Problem Statement:

A business is using an instagram profile/page to reach out its followers and trying to find out the what impacts the most reach to its follower. The business wants to find out the individual impact of various KPIs on the business reach.

In [1]:
```
pip install wordcloud
```

```
Requirement already satisfied: wordcloud in c:\users\saad\anaconda3\lib\site-packages (1.8.2.2)
Requirement already satisfied: numpy>=1.6.1 in c:\users\saad\anaconda3\lib\site-packages (from wordcloud) (1.19.5)
Requirement already satisfied: matplotlib in c:\users\saad\anaconda3\lib\site-packages (from wordcloud) (3.2.2)
Requirement already satisfied: pillow in c:\users\saad\anaconda3\lib\site-packages (from wordcloud) (9.0.1)
Requirement already satisfied: cycler>=0.10 in c:\users\saad\anaconda3\lib\site-packages (from matplotlib->wordcloud) (0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in c:\users\saad\anaconda3\lib\site-packages (from matplotlib->wordcloud) (3.0.4)
Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\saad\anaconda3\lib\site-packages (from matplotlib->wordcloud) (1.3.2)
Requirement already satisfied: python-dateutil>=2.1 in c:\users\saad\anaconda3\lib\site-packages (from matplotlib->wordcloud) (2.8.2)
Requirement already satisfied: six>=1.5 in c:\users\saad\anaconda3\lib\site-packages (from python-dateutil>=2.1->matplotlib->wordcloud) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

In [2]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
from sklearn.model_selection import train_test_split
from sklearn.linear_model import PassiveAggressiveRegressor
```

In [3]:
```
df = pd.read_csv('Instagram data.csv', encoding = 'latin1')
df.head()
```

Out[3]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits	Follows	Caption	Hashtags
0	3920	2586	1028	619	56	98	9	5	162	35	2	Here are some of the most important data visua...	#finance #money #business #investing #investme...
1	5394	2727	1838	1174	78	194	7	14	224	48	10	Here are some of the best data science project...	#healthcare #health #covid #data #datascience ...
2	4021	2085	1188	0	533	41	11	1	131	62	12	Learn how to train a machine learning model an...	#data #datascience #dataanalysis #dataanalytic...
3	4528	2700	621	932	73	172	10	7	213	23	8	Here□s how you can write a Python program to d...	#python #pythonprogramming #pythonprojects #py...
4	2518	1704	255	279	37	96	5	4	123	8	0	Plotting annotations while visualizing your da...	#datavisualization #datascience #data #dataana...

In [4]:
```
#Checking null values
df.isnull().sum()
```

Out[4]:
```
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
```

The dataset contains no null values

In [5]:
```
#Lets have a look at the culumns and datatype of each column
df.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
```

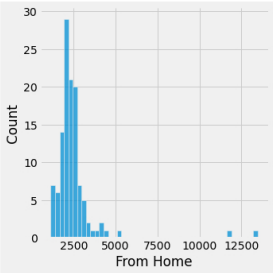
In [6]:
```
#Here we are checking a descriptive statistical  overview of the dataset
df.describe()
```

Out[6]:

	Impressions	From Home	From Hashtags	From Explore	From Other	Saves	Comments	Shares	Likes	Profile Visits	Follows
count	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000	119.000000
mean	5703.991597	2475.789916	1887.512605	1078.100840	171.092437	153.310924	6.663866	9.361345	173.781513	50.621849	20.756303
std	4843.780105	1489.386348	1884.361443	2613.026132	289.431031	156.317731	3.544576	10.089205	82.378947	87.088402	40.921580
min	1941.000000	1133.000000	116.000000	0.000000	9.000000	22.000000	0.000000	0.000000	72.000000	4.000000	0.000000
25%	3467.000000	1945.000000	726.000000	157.500000	38.000000	65.000000	4.000000	3.000000	121.500000	15.000000	4.000000
50%	4289.000000	2207.000000	1278.000000	326.000000	74.000000	109.000000	6.000000	6.000000	151.000000	23.000000	8.000000
75%	6138.000000	2602.500000	2363.500000	689.500000	196.000000	169.000000	8.000000	13.500000	204.000000	42.000000	18.000000
max	36919.000000	13473.000000	11817.000000	17414.000000	2547.000000	1095.000000	19.000000	75.000000	549.000000	611.000000	260.000000

In [7]:
```
# Impressions received from home
plt.figure(figsize=(10, 8))
plt.style.use('fivethirtyeight')
#plt.title("Distribution of Impressions From Home")
sns.displot(df['From Home'])
plt.show()
```

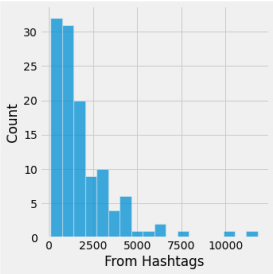
```
<Figure size 720x576 with 0 Axes>
```



It seems that it is hard to reach most of the follower from home.

In [8]:
```
#From hashtags
plt.figure(figsize=(10, 8))
#plt.title("Distribution of Impressions From Hashtags")
sns.displot(df['From Hashtags'])
plt.show()
```

```
<Figure size 720x576 with 0 Axes>
```

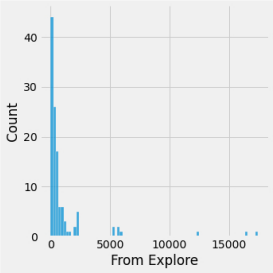


- Hashtags refers to the catagory of posts use to reach target users.

It is clear that hashtags are helpful to reach new users but it is not always possible to reach all the followers using hashtags.

In [9]:
```
#From Explore
plt.figure(figsize=(18, 14))
#plt.title("Distribution of Impressions From Explore")
sns.displot(df['From Explore'])
plt.show()
```

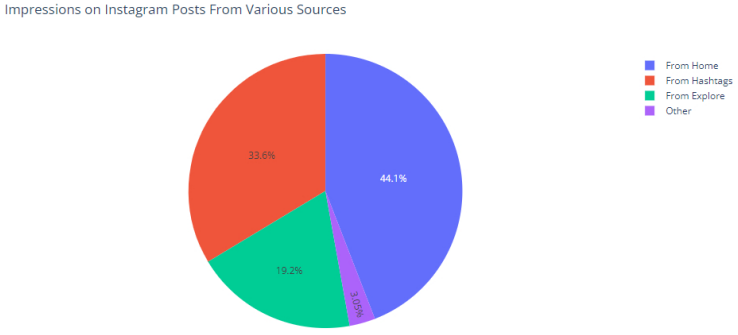
```
<Figure size 1296x1008 with 0 Axes>
```



- Explore is basically a recomendation algorithm on instagram that helps post to rach meaningful users based on their catagory of interests.

From the the graph we found out that instagram doesnot recomend/show our post to expected amount of users. Although some of the posts receives good reach but comperatively lower than the reach we received from hashtags. It might also implies that there might be some issues regarding post production/making. For instance, lower ranking keywords are being used or posting schedule etc.

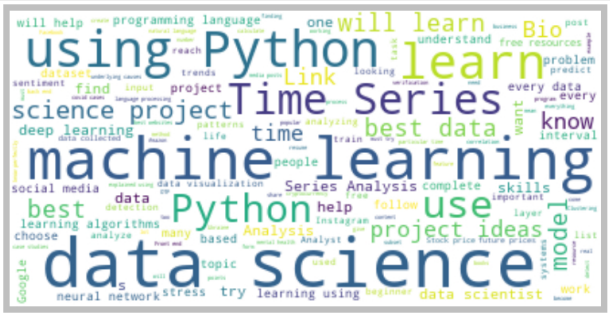
In [10]:
```
# Let us explore the impression from all the sources.
home = df["From Home"].sum()
hashtags = df["From Hashtags"].sum()
explore = df["From Explore"].sum()
other = df["From Other"].sum()

labels = ['From Home','From Hashtags','From Explore','Other']
values = [home, hashtags, explore, other]

fig = px.pie(df, values=values, names=labels,
             title='Impressions on Instagram Posts From Various Sources')
fig.show()
```



We receive most (around 45%) of our reach from the followers whereas lowest reach comes from other sources. Except followers, it seems that hashtags can be an effective way to reach other users also.

In [11]:
```
#Lets have a look at the most used word in the captions.
text = " ".join(i for i in df.Caption)
```

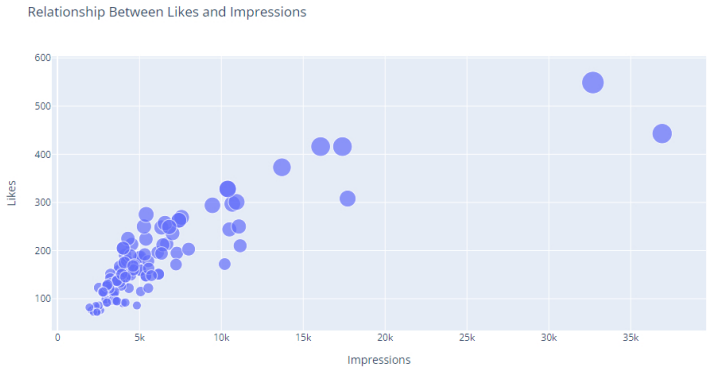
```
stopwords = set(STOPWORDS)
wordcloud = WordCloud(stopwords=stopwords, background_color="white").generate(text)
plt.style.use('classic')
plt.figure( figsize=(12,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.show()
```



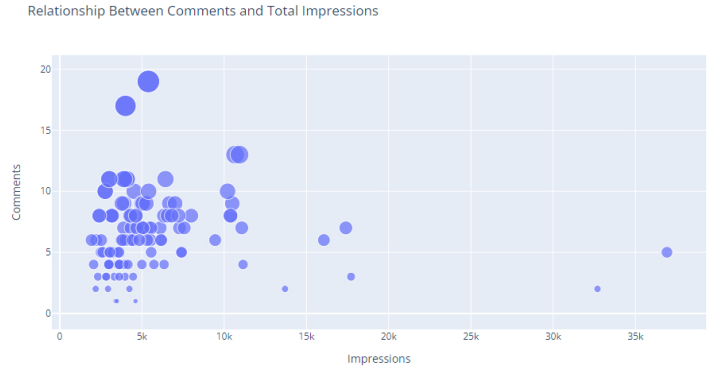
As we can see that the most used word in the caption of our posts are machine learning, time series, data sciences etc.

Let us analyse the relationship among different variables.

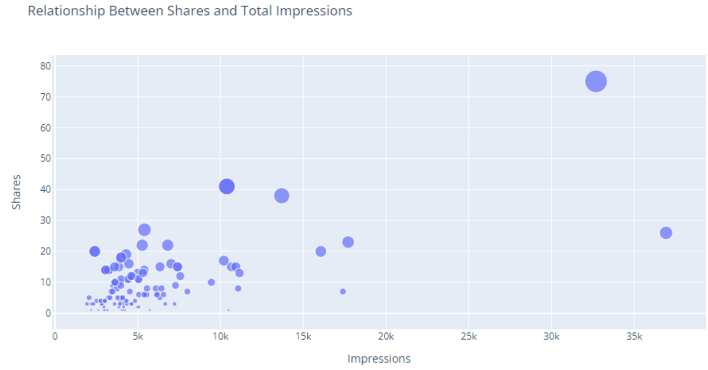
In [12]:
```
figure = px.scatter(data_frame = df, x="Impressions",
                    y="Likes", size="Likes",
                    title = "Relationship Between Likes and Impressions")
figure.show()
```



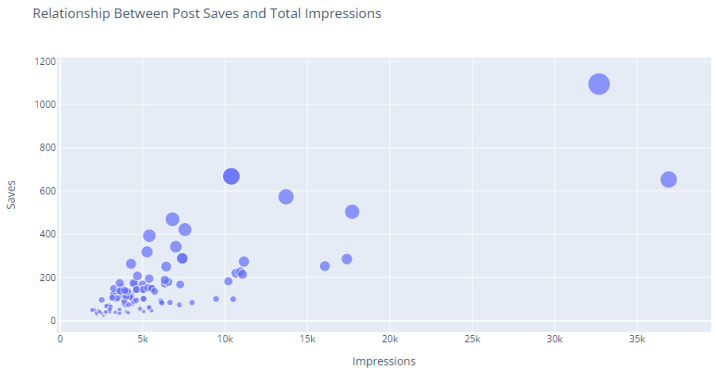
In [13]:
```
figure = px.scatter(data_frame = df, x="Impressions",
                    y="Comments", size="Comments",
                    title = "Relationship Between Comments and Total Impressions")
figure.show()
```



In [14]:
```
figure = px.scatter(data_frame = df, x="Impressions",
                    y="Shares", size="Shares",
                    title = "Relationship Between Shares and Total Impressions")
figure.show()
```



In [15]:
```
figure = px.scatter(data_frame = df, x="Impressions",
                    y="Saves", size="Saves",
                    title = "Relationship Between Post Saves and Total Impressions")
figure.show()
```



From the above analysis we found out the following:

- There is strong correlation between 'likes' and 'Impressions'. The more the likes are, the more the amount of impressions.
- Fromt the second analysis, it is clear that the relationship between 'comments' and 'impression' is not linear rather scattered. Comment has less impact on the impressions.
- Shares and impressions are also correlated. However, the impact of shares wont be so significant.
- Almost same in the case of relationship between 'saves' and 'Impressions'. Number of impressions increases as the number of posts saves increase.

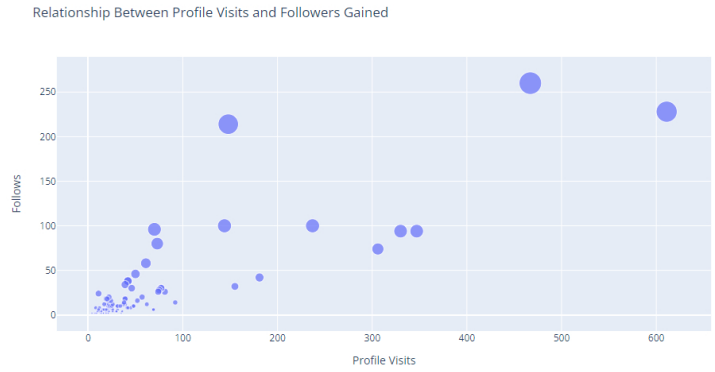
In [16]:
```
# Just having a look at the correlation with impression of all columns.
corr = df.corr()
print(corr["Impressions"].sort_values(ascending=False))
```

```
Impressions       1.000000
From Explore      0.893607
Follows           0.889363
Likes             0.849835
From Home         0.844698
Saves             0.779231
Profile Visits    0.760981
Shares            0.634675
From Other        0.592960
From Hashtags     0.560760
Comments         -0.028524
Name: Impressions, dtype: float64
```

In [17]:
```
# How about the conversion rate?
conversion_rate = (df["Follows"].sum() / df["Profile Visits"].sum()) * 100
print('Rate of Conversion:',conversion_rate)
```

```
Rate of Conversion: 41.0026560424966 8
```

In [18]:
```
figure = px.scatter(data_frame = df, x="Profile Visits",
                    y="Follows", size="Follows",
                    title = "Relationship Between Profile Visits and Followers Gained")
figure.show()
```



Now it is clear that the number of follower increases with the increase number of profile visit, meaning that both the variables have linear relationship.

Conclusion:

From the above analysis we can come to the decision that the company should focus on the using proper hashtags to reach more users outside of its followers. This will help the business gaining more reach and impression as well.