# 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]:
```
%%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_1637602997939_0001 | pyspark | dead | Link | Link | |

In [2]:
```
sc.install_pypi_package("pandas==1.0.3")
sc.install_pypi_package("matplotlib==3.2.1")
#sc.install_pypi_package("seaborn==0.11.2")
```

```
Starting Spark application
```

| ID | YARN Application ID | Kind | State | Spark UI | Driver log | Current session? |
|---|---|---|---|---|---|---|
| 1 | application_1637602997939_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-cp37m-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/36/7a/87837f39d0296e723bb9b62bbb257d0355c7f6128853c78955f57342a56
d/python_dateutil-2.8.2-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-2.8.2

Collecting matplotlib==3.2.1
  Using cached https://files.pythonhosted.org/packages/b2/c2/71fcf957710f3ba1f09088b35776a799ba7dd95f7c2b195ec800933b276
b/matplotlib-3.2.1-cp37-cp37m-manylinux1_x86_64.whl
Requirement already satisfied: python-dateutil>=2.1 in /mnt/tmp/1637603946154-0/lib/python3.7/site-packages (from matplo
tlib==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/a0/34/895006117f6fce0b4de045c87e154ee4a20c68ec0a4c9a36d900888fb6b
c/pyparsing-3.0.6-py3-none-any.whl
Collecting cycler>=0.10 (from matplotlib==3.2.1)
  Using cached https://files.pythonhosted.org/packages/5c/f9/695d6bedebd747e5eb0fe8fad57b72fdf25411273a39791cde838d5a8f5
1/cycler-0.11.0-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/09/6b/6e567cb2e86d4e5939a9233f8734e26021b6a9c1bc4b1edccba236a84cc
2/kiwisolver-1.3.2-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.whl
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/site-packages (from python-dateutil>=2.1->matplotlib
==3.2.1)
Installing collected packages: pyparsing, cycler, kiwisolver, matplotlib
Successfully installed cycler-0.11.0 kiwisolver-1.3.2 matplotlib-3.2.1 pyparsing-3.0.6
```

# Importing

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

In [3]:

```
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 [4]:
```
business = spark.read.json('s3://sta9760yelpdataset/yelp/yelp_academic_dataset_business.json')
review = spark.read.json('s3://sta9760yelpdataset/yelp/yelp_academic_dataset_review.json')
```

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

```
+-------------------+--------------------+--------------------+--------------------+-----------+--------------------+---
----+-------------+---------------+--------------------+-----------+------------+-----+-----+
|            address|          attributes|         business_id|          categories|       city|               hours|is_
open|     latitude|      longitude|                name|postal_code|review_count|stars|state|
+-------------------+--------------------+--------------------+--------------------+-----------+--------------------+---
----+-------------+---------------+--------------------+-----------+------------+-----+-----+
|       921 Pearl St|[,, 'beer_and_win...|6iYb2HFDywm3zjuRg...|Gastropubs, Food,...|    Boulder|[11:0-23:0, 11:0-...|
1|   40.0175444|   -105.2833481| Oskar Blues Taproom|      80302|          86|  4.0|   CO|
|7000 NE Airport Way|[,, u'beer_and_wi...|tCbdrRPZA0oiIYSmH...|Salad, Soup, Sand...|   Portland|[5:0-18:0, 5:0-18...|
1|45.5889058992|-122.5933307507|Flying Elephants ...|      97218|         126|  4.0|   OR|
| 4720 Hawthorne Ave|[,,,,,,, False,, ...|bvN78flM8NLprQ1a1...|Antiques, Fashion...|   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, Ha...|Orange City|                null|
1|   28.9144823|    -81.2959787|         Great Clips|      32763|           8|  3.0|   FL|
|1046 Memorial Dr SE|[,,,,,,,,, True, ...|PE9uqAjdw0E4-8mjG...|Gyms, Active Life...|    Atlanta|[16:0-19:0, 16:0-...|
1|   33.7470274|    -84.3534244|   Crossfit 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 [6]:
```
print(f"Number of columns in Business table: {len(business.columns)}")
print(f"Number of rows in Business table: {business.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 Review table: 9
Number of rows in Review table: 8635403
```

Display the DataFrame schema below.

In [7]:
```
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 [8]:

```
business.select("business_id","name","city","state","categories").show(5)
```

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

| business_id | category |
|---|---|
| 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]:
```
business_sel = business.select("business_id","categories")
business_sel.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 [11]:
```
business_sel_explod = business_sel.withColumn('categories',explode(split('categories',', ')))
business_sel_explod.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 [12]:

```
business_sel_explod.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 [13]:

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

```
+--------------------+-----+
|          categories|count|
+--------------------+-----+
|      Dermatologists|  351|
|      Paddleboarding|   67|
|        Aerial Tours|    8|
|         Hobby Shops|  610|
|          Bubble Tea|  779|
|             Embassy|    9|
|             Tanning|  701|
|            Handyman|  507|
|      Aerial Fitness|   13|
|             Falafel|  141|
|       Outlet Stores|  184|
|        Summer Camps|  308|
|     Clothing Rental|   37|
|      Sporting Goods| 1864|
|     Cooking Schools|  114|
|  College Counseling|   20|
|  Lactation Services|   47|
|Ski & Snowboard S...|   55|
|             Museums|  336|
|     Baseball Fields|   17|
+--------------------+-----+
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]:
```
business_cat_sorted = business_sel_explod.groupby('categories').count().orderBy('count',ascending = False)
business_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 [15]:

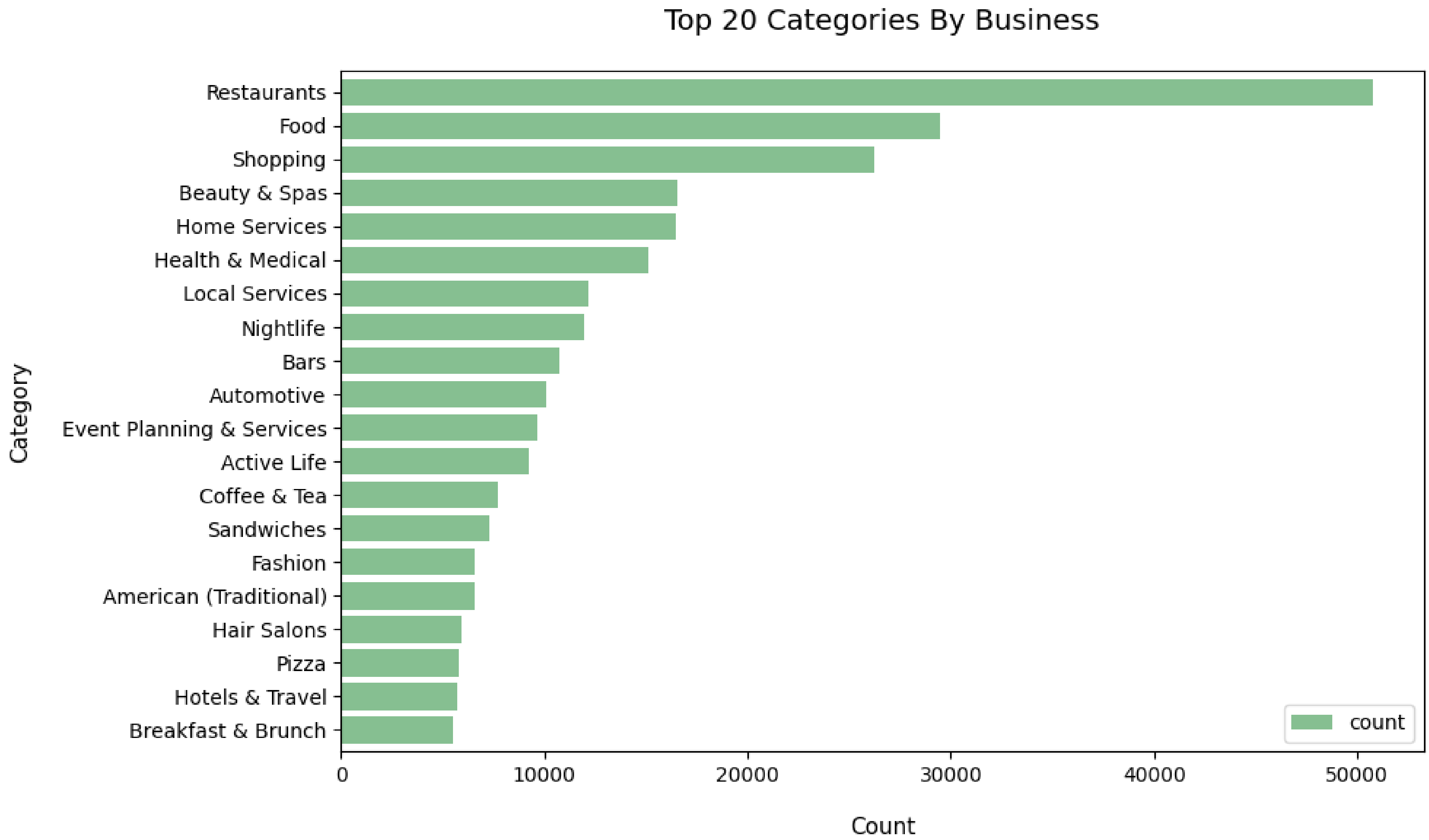
```
business_top20_df = business_cat_sorted.limit(20).toPandas()
business_top20_df
```

| | 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 [16]:

```
ax = business_top20_df.plot(kind='barh', x='categories', y='count',
            figsize=(10, 6), color = '#86bf91', 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 [17]:

```
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 [18]:

```
review_sel = review.select('business_id','stars')
review_sel.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 [19]:
```
avg_stars = review_sel.groupby('business_id').mean()
avg_stars.show(5)
```

```
+--------------------+-----------------+
|         business_id|       avg(stars)|
+--------------------+-----------------+
|yHtuNAlYKtRZniO8O...|4.714285714285714|
|R0IJhEI-zSJpYT1YN...|3.606060606060606|
|uEUweopM30lHcVxjO...|              3.0|
|L3WCfeVozu5etMhz4...|              4.2|
|XzXcpPCb8Y5huklEN...|4.666666666666667|
+--------------------+-----------------+
only showing top 5 rows
```

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

In [20]:
```
business_sub = business.select('business_id', 'name', 'city', 'state', 'stars')
rev_sel = avg_stars.join(business_sub, business_sub.business_id == avg_stars.business_id)
```

Let's see a few of these:

In [21]:
```
rev_sel_1 = rev_sel.select("name","city","state","avg(stars)","stars")
rev_sel_1.show(5)
```

```
+--------------------+----------+-----+-----------------+-----+
|                name|      city|state|       avg(stars)|stars|
+--------------------+----------+-----+-----------------+-----+
|    CheraBella Salon|   Peabody|   MA|              5.0|  5.0|
|Mezcal Cantina & ...|  Columbus|   OH|            3.875|  4.0|
|    Red Table Coffee|    Austin|   TX|3.866666666666667|  4.0|
|          WonderWell|    Austin|   TX|              5.0|  5.0|
|         Avalon Oaks|Wilmington|   MA|            3.375|  3.5|
+--------------------+----------+-----+-----------------+-----+
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 [22]:

```
from pyspark.sql.functions import col
rev_skew = rev_sel_1.withColumn("skew",(col("avg(stars)") - col("stars")) / col("stars"))
skew = rev_skew.select('skew').toPandas()
rev_skew.show(5)
```

```
+--------------------+----------+-----+------------------+-----+--------------------+
|                name|      city|state|        avg(stars)|stars|                skew|
+--------------------+----------+-----+------------------+-----+--------------------+
|    CheraBella Salon|   Peabody|   MA|               5.0|  5.0|                 0.0|
|Mezcal Cantina & ...|  Columbus|   OH|             3.875|  4.0|            -0.03125|
|     Red Table Coffee|    Austin|   TX|3.8666666666666667|  4.0|-0.03333333333333...|
|         WonderWell|    Austin|   TX|               5.0|  5.0|                 0.0|
|         Avalon Oaks|Wilmington|   MA|             3.375|  3.5|-0.03571428571428571|
+--------------------+----------+-----+------------------+-----+--------------------+
only showing top 5 rows
```

And finally, graph it!

In [23]:

```
rating_skew_only = rev_skew.select('skew')
rating_temp = rating_skew_only.toPandas()
```

In [24]:

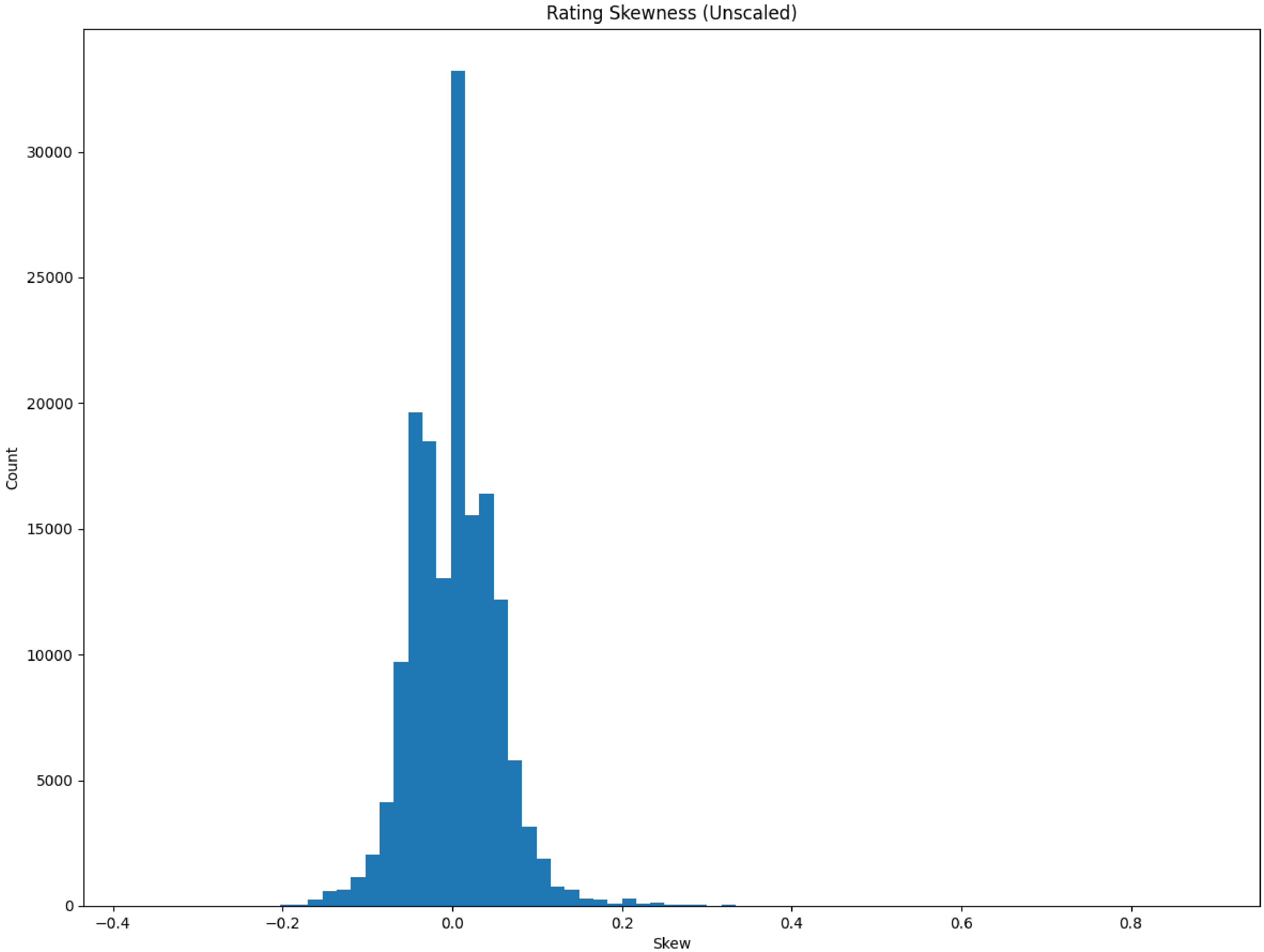
```
plt.clf()
```

In [25]:

```
import matplotlib
```

```
skew = rating_temp['skew']

ax = plt.hist(skew,bins = 75)
plt.tight_layout()
plt.xlabel('Skew')
plt.ylabel('Count')
plt.title('Rating Skewness (Unscaled)')
fig = matplotlib.pyplot.gcf()
fig.set_size_inches(12,9)
plt.show()
%matplot plt
```


Rating Skewness (Unscaled)
Count
Skew
0
5000
10000
15000
20000
25000
30000
−0.4
−0.2
0.0
0.2
0.4
0.6
0.8

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

# Part1

Finding out if an elite user can be trusted or not by comparing an elite user rating to the actual business rating.

Load the user data from s3.

In [26]:
```
user = spark.read.json('s3://sta9760yelpdataset/yelp/yelp_academic_dataset_user.json')
```

Begin by joining the business dataframe and the review dataframe on business_id.As both dataframe has same column named 'stars',so in order to avoid the repetition of the two columns that have the same name,it is necessary to change the name to business_stars and review_stars in the business dataframe and review dataframe, respectively.

In [27]:
```
business = business.withColumnRenamed('stars',"business_stars")
review = review.withColumnRenamed('stars',"review_stars")
```

In [28]:
```
business_join_review = business.join(review, on=['business_id'], how='inner')
```

Then,to join the user dataframe with the business_join_review dataframe to see what rating does a user give to a restaurant.

In [29]:
```
business_user_review = user.join(business_join_review, on=['user_id'], how='inner')
```

Filtering out the non-elite user to see only elite users.

In [30]:
```
business_user_review.select('business_id','business_stars','review_stars','user_id','elite').sort('business_id','user_i
```

```
+--------------------+--------------+------------+--------------------+--------------------+
|         business_id|business_stars|review_stars|             user_id|               elite|
+--------------------+--------------+------------+--------------------+--------------------+
|--0zrn43LEaB4jUWT...|           1.0|         1.0|Du8CplP209Es9T3FY...|                2008|
|--164t1nclzzmca7e...|           4.0|         3.0|1P9BpFZ_d3PGCdytD...|      2010,2011,2012|
|--164t1nclzzmca7e...|           4.0|         5.0|3d4fac-e3Plyib8QU...|2017,2018,2019,20,20|
|--164t1nclzzmca7e...|           4.0|         4.0|4ZfHbIbmyTuCX0BXN...| 2012,2013,2014,2015|
|--164t1nclzzmca7e...|           4.0|         5.0|5GHfNK-pcCYJon1cS...|                2010|
|--164t1nclzzmca7e...|           4.0|         5.0|5GHfNK-pcCYJon1cS...|                2010|
|--164t1nclzzmca7e...|           4.0|         1.0|8P8dgzKDQg7OSlEiA...|     2018,2019,20,20|
|--164t1nclzzmca7e...|           4.0|         4.0|8XlB-J73QOFV91Y0e...|2009,2010,2011,20...|
|--164t1nclzzmca7e...|           4.0|         2.0|A9-iDWYBSM4MtolTz...| 2014,2015,2016,2017|
|--164t1nclzzmca7e...|           4.0|         3.0|BdLon9gg9reglwmdD...|2010,2011,2012,20...|
+--------------------+--------------+------------+--------------------+--------------------+
only showing top 10 rows
```

Appending a column to represent percentage change between the business actual rating and the rating given by an elite user by using the following formula:

$$(abs(review\_stars - business\_stars) / business\_stars) * 100$$

It is necessary to get the figure in positive number while taking a difference of the business rating and the user rating so making use of abs built in function.The main output is to get how much is the difference between the business rating and the user rating.

In [31]:
```
from pyspark.sql.functions import mean, stddev, col, abs, split, explode
from pyspark.sql import functions as F
```

In [32]:
```
business_user_review = business_user_review.withColumn('%_difference',(abs((business_user_review['review_stars']-busine
```

In [33]:
```
business_user_review = business_user_review.select('business_id','business_stars','review_stars','%_difference','user_i
business_user_review.show(10)
```

```
+--------------------+--------------+------------+------------+--------------------+--------------------+
|         business_id|business_stars|review_stars|%_difference|             user_id|               elite|
+--------------------+--------------+------------+------------+--------------------+--------------------+
|--0zrn43LEaB4jUWT...|           1.0|         1.0|         0.0|Du8CplP209Es9T3FY...|                2008|
|--164t1nclzzmca7e...|           4.0|         5.0|        25.0|1lksdcDyLTNkiibAQ...|2009,2010,2011,20...|
|--164t1nclzzmca7e...|           4.0|         5.0|        25.0|kTY5w80WqY4Ak-jac...|           2012,2013|
|--164t1nclzzmca7e...|           4.0|         1.0|        75.0|Jgxz4UF56FK0taE4i...|           2012,2013|
|--164t1nclzzmca7e...|           4.0|         3.0|        25.0|wwrlJT3JLb-A_0Nrl...|2008,2009,2010,20...|
|--164t1nclzzmca7e...|           4.0|         4.0|         0.0|DA90NhtNTNpXxdrXI...|2010,2011,2012,20...|
|--164t1nclzzmca7e...|           4.0|         3.0|        25.0|LhnoqfSZobV3bch7o...|2010,2011,2012,20...|
|--164t1nclzzmca7e...|           4.0|         5.0|        25.0|WJDYWvNrnMx2PWgfK...|                2012|
|--164t1nclzzmca7e...|           4.0|         3.0|        25.0|1P9BpFZ_d3PGCdytD...|      2010,2011,2012|
|--164t1nclzzmca7e...|           4.0|         4.0|         0.0|4ZfHbIbmyTuCX0BXN...| 2012,2013,2014,2015|
+--------------------+--------------+------------+------------+--------------------+--------------------+
only showing top 10 rows
```

Descriptive statistics of the percentage differnece.

In [34]:
```
business_user_review.describe(['%_difference']).show()
```

```
+-------+------------------+
|summary|      %_difference|
+-------+------------------+
|  count|           2169088|
|   mean|22.243313121181657|
| stddev| 21.02747472303388|
|    min|               0.0|
```

```
|    max|              400.0|
+-------+------------------+
```

Creating a histogram based on the percentage difference of an elite user rating and a business rating.

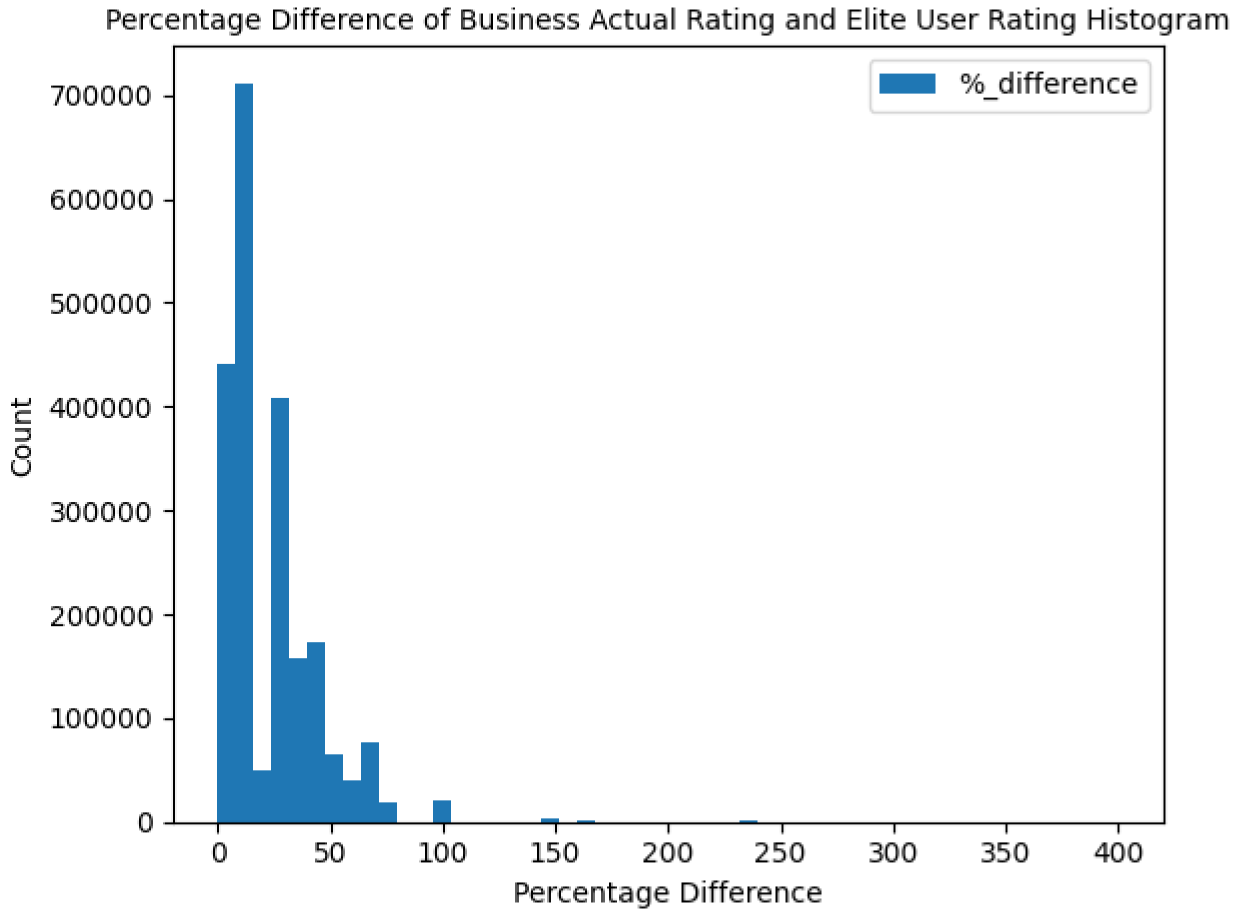
In [35]:

```
business_user_review_plot = business_user_review.select('%_difference').toPandas()
business_user_review_plot.plot.hist(bins=50)
```

```
<matplotlib.axes._subplots.AxesSubplot object at 0x7f37b0153a90>
```

In [36]:

```
import matplotlib.pyplot as plt
plt.xlabel('Percentage Difference')
plt.ylabel('Count')
plt.xticks()
plt.yticks()
plt.title('Percentage Difference of Business Actual Rating and Elite User Rating Histogram',fontsize=10)
plt.tight_layout()
plt.show()
%matplot plt
```




The histogram displays that the elite user review are 50% less different from the actual business review.

In order to get more detailed insights of how the elite user reviews is different from the business review,it is necessary to look at the percentage of different ranges.

In [37]:

```
total = business_user_review.count()

less_25 = business_user_review.filter(business_user_review['%_difference'] <= 25).count()
print(f'Percentage Difference <= 25%: {less_25}, Percentage: {(less_25/total)*100}%')

greate_25_less_50 = business_user_review.filter(business_user_review['%_difference'] > 25).filter(business_user_review[
print(f'Percentage Difference >25 and <= 50%: {greate_25_less_50}, Percentage: {(greate_25_less_50/total)*100}%')
```

```
greate_50_less_75 = business_user_review.filter(business_user_review['%_difference'] > 50).filter(business_user_review[
print(f'Percentage Difference >40 and <= 60%: {greate_50_less_75}, Percentage: {(greate_50_less_75/total)*100}%')

greate_75_less_100 = business_user_review.filter(business_user_review['%_difference'] > 75).filter(business_user_review
print(f'Percentage Difference >60 and <= 80%: {greate_75_less_100}, Percentage: {(greate_75_less_100/total)*100}%')

greate_100 = business_user_review.filter(business_user_review['%_difference'] > 100).count()
print(f'Percentage Difference >100: {greate_100}, Percentage: {(greate_100/total)*100}%')
```

```
Percentage Difference <= 25%: 1611488, Percentage: 74.29334356190252%
Percentage Difference >25 and <= 50%: 386522, Percentage: 17.819562876194972%
Percentage Difference >40 and <= 60%: 140623, Percentage: 6.483047253039064%
Percentage Difference >60 and <= 80%: 24787, Percentage: 1.1427383305794878%
Percentage Difference >100: 5668, Percentage: 0.2613079782839608%
```

In [38]:

```
df_percentage = spark.createDataFrame(
    [
        ('[0%,25%]', (less_25/total)*100),
        ('(25%,50%]', (greate_25_less_50/total)*100),
        ('(50%,75%]', (greate_50_less_75/total)*100),
        ('(75%,100%]', (greate_75_less_100/total)*100),
        ('(100%,∞)', (greate_100/total)*100),
    ],
    ['Difference_Percentage_Range', 'Percentage']
)

df_percentage.show()
```

```
+---------------------------+------------------+
|Difference_Percentage_Range|        Percentage|
+---------------------------+------------------+
|                   [0%,25%]| 74.29334356190252|
|                  (25%,50%]|17.819562876194972|
|                  (50%,75%]| 6.483047253039064|
|                 (75%,100%]|1.1427383305794878|
|                   (100%,∞)|0.2613079782839608|
+---------------------------+------------------+
```

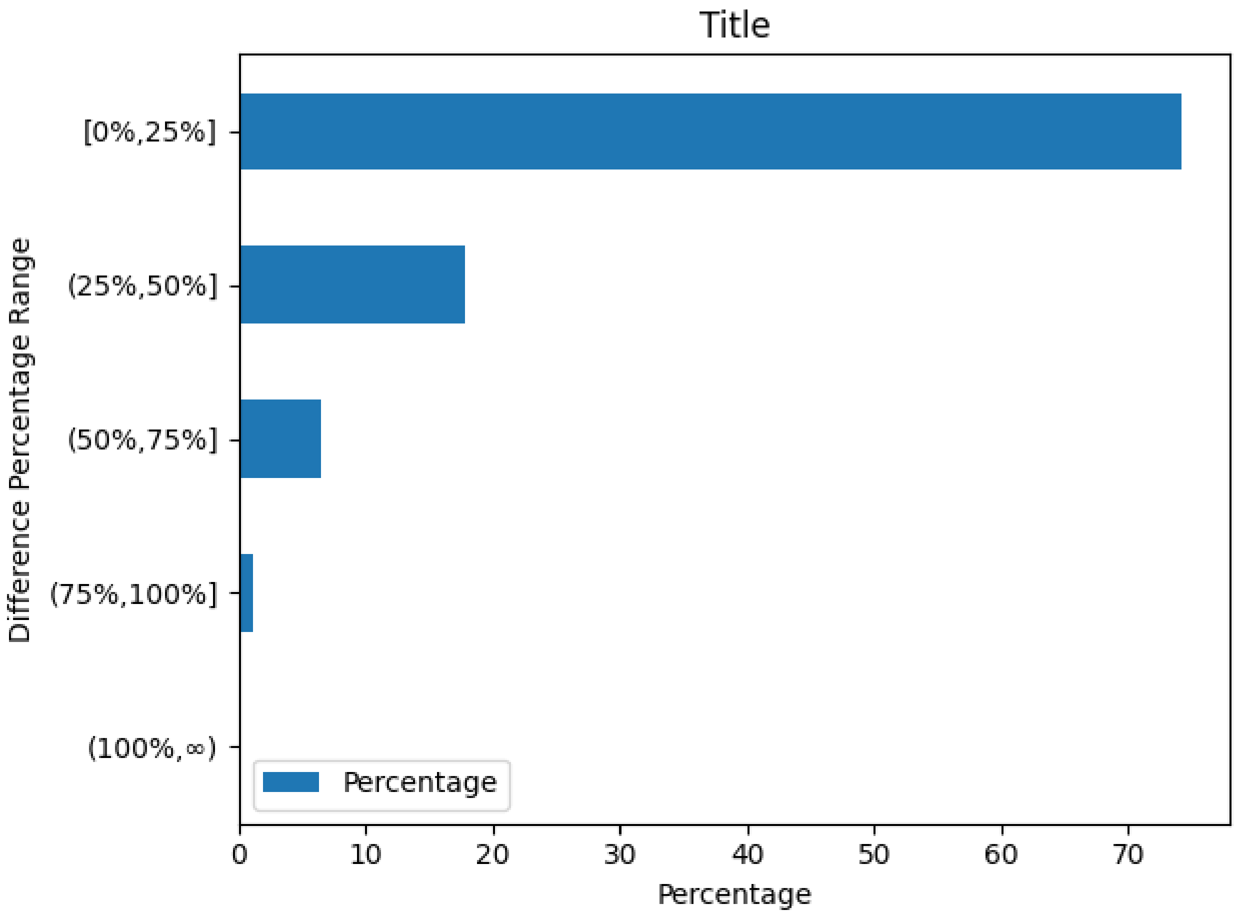
In [39]:

```
df_percentage_pandas = df_percentage.toPandas()
```

```
df_percentage_pandas = df_percentage_pandas.set_index('Difference_Percentage_Range')
```

In [40]:

```
df_percentage_pandas.plot.barh().invert_yaxis()
plt.title('Title')
plt.xlabel('Percentage')
plt.ylabel('Difference Percentage Range')
plt.xticks()
plt.yticks()
plt.tight_layout()
plt.show()
%matplot plt
```


Title
[0%,25%]
(25%,50%]
(50%,75%]
(75%,100%]
(100%,∞)
Difference Percentage Range
Percentage
0
10
20
30
40
50
60
70
Percentage

```
In [ ]:
```

```
In [ ]:
```