escalating issues directly to a business owner/manager by proving feedbacks on Yelp. Hypothetically, customers who wrote an actual review probably were dissatisfied with the business and spent some time on writing a review on Yelp as a way to inform the business management. On contrary, customers that were satisfied with the business and had no issues with service/product usually have no incentives to write a good review unless it is paid or rewarded. Therefore, a slight negative difference in ratings between written reviews and "a star rating without a written review" could exist. It might not necessarily related directly to reviewers who wrote an actual review as more pessimistic. They had an incentive to write their review in order to communicate the issue to the business directly on Yelp. In this case, when the overall rating of the business is better, the business rating could be a better metric for business evaluation and customer satisfaction. My plot interpretation above requires additional data analysis on reviewers' rating and written reviews to confirm my skew graph interpretation.

Should the Elite be Trusted?

How accurate or close are the ratings of an "elite" user (check Users table schema) vs the actual business rating? `s3://cis9760-yelpdataset/yelp-light/*user.json`

Feel free to use any and all methodologies at your disposal. You must render one visualization in your analysis and interpret your findings.

In [31]:
```
user = spark.read.json('s3://project02-data/yelp_academic_dataset_user.json')
```

▸ Spark Job Progress

In [32]:
```
user.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)
```

In [33]:

```
# to filter elite users from the list of all users
user1 = user.select("user_id","average_stars", "elite", "review_count", "usef
user1.show()
```

▸ Spark Job Progress

```
+--------------------+-------------+--------------------+------------+-----
-+
|             user_id|average_stars|               elite|review_count|usefu
l|
+--------------------+-------------+--------------------+------------+-----
-+
|qVc8ODYU5SZjKXVBg...|         3.91|                2007|         585|  721
7|
|j14WgRoU_-2ZE1aw1...|         3.74|2009,2010,2011,20...|        4333| 4309
1|
|2WnXYQFK0hXEoTxPt...|         3.32|2009,2010,2011,20...|         665|  208
6|
|SZDeASXq7o05mMNLs...|         4.27|      2009,2010,2011|         224|   51
2|
|hA5lMy-EnncsH4JoR...|         3.54|                    |          79|    2
9|
|q_QQ5kBBwlCcbL1s4...|         3.85|2006,2007,2008,20...|        1221| 1495
3|
|cxuxXkcihfCbqt5By...|         2.75|                    |          12|     
6|
|E9kcWJdJUHuTKfQur...|         3.73|                    |         358|   39
9|
|lO1iq-f75hnPNZkTy...|         4.04|                    |          40|   10
9|
|AUi8MPWJ0mLkMfwbu...|          3.4|                    |         109|   15
4|
|iYzhPPqnrjJkg1JHZ...|          4.0|                    |           4|     
1|
|xoZvMJPDW6Q9pDAXI...|         3.89| 2009,2010,2011,2012|         535|  113
0|
|vVukUtqoLF5BvH_Vt...|         4.51|                    |          37|    6
3|
|_crIokUeTCHVK_JVO...|         3.08|                    |          11|    3
0|
|1McG5Rn_UDkmlkZOr...|         4.29|                    |           7|    1
8|
|SgiBkhXeqIKl1PlFp...|         3.75|2007,2008,2009,20...|         682|  181
9|
|fJZO_skqpnhk1kvom...|         4.15|                    |          25|    2
9|
|x7YtLnBW2dUnrrpwa...|         3.84|                    |          37|    5
6|
|QF1Kuhs8iwLWANNZx...|         4.11|2010,2011,2012,20...|         607|  457
3|
|VcLRGCG_VbAo8MxOm...|          3.6|                    |         133|   20
1|
+--------------------+-------------+--------------------+------------+-----
-+
only showing top 20 rows
```

In [34]:
```python
print(f"Number of rows in the user1 table: {user1.count():,}")
print(f"Number of columns in the user1 table: {len(user1.dtypes)}")
```

▸ Spark Job Progress

```
Number of rows in the user1 table: 1,987,897
Number of columns in the user1 table: 5
```

In [35]:
```python
# searching for blanks
user2 = user1.filter(user1.elite == "").sort(user1.review_count.desc())
user2.show()
```

▸ Spark Job Progress

```
+--------------------+-------------+-----+------------+------+
|             user_id|average_stars|elite|review_count|useful|
+--------------------+-------------+-----+------------+------+
|Xwnf20FKuikiHcSpc...|         3.32|     |        6766|  8348|
|ILk4dRvuBf6Axfq3q...|         3.59|     |        3381| 10950|
|sjV4NqZx5d0NqY1y7...|         4.99|     |        3332|   718|
|3xBFFH866WoySDG7u...|         3.96|     |        3204| 35967|
|gAvuqk1q2uAo2BJzZ...|         4.64|     |        3193|  9818|
|s3kRi7b8t2sdtYcsM...|         3.39|     |        2908|  1792|
|UE-rXhA8njNnADFkD...|         3.55|     |        2651|  1837|
|ES12kMOR5fdoEnSXv...|         3.38|     |        2500|  1611|
|BOU25_BWQnLdFJBKU...|         2.58|     |        2372|  3660|
|Zl1fJNTzNULZiqBRS...|          3.3|     |        2349| 10249|
|ELcQDlf69kb-ihJfx...|         3.08|     |        2337|  5208|
|kZJWAY828P8QZTqVY...|         3.69|     |        2302| 17030|
|-shHTy1CEmSMPVSeh...|         3.35|     |        2112|  1876|
|Rhvt5HoMG7mayNd43...|         4.11|     |        2109| 22573|
|RCZ5M9o2-fxgFuurp...|         3.91|     |        2103|  2728|
|_BHTC7nyCBoZcfiiD...|         3.96|     |        2098|  9839|
|yz0s55qwi_WqVjmby...|         3.31|     |        2014|  2948|
|VYOQLKuR0Ugy9lU-Q...|         3.73|     |        2002|  1709|
|Tqm7Wu7IBJ1td3Ab5...|         4.27|     |        1996| 44130|
|AyVI_VJ3My6ibiIkc...|         3.53|     |        1993|  3518|
+--------------------+-------------+-----+------------+------+
only showing top 20 rows
```

In [36]:
```
elite = user1.filter(user1.elite != "").sort(user1.review_count.desc())
elite.show()
```

▸ Spark Job Progress

```
+--------------------+------------+--------------------+------------+-----
-+
|             user_id|average_stars|               elite|review_count|usefu
l|
+--------------------+------------+--------------------+------------+-----
-+
|Hi10sGSZNxQH3NLyW...|        3.77|2014,2015,2016,20...|       17473|20629
6|
|8k3aO-mPeyhbR5HUu...|        3.35|2008,2009,2010,20...|       16978|15297
9|
|hWDybu_KvYLSdEFzG...|        3.67|2010,2011,2012,20...|       16567|17308
9|
|RtGqdDBvvBCjcu5dU...|        3.87|2012,2013,2014,20...|       12868| 1110
9|
|P5bUL3Engv-2z6kKo...|        3.81|2006,2007,2008,20...|        9941| 2754
9|
|nmdkHL2JKFx55T3nq...|        3.75|2012,2013,2014,20...|        8363| 5724
2|
|bQCHF5rn5lMI9c5kE...|        3.87|2012,2013,2014,20...|        8354| 4295
9|
|8RcEwGrFIgkt9WQ35...|        3.49|           2010,2011|        7738|  811
0|
|CxDOIDnH8gp9KXzpB...|        3.34|2009,2010,2011,20...|        6679| 2325
4|
|IucvvxdQXXhjQ4z6O...|        3.53|2009,2010,2011,20...|        6459|  823
3|
|HFECrzYDpgbS5EmTB...|        3.94|2008,2009,2010,20...|        5887| 4147
0|
|m07sy7eLtOjVdZ8oN...|        3.71|2006,2007,2008,20...|        5800| 7352
8|
|kS1MQHYwIfD0462PE...|        3.84|2008,2009,2010,20...|        5511| 1335
1|
|IlGYj_XAMG3v75rfm...|         4.2|2018,2019,20,20,2021|        5434|  326
7|
|Eypq5gLLjCapBVVnM...|        3.99|2008,2009,2010,20...|        5163|  562
0|
|U4INQZOPSUaj8hMjL...|        3.94|2008,2010,2011,20...|        5061| 3180
3|
|bLbSNkLggFnqwNNzz...|        3.43|2012,2013,2014,20...|        5014| 5825
8|
|wZPizeBxMAyOSl0M0...|        3.65|2009,2010,2011,20...|        5002| 2163
7|
|GHoG4X4FY8D8L563z...|        3.78|2013,2014,2015,20...|        4994| 3507
7|
|XYSDrIef7g4Gmp3lN...|        3.97|2007,2008,2009,20...|        4967| 1582
1|
+--------------------+------------+--------------------+------------+-----
-+
only showing top 20 rows
```

In [37]:
```
user2.count()
```

▸ Spark Job Progress

```
1896699
```

In [38]:
```
elite.count()
```

▸ Spark Job Progress

```
91198
```

In [39]:
```
elite = elite.withColumnRenamed("user_id","userid")
```

In [40]:
```
#joined on the review.json

rev1 = review.select("user_id", "business_id", "stars")
merged = elite.join(rev1, elite.userid == rev1.user_id)
```

In [41]:
```
merged.printSchema()
merged.count()
```

▸ Spark Job Progress

```
root
 |-- userid: string (nullable = true)
 |-- average_stars: double (nullable = true)
 |-- elite: string (nullable = true)
 |-- review_count: long (nullable = true)
 |-- useful: long (nullable = true)
 |-- user_id: string (nullable = true)
 |-- business_id: string (nullable = true)
 |-- stars: double (nullable = true)

1725658
```

In [42]:

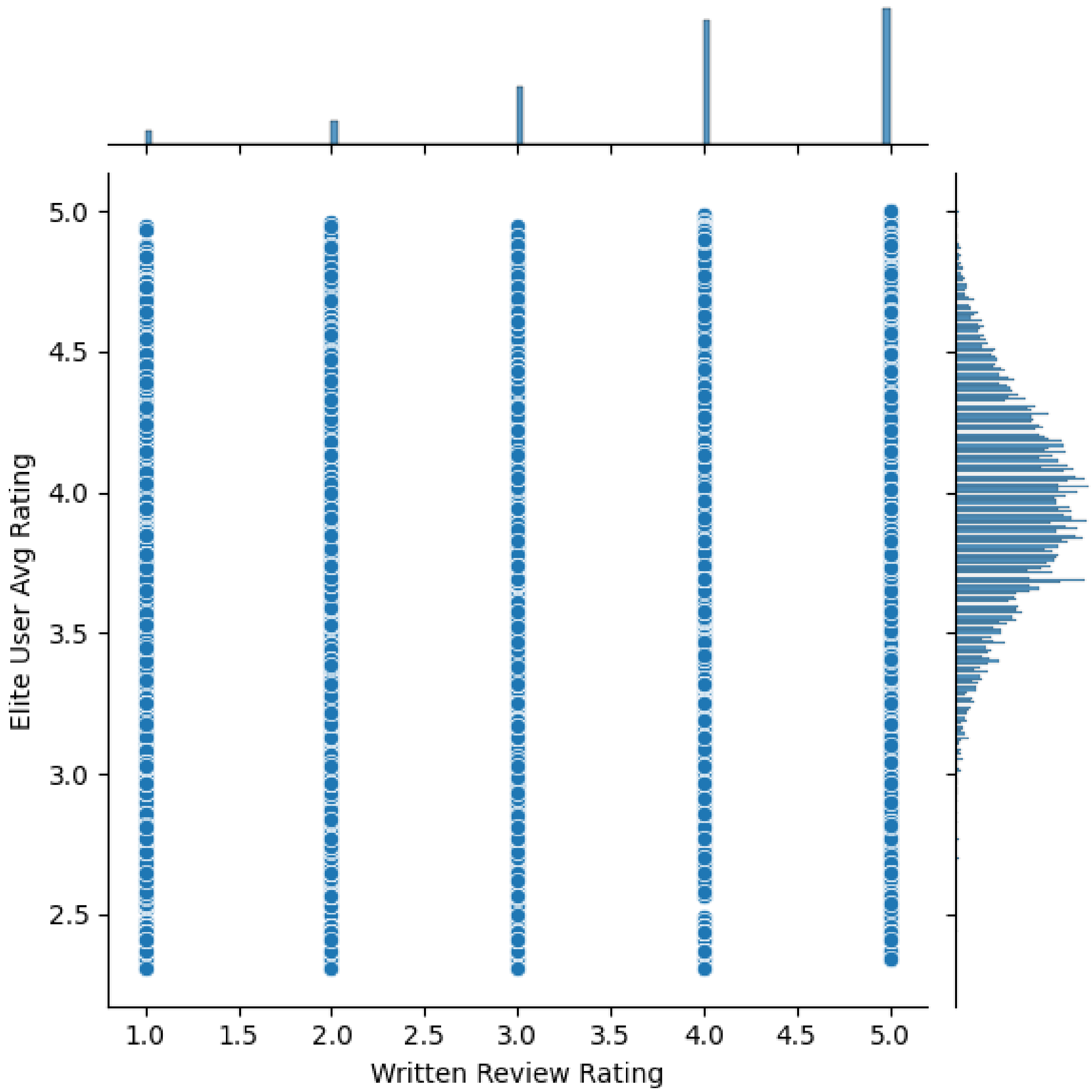
```
pl = merged.toPandas()
pl
```

▸ Spark Job Progress

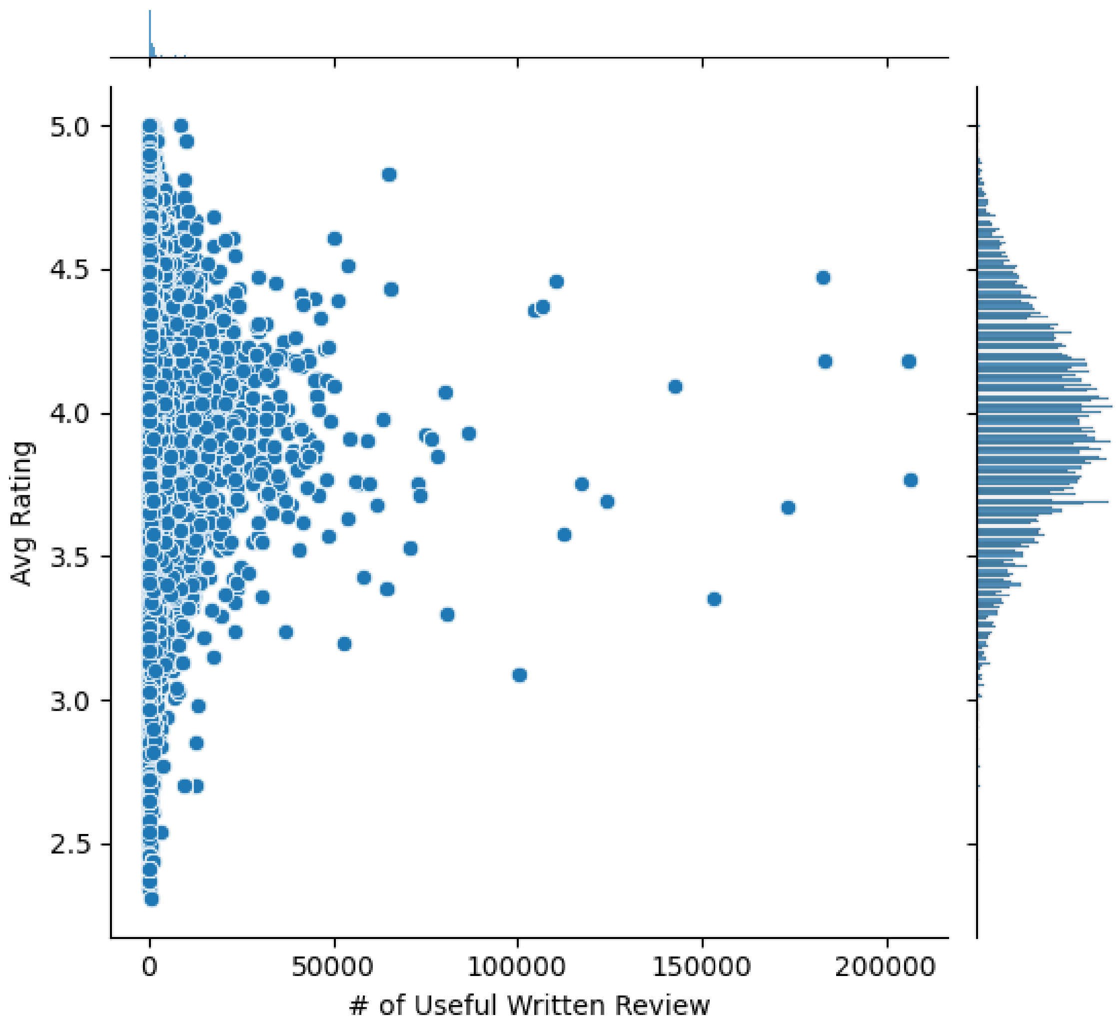
```
                      userid  average_stars  ...             business_id  
stars
0        IeSz60ozr1yAVIH8CX9w9w           4.19  ...  TV81bpCQ6p6o4Hau5hk-zw  
4.0
1        xW2A0MciHB0pLB4RHTi0nw           3.86  ...  W4ZEKkva9HpAdZG88juwyQ  
5.0
2        SSafXe2aUO0cXgQhEdtzrA           4.05  ...  E-4t5Hoon6aVFTWDPz26fQ  
5.0
3        yiYUEExKfZEv_T8CFTBGRA           3.72  ...  _pbx96FZ3eHJw-V_R4h-Vg  
3.0
4        A3EiqW7_k00gvaiQi6qWTQ           4.37  ...  8uF-bhJFgT4Tn6DTb27viA  
5.0
...                         ...            ...  ...                     ...  
...
1725653  uTV9DQUd8-8y9LvbXowzzQ           4.15  ...  K59I711q4mFXw7ZBxdwBTg  
1.0
1725654  im1piwjKBavmW1-tbqhqEw           3.69  ...  -6JdVK-DHB4_43PEksbg1A  
4.0
1725655  im1piwjKBavmW1-tbqhqEw           3.69  ...  4hwuN5Z504_EbRS1XjoXsA  
4.0
1725656  Vqgtngey014F0bqj71q0aw           3.91  ...  R1WdznjbaFJ25eaAjvjExA  
4.0
1725657  im1piwjKBavmW1-tbqhqEw           3.69  ...  z-U6eeQ4QszzXxS1fNuajQ  
4.0

[1725658 rows x 8 columns]
```

In [43]:
```
fig, ax=plt.subplots(figsize=(10,6))
sb.jointplot(pl["stars"], pl["average_stars"]).set_axis_labels(xlabel="Writte
%matplot plt
```



In [44]:
```
fig, ax=plt.subplots(figsize=(10,6))
sb.jointplot(pl["useful"], pl["average_stars"]).set_axis_labels(xlabel="# of
%matplot plt
```



In [45]:
```
merged = merged.drop("elite", "user_id")
merged.show()
```

▸ Spark Job Progress

```
+--------------------+------------+------------+------+------------------
-+-----+
|              userid|average_stars|review_count|useful|         business_i
d|stars|
+--------------------+------------+------------+------+------------------
-+-----+
|IeSz6Oozr1yAVIH8C...|        4.19|         466|   616|TV81bpCQ6p6o4Hau
5...|  4.0|
|xW2A0MciHB0pLB4RH...|        3.86|         600|  1218|W4ZEKkva9HpAdZG8
8...|  5.0|
|SSafXe2aUO0cXgQhE...|        4.05|         228|   304|E-4t5Hoon6aVFTWD
P...|  5.0|
|yiYUEExKfZEv_T8CF...|        3.72|          96|   134|_pbx96FZ3eHJw-V_
R...|  3.0|
|A3EiqW7_k00gvaiQi...|        4.37|          45|    27|8uF-bhJFgT4Tn6DT
b...|  5.0|
|Zsucq1c-sjuGxs5jZ...|        3.73|         253|   817|zaC6coZ5Gp8mLjeg
7...|  4.0|
|aX3vDE1UmbdrWeOsg...|        4.17|         197|   129|EqEcDeXqIq1YwnzH
g...|  5.0|
|aHiQYaTXrmQTeG610...|        4.13|         458|   940|3w7NRntdQ9h0KwDs
k...|  4.0|
|g34Qcj06LmCDhKzks...|        3.99|         293|  1460|yE1raqkLX7OZsjmX
3...|  5.0|
|yiYUEExKfZEv_T8CF...|        3.72|          96|   134|EP2jFD3aGoSBCWb7
i...|  4.0|
|OTG7-L3N4geWEB_0q...|        3.58|         200|   125|hS6KNGCQVTYUdLb2
e...|  4.0|
|xHU37ocClTtu1rS4L...|        4.55|          76|   145|uW8L6awmCyjovD9O
h...|  5.0|
|wwoLHw7FX0CaeOmw1...|        4.19|          84|    91|6kAXOzE7fqaBZINQ
V...|  4.0|
|Zsucq1c-sjuGxs5jZ...|        3.73|         253|   817|yLIn3po-fKb0T3UI
o...|  5.0|
|417svAEVHreK6c3SK...|        4.21|         620|  6292|oQ5CPRt0R3AzFvcj
N...|  3.0|
|qCNZXu0nA1m9_qQDS...|        3.13|         636|  1430|psI9u_iVuWFcchWh
e...|  3.0|
|wwoLHw7FX0CaeOmw1...|        4.19|          84|    91|wzE61ThXOdrSegvw
S...|  5.0|
|Zsucq1c-sjuGxs5jZ...|        3.73|         253|   817|z6SVTb9eFIcWVpKX
I...|  4.0|
|Zsucq1c-sjuGxs5jZ...|        3.73|         253|   817|hdVqM-QngiiLRaMO
v...|  5.0|
|Zsucq1c-sjuGxs5jZ...|        3.73|         253|   817|kPG6r0h73sPgXBei
0...|  4.0|
+--------------------+------------+------------+------+------------------
-+-----+
only showing top 20 rows
```

In [46]:
```
avg_star_rev = merged.groupBy("userid").avg("stars")
avg_star_rev = avg_star_rev.withColumnRenamed("userid", "user_id")
avg_star_rev.show(5)
```

▸ Spark Job Progress

```
+--------------------+------------------+
|             user_id|        avg(stars)|
+--------------------+------------------+
|IeSz6Oozr1yAVIH8C...| 4.289592760180995|
|xW2A0MciHB0pLB4RH...|3.4444444444444446|
|SSafXe2aUO0cXgQhE...| 3.884297520661157|
|yiYUEExKfZEv_T8CF...| 3.742857142857143|
|A3EiqW7_k00gvaiQi...|               5.0|
+--------------------+------------------+
only showing top 5 rows
```

In [47]:
```
merged1 = merged.select("userid", "business_id", "stars", "average_stars")
merged2 = merged.join(avg_star_rev, merged.userid == avg_star_rev.user_id)
merged2.show()
```

▸ Spark Job Progress

In [48]:
```
#elite users that have written reviews
mer = merged2.select("userid", "business_id", "avg(stars)")
mer.show(5)
```

▸ Spark Job Progress

```
+--------------------+--------------------+------------------+
|              userid|         business_id|        avg(stars)|
+--------------------+--------------------+------------------+
|IeSz6Oozr1yAVIH8C...|TV81bpCQ6p6o4Hau5...| 4.289592760180995|
|xW2A0MciHB0pLB4RH...|W4ZEKkva9HpAdZG88...|3.4444444444444446|
|SSafXe2aUO0cXgQhE...|E-4t5Hoon6aVFTWDP...| 3.884297520661157|
|yiYUEExKfZEv_T8CF...|_pbx96FZ3eHJw-V_R...| 3.742857142857143|
|A3EiqW7_k00gvaiQi...|8uF-bhJFgT4Tn6DTb...|               5.0|
+--------------------+--------------------+------------------+
only showing top 5 rows
```

In [49]:
```
bus1 = business.select("business_id", "stars")
mer1 = mer.join(bus1, mer.business_id == bus1.business_id)
```

In [50]:
```
#mer1.drop("business_id", "userid")
```

In [51]:
```
mer1.show()
```

▸ Spark Job Progress

```
+--------------------+--------------------+------------------+------------
-------+-----+
|              userid|         business_id|        avg(stars)|        busi
ness_id|stars|
+--------------------+--------------------+------------------+------------
-------+-----+
|IeSz60ozr1yAVIH8C...|TV81bpCQ6p6o4Hau5...| 4.289592760180995|TV81bpCQ6p6o4
Hau5...|  4.5|
|xW2A0MciHB0pLB4RH...|W4ZEKkva9HpAdZG88...|3.4444444444444446|W4ZEKkva9HpAd
ZG88...|  4.0|
|SSafXe2aUO0cXgQhE...|E-4t5Hoon6aVFTWDP...| 3.884297520661157|E-4t5Hoon6aVF
TWDP...|  4.0|
|yiYUEExKfZEv_T8CF...|_pbx96FZ3eHJw-V_R...| 3.742857142857143|_pbx96FZ3eHJw
-V_R...|  2.5|
|A3EiqW7_k00gvaiQi...|8uF-bhJFgT4Tn6DTb...|               5.0|8uF-bhJFgT4Tn
6DTb...|  4.5|
|Zsucq1c-sjuGxs5jZ...|zaC6coZ5Gp8mLjeg7...| 3.712328767123288|zaC6coZ5Gp8mL
jeg7...|  4.5|
|aX3vDE1UmbdrWeOsg...|EqEcDeXqIq1YwnzHg...| 4.110429447852761|EqEcDeXqIq1Yw
nzHg...|  4.5|
|aHiQYaTXrmQTeG610...|3w7NRntdQ9h0KwDsk...| 4.109181141439206|3w7NRntdQ9h0K
wDsk...|  2.0|
|g34Qcj06LmCDhKzks...|yE1raqkLX7OZsjmX3...|               4.0|yE1raqkLX7OZs
jmX3...|  4.0|
|yiYUEExKfZEv_T8CF...|EP2jFD3aGoSBCWb7i...| 3.742857142857143|EP2jFD3aGoSBC
Wb7i...|  4.0|
|OTG7-L3N4geWEB_0q...|hS6KNGCQVTYUdLb2e...|3.7777777777777777|hS6KNGCQVTYUd
Lb2e...|  3.5|
|xHU37ocClTtu1rS4L...|uW8L6awmCyjovD9Oh...| 4.391304347826087|uW8L6awmCyjov
D9Oh...|  4.5|
|wwoLHw7FX0CaeOmw1...|6kAXOzE7fqaBZINQV...| 4.113636363636363|6kAXOzE7fqaBZ
INQV...|  3.5|
|Zsucq1c-sjuGxs5jZ...|yLIn3po-fKb0T3UIo...| 3.712328767123288|yLIn3po-fKb0T
3UIo...|  4.0|
|417svAEVHreK6c3SK...|oQ5CPRt0R3AzFvcjN...| 4.071823204419889|oQ5CPRt0R3AzF
vcjN...|  4.0|
|qCNZXu0nA1m9_qQDS...|psI9u_iVuWFcchWhe...|            3.9375|psI9u_iVuWFcc
hWhe...|  2.5|
|wwoLHw7FX0CaeOmw1...|wzE61ThXOdrSegvwS...| 4.113636363636363|wzE61ThXOdrSe
gvwS...|  4.0|
|Zsucq1c-sjuGxs5jZ...|z6SVTb9eFIcWVpKXI...| 3.712328767123288|z6SVTb9eFIcWV
pKXI...|  4.0|
|Zsucq1c-sjuGxs5jZ...|hdVqM-QngiiLRaMOv...| 3.712328767123288|hdVqM-QngiiLR
aMOv...|  4.0|
|Zsucq1c-sjuGxs5jZ...|kPG6r0h73sPgXBei0...| 3.712328767123288|kPG6r0h73sPgX
Bei0...|  4.5|
+--------------------+--------------------+------------------+------------
-------+-----+
only showing top 20 rows
```

In [52]:

```
mer2 = mer1.withColumn('skew', ( mer1['avg(stars)'] - mer1['stars'] ) / mer1[
mer2.show(2)
```

▸ Spark Job Progress

```
+--------------------+--------------------+------------------+-------------
-------+-----+--------------------+
|              userid|         business_id|        avg(stars)|         busi
ness_id|stars|                skew|
+--------------------+--------------------+------------------+-------------
-------+-----+--------------------+
|IeSz60ozr1yAVIH8C...|TV81bpCQ6p6o4Hau5...| 4.289592760180995|TV81bpCQ6p6o4
Hau5...|  4.5|-0.04675716440422...|
|xW2A0MciHB0pLB4RH...|W4ZEKkva9HpAdZG88...|3.4444444444444446|W4ZEKkva9HpAd
ZG88...|  4.0|-0.13888888888888884|
+--------------------+--------------------+------------------+-------------
-------+-----+--------------------+
only showing top 2 rows
```

In [53]:

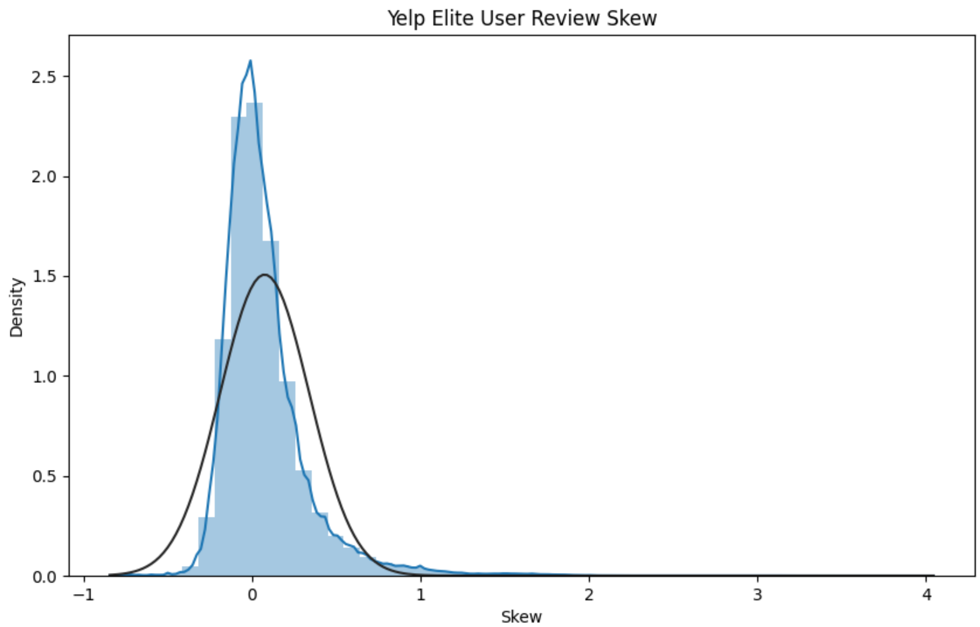
```
pd = mer2.select("skew")
pd = pd.toPandas()
pd
```

▸ Spark Job Progress

```
             skew
0       -0.046757
1       -0.138889
2       -0.028926
3        0.497143
4        0.111111
...           ...
1725653  0.346801
1725654 -0.087025
1725655 -0.087025
1725656 -0.102941
1725657  0.217300

[1725658 rows x 1 columns]
```

In [54]:
```
#To check against normal distribution
plt.figure(figsize=(10,6))
from scipy.stats import norm
sb.distplot(pd, axlabel='Skew', fit = norm, kde=True).set(title='Yelp Elite U
%matplot plt
```



FINDINGS:

No, the Elite should not be trusted based on my explanation on finding below. The first scatterplot with linear regression and marginal distributions graph shows no strong linear relationship between the Elite User's Average Rating and Written Review Rating. It shows that Elite Users write reviews with bad and good rating. It means the elite users' reviews has a normal average rating distribution. The marginal distribution displays a 5- and 4-rating written reviews represent major part of elite users writing reviews. Therefore, my previous assumption that the written reviews ratings in general are in a low rating range is incorrect for elite users data sample. The second scatter plot with linear regression and marginal distributions graph shows no strong linear relationship between the Elite User's Average Rating and their total reviews' usefulness. Similarly, the second scatter plot does not display a linear relationship between Elite User's Average Rating and their reviews' usefulness for all their written reviews. In addition, it shows that Elite users' average rate range is from 1 to 5 have been useful with their written comments to some extent. However, there are more written reviews that have been useful from the Elite users that have an average rating between 3.5 and 4.5. The majority of reviews have been written by Elite users that have a low record of total usefulness as indicates the marginal distribution figure. Therefore, Elite users have more positive written reviews. The Elite users' skew graph is more "skewed right" which means that Elite reviewers who wrote an actual review are generally more optimistic as compared to the overall business rating. This contradiction in comparative analysis on written reviews between Elite users and all users requires additional analysis to understand the trend and outliers.

IMPLICATIONS:

Comparative analysis is necessary in order to confirm if Elite users are trustworthy, we need to compare rating distribution, usefulness and its' relationship from other users to Elite users. It will help to rule out Elite users' bias on written reviews.

Extra Credit (3 points)

What users (elite or non-elite) provide useful reviews and are trustworth?

Try and analyze some interesting dimension to this data. **Requirements:**

You must use the **Users** dataset and join on either the "**business** or **reviews** dataset.

You must render **one visual**

Since the elite users have provided mostly 4 and 5-rating written reviews as above analysis, it makes sense to compare relationship of usefulness of written comment, total number of comments per user with a review rating to support the creditability of the elite and non-elite reviewers.

In [55]:
```
rev_use = review.select("user_id","review_id", "stars", "useful")
rev_use = rev_use.withColumnRenamed("useful","review_useful")
rev_use = rev_use.withColumnRenamed("star","review_star")
```

In [56]:
```
users = user2.withColumnRenamed("user_id","userid")
```

In [57]:
```
#joined on the review for elite users
elite_user = elite.join(rev_use, elite.userid == rev_use.user_id)
```

In [58]:
```
#joined on the review for other users but not elite
other_user = users.join(rev_use, users.userid == rev_use.user_id)
```

In [59]:
```
#Threshold for users with >1000 written reviews
elite_user_treshold = elite_user.filter(elite_user.review_count > '1000').sor
other_user_treshold = other_user.filter(other_user.review_count > '1000').sor
```

In [60]:
```
#calculate the ratio of useful reviews count and total # of written reviews f
elite_ratio = elite_user_treshold.withColumn('ratio of useful/ttl reviews', (
```

In [61]:
```
io of useful review count and total # of written reviews for non-elite users
_user_treshold.withColumn('ratio of useful/ttl reviews', ( other_user_treshol
```

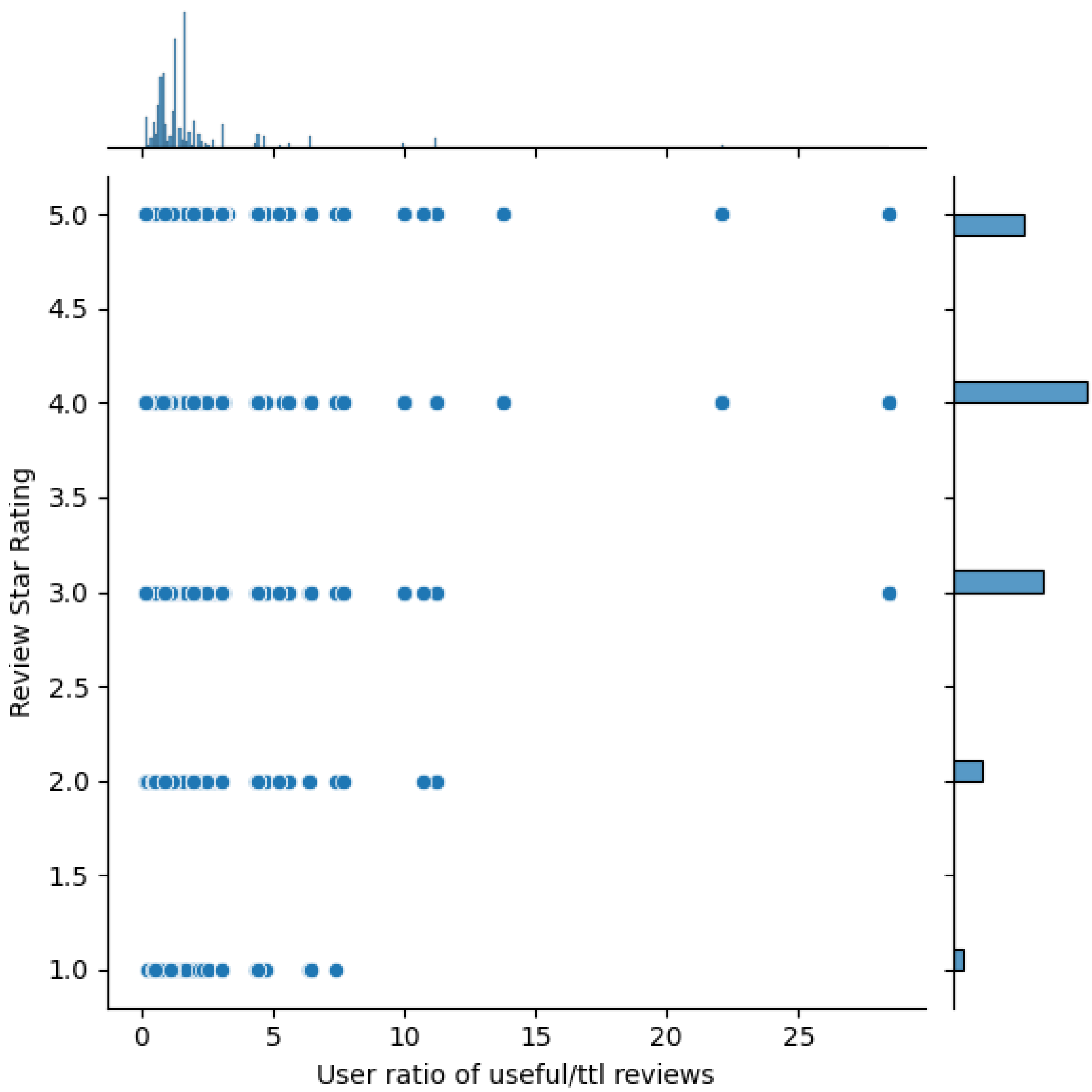
In [62]:
```
elite_tb = elite_ratio.select("ratio of useful/ttl reviews", "stars")
users_tb = users_ratio.select("ratio of useful/ttl reviews", "stars")
```

In [63]:
```
elite_tb1 = elite_tb.toPandas()
users_tb1 = users_tb.toPandas()
```

Spark Job Progress

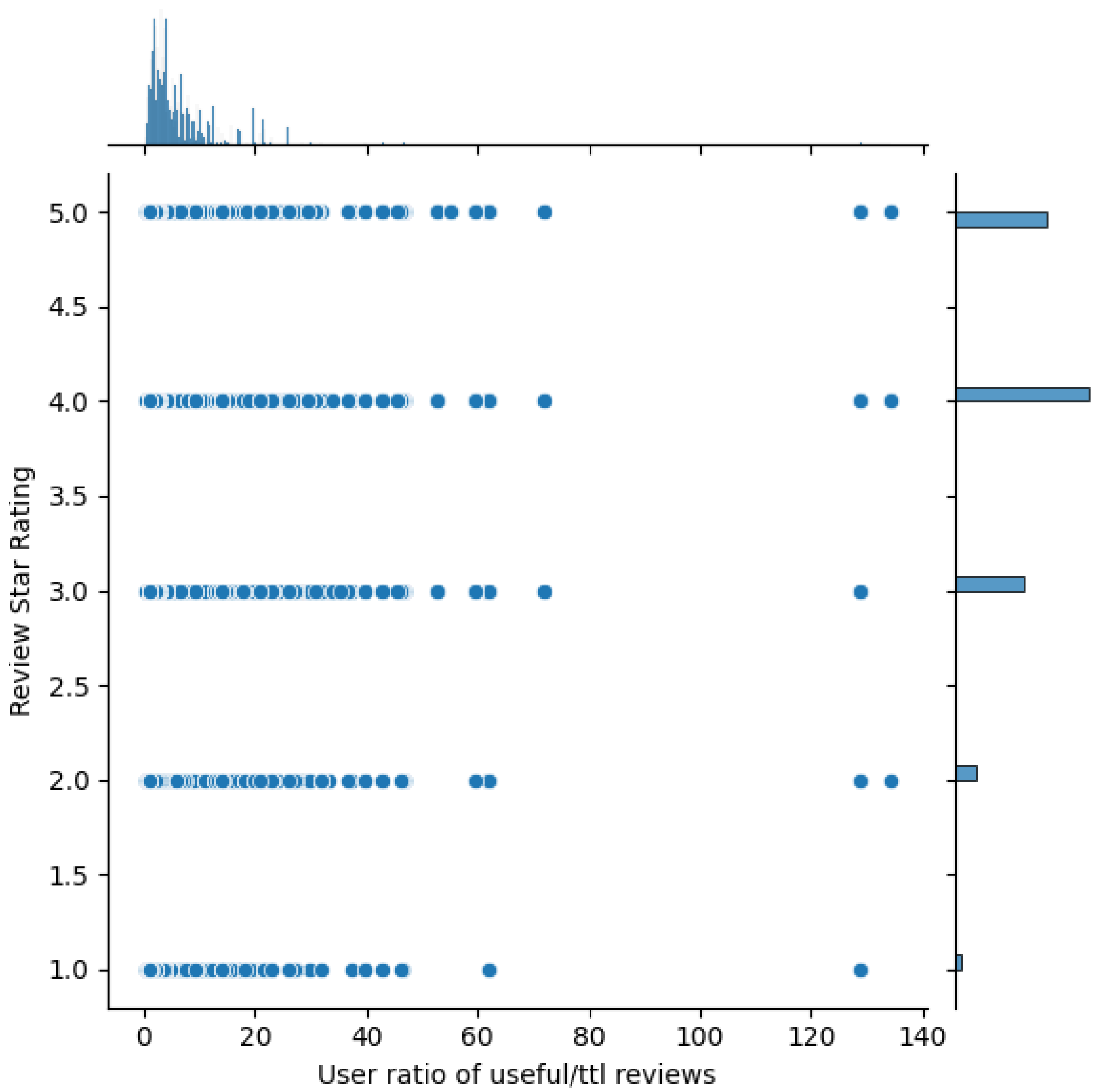
In [66]:

```
# comparative visualization Elite users vs Non-elite users
fig, ax=plt.subplots(figsize=(10,6))
sb.jointplot(users_tb1["ratio of useful/ttl reviews"], users_tb1["stars"]).se
%matplot plt
```



In [67]:

```
fig, ax=plt.subplots(figsize=(10,6))
sb.jointplot(elite_tb1["ratio of useful/ttl reviews"], elite_tb1["stars"]).se
%matplot plt
```



FINDINGS/CONCLUSION:

On x-axis is a ratio of useful reviews total count and total # of written reviews for that specific user (the higher the ratio, more useful reviews the user provided in total) On y-axis is a star rating for each review.

The first figure for non-elite users demonstrates that their reviews mostly are a 4-star rating. These users did not provide many useful reviews historically. The threshold for the users with a ratio on useful reviews historically is from 8 to 11. This demonstrates that non-elite users with a low ration of useful reviews historically tend to write a 4-star review more often. Mostly non-elite users that have historically the lowest ratio on review usefulness have written reviews with a 1-star rating. Only a few Non-elite reviewers that historically have the highest ratio on useful reviews did not write any a 1-star rating reviews. Therefore, non-elite reviewers leave a good rating review more often and less frequently a low rating review. All these non-elite users’ reviews do not demonstrate a high level of usefulness on average historically.

The second figure for Elite users demonstrates that their reviews mostly are a 4-star rating same as with non-elite reviewers. Elite users have provided many useful reviews historically comparing to non-elite users. The threshold for the Elite users with a ratio on useful reviews historically is from 50 to 60. This demonstrates that Elite reviewers tend to leave a good review and bad reviews that are more useful to others users.

In conclusion, this analysis provides some information that highlights that the Elite users have more creditability and can be trusted on their reviews.