Exploratory Data Analysis Based on Instagram reach using Python

Exploratory data analysis (EDA) is a Data Science concept where we analyze a dataset to discover patterns, trends, and relationships within the data. It helps us better understand the information contained in the dataset and guides us in making informed decisions and formulating strategies to solve real business problems. If you want to understand Exploratory Data Analysis practically, this article is for you. In this article, I will take you through an implementation of Exploratory Data Analysis using Python.

To show how to perform Exploratory Data Analysis using Python, I will use a dataset based on a Instagram reach.

In [10]:
```
import pandas as pd
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio
pio.templates.default = "plotly_white"

data = pd.read_csv(r"C:\Users\shali\Downloads\archive (4)\Instagram data.csv", encoding='latin1')
```

Now let's have a look at the first five rows of the data:

In [11]:
```
print(data.head())
```

```
   Impressions  From Home  From Hashtags  From Explore  From Other  Saves  \
0         3920       2586           1028           619          56     98
1         5394       2727           1838          1174          78    194
2         4021       2085           1188             0         533     41
3         4528       2700            621           932          73    172
4         2518       1704            255           279          37     96

   Comments  Shares  Likes  Profile Visits  Follows  \
0         9       5    162              35        2
1         7      14    224              48       10
2        11       1    131              62       12
3        10       7    213              23        8
4         5       4    123               8        0

                                             Caption  \
0  Here are some of the most important data visua...
1  Here are some of the best data science project...
2  Learn how to train a machine learning model an...
3  Here’s how you can write a Python program to d...
4  Plotting annotations while visualizing your da...

                                            Hashtags
0  #finance #money #business #investing #investme...
1  #healthcare #health #covid #data #datascience ...
2  #data #datascience #dataanalysis #dataanalytic...
3  #python #pythonprogramming #pythonprojects #py...
4  #datavisualization #datascience #data #dataana...
```

Now let's have a look at all the columns the dataset contains:

In [12]:
```
print(data.columns)
```

```
Index(['Impressions', 'From Home', 'From Hashtags', 'From Explore',
       'From Other', 'Saves', 'Comments', 'Shares', 'Likes', 'Profile Visits',
       'Follows', 'Caption', 'Hashtags'],
      dtype='object')
```

Now let's have a look at the column info:

In [14]:
```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 119 entries, 0 to 118
Data columns (total 13 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Impressions     119 non-null    int64
 1   From Home       119 non-null    int64
 2   From Hashtags   119 non-null    int64
 3   From Explore    119 non-null    int64
 4   From Other      119 non-null    int64
 5   Saves           119 non-null    int64
 6   Comments        119 non-null    int64
 7   Shares          119 non-null    int64
 8   Likes           119 non-null    int64
 9   Profile Visits  119 non-null    int64
 10  Follows         119 non-null    int64
 11  Caption         119 non-null    object
 12  Hashtags        119 non-null    object
dtypes: int64(11), object(2)
memory usage: 12.2+ KB
None
```

Next, we look at the descriptive statistics of the data:

In [15]:
```
print(data.describe())
```

```
        Impressions     From Home  From Hashtags  From Explore   From Other  \
count    119.000000    119.000000     119.000000    119.000000   119.000000
mean    5703.991597   2475.789916    1887.512605   1078.100840   171.092437
std     4843.780105   1489.386348    1884.361443   2613.026132   289.431031
min     1941.000000   1133.000000     116.000000      0.000000     9.000000
25%     3467.000000   1945.000000     726.000000    157.500000    38.000000
50%     4289.000000   2207.000000    1278.000000    326.000000    74.000000
75%     6138.000000   2602.500000    2363.500000    689.500000   196.000000
max    36919.000000  13473.000000   11817.000000  17414.000000  2547.000000

             Saves    Comments      Shares       Likes  Profile Visits  \
count   119.000000  119.000000  119.000000  119.000000      119.000000
mean    153.310924    6.663866    9.361345  173.781513       50.621849
std     156.317731    3.544576   10.089205   82.378947       87.088402
min      22.000000    0.000000    0.000000   72.000000        4.000000
25%      65.000000    4.000000    3.000000  121.500000       15.000000
50%     109.000000    6.000000    6.000000  151.000000       23.000000
75%     169.000000    8.000000   13.500000  204.000000       42.000000
max    1095.000000   19.000000   75.000000  549.000000      611.000000

           Follows
count  119.000000
mean    20.756303
std     40.921580
min      0.000000
25%      4.000000
50%      8.000000
75%     18.000000
max    260.000000
```

Now, before moving forward, always have a look if your data contains any missing values or not:

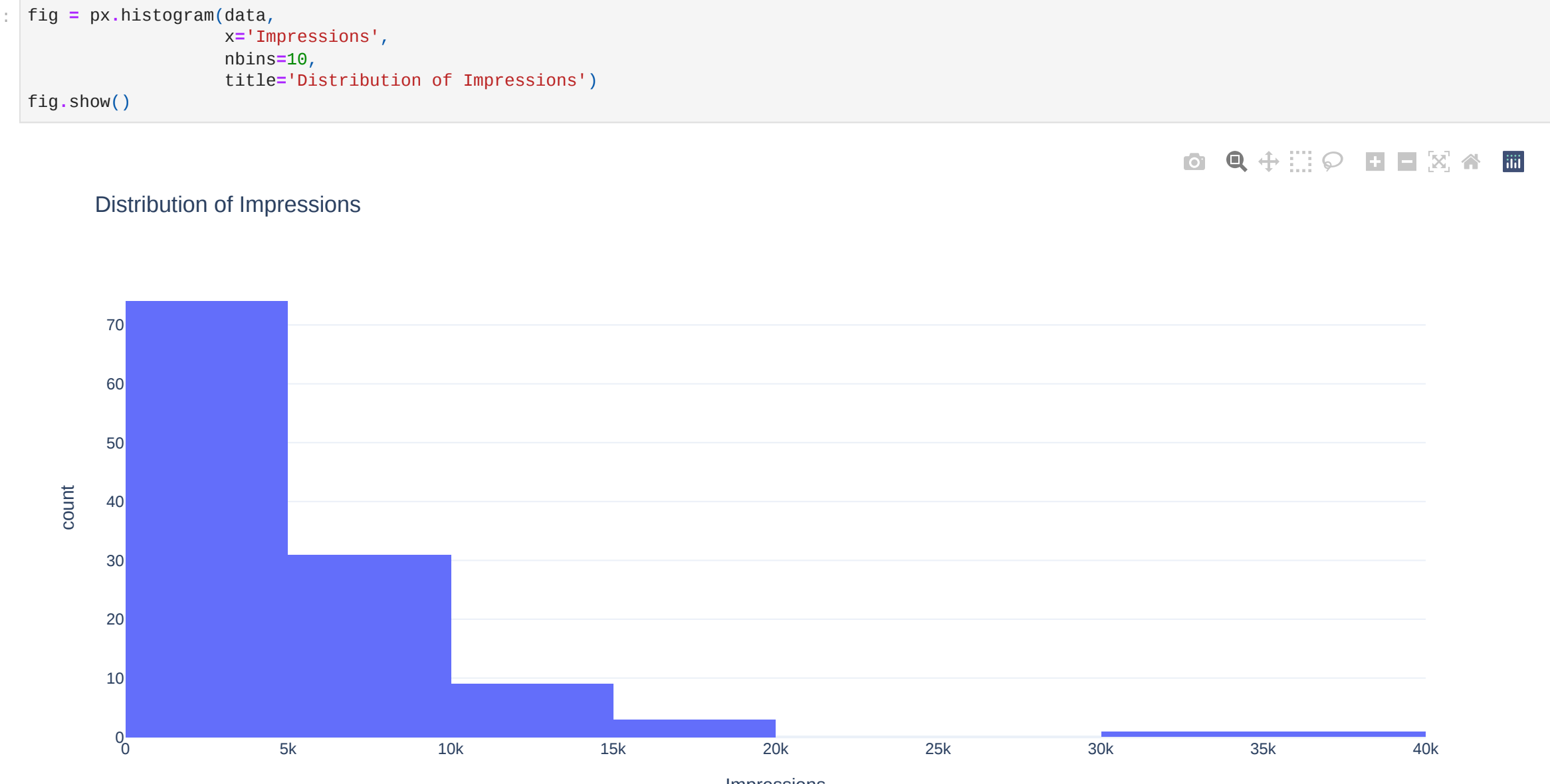
In [16]:
```
print(data.isnull().sum())
```

```
Impressions       0
From Home         0
From Hashtags     0
From Explore      0
From Other        0
Saves             0
Comments          0
Shares            0
Likes             0
Profile Visits    0
Follows           0
Caption           0
Hashtags          0
dtype: int64
```

Luckily, this dataset doesn't have any missing values.

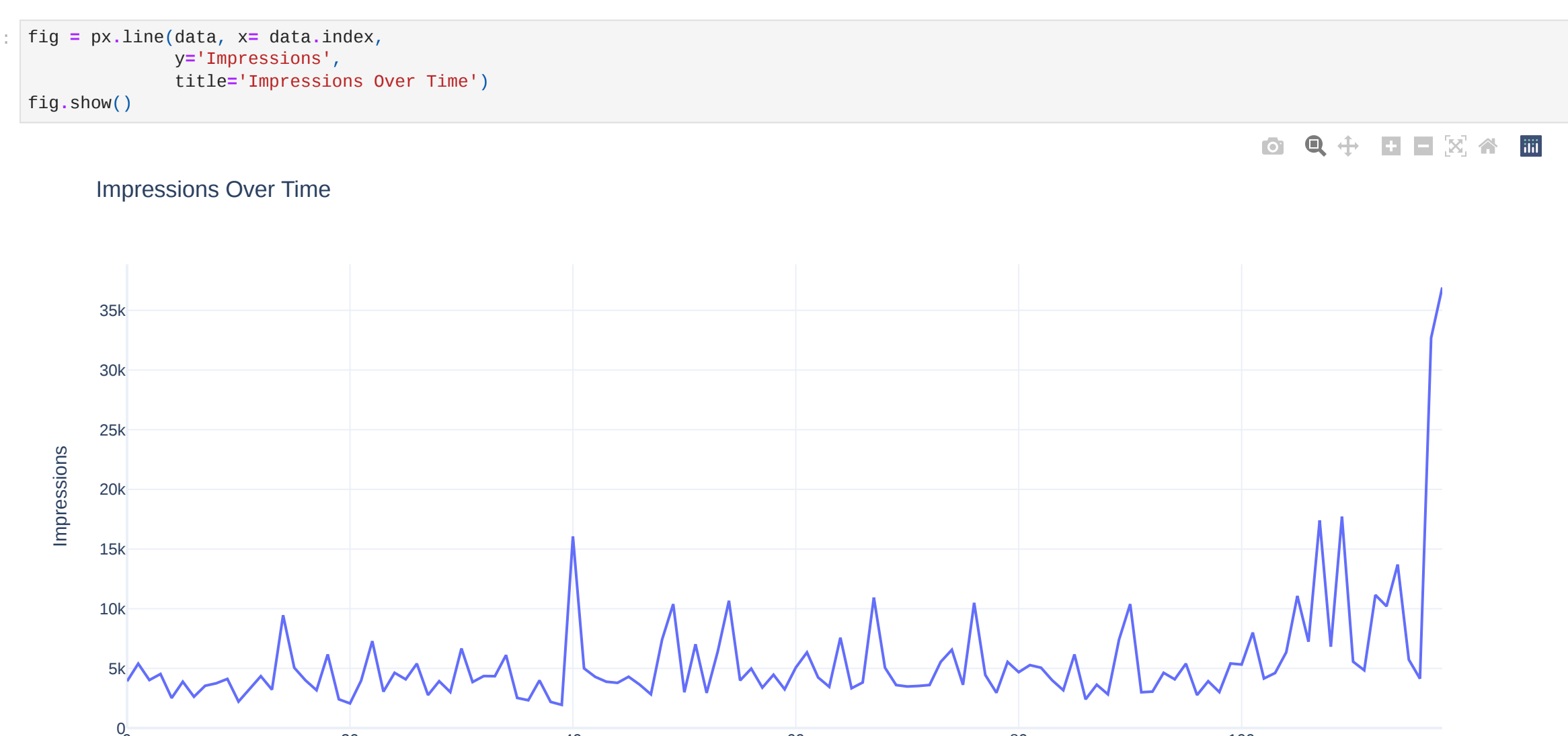
When you start exploring your data, always start by exploring the main feature of your data. For example, as we are working on a dataset based on Instagram Reach, we should start by exploring the feature that contains data about reach. In our data, the Impressions column contains the data about the reach of an Instagram post. So let's have a look at the distribution of the Impressions:

In [17]:
```
fig = px.histogram(data,
                   x='Impressions',
                   nbins=10,
                   title='Distribution of Impressions')
fig.show()
```



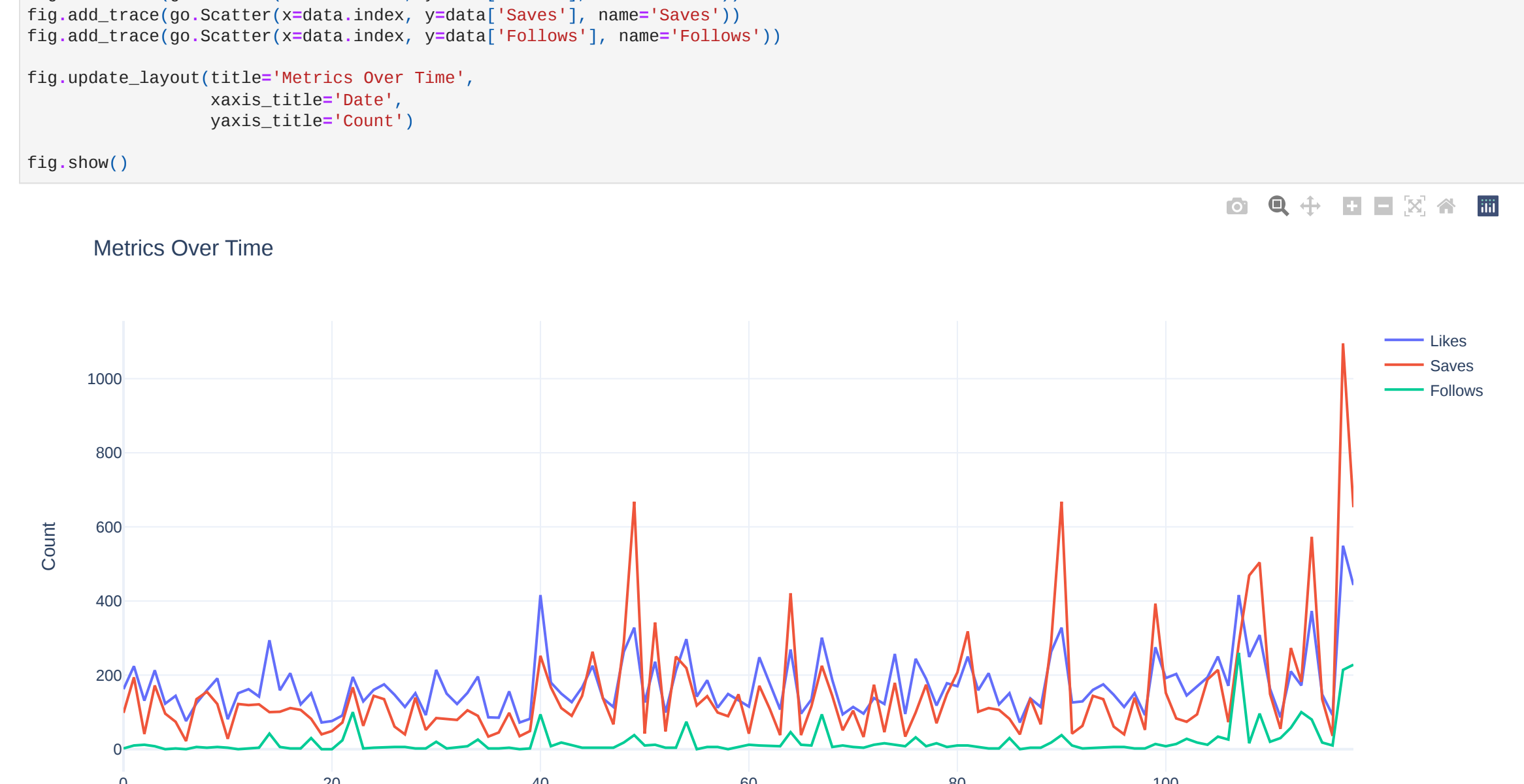
Now let's have a look at the number of impressions on each post over time:

In [18]:
```
fig = px.line(data, x= data.index,
              y='Impressions',
              title='Impressions Over Time')
fig.show()
```



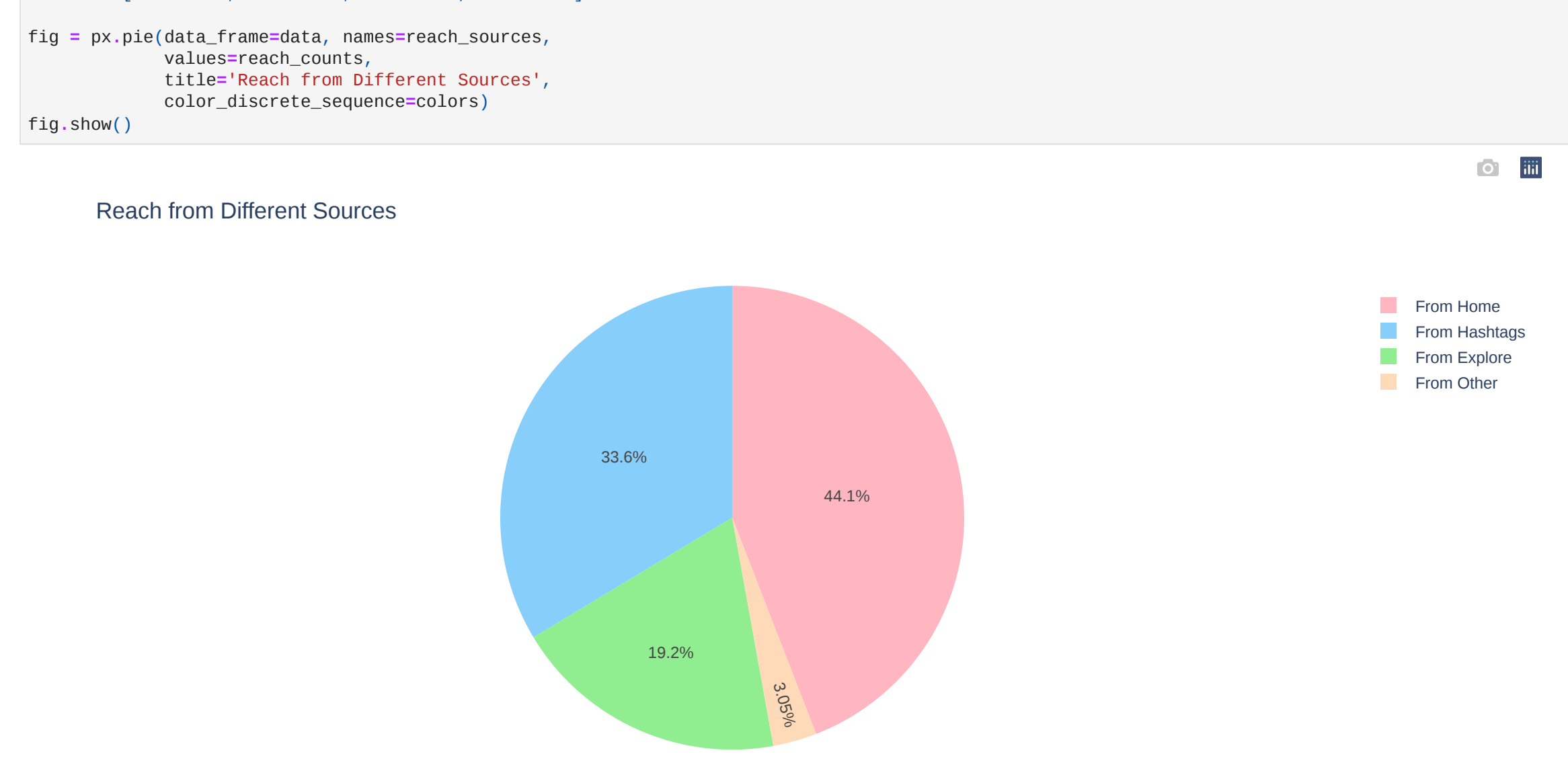
Now let's have a look at all the metrics like Likes, Saves, and Follows from each post over time:

In [20]:
```
fig = go.Figure()

fig.add_trace(go.Scatter(x=data.index, y=data['Likes'], name='Likes'))
fig.add_trace(go.Scatter(x=data.index, y=data['Saves'], name='Saves'))
fig.add_trace(go.Scatter(x=data.index, y=data['Follows'], name='Follows'))

fig.update_layout(title='Metrics Over Time',
                  xaxis_title='Date',
                  yaxis_title='Count')

fig.show()
```



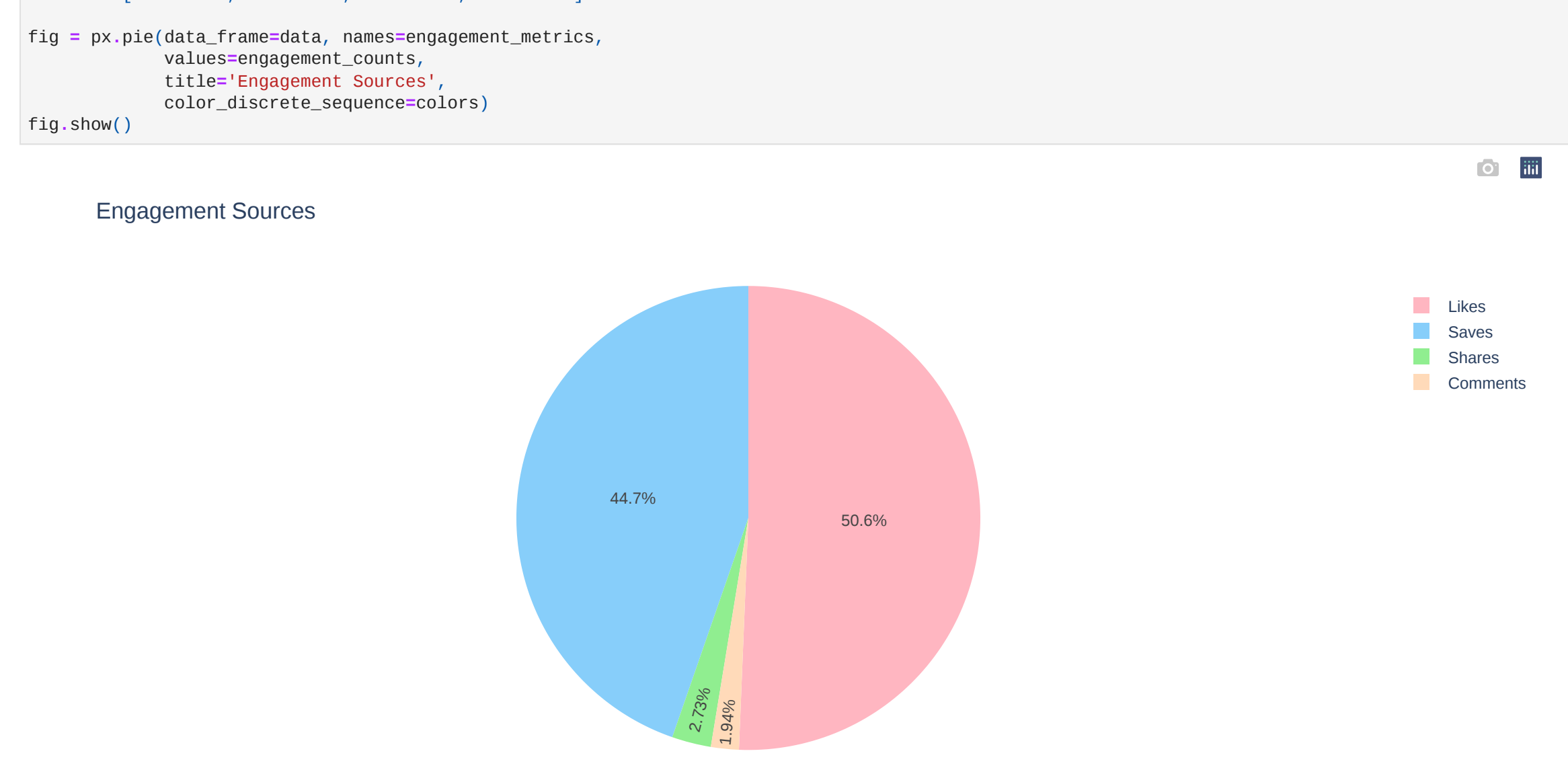
Now let's have a look at the distribution of reach from different sources:

In [22]:
```
reach_sources = ['From Home', 'From Hashtags', 'From Explore', 'From Other']
reach_counts = [data[source].sum() for source in reach_sources]

colors = ['#FFB6C1', '#87CEFA', '#90EE90', '#FFDAB9']

fig = px.pie(data_frame=data, names=reach_sources,
             values=reach_counts,
             title='Reach from Different Sources',
             color_discrete_sequence=colors)
fig.show()
```



Now let's have a look at the distribution of engagement sources:

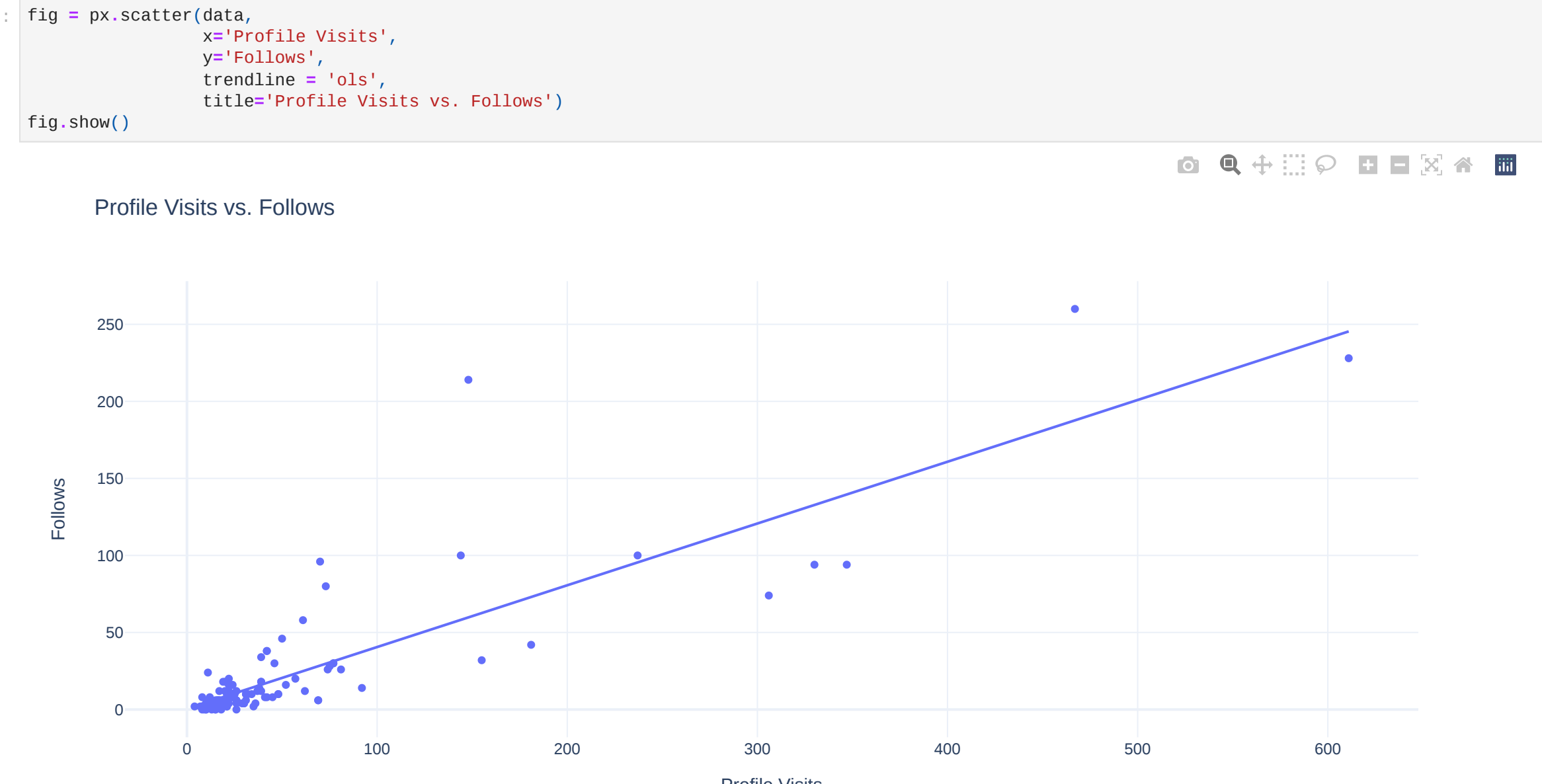
In [23]:
```
engagement_metrics = ['Saves', 'Comments', 'Shares', 'Likes']
engagement_counts = [data[metric].sum() for metric in engagement_metrics]

colors = ['#FFB6C1', '#87CEFA', '#90EE90', '#FFDAB9']

fig = px.pie(data_frame=data, names=engagement_metrics,
             values=engagement_counts,
             title='Engagement Sources',
             color_discrete_sequence=colors)
fig.show()
```



Now let's have a look at the relationship between the number of profile visits and follows:

A trendline, in the context of data visualization, is a line that represents the general trend or pattern in a scatter plot or other type of graph. It's often used to visually highlight the direction or tendency of the relationship between two variables

In [24]:
```
fig = px.scatter(data,
                 x='Profile Visits',
                 y='Follows',
                 trendline = 'ols',
                 title='Profile Visits vs. Follows')
fig.show()
```



Now let's have a look at the type of hashtags used in the posts using a wordcloud:

In [25]:
```
from wordcloud import WordCloud

hashtags = ' '.join(data['Hashtags'].astype(str))
wordcloud = WordCloud().generate(hashtags)

fig = px.imshow(wordcloud, title='Hashtags Word Cloud')
fig.show()
```

```
---------------------------------------------------------------------------
ModuleNotFoundError                       Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_28836\1857083643.py in <module>
----> 1 from wordcloud import WordCloud
      2
      3 hashtags = ' '.join(data['Hashtags'].astype(str))
      4 wordcloud = WordCloud().generate(hashtags)
      5

ModuleNotFoundError: No module named 'wordcloud'
```

Now let's have a look at the correlation between all the features:

The correlation coefficient is a statistical measure that describes the strength and direction of a relationship between two variables.

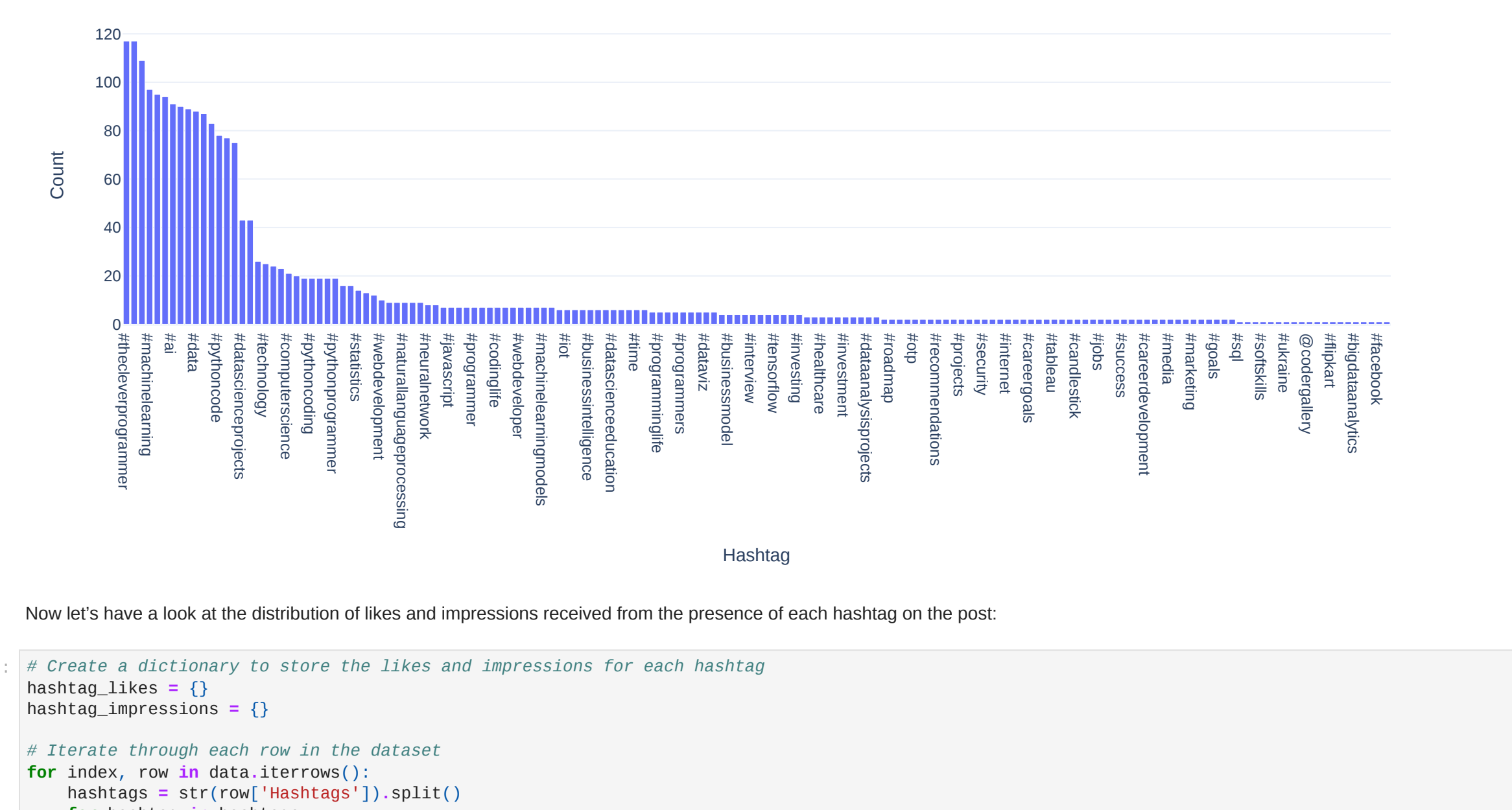
The correlation coefficient can range from -1 to 1:

- 1 indicates a perfect positive correlation: as one variable increases, the other variable also increases proportionally.
- -1 indicates a perfect negative correlation: as one variable increases, the other variable decreases proportionally.
- 0 indicates no correlation: the variables are independent of each other.

In [26]:
```
corr_matrix = data.corr()

fig = go.Figure(data=go.Heatmap(z=corr_matrix.values,
                                x=corr_matrix.columns,
                                y=corr_matrix.index,
                                colorscale='RdBu',
                                zmin=-1,
                                zmax=1))

fig.update_layout(title='Correlation Matrix',
                  xaxis_title='Features',
                  yaxis_title='Features')

fig.show()
```

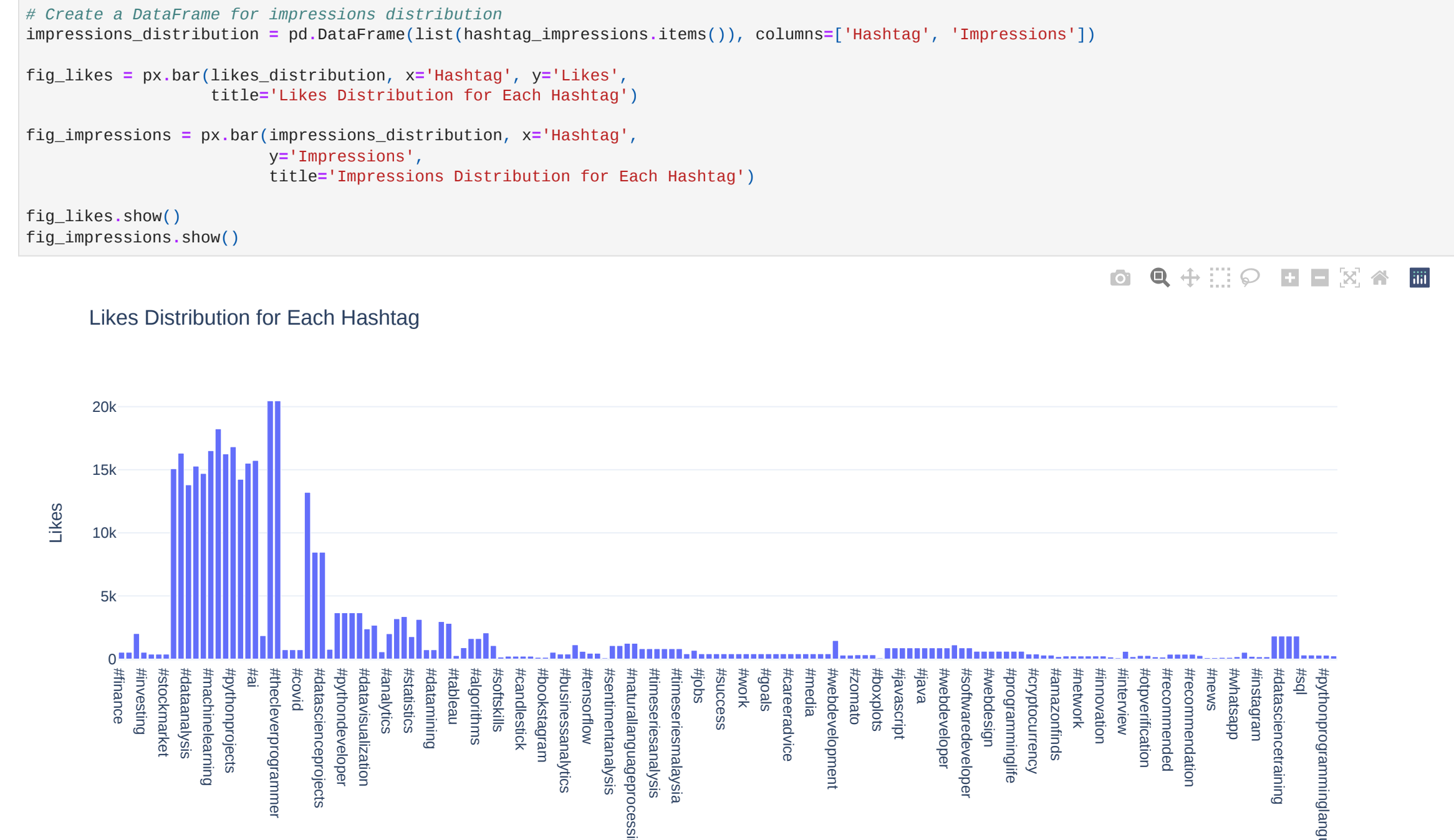
Now let's explore the hashtags column in detail. Each post contains different combinations of hashtags, which impacts reach on Instagram. So let's have a look at the distribution of hashtags to see which hashtag is used the most in all the posts:

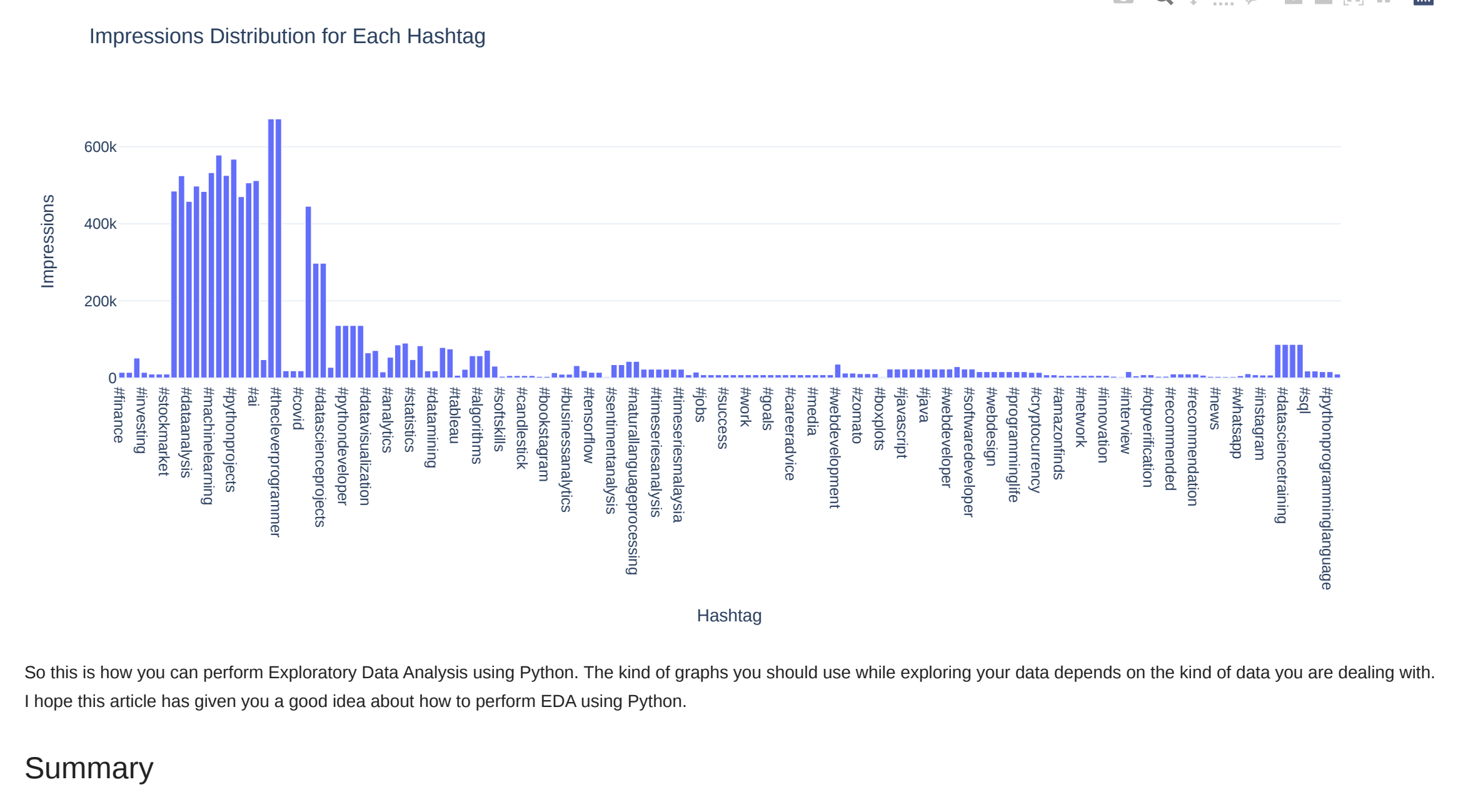
In [27]:
```
# Create a list to store all hashtags
all_hashtags = []

# Iterate through each row in the 'Hashtags' column
for row in data['Hashtags']:
    hashtags = str(row).split()
    hashtags = [tag.strip() for tag in hashtags]
    all_hashtags.extend(hashtags)

# Create a pandas DataFrame to store the hashtag distribution
hashtag_distribution = pd.Series(all_hashtags).value_counts().reset_index()
hashtag_distribution.columns = ['Hashtag', 'Count']

fig = px.bar(hashtag_distribution, x='Hashtag',
             y='Count', title='Distribution of Hashtags')
fig.show()
```



Now let's have a look at the distribution of likes and impressions received from the presence of each hashtag on the post:

In [28]:
```
# Create a dictionary to store the likes and impressions for each hashtag
hashtag_likes = {}
hashtag_impressions = {}

# Iterate through each row in the dataset
for index, row in data.iterrows():
    hashtags = str(row['Hashtags']).split()
    for hashtag in hashtags:
        hashtag = hashtag.strip()
        if hashtag not in hashtag_likes:
            hashtag_likes[hashtag] = 0
            hashtag_impressions[hashtag] = 0
        hashtag_likes[hashtag] += row['Likes']
        hashtag_impressions[hashtag] += row['Impressions']

# Create a DataFrame for likes distribution
likes_distribution = pd.DataFrame(list(hashtag_likes.items()), columns=['Hashtag', 'Likes'])

# Create a DataFrame for impressions distribution
impressions_distribution = pd.DataFrame(list(hashtag_impressions.items()), columns=['Hashtag', 'Impressions'])

fig_likes = px.bar(likes_distribution, x='Hashtag', y='Likes',
                   title='Likes Distribution for Each Hashtag')

fig_impressions = px.bar(impressions_distribution, x='Hashtag',
                         y='Impressions',
                         title='Impressions Distribution for Each Hashtag')

fig_likes.show()
fig_impressions.show()
```





So this is how you can perform Exploratory Data Analysis using Python. The kind of graphs you should use while exploring your data depends on the kind of data you are dealing with. I hope this article has given you a good idea about how to perform EDA using Python.

Summary

Exploratory data analysis (EDA) is a Data Science concept where we analyze a dataset to discover patterns, trends, and relationships within the data. It helps us better understand the information contained in the dataset and guides us in making informed decisions and formulating strategies to solve real business problems. I hope you liked this article on Exploratory Data Analysis using Python. Feel free to ask valuable questions in the comments section below.

In [ ]: