Ihor Lukianov - Trementum Test Task

March 26, 2022

1 Trementum Test Task - Ihor Lukianov - 26-03-2022

1.1 Packages and overview

[1]:
```
# import packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats

%matplotlib inline
```

[2]:
```
# import data from excel file
df = pd.read_excel("Analytics Test Task - Trementum.
↪xlsx",sheet_name="Dataset",index_col=0)
```

[3]:
```
# quick overview of the dataset
df.head()
```

[3]:
```
    gender last_connection         x1          x2         x3           t1  \
ids
1        F      2015-04-27  37.796189  292.189338  85.871732  1102.896732
2        M      2015-04-27  44.523437  294.989423  96.432040  1116.845895
3        F      2015-02-16  90.593723  298.219531  96.915476  1290.882244
4        M      2015-04-18  44.055440  303.041350  96.422230  1173.231390
5        F      2015-03-08   9.753165  298.005909  95.192099  1036.007131

              t2
ids
1    1814.852022
2    1679.957691
3    1841.987889
4    1712.165400
5    1841.026590
```

[4]:
```
df.describe()
```

[4]:

	x1	x2	x3	t1	t2
count	10000.000000	10000.000000	10000.000000	10000.000000	10000.000000
mean	50.067047	300.068631	95.055902	1174.859697	1769.174820
std	28.931639	9.889459	9.911644	118.724074	86.214259
min	0.004004	264.463035	62.029833	897.883743	1557.852139
25%	24.719006	293.396488	92.997142	1084.746402	1696.077169
50%	49.876050	300.225596	95.889497	1175.567545	1752.607393
75%	75.389142	306.557144	97.995304	1264.322678	1846.609079
max	99.904798	339.416551	1000.000000	1449.617809	2027.374480

Find if there are any **nulls** in the data frame.

[5]:
```
#missing data
total = df.isnull().sum().sort_values(ascending=False)
percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
missing_data.head(20)
```

[5]:

	Total	Percent
last_connection	100	0.01
gender	0	0.00
x1	0	0.00
x2	0	0.00
x3	0	0.00
t1	0	0.00
t2	0	0.00

Some missing values are in the **last_connection** category. I'll pay attention to it in the relevant section.

1.2 Step1: Describe each category

Step 1 Field types

Please describe the fields gender, last_connection, x1, x2 & x3 independently from any other fields.

You do not need to write full sentences, but your answer should cover the following questions: - What kind of data is in the field? - Is the data complete? - Does it all look fine? - Are there obvious patterns in the data?

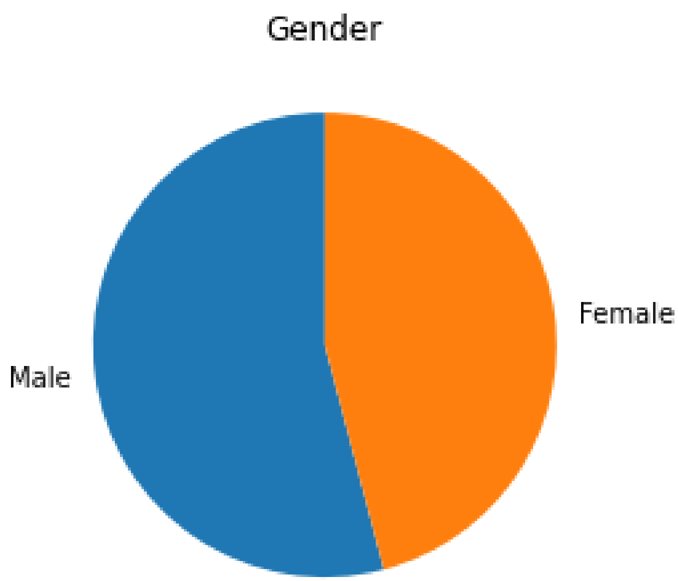
(Don't spend more than 10 minutes per field)

1.2.1 Gender

The first column - **gender**, contains only two values - **male(M)** and **female(F)**.

[6]:
```
plt.pie(df['gender'].value_counts(),labels=['Male','Female'],startangle=90)
plt.title('Gender')
```

[6]: Text(0.5, 1.0, 'Gender')



[7]:
```
df["gender"].value_counts()
```

[7]:
```
M    5410
F    4590
Name: gender, dtype: int64
```

Everything looks fine here. The data contains all 10000 values, there are slightly more male connections than female, but the balance is normal.

1.2.2 Last Connection

Second column - last_connection with dates. First of all, there are only 9900 values. So, we don't know the information for 100 values.

[8]:
```
df["last_connection"].count()
```

[8]:
```
9900
```

[9]:
```
# create a dataframe for all missing values
dfNoDate = df[df['last_connection'].isna() == True]
dfNoDate.head()
```

[9]:
```
    gender last_connection         x1          x2         x3           t1  \
ids
72       F             NaT  94.193060  296.728093  96.624358  1390.429021
201      F             NaT  14.513138  297.742944  93.439564   998.956686
231      M             NaT  78.566415  286.127010  97.942381  1275.986271
```

```
667      M            NaT  86.706631  298.665773  96.278532  1246.407489
718      M            NaT  33.657190  300.989347  96.639078  1212.422614

              t2
ids
72   1835.276418
201  1839.843246
231  1644.508038
667  1694.663093
718  1703.957389
```

[10]:
```
dfNoDate['gender'].value_counts()
```

[10]:
```
M    58
F    42
Name: gender, dtype: int64
```

According to the results, this information is simply missing from the data. The best decision is to make further investigation on the root of this problem. As for the current task, we can just delete these values from our dataset. We can exclude up to 5% of data still to have good research. Our missing data is just 1%.

[11]:
```
df = df[df['last_connection'].isna() == False]
```

[12]:
```
df.describe()
```

[12]:
```
                x1           x2           x3           t1           t2
count  9900.000000  9900.000000  9900.000000  9900.000000  9900.000000
mean     50.074626   300.065249    95.059389  1174.873047  1769.220700
std      28.926705     9.878200     9.951427   118.637538    86.215166
min       0.004004   264.463035    62.029833   897.883743  1557.852139
25%      24.719006   293.397245    92.996984  1084.938311  1696.160393
50%      49.869093   300.223222    95.893075  1175.500124  1752.584470
75%      75.378214   306.542491    97.994288  1264.264403  1846.673508
max      99.904798   339.416551  1000.000000  1449.617809  2027.374480
```

[13]:
```
df.sort_values(by='last_connection')
```

[13]:
```
     gender last_connection         x1          x2         x3           t1  \
ids
4997      M      2015-01-31  95.266111  300.086481  97.105300  1229.848477
3277      F      2015-01-31  11.421857  315.311323  96.033644   984.792560
2706      M      2015-01-31  91.303795  290.372681  90.893020  1337.735450
210       M      2015-01-31  27.326659  291.908337  99.963776  1038.541277
7769      F      2015-01-31   5.340187  304.524024  94.290626   986.415864
…     …             …        …          …           …          …
3114      F      2015-05-10  61.872095  288.909572  89.588931  1227.084921
```

```
7539      F      2015-05-10   4.723329  297.134979  97.074443  1094.786799
3954      F      2015-05-10  41.377053  294.424879  96.840659  1204.394810
49        M      2015-05-10  71.783058  310.085439  90.773446  1196.323557
6534      F      2015-05-10  56.656165  281.180737  90.053271  1110.903969

               t2
ids
4997  1700.345924
3277  1918.900954
2706  1661.490722
210   1667.633349
7769  1870.358109
…             …
3114  1800.093074
7539  1837.107407
3954  1824.911955
49    1740.341758
6534  1765.313318

[9900 rows x 7 columns]
```

As we can see, our data was collected between January 31, 2015 and May 10, 2015.

1.2.3 x1

From the description of this column, it is clear that the values are in the range from 0 to 100 and the average almost in the middle (50).

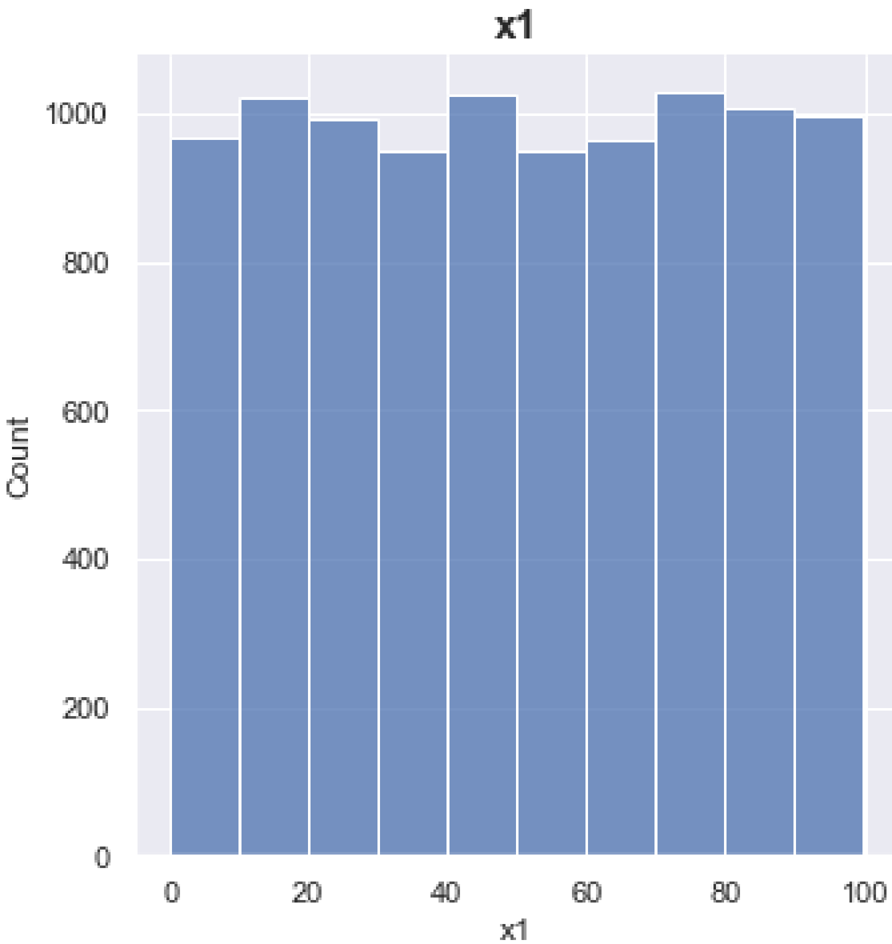
[16]:
```
df['x1'].describe()
```

[16]:
```
count    9900.000000
mean       50.074626
std        28.926705
min         0.004004
25%        24.719006
50%        49.869093
75%        75.378214
max        99.904798
Name: x1, dtype: float64
```

The distribution shows us that values are equally distributed in this range.

[17]:
```
#count by groups of each 10% usiing distripution
sns.set_theme()
sns.displot(data = df,x='x1',bins=10)
plt.title('x1', fontdict={'weight':'bold','size': 15})
```

[17]:
```
Text(0.5, 1.0, 'x1')
```



1.2.4 x2

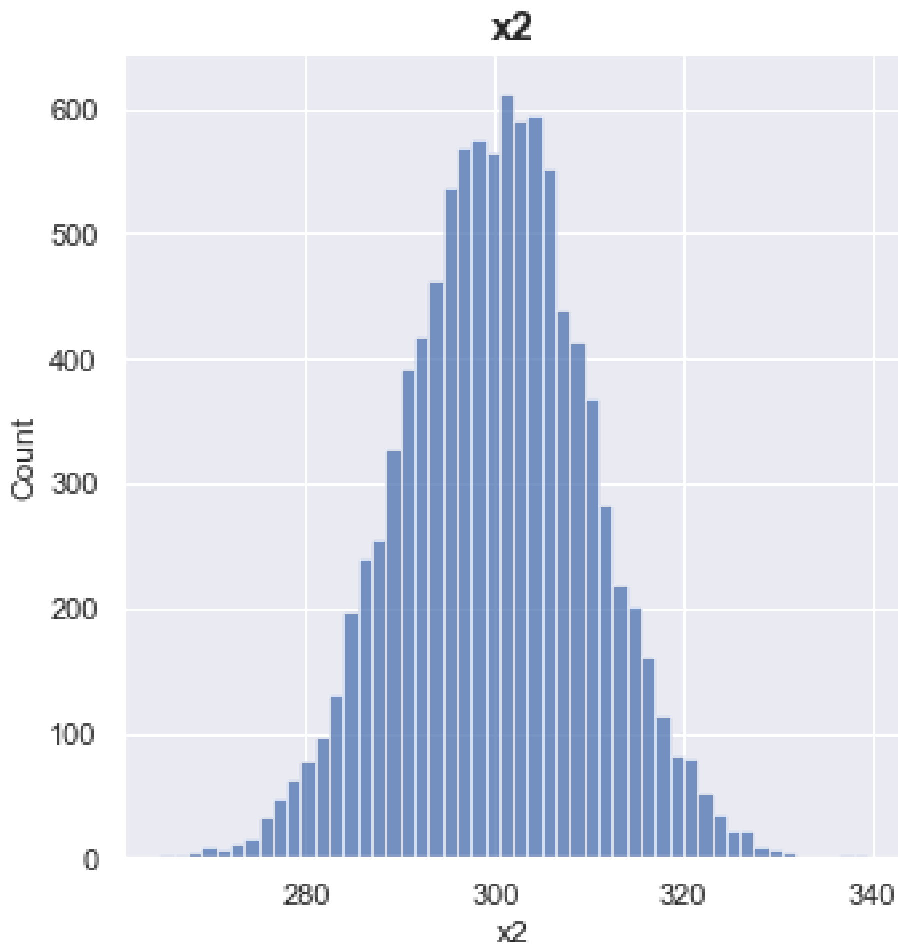
This data is normally distributed and doesn't have any missing values.

[18]:
```
df['x2'].describe()
```

[18]:
```
count    9900.000000
mean      300.065249
std         9.878200
min       264.463035
25%       293.397245
50%       300.223222
75%       306.542491
max       339.416551
Name: x2, dtype: float64
```

```
[19]: sns.displot(data = df,x='x2',bins=50)
      plt.title('x2',fontdict={'weight':'bold','size': 15})
```

```
[19]: Text(0.5, 1.0, 'x2')
```



1.2.5 x3

From the description, we see the maximum value - 1000, while the mean of the category is 95. Something is wrong with it.

```
[20]: df['x3'].describe()
```

```
[20]: count    9900.000000
      mean       95.059389
      std         9.951427
      min        62.029833
      25%        92.996984
```

```
50%        95.893075
75%        97.994288
max      1000.000000
Name: x3, dtype: float64
```

[21]:
```
df[df['x3']==1000]
```

[21]:
```
     gender last_connection        x1          x2      x3          t1  \
ids
5047      F      2015-03-13  1.753303  309.768426  1000.0  917.235502

               t2
ids
5047  1893.957918
```

It seems to be some type of error, like a misprint. There are two possible ways to fix this problem - either to drop this value from our data frame or give it an average value in the x3 category. As for this case, I gonna change it with the mean value.

[22]:
```
df.loc[df['x3'] == 1000, 'x3'] = df['x3'].mean()
```

[23]:
```
# check the result
df.loc[5047]
```

[23]:
```
gender                               F
last_connection    2015-03-13 00:00:00
x1                            1.753303
x2                          309.768426
x3                           95.059389
t1                          917.235502
t2                         1893.957918
Name: 5047, dtype: object
```

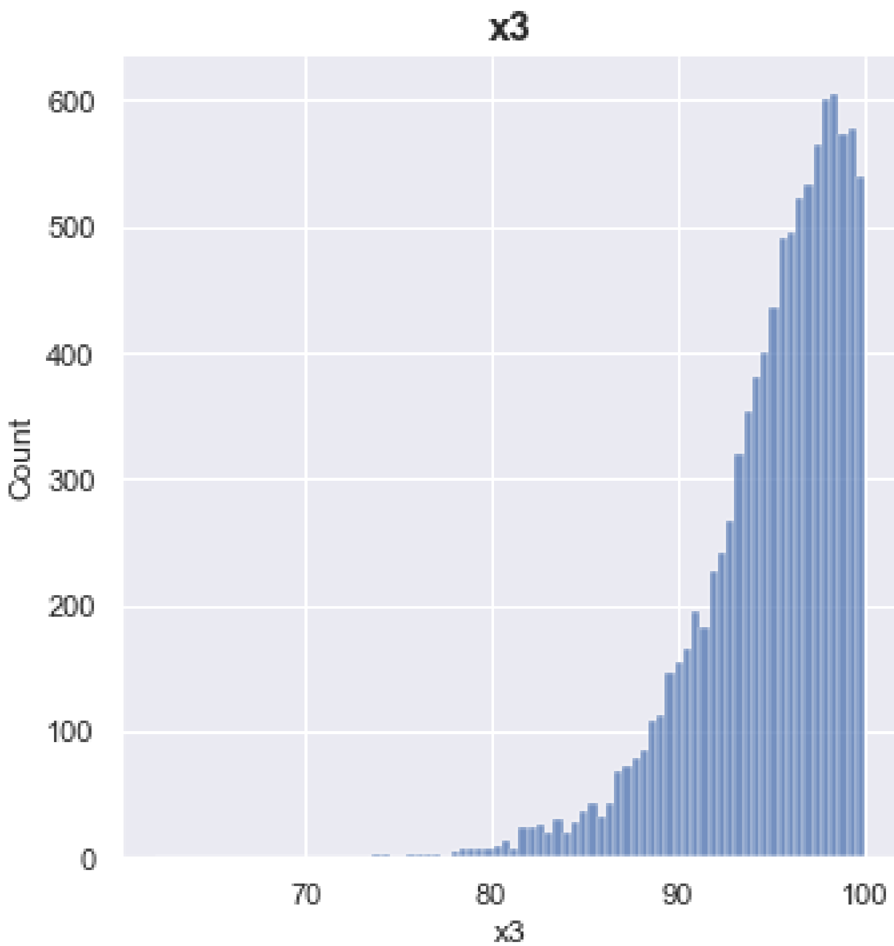
[24]:
```
df['x3'].describe()
```

[24]:
```
count    9900.000000
mean       94.967981
std         4.036736
min        62.029833
25%        92.996984
50%        95.892884
75%        97.993536
max        99.999098
Name: x3, dtype: float64
```

Now the data is clear.

```
[25]: sns.displot(data = df,x='x3')
plt.title('x3',fontdict={'weight':'bold','size': 15})
```

```
[25]: Text(0.5, 1.0, 'x3')
```



The distribution plot shows, that the range of values is between 60 and 100.

2 Correlation analysis

Step 2

Finding correlations / modeling

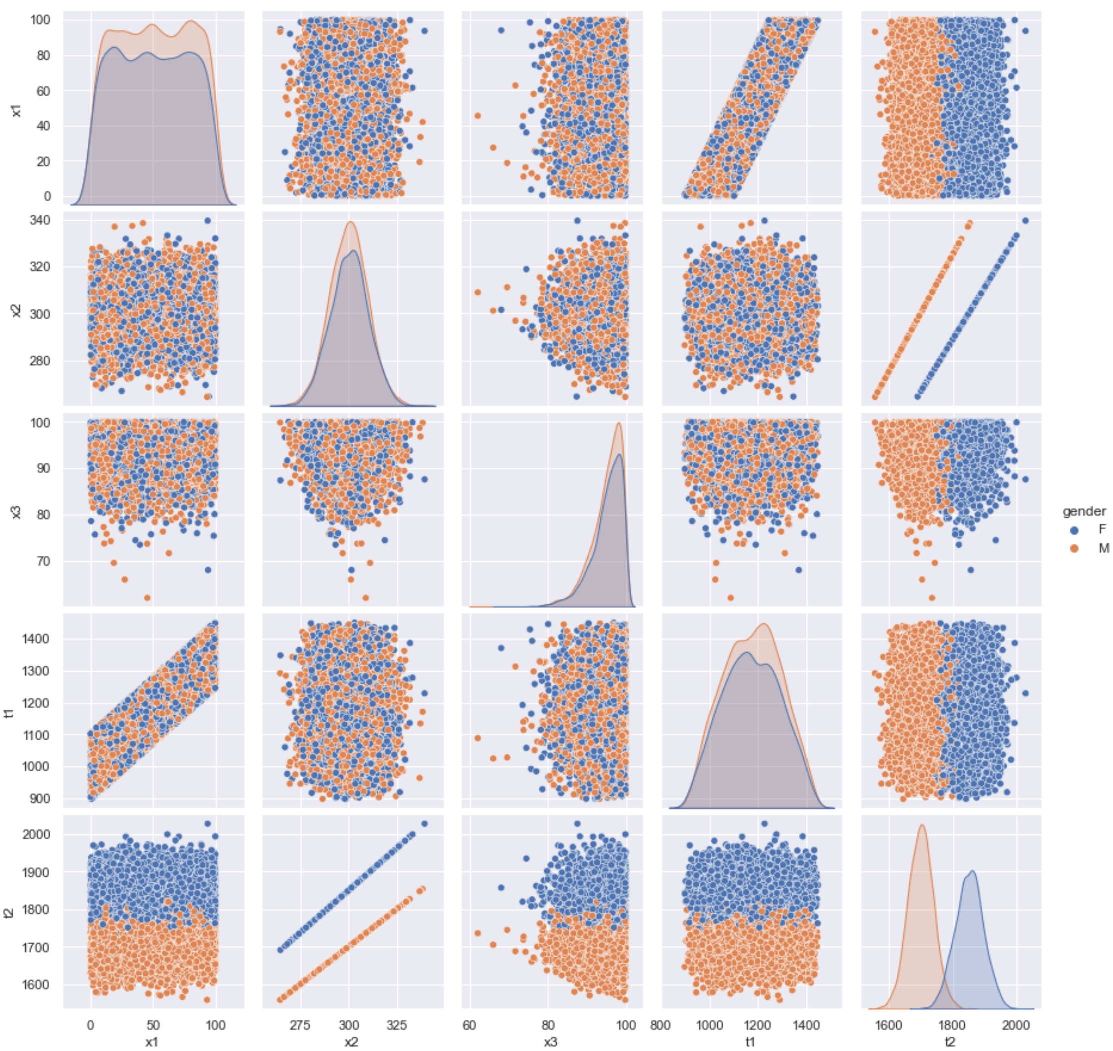
Legend: The team sending us the data believe that there might be some correlations in the data. They tell us that t1 and t2 are collected one month after x1, x2 and x3.

They believe t1 and t2 could somehow be predicted in advance. How would you go about testing this? Can you make your findings obvious to someone who thinks they don't "get maths"?

First of all, I'm using pairplot to see a visualization of all relations between numeric values.

```
[26]: sns.pairplot(df,hue = 'gender')
```

```
[26]: <seaborn.axisgrid.PairGrid at 0x1d56c9ad040>
```



As a result of this visualization, it's easy to notice a strong correlation in pairs **x1-t1** and **x2-t2**.

Now we can find all correlations in this dataframe. I also want to check the correlation between gender and out **t1** and **t2** values. For this perpose use dummy varaibles.

```
[27]: df['ifMale'] = pd.get_dummies(data=df.gender,drop_first=True)
```

```
[28]: corr = df.corr()
      corr
```

[28]:

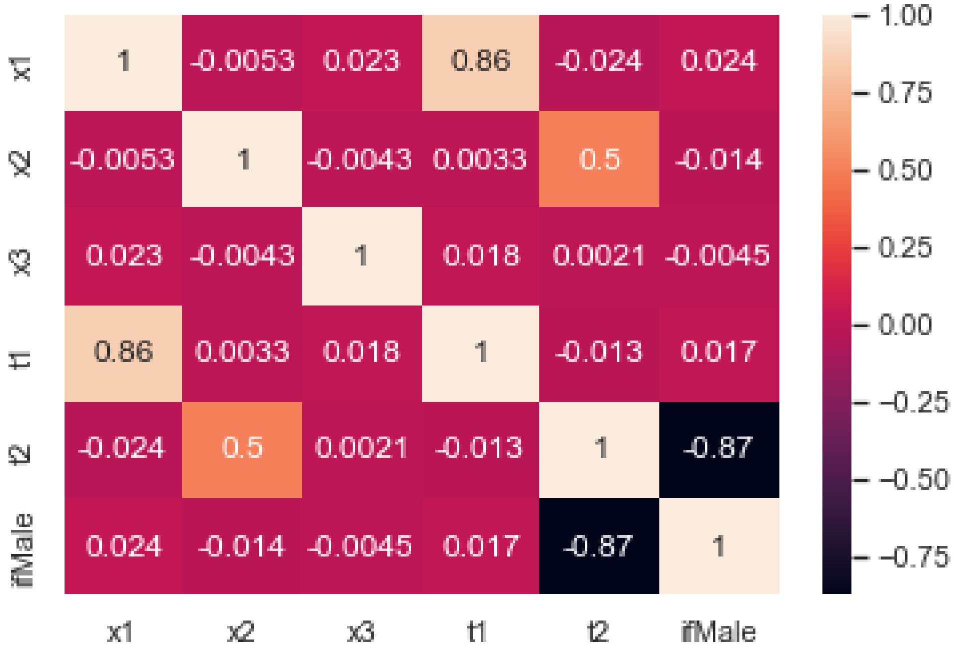
```
              x1        x2        x3        t1        t2    ifMale
x1      1.000000 -0.005280  0.022564  0.860219 -0.024075  0.024421
x2     -0.005280  1.000000 -0.004348  0.003250  0.497048 -0.014475
x3      0.022564 -0.004348  1.000000  0.018200  0.002121 -0.004531
t1      0.860219  0.003250  0.018200  1.000000 -0.013454  0.016744
t2     -0.024075  0.497048  0.002121 -0.013454  1.000000 -0.874358
ifMale  0.024421 -0.014475 -0.004531  0.016744 -0.874358  1.000000
```

[29]:

```python
sns.heatmap(corr,annot=True)
```

[29]:

```
<AxesSubplot:>
```



From the heatmap, we can notice a strong correlation in pairs **x1-t1**, **x2-t2**, and **gender-t2**.

[30]:

```python
#drop column ifMale
df.drop('ifMale',axis=1,inplace=True)
```

[31]:

```python
#make dataframes for male and female values only
df_M = df[df['gender']=='M']
df_F = df[df['gender']=='F']
```

[32]:

```python
#correlatios in these dataframes
df_M.corr()
```

[32]:

	x1	x2	x3	t1	t2
x1	1.000000	0.005856	0.031551	0.859610	0.005856
x2	0.005856	1.000000	-0.013980	0.019841	1.000000
x3	0.031551	-0.013980	1.000000	0.025274	-0.013980
t1	0.859610	0.019841	0.025274	1.000000	0.019841
t2	0.005856	1.000000	-0.013980	0.019841	1.000000

[33]:
```
df_F.corr()
```

[33]:

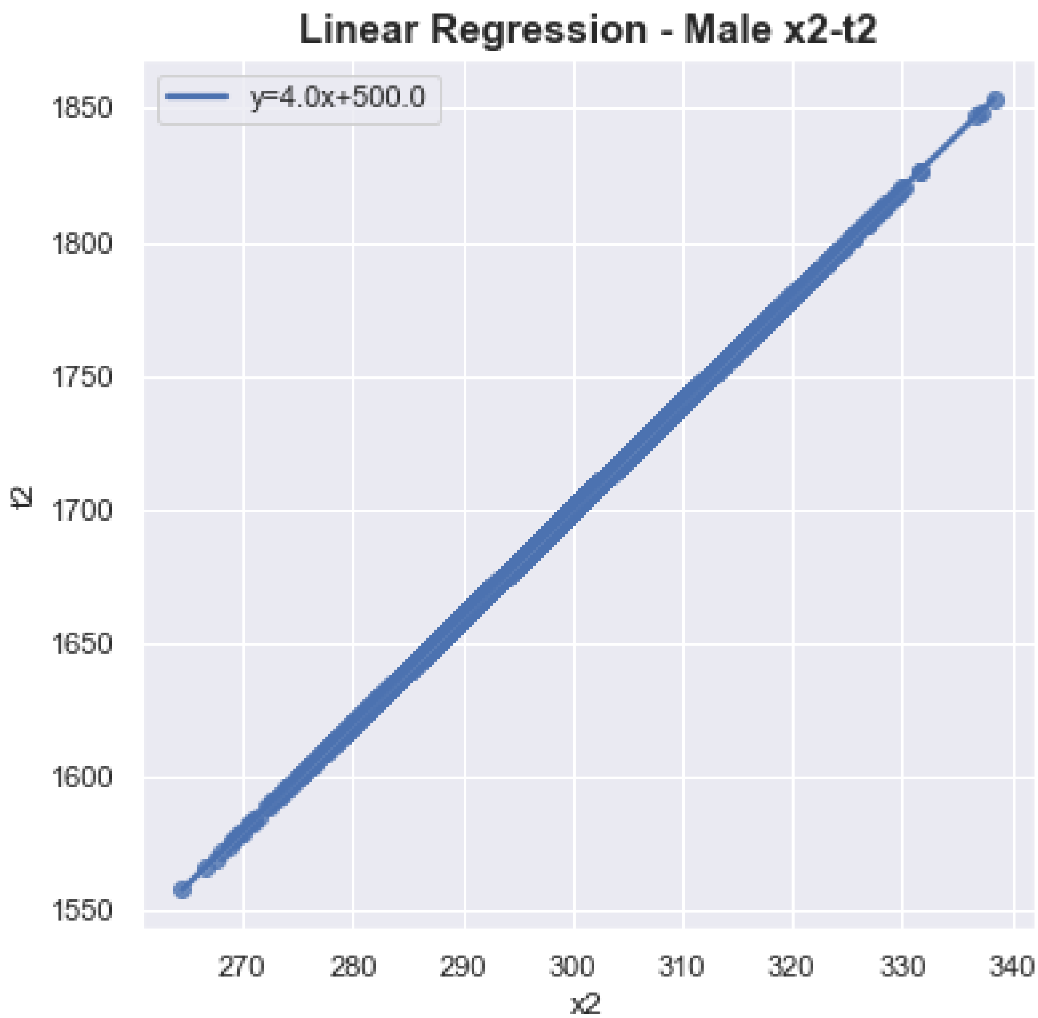
	x1	x2	x3	t1	t2
x1	1.000000	-0.017736	0.012134	0.860884	-0.017736
x2	-0.017736	1.000000	0.006960	-0.015754	1.000000
x3	0.012134	0.006960	1.000000	0.010032	0.006960
t1	0.860884	-0.015754	0.010032	1.000000	-0.015754
t2	-0.017736	1.000000	0.006960	-0.015754	1.000000

We found a perfect positive correlation between x2 and t2

Now we can find linear regression equations.

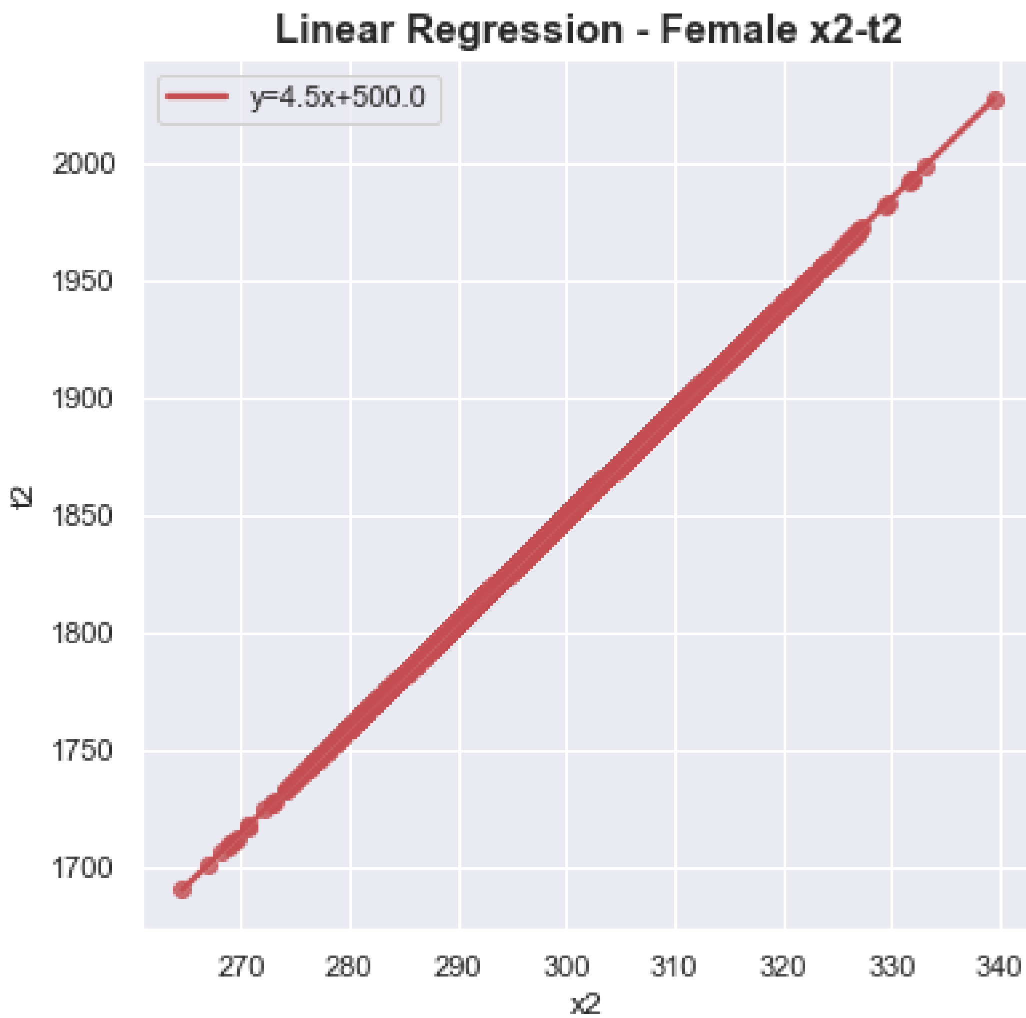
[34]:
```
slope, intercept, r_value, p_value, std_err = stats.linregress(df_M␣
↪['x2'],df_M['t2'])
# line label for legend
plt.figure(figsize=(6,6))
ax = sns.regplot(x="x2", y="t2", data=df_M, color='b',
line_kws={'label':"y={0:.1f}x+{1:.1f}".format(slope,intercept)})
ax.legend()
plt.title('Linear Regression - Male x2-t2', fontdict={'weight':'bold','size':␣
↪15})
```

[34]:
```
Text(0.5, 1.0, 'Linear Regression - Male x2-t2')
```




```
[35]: slope, intercept, r_value, p_value, std_err = stats.linregress(df_F␣
        ↪['x2'],df_F['t2'])
      plt.figure(figsize=(6,6))
      ax = sns.regplot(x="x2", y="t2", data=df_F, color='r',
      line_kws={'label':"y={0:.1f}x+{1:.1f}".format(slope,intercept)})
      ax.legend()
      plt.title('Linear Regression - Female x2-t2', fontdict={'weight':'bold','size':␣
        ↪15})
```

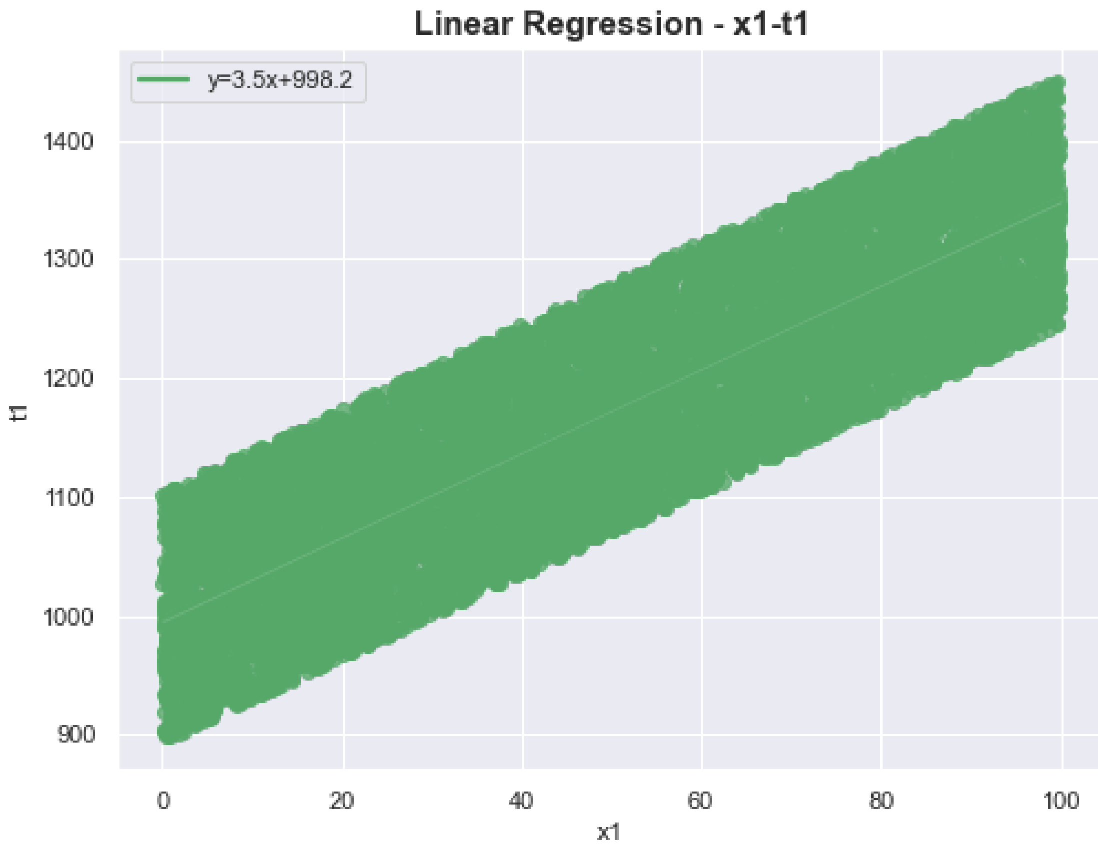
```
[35]: Text(0.5, 1.0, 'Linear Regression - Female x2-t2')
```



x1 and t1 also have strong positive correlation - **0.86**.

[36]:
```
slope, intercept, r_value, p_value, std_err = stats.linregress(df␣
↪['x1'],df['t1'])
plt.figure(figsize=(8,6))
ax = sns.regplot(x="x1", y="t1", data=df, color='g',
line_kws={'label':"y={0:.1f}x+{1:.1f}".format(slope,intercept)})
ax.legend()
plt.title('Linear Regression - x1-t1', fontdict={'weight':'bold','size': 15})
```

[36]:
```
Text(0.5, 1.0, 'Linear Regression - x1-t1')
```



For all these equation there are explanations: - x1-t1 (t1=3.5*x1 + 998.2) - every increase of x1 by 1 results in the increase of t1 by 3.5 - x2-t2 Male (t2=4.0*x2 + 500) - every increse of x2 by 1 results in the increase of t2 by 4 - x2-t2 Female (t2=4.5*x2 + 500) - every increse of x2 by 1 results in the increase of t2 by 4.5

We can use these equations to predict future values of t1 and t2.