DATA3406 Week 8 Mini-Assignment

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12-RED

Part 1: Some Pandas tutorials to run through

Useful Things Learnt:

- Pandas is VERY useful for reading and writing data, as well as manipulating data in time/space efficient ways. Since it builds off of numpy and matplotlib, there are a lot of inbuilt functionality for stats and graphing
- Matplotlib is great for more complicated custom graphs, and can be useful for EDA with pairplots and distribution plots.
- I???? Didn't ?? Know??? About??? `plt.subplot2grid` ????? *Where has this been all my life*. It's a much more intuitive version of `plt.subplots()` and allows you to group conceptually similar plots together in one code cell
- Seaborn heatmaps are a god at visualising correlation plots
- Altair!!! Would be very useful for zooming in and out on a plot to control the level of detail we want to look at

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Part 2: Hurdle Task for Assignment 2

Topic 3 comes with data for two users. The overarching goal of this part is to explore the intricacies of these two datasets, highlighting any caveats or potential issues, and mark any ideas for feature engineering.

Importing relevant packages and reading in the user data.

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [101…
```
user1_raw_data = pd.read_csv("../data/User1.csv")
user2_raw_data = pd.read_csv("../data/User2.csv")
```

Now we print the dataframe and info for the User1 data to get an idea for what the structure of the data looks like.

In [3]:
```
user1_raw_data
```

Out[3]:

	Start	Finish	Steps (count)

	Start	Finish	Steps (count)
0	07-Dec-2014 09:00	07-Dec-2014 10:00	941.0
1	07-Dec-2014 10:00	07-Dec-2014 11:00	408.0
2	07-Dec-2014 11:00	07-Dec-2014 12:00	157.0
3	07-Dec-2014 12:00	07-Dec-2014 13:00	1017.0
4	07-Dec-2014 13:00	07-Dec-2014 14:00	0.0
...	...	...	...
42071	25-Sep-2019 07:00	25-Sep-2019 08:00	0.0
42072	25-Sep-2019 08:00	25-Sep-2019 09:00	0.0
42073	25-Sep-2019 09:00	25-Sep-2019 10:00	0.0
42074	25-Sep-2019 10:00	25-Sep-2019 11:00	0.0
42075	25-Sep-2019 11:00	25-Sep-2019 12:00	0.0

42076 rows × 3 columns

In [4]:
```
user1_raw_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42076 entries, 0 to 42075
Data columns (total 3 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Start          42076 non-null  object 
 1   Finish         42076 non-null  object 
 2   Steps (count)  42076 non-null  float64
dtypes: float64(1), object(2)
memory usage: 986.3+ KB
```

There are three columns for each user: two indicating the start and end of the timestamp (which appear to be in one hour increments) and a step count for that hour block. There are 42076 rows, which should cover around 5 years of data (assuming there are no breaks in the hour increments), and no missing values.

The timestamps are currently parsed in as strings though, so we need to convert them to datetimes first.

In [5]:
```
user1_df = user1_raw_data.copy()
user1_df['Start'] = pd.to_datetime(user1_df['Start'], format='%d-%b-%Y %H:%M')
user1_df['Finish'] = pd.to_datetime(user1_df['Finish'], format='%d-%b-%Y %H:%M')
```

Running a describe to get a feel for the columns

In [6]:
```
user1_df.describe()
```

Out[6]:

	Steps (count)
count	42076.000000
mean	203.142842

	Steps (count)
std	517.158855
min	0.000000
25%	0.000000
50%	0.000000
75%	122.855812
max	7204.611321

In [7]:
```
user1_df[['Start', 'Finish']].describe()
```

```
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/ipykernel_launcher.py:1: FutureWarning: Treating datetime data as categorical rather t
han numeric in `.describe` is deprecated and will be removed in a future version of pand
as. Specify `datetime_is_numeric=True` to silence this warning and adopt the future beha
vior now.
  """Entry point for launching an IPython kernel.
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/ipykernel_launcher.py:1: FutureWarning: Treating datetime data as categorical rather t
han numeric in `.describe` is deprecated and will be removed in a future version of pand
as. Specify `datetime_is_numeric=True` to silence this warning and adopt the future beha
vior now.
  """Entry point for launching an IPython kernel.
```

Out[7]:

	Start	Finish
count	42076	42076
unique	42071	42071
top	2018-04-01 02:00:00	2018-04-01 02:00:00
freq	2	2
first	2014-12-07 09:00:00	2014-12-07 10:00:00
last	2019-09-25 11:00:00	2019-09-25 12:00:00

The average step count for User 1 is 203 steps per day with a standard deviation of 517 steps. This is a very unreliable measure, however, because 0 step counts account for at least half of all the data set, making this dataset very sparse. The max step count for one hour is 7204, which seems a little high.

On average, it takes around 1500 steps to walk a kilometre, or 1000 to run, so that means the user travelled around 5km in one hour walking, or 7km running. Average human walking speed is around 3km/hour, so this might be an outlier or error that is worth examining closer.

Observing the start and finish timestamps, one thing stands out: there are duplicate timestamps. `2018-04-01 02:00:00` has two entries in the dataset. External research suggests that the 1st Apr 2018 was the end of Daylight Savings, so 3am was turned back to 2am and resulted in duplicate 2am's.

In [8]:
```
start_counts = user1_df['Start'].value_counts()
multicounts = start_counts[start_counts > 1]
```

```
multicounts
```

Out[8]:
```
2018-04-01 02:00:00    2
2016-04-03 02:00:00    2
2019-04-07 02:00:00    2
2015-04-05 02:00:00    2
2017-04-02 02:00:00    2
Name: Start, dtype: int64
```

In [9]:
```
user1_df[user1_df['Start'].isin(multicounts.index.values)]
```

Out[9]:

	Start	Finish	Steps (count)
2849	2015-04-05 02:00:00	2015-04-05 02:00:00	0.000000
2850	2015-04-05 02:00:00	2015-04-05 03:00:00	0.000000
11585	2016-04-03 02:00:00	2016-04-03 02:00:00	0.000000
11586	2016-04-03 02:00:00	2016-04-03 03:00:00	0.000000
20321	2017-04-02 02:00:00	2017-04-02 02:00:00	0.000000
20322	2017-04-02 02:00:00	2017-04-02 03:00:00	0.000000
29057	2018-04-01 02:00:00	2018-04-01 02:00:00	0.000000
29058	2018-04-01 02:00:00	2018-04-01 03:00:00	0.000000
37961	2019-04-07 02:00:00	2019-04-07 02:00:00	0.067778
37962	2019-04-07 02:00:00	2019-04-07 03:00:00	3.801039

These duplicate times only occur once a year, and take on the form of 2am-2am. All of these are essentially 0, so we will drop them altogether, as removing some 0's from the sparse dataset won't make a very big difference.

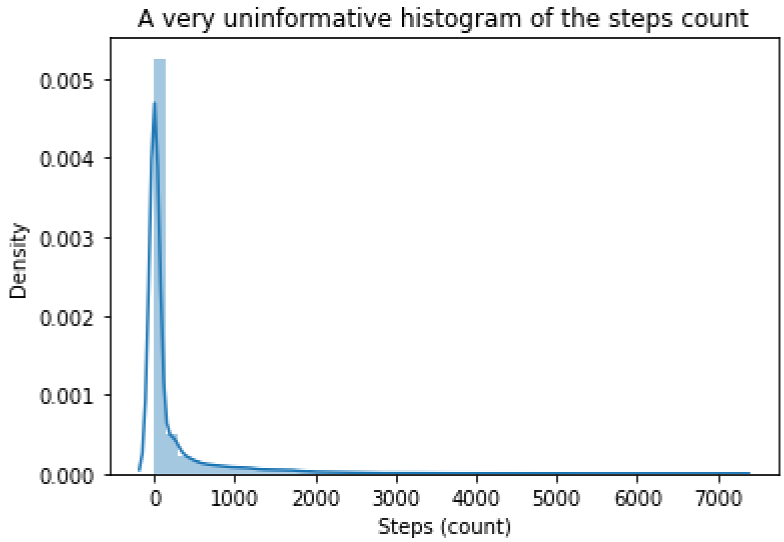
In [10]:
```
user1_df = user1_df[~ (user1_df['Start'].isin(multicounts.index.values) &
            user1_df['Finish'].isin(multicounts.index.values) )]
```

Now we're checking the first issue we noted: plausibly uncommon step counts. We'll plot a histogram and kde of the step counts.

In [11]:
```
sns.distplot(user1_df['Steps (count)'])
plt.title("A very uninformative histogram of the steps count")
```

```
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

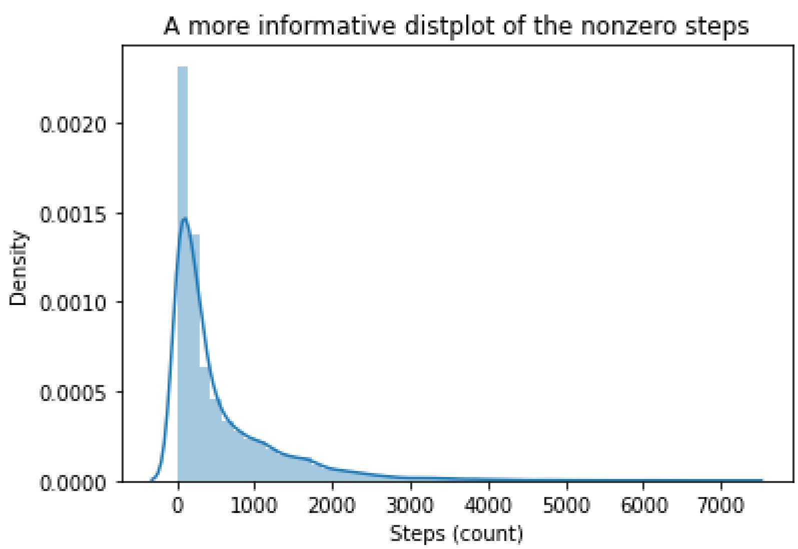
Out[11]:
```
Text(0.5, 1.0, 'A very uninformative histogram of the steps count')
```



In [12]:
```
sns.distplot(user1_df[user1_df['Steps (count)'] != 0]['Steps (count)'])
plt.title("A more informative distplot of the nonzero steps")
```

```
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

Out[12]:
```
Text(0.5, 1.0, 'A more informative distplot of the nonzero steps')
```



The distplot including the zeroes is not very informative, but filtering out the zeroes makes it a little better. The steps seem to be more poisson distributed, which makes sense, but there is a rather long right tail, which will affect the significance of any hypothesis tests we do that assume parametric data.

Time-Related Breakdowns

Now looking at some time-related breakdowns. We set up the data in preparation to aggregate by:

- year
- month
- week
- day
- day of week
- hour

Using the Start time as the basis for our timestamps makes more sense.

First, defining some functions for plotting data to make it easier to explore.

In [74]:
```
def plot_scatterplot(df):
    plt.plot(df.index, df['mean'])
    plt.scatter(df.index, df['mean'])
    plt.ylabel("Average steps")
    plt.xlabel("Time")
    plt.title("Average steps")
    plt.grid()
    plt.show()
```

Creating some features that will allow us to aggregate easier:

In [87]:
```
user1_df['year'] = user1_df['Start'].dt.year
user1_df['month'] = user1_df['Start'].dt.month
user1_df['week'] = user1_df['Start'].dt.isocalendar().week
user1_df['day'] = user1_df['Start'].dt.day
user1_df['dayofweek'] = user1_df['Start'].dt.dayofweek
user1_df['hour'] = user1_df['Start'].dt.hour
```

In [76]:
```
steps_describe_columns = [('Steps (count)', 'count'), ('Steps (count)',  'mean'), ('Ste
                          ('Steps (count)',   'min'), ('Steps (count)',   '25%'), ('Ste
                          ('Steps (count)',   '75%'), ('Steps (count)',   'max')
                        ]

steps_aggs = {'Steps (count)': ['sum', 'mean', 'std', 'min', 'median', 'max', 'count']}
```

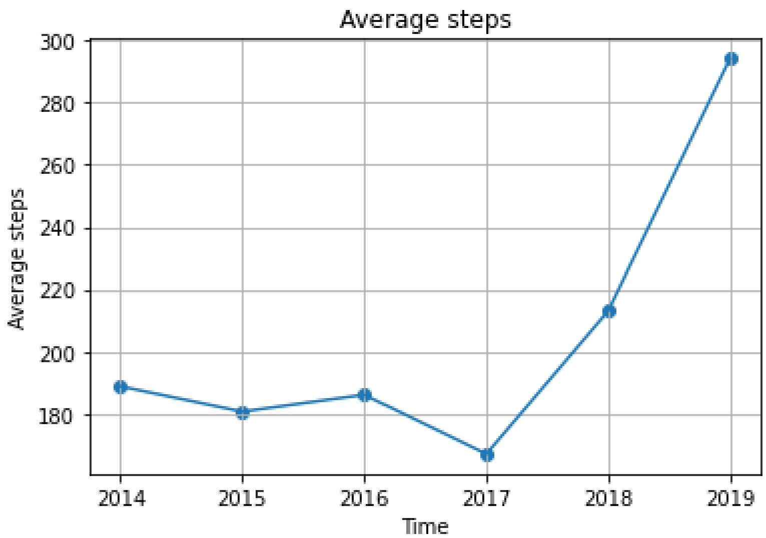
First, looking at year aggregations.

In [77]:
```
year_aggs = user1_df.groupby("year").agg(steps_aggs)
year_aggs.columns = [x[1] for x in year_aggs.columns]
year_aggs
```

Out[77]:

year	sum	mean	std	min	median	max	count
2014	1.115900e+05	188.815567	495.522895	0.0	0.000000	3678.000000	591
2015	1.582732e+06	180.697797	517.354050	0.0	0.000000	6476.569805	8759
2016	1.634559e+06	186.104827	501.083499	0.0	0.000000	6052.441276	8783
2017	1.463320e+06	167.064733	492.293485	0.0	0.000000	6272.645042	8759
2018	1.866431e+06	213.087201	493.942794	0.0	0.000000	7204.611321	8759
2019	1.888807e+06	294.206647	589.012723	0.0	6.702548	5777.462429	6420

In [78]:
```
plot_scatterplot(year_aggs)
```



From the summary, we have full year's worth of data for 2015-2018, 691 days for 2014, and 6420 days for 2019. The mean steps taken per hour was highest in 2019, and lowest in 2017. Standard deviation was lowest in 2017, and highest in 2019.

This suggests that User 1 walked more steps on average in 2019, but had more variation in how much they walked per hour, whereas they walked the least steps on average in 2017, but were more consistent in that number. This may also be a function of the fewer data points in 2019.

Looking at aggregating by month

In [79]:
```
month_aggs = user1_df.groupby("month").agg(steps_aggs)
month_aggs.columns = [x[1] for x in month_aggs.columns]
month_aggs
```

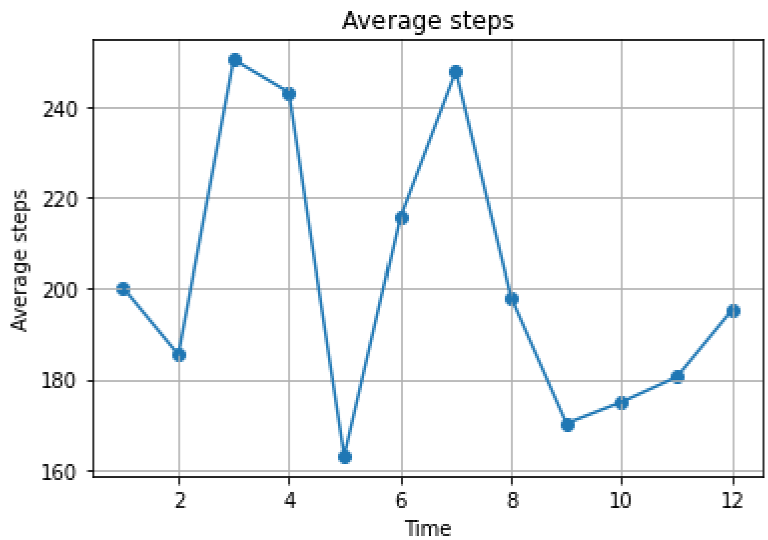
Out[79]:

month	sum	mean	std	min	median	max	count
1	744761.114803	200.204601	504.273415	0.0	0.0	6444.000000	3720
2	627560.340006	185.449273	478.116770	0.0	0.0	5241.669732	3384
3	931391.794740	250.374138	566.153040	0.0	0.0	6023.499884	3720
4	875194.491326	243.109581	555.893625	0.0	0.0	6476.569805	3600
5	606693.635922	163.089687	468.775422	0.0	0.0	6195.616054	3720
6	775956.000000	215.543333	574.587724	0.0	0.0	5873.330051	3600
7	921782.000000	247.790860	664.738524	0.0	0.0	6055.166833	3720
8	736871.000000	198.083602	487.165118	0.0	0.0	5214.052265	3720
9	590481.000000	170.265571	463.933524	0.0	0.0	6272.645042	3468
10	520073.548232	174.991100	424.410401	0.0	0.0	6052.441276	2972
11	519915.970489	180.526379	416.393673	0.0	0.0	5423.273163	2880

	sum	mean	std	min	median	max	count
month							
12	696757.273837	195.334251	496.960888	0.0	0.0	7204.611321	3567

In [80]:

```
plot_scatterplot(month_aggs)
```



Spikey.

The average steps per hour aggregated by month seems to suggest certain months have systematically higher levels of walking, such as March, April, and July, and lower levels of walking such as September - November.

Looking at aggregating by week now

In [81]:

```
week_aggs = user1_df.groupby("week").agg(steps_aggs)
week_aggs.columns = [x[1] for x in week_aggs.columns]
week_aggs
```

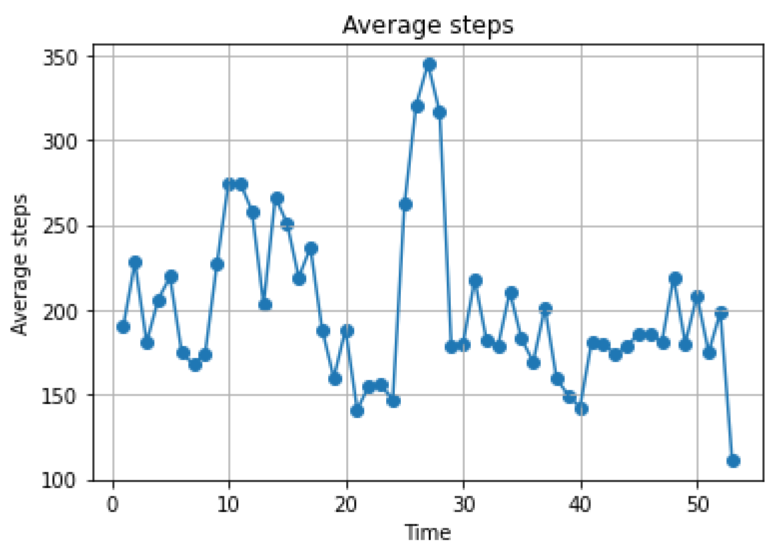
Out[81]:

	sum	mean	std	min	median	max	count
week							
1	159691.018786	190.108356	470.578745	0.0	0.0	3917.245696	840
2	191406.525689	227.864912	491.638966	0.0	0.0	3866.168899	840
3	151858.652796	180.784110	466.946471	0.0	0.0	4273.000000	840
4	173310.446406	206.321960	573.509584	0.0	0.0	6444.000000	840
5	184310.698686	219.417498	591.571387	0.0	0.0	5241.669732	840
6	146811.068054	174.775081	443.565962	0.0	0.0	3962.328963	840
7	140834.626750	167.660270	444.085200	0.0	0.0	3545.000000	840
8	146337.992778	174.211896	429.016416	0.0	0.0	3289.000000	840
9	190201.594168	226.430469	523.903885	0.0	0.0	4178.738385	840

week	sum	mean	std	min	median	max	count
10	230768.118590	274.723951	614.631521	0.0	0.0	6023.499884	840
11	230717.586843	274.663794	615.222961	0.0	0.0	5172.000000	840
12	216720.394223	258.000469	543.044252	0.0	0.0	4788.962521	840
13	170785.800315	203.316429	523.797996	0.0	0.0	5078.638876	840
14	223506.453954	266.079112	639.800969	0.0	0.0	6476.569805	840
15	210698.630502	250.831703	511.126970	0.0	0.0	3558.286886	840
16	183790.004143	218.797624	513.223436	0.0	0.0	3918.477889	840
17	198633.494523	236.468446	520.787028	0.0	0.0	3430.418948	840
18	158409.209011	188.582392	448.672494	0.0	0.0	4221.000000	840
19	134178.864182	159.736743	394.746501	0.0	0.0	3395.949033	840
20	158390.701831	188.560359	569.118756	0.0	0.0	6195.616054	840
21	118455.000000	141.017857	494.016048	0.0	0.0	4881.000000	840
22	130492.000000	155.347619	418.788746	0.0	0.0	3132.730796	840
23	130898.000000	155.830952	422.830987	0.0	0.0	3117.000000	840
24	123538.000000	147.069048	423.350573	0.0	0.0	3520.712012	840
25	220279.000000	262.236905	704.894603	0.0	0.0	5873.330051	840
26	269420.000000	320.738095	718.100492	0.0	0.0	4849.054311	840
27	289540.000000	344.690476	793.044523	0.0	0.0	6053.737707	840
28	265901.000000	316.548810	776.471039	0.0	0.0	6055.166833	840
29	149701.000000	178.215476	546.231720	0.0	0.0	5586.988359	840
30	151415.000000	180.255952	541.837236	0.0	0.0	6039.118662	840
31	182786.000000	217.602381	550.068727	0.0	0.0	4342.103816	840
32	153329.000000	182.534524	467.630456	0.0	0.0	3752.965823	840
33	150295.000000	178.922619	410.006626	0.0	0.0	2752.073630	840
34	176935.000000	210.636905	514.603051	0.0	0.0	5214.052265	840
35	153645.000000	182.910714	448.383077	0.0	0.0	3197.727345	840
36	142171.000000	169.251190	421.765997	0.0	0.0	3273.480036	840
37	169021.000000	201.215476	541.366311	0.0	0.0	4671.125958	840
38	133975.000000	159.494048	440.690450	0.0	0.0	4336.791175	840
39	109091.000000	149.439726	460.556384	0.0	0.0	6272.645042	730
40	95492.005595	142.525381	387.135280	0.0	0.0	6052.441276	670
41	121850.994405	181.325885	420.462037	0.0	0.0	5390.865355	672

week	sum	mean	std	min	median	max	count
42	120973.000000	180.019345	488.988532	0.0	0.0	4750.059460	672
43	116830.374184	173.854723	385.346491	0.0	0.0	4784.251728	672
44	119895.733652	178.416270	346.907414	0.0	0.0	3559.000000	672
45	124910.154269	185.878206	473.549610	0.0	0.0	5423.273163	672
46	125024.974748	186.049070	414.767249	0.0	0.0	3311.470641	672
47	121574.653554	180.914663	384.119841	0.0	0.0	4688.717810	672
48	147222.717856	219.081425	508.595872	0.0	0.0	3698.000000	672
49	123858.050834	180.288284	442.190392	0.0	0.0	3843.027057	687
50	174977.128086	208.306105	505.823124	0.0	0.0	3533.000000	840
51	146912.877539	174.896283	448.382409	0.0	0.0	3107.678084	840
52	166937.622403	198.735265	557.400527	0.0	0.0	7204.611321	840
53	18729.000000	111.482143	359.321094	0.0	0.0	2179.979932	168

In [82]:
```
plot_scatterplot(week_aggs)
```



Breaking the step counts down by week of the year, it looks like certain weeks of the year have higher average step counts per hour (peaking at 350 steps) compared to others (e.g. 150 steps). They seem more varied in the earlier weeks of the year compared to later, and become more stable in later weeks before dropping off. No discernible trends which aren't explained by month already.

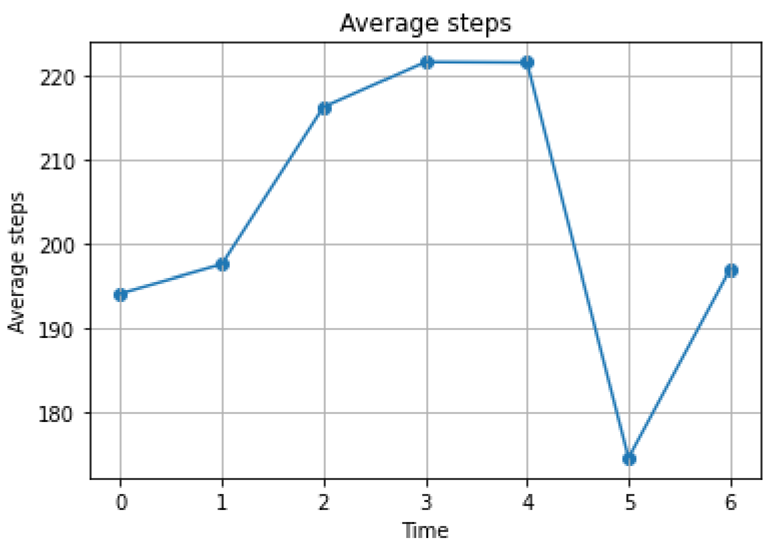
Aggregating by day of week, we use `dayofweek()` where Monday = 0 and Sunday = 6.

In [88]:
```
dow_aggs = user1_df.groupby("dayofweek").agg(steps_aggs)
dow_aggs.columns = [x[1] for x in dow_aggs.columns]
dow_aggs
```

Out[88]:

	sum	mean	std	min	median	max	count
dayofweek							
0	1.168919e+06	194.043589	509.428204	0.0	0.0	5769.000000	6024
1	1.189750e+06	197.501639	491.770749	0.0	0.0	6272.645042	6024
2	1.299812e+06	216.203003	535.789291	0.0	0.0	6055.166833	6012
3	1.329376e+06	221.562665	530.524977	0.0	0.0	7204.611321	6000
4	1.329018e+06	221.502940	521.759929	0.0	0.0	5423.273163	6000
5	1.046901e+06	174.483537	515.289055	0.0	0.0	6444.000000	6000
6	1.183662e+06	196.916056	513.098491	0.0	0.0	6476.569805	6011

In [89]:
```
plot_scatterplot(dow_aggs)
```



From the graph, it certainly seems like User 1 walks increasingly more as the week goes on, and then sharply drops off during the weekend. A potential explanation would be that the user works Mon-Fri, and so remembers to exercise during the workweek, and then stays at home during the weekend. This does give a lot of insight into the habits of the user.

Now examining by hour

In [90]:
```
hour_aggs = user1_df.groupby("hour").agg(steps_aggs)
hour_aggs.columns = [x[1] for x in hour_aggs.columns]
hour_aggs
```

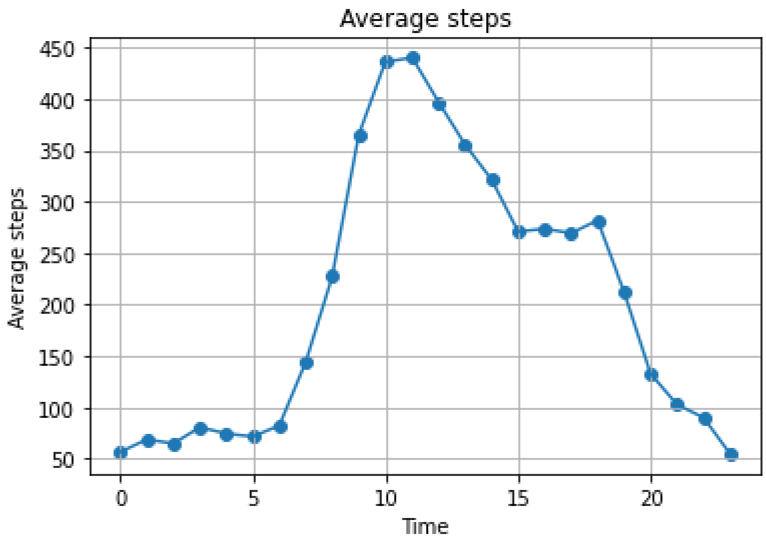
Out[90]:

	sum	mean	std	min	median	max	count
hour							
0	99191.034272	56.583591	298.144179	0.0	0.000000	4112.889022	1753
1	120662.729550	68.832133	362.724302	0.0	0.000000	5716.821371	1753
2	113250.652023	64.751659	322.903802	0.0	0.000000	6053.737707	1749

	sum	mean	std	min	median	max	count
hour							
3	141353.544622	80.635222	396.392945	0.0	0.000000	4838.945689	1753
4	130494.615958	74.440739	356.741978	0.0	0.000000	5057.785598	1753
5	125396.699008	71.532629	395.412857	0.0	0.000000	5769.000000	1753
6	144368.358298	82.355025	361.163701	0.0	0.000000	5873.330051	1753
7	253169.637969	144.420786	440.614590	0.0	0.000000	4881.000000	1753
8	399095.817454	227.664471	618.491285	0.0	0.000000	7204.611321	1753
9	640677.315516	365.266428	619.722242	0.0	88.588822	6444.000000	1754
10	765069.417532	436.185529	673.366405	0.0	119.504181	6039.118662	1754
11	772590.971528	440.473758	713.612456	0.0	45.000000	6052.441276	1754
12	695780.348352	396.908356	682.988407	0.0	16.000000	6476.569805	1753
13	623167.995159	355.486592	595.870534	0.0	0.000000	4336.791175	1753
14	563582.388688	321.495943	602.514275	0.0	0.000000	5172.000000	1753
15	474729.684995	270.809860	553.542094	0.0	0.000000	5390.865355	1753
16	479583.587812	273.578772	592.041108	0.0	0.000000	6055.166833	1753
17	472101.893571	269.310835	523.720537	0.0	14.000000	6023.499884	1753
18	494053.668200	281.833239	561.970687	0.0	24.000000	5777.462429	1753
19	372249.702117	212.350087	503.848738	0.0	0.000000	4788.962521	1753
20	232780.765092	132.789940	390.595406	0.0	0.000000	4688.717810	1753
21	180155.108908	102.769600	388.908600	0.0	0.000000	5336.466384	1753
22	157877.740518	90.061461	355.777043	0.0	0.000000	4468.643581	1753
23	96054.492211	54.794348	281.167407	0.0	0.000000	4718.000000	1753

In [91]:

```
plot_scatterplot(hour_aggs)
```



When we see the hourly breakdown, it becomes clearer what the user's schedule looks like. They wake up sometime around 7am, and steadily increase their wakling until 10am (at 450 steps), and then steadily decrease from there, plateauing from 3pm to 6pm before falling sharply.

It's also worth noting that step counts hover around 50-100 from the hours of 10pm to 6am, but don't quite dip to zero, suggesting that there may be calibration issues with the step measurements, or that the person genuinely does not sleep.

Examining the Same for User 2

We will now examine the same measures for User 2. First, using what we learnt from user 1 to code up some auto-cleaning functions

In [108…

```
def clean_user(raw_df):
    raw_df['Start'] = pd.to_datetime(raw_df['Start'], format='%d-%b-%Y %H:%M')
    raw_df['Finish'] = pd.to_datetime(raw_df['Finish'], format='%d-%b-%Y %H:%M')
    start_counts = raw_df['Start'].value_counts()
    multicounts = start_counts[start_counts > 1]

    raw_df = raw_df[~ (raw_df['Start'].isin(multicounts.index.values) &
        raw_df['Finish'].isin(multicounts.index.values) )]

    return raw_df
```

In [109…

```
user2_df = clean_user(user2_raw_data)
user2_df
```

Out[109…

	Start	Finish	Steps (count)
0	2014-11-29 00:00:00	2014-11-29 01:00:00	502.666667
1	2014-11-29 01:00:00	2014-11-29 02:00:00	502.666667
2	2014-11-29 02:00:00	2014-11-29 03:00:00	502.666667
3	2014-11-29 03:00:00	2014-11-29 04:00:00	502.666667
4	2014-11-29 04:00:00	2014-11-29 05:00:00	502.666667

	Start	Finish	Steps (count)
...	...	...	...
42272	2019-09-25 07:00:00	2019-09-25 08:00:00	0.000000
42273	2019-09-25 08:00:00	2019-09-25 09:00:00	0.000000
42274	2019-09-25 09:00:00	2019-09-25 10:00:00	31.000000
42275	2019-09-25 10:00:00	2019-09-25 11:00:00	418.000000
42276	2019-09-25 11:00:00	2019-09-25 12:00:00	726.000000

42272 rows × 3 columns

One immediate observation from seeing the head is just how much the same step count repeats over multiple hours. While it's not impossible that the user has walked exactly 502.667 steps per hour from 1am to sometime after 5am, it does seem highly improbable.

One potential explanation for this based on personal observation and experience with the QS App is that step data stored by Apple are recorded in non-binned form, so if the time block takes up more than an hour, they will divide it evenly over the hour increment. So it's possible that their phone recorded a high step count while the person is sleeping, and then spread it evenly across the full timeblock instead of attributing it to a specific hour. **This is a behaviour which will definitely intefere with analysis, and will need to be identified and dealt with**

In [110…

```
user2_df.describe()
```

Out[110…

	Steps (count)
count	42272.000000
mean	415.899515
std	726.094524
min	0.000000
25%	0.000000
50%	177.878115
75%	479.318182
max	7261.816867

In [111…

```
user2_df[['Start', 'Finish']].describe()
```

```
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/ipykernel_launcher.py:1: FutureWarning: Treating datetime data as categorical rather t
han numeric in `.describe` is deprecated and will be removed in a future version of pand
as. Specify `datetime_is_numeric=True` to silence this warning and adopt the future beha
vior now.
  """Entry point for launching an IPython kernel.
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/ipykernel_launcher.py:1: FutureWarning: Treating datetime data as categorical rather t
han numeric in `.describe` is deprecated and will be removed in a future version of pand
as. Specify `datetime_is_numeric=True` to silence this warning and adopt the future beha
```

```
vior now.
  """Entry point for launching an IPython kernel.
```

Out[111…

	Start	Finish
count	42272	42272
unique	42272	42272
top	2017-05-31 04:00:00	2017-05-31 04:00:00
freq	1	1
first	2014-11-29 00:00:00	2014-11-29 01:00:00
last	2019-09-25 11:00:00	2019-09-25 12:00:00

We have already dealt with the Daylight Savings duplicate time issue in our cleaning function, so thankfully the most frequent date only has a frequency of 1. This dataset has 42272 rows, and also spans around 5 years of data.

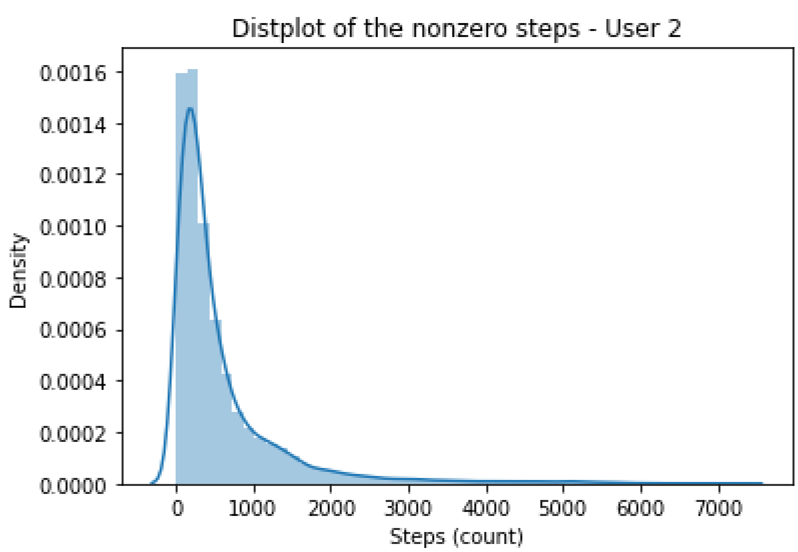
In [113…

```
sns.distplot(user2_df[user2_df['Steps (count)'] != 0]['Steps (count)'])
plt.title("Distplot of the nonzero steps - User 2")
```

```
/mnt/c/Users/SerenaGao/Desktop/Uni/Data3406_Assignment2/venv/lib/python3.6/site-package
s/seaborn/distributions.py:2551: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-level function for
histograms).
  warnings.warn(msg, FutureWarning)
```

Out[113…

```
Text(0.5, 1.0, 'Distplot of the nonzero steps - User 2')
```



We're seeing a trend that user steps will definitely be very right skewed, with most step counts being closer to zero. We may need to use a threshold to indicate the times that a person actually walked, or if it was likely due to random chance or other movements-- e.g. can picking up your phone be misconstrued as a step?

Now we'll make a function that adds our extra time-related features and a function that plots our averages for reusability

In [119…

```
def add_time_features(df):
    df = df.copy()
```

```
    df['year'] = df['Start'].dt.year
    df['month'] = df['Start'].dt.month
    df['week'] = df['Start'].dt.isocalendar().week
    df['day'] = df['Start'].dt.day
    df['dayofweek'] = df['Start'].dt.dayofweek
    df['hour'] = df['Start'].dt.hour

    return df

def display_mean_plot(df, mode):
    aggs = df.groupby(mode).agg(steps_aggs)
    aggs.columns = [x[1] for x in aggs.columns]

    plot_scatterplot(aggs)
```

In [118…

```
user2_df = add_time_features(user2_df)
user2_df
```

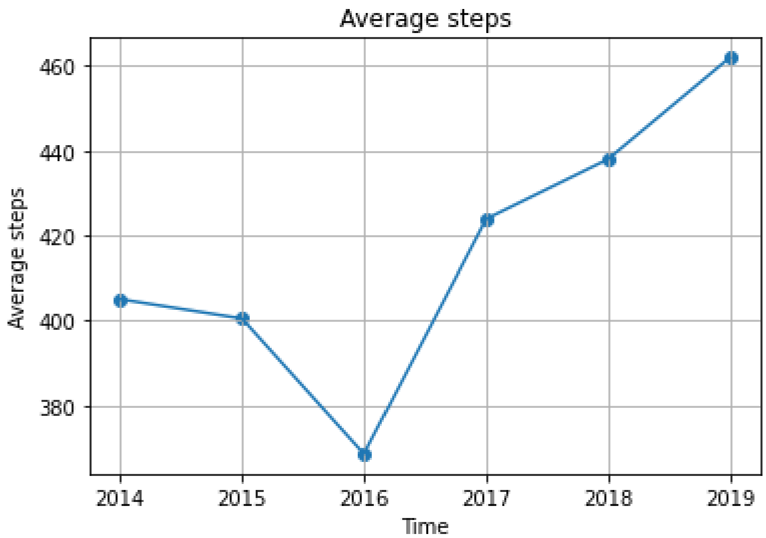
Out[118…

	Start	Finish	Steps (count)	year	month	week	day	dayofweek	hour
0	2014-11-29 00:00:00	2014-11-29 01:00:00	502.666667	2014	11	48	29	5	0
1	2014-11-29 01:00:00	2014-11-29 02:00:00	502.666667	2014	11	48	29	5	1
2	2014-11-29 02:00:00	2014-11-29 03:00:00	502.666667	2014	11	48	29	5	2
3	2014-11-29 03:00:00	2014-11-29 04:00:00	502.666667	2014	11	48	29	5	3
4	2014-11-29 04:00:00	2014-11-29 05:00:00	502.666667	2014	11	48	29	5	4
...	...	...	...	...	...	...	...	...	...
42272	2019-09-25 07:00:00	2019-09-25 08:00:00	0.000000	2019	9	39	25	2	7
42273	2019-09-25 08:00:00	2019-09-25 09:00:00	0.000000	2019	9	39	25	2	8
42274	2019-09-25 09:00:00	2019-09-25 10:00:00	31.000000	2019	9	39	25	2	9
42275	2019-09-25 10:00:00	2019-09-25 11:00:00	418.000000	2019	9	39	25	2	10
42276	2019-09-25 11:00:00	2019-09-25 12:00:00	726.000000	2019	9	39	25	2	11

42272 rows × 9 columns

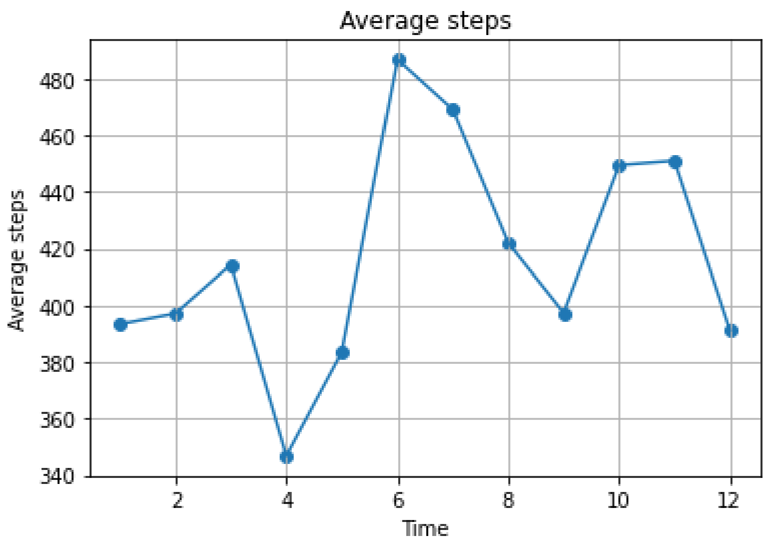
In [120…

```
display_mean_plot(user2_df, 'year')
```



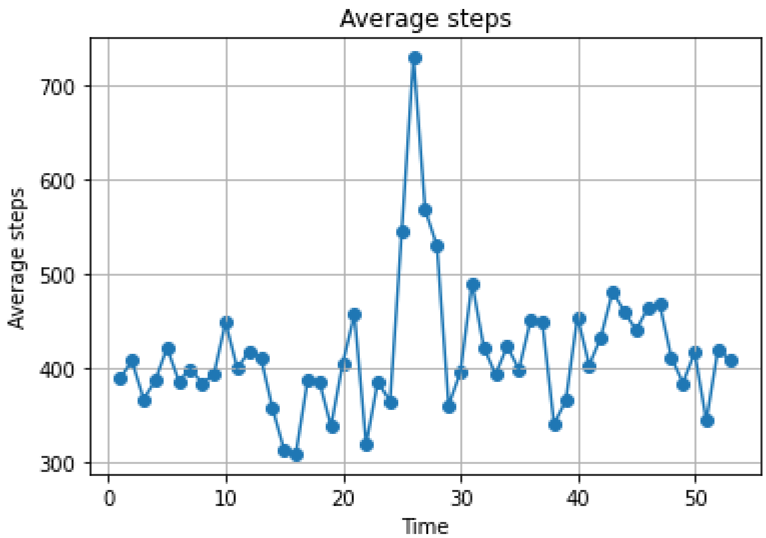
This user has a slightly different pattern: their average step count aggregated over the year almost steadily climbs up every year, with a very low dip in 2016 where they didn't walk much-- though it's possible this is due to a lack of use/records rather than a lack of steps.

In [121…
```
display_mean_plot(user2_df, 'month')
```



Aggregating by month, we also see a spike in step count around June and July. If we had more knowledge on the users, perhaps this could be attributed to school holidays, and hence more opportunity for walking during vacation/break.

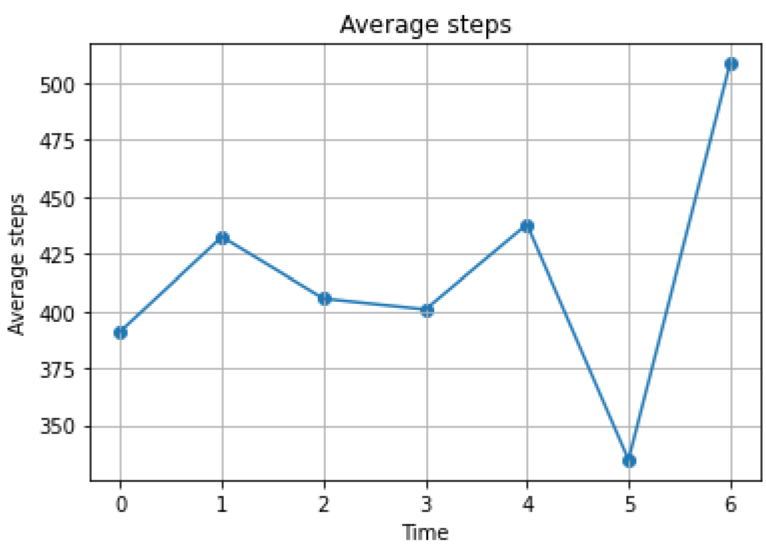
In [122…
```
display_mean_plot(user2_df, 'week')
```



As I'm doing these graphs, it becomes apparent to me that I have very little knowledge of the user themselves, and hence what could be possible reasons for the data that we see. There's a very clear spike around week 26, which happens to be exactly in the middle of the year, but otherwise the steps also trend upwards as the year progresses.

In [123…

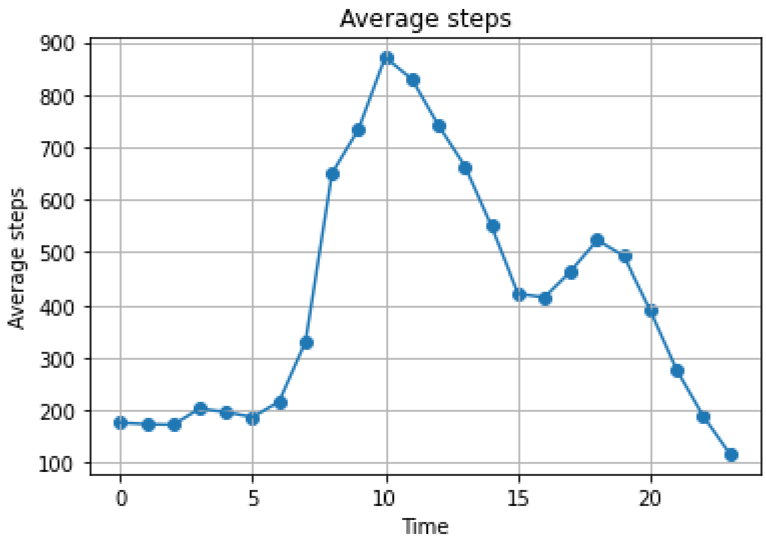
```
display_mean_plot(user2_df, 'dayofweek')
```



Here, we see a slightly different trend. User 2 appears to walk consistently over the week, with the exception of Saturday where they walk much less than usual, and Sunday, where they walk more than usual.

In [124…

```
display_mean_plot(user2_df, 'hour')
```



Aggregating by hour, steps build up until 10am, where it peaks at close to 1000 steps and drops until 3pm, where it rises until 6pm and falls again. For this user, their base level of activity seems to be around 200 (looking at midnight to 5am), which may be related to the time-block issue we saw before. We can potentially attribute those steps to the next hour that doesn't match the repeated step counts, or use it as a baseline or threshold for what constitutes as "active steps"

Identifying anomalous days of exercise

From human experience, we aren't always consistent with our walking. The goal here is to do some exploration and see if there are particular days which the user walked more in, and identify outliers in the data.

Here, we will sum up data over each month and plot the steps over time to see if there is a trend in more aggregated data.

In [127…

```
user2_df = user2_df.set_index('Start')
user2_df
```

Out[127…

	Finish	Steps (count)	year	month	week	day	dayofweek	hour
Start								
2014-11-29 00:00:00	2014-11-29 01:00:00	502.666667	2014	11	48	29	5	0
2014-11-29 01:00:00	2014-11-29 02:00:00	502.666667	2014	11	48	29	5	1
2014-11-29 02:00:00	2014-11-29 03:00:00	502.666667	2014	11	48	29	5	2
2014-11-29 03:00:00	2014-11-29 04:00:00	502.666667	2014	11	48	29	5	3
2014-11-29 04:00:00	2014-11-29 05:00:00	502.666667	2014	11	48	29	5	4
...	...	...	...	...	...	...	...	...
2019-09-25 07:00:00	2019-09-25 08:00:00	0.000000	2019	9	39	25	2	7
2019-09-25 08:00:00	2019-09-25 09:00:00	0.000000	2019	9	39	25	2	8
2019-09-25 09:00:00	2019-09-25 10:00:00	31.000000	2019	9	39	25	2	9

	Finish	Steps (count)	year	month	week	day	dayofweek	hour
Start								
2019-09-25 10:00:00	2019-09-25 11:00:00	418.000000	2019	9	39	25	2	10
2019-09-25 11:00:00	2019-09-25 12:00:00	726.000000	2019	9	39	25	2	11

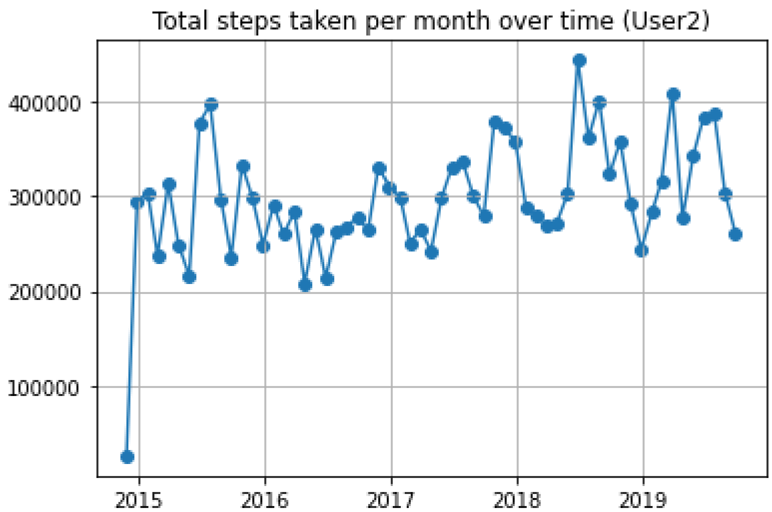
42272 rows × 8 columns

In [140…

```
monthly_year_agg = user2_df.resample("M").sum()
plt.plot(monthly_year_agg.index, monthly_year_agg['Steps (count)'])
plt.scatter(monthly_year_agg.index, monthly_year_agg['Steps (count)'])
plt.grid()
plt.title("Total steps taken per month over time (User2)")
```

Out[140…

```
Text(0.5, 1.0, 'Total steps taken per month over time (User2)')
```



Summing steps over the month, it seems like for the most part User2 was very consistent in how they walked, with a slight trend upwards as the years progressed.

So now we look at per-week data:

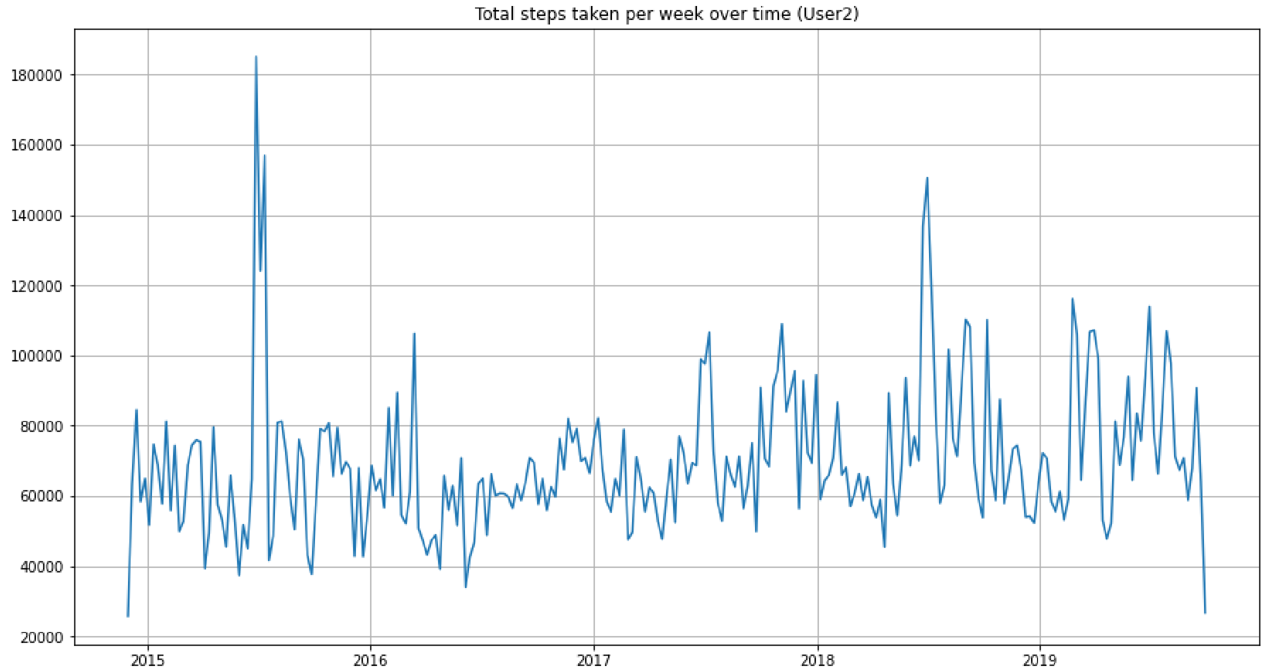
In [141…

```
plt.figure(figsize=(15,8))
weekly_year_agg = user2_df.resample("W").sum()
plt.plot(weekly_year_agg.index, weekly_year_agg['Steps (count)'])

plt.grid()
plt.title("Total steps taken per week over time (User2)")
```

Out[141…

```
Text(0.5, 1.0, 'Total steps taken per week over time (User2)')
```



Now there are definitely more outliers, around the middle of the years 2015, 2017, and 2018. These figures would definitely skew our average-based measures, so we may want to deal with these in some appropriate way.

Looking at daily steps now...

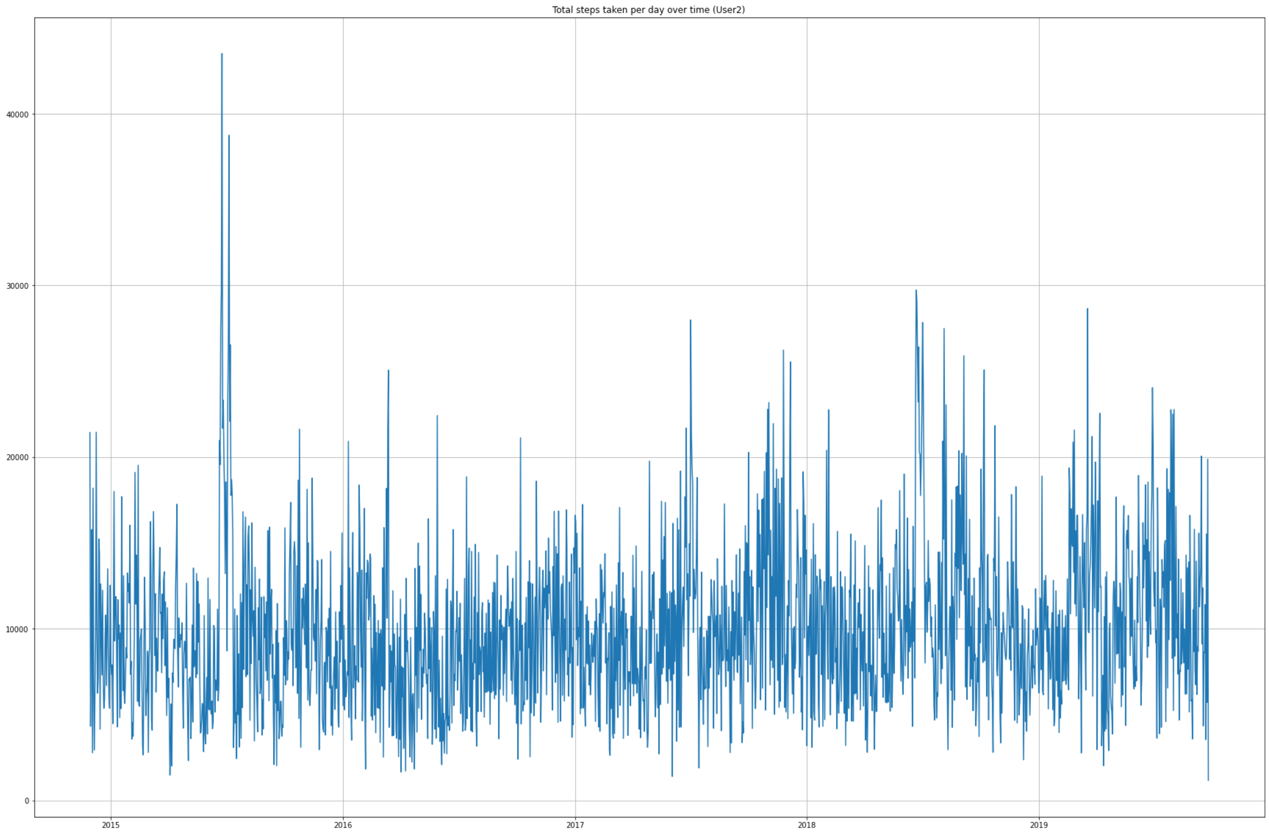
In [151...

```
plt.figure(figsize=(30,20))
daily_year_agg = user2_df.resample("D").sum()
plt.plot(daily_year_agg.index, daily_year_agg['Steps (count)'])

plt.grid()
plt.title("Total steps taken per day over time (User2)")
```

Out[151...

```
Text(0.5, 1.0, 'Total steps taken per day over time (User2)')
```



So this is aggregated daily step count for User 2, and some of the numbers start seeming a bit suss. E.g. At it's peak, there was 40,000 steps in one day, which translates to roughly 30km. Whilst not impossible (there are 30km walks you can do), it does seem to suggest that the person is very fit.

Cross-Referencing with User 1

We'll cross-reference with User1 to see if we get similar step counts

In [152…

```
monthly_year_agg1 = user1_df.resample("M", on='Start').sum()
plt.plot(monthly_year_agg1.index, monthly_year_agg1['Steps (count)'])
plt.scatter(monthly_year_agg1.index, monthly_year_agg1['Steps (count)'])
plt.grid()
plt.title("Total steps taken per month over time (User1)")
```

Out[152…

```
Text(0.5, 1.0, 'Total steps taken per month over time (User1)')
```

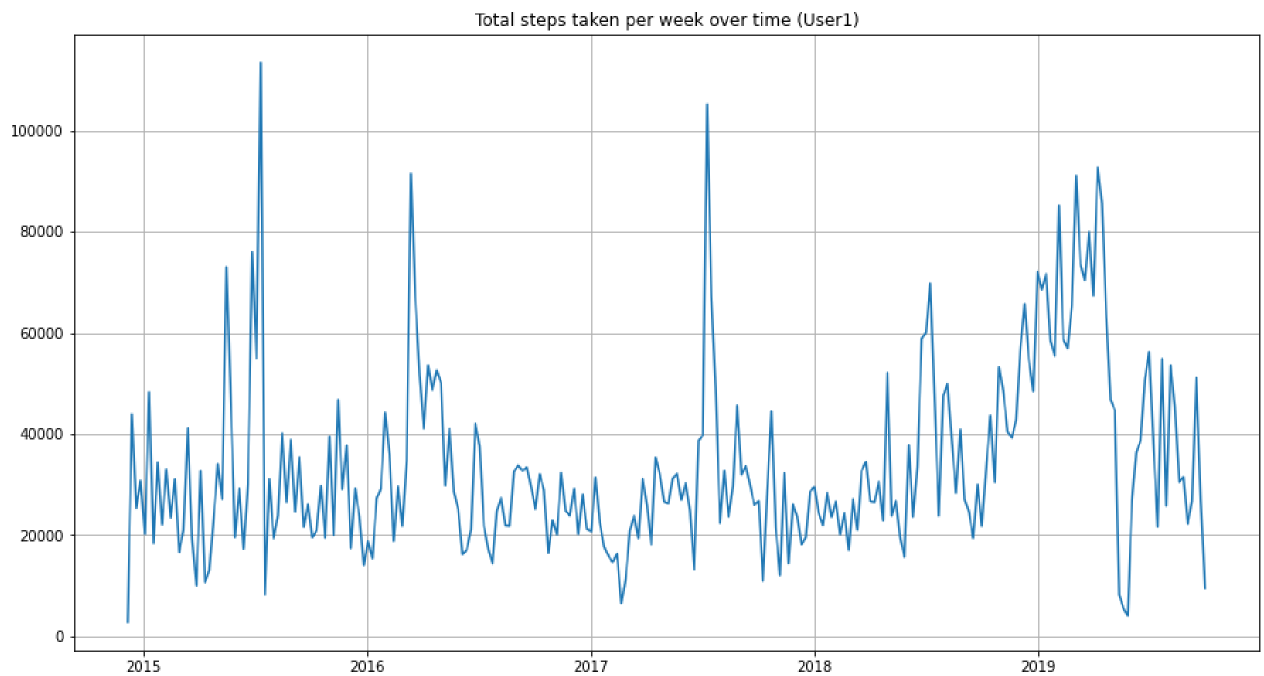
In [153…

```
plt.figure(figsize=(15,8))

weekly_year_agg1 = user1_df.resample("W",  on='Start').sum()
plt.plot(weekly_year_agg1.index, weekly_year_agg1['Steps (count)'])

plt.grid()
plt.title("Total steps taken per week over time (User1)")
```

Out[153… Text(0.5, 1.0, 'Total steps taken per week over time (User1)')

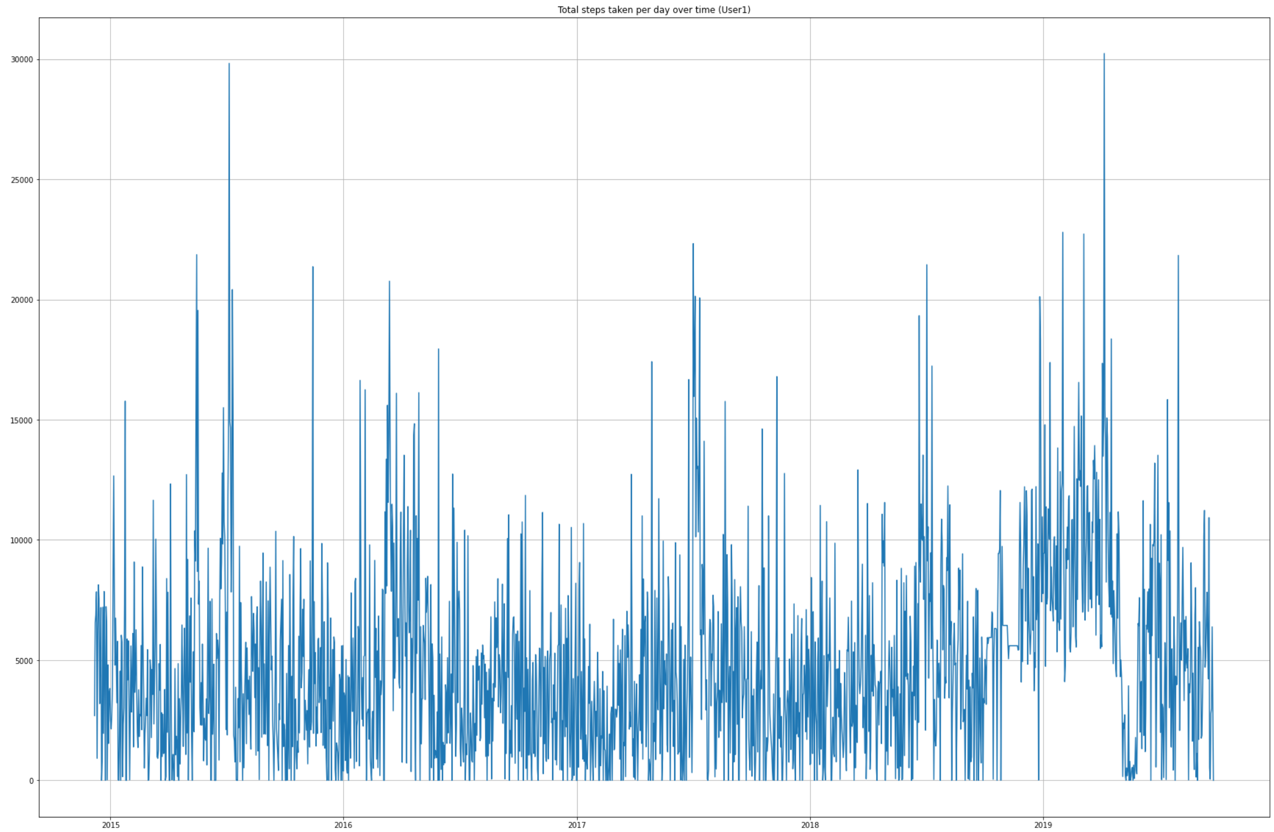


In [154…

```
plt.figure(figsize=(30,20))
daily_year_agg1 = user1_df.resample("D", on='Start').sum()
plt.plot(daily_year_agg1.index, daily_year_agg1['Steps (count)'])

plt.grid()
plt.title("Total steps taken per day over time (User1)")
```

Out[154… Text(0.5, 1.0, 'Total steps taken per day over time (User1)')



And yeah, User1 definitely has a lower baseline of stepcount compared to User2 (so my analysis has been correctly implemented). The seem to have picked up the steps from 2018 to 2019 (perhaps training for a 30k steps run?), but then sharply dropped off (injury?) for a few months.

In [ ]:

```

```