Task1

September 28, 2024

[1]:
```
import pandas as pd
import plotly
import plotly.io as pio
import plotly.offline as pyo
pyo.init_notebook_mode()
from math import sqrt
import numpy as np
import seaborn as sns
from matplotlib import pyplot as plt
import warnings
from matplotlib_dashboard import MatplotlibDashboard
import duckdb
import plotly.graph_objects as go
warnings.filterwarnings("ignore")
import math
```

1 Checking Data

[2]:
```
checkout_1 = pd.read_csv('checkout_1.csv')
checkout_1['time'] = pd.to_datetime(checkout_1['time'], format='%Hh').dt.
↪strftime('%H:%M')
checkout_1
```

[2]:

	time	today	yesterday	same_day_last_week	avg_last_week	avg_last_month
0	00:00	9	12	11	6.42	4.85
1	01:00	3	5	1	1.85	1.92
2	02:00	1	0	0	0.28	0.82
3	03:00	1	0	0	0.42	0.46
4	04:00	0	0	1	0.42	0.21
5	05:00	1	1	2	1.28	0.75
6	06:00	1	1	5	2.85	2.28
7	07:00	2	3	9	5.57	5.21
8	08:00	0	1	18	8.71	10.42
9	09:00	2	9	30	20.00	19.07
10	10:00	55	51	45	29.42	28.35
11	11:00	36	44	38	33.71	28.50
12	12:00	51	39	39	27.57	25.42

13	13:00	36	41	43	25.85	24.21
14	14:00	32	35	36	26.14	25.21
15	15:00	51	35	49	28.14	27.71
16	16:00	41	36	48	27.71	25.64
17	17:00	45	30	29	20.42	22.28
18	18:00	32	25	25	21.57	18.28
19	19:00	33	39	42	22.14	18.67
20	20:00	25	24	34	17.42	18.92
21	21:00	30	35	34	18.71	17.57
22	22:00	28	29	23	15.42	15.64
23	23:00	11	28	10	9.57	8.75

[3]:
```
checkout_2 = pd.read_csv('checkout_2.csv')
checkout_2['time'] = pd.to_datetime(checkout_2['time'], format='%Hh').dt.
↪strftime('%H:%M')
checkout_2
```

[3]:

	time	today	yesterday	same_day_last_week	avg_last_week	avg_last_month
0	00:00	6	9	5	5.000	4.92
1	01:00	3	3	2	2.000	1.92
2	02:00	3	1	2	0.420	0.75
3	03:00	0	1	1	0.420	0.46
4	04:00	0	0	0	0.140	0.21
5	05:00	2	1	1	0.710	0.71
6	06:00	3	1	2	1.420	2.10
7	07:00	10	2	9	3.000	5.03
8	08:00	25	0	12	3.710	9.82
9	09:00	36	2	27	10.140	17.64
10	10:00	43	55	42	26.140	28.57
11	11:00	44	36	47	25.000	28.28
12	12:00	46	51	46	24.000	25.89
13	13:00	45	36	31	20.280	24.17
14	14:00	19	32	35	19.570	24.89
15	15:00	0	51	42	22.427	27.78
16	16:00	0	41	36	21.570	25.53
17	17:00	0	45	19	17.710	22.67
18	18:00	13	32	29	16.850	18.46
19	19:00	32	33	29	18.000	18.21
20	20:00	23	25	17	12.140	18.53
21	21:00	28	30	23	14.850	17.82
22	22:00	29	28	17	12.710	15.50
23	23:00	17	11	14	8.280	8.75

We can see the entire dataset, and in both cases we have no missing values or out of place values. We will skip looking for errors in data

2 Analysing Data Similarity

We need to compare both files and check if they are from the same context/distribution. We can do this in 3 steps:

- Analyse Similarity in Distributions (**Kolmogorov-Smirnov test**)
- Covariance
- Correlation

But the data points we have are too few for this analysis, specially because the different hours have different behaviors. We will use our few data points to add in a Standard Deviation, since we have the mean to compare. With the standard deviation and the mean, we can simulate a distribution with more data points, and compare both files.

We will be using the monthly average because it has a larger population and is closer to reality. Standard deviation is calculated using different days presented in the data (today, yesterday, same day last week). It is not ideal to use the monthly average to measure the standard deviation of 3 days of data, but it is what we have.

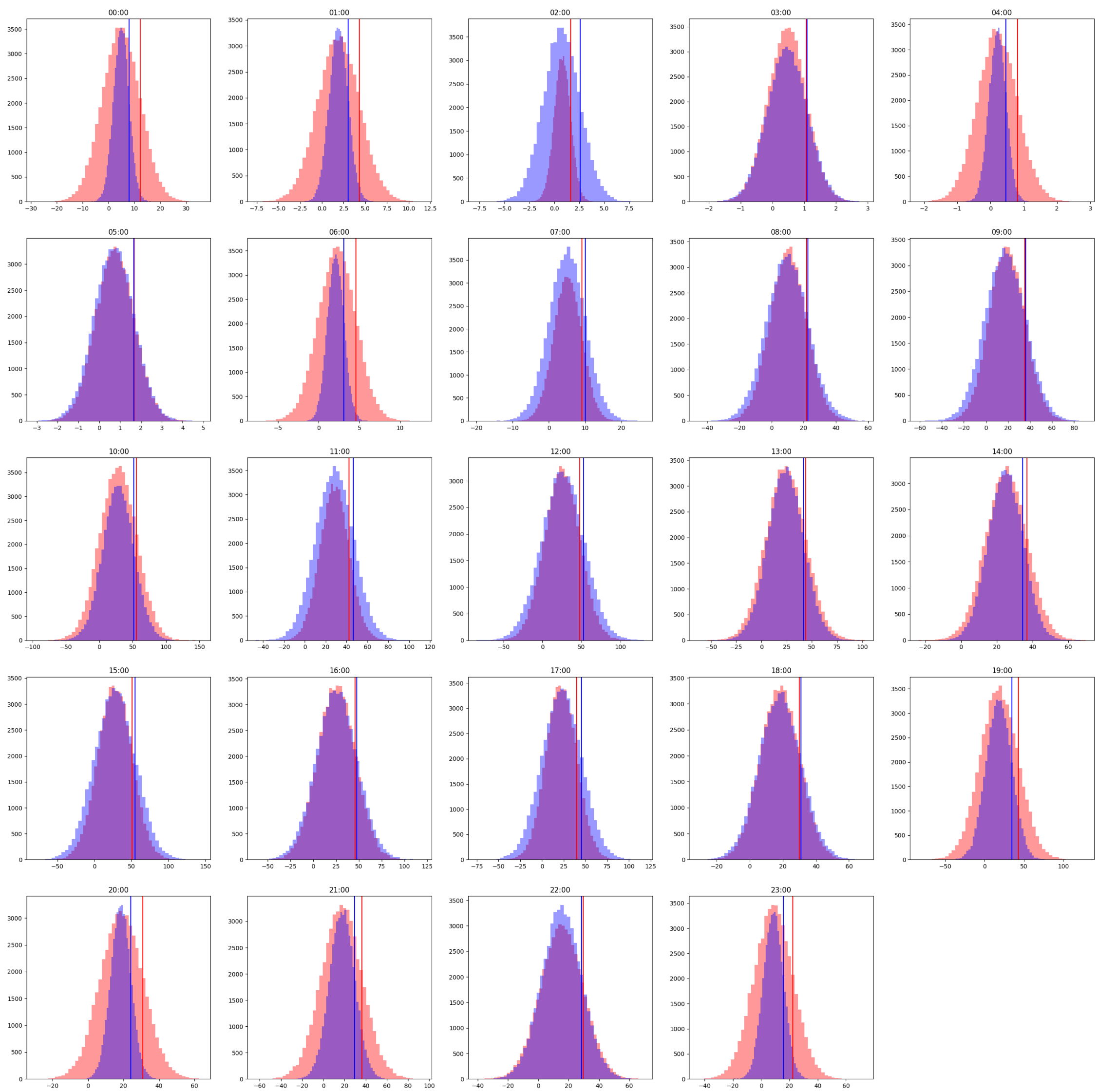
[4]:
```
checkout_1['std_hour'] = ((checkout_1['today'] - ␣
↪checkout_1['avg_last_month'])**2 +
                        (checkout_1['yesterday'] - ␣
↪checkout_1['avg_last_month'])**2 +
                        (checkout_1['same_day_last_week'] - ␣
↪checkout_1['avg_last_month'])**2) / (3-1)#n-1 (sample)

checkout_1['std_hour'] = np.sqrt(checkout_1['std_hour'])
```

[5]:
```
checkout_2['std_hour'] = ((checkout_2['today'] - ␣
↪checkout_2['avg_last_month'])**2 +
                        (checkout_2['yesterday'] - ␣
↪checkout_2['avg_last_month'])**2 +
                        (checkout_2['same_day_last_week'] - ␣
↪checkout_2['avg_last_month'])**2) / (3-1)#n-1 (sample)

checkout_2['std_hour'] = np.sqrt(checkout_2['std_hour'])
```

2.0.1 Simulated Distributions of Sales from each file p/hour

[6]:
```
fig = plt.figure(figsize=(32,32))
fig.subplots_adjust(hspace=0.2, wspace=0.2)
for i in checkout_1.index:
    avg = checkout_1.loc[i, 'avg_last_month']
    std = checkout_1.loc[i, 'std_hour']
    group_1 = np.random.normal(loc=avg, scale=std, size=50000)
    avg = checkout_2.loc[i, 'avg_last_month']
    std = checkout_2.loc[i, 'std_hour']
    group_2 = np.random.normal(loc=avg, scale=std, size=50000)
```

```
    ax = fig.add_subplot(5, 5, i+1)

    sns.distplot(group_1, kde=False, ax=ax, color='red')
    ax.axvline(np.mean(group_1) + np.std(group_1), color='red')
    sns.distplot(group_2, kde=False, ax=ax, color='blue')
    ax.axvline(np.mean(group_2) + np.std(group_2), color='blue')

    ax.set_title(str(checkout_1.loc[i, 'time']))


plt.show()
```



2.1 Kolmogorov-Smirnov

The Kolmogorov-Smirnov 2 sample test evaluates the likelihood of 2 samples being sampled from the same distribution, giving a *p value* to accept or reject the hypothesis. P values above 0.05 (5% significance) are considered accepting of the null hypothesis i.e. the 2 samples are sampled from very similar distributions.

[24]:
```
from scipy.stats import ks_2samp

for i in checkout_1.index:
    avg = checkout_1.loc[i, 'avg_last_month']
    std = checkout_1.loc[i, 'std_hour']
    group_1 = np.random.normal(loc=avg, scale=std, size=1000)
    avg = checkout_2.loc[i, 'avg_last_month']
    std = checkout_2.loc[i, 'std_hour']
    group_2 = np.random.normal(loc=avg, scale=std, size=1000)#smaller sample as␣
 ↪KS test gives false negatives on larger samples
    result = ks_2samp(group_1, group_2)

    print(checkout_2.loc[i, 'time'], '\t', result[1], '\t\tNull Hypothesis: ',␣
 ↪result[1]>0.05 )
```

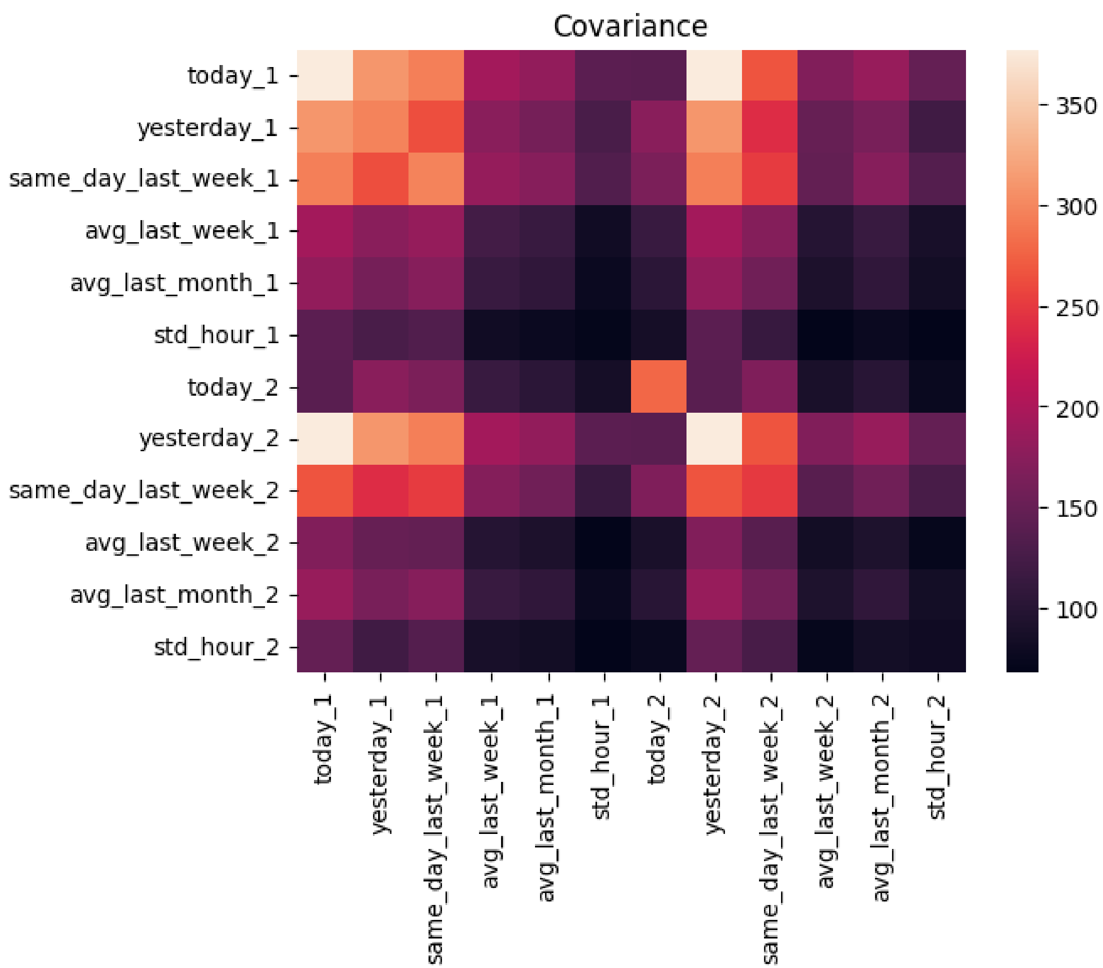
```
00:00    1.2672018670773729e-27             Null Hypothesis:   False
01:00    6.6131216618004355e-18             Null Hypothesis:   False
02:00    6.954764781424622e-15         Null Hypothesis:   False
03:00    0.9357699014782725            Null Hypothesis:   True
04:00    1.1979681866777803e-20             Null Hypothesis:   False
05:00    0.37012017606173              Null Hypothesis:   True
06:00    5.032549473768586e-16         Null Hypothesis:   False
07:00    0.002393409648884169          Null Hypothesis:   False
08:00    0.37012017606173              Null Hypothesis:   True
09:00    0.3136800387320582            Null Hypothesis:   True
10:00    0.07761108123267829           Null Hypothesis:   True
11:00    0.0038826726503625613         Null Hypothesis:   False
12:00    0.012912352230759101          Null Hypothesis:   False
13:00    0.43260886958153144           Null Hypothesis:   True
14:00    0.14836452078962484           Null Hypothesis:   True
15:00    0.06917625399020766           Null Hypothesis:   True
16:00    0.13385273551786803           Null Hypothesis:   True
17:00    0.017090148468768534          Null Hypothesis:   False
18:00    0.26347172719864703           Null Hypothesis:   True
19:00    2.798513019401821e-06         Null Hypothesis:   False
20:00    6.954764781424622e-15         Null Hypothesis:   False
21:00    7.709567304002036e-09         Null Hypothesis:   False
22:00    0.37012017606173              Null Hypothesis:   True
23:00    2.6255784492506013e-11             Null Hypothesis:   False
```

In a lot of cases The p-value is greater than 0.05, which means it is likely that both samples were taken from the same ditribution. Which means the distributions are similar.

2.2 Covariance

[7]:
```
joined_df = pd.merge(checkout_1, checkout_2, on='time', suffixes=['_1','_2'])

ax = sns.heatmap(joined_df.drop('time', axis=1).cov())
plt.title('Covariance')
```

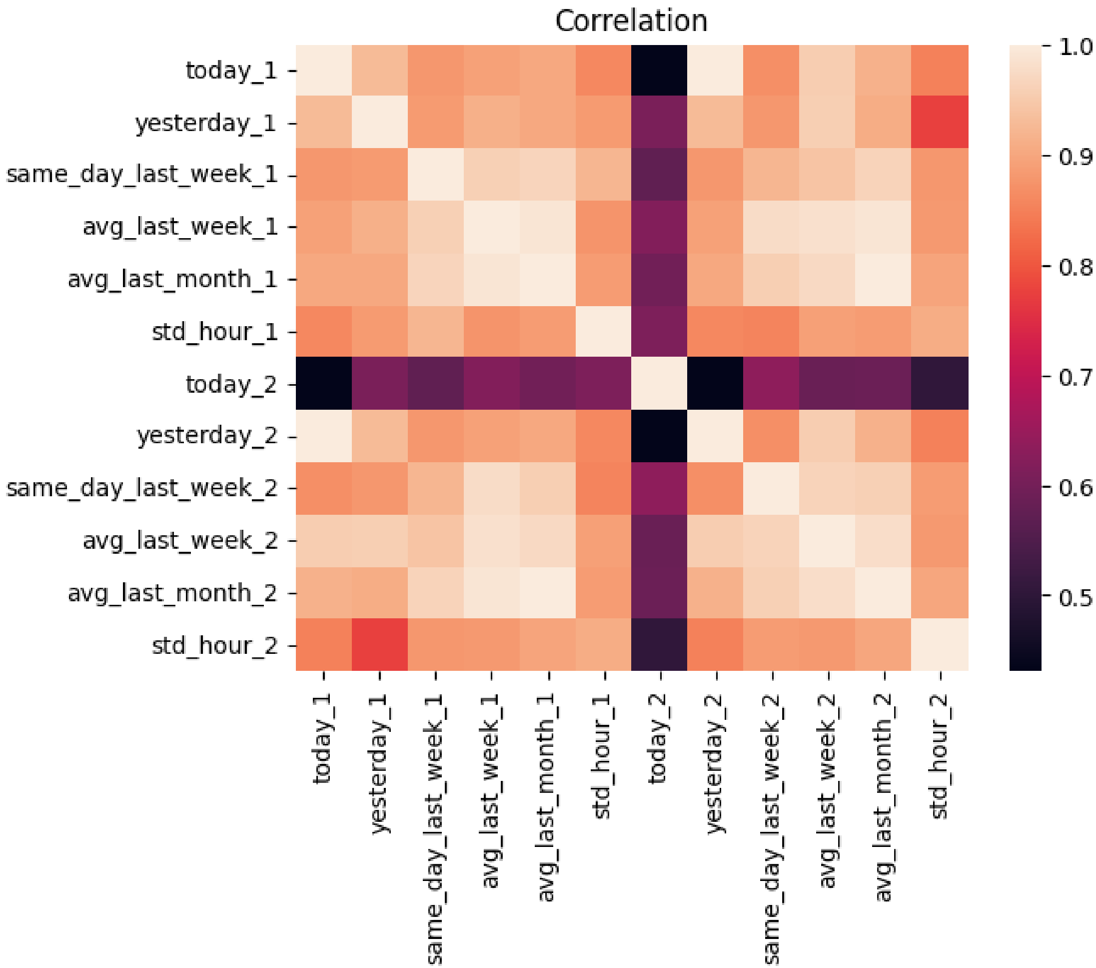
[7]:
```
Text(0.5, 1.0, 'Covariance')
```



2.3 Correlation

[8]:
```
sns.heatmap(joined_df.drop('time', axis=1).corr())
plt.title('Correlation')
```

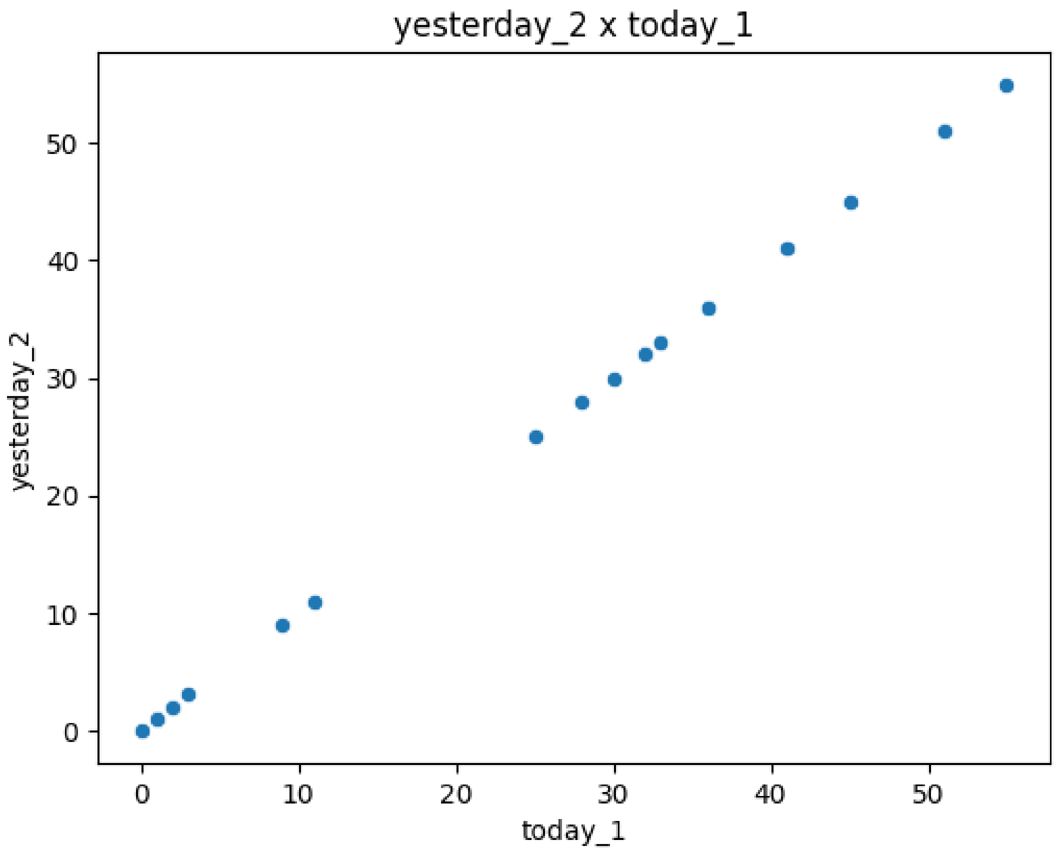
[8]:
```
Text(0.5, 1.0, 'Correlation')
```



Notes:

- The column *today2* has a high lack of covariance and correlation, especially when compared to the other columns, this indicates an anomolous behavior
- *yesterday_2* and *today_1* have a high correlation, that can mean they are the same and the files are from consecutive days

[9]:
```
ax = sns.scatterplot(x=joined_df.today_1, y=joined_df.yesterday_2)
plt.title('yesterday_2 x today_1')
plt.show()
```



It is a perfect 1 to 1. We will concatenate the dataframes in sequence for further analysis

[10]:
```
main_df = pd.concat([checkout_1, checkout_2])
main_df
```

[10]:

	time	today	yesterday	same_day_last_week	avg_last_week	\
0	00:00	9	12	11	6.420	
1	01:00	3	5	1	1.850	
2	02:00	1	0	0	0.280	
3	03:00	1	0	0	0.420	
4	04:00	0	0	1	0.420	
5	05:00	1	1	2	1.280	
6	06:00	1	1	5	2.850	
7	07:00	2	3	9	5.570	
8	08:00	0	1	18	8.710	
9	09:00	2	9	30	20.000	
10	10:00	55	51	45	29.420	
11	11:00	36	44	38	33.710	
12	12:00	51	39	39	27.570	
13	13:00	36	41	43	25.850	

14	14:00	32	35	36	26.140
15	15:00	51	35	49	28.140
16	16:00	41	36	48	27.710
17	17:00	45	30	29	20.420
18	18:00	32	25	25	21.570
19	19:00	33	39	42	22.140
20	20:00	25	24	34	17.420
21	21:00	30	35	34	18.710
22	22:00	28	29	23	15.420
23	23:00	11	28	10	9.570
0	00:00	6	9	5	5.000
1	01:00	3	3	2	2.000
2	02:00	3	1	2	0.420
3	03:00	0	1	1	0.420
4	04:00	0	0	0	0.140
5	05:00	2	1	1	0.710
6	06:00	3	1	2	1.420
7	07:00	10	2	9	3.000
8	08:00	25	0	12	3.710
9	09:00	36	2	27	10.140
10	10:00	43	55	42	26.140
11	11:00	44	36	47	25.000
12	12:00	46	51	46	24.000
13	13:00	45	36	31	20.280
14	14:00	19	32	35	19.570
15	15:00	0	51	42	22.427
16	16:00	0	41	36	21.570
17	17:00	0	45	19	17.710
18	18:00	13	32	29	16.850
19	19:00	32	33	29	18.000
20	20:00	23	25	17	12.140
21	21:00	28	30	23	14.850
22	22:00	29	28	17	12.710
23	23:00	17	11	14	8.280

	avg_last_month	std_hour
0	4.85	7.285860
1	1.92	2.397832
2	0.82	0.829819
3	0.46	0.597829
4	0.21	0.596783
5	0.75	0.918559
6	2.28	2.310325
7	5.21	3.843976
8	10.42	11.286479
9	19.07	16.003979
10	28.35	27.390395

```
11             28.50  13.905934
12             25.42  22.618236
13             24.21  19.671964
14             25.21  11.366009
15             27.71  22.900134
16             25.64  20.533251
17             22.28  17.620375
18             18.28  11.801593
19             18.67  24.113759
20             18.92  12.045314
21             17.57  19.082121
22             15.64  13.882161
23              8.75  13.732944
0               4.92   2.984895
1               1.92   1.081480
2               0.75   1.828592
3               0.46   0.630397
4               0.21   0.257196
5               0.71   0.957157
6               2.10   1.007472
7               5.03   4.982103
8               9.82  12.876669
9              17.64  18.293562
10             28.57  23.314531
11             28.28  18.126710
12             25.89  26.826631
13             24.17  17.613726
14             24.89   9.681330
15             27.78  27.505501
16             25.53  22.368758
17             22.67  22.649798
18             18.46  12.732533
19             18.21  16.206978
20             18.53   5.664923
21             17.82  11.807142
22             15.50  13.052777
23              8.75   7.095333
```

Conclusion: The checkout files are very similar in distribution, measures and numbers. It seems we can safely assume they are the same POS, in consecutive days. And we will assume such for the rest of the analysis

Now we will use both files and try to detect anomalies

3 Data Augmentation

- **last_week_total_est**: Estimate of total sales from that hour in the week, using *avg_last_week x 7*

- **last_month_total_est**: Estimate of total sales from that hour in the last month, using *avg_last_month x 30*. Uses only avg from file 1 since both are very similar
- **std_hour**: Standard deviation of sales from that hour, uses all data entries from singular days (today, yesterday, same_day_last_week) as data points for the calculation.

[11]:
```
analysis_df = duckdb.query("""
SELECT time, today, yesterday, same_day_last_week,avg_last_week, avg_last_month,
    avg_last_week * 7 as last_week_total_est,
    avg_last_month * 30 as last_month_total_est,

     sqrt(
        (today - avg_last_month)**2 +
        (yesterday - avg_last_month)**2 +
        (same_day_last_week - avg_last_month)**2
         / (3-1)
        ) as std_hour
FROM main_df
             """).df()
analysis_df
```

[11]:
```
     time  today  yesterday  same_day_last_week  avg_last_week  \
0   00:00      9         12                  11          6.420
1   01:00      3          5                   1          1.850
2   02:00      1          0                   0          0.280
3   03:00      1          0                   0          0.420
4   04:00      0          0                   1          0.420
5   05:00      1          1                   2          1.280
6   06:00      1          1                   5          2.850
7   07:00      2          3                   9          5.570
8   08:00      0          1                  18          8.710
9   09:00      2          9                  30         20.000
10  10:00     55         51                  45         29.420
11  11:00     36         44                  38         33.710
12  12:00     51         39                  39         27.570
13  13:00     36         41                  43         25.850
14  14:00     32         35                  36         26.140
15  15:00     51         35                  49         28.140
16  16:00     41         36                  48         27.710
17  17:00     45         30                  29         20.420
18  18:00     32         25                  25         21.570
19  19:00     33         39                  42         22.140
20  20:00     25         24                  34         17.420
21  21:00     30         35                  34         18.710
22  22:00     28         29                  23         15.420
23  23:00     11         28                  10          9.570
24  00:00      6          9                   5          5.000
25  01:00      3          3                   2          2.000
```

26	02:00	3	1	2	0.420
27	03:00	0	1	1	0.420
28	04:00	0	0	0	0.140
29	05:00	2	1	1	0.710
30	06:00	3	1	2	1.420
31	07:00	10	2	9	3.000
32	08:00	25	0	12	3.710
33	09:00	36	2	27	10.140
34	10:00	43	55	42	26.140
35	11:00	44	36	47	25.000
36	12:00	46	51	46	24.000
37	13:00	45	36	31	20.280
38	14:00	19	32	35	19.570
39	15:00	0	51	42	22.427
40	16:00	0	41	36	21.570
41	17:00	0	45	19	17.710
42	18:00	13	32	29	16.850
43	19:00	32	33	29	18.000
44	20:00	23	25	17	12.140
45	21:00	28	30	23	14.850
46	22:00	29	28	17	12.710
47	23:00	17	11	14	8.280

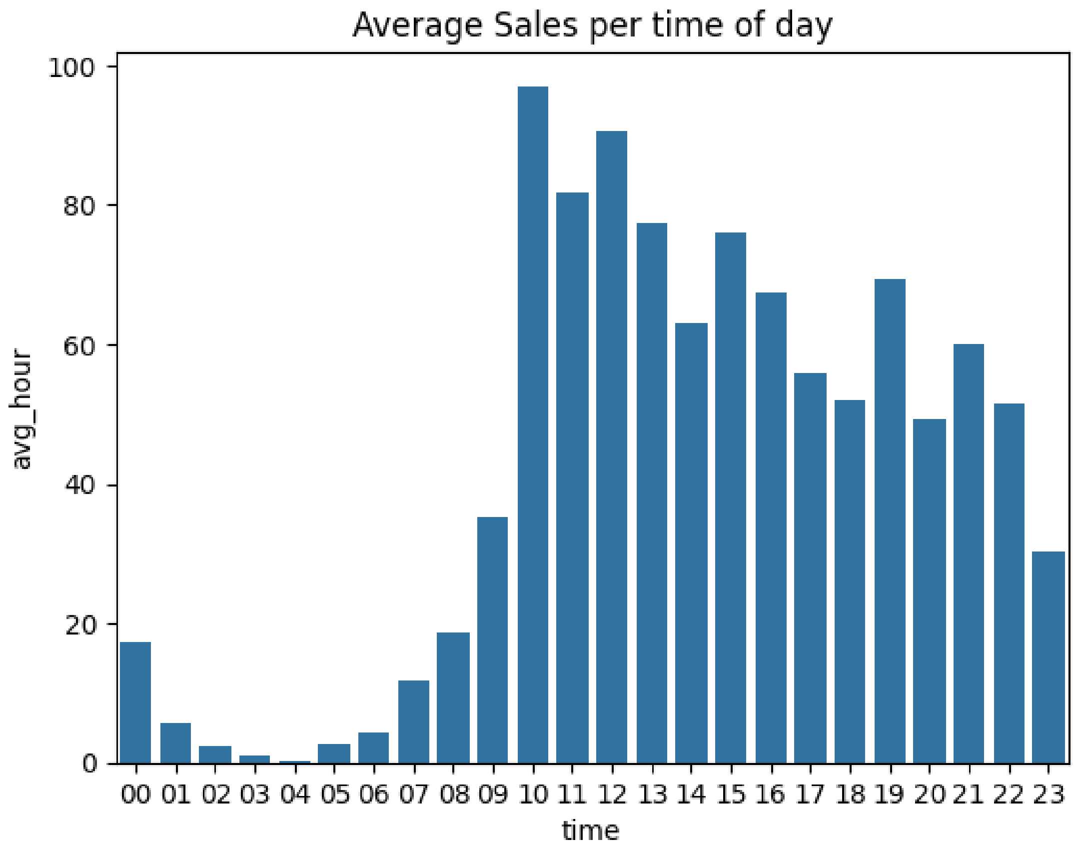
	avg_last_month	last_week_total_est	last_month_total_est	std_hour
0	4.85	44.940	145.5	9.341105
1	1.92	12.950	57.6	3.328062
2	0.82	1.960	24.6	1.020294
3	0.46	2.940	13.8	0.780385
4	0.21	2.940	6.3	0.632653
5	0.75	8.960	22.5	0.951972
6	2.28	19.950	68.4	2.641212
7	5.21	38.990	156.3	4.729720
8	10.42	60.970	312.6	15.034660
9	19.07	140.000	572.1	21.272570
10	28.35	205.940	850.5	36.903337
11	28.50	235.970	855.0	18.483100
12	25.42	192.990	762.6	30.511654
13	24.21	180.950	726.3	24.442591
14	25.21	182.980	756.3	14.147800
15	27.71	196.980	831.3	28.674034
16	25.64	193.970	769.2	24.356601
17	22.28	142.940	668.4	24.461725
18	18.28	150.990	548.4	15.999250
19	18.67	154.980	560.1	29.846310
20	18.92	121.940	567.6	13.284427
21	17.57	130.970	527.1	24.357386
22	15.64	107.940	469.2	18.929976

23	8.75	66.990	262.5	19.401192
24	4.92	35.000	147.6	4.220900
25	1.92	14.000	57.6	1.528398
26	0.75	2.940	22.5	2.430278
27	0.46	2.940	13.8	0.805605
28	0.21	0.980	6.3	0.332039
29	0.71	4.970	21.3	1.338002
30	2.10	9.940	63.0	1.423025
31	5.03	21.000	150.9	6.462372
32	9.82	25.970	294.6	18.144999
33	17.64	70.980	529.2	25.010078
34	28.57	182.980	857.1	31.574551
35	28.28	175.000	848.4	21.953041
36	25.89	168.000	776.7	35.172862
37	24.17	141.960	725.1	24.436903
38	24.89	136.990	746.7	11.676911
39	27.78	156.989	833.4	37.576602
40	25.53	150.990	765.9	30.755686
41	22.67	123.970	680.1	31.926357
42	18.46	117.950	553.8	16.391736
43	18.21	126.000	546.3	21.612965
44	18.53	84.980	555.9	7.938026
45	17.82	103.950	534.6	16.291133
46	15.50	88.970	465.0	18.428917
47	8.75	57.960	262.5	9.322352

4 Analysis

It seems there is a trend of sales following the different times of day. Let's take the average of all the sales data related to single days (today, yesterday, same_day_last_week) and show it in a graph to better see this trend.

[12]:
```
bar = duckdb.query("""
SELECT REPLACE(CAST(time as STRING),':00','') as time, SUM( (today + yesterday␣
↪+ same_day_last_week)/3 ) as avg_hour
FROM analysis_df
GROUP BY time
""").df().sort_values('time')
sns.barplot(bar, x='time', y='avg_hour')
plt.title('Average Sales per time of day')
plt.show()
```



Let's see the trend for each individual day

[13]:
```
lines = duckdb.query("""
SELECT REPLACE(CAST(chk1.time as STRING),':00','') as time, chk1.today, chk1.
 ↪yesterday, chk1.same_day_last_week, chk2.today as today_2
FROM checkout_1 as chk1
LEFT JOIN checkout_2 as chk2 ON chk1.time = chk2.time
""").df()



fig = go.Figure()
fig.add_trace(go.Scatter(x=lines.time, y=lines.today,
                    mode='lines',
                    name='today'))

fig.add_trace(go.Scatter(x=lines.time, y=lines.today_2,
                    mode='lines',
                    name='today_2'))
```

```python
fig.add_trace(go.Scatter(x=lines.time, y=lines.yesterday,
                    mode='lines',
                    name='yesterday'))

fig.add_trace(go.Scatter(x=lines.time, y=lines.same_day_last_week,
                    mode='lines',
                    name='same_day_last_week'))


fig.show()
```

Clearly, the various days follow the same trend in sales through the hours. Except for **today_2** which is from the second file

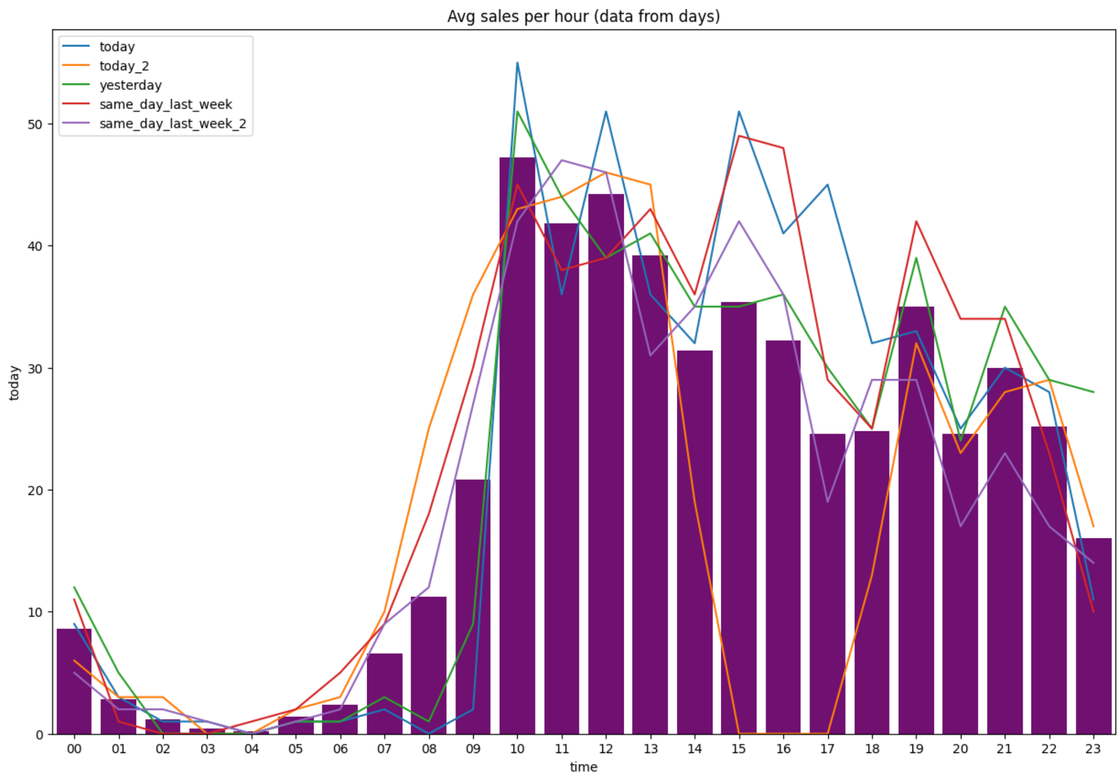
As we have seen before, *today_2*

And here we have it. *today_2* is the only variable that doesn't have a correlation very close to 1.

Just to reinforce the idea that this is an anomaly, we will compare all days to different averages side by side.

[14]:
```python
lines = duckdb.query("""
SELECT REPLACE(CAST(chk1.time as STRING),':00','') as time, chk1.today, chk1.
 ↪yesterday, chk1.same_day_last_week, chk2.today as today_2,
    chk2.same_day_last_week as same_day_last_week_2, chk1.avg_last_month as␣
 ↪avg_last_month,
    (chk1.today + chk1.yesterday + chk1.same_day_last_week + chk2.today + chk2.
 ↪same_day_last_week)/5 as avg_hour
FROM checkout_1 as chk1
LEFT JOIN checkout_2 as chk2 ON chk1.time = chk2.time
""").df()

plt.figure(figsize=(15,10))
sns.lineplot(lines, x='time', y='today', label='today')
sns.lineplot(lines, x='time', y='today_2', label='today_2')
sns.lineplot(lines, x='time', y='yesterday', label='yesterday')
sns.lineplot(lines, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week')
sns.lineplot(lines, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2')
sns.barplot(lines, x='time', y='avg_hour', color='purple')
plt.title('Avg sales per hour (data from days)')
plt.legend(loc="upper left")
```

[14]:
```
<matplotlib.legend.Legend at 0x180ffed53a0>
```



If you look closely to the graph, there is a trend from hour 14 to 15 where sales increase and then decrease. A better way to check and expose this better is to check the percentage change from row to row and compare the different variables.

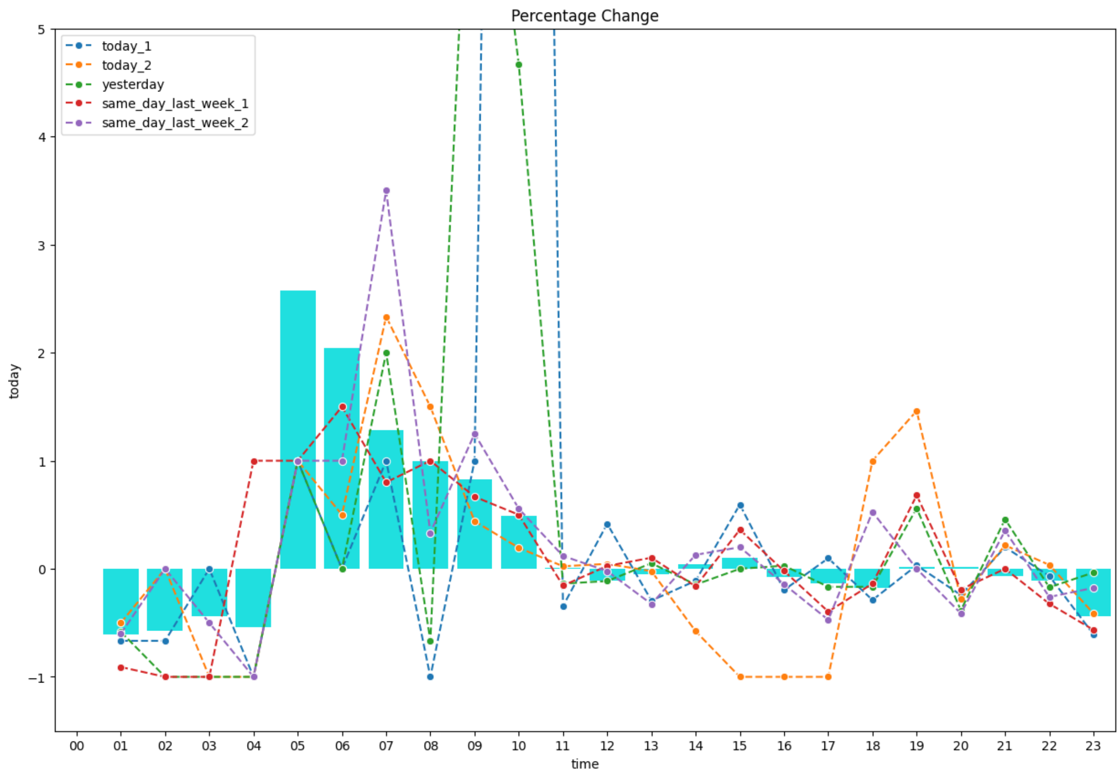
Notes: - *pandas.Dataframe.pct_change* creates NaNs and Infinites when zeros are involved. - For the first 0 after a number, pct_change will be -100%, we will forward this for Nans - The first number after a 0 will be Infinite, we will replace this with +100%

[15]:
```
pct_changes = lines.drop('time',axis=1).pct_change().fillna(method='ffill').
 ↪replace([np.inf], 1.00)
pct_changes['time'] = lines['time']
```

[16]:
```
pct_change_analysis =pct_changes



plt.figure(figsize=(15,10))
sns.lineplot(pct_change_analysis, x='time', y='today', label='today_1',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='today_2', label='today_2',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='yesterday', label='yesterday',␣
 ↪marker='o',linestyle="dashed")
```

```
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week_1', marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2', marker='o',linestyle="dashed")

ax = sns.barplot(pct_change_analysis, x='time', y='avg_last_month',␣
 ↪color='cyan')
ax.set_ylim(-1.5,5)

plt.title('Percentage Change')
plt.legend(loc="upper left")
```

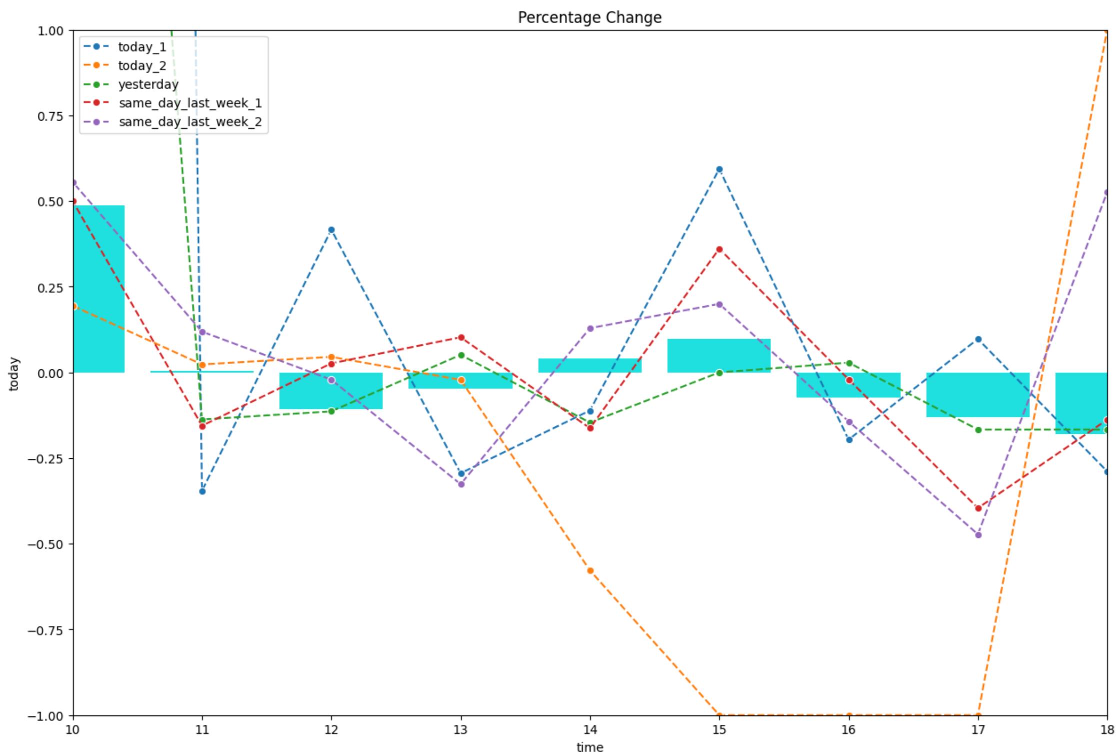
[16]: <matplotlib.legend.Legend at 0x1809ddc0560>




```
[17]: plt.figure(figsize=(15,10))
sns.lineplot(pct_change_analysis, x='time', y='today', label='today_1',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='today_2', label='today_2',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='yesterday', label='yesterday',␣
 ↪marker='o',linestyle="dashed")
```

```
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week_1', marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2', marker='o',linestyle="dashed")

ax = sns.barplot(pct_change_analysis, x='time', y='avg_last_month',␣
 ↪color='cyan')
ax.set_ylim(-1,1)
ax.set_xlim(10,18)
plt.title('Percentage Change')
plt.legend(loc="upper left")
```

[17]: <matplotlib.legend.Legend at 0x1809d5c1160>

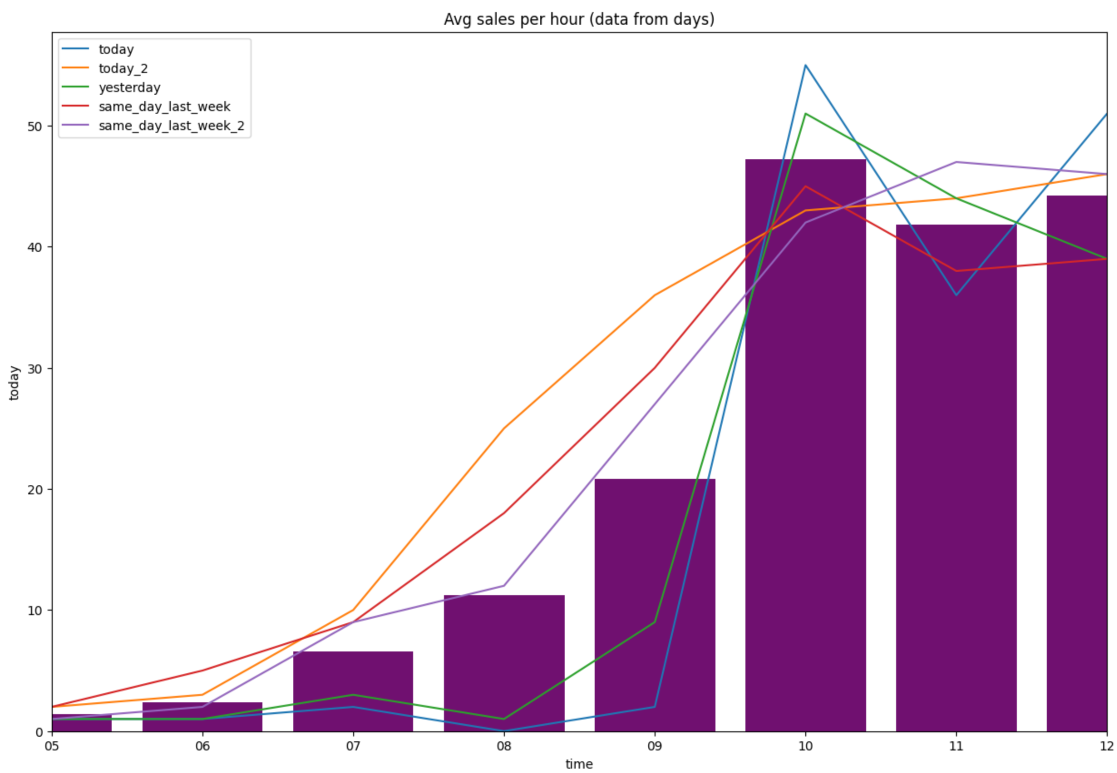


As we can see here, all other variables we have on sales has a growth from hour 14 to 15, *except* today_2, which goes down to 0 sales and stays there for some hours. Thus proving further it is an anomaly, probably the POS went down for some time.

5 Anomalies without context and data

[18]:
```
plt.figure(figsize=(15,10))
sns.lineplot(lines, x='time', y='today', label='today')
sns.lineplot(lines, x='time', y='today_2', label='today_2')
sns.lineplot(lines, x='time', y='yesterday', label='yesterday')
sns.lineplot(lines, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week')
sns.lineplot(lines, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2')
ax = sns.barplot(lines, x='time', y='avg_hour', color='purple')

ax.set_xlim(5,12)
plt.title('Avg sales per hour (data from days)')
plt.legend(loc="upper left")
```

[18]: <matplotlib.legend.Legend at 0x1809fd97080>



From 7am to 10am we have a smaller number of sales and a sudden spike in *today* and *yesterday*. Although it looks anomalous, we cannot declare it an anomaly with 100% certainty. This can easily be just a normal variance in the whole, or it could have an easy explanation from an unseen underlying variable, such as:

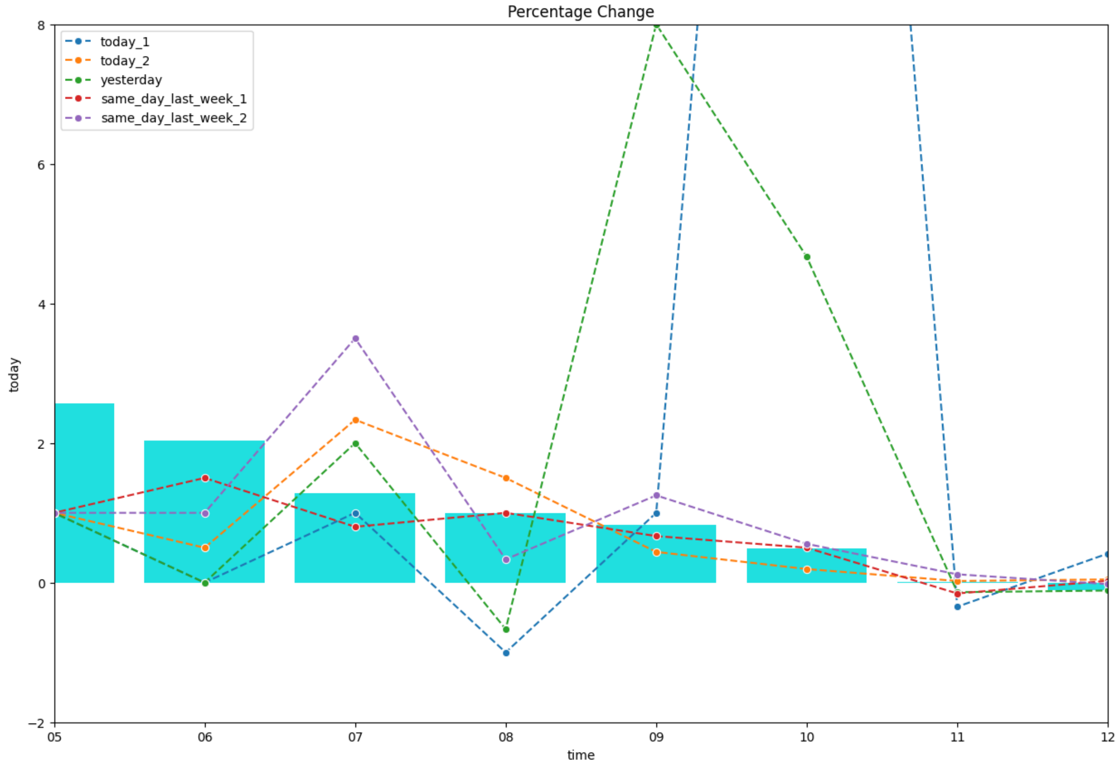
- Holidays: people wake up later on holidays and weekends. We have data that contradicts this as a weekend (*same_day_last_week*), but it could be that this time around we have a holiday, which explains a peak later on in the day.

- Sale: There could have been a sale announced on this website, and it could be starting at 10 am, so most people were waiting on the sale to start buying, thus the spike in sales surpasses every other day
- A bad week: Sometimes larger things are at play in society, and this could just be one of those bad weeks in sales. People in the business would know, it just happens sometimes.

To further show how this could be just a normal variance of the data, here are the percentage changes from 5am to 12pm.

[19]:
```
plt.figure(figsize=(15,10))
sns.lineplot(pct_change_analysis, x='time', y='today', label='today_1',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='today_2', label='today_2',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='yesterday', label='yesterday',␣
 ↪marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week_1', marker='o',linestyle="dashed")
sns.lineplot(pct_change_analysis, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2', marker='o',linestyle="dashed")

ax = sns.barplot(pct_change_analysis, x='time', y='avg_last_month',␣
 ↪color='cyan')
ax.set_ylim(-2, 8)
ax.set_xlim(5,12)
plt.title('Percentage Change')
plt.legend(loc="upper left")
```

[19]:
```
<matplotlib.legend.Legend at 0x1809ff768a0>
```

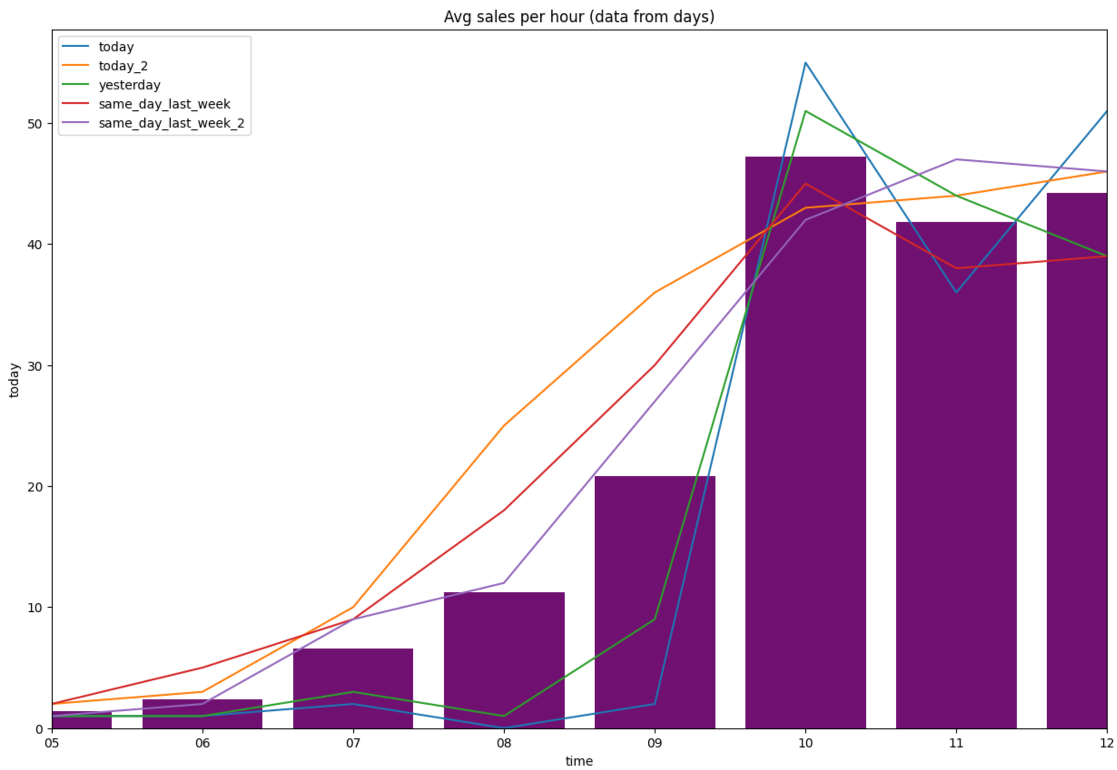


As we can see, even with the numbers being few, *today_1* and *yesterday* follow all the trends clearly and correctly, even within the big spikes and percentage changes. If anything, *same_day_last_week* seems to not follow the same trend as the other days, growing in sales in hours other days fell shorter in sales, and falling short when other days grew.

Of course the spikes are notable, but looking back at the pure numbers, with the percentages in mind:

[20]:
```
plt.figure(figsize=(15,10))
sns.lineplot(lines, x='time', y='today', label='today')
sns.lineplot(lines, x='time', y='today_2', label='today_2')
sns.lineplot(lines, x='time', y='yesterday', label='yesterday')
sns.lineplot(lines, x='time', y='same_day_last_week',␣
 ↪label='same_day_last_week')
sns.lineplot(lines, x='time', y='same_day_last_week_2',␣
 ↪label='same_day_last_week_2')
ax = sns.barplot(lines, x='time', y='avg_hour', color='purple')

ax.set_xlim(5,12)
plt.title('Avg sales per hour (data from days)')
plt.legend(loc="upper left")
```

[20]: <matplotlib.legend.Legend at 0x1809f32d130>



All the numbers are within the trend.

Ultimately this could be a anomaly, or it could not be. We can only be sure with further investigation within the whole data and it's context.

5.1 Conclusion

We found that, in the *checkout_2* file, from hours 14 to 17 on the current day, there was most probably an anomaly. Indications of an anomaly are: - A clear and defined trend of sales in certain hours, in which the anomaly doesn't follow - Big difference in numbers between anomalous data and other data from different days - Lack of correlation, when other days on sales and other variables are highly correlated (reinforces arguments 1 and 2)

5.1.1 Notes:

- It was also found that *yesterday_2* and *today_1* are exactly the same (see plotly graph). Which indicates that checkout_2 is from a day after checkout_1.
- Another somewhat anomalous behavior in the data is from *yesterday_2*, where from hours 9 to 10 sales went from 2 to 55, an increase of 2600%. Similar behavior was found in *yesterday_1* with 1000% increase. But as said before, this can be explained by other things, and we can't ultimately decrete it as an anomaly. We would need more context and data.
- **AI and any machine learning models were discarded from start because data was too small**, focusing on using any model would only distract and confuse the analysis.
- With more data, a model to predict sales for each hour seems very possible