# 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 [3]:
```
%%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'}`

| ID | YARN Application ID | Kind | State | Spark UI | Driver log | Current session? |
|---|---|---|---|---|---|---|
| 0 | application_1606234114126_0001 | pyspark | idle | Link | Link | ✔ |

In [1]:
```
sc.install_pypi_package("pandas==1.0.3")
```

```
Starting Spark application
```

| ID | YARN Application ID | Kind | State | Spark UI | Driver log | Current session? |
|---|---|---|---|---|---|---|
| 1 | application_1606234114126_0002 | pyspark | idle | Link | Link | ✔ |

```
SparkSession available as 'spark'.

Collecting pandas==1.0.3
  Using cached https://files.pythonhosted.org/packages/4a/6a/94b219b8ea0f2d580169e85ed1edc0163743f55aaeca8a44c2e8fc1e344e/pandas-1.0.3-cp37-cp37
m-manylinux1_x86_64.whl
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/site-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/d4/70/d60450c3dd48ef87586924207ae8907090de0b306af2bce5d134d78615cb/python_dateutil-2.8.1-
py2.py3-none-any.whl
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (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/c2/71fcf957710f3ba1f09088b35776a799ba7dd95f7c2b195ec800933b276b/matplotlib-3.2.1-cp37-
cp37m-manylinux1_x86_64.whl
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1606235528082-0/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/488841f56197b13700afd5658fc279a2025a39e22449b7cf29864669b15d/pyparsing-2.4.7-py2.py
3-none-any.whl
Collecting cycler>=0.10 (from matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/f7/d2/e07d3ebb2bd7af696440ce7e754c59dd546ffe1bbe732c8ab68b9c834e61/cycler-0.10.0-py2.py3-
none-any.whl
Requirement already satisfied: numpy>=1.11 in /usr/local/lib64/python3.7/site-packages (from matplotlib==3.2.1)
Collecting kiwisolver>=1.0.1 (from matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/d2/46/231de802ade4225b76b96cffe419cf3ce52bbe92e3b092cf12db7d11c207/kiwisolver-1.3.1-cp37-
cp37m-manylinux1_x86_64.whl
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (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==0.10.0")
```

```
Collecting seaborn==0.10.0
  Using cached https://files.pythonhosted.org/packages/70/bd/5e6bf595fe6ee0f257ae49336dd180768c1ed3d7c7155b2fdf894c1c808a/seaborn-0.10.0-py3-non
e-any.whl
Requirement already satisfied: pandas>=0.22.0 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from seaborn==0.10.0)
Requirement already satisfied: numpy>=1.13.3 in /usr/local/lib64/python3.7/site-packages (from seaborn==0.10.0)
Collecting scipy>=1.0.1 (from seaborn==0.10.0)
  Using cached https://files.pythonhosted.org/packages/dc/7e/8f6a79b102ca1ea928bae8998b05bf5dc24a90571db13cd119f275ba6252/scipy-1.5.4-cp37-cp37m
-manylinux1_x86_64.whl
Requirement already satisfied: matplotlib>=2.1.2 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from seaborn==0.10.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/site-packages (from pandas>=0.22.0->seaborn==0.10.0)
Requirement already satisfied: python-dateutil>=2.6.1 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from pandas>=0.22.0->seaborn==0.1
0.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from matplotlib
>=2.1.2->seaborn==0.10.0)
Requirement already satisfied: cycler>=0.10 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from matplotlib>=2.1.2->seaborn==0.10.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /mnt/tmp/1606235528082-0/lib/python3.7/site-packages (from matplotlib>=2.1.2->seaborn==0.10.
0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (from python-dateutil>=2.6.1->pandas>=0.22.0->seaborn==0.10.0)
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 [4]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

## 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]:
```
df = spark.read.json('s3://sta9760-project2-dataset/yelp_academic_dataset_business.json')
```

## Overview of Data

Display the number of rows and columns in our dataset.

In [6]:
```
print(f'Columns: {len(df.dtypes)}', '|', f'Rows: {df.count():,}')
```

```
Columns: 14 | Rows: 209,393
```

In [7]:
```
df.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 [8]:
```
df.select('business_id','name','city','state','stars','categories').show(5)
```

```
+--------------------+--------------------+---------------+-----+-----+--------------------+
|         business_id|                name|           city|state|stars|          categories|
+--------------------+--------------------+---------------+-----+-----+--------------------+
|f9NumwFMBDn751xgF...|The Range At Lake...|      Cornelius|   NC|  3.5|Active Life, Gun/...|
```

```
|Yzvjg0SayhoZgCljU...|   Carlos Santo, NMD|     Scottsdale|   AZ|  5.0|Health & Medical,...|
|XNoUzKckATkOD1hP6...|             Felinus|       Montreal|   QC|  5.0|Pets, Pet Service...|
|6OAZjbxqM5ol29BuH...|Nevada House of Hose|North Las Vegas|   NV|  2.5|Hardware Stores, ...|
|51M2Kk903DFYI6gnB...|USE MY GUY SERVIC...|           Mesa|   AZ|  4.5|Home Services, Pl...|
+--------------------+--------------------+---------------+-----+-----+--------------------+
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 | categories |
|---|---|
| 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 [9]:
```
from pyspark.sql.functions import explode, split
```

In [10]:
```
fdf = df.withColumn('category',explode(split('categories',", ")))
```

In [11]:
```
fdf.select('business_id','category').show(5)
```

```
+--------------------+----------------+
|         business_id|        category|
+--------------------+----------------+
|f9NumwFMBDn751xgF...|     Active Life|
|f9NumwFMBDn751xgF...|Gun/Rifle Ranges|
|f9NumwFMBDn751xgF...|     Guns & Ammo|
|f9NumwFMBDn751xgF...|        Shopping|
|Yzvjg0SayhoZgCljU...|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 [12]:
```
fdf.select('category').distinct().count()
```

```
1336
```

# 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 |

| category | count |
|---|---|
| c | 45 |

Or something to that effect.

In [13]:
```
fdf.groupby('category').count().show()
```

```
+--------------------+-----+
|            category|count|
+--------------------+-----+
|      Dermatologists|  341|
|      Paddleboarding|   36|
|        Aerial Tours|   28|
|         Hobby Shops|  828|
|          Bubble Tea|  720|
|             Embassy|   13|
|            Handyman|  682|
|             Tanning|  938|
|      Aerial Fitness|   29|
|             Tempura|    1|
|             Falafel|  159|
|       Outlet Stores|  399|
|        Summer Camps|  318|
|     Clothing Rental|   55|
|      Sporting Goods| 2311|
|     Cooking Schools|  118|
|  College Counseling|   15|
|  Lactation Services|   50|
|Ski & Snowboard S...|   50|
|             Museums|  359|
+--------------------+-----+
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
```

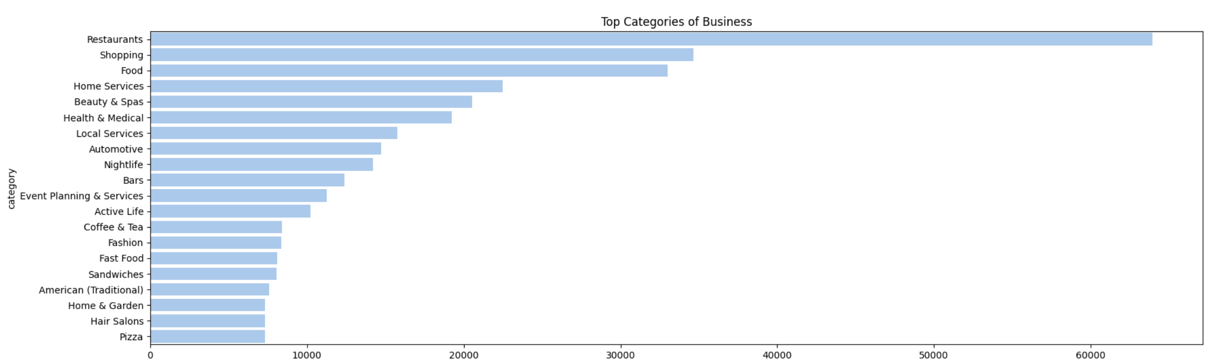
In [14]:
```
cdf=fdf.groupby('category').count().orderBy('count',ascending=False)
```

In [15]:
```
cdf=cdf.toPandas()
```

In [16]:
```
plt.figure(figsize=(20,6))
sns.set_color_codes("pastel")
sns.barplot(x="count", y="category", data=cdf.head(20),color="b")
```

```
<matplotlib.axes._subplots.AxesSubplot object at 0x7f98e41edad0>
```

In [17]:
```
plt.title("Top Categories of Business")
%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 [18]:
```
df2 = spark.read.json('s3://sta9760-project2-dataset/yelp_academic_dataset_review.json')
```

In [19]:
```
df2.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 [20]:
```
df2.select('business_id','stars').show(5)
```

```
+--------------------+-----+
|         business_id|stars|
+--------------------+-----+
|-MhfebM0QIsKt87iD...|  2.0|
|lbrU8StCq3yDfr-QM...|  1.0|
|HQl28KMwrEKHqhFrr...|  5.0|
|5JxlZaqCnk1MnbgRi...|  1.0|
|IS4cv902ykd8wj1TR...|  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 [21]:
```
df2.createOrReplaceTempView("YELP")
fdf2=spark.sql('select business_id,avg(stars) from YELP group by business_id')
```

In [22]:
```
fdf2.show(5)
```

```
+--------------------+------------------+
|         business_id|        avg(stars)|
+--------------------+------------------+
|RMjCnixEY5i12Ciqn...|3.5316455696202533|
|VHsNB3pdGVcRgs6C3...| 3.411764705882353|
|kpbhERZoj1eTDRnMV...| 2.033333333333333|
|ipFreSFhjClfNETuM...|               2.6|
|9A_mB7Ez3RIh26EN5...|               2.6|
+--------------------+------------------+
only showing top 5 rows
```

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

In [23]:
```
fdf2.createOrReplaceTempView("AVG")
df.createOrReplaceTempView("BUSINESS")
join_df_df2=spark.sql('select distinct * from BUSINESS b,AVG a where b.business_id=a.business_id ')
```

In [24]:
```
join_df_df2.select('avg(stars)','stars','name','city','state').show(5)
```

```
+----------------+-----+--------------------+---------+-----+
|      avg(stars)|stars|                name|     city|state|
+----------------+-----+--------------------+---------+-----+
|4.11784140969163|  4.0|Delmonico Steakhouse|Las Vegas|   NV|
|             4.5|  4.5|Mr. Pancho Mexica...|     Mesa|   AZ|
|            3.75|  4.0|Maricopa County D...|  Phoenix|   AZ|
|             4.0|  4.0|Double Play Sport...|Las Vegas|   NV|
|          2.6875|  2.5|  Impressions Dental| Chandler|   AZ|
+----------------+-----+--------------------+---------+-----+
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']

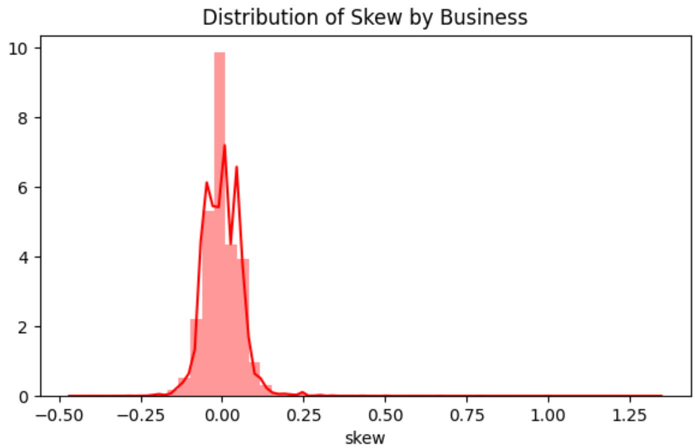
If the **skew** is negative, we can interpret that to be: reviewers who left a written response were more dissatisfied than normal. If skew is positive, we can interpret that to be: reviewers who left a written response were more satisfied than normal.

In [25]:
```
skew_df=join_df_df2.withColumn('skew', (join_df_df2['avg(stars)'] - join_df_df2['stars']) / join_df_df2['stars'] )
```

And finally, graph it!

In [26]:
```
ndf=skew_df.toPandas()
```

In [41]:
```
f= plt.figure(figsize=(7,3.9))
ax=sns.distplot(ndf['skew'],color='red')
ax.set_title('Distribution of Skew by Business')
%matplot plt
```




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

## 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

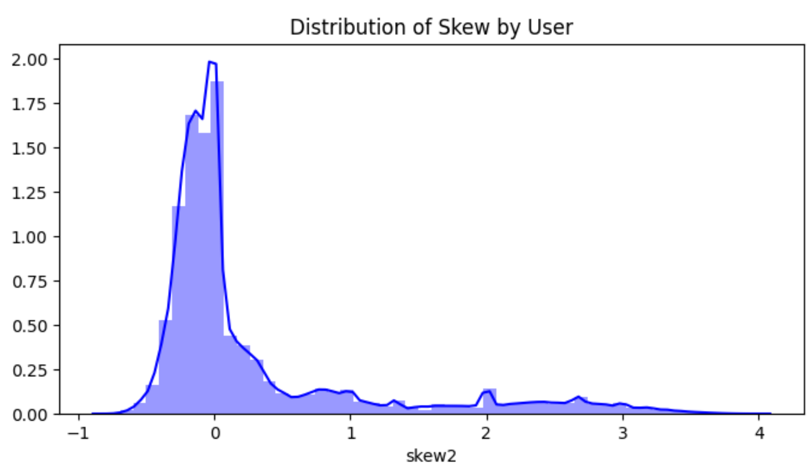
In [42]:
```
df3 = spark.read.json('s3://sta9760-project2-dataset/yelp_academic_dataset_user.json')
```

In [43]:
```
df3.createOrReplaceTempView("USER")
df2.createOrReplaceTempView("REVIEW")
join_user_review=spark.sql('select distinct * from REVIEW r,USER u where r.user_id=u.user_id ')
```

In [44]:
```
skew2_df=join_user_review.withColumn('skew2', (join_user_review['average_stars'] - join_user_review['stars']) / join_user_review['stars'] )
```

In [45]:
```
ndf2=skew2_df.select('average_stars','stars','skew2').toPandas()
```

In [46]:
```
f= plt.figure(figsize=(8,4))
ax1=sns.distplot(ndf2['skew2'],color='blue')
ax1.set_title('Distribution of Skew by User')
%matplot plt
```




In [ ]: