Which one is a better plan?

Purpose

The purpose of this project remains to analyze the data provided by the telecom operator Megaline. With an offering of two plans, Surf and Ultimate, the goal of this project is to determine optimal capital allocation. We will determine which plan brings in more revenue. This will result in an adjustment of the advertising budget, as a means to further increase revenue. The dataset provided is a sample of the population of Megaline customers, across different cities in 2018. We will conduct further analysis on the client behavior, as well as look at other important insights found in the data.

Hypotheses

Initial thoughts suggest the Surf plan would bring in more revenue, as the overage charges, combined with the limited plan allotment, would lead to many customers paying fees. The Ultimate plan is more than double the price of the Surf plan, and the company lacks and middle tier plan. As a result, we hypothesize that the Surf plan would be far more popular than the Ultimate plan, further contributing to the differences in revenue. Yet another factor could be the overages charges on the Ultimate plan, as they are far lower than those of the Surf plan. We expect to see differences in plan preference based on age, as well as revenue when looking across age groups.

Initialization

First, we need to load useful libraries that will aid us in evaluating the data.

In [3]:
```
# Loading all the libraries

import pandas as pd
import math as mt
import numpy as np
from scipy import stats as st
from matplotlib import pyplot as plt
```

Load data

In [4]:
```
# Load the data files into different DataFrames
df_calls = pd.read_csv('datasets/megaline_calls.csv')
df_int = pd.read_csv('datasets/megaline_internet.csv')
df_msg = pd.read_csv('datasets/megaline_messages.csv')
df_plans = pd.read_csv('datasets/megaline_plans.csv')
df_users = pd.read_csv('datasets/megaline_users.csv')
```

In [5]:
```
# Display files to have a visual of the data
display(df_calls)
display(df_int)
display(df_msg)
display(df_plans)
display(df_users)
```

	id	user_id	call_date	duration
0	1000_93	1000	2018-12-27	8.52
1	1000_145	1000	2018-12-27	13.66
2	1000_247	1000	2018-12-27	14.48
3	1000_309	1000	2018-12-28	5.76
4	1000_380	1000	2018-12-30	4.22
...	...	...	...	...
137730	1499_199	1499	2018-11-21	8.72
137731	1499_200	1499	2018-10-20	10.89
137732	1499_201	1499	2018-09-21	8.12
137733	1499_202	1499	2018-10-10	0.37
137734	1499_203	1499	2018-12-29	13.86

137735 rows × 4 columns

	id	user_id	session_date	mb_used
0	1000_13	1000	2018-12-29	89.86
1	1000_204	1000	2018-12-31	0.00
2	1000_379	1000	2018-12-28	660.40
3	1000_413	1000	2018-12-26	270.99
4	1000_442	1000	2018-12-27	880.22
...	...	...	...	...
104820	1499_215	1499	2018-10-20	218.06
104821	1499_216	1499	2018-12-30	304.72
104822	1499_217	1499	2018-09-22	292.75
104823	1499_218	1499	2018-12-07	0.00
104824	1499_219	1499	2018-12-24	758.31

104825 rows × 4 columns

	id	user_id	message_date
0	1000_125	1000	2018-12-27
1	1000_160	1000	2018-12-31
2	1000_223	1000	2018-12-31
3	1000_251	1000	2018-12-27
4	1000_255	1000	2018-12-26
...	...	...	...
76046	1497_526	1497	2018-12-24
76047	1497_536	1497	2018-12-24
76048	1497_547	1497	2018-12-31
76049	1497_558	1497	2018-12-24
76050	1497_613	1497	2018-12-23

76051 rows × 3 columns

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan_name
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaN
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaN
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaN
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaN
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaN
...	...	...	...	...	...	...	...	...
495	1495	Fidel	Sharpe	67	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-09-04	surf	NaN
496	1496	Ariel	Shepherd	49	New Orleans-Metairie, LA MSA	2018-02-20	surf	NaN
497	1497	Donte	Barrera	49	Los Angeles-Long Beach-Anaheim, CA MSA	2018-12-10	ultimate	NaN
498	1498	Scot	Williamson	51	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-02-04	surf	NaN
499	1499	Shena	Dickson	37	Orlando-Kissimmee-Sanford, FL MSA	2018-05-06	surf	NaN

Initial Thoughts

Looking at the data we see all the information needed to calculate total revenue of the two plans. However, several dataframes would need to be merged, grouped, and appended with summary columns. The user ID column appears in many tables, so that can be the key to merging the different dataframes. We would also need to categorize the data by the specific plans: Surf and Unlimited. The call, message, and session dates can be used to append the data tables with a column that specifies the month. Then, we can categorize data by month to month. Analyzing the data based on a year would me a logical fallacy, as fluctuations in usage are expected on a monthly basis. In other words, some users may exceed their plan some months, and be charged fees, while also under use their allotment another month.

Prepare the data

The data will be explored to determine the need for removing duplicates, missing values, or unnecessary columns.

Plans

In [6]:
```
# Print the general/summary information about the plans' DataFrame
df_plans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2 entries, 0 to 1
Data columns (total 8 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   messages_included      2 non-null      int64  
 1   mb_per_month_included  2 non-null      int64  
 2   minutes_included       2 non-null      int64  
 3   usd_monthly_pay        2 non-null      int64  
 4   usd_per_gb             2 non-null      int64  
 5   usd_per_message        2 non-null      float64
 6   usd_per_minute         2 non-null      float64
 7   plan_name              2 non-null      object 
dtypes: float64(2), int64(5), object(1)
memory usage: 256.0+ bytes
```

In [7]:
```
# Print a sample of data for plans
display(df_plans)
```

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan_name
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

We have a dataset that provides the variables for the two plans. We will use this data to calculate the monthly cost per customer, including overages charged to the customer. No missing values are present.

Fix data

[Fix obvious issues with the data given the initial observations.]

In [8]:
```
# Looking at column names
df_plans.columns = ['messages_included', 'mb_per_month_included', 'minutes_included',
       'usd_monthly_pay', 'usd_per_gb', 'usd_per_message', 'usd_per_minute',
       'plan']
df_plans
```

Out[8]:

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

Nothing needs to be fixed continue to the next dataset.

Users

In [9]:
```
# Print the general/summary information about the users' DataFrame
df_users.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 8 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   user_id     500 non-null    int64 
 1   first_name  500 non-null    object
 2   last_name   500 non-null    object
 3   age         500 non-null    int64 
 4   city        500 non-null    object
 5   reg_date    500 non-null    object
 6   plan        500 non-null    object
 7   churn_date  34 non-null     object
dtypes: int64(2), object(6)
memory usage: 31.4+ KB
```

Two date columns are not in the date/time format. We need to change at least the reg date to extract data from the column. We are less concerned with churn date at the moment.

In [10]:
```
# Check for duplicates
df_users.duplicated().sum()
```

Out[10]:
```
0
```

In [11]:
```
# looking at unique values
df_users.nunique()
```

Out[11]:
```
user_id       500
first_name    458
last_name     399
age            58
city           73
reg_date      266
plan            2
churn_date     29
dtype: int64
```

In [12]:
```
# Quick overview of tables and values
df_users.describe(include='all',datetime_is_numeric=True)
```

Out[12]:

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
count	500.000000	500	500	500.000000	500	500	500	34
unique	NaN	458	399	NaN	73	266	2	29
top	NaN	Leonila	David	NaN	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-03-08	surf	2018-12-18
freq	NaN	3	3	NaN	80	5	339	3
mean	1249.500000	NaN	NaN	45.486000	NaN	NaN	NaN	NaN
std	144.481833	NaN	NaN	16.972269	NaN	NaN	NaN	NaN
min	1000.000000	NaN	NaN	18.000000	NaN	NaN	NaN	NaN
25%	1124.750000	NaN	NaN	30.000000	NaN	NaN	NaN	NaN
50%	1249.500000	NaN	NaN	46.000000	NaN	NaN	NaN	NaN
75%	1374.250000	NaN	NaN	61.000000	NaN	NaN	NaN	NaN
max	1499.000000	NaN	NaN	75.000000	NaN	NaN	NaN	NaN

We notice all user ID's are unique, so there are no duplicates in the data. Although there are only 458 unique first names, we expect some people could have the same name. This also applies to last names. We see this data is distributed among 73 cities.

In [13]:
```
# Users who cancelled their plans
df_users.groupby('user_id')['churn_date'].value_counts().nlargest(35)
```

Out[13]:
```
user_id  churn_date
1006     2018-12-18    1
1363     2018-08-16    1
1281     2018-11-14    1
1296     2018-12-18    1
1298     2018-12-19    1
1300     2018-12-19    1
1315     2018-10-03    1
1358     2018-10-22    1
1402     2018-12-26    1
1012     2018-11-16    1
1414     2018-09-01    1
1416     2018-11-21    1
1441     2018-08-19    1
1451     2018-12-10    1
1466     2018-09-17    1
1467     2018-11-18    1
1269     2018-12-15    1
1246     2018-07-31    1
1220     2018-10-13    1
1191     2018-11-30    1
1186     2018-12-31    1
1180     2018-12-22    1
1172     2018-11-29    1
1129     2018-12-27    1
1106     2018-11-14    1
1094     2018-12-12    1
1084     2018-11-11    1
1083     2018-12-18    1
1067     2018-11-24    1
1054     2018-12-31    1
1050     2018-10-07    1
1040     2018-12-30    1
1022     2018-09-07    1
1491     2018-09-18    1
Name: churn_date, dtype: int64
```

In [14]:
```
# Print a sample of data for users
display(df_users)
```

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaN
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaN
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaN
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaN
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaN
...	...	...	...	...	...	...	...	...
495	1495	Fidel	Sharpe	67	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-09-04	surf	NaN
496	1496	Ariel	Shepherd	49	New Orleans-Metairie, LA MSA	2018-02-20	surf	NaN
497	1497	Donte	Barrera	49	Los Angeles-Long Beach-Anaheim, CA MSA	2018-12-10	ultimate	NaN
498	1498	Scot	Williamson	51	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-02-04	surf	NaN
499	1499	Shena	Dickson	37	Orlando-Kissimmee-Sanford, FL MSA	2018-05-06	surf	NaN

500 rows × 8 columns

This dataset includes customers, their location, registration date, plan, and churn date. We have missing values in the churn date column we do not need to fix. We could set the missing values to 'active', to denote the plans are still active, yet that will convert the column data type. However, we need to change reg date to date/time format.

Fix Data

In [15]:
```
# Convert churn date column format to date/time
df_users['churn_date'] = pd.to_datetime(df_users['churn_date'], format='%Y-%m-%d')
```

In [16]:
```
# Convert reg date column format to date/time
df_users['reg_date'] = pd.to_datetime(df_users['reg_date'], format='%Y-%m-%d')
```

In [17]:
```
# confirm type change
df_users.dtypes
```

Out[17]:
```
user_id                int64
first_name            object
last_name             object
age                    int64
city                  object
reg_date      datetime64[ns]
plan                  object
churn_date    datetime64[ns]
dtype: object
```

Not changing value to active, as this will change the column type.

In [18]:
```
# look at users dataframe
display(df_users)
```

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaT
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaT
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaT
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaT
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaT
...	...	...	...	...	...	...	...	...
495	1495	Fidel	Sharpe	67	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-09-04	surf	NaT
496	1496	Ariel	Shepherd	49	New Orleans-Metairie, LA MSA	2018-02-20	surf	NaT
497	1497	Donte	Barrera	49	Los Angeles-Long Beach-Anaheim, CA MSA	2018-12-10	ultimate	NaT
498	1498	Scot	Williamson	51	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-02-04	surf	NaT
499	1499	Shena	Dickson	37	Orlando-Kissimmee-Sanford, FL MSA	2018-05-06	surf	NaT

500 rows × 8 columns

Do not need to delete data based on churn date.

Enrich Data

In [19]:
```
# Add a month start column
df_users['month_start'] = df_users['reg_date'].dt.month
```

In [20]:
```
# check proper implementation
display(df_users)
```

	user_id	first_name	last_name	age	city	reg_date	plan	churn_date	month_start
0	1000	Anamaria	Bauer	45	Atlanta-Sandy Springs-Roswell, GA MSA	2018-12-24	ultimate	NaT	12
1	1001	Mickey	Wilkerson	28	Seattle-Tacoma-Bellevue, WA MSA	2018-08-13	surf	NaT	8
2	1002	Carlee	Hoffman	36	Las Vegas-Henderson-Paradise, NV MSA	2018-10-21	surf	NaT	10
3	1003	Reynaldo	Jenkins	52	Tulsa, OK MSA	2018-01-28	surf	NaT	1
4	1004	Leonila	Thompson	40	Seattle-Tacoma-Bellevue, WA MSA	2018-05-23	surf	NaT	5
...	...	...	...	...	...	...	...	...	...
495	1495	Fidel	Sharpe	67	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-09-04	surf	NaT	9
496	1496	Ariel	Shepherd	49	New Orleans-Metairie, LA MSA	2018-02-20	surf	NaT	2
497	1497	Donte	Barrera	49	Los Angeles-Long Beach-Anaheim, CA MSA	2018-12-10	ultimate	NaT	12
498	1498	Scot	Williamson	51	New York-Newark-Jersey City, NY-NJ-PA MSA	2018-02-04	surf	NaT	2
499	1499	Shena	Dickson	37	Orlando-Kissimmee-Sanford, FL MSA	2018-05-06	surf	NaT	5

500 rows × 9 columns

Added the month start colum for ease in merging data.

Calls

In [21]:
```
# Print the general/summary information about the calls' DataFrame
df_calls.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 137735 entries, 0 to 137734
Data columns (total 4 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   id         137735 non-null  object 
 1   user_id    137735 non-null  int64  
 2   call_date  137735 non-null  object 
 3   duration   137735 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 4.2+ MB
```

In [22]:
```
# Print a sample of data for calls
display(df_calls)
```

	id	user_id	call_date	duration
0	1000_93	1000	2018-12-27	8.52
1	1000_145	1000	2018-12-27	13.66
2	1000_247	1000	2018-12-27	14.48
3	1000_309	1000	2018-12-28	5.76
4	1000_380	1000	2018-12-30	4.22
...	...	...	...	...
137730	1499_199	1499	2018-11-21	8.72
137731	1499_200	1499	2018-10-20	10.89
137732	1499_201	1499	2018-09-21	8.12
137733	1499_202	1499	2018-10-10	0.37
137734	1499_203	1499	2018-12-29	13.86

137735 rows × 4 columns

In [23]:
```
# Number of unique values per column
df_calls.nunique()
```

Out[23]:
```
id           137735
user_id         481
call_date       351
duration       2802
dtype: int64
```

In [24]:
```
# Quick summary of data in columns
df_calls.describe(include='all')
```

Out[24]:

	id	user_id	call_date	duration
count	137735	137735.000000	137735	137735.000000
unique	137735	NaN	351	NaN
top	1000_93	NaN	2018-12-27	NaN
freq	1	NaN	1091	NaN
mean	NaN	1247.658046	NaN	6.745927
std	NaN	139.416268	NaN	5.839241
min	NaN	1000.000000	NaN	0.000000
25%	NaN	1128.000000	NaN	1.290000
50%	NaN	1247.000000	NaN	5.980000
75%	NaN	1365.000000	NaN	10.690000
max	NaN	1499.000000	NaN	37.600000

Calls data is complete with no missing values. We are not concerned with duplicates. The call date column should be changed to date/time format. We would also need to extract the month from the date, and categorize our values by user id and month.

Fix data

In [25]:
```
# Changing call date colum format to date/time
df_calls['call_date'] = pd.to_datetime(df_calls['call_date'], format='%Y-%m-%d')
```

In [26]:
```
# Check for proper implementation
df_calls.dtypes
```

Out[26]:
```
id                   object
user_id               int64
call_date    datetime64[ns]
duration            float64
dtype: object
```

Enrich data

In [27]:
```
# Create a month column
df_calls['month'] = df_calls['call_date'].dt.month
```

In [28]:
```
# Check for proper implementation
display(df_calls)
```

	id	user_id	call_date	duration	month
0	1000_93	1000	2018-12-27	8.52	12
1	1000_145	1000	2018-12-27	13.66	12
2	1000_247	1000	2018-12-27	14.48	12
3	1000_309	1000	2018-12-28	5.76	12
4	1000_380	1000	2018-12-30	4.22	12
...	...	...	...	...	...
137730	1499_199	1499	2018-11-21	8.72	11
137731	1499_200	1499	2018-10-20	10.89	10
137732	1499_201	1499	2018-09-21	8.12	9
137733	1499_202	1499	2018-10-10	0.37	10
137734	1499_203	1499	2018-12-29	13.86	12

137735 rows × 5 columns

In [29]:
```
# Group data by user ID and month, then take the sum of the call duration
df_calls_mo = df_calls.groupby(['user_id','month'])['duration'].sum()
display(df_calls_mo)
```

```
user_id  month
1000     12       116.83
1001     8        171.14
         9        297.69
         10       374.11
         11       404.59
                   ...
1498     12       324.77
1499     9        330.37
         10       363.28
         11       288.56
         12       468.10
Name: duration, Length: 2258, dtype: float64
```

In [30]:

```
# Pivot table illustrating call duration
df_calls_pivot = df_calls.pivot_table(index='user_id',
                            columns='month',
                            values='duration',
                            aggfunc='sum'
                                     )
display(df_calls_pivot)
```

month	1	2	3	4	5	6	7	8	9	10	11	12
user_id												
1000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	116.83
1001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	171.14	297.69	374.11	404.59	392.93
1002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	54.13	359.76	363.24
1003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1041.00
1004	NaN	NaN	NaN	NaN	181.58	261.32	358.45	334.86	284.60	341.63	452.98	403.53
...	...	...	...	...	...	...	...	...	...	...	...	...
1495	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	283.46	578.03	337.45	467.47
1496	NaN	NaN	NaN	NaN	NaN	NaN	NaN	114.62	389.94	301.16	291.88	278.61
1497	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	276.53
1498	NaN	231.87	247.72	344.18	275.13	225.57	304.49	244.57	344.62	278.06	208.99	324.77
1499	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	330.37	363.28	288.56	468.10

481 rows × 12 columns

We changed the call date colum to the date/time type, and extracted the month to create a column that distinguishes the months of the data. We notice some missing values in the data, but we will keep them. It is not unusual for some months to have no data, as users could start in different months. Users could also not make any calls in a particular month, which is less likely, but still a possibility.

Messages

In [31]:
```
# Print the general/summary information about the messages' DataFrame
df_msg.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 76051 entries, 0 to 76050
Data columns (total 3 columns):
 #   Column        Non-Null Count  Dtype 
---  ------        --------------  ----- 
 0   id            76051 non-null  object
 1   user_id       76051 non-null  int64 
 2   message_date  76051 non-null  object
dtypes: int64(1), object(2)
memory usage: 1.7+ MB
```

In [32]:
```
# Print a sample of data for messages
display(df_msg)
```

	id	user_id	message_date
0	1000_125	1000	2018-12-27
1	1000_160	1000	2018-12-31
2	1000_223	1000	2018-12-31
3	1000_251	1000	2018-12-27
4	1000_255	1000	2018-12-26
...	...	...	...
76046	1497_526	1497	2018-12-24
76047	1497_536	1497	2018-12-24
76048	1497_547	1497	2018-12-31
76049	1497_558	1497	2018-12-24
76050	1497_613	1497	2018-12-23

76051 rows × 3 columns

In [33]:
```
# Quick overview of the data in user ID column
df_msg.describe()
```

Out[33]:

	user_id
count	76051.000000
mean	1245.972768
std	139.843635
min	1000.000000
25%	1123.000000
50%	1251.000000
75%	1362.000000
max	1497.000000

Message dataframe has a message date column that needs to be changed to date/time format. We do not see missing values, and are not concerned with duplicates. We would need to extract the month from the message day, group by user id, and count the number of messages for that month.

Fix data

In [34]:
```
# convert column message date format to date/time
df_msg['message_date'] = pd.to_datetime(df_msg['message_date'], format='%Y-%m-%d')
```

In [35]:
```
# Ensure proper implementation
df_msg.dtypes
```

Out[35]:
```
id                      object
user_id                  int64
message_date    datetime64[ns]
dtype: object
```

Enrich data

In [36]:
```
# Create a month column from message date
df_msg['month'] = df_msg['message_date'].dt.month
```

In [37]:
```
# Visual of new column, month
display(df_msg)
```

	id	user_id	message_date	month
0	1000_125	1000	2018-12-27	12
1	1000_160	1000	2018-12-31	12
2	1000_223	1000	2018-12-31	12
3	1000_251	1000	2018-12-27	12
4	1000_255	1000	2018-12-26	12
...	...	...	...	...
76046	1497_526	1497	2018-12-24	12
76047	1497_536	1497	2018-12-24	12
76048	1497_547	1497	2018-12-31	12
76049	1497_558	1497	2018-12-24	12
76050	1497_613	1497	2018-12-23	12

76051 rows × 4 columns

In [38]:

```
# grouping data by user ID and month, then counting the number of times a message was sent in that month
df_msg_mo = df_msg.groupby(['user_id','month'])['message_date'].count().reset_index()
df_msg_mo.columns = ['user_id', 'month', 'message_count']
display(df_msg_mo)
```

	user_id	month	message_count
0	1000	12	11
1	1001	8	30
2	1001	9	44
3	1001	10	53
4	1001	11	36
...	...	...	...
1801	1496	9	21
1802	1496	10	18
1803	1496	11	13
1804	1496	12	11
1805	1497	12	50

1806 rows × 3 columns

In [39]:

```
# Pivot table showing the number of messages
df_msg_pivot = df_msg.pivot_table(index='user_id',
                            columns='month',
                            aggfunc='count'
                                      )
display(df_msg_pivot)
```

	id										...	message_date									
month	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**...**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
user_id																					
1000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	11.0
1001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	30.0	44.0	53.0	...	NaN	NaN	NaN	NaN	NaN	30.0	44.0	53.0	36.0	44.0
1002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	15.0	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	15.0	32.0	41.0
1003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	50.0
1004	NaN	NaN	NaN	NaN	7.0	18.0	26.0	25.0	21.0	24.0	...	NaN	NaN	7.0	18.0	26.0	25.0	21.0	24.0	25.0	31.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
1491	NaN	NaN	NaN	6.0	45.0	54.0	64.0	50.0	50.0	51.0	...	NaN	6.0	45.0	54.0	64.0	50.0	50.0	51.0	46.0	43.0
1492	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	11.0	29.0	...	NaN	NaN	NaN	NaN	NaN	NaN	11.0	29.0	31.0	37.0
1494	NaN	NaN	NaN	NaN	NaN	NaN	20.0	27.0	21.0	38.0	...	NaN	NaN	NaN	NaN	20.0	27.0	21.0	38.0	35.0	33.0
1496	NaN	NaN	NaN	NaN	NaN	NaN	NaN	2.0	21.0	18.0	...	NaN	NaN	NaN	NaN	NaN	2.0	21.0	18.0	13.0	11.0
1497	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	50.0

402 rows × 24 columns

We see some missing values, as expected, due to people starting their plans in different months. We will not fill in the missing data.

Internet

In [40]:
```
# Print the general/summary information about the internet DataFrame
df_int.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 104825 entries, 0 to 104824
Data columns (total 4 columns):
 #   Column        Non-Null Count   Dtype  
---  ------        --------------   -----  
 0   id            104825 non-null  object 
 1   user_id       104825 non-null  int64  
 2   session_date  104825 non-null  object 
 3   mb_used       104825 non-null  float64
dtypes: float64(1), int64(1), object(2)
memory usage: 3.2+ MB
```

In [41]:
```
# Print a sample of data for the internet traffic
display(df_int.head())
```

	id	user_id	session_date	mb_used
0	1000_13	1000	2018-12-29	89.86
1	1000_204	1000	2018-12-31	0.00
2	1000_379	1000	2018-12-28	660.40
3	1000_413	1000	2018-12-26	270.99
4	1000_442	1000	2018-12-27	880.22

The internet data does not contain missing values, and we are not concerned with duplicates. We would need to perform similar strategies with the previous tables. We should extract the month, and organize the mb used by user id and month.

Fix data

In [42]:
```
# Convert session date format to date/time
df_int['session_date'] = pd.to_datetime(df_int['session_date'], format='%Y-%m-%d')
```

In [43]:
```
# Check proper implementation
df_int.dtypes
```

Out[43]:
```
id                      object
user_id                  int64
session_date    datetime64[ns]
mb_used                float64
dtype: object
```

Converted session date to date/time format.

Enrich data

In [44]:
```
# Created a month column from session date
df_int['month'] = df_int['session_date'].dt.month
```

In [45]:
```
# check proper implementation
display(df_int.head())
```

	id	user_id	session_date	mb_used	month
0	1000_13	1000	2018-12-29	89.86	12
1	1000_204	1000	2018-12-31	0.00	12
2	1000_379	1000	2018-12-28	660.40	12
3	1000_413	1000	2018-12-26	270.99	12
4	1000_442	1000	2018-12-27	880.22	12

Added a month column to group data based on month.

In [46]:
```
# Grouped the data based on user ID and month, then took the sum of the data used
df_int_mo = df_int.groupby(['user_id', 'month'])['mb_used'].sum()
display(df_int_mo)
```

```
user_id  month
1000     12        1901.47
1001     8         6919.15
         9        13314.82
         10       22330.49
         11       18504.30
                    ...
1498     12       23137.69
1499     9        12984.76
         10       19492.43
         11       16813.83
         12       22059.21
Name: mb_used, Length: 2277, dtype: float64
```

In [47]:
```
# Pivot table of data used per month
df_int_pivot = df_int.pivot_table(index='user_id',
                            columns='month',
                            values='mb_used',
                            aggfunc='sum'
                                     )
display(df_int_pivot)
```

month user_id	1	2	3	4	5	6	7	8	9	10	11	12
1000	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1901.47
1001	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6919.15	13314.82	22330.49	18504.30	19369.18
1002	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	6552.01	19345.08	14396.24
1003	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	27044.14
1004	NaN	NaN	NaN	NaN	6547.21	20672.82	24516.62	27981.74	18852.72	14541.63	21850.78	21389.29
...	...	...	...	...	...	...	...	...	...	...	...	...
1495	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22981.37	26899.41	24912.78	24097.40
1496	NaN	NaN	NaN	NaN	NaN	NaN	NaN	8605.66	16389.27	14287.36	8547.36	16438.99
1497	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	11106.55
1498	NaN	19822.04	19744.34	19878.86	22462.17	14807.18	24834.37	20261.89	22827.28	20580.76	19168.55	23137.69
1499	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	12984.76	19492.43	16813.83	22059.21

489 rows × 12 columns

Pivot table groups data by user id and month, then sums the data used in megabytes. We will keep the missing values.

Study plan conditions

In [48]:
```
# Print out the plan conditions
df_plans
```

Out[48]:

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

There are two plans: Surf and Ultimate. Surf costs 20 dollars per month, and includes overage fees. The ultimate plan is 70 dollars per month and also includes overage fees, but they are less than that of Surf. Data included in the plans is in megabytes, yet the cost is in gigabytes. We will use the conversion factor of 1 gb = 1024 mb. We note that the currency is US dollars.

Aggregate data per user

In [49]:
```
# Calculate the number of calls made by each user per month. Save the result.

df_calls_num = df_calls.groupby(['user_id','month'])['duration'].count().reset_index()
df_calls_num.columns = ['user_id', 'month', 'calls']
```

In [50]:
```
# Reset index
df_calls_mo.reset_index()
```

Out[50]:

	user_id	month	duration
0	1000	12	116.83
1	1001	8	171.14
2	1001	9	297.69
3	1001	10	374.11
4	1001	11	404.59
...	...	...	...
2253	1498	12	324.77
2254	1499	9	330.37
2255	1499	10	363.28
2256	1499	11	288.56
2257	1499	12	468.10

2258 rows × 3 columns

In [51]:

```
# Reset index
df_msg = df_msg.loc[:,'user_id':]
```

In [52]:

```
# Calculate the number of messages sent by each user per month. Save the result.
df_msg_mo
```

Out[52]:

	user_id	month	message_count
0	1000	12	11
1	1001	8	30
2	1001	9	44
3	1001	10	53
4	1001	11	36
...	...	...	...
1801	1496	9	21
1802	1496	10	18
1803	1496	11	13
1804	1496	12	11
1805	1497	12	50

1806 rows × 3 columns

In [53]:

```
# Calculate the volume of internet traffic used by each user per month. Save the result.
df_int_mo.reset_index()
```

Out[53]:

	user_id	month	mb_used
0	1000	12	1901.47
1	1001	8	6919.15
2	1001	9	13314.82
3	1001	10	22330.49
4	1001	11	18504.30
...	...	...	...
2272	1498	12	23137.69
2273	1499	9	12984.76
2274	1499	10	19492.43
2275	1499	11	16813.83
2276	1499	12	22059.21

2277 rows × 3 columns

In [54]:
```
# Merge the data for calls, minutes, messages, internet based on user_id and month
df_1 = df_calls_num.merge(df_calls_mo, on=('user_id', 'month'), how='outer')
```

In [55]:
```
# Appending data column
df_2 = df_1.merge(df_int_mo, on=('user_id', 'month'), how='outer')
```

In [56]:
```
# Appending number of messages column
df_3= df_2.merge(df_msg_mo, on=('user_id', 'month'), how='outer')
df_3.columns = ['user_id', 'month', 'num_calls', 'call_duration', 'mb_used', 'num_messages']
```

In [57]:
```
# User ID and plan table
df_user_plan = df_users[['user_id', 'plan']]
```

In [58]:
```
# Add the plan information, merge on user ID
df_4 = df_3.merge(df_user_plan, on='user_id', how='outer')
```

In [59]:
```
# Visual of plans table
df_plans
```

Out[59]:

	messages_included	mb_per_month_included	minutes_included	usd_monthly_pay	usd_per_gb	usd_per_message	usd_per_minute	plan
0	50	15360	500	20	10	0.03	0.03	surf
1	1000	30720	3000	70	7	0.01	0.01	ultimate

In [60]:
```
# Merging for final dataset
df_merged = df_4.merge(df_plans, on='plan', how='outer')
df_merged = df_merged.fillna(0)
```

In [61]:
```
# check for missing values
df_merged.isna().sum()
```

Out[61]:
```
user_id                  0
month                    0
num_calls                0
call_duration            0
mb_used                  0
num_messages             0
plan                     0
messages_included        0
mb_per_month_included    0
minutes_included         0
usd_monthly_pay          0
usd_per_gb               0
usd_per_message          0
usd_per_minute           0
dtype: int64
```

[Calculate the monthly revenue from each user (subtract the free package limit from the total number of calls, text messages, and data; multiply the result by the calling plan value; add the monthly charge depending on the calling plan).]

In [62]:
```
# Function to round up minutes, gb data
def round_up(n, decimals=0):
    multiplier = 10 ** decimals
    return mt.ceil(n * multiplier) / multiplier
```

In [63]:
```
# Checking functionality of round function
round_up(31.366)
```

Out[63]: 32.0

In [64]:
```
# Calculate the monthly revenue for each user
# using megabytes instead of gigabytes, converted cost to appropriate value

def revenue(row) :

    additional_mins = 0                        # to add additional minutes
    additional_messages = 0                    # to add additional messages
    additional_gb = 0                          # to add additional data
    surf = 20                                  # base price of Surf plan
    ultimate = 70                              # base price of Ultimate Plan

    plan = row['plan']                         # looking at the plan row
    call = round_up(row['call_duration'])      # rounding the call duration to the nearest minute
    gb = round_up(row['mb_used'] / 1024)       # rounding the data to the nearest gigabyte


    if plan == 'surf' :
        if call > 500 :
            additional_mins = call - 500
        if row['num_messages'] > 50 :
            additional_messages = row['num_messages'] - 50
        if gb > 15 :
            additional_gb = gb - 15
        profit = (additional_mins * 0.03) + (additional_messages * 0.03) + (additional_gb * 10 )
        if profit == 0 :
            return surf
        else :
            return profit + surf


    if plan == 'ultimate' :
        if call > 3000 :
            additional_mins = call - 3000
        if row['num_messages'] > 1000 :
            additional_messages = row['num_messages'] - 1000
        if gb > 30 :
            additional_gb = gb - 30
        profit = (additional_mins * 0.01) + (additional_messages * 0.01) + (additional_gb * 7 )
        if profit == 0 :
            return ultimate
        else :
            return profit + ultimate
```

Study User Behavior

Here, we will calculate some useful descriptive statistics for the aggregated and merged data, to reveal an overall picture captured by the data. We will display useful plots to help with the understanding of the given data. Given that the main task is to compare the plans and decide on which one is more profitable, the statistics and the plots will be calculated on a per-plan, and on a per month basis. Insights will be given on the relationships of the data among the various parameters, including age and location.

Calls

In [65]:
```
# Compare average duration of calls per each plan per each distinct month. Plot a bar plat to visualize it.
df_merged_calls = df_merged.groupby(['plan', 'month'])['call_duration'].mean()
display(df_merged_calls.reset_index())
```

	plan	month	call_duration
0	surf	0.0	0.000000
1	surf	1.0	192.840000
2	surf	2.0	280.851111
3	surf	3.0	310.970000
4	surf	4.0	332.380000
5	surf	5.0	377.053247
6	surf	6.0	407.208866
7	surf	7.0	424.523223
8	surf	8.0	387.169630
9	surf	9.0	390.992062
10	surf	10.0	405.692363
11	surf	11.0	399.599823
12	surf	12.0	447.475283
13	ultimate	0.0	0.000000
14	ultimate	1.0	183.162500
15	ultimate	2.0	379.861429
16	ultimate	3.0	285.701667
17	ultimate	4.0	316.508095
18	ultimate	5.0	383.664828
19	ultimate	6.0	349.811064
20	ultimate	7.0	403.767288
21	ultimate	8.0	397.274789
22	ultimate	9.0	413.287326
23	ultimate	10.0	425.168019
24	ultimate	11.0	420.477559

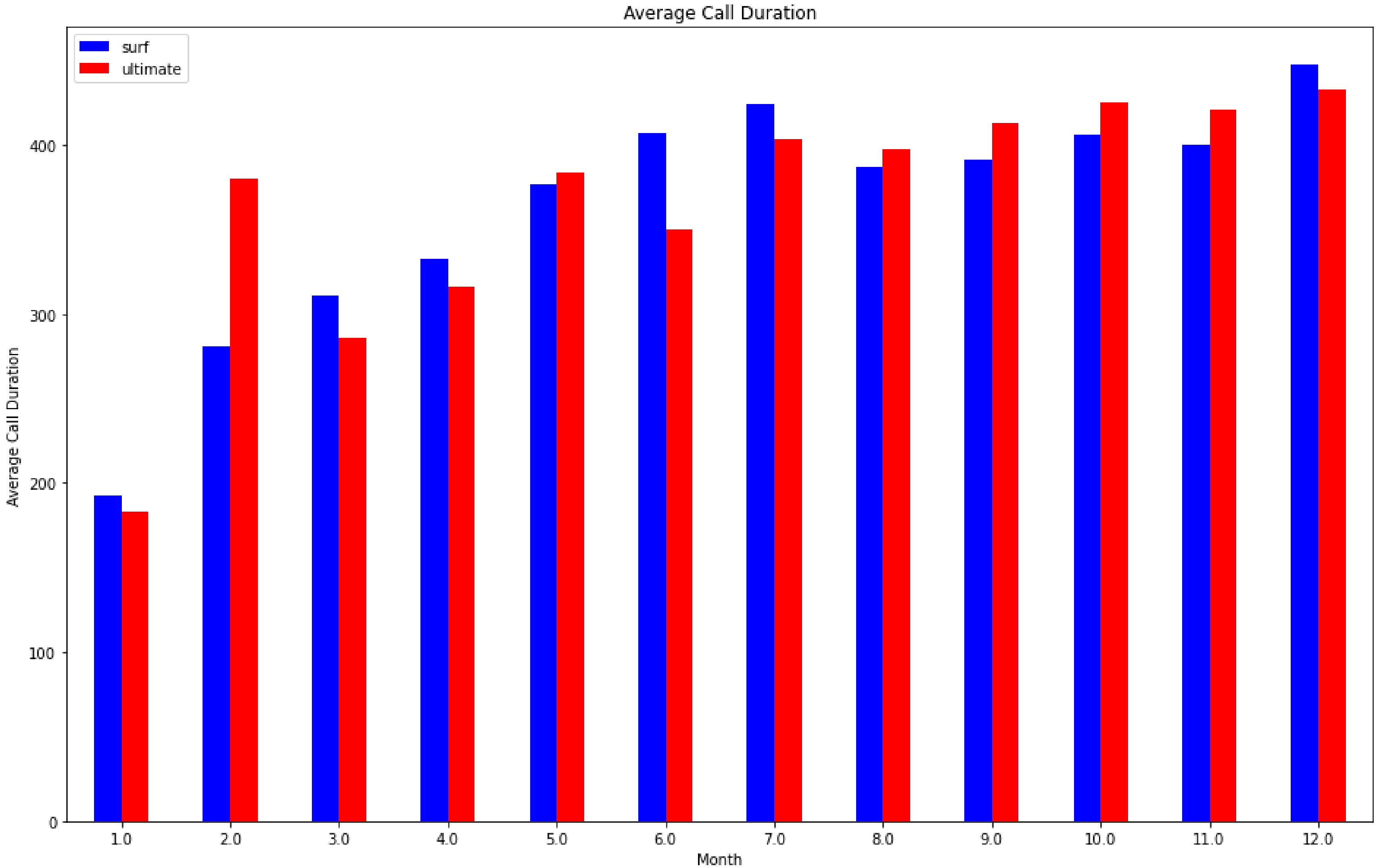
	plan	month	call_duration
25	ultimate	12.0	433.012583

In [66]:
```
# Separated calls on Surf plan
df_surf_calls = df_merged_calls[1:13].reset_index('plan')
```

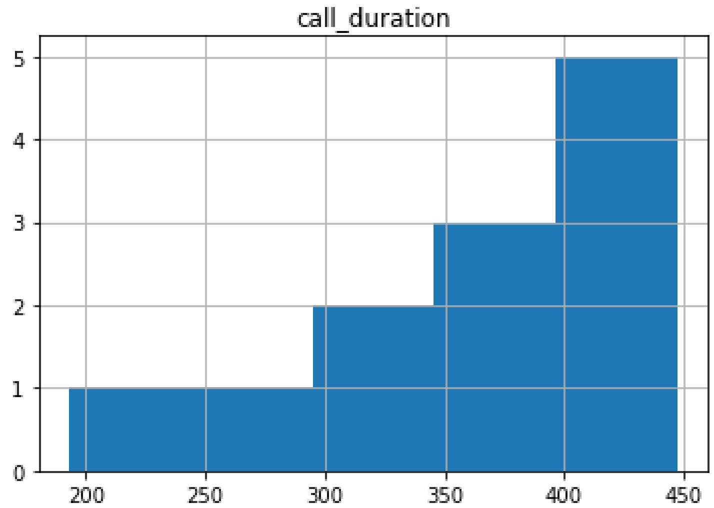
In [67]:
```
# Separated calls on Ultimate plan
df_ultimate_calls = df_merged_calls.reset_index('plan').tail(12)
```

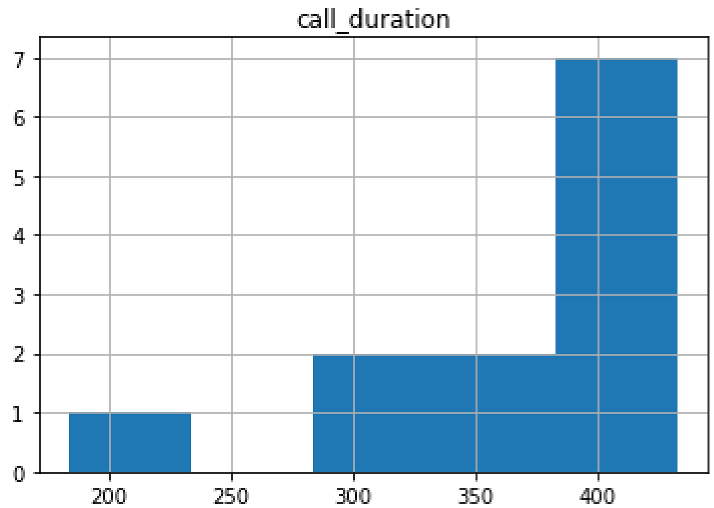
In [68]:
```
# merged Surf and Ultimate call plans side by side
df_all_calls = df_surf_calls.merge(df_ultimate_calls, on='month', how='outer')
df_all_calls.columns = ['plan_s', 'surf', 'plan_u', 'ultimate']
```

In [69]:
```
# Plot call duration on Surf and Ultimate plans, by month
df_all_calls.plot(kind='bar',
                    title='Average Call Duration',
                  xlabel='Month',
                  ylabel='Average Call Duration',
                  color=('blue', 'red'),
                  rot=0,
                  figsize= (16,10)
                    )
plt.show()
```

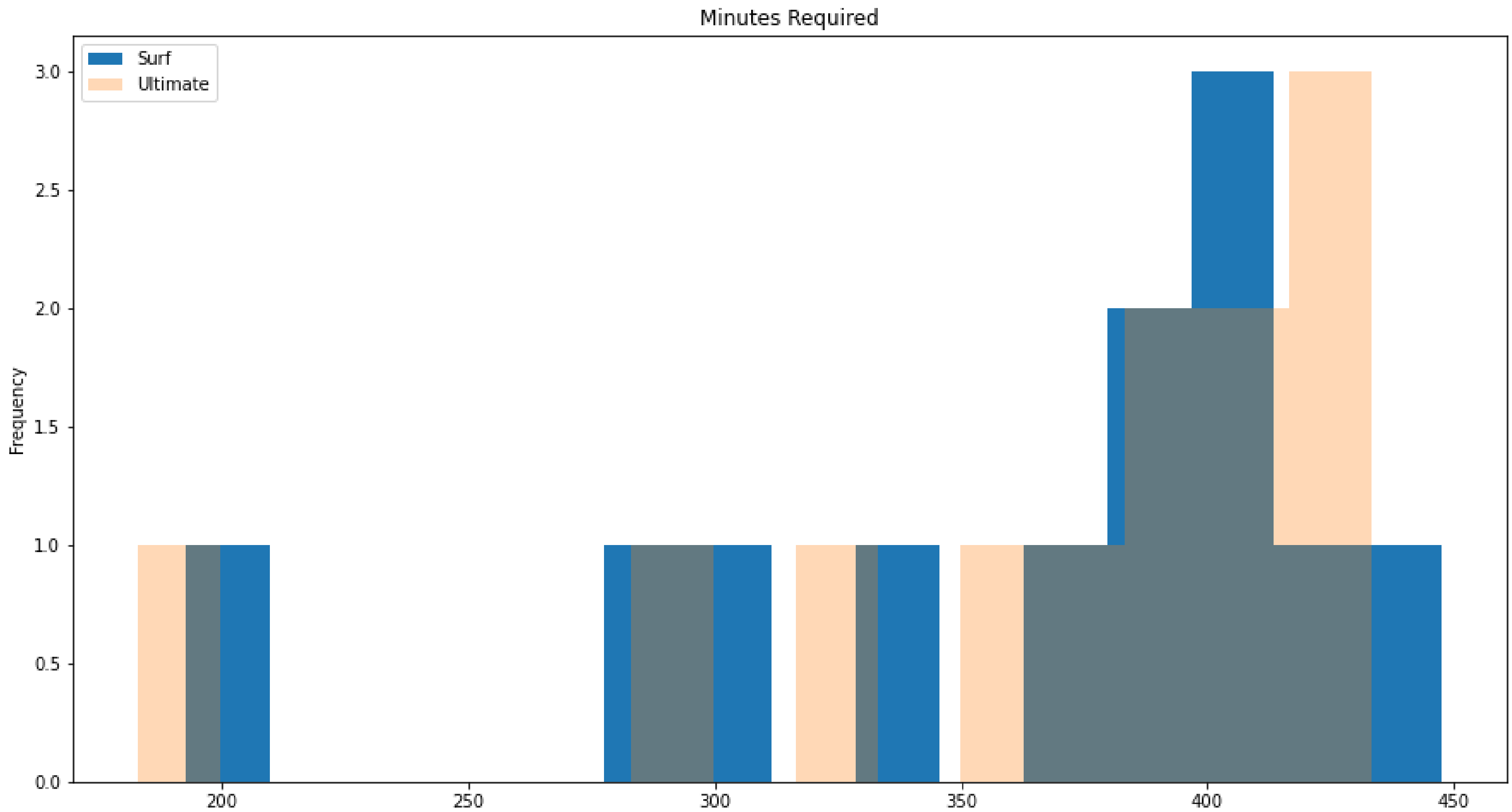


In [70]:
```
# Compare the number of minutes users of each plan require each month. Plot a histogram.
df_surf_calls.hist(bins=5)
df_ultimate_calls.hist(bins=5)
plt.title='Minutes Required'
plt.show()
```





In [71]:
```
# The merged histograms
df_surf_calls['call_duration'].plot(kind='hist', bins=15, title='Minutes Required', ylabel='Frequency', figsize=(15,8))
df_ultimate_calls['call_duration'].plot(kind='hist', bins=15, alpha=0.3)

plt.legend(['Surf', 'Ultimate'])
plt.show()
```



[Calculate the mean and the variable of the call duration to reason on whether users on the different plans have different behaviours for their calls.]

In [72]:
```
# Calculate the mean and the variance of the monthly call duration, Surf plan
print('mean')
print(df_surf_calls.mean())
print()
print('variance')
print(df_surf_calls.var())
```

```
mean
call_duration    363.062967
dtype: float64

variance
call_duration    5177.321155
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3673763875.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_calls.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3673763875.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_calls.var())
```

In [73]:

```
# Calculate the mean and the variance of the monthly call duration, Ultimate plan
print('mean')
print(df_ultimate_calls.mean())
print()
print('variance')
print(df_ultimate_calls.var())
```

```
mean
call_duration    365.974762
dtype: float64

variance
call_duration    5335.727136
dtype: float64
```

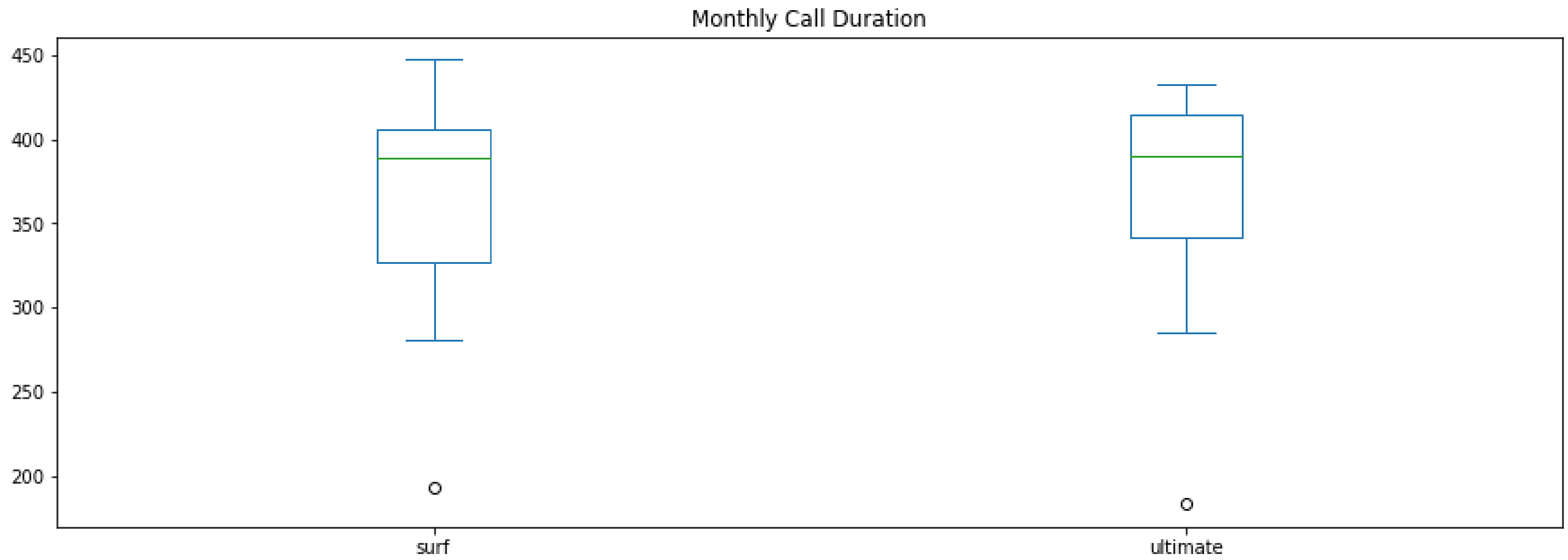
```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\848826890.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_calls.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\848826890.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_calls.var())
```

In [74]:

```
# Plot a boxplot to visualize the distribution of the monthly call duration
df_all_calls.plot(kind='box', title='Monthly Call Duration', figsize=(15,5))
```

Out[74]:

```
<AxesSubplot:title={'center':'Monthly Call Duration'}>
```



In [75]:
```
# surf call durations
surf_calls = df_surf_calls['call_duration'].values.tolist()
```

In [76]:
```
# ultimate call durations
ultimate_calls = df_ultimate_calls['call_duration'].values.tolist()
```

Null hypothesis that the mean call durations for both plans is similar

In [77]:
```
# Test the hypotheses
# Null hypothesis that the two means are the same
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis

results = st.ttest_ind(surf_calls, ultimate_calls)

print('p-value: ', results.pvalue)

if results.pvalue < alpha:
    print("We reject the null hypothesis, the average call durations differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  0.9225249438414813
We can't reject the null hypothesis
```

The users of the two plans seem to have similar calling behavior, when considering call durations. In general, Surf plan customers and Ultimate plan customers have more messages 6 months each, out of the year. The mean call durations for both plans appeared to be similar, further visualized by the box plots, but we will test this hypothesis statistically. The Ultimate plan sees a greater variance in call duration compared to the Surf plan. This may be attributed to the outlier we see in the box plot of the Ultimate plan, yet the Surf plan has an outlier as well. Hypothesis testing suggests we cannot reject the null hypothesis that the mean call duration of both plans is similar.

Messages

In [78]:
```python
# Visual of dataset we are working with
df_merged
```

Out[78]:

	user_id	month	num_calls	call_duration	mb_used	num_messages	plan	messages_included	mb_per_month_included	minutes_inclu
0	1000	12.0	16.0	116.83	1901.47	11.0	ultimate	1000	30720	3
1	1006	11.0	2.0	9.32	2068.37	15.0	ultimate	1000	30720	3
2	1006	12.0	9.0	54.79	32118.82	139.0	ultimate	1000	30720	3
3	1008	10.0	71.0	450.21	17106.99	21.0	ultimate	1000	30720	3
4	1008	11.0	63.0	422.81	23676.72	37.0	ultimate	1000	30720	3
...	...	...	...	...	...	...	...	...	...	
2298	1143	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2299	1307	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2300	1319	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2301	1378	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2302	1473	0.0	0.0	0.00	0.00	0.0	surf	50	15360	

2303 rows × 14 columns

In [79]:
```python
# Compare the number of messages users of each plan tend to send each month
df_merged_msg = df_merged.groupby(['plan', 'month'])['num_messages'].mean()
```

```
display(df_merged_msg.reset_index())
```

	plan	month	num_messages
0	surf	0.0	0.000000
1	surf	1.0	10.500000
2	surf	2.0	12.000000
3	surf	3.0	15.260870
4	surf	4.0	17.400000
5	surf	5.0	24.012987
6	surf	6.0	25.298969
7	surf	7.0	27.033058
8	surf	8.0	28.777778
9	surf	9.0	30.762887
10	surf	10.0	33.839662
11	surf	11.0	32.385159
12	surf	12.0	38.600629
13	ultimate	0.0	0.000000
14	ultimate	1.0	15.500000
15	ultimate	2.0	21.571429
16	ultimate	3.0	20.250000
17	ultimate	4.0	22.047619
18	ultimate	5.0	32.103448
19	ultimate	6.0	29.340426
20	ultimate	7.0	32.830508
21	ultimate	8.0	38.478873
22	ultimate	9.0	37.895349
23	ultimate	10.0	39.443396
24	ultimate	11.0	38.606299

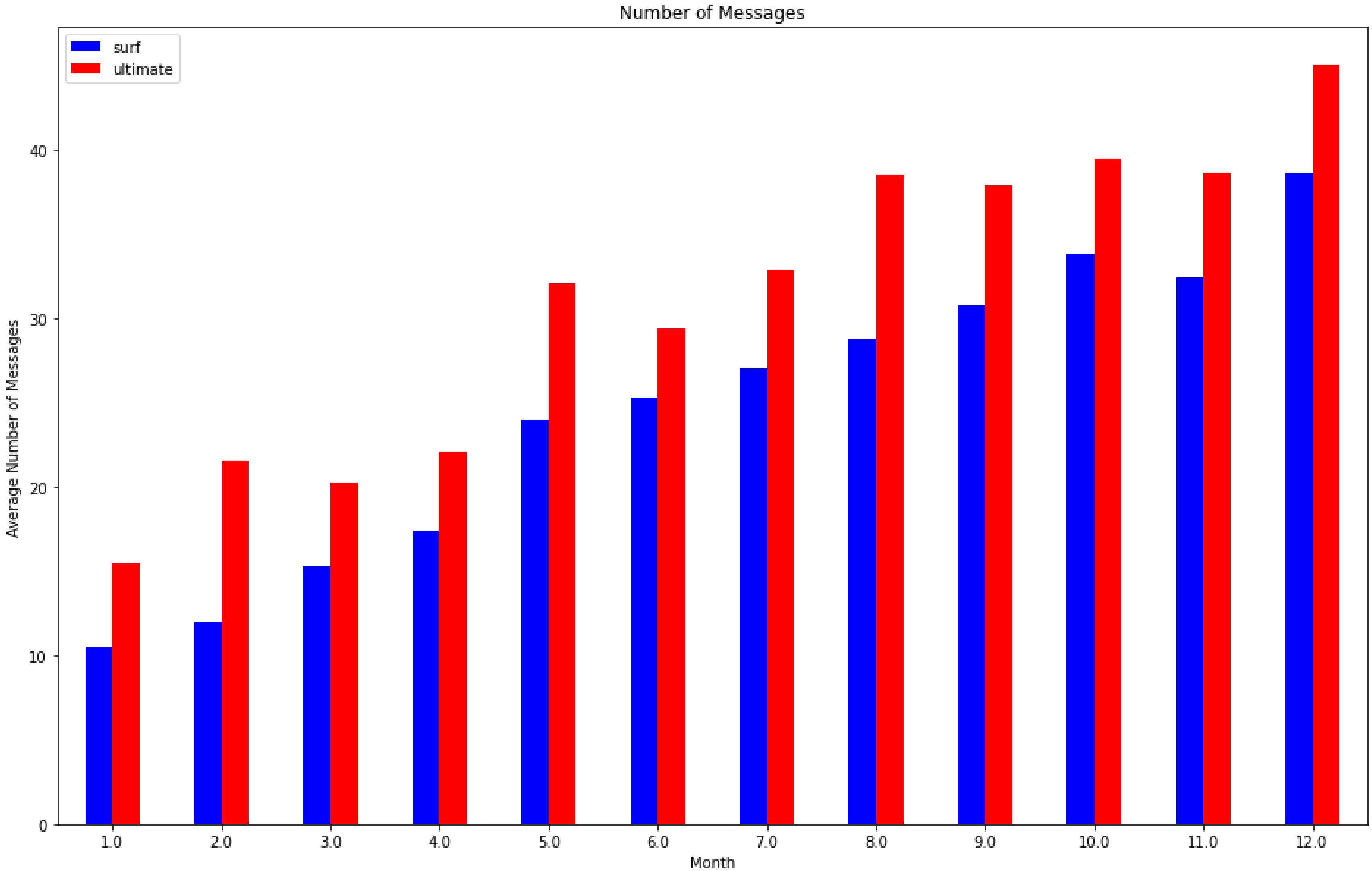
	plan	month	num_messages
25	ultimate	12.0	45.006623

In [80]:
```
# number of messages sent per month, Surf plan
df_surf_msgs = df_merged_msg[1:13].reset_index('plan')
```

In [81]:
```
# number of messages sent per month, Ultimate plan
df_ultimate_msgs = df_merged_msg.reset_index('plan').tail(12)
```

In [82]:
```
# Merged the dataset of the two plans side by side
df_all_msgs = df_surf_msgs.merge(df_ultimate_msgs, on='month', how='outer')
df_all_msgs.columns = ['plan_s', 'surf', 'plan_u', 'ultimate']
```

In [83]:
```
# Displaying chart of the number of messages per plan, per month
df_all_msgs.plot(kind='bar',
                    title='Number of Messages',
                  xlabel='Month',
                  ylabel='Average Number of Messages',
                  color=('blue', 'red'),
                 rot=0,
                  figsize= (16,10)
                    )
plt.show()
```



In [84]:
```
# showing statistical metrics
print('mean')
print(df_surf_msgs.mean())
print()
print('variance')
print(df_surf_msgs.var())
```

```
mean
num_messages    24.656
dtype: float64

variance
num_messages    81.888846
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\2921719458.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_msgs.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\2921719458.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_msgs.var())
```

In [85]:

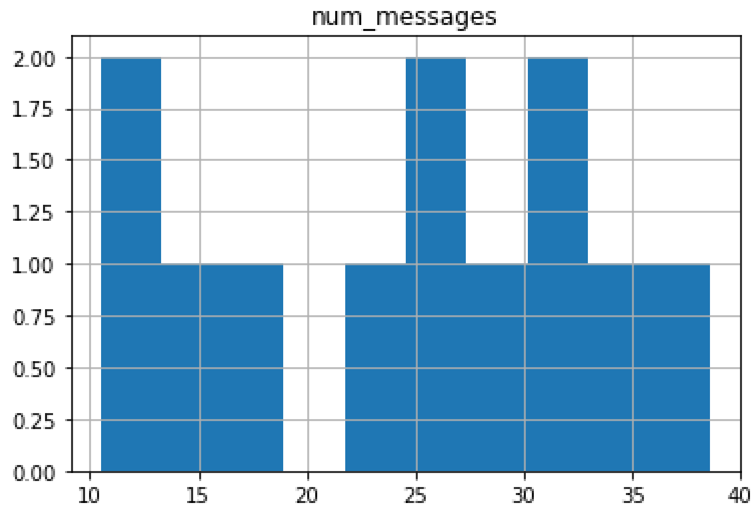
```
# Mean and variance of ultimate messages
print('mean')
print(df_ultimate_msgs.mean())
print()
print('variance')
print(df_ultimate_msgs.var())
```

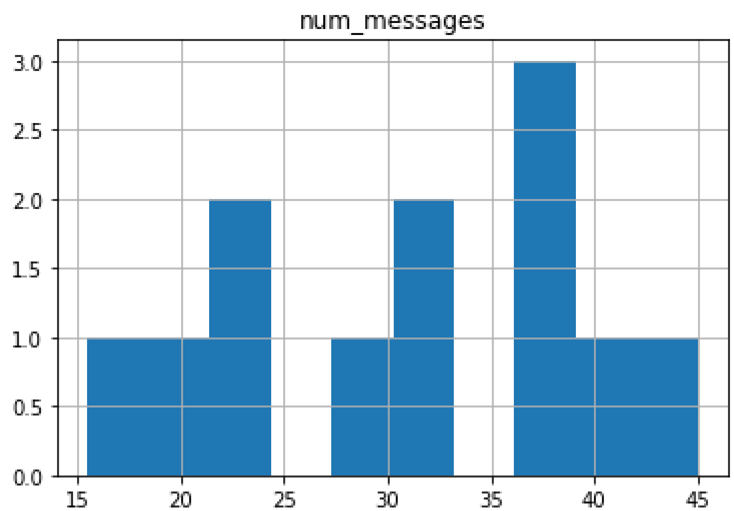
```
mean
num_messages    31.089497
dtype: float64

variance
num_messages    87.353963
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\1981465832.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_msgs.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\1981465832.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_msgs.var())
```

In [86]:

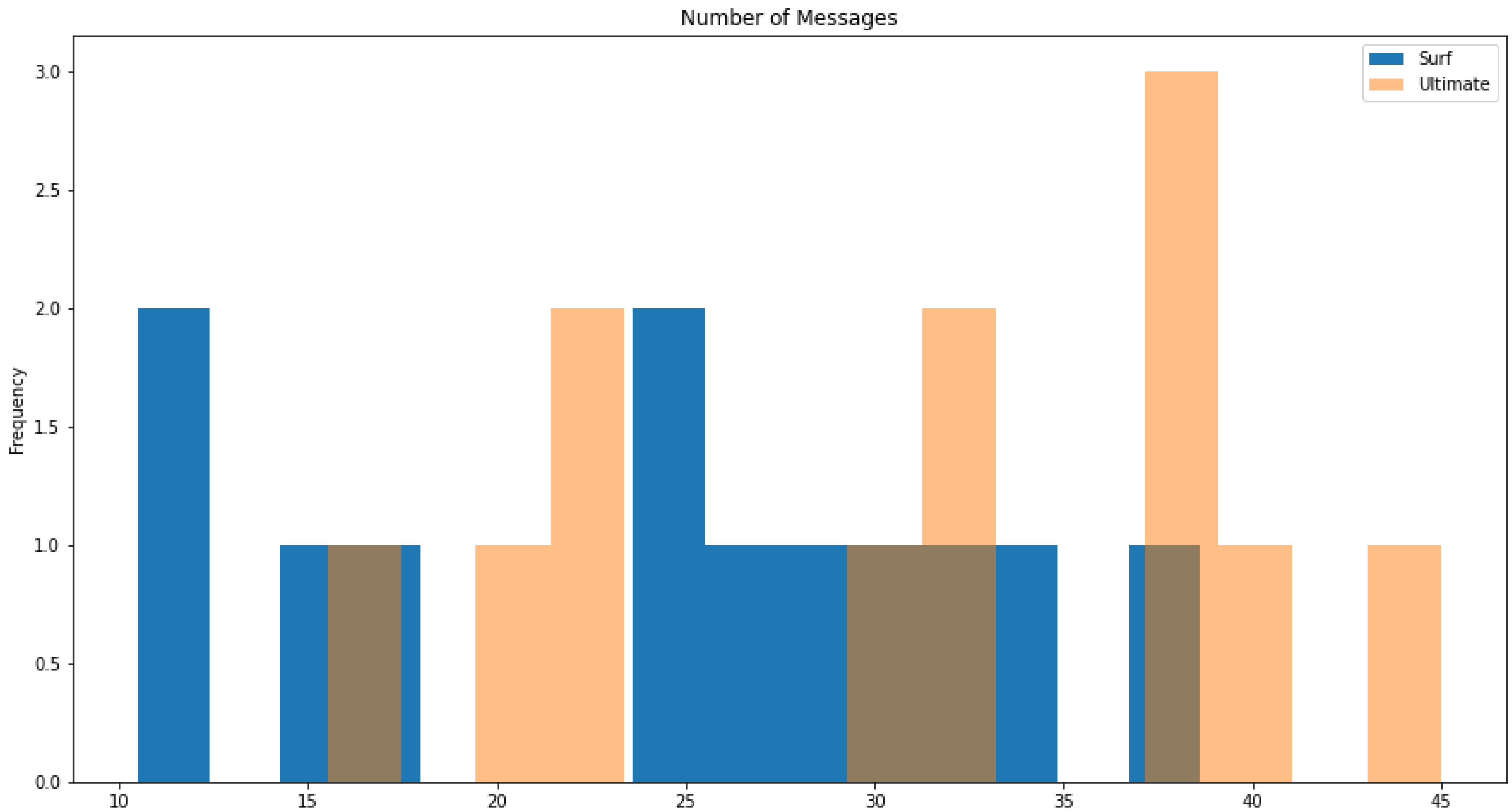
```
# distribution of surf messages
df_surf_msgs.hist(bins=10)
df_ultimate_msgs.hist(bins=10)
plt.title='Messages'
plt.show()
```





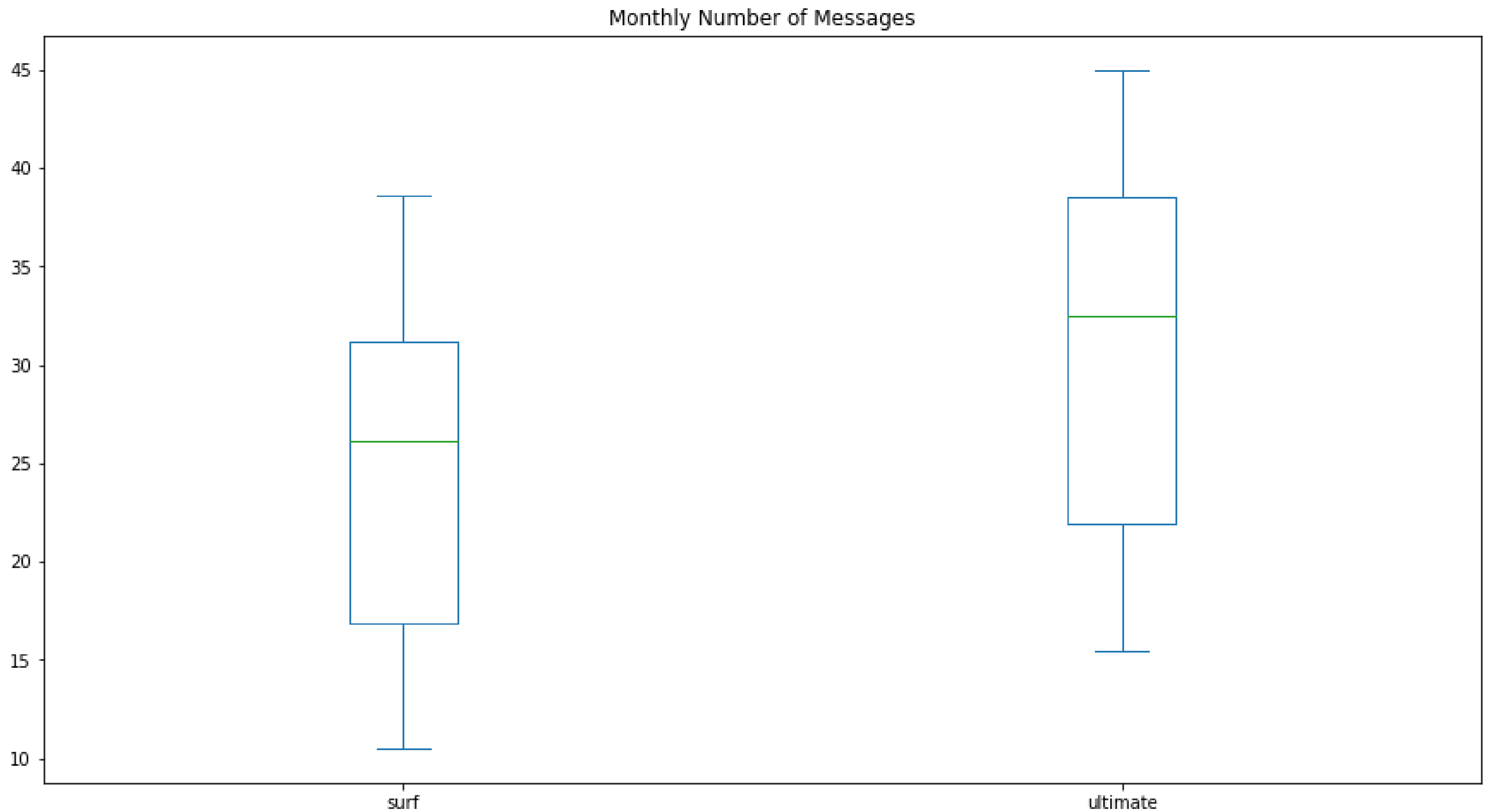
In [87]:

```
# surf and ultimate messages
df_surf_msgs['num_messages'].plot(kind='hist', bins=15, title='Number of Messages', ylabel='Frequency', figsize=(15,8))
df_ultimate_msgs['num_messages'].plot(kind='hist', bins=15, alpha=0.5)

plt.legend(['Surf', 'Ultimate'])
plt.show()
```



In [88]:
```
# Plot a boxplot to visualize the distribution of the monthly call duration
df_all_msgs.plot(kind='box', title='Monthly Number of Messages', figsize=(15,8))
```

Out[88]:
```
<AxesSubplot:title={'center':'Monthly Number of Messages'}>
```



In [89]:
```
# surf message values
surf_msgs = df_surf_msgs['num_messages'].values.tolist()
```

In [90]:
```
# ultimate message values
ultimate_msgs = df_ultimate_msgs['num_messages'].values.tolist()
```

Null hypothesis is the mean number of messages for the plans are similar

In [91]:
```
# Test the hypotheses
# Null hypothesis that the two means are the same
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis
```

```
results = st.ttest_ind(surf_msgs, ultimate_msgs)

print('p-value: ', results.pvalue)

if results.pvalue < alpha:
    print("We reject the null hypothesis, the average number of messages differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  0.10075353966021278
We can't reject the null hypothesis
```

The number of messages sent by customers of the Ultimate plan is consistently greater than that of Surf customers. The mean of the number of messages of the two plans appear different, however, we need to test this. Looking at the boxplot, we see the two plans are similar, and both have wide upper and lower bounds. Hypothesis testing suggests the average number of messages does not differ, contrary to our earlier thoughts.

Internet

In [92]:
```
# Compare the amount of internet traffic consumed by users per plan
df_merged
```

Out[92]:

	user_id	month	num_calls	call_duration	mb_used	num_messages	plan	messages_included	mb_per_month_included	minutes_inclu
0	1000	12.0	16.0	116.83	1901.47	11.0	ultimate	1000	30720	3
1	1006	11.0	2.0	9.32	2068.37	15.0	ultimate	1000	30720	3
2	1006	12.0	9.0	54.79	32118.82	139.0	ultimate	1000	30720	3
3	1008	10.0	71.0	450.21	17106.99	21.0	ultimate	1000	30720	3
4	1008	11.0	63.0	422.81	23676.72	37.0	ultimate	1000	30720	3
...	...	...	...	...	...	...	...	...	...	
2298	1143	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2299	1307	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2300	1319	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2301	1378	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2302	1473	0.0	0.0	0.00	0.00	0.0	surf	50	15360	

2303 rows × 14 columns

In [93]:

```
# Compare the amount of internet traffic consumed by users per plan
df_ints_traffic = df_merged.groupby(['plan', 'month'])['mb_used'].count()

df_ints_traffic.columns = ['plan', 'month', 'internet_traffic']
display(df_ints_traffic.reset_index())
```

	plan	month	mb_used
0	surf	0.0	6
1	surf	1.0	2
2	surf	2.0	9
3	surf	3.0	23
4	surf	4.0	50
5	surf	5.0	77
6	surf	6.0	97
7	surf	7.0	121
8	surf	8.0	162
9	surf	9.0	194
10	surf	10.0	237
11	surf	11.0	283
12	surf	12.0	318
13	ultimate	0.0	4
14	ultimate	1.0	4
15	ultimate	2.0	7
16	ultimate	3.0	12
17	ultimate	4.0	21
18	ultimate	5.0	29
19	ultimate	6.0	47
20	ultimate	7.0	59
21	ultimate	8.0	71
22	ultimate	9.0	86
23	ultimate	10.0	106
24	ultimate	11.0	127

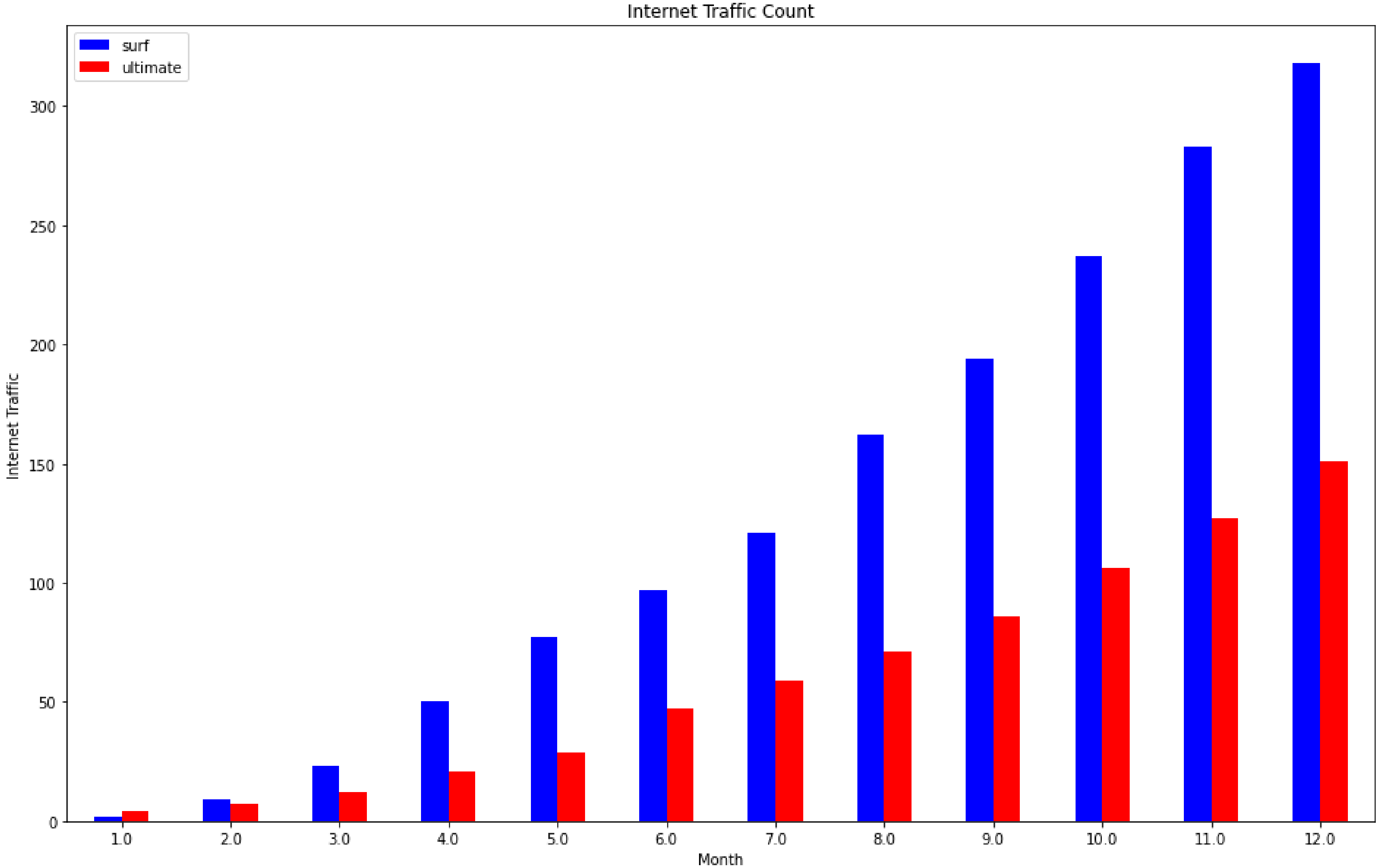
	plan	month	mb_used
25	ultimate	12.0	151

In [94]:
```
# Internet traffic for Surf customers
df_surf_ints_traffic = df_ints_traffic[1:13].reset_index('plan')
```

In [95]:
```
# Internet traffic for Ultimate customers
df_ultimate_ints_traffic = df_ints_traffic.reset_index('plan').tail(12)
```

In [96]:
```
# internet trffic for both Surf and Ultiate customers, merged on month
df_all_ints_traffic = df_surf_ints_traffic.merge(df_ultimate_ints_traffic, on='month', how='outer')
df_all_ints_traffic.columns = ['plan_s', 'surf', 'plan_u', 'ultimate']
```

In [97]:
```
# Display chart on Internet traffic by plan, by month
df_all_ints_traffic.plot(kind='bar',
                    title='Internet Traffic Count',
                  xlabel='Month',
                  ylabel='Internet Traffic',
                  color=('blue', 'red'),
                 rot=0,
                  figsize= (16,10)
                    )
plt.show()
```



In [98]:
```
# Surf internet traffic mean and variance
print('mean')
print(df_surf_ints_traffic.mean())
print()
print('variance')
print(df_surf_ints_traffic.var())
```

```
mean
mb_used    131.083333
dtype: float64

variance
mb_used    11650.992424
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3245096143.py:3: FutureWarning: Dropping of nuisance columns in DataFra
me reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only val
id columns before calling the reduction.
  print(df_surf_ints_traffic.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3245096143.py:6: FutureWarning: Dropping of nuisance columns in DataFra
me reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only val
id columns before calling the reduction.
  print(df_surf_ints_traffic.var())
```

In [99]:

```
# Ultimate internet traffic mean and variance
print('mean')
print(df_ultimate_ints_traffic.mean())
print()
print('variance')
print(df_ultimate_ints_traffic.var())
```

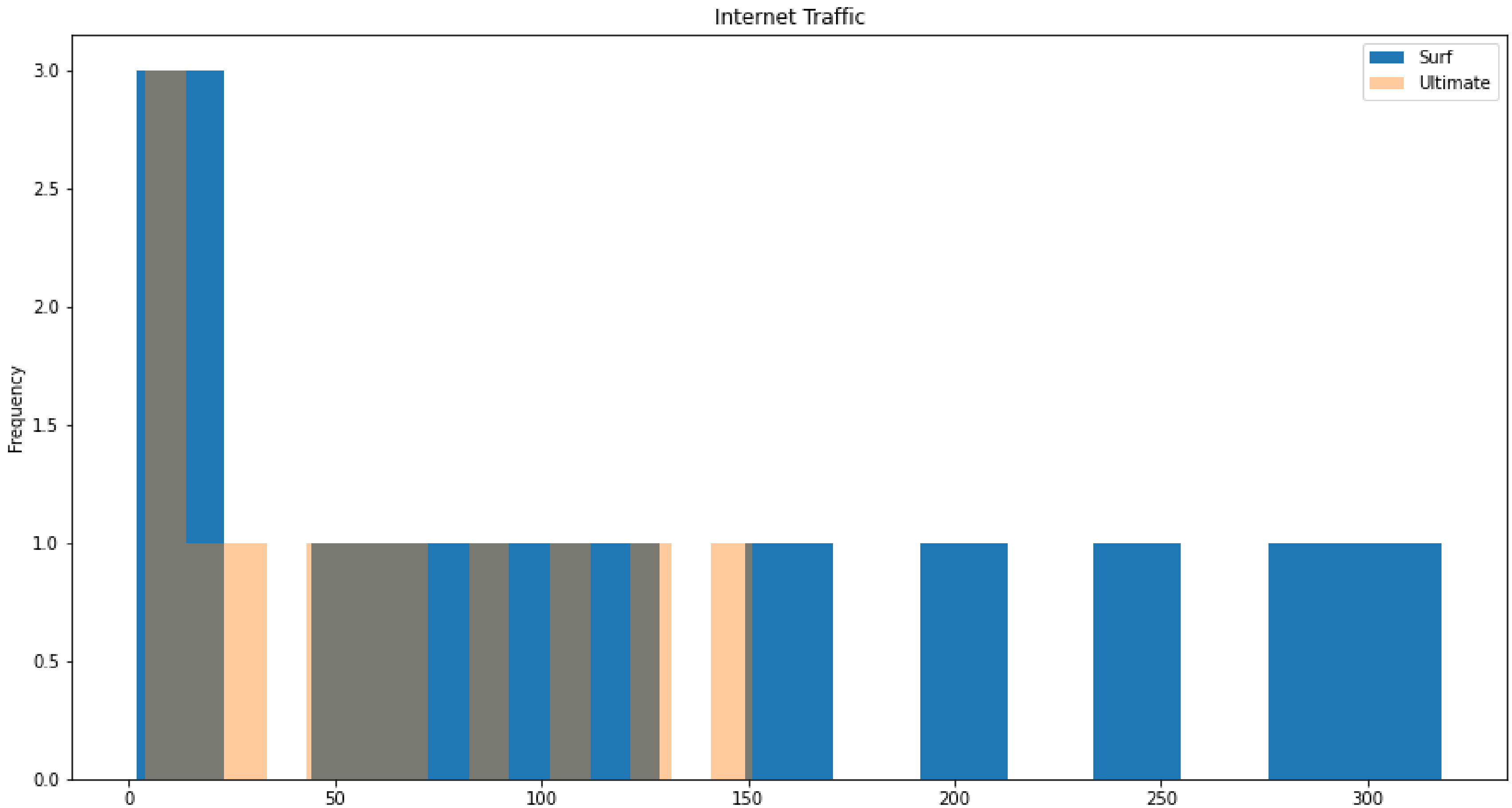
```
mean
mb_used    60.0
dtype: float64

variance
mb_used    2416.727273
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\94670807.py:3: FutureWarning: Dropping of nuisance columns in DataFrame
reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid
columns before calling the reduction.
  print(df_ultimate_ints_traffic.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\94670807.py:6: FutureWarning: Dropping of nuisance columns in DataFrame
reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid
columns before calling the reduction.
  print(df_ultimate_ints_traffic.var())
```

In [100…

```
# Display histogram of internet traffic per month, per plan
df_surf_ints_traffic['mb_used'].plot(kind='hist', bins=15, title='Internet Traffic', ylabel='Frequency', figsize=(15,8)
df_ultimate_ints_traffic['mb_used'].plot(kind='hist', bins=15, alpha=0.4)
```

```
plt.legend(['Surf', 'Ultimate'])
plt.show()
```

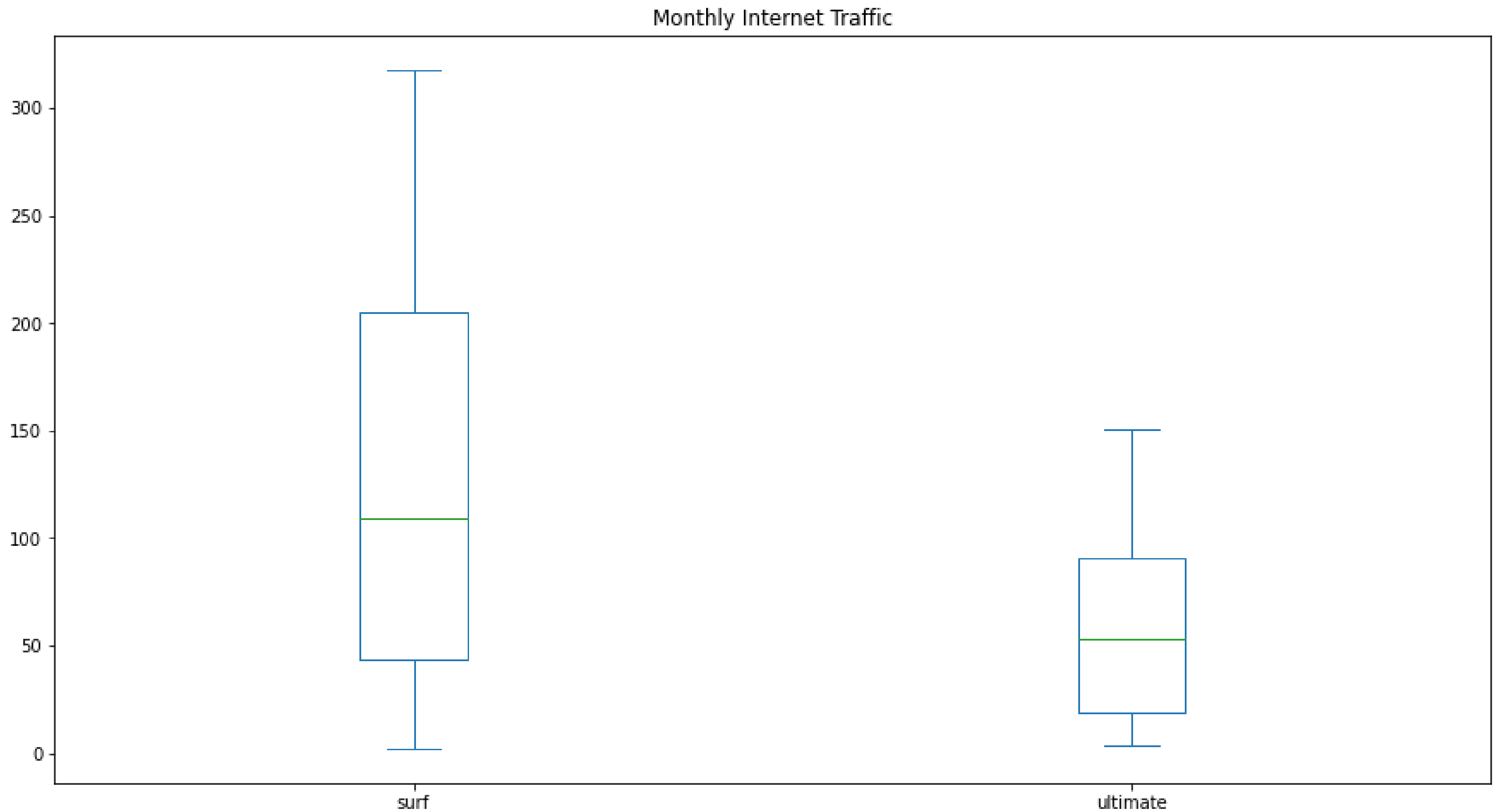


In [101…

```
# Plot a boxplot to visualize the distribution of the monthly internet traffic
df_all_ints_traffic.plot(kind='box', title='Monthly Internet Traffic', figsize=(15,8))
```

Out[101]:

```
<AxesSubplot:title={'center':'Monthly Internet Traffic'}>
```



In [102…
```
# surf traffic values
surf_ints_traffic = df_surf_ints_traffic['mb_used'].values.tolist()
```

In [103…
```
# ultimate traffic values
ultimate_ints_traffic = df_ultimate_ints_traffic['mb_used'].values.tolist()
```

Null hypothesis is that the two mean data traffic numbers are the same

In [104…
```
# Test the hypotheses
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis

results = st.ttest_ind(surf_ints_traffic, ultimate_ints_traffic)
```

```
print('p-value: ', results.pvalue)

if results.pvalue < alpha:
    print("We reject the null hypothesis, the average data traffic numbers differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  0.04977590665959082
We reject the null hypothesis, the average data traffic numbers differ
```

The Surf plan consistently sees more internet traffic than the Ultimate plan, with one exception. The mean internet traffic values appears to be quite different, further emphasized by the box plot. The upper and lower bounds of the Surf plan are wider than that of the Ultimate plan. This is made evident by the variance in the Surf data usage. Hypothesis testing further supports that the average traffic data numbers differ.

In [105…

```
# Compare average mb used per each plan per each distinct month. Plot a bar plat to visualize it.
df_merged_ints = df_merged.groupby(['plan', 'month'])['mb_used'].mean()
display(df_merged_ints.reset_index())
```

	plan	month	mb_used
0	surf	0.0	0.000000
1	surf	1.0	4874.860000
2	surf	2.0	12178.843333
3	surf	3.0	13345.440000
4	surf	4.0	11984.203000
5	surf	5.0	13936.354935
6	surf	6.0	15301.529175
7	surf	7.0	16783.600579
8	surf	8.0	16795.331358
9	surf	9.0	16591.431289
10	surf	10.0	17311.335063
11	surf	11.0	16339.254417
12	surf	12.0	18132.469371
13	ultimate	0.0	0.000000
14	ultimate	1.0	6918.092500
15	ultimate	2.0	17128.808571
16	ultimate	3.0	18321.518333
17	ultimate	4.0	16121.654762
18	ultimate	5.0	16624.482414
19	ultimate	6.0	15337.921064
20	ultimate	7.0	16344.744407
21	ultimate	8.0	17814.720141
22	ultimate	9.0	16969.869535
23	ultimate	10.0	17612.553396
24	ultimate	11.0	17033.685354

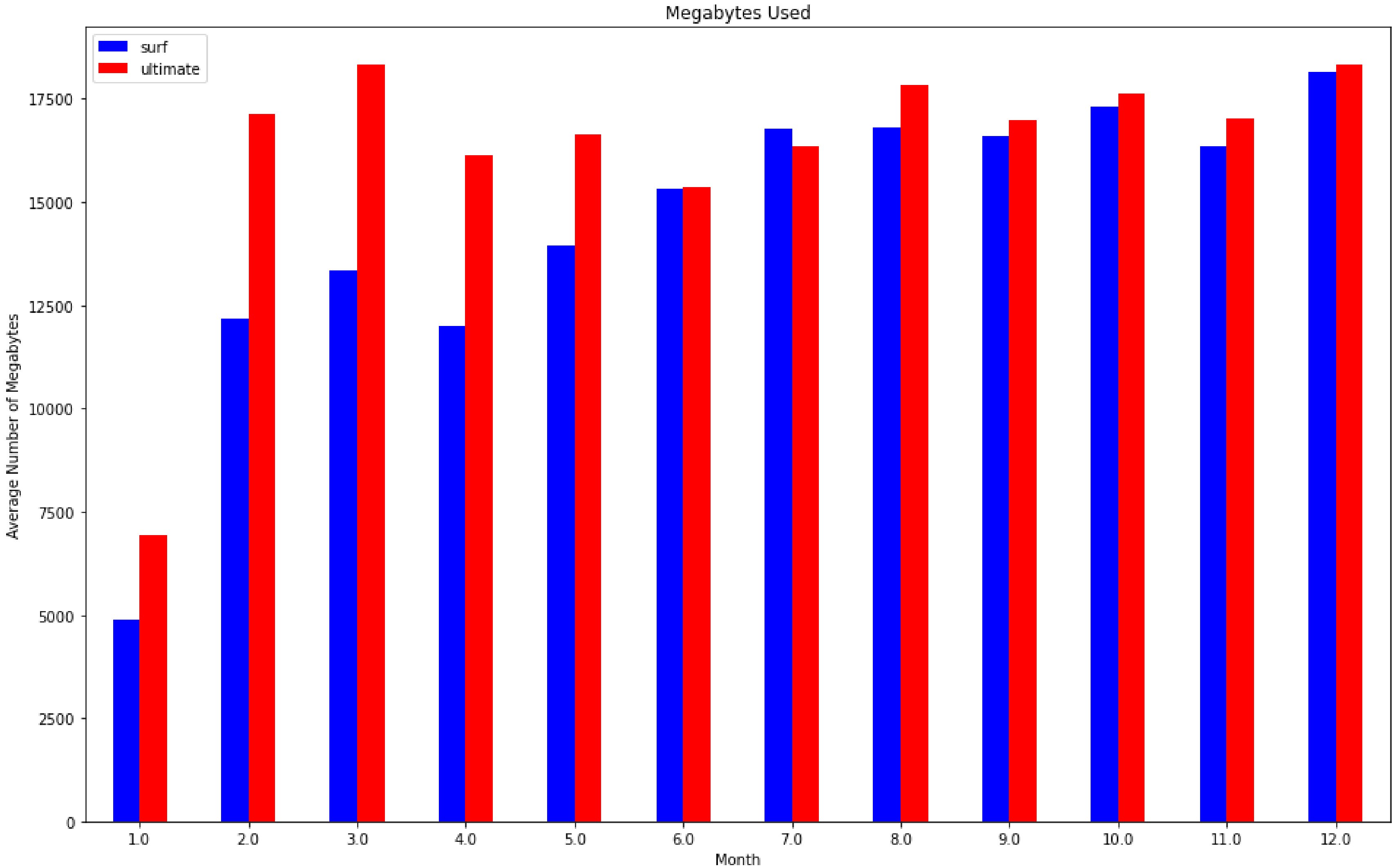
	plan	month	mb_used
25	ultimate	12.0	18323.191854

In [106…
```
# Data used per month in Surf plan
df_surf_ints = df_merged_ints[1:13].reset_index('plan')
```

In [107…
```
# Data used per month in Ultimate plan
df_ultimate_ints = df_merged_ints.reset_index('plan').tail(12)
```

In [108…
```
# Merging of Surf and Ultimate data usage, per month
df_all_ints = df_surf_ints.merge(df_ultimate_ints, on='month', how='outer')
df_all_ints.columns = ['plan_s', 'surf', 'plan_u', 'ultimate']
```

In [109…
```
# Display visual of internet usage per month, per plan
df_all_ints.plot(kind='bar',
                    title='Megabytes Used',
                  xlabel='Month',
                  ylabel='Average Number of Megabytes',
                  color=('blue', 'red'),
                 rot=0,
                  figsize= (16,10)
                    )
plt.show()
```



In [110…

```
# Mean and variance of Surf data usage
print('mean')
print(df_surf_ints.mean())
print()
print('variance')
print(df_surf_ints.var())
```

```
mean
mb_used    14464.554377
dtype: float64

variance
mb_used    1.327065e+07
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3548975033.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_ints.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3548975033.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_ints.var())
```

In [111…

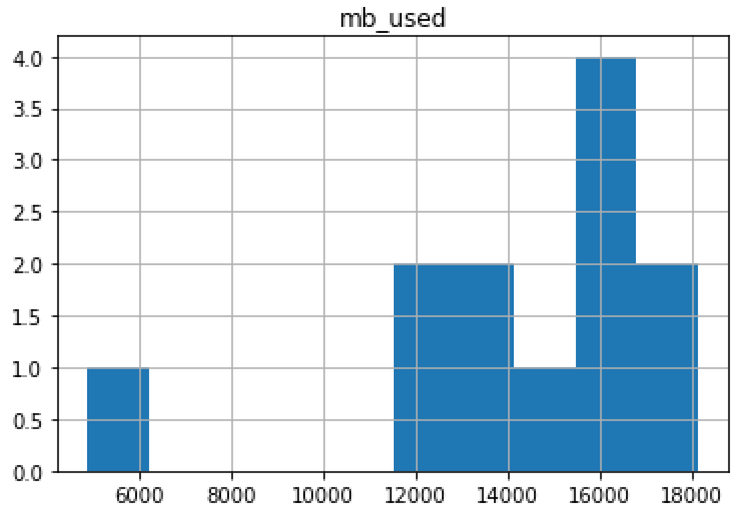
```
# Mean and variance of Ultimate data usage
print('mean')
print(df_ultimate_ints.mean())
print()
print('variance')
print(df_ultimate_ints.var())
```

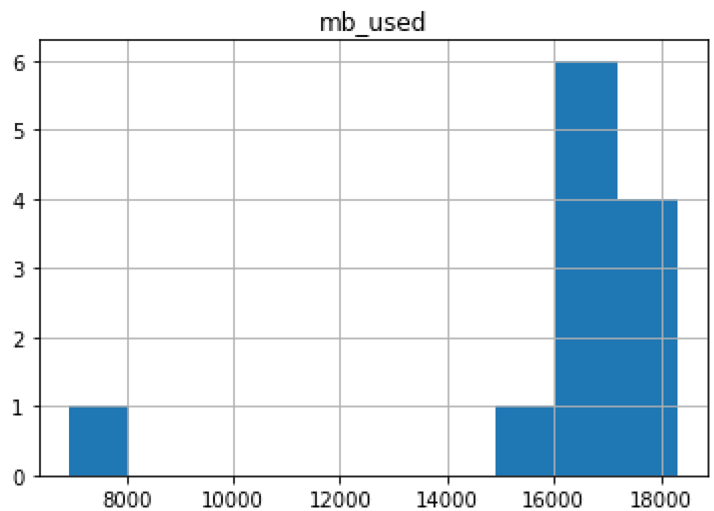
```
mean
mb_used    16212.603528
dtype: float64

variance
mb_used    9.351289e+06
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3184717699.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_ints.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3184717699.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_ints.var())
```

In [112…

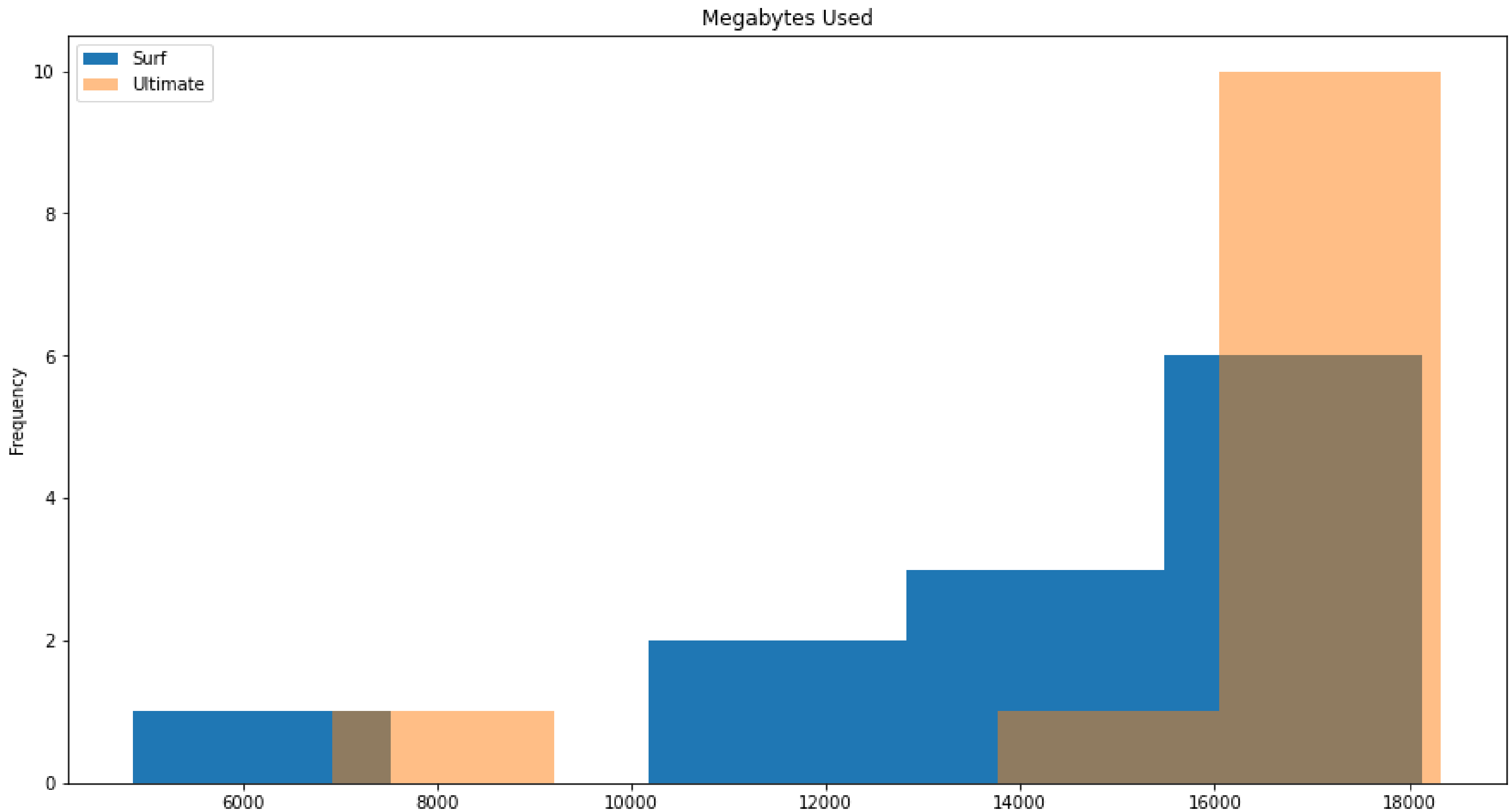
```
# Histogras of Surf and Ultimate data usage
df_surf_ints.hist(bins=10)
df_ultimate_ints.hist(bins=10)
plt.title='Megabytes'
plt.show()
```





In [113…

```
# Merged histogram of Surf and Ultimate dat usage
df_surf_ints['mb_used'].plot(kind='hist', bins=5, title='Megabytes Used', ylabel='Frequency', figsize=(15,8))
df_ultimate_ints['mb_used'].plot(kind='hist', bins=5, alpha=0.5)


plt.legend(['Surf', 'Ultimate'])
plt.show()
```

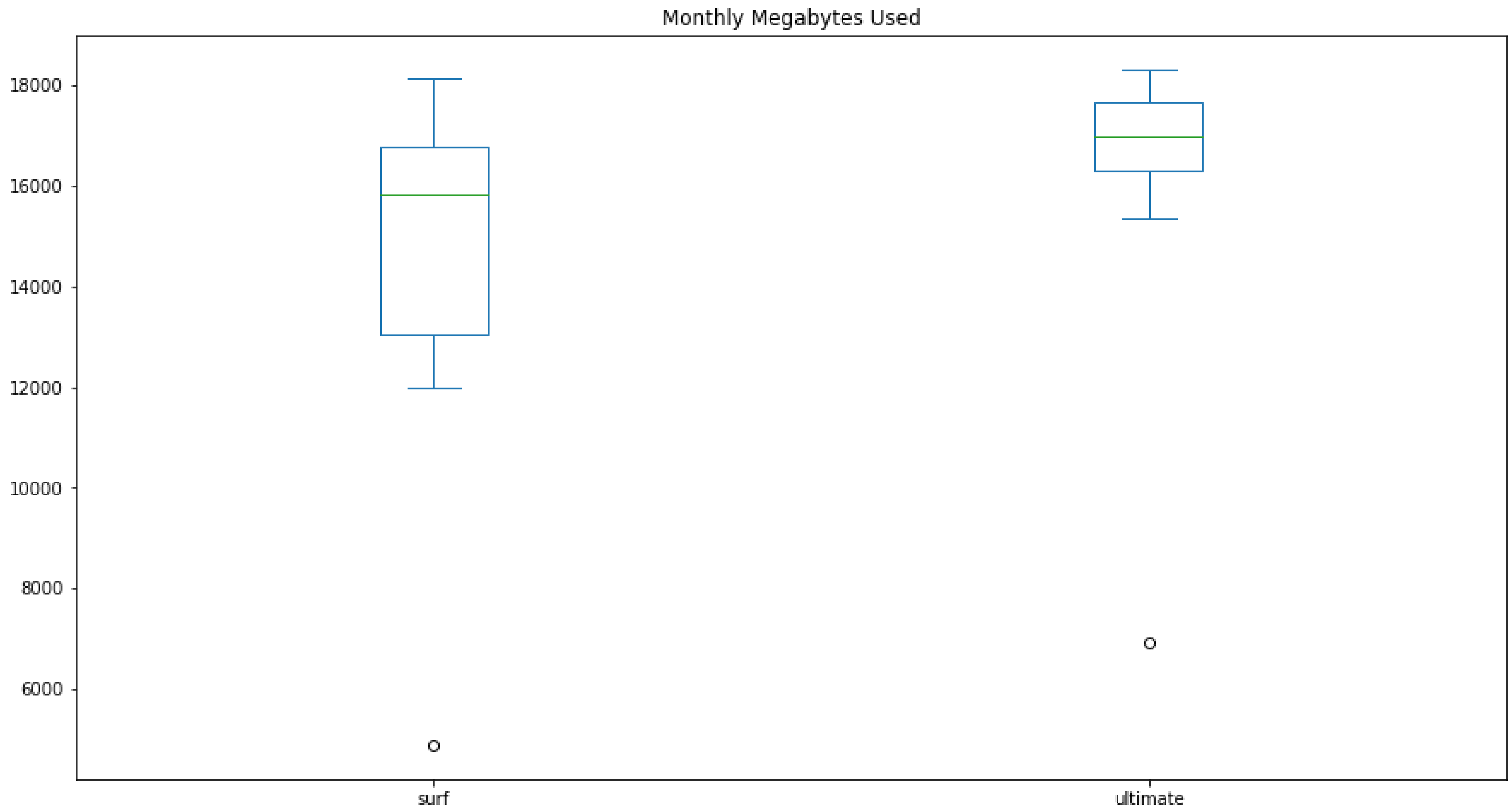


In [114…

```
# Plot a boxplot to visualize the distribution of the monthly call duration
df_all_ints.plot(kind='box', title='Monthly Megabytes Used', figsize=(15,8))
```

Out[114]:

```
<AxesSubplot:title={'center':'Monthly Megabytes Used'}>
```



In [115…
```
# surf mb values
surf_ints = df_surf_ints['mb_used'].values.tolist()
```

In [116…
```
# surf megabyte values
ultimate_ints = df_ultimate_ints['mb_used'].values.tolist()
```

Null hypothesis that mean data usage is similar

In [117…
```
# Test the hypotheses
# Null hypothesis that the two means are the same
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis

results = st.ttest_ind(surf_ints, ultimate_ints)
```

```
print('p-value: ', results.pvalue)

if results.pvalue < alpha:
    print("We reject the null hypothesis, the average data usages differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  0.216254346644245556
We can't reject the null hypothesis
```

The Ultimate plan customers consistently used more data than those of the Surf plan, with the exception of one month out of the year. The mean data usage of both plans appears to be quite similar, further emphasized by the box plot. The Surf plan has an outlier on the lower side of data usage, and the upper and lower bounds are quite wide. The box plot of the Ultimate plan is tighter, with one outlier as well. Hypothesis testing suggests the mean data usage between plans is not different.

Revenue

Statistically describe the revenue between the plans

In [118…
```
# Create a monthly revenue column
df_merged['monthly_revenue'] = df_merged.apply(revenue, axis=1)
```

In [119…
```
# Visual of the new column
df_merged
```

Out[119]:

	user_id	month	num_calls	call_duration	mb_used	num_messages	plan	messages_included	mb_per_month_included	minutes_inclu
0	1000	12.0	16.0	116.83	1901.47	11.0	ultimate	1000	30720	3
1	1006	11.0	2.0	9.32	2068.37	15.0	ultimate	1000	30720	3
2	1006	12.0	9.0	54.79	32118.82	139.0	ultimate	1000	30720	3
3	1008	10.0	71.0	450.21	17106.99	21.0	ultimate	1000	30720	3
4	1008	11.0	63.0	422.81	23676.72	37.0	ultimate	1000	30720	3
...	...	...	...	...	...	...	...	...	...	
2298	1143	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2299	1307	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2300	1319	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2301	1378	0.0	0.0	0.00	0.00	0.0	surf	50	15360	
2302	1473	0.0	0.0	0.00	0.00	0.0	surf	50	15360	

2303 rows × 15 columns

In [120…

```
# Greatest contributor to revenue
df_merged[['num_calls', 'call_duration','month', 'mb_used', 'num_messages', 'monthly_revenue']] .corr()
```

Out[120]:

	num_calls	call_duration	month	mb_used	num_messages	monthly_revenue
num_calls	1.000000	0.980393	0.134690	0.341054	0.247941	0.227388
call_duration	0.980393	1.000000	0.135112	0.331108	0.246878	0.218230
month	0.134690	0.135112	1.000000	0.157701	0.170708	0.098734
mb_used	0.341054	0.331108	0.157701	1.000000	0.226509	0.774237
num_messages	0.247941	0.246878	0.170708	0.226509	1.000000	0.158293
monthly_revenue	0.227388	0.218230	0.098734	0.774237	0.158293	1.000000

In [121…

```
# revenues of both plans
df_merged_revs = df_merged.groupby(['plan', 'month'])['monthly_revenue'].mean()
display(df_merged_revs.reset_index())
```

	plan	month	monthly_revenue
0	surf	0.0	20.000000
1	surf	1.0	20.000000
2	surf	2.0	34.260000
3	surf	3.0	45.792609
4	surf	4.0	40.458600
5	surf	5.0	47.240130
6	surf	6.0	48.935155
7	surf	7.0	62.226281
8	surf	8.0	63.576728
9	surf	9.0	57.952320
10	surf	10.0	65.051097
11	surf	11.0	57.633463
12	surf	12.0	70.108176
13	ultimate	0.0	70.000000
14	ultimate	1.0	70.000000
15	ultimate	2.0	70.000000
16	ultimate	3.0	74.666667
17	ultimate	4.0	73.000000
18	ultimate	5.0	70.724138
19	ultimate	6.0	71.638298
20	ultimate	7.0	71.898305
21	ultimate	8.0	72.859155
22	ultimate	9.0	72.034884
23	ultimate	10.0	72.311321
24	ultimate	11.0	71.708661

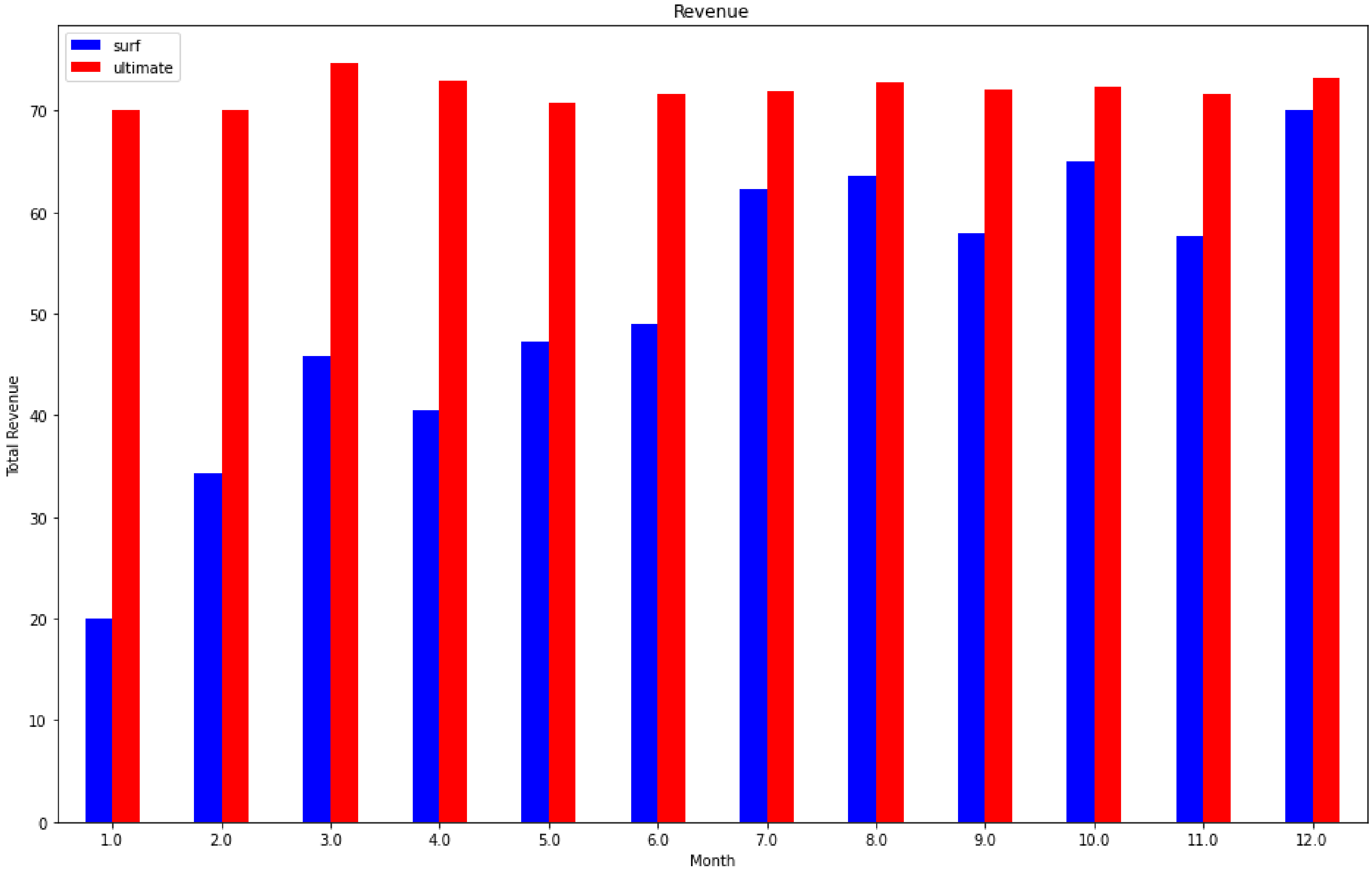
	plan	month	monthly_revenue
25	ultimate	12.0	73.291391

In [122...
```
# Separate monthly revenue of Surf plan
df_surf_revs = df_merged_revs[1:13].reset_index('plan')
```

In [123...
```
# Separate monthly revenue of Ultimate plan
df_ultimate_revs = df_merged_revs.reset_index('plan').tail(12)
```

In [124...
```
# Recombine revenue of both plans, per month
df_all_revs = df_surf_revs.merge(df_ultimate_revs, on='month', how='outer')
df_all_revs.columns = ['plan_s', 'surf', 'plan_u', 'ultimate']
```

In [125...
```
# Plot revenue per month, per plan
df_all_revs.plot(kind='bar',
                    title='Revenue',
                  xlabel='Month',
                  ylabel='Total Revenue',
                  color=('blue', 'red'),
                 rot=0,
                  figsize= (16,10)
                    )
plt.show()
```



In [126…

```
# Surf revenue mean and variance
print('mean')
print(df_surf_revs.mean())
print()
print('variance')
print(df_surf_revs.var())
```

```
mean
monthly_revenue    51.10288
dtype: float64

variance
monthly_revenue    212.439602
dtype: float64
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3926635512.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_revs.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3926635512.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_surf_revs.var())
```

In [127…

```
# Surf revenue mean and variance
print('mean')
print(df_ultimate_revs.mean())
print()
print('variance')
print(df_ultimate_revs.var())
```

```
mean
monthly_revenue    72.011068
dtype: float64

variance
monthly_revenue    1.860681
dtype: float64
```

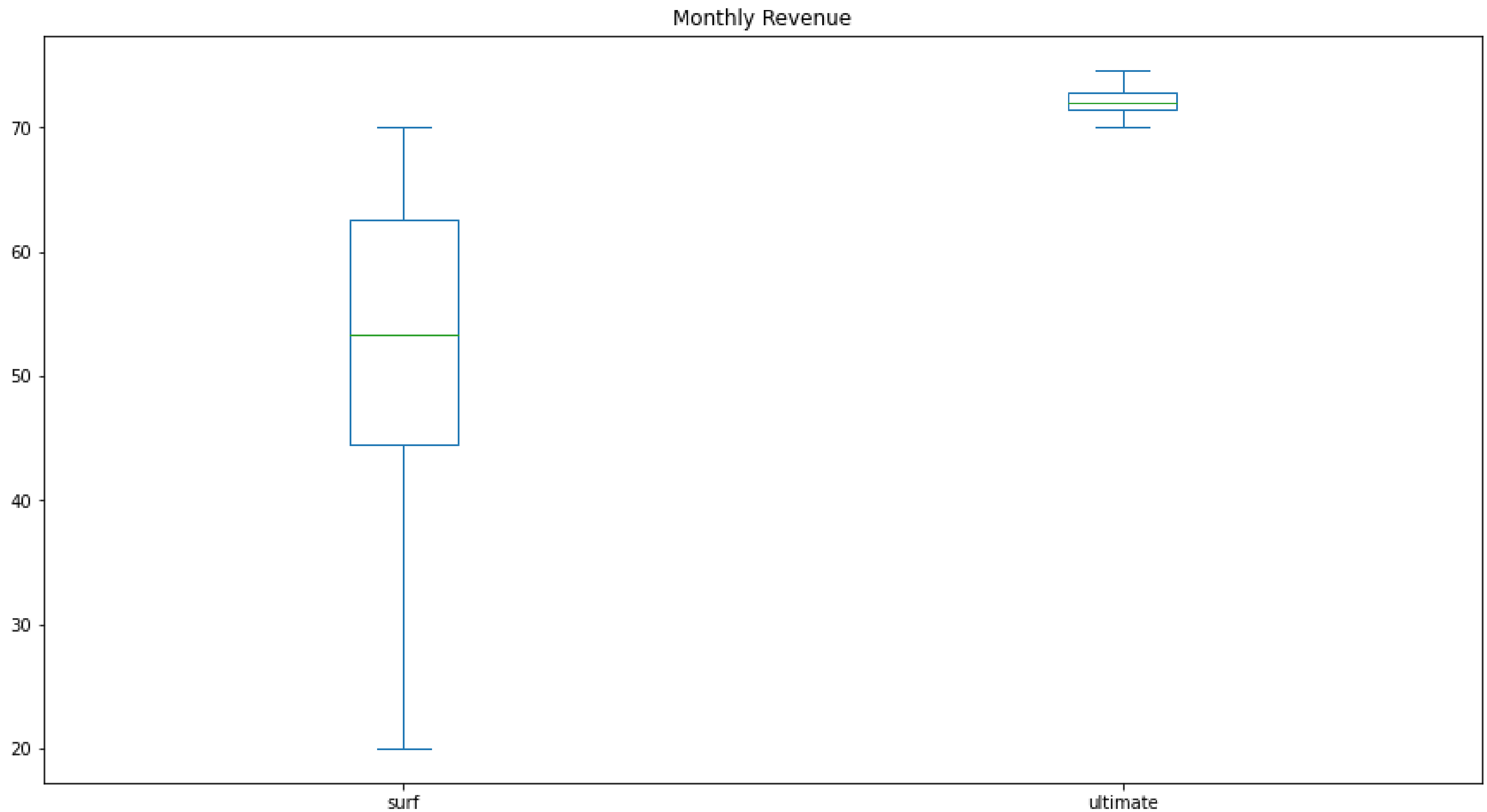
```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3365555136.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_revs.mean())
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\3365555136.py:6: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  print(df_ultimate_revs.var())
```

In [128…

```
# Plot a boxplot to visualize the distribution of the monthly call duration
df_all_revs.plot(kind='box', title='Monthly Revenue', figsize=(15,8))
```

Out[128]:

```
<AxesSubplot:title={'center':'Monthly Revenue'}>
```



The Ultimate plan consistently sees more revenue on a monthly basis. The mean revenues for the two plans appears to be different, but this will be further explored statistically. Looking at the box plot, we see the differences in the mean revenues. The Ultimate plan has a tighter range, while the Surf plan has a wider range and variance.

Test statistical hypotheses

Testing the hypothesis that the average revenues from users of the Ultimate and Surf calling plans differ.

In [129…

```
# Extracting the revenues from the Surf plan
surf_revs = df_surf_revs['monthly_revenue'].values.tolist()
```

In [130…
```
# Extracting the revenues from the Ultimate Plan
ultimate_revs = df_ultimate_revs['monthly_revenue'].values.tolist()
```

Null hypothesis is the mean revenues of the Surf and Ultimate plans are similar

In [131…
```
# Test the hypotheses
# Null hypothesis that the two means are the same
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis

results = st.ttest_ind(surf_revs, ultimate_revs)

print('p-value: ', results.pvalue)

if results.pvalue < alpha:
    print("We reject the null hypothesis, the average revenues differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  5.981445309161515e-05
We reject the null hypothesis, the average revenues differ
```

Our earlier thoughts were wrong. Statistically, the mean revenues of both plans are different, but it is the Ultimate plan that brings in more revenue.

Testing the hypothesis that the average revenue from users in the NY-NJ area is different from that of the users from the other regions.

In [161…
```
# Separating data based on user ID and city
df_user_city = df_users[['user_id','city']]
```

In [162…
```
# Adding data on plan and monthly revenue, merged by user ID
df_all_cities = df_merged[['user_id', 'plan','monthly_revenue']].merge(df_user_city, on='user_id', how='left')
```

In [163…
```
# Grouping the monthly revenue by city
df_cities = df_all_cities.groupby('city')['monthly_revenue'].mean().reset_index()
```

In [135…
```
# Sorting monthly revenue in descending order, by city
df_cities_sorted = df_cities.sort_values(by='monthly_revenue', ascending=False)
display(df_cities_sorted.head(20))
```

	city	monthly_revenue
0	Albany-Schenectady-Troy, NY MSA	147.794000
17	Colorado Springs, CO MSA	135.017500
70	Urban Honolulu, HI MSA	112.408095
6	Baton Rouge, LA MSA	104.012500
25	Fresno, CA MSA	99.405789
21	Dayton-Kettering, OH MSA	95.582222
63	San Jose-Sunnyvale-Santa Clara, CA MSA	94.625806
9	Bridgeport-Stamford-Norwalk, CT MSA	89.955789
58	Sacramento–Roseville–Folsom, CA MSA	87.781667
30	Jacksonville, FL MSA	86.170000
53	Providence-Warwick, RI-MA MSA	82.198182
39	Minneapolis-St. Paul-Bloomington, MN-WI MSA	80.859500
65	St. Louis, MO-IL MSA	79.145455
47	Orlando-Kissimmee-Sanford, FL MSA	77.181765
35	Louisville/Jefferson County, KY-IN MSA	76.929706
69	Tulsa, OK MSA	75.393333
26	Grand Rapids-Kentwood, MI MSA	75.176667
2	Atlanta-Sandy Springs-Roswell, GA MSA	74.823469
37	Miami-Fort Lauderdale-West Palm Beach, FL MSA	72.100656
12	Charleston-North Charleston, SC MSA	71.615385

In [136…

```
# Extracting rows based on the keywords that distinguish NY
df_ny = df_all_cities[df_all_cities['city'].str.contains('New York-Newark-Jersey City, NY-NJ-PA MSA')]
df_ny.reset_index()
```

Out[136]:

	index	user_id	plan	monthly_revenue	city
0	30	1031	ultimate	70.00	New York-Newark-Jersey City, NY-NJ-PA MSA
1	31	1031	ultimate	70.00	New York-Newark-Jersey City, NY-NJ-PA MSA
2	32	1031	ultimate	70.00	New York-Newark-Jersey City, NY-NJ-PA MSA
3	33	1031	ultimate	70.00	New York-Newark-Jersey City, NY-NJ-PA MSA
4	34	1031	ultimate	70.00	New York-Newark-Jersey City, NY-NJ-PA MSA
...	...	...	...	...	...
373	2270	1080	surf	80.00	New York-Newark-Jersey City, NY-NJ-PA MSA
374	2271	1080	surf	120.42	New York-Newark-Jersey City, NY-NJ-PA MSA
375	2272	1080	surf	170.27	New York-Newark-Jersey City, NY-NJ-PA MSA
376	2273	1080	surf	200.00	New York-Newark-Jersey City, NY-NJ-PA MSA
377	2274	1080	surf	110.33	New York-Newark-Jersey City, NY-NJ-PA MSA

378 rows × 5 columns

In [137…

```
# Grouping NY revenue by user ID and monthly revenues
df_ny_rev = df_ny.groupby('user_id')['monthly_revenue'].mean()
df_ny_rev.reset_index()
```

Out[137]:

	user_id	monthly_revenue
0	1014	28.475000
1	1022	55.738750
2	1024	20.930000
3	1027	33.333333
4	1031	70.000000
...	...	...
75	1469	100.000000
76	1482	70.000000
77	1494	30.430000
78	1495	118.092500
79	1498	77.272727

80 rows × 2 columns

In [138…

```
# Extracting the mean revenues from the NY data
ny = df_ny_rev.values.tolist()
```

In [139…

```
# Mean of NY revenue
print('Mean: ')
df_ny_rev.mean()
```

```
Mean: 
```

Out[139]:

```
59.72249310064935
```

In [140…

```
# Standard Deviation of NY revenue
print('Standard Deviation: ')
df_ny_rev.std()
```

```
Standard Deviation: 
```

Out[140]:

```
32.5551036141766
```

In [141…

```
# Creating cities data without NY, by index
# Should see total rows drop from 73 to 72
```

```
df_cities_2 = df_cities.drop(labels=43, axis=0)
```

In [142…

```
# Mean revenue of all the other cities
print('Mean :')
df_cities_2.mean()
```

```
Mean :
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\4283063849.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  df_cities_2.mean()
```

Out[142]:

```
monthly_revenue    65.443134
dtype: float64
```

In [143…

```
# Standard deviation of revenue of all the other cities
print('Standard Deviation :')
df_cities_2.std()
```

```
Standard Deviation :
```

```
C:\Users\XIX\AppData\Local\Temp\ipykernel_24004\2224394961.py:3: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will raise TypeError.  Select only valid columns before calling the reduction.
  df_cities_2.std()
```

Out[143]:

```
monthly_revenue    21.740895
dtype: float64
```

In [144…

```
#confirming NY is not in cities 2 data
df_cities_2.tail(30)
```

Out[144]:

	city	monthly_revenue
42	New Orleans-Metairie, LA MSA	35.015000
44	North Port-Sarasota-Bradenton, FL MSA	58.922500
45	Oklahoma City, OK MSA	67.980500
46	Omaha-Council Bluffs, NE-IA MSA	20.000000
47	Orlando-Kissimmee-Sanford, FL MSA	77.181765
48	Oxnard-Thousand Oaks-Ventura, CA MSA	38.520000
49	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA	63.490732
50	Phoenix-Mesa-Chandler, AZ MSA	66.703250
51	Pittsburgh, PA MSA	66.506667
52	Portland-Vancouver-Hillsboro, OR-WA MSA	49.870909
53	Providence-Warwick, RI-MA MSA	82.198182
54	Raleigh-Cary, NC MSA	20.000000
55	Richmond, VA MSA	50.638000
56	Riverside-San Bernardino-Ontario, CA MSA	53.825111
57	Rochester, NY MSA	58.898667
58	Sacramento–Roseville–Folsom, CA MSA	87.781667
59	Salt Lake City, UT MSA	63.750000
60	San Antonio-New Braunfels, TX MSA	70.331176
61	San Diego-Chula Vista-Carlsbad, CA MSA	56.351250
62	San Francisco-Oakland-Berkeley, CA MSA	55.998772
63	San Jose-Sunnyvale-Santa Clara, CA MSA	94.625806
64	Seattle-Tacoma-Bellevue, WA MSA	62.128113
65	St. Louis, MO-IL MSA	79.145455
66	Stockton, CA MSA	35.000000
67	Tampa-St. Petersburg-Clearwater, FL MSA	61.511875

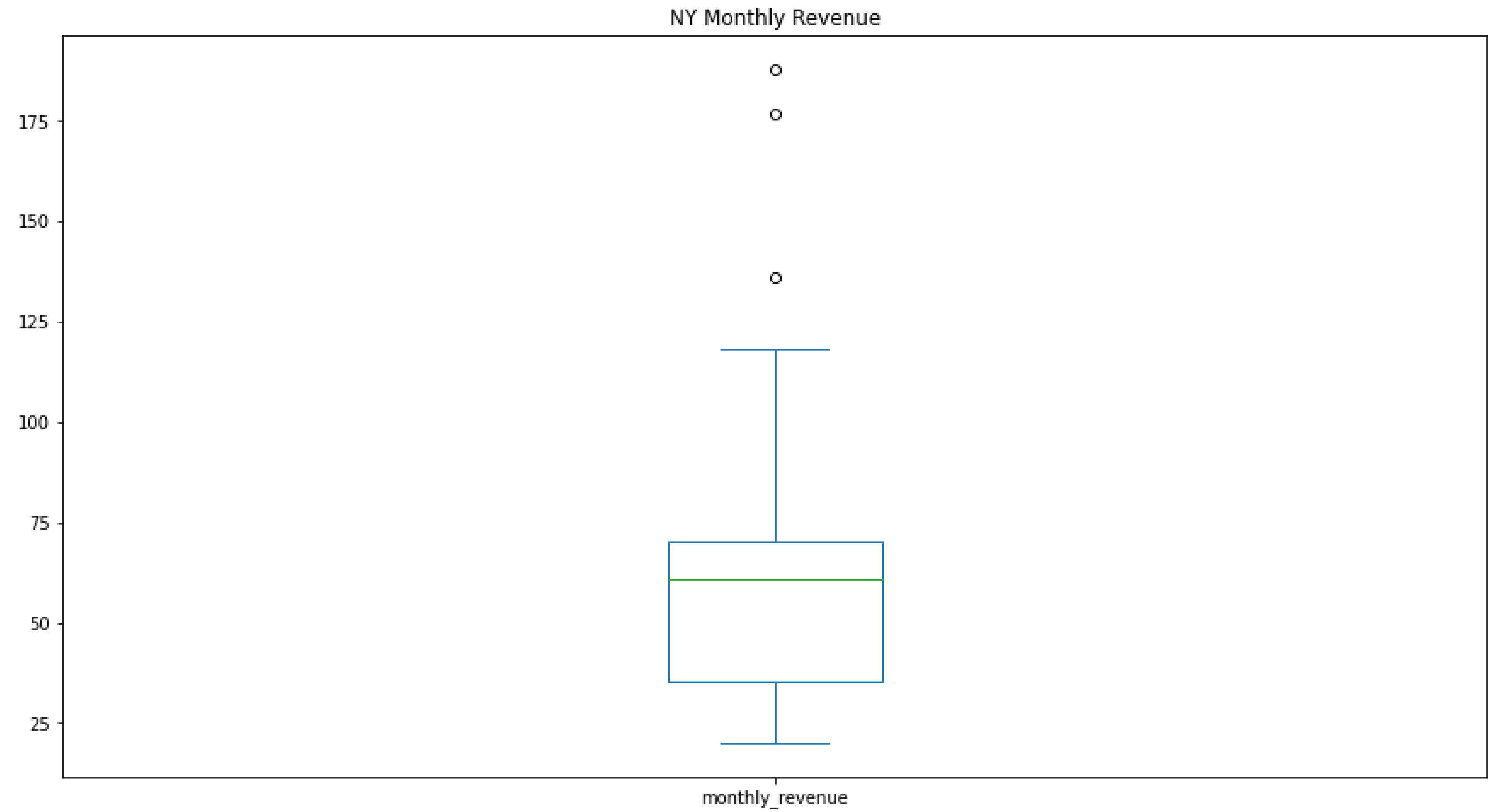
	city	monthly_revenue
68	Tucson, AZ MSA	65.000000
69	Tulsa, OK MSA	75.393333
70	Urban Honolulu, HI MSA	112.408095
71	Virginia Beach-Norfolk-Newport News, VA-NC MSA	65.000000
72	Washington-Arlington-Alexandria, DC-VA-MD-WV MSA	57.576290

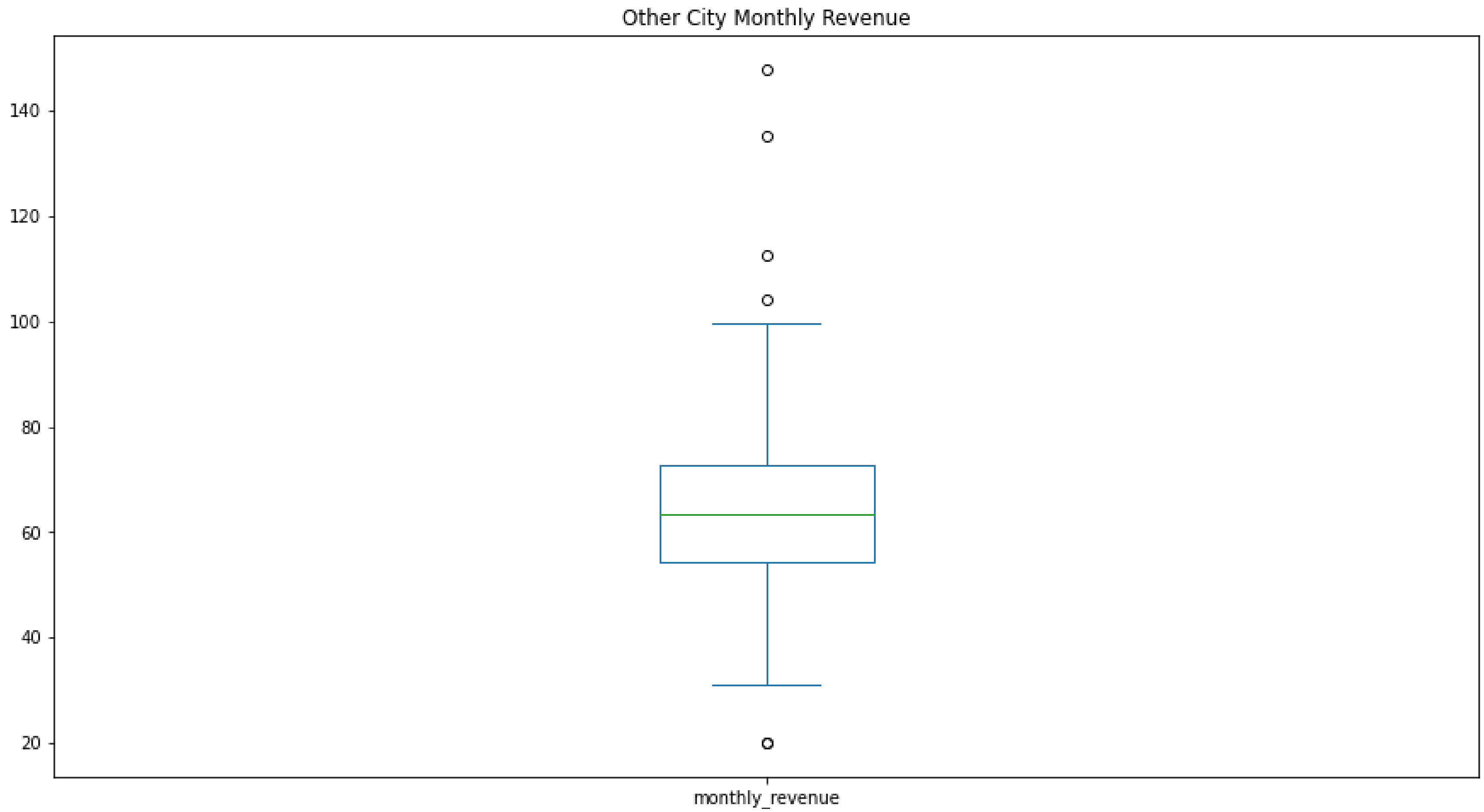
In [145…

```
# Plot a boxplot to visualize the distribution of the monthly call duration
df_ny_rev.plot(kind='box', title='NY Monthly Revenue', figsize=(15,8))
df_cities_2.plot(kind='box', title='Other City Monthly Revenue',figsize=(15,8))
```

Out[145]:

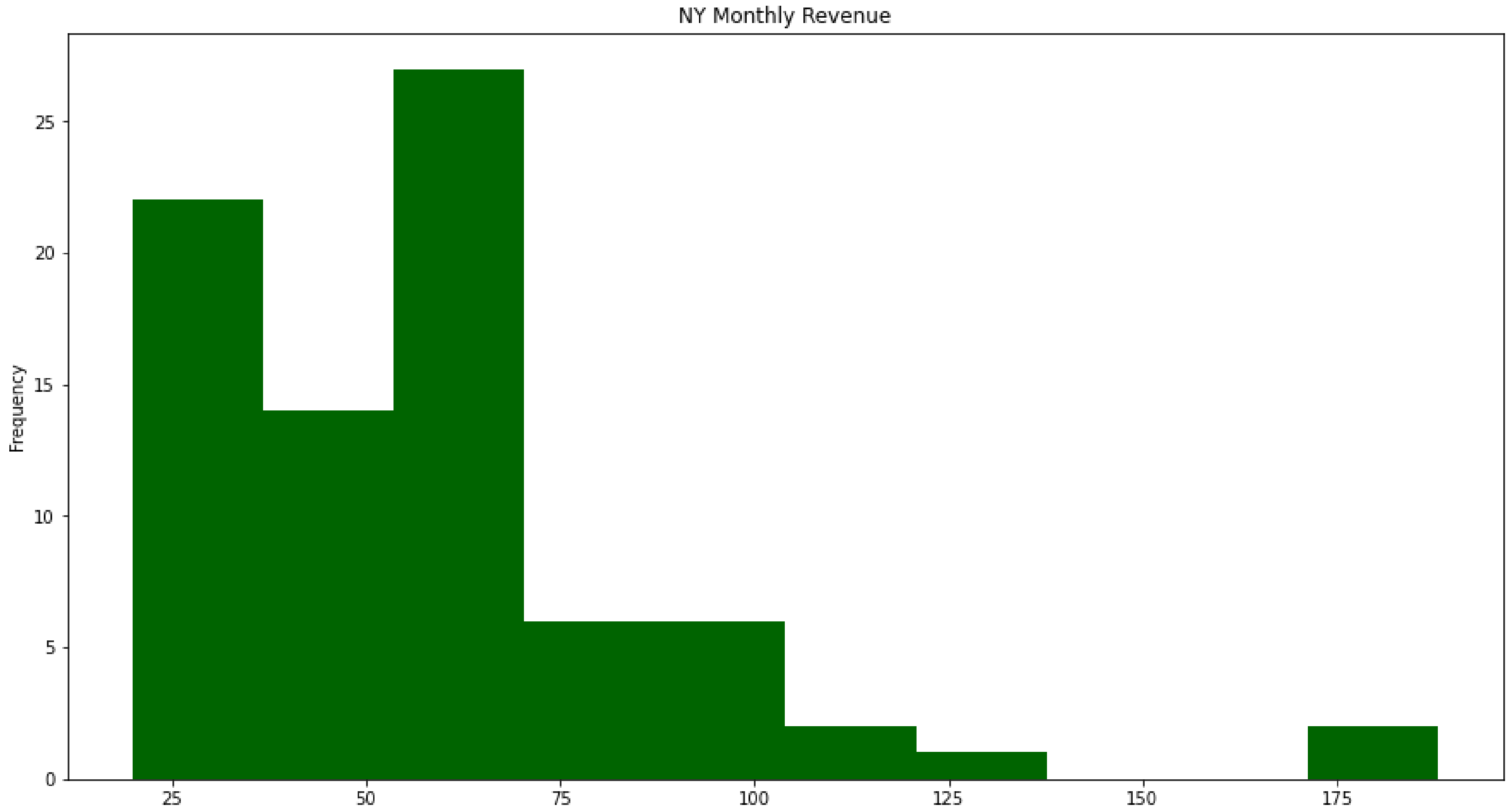
```
<AxesSubplot:title={'center':'Other City Monthly Revenue'}>
```

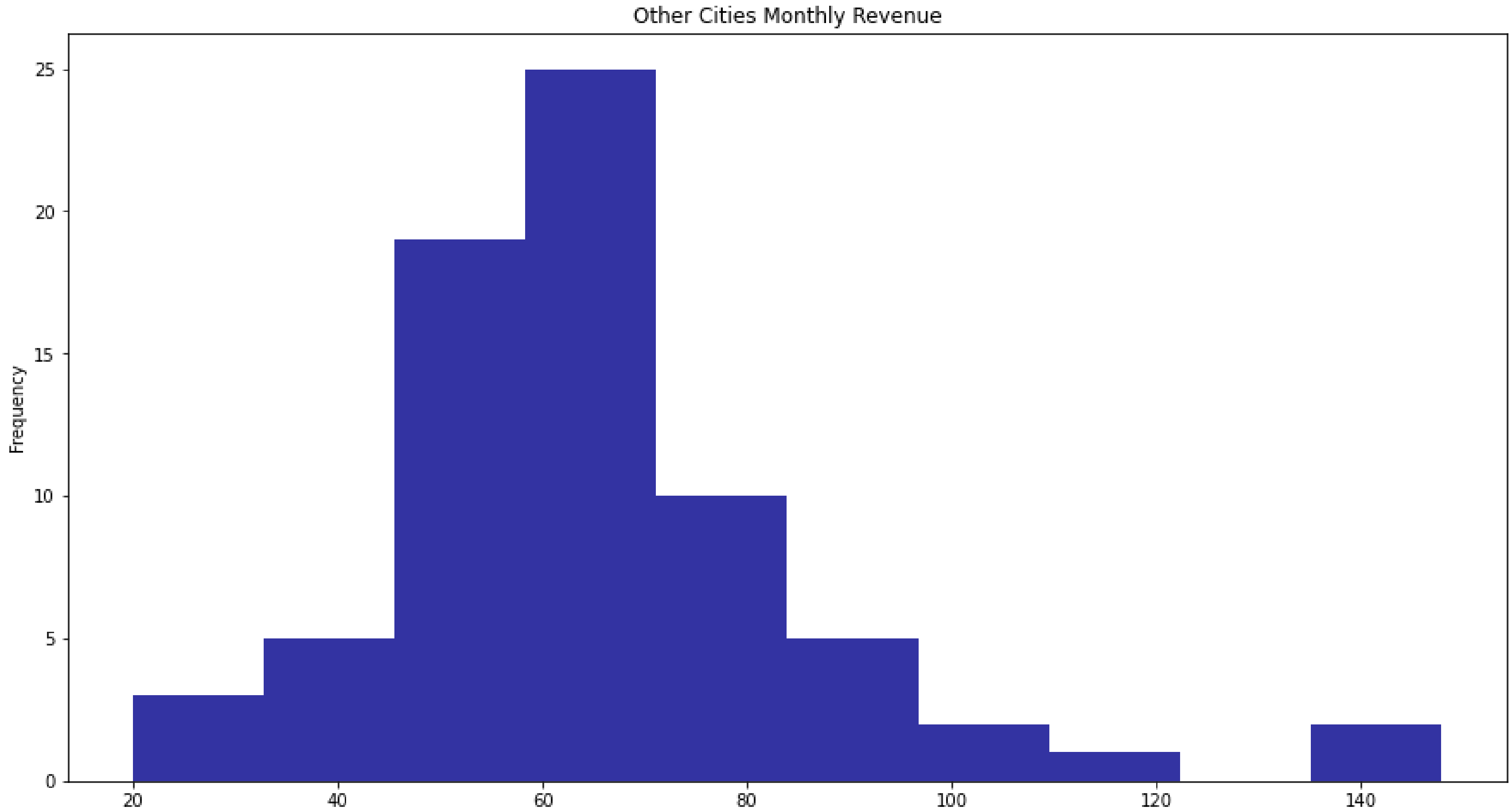

NY Monthly Revenue
175
150
125
100
75
50
25
monthly_revenue



In [146…

```
df_ny_rev.plot(kind='hist', title='NY Monthly Revenue', figsize=(15,8), color='darkgreen')
df_cities_2.plot(kind='hist', title='Other Cities Monthly Revenue',figsize=(15,8), color='darkblue', alpha=.8, legend=F

plt.show()
```


NY Monthly Revenue
Frequency
0
5
10
15
20
25
25
50
75
100
125
150
175



In [147…

```
# Extracting mean revenues from cities 2 data
cities_2 = df_cities_2['monthly_revenue'].values.tolist()
```

Null hypothesis that the mean revenue of Ny vs the other cities is similar

In [148…

```
# Test the hypotheses
# Null hypothesis that the mean of NY is the same as the mean of the other cities
alpha = 0.05  # critical statistical significance level
# if the p-value is less than alpha, we reject the hypothesis

results = st.ttest_ind(ny, cities_2)

print('p-value: ', results.pvalue)
```

```
if results.pvalue < alpha:
    print("We reject the null hypothesis, the average revenues differ")
else:
    print("We can't reject the null hypothesis")
```

```
p-value:  0.2098498653029106
We can't reject the null hypothesis
```

After statistical testing, we can not reject the null hypothesis that the mean of NY revenue is similar the the mean revenue of all the other cities. This suggests that they are indeed similar. This finding is further supported by the box plots, and histograms.

Relationship between revenue and age

In [149…

```
# Making a dataset of the customers plan and monthly revenue, based on age
df_age_rev = df_users[['age', 'user_id']].merge(df_merged, on='user_id', how='outer')
df_age= df_age_rev[['age', 'user_id', 'plan', 'monthly_revenue']]
```

In [150…

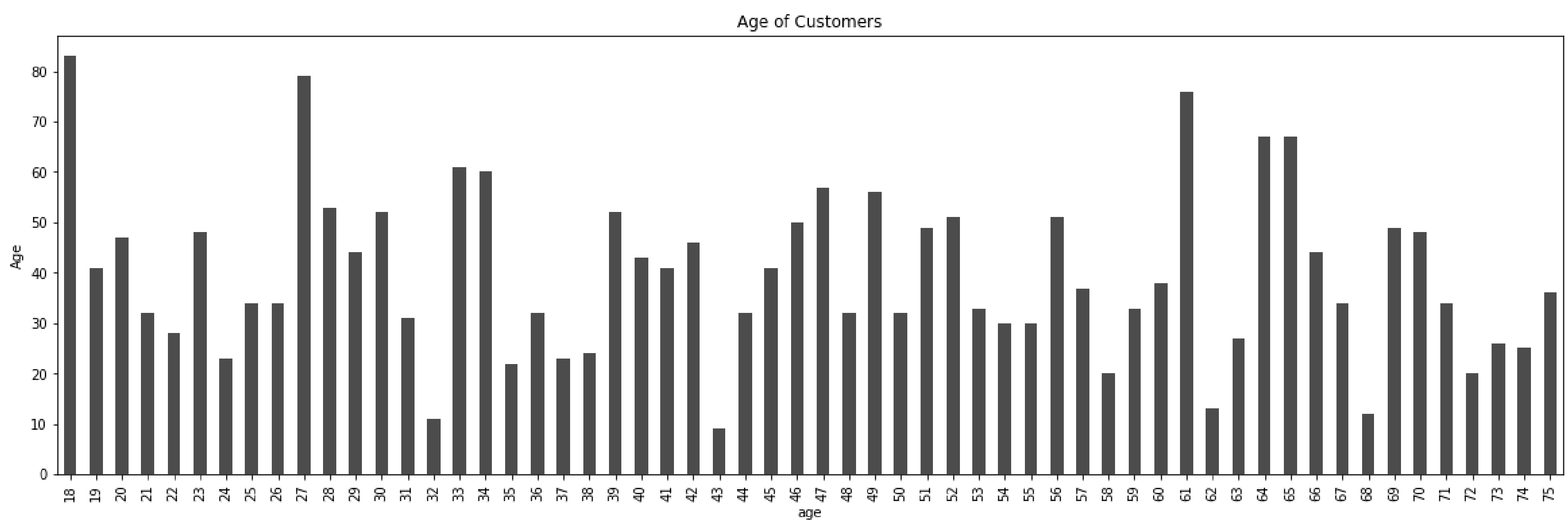
```
# Getting a count of the number of customers at each age
df_customers = df_age.groupby('age')['age'].count()
```

In [151…

```
# plotting the distribution of customer ages, across both plans
df_customers.plot(kind='bar', figsize=(20,6), ylabel='Age', title='Age of Customers', color='black', alpha=.7)
```

Out[151]:

```
<AxesSubplot:title={'center':'Age of Customers'}, xlabel='age', ylabel='Age'>
```



In [152…
```
# Grouping by ages and plans
df_customer_plans = df_age.groupby(['age', 'plan'])['user_id'].count()
df_customer_plans = pd.DataFrame(df_customer_plans).reset_index(level=1)
df_customer_plans.columns = ['plan', 'customers']
```

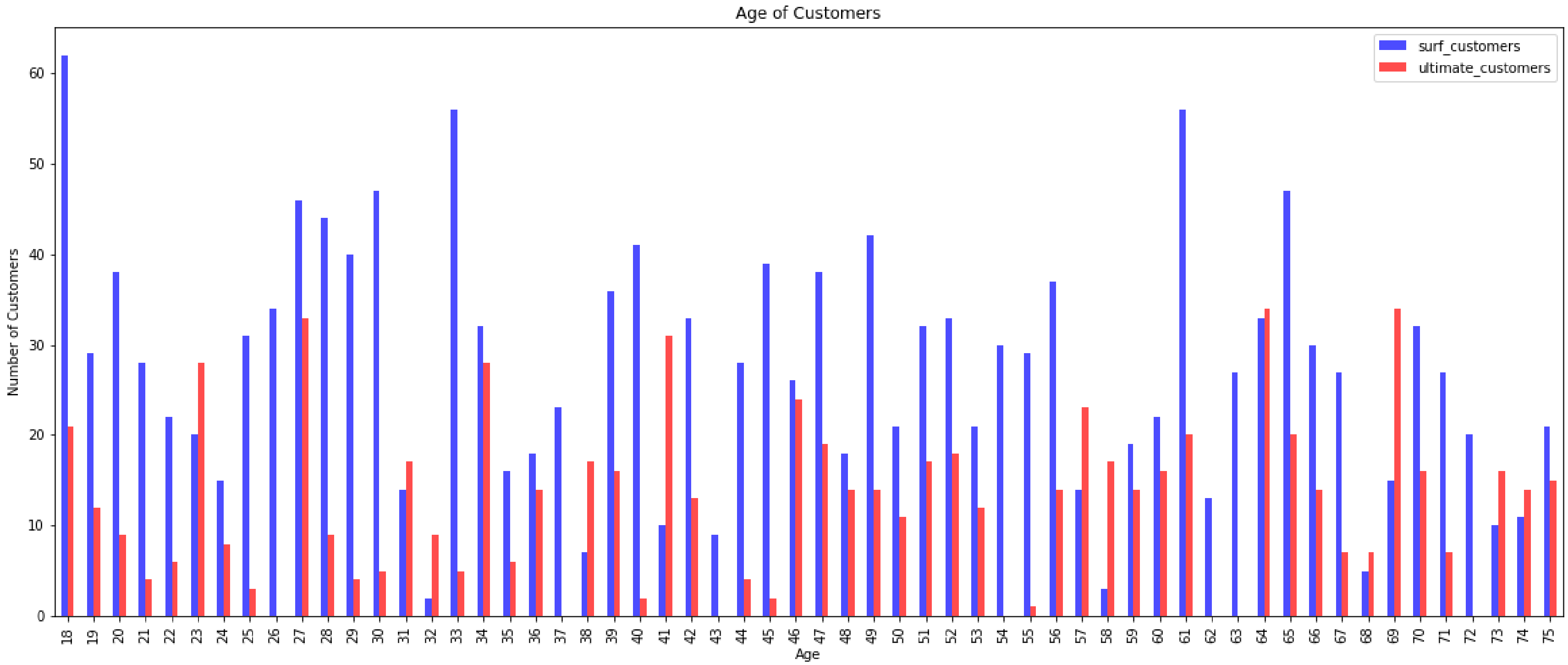
In [153…
```
# Extracting all age groups with Surf plan
df_surf_customers = df_customer_plans[df_customer_plans['plan'].str.contains('surf')]
```

In [154…
```
# Extracting all age groups with Ultimate plan
df_ultimate_customers = df_customer_plans[df_customer_plans['plan'].str.contains('ultimate')]
```

In [155…
```
# Recombining Surf and Ultimate customers, based on age
df_plan_ages = df_surf_customers.merge(df_ultimate_customers, on='age', how='left')
df_plan_ages.columns = ['plan_s', 'surf_customers', 'plan_u', 'ultimate_customers']
```

In [156…
```
# Showing the distributon of plan choices, based on age
df_plan_ages.plot(kind='bar', figsize=(20,8), ylabel='Number of Customers', xlabel='Age',
                  title='Age of Customers', color=('blue', 'red'), alpha=.7)
```

Out[156]:
```
<AxesSubplot:title={'center':'Age of Customers'}, xlabel='Age', ylabel='Number of Customers'>
```



We see most age groups prefer the Surf plan, with a few exceptions that prefer the Ultimate plan. We were expecting to see a pattern that suggests younger customers prefer the cheaper plan, yet the data does not suggest that.

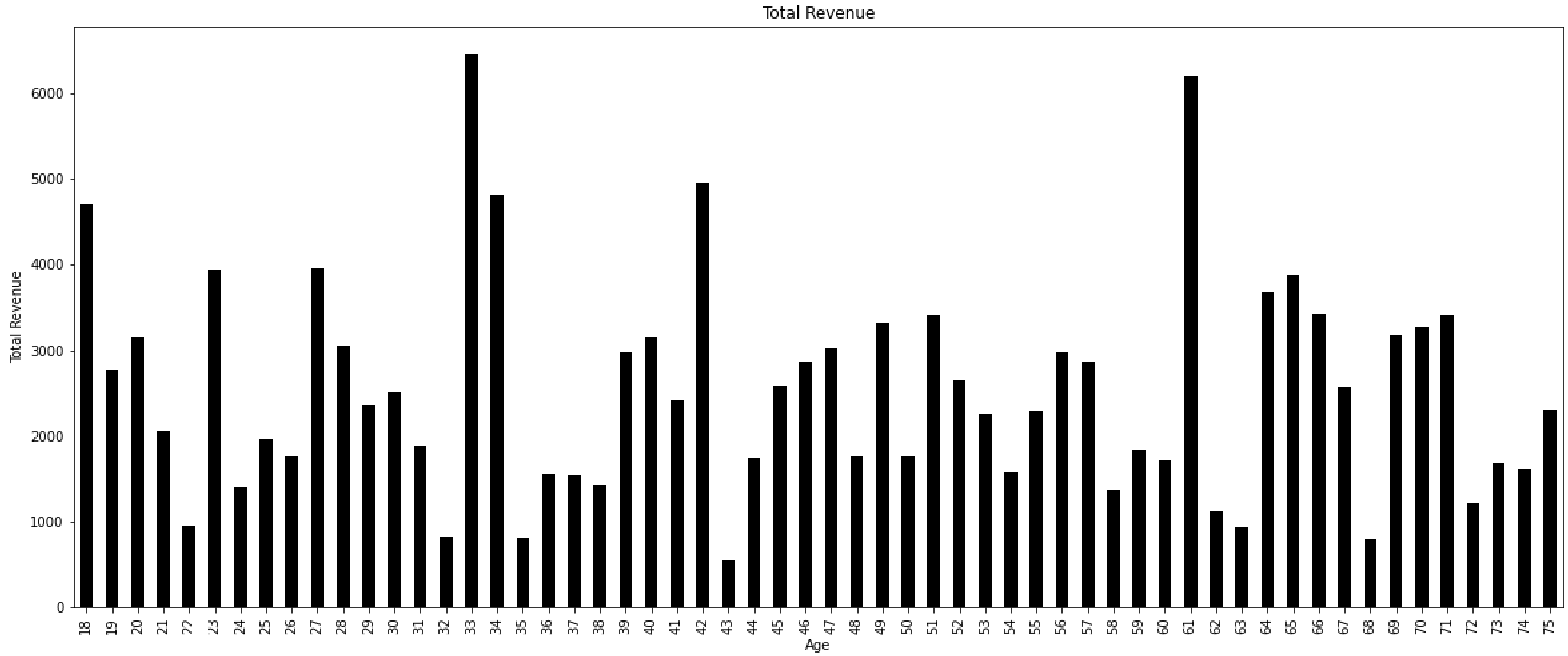
Comparing revenue and age

In [157…
```
# Mean Revenue based on age
age_rev_mean = df_age.groupby('age')['monthly_revenue'].mean()
```

In [158…
```
# Total monthly revenue based on age
age_rev_sum = df_age.groupby('age')['monthly_revenue'].sum()
```

In [159…
```
# Displaying total revenue, based on age
age_rev_sum.plot(kind='bar', figsize=(20,8), ylabel='Total Revenue', xlabel='Age', title='Total Revenue', color='black'
```

Out[159]:
```
<AxesSubplot:title={'center':'Total Revenue'}, xlabel='Age', ylabel='Total Revenue'>
```

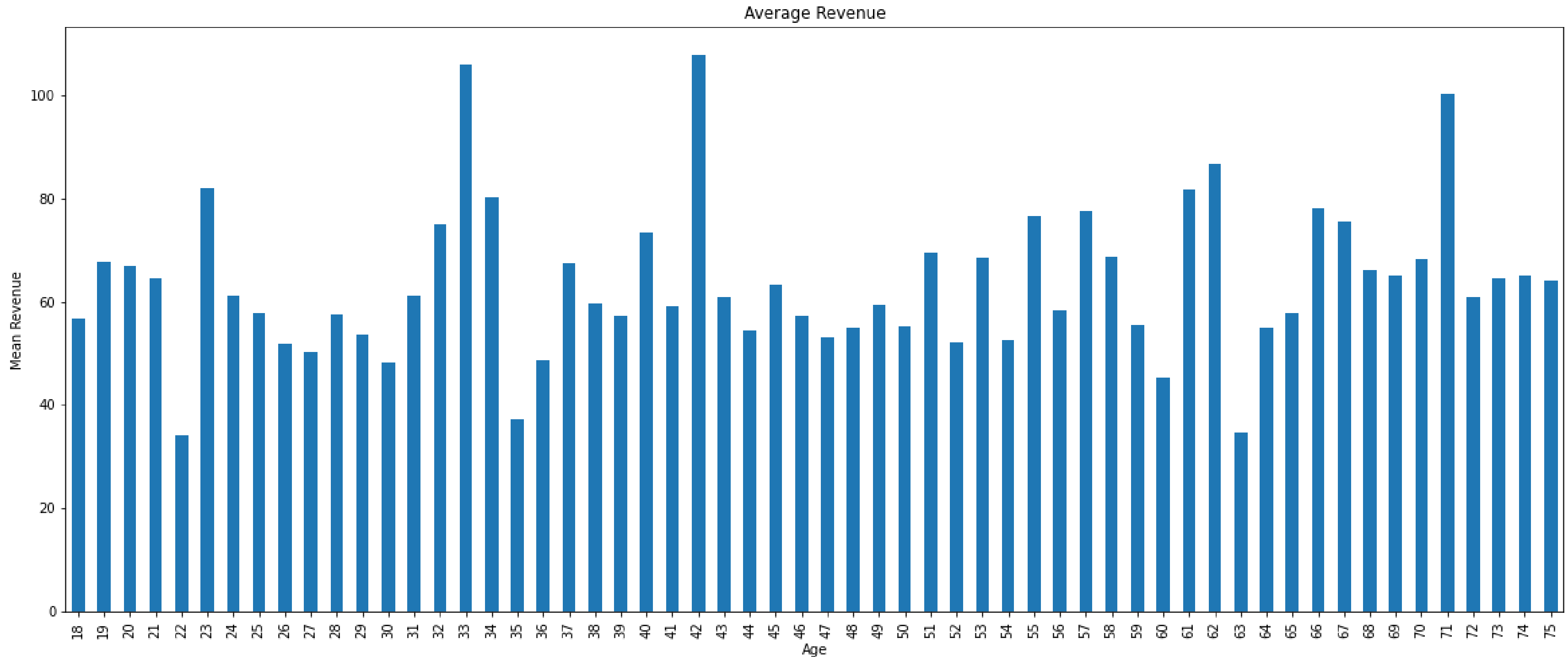


In [160…

```
# Displaying mean revenue, based on age
age_rev_mean.plot(kind='bar', figsize=(20,8), ylabel='Mean Revenue', xlabel='Age', title='Average Revenue')
```

Out[160]:

```
<AxesSubplot:title={'center':'Average Revenue'}, xlabel='Age', ylabel='Mean Revenue'>
```



We see that looking at total revenue based on age could be misleading, as we demonstrated the distribution of the number of customers in each age group earlier. Therefore, mean revenue would be better for making comparisons across age groups. We do not see any noticeable pattern in the data. We anticipated that younger customers would show a spike in revenue, due to their perceived lack of maturity. However, that was not the case. We only see spikes in the data with Ultimate plan customers in a few age groups. The age groups with the smallest mean revenue are 22, 35, and 63 year olds. Those with the highest revenue are 33, 42, and 71 year olds.

Conclusions

The data shows statistical differences in mean revenue among the two plans, as the Ultimate plan brings in more revenue. Our significance level was set to 5%, and our p value was much higher. In simpler words, we reject our null hypothesis that the mean revenues were similar.

The data shows us that capital allocation to marketing the Ultimate plan would likely yield a better cash on cash return, not based on popularity, but on revenue. As the Surf plan is more popular, new customers should be lead to the Ultimate plan instead. We saw many Surf customers would experience overages on their plan. These would be the prime customer base to push towards the ultimate plan.

We see that the mean revenue of customers in New York appears to be similar to that of all the other cities combined. Yet, Honolulu, Albany, and Colorado Springs are the cities with the highest average revenue. A marketing push may also be a good idea in those areas, to further increase revenue, while also considering market saturation. We did not see a preference of plans of customers of different age groups, as most preferred the Surf plan.

Overall, the Ultimate plan is not very popular. As such, maybe it would be beneficial to test a middle tier plan, in order to capture customers who may be dismayed by the gap in plan prices. Another method that would lead to increased revenue would be to slightly increase the overage fees on the Surf plan. Yet, a smart revenue strategy remains in rounding up minutes, and more substantially, rounding up data used to the nearest gigabyte. Data usage appears to be the largest contributor to revenue.

Finally, Hypothesis testing suggests the mean of the call durations and number of messages were not different. On the other hand, internet traffic is different, when conducting statistical tests on the means.