Week 2

```
import pandas as pd
import numpy as np
import seaborn as sns
import altair as alt
import janitor
import statsmodels.api as sm
from statsmodels.tsa.seasonal import seasonal_decompose
import matplotlib.pyplot as plt

plt.rcParams["figure.figsize"] = (14,6)

%matplotlib inline
%config InlineBackend.figure_format = 'retina'  # Optional: For higher quality plots

alt.renderers.enable('default')
alt.renderers.set_embed_options(width=1000)
```

```
RendererRegistry.enable('default')
```

```
dat = pd.read_csv("data/data.csv", parse_dates=['Date']).clean_names()
dat
```

	date	company_sales	product_sales
0	2019-01-01	1500.0	8
1	2019-02-01	2600.0	0
2	2019-03-01	2000.0	14
3	2019-04-01	2700.0	0
4	2019-05-01	3000.0	3
...	...	...	...
1091	2021-12-27	5550.0	41
1092	2021-12-28	1648.0	3
1093	2021-12-29	1424.0	19
1094	2021-12-30	6076.0	0
1095	2021-12-31	1606.0	9

Exercise A

Exercise A. The first series of the dataset presents the daily sales of a retail store, expressed in Euros. You are asked: - To visualize the original series. - To identify the missing values and fill them using an appropriate method. - To identify the outliers present and normalize their values. - To create and visualize the respective weekly and monthly series. - To decompose the monthly series and visualize its trend and seasonal components. - To compute the average sales per weekday and month.

Daily Sales Time Series

```
alt.Chart(dat).\
    mark_line(point=alt.OverlayMarkDef(filled=False, fill="white")).\
        encode(x = 'date:T', y = 'company_sales:Q', tooltip=['date', 'company_sales']).\
            interactive()
```

```
alt.Chart(...)
```

Missing Values

There are some missing values here.

```
dat[dat.company_sales.isna()]
```

	date	company_sales	product_sales
85	2019-03-27	NaN	0
87	2019-03-29	NaN	0
88	2019-03-30	NaN	0
89	2019-03-31	NaN	0
125	2019-06-05	NaN	0
127	2019-08-05	NaN	0
131	2019-12-05	NaN	0
173	2019-06-23	NaN	0
177	2019-06-27	NaN	0
214	2019-03-08	NaN	0
217	2019-06-08	NaN	0
227	2019-08-16	NaN	0
228	2019-08-17	NaN	0

	date	company_sales	product_sales
230	2019-08-19	NaN	0

Using a linear interpolation to fill these values.

```
dat.set_index('date', inplace=True)
dat.interpolate(method="linear", inplace=True)
assert dat.isnull().sum().sum() == 0
```

Outliers

One way we could identify outliers is using a lower 2.5th and upper 97.5th percentile to identify points.

```
def outliers_by_quantiles(df, columns):
    for column in columns:
        quantile_5 = df[column].quantile(0.025)
        quantile_95 = df[column].quantile(0.975)

        df[column + '_outlier'] = df[column].apply(lambda x: True if x < quantile_5 or x >

    return df

dat = outliers_by_quantiles(dat, ['company_sales'])
dat
```

	company_sales	product_sales	company_sales_outlier
date			
2019-01-01	1500.0	8	False
2019-02-01	2600.0	0	False
2019-03-01	2000.0	14	False
2019-04-01	2700.0	0	False
2019-05-01	3000.0	3	False
...	...	...	...
2021-12-27	5550.0	41	True
2021-12-28	1648.0	3	False
2021-12-29	1424.0	19	False
2021-12-30	6076.0	0	True
2021-12-31	1606.0	9	False

```
def tplot(df):
    line = alt.Chart(df.reset_index()).\
    mark_line().\
    encode(x = 'date:T', y = 'company_sales:Q', tooltip=['date', 'company_sales', 'company

    points = alt.Chart(df.reset_index()).\
        mark_point().\
        encode(x = 'date:T', y = 'company_sales:Q', color='company_sales_outlier', fill='c

    return (line + points).interactive()

def lplot(df):
    line = alt.Chart(df.reset_index()).\
        mark_line().\
        encode(x = 'date:T', y = 'company_sales:Q', tooltip=['date', 'company_sales', 'com

    return (line).interactive()

tplot(dat)
```

```
alt.LayerChart(...)
```

We could "normalize" these values, say, by capping them to the quantile values. Not sure how right it is to do it on these series in this way, but for illustrative purposes, I'll proceeed.

```
dat.loc[dat.company_sales>dat.company_sales.quantile(0.975), "company_sales"] = dat.compan
dat.loc[dat.company_sales<dat.company_sales.quantile(0.025), "company_sales"] = dat.compan

tplot(dat)
```

```
alt.LayerChart(...)
```

Weekly and Monthly Series

One way we could look at the monthly series is by year-month…

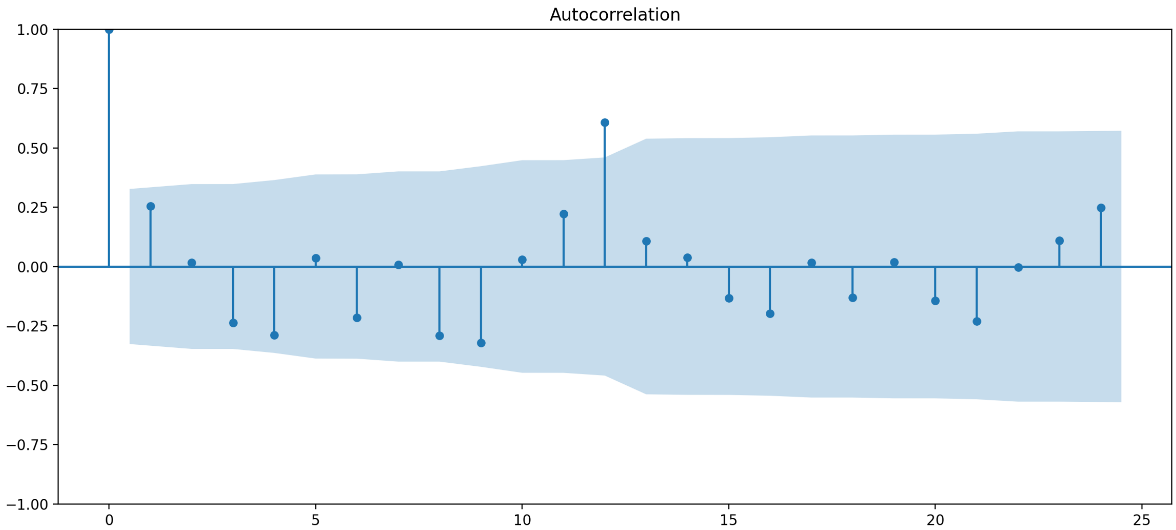
```
monthly = dat.resample('M').mean()
monthly
```

date	company_sales	product_sales	company_sales_outlier
2019-01-31	2116.129032	5.483871	0.000000
2019-02-28	2186.406250	5.785714	0.035714
2019-03-31	1782.258065	2.967742	0.000000
2019-04-30	2070.645833	7.233333	0.033333
2019-05-31	2145.786290	2.741935	0.032258
2019-06-30	2158.333333	6.100000	0.000000
2019-07-31	2019.979839	7.096774	0.032258
2019-08-31	1816.129032	5.193548	0.000000
2019-09-30	2103.333333	5.300000	0.000000
2019-10-31	2061.290323	4.322581	0.000000
2019-11-30	2360.000000	9.066667	0.000000
2019-12-31	2651.512097	8.032258	0.161290
2020-01-31	2132.334677	5.903226	0.032258
2020-02-29	2003.758621	3.862069	0.000000
2020-03-31	1506.903226	4.387097	0.000000
2020-04-30	2230.570833	7.266667	0.100000
2020-05-31	1963.290323	3.548387	0.000000
2020-06-30	1807.533333	5.733333	0.000000
2020-07-31	1914.967742	7.838710	0.000000
2020-08-31	1618.354839	3.064516	0.000000
2020-09-30	2079.633333	6.466667	0.000000
2020-10-31	2066.870968	6.709677	0.000000
2020-11-30	2310.733333	7.300000	0.000000
2020-12-31	2528.318548	8.129032	0.161290
2021-01-31	2197.915323	5.903226	0.032258
2021-02-28	1959.763393	3.428571	0.035714
2021-03-31	1592.935484	3.612903	0.000000
2021-04-30	2140.112500	6.966667	0.033333
2021-05-31	1920.741935	3.419355	0.000000
2021-06-30	1910.000000	6.366667	0.000000
2021-07-31	1931.806452	7.677419	0.000000
2021-08-31	1746.947581	3.741935	0.032258
2021-09-30	2065.433333	5.200000	0.000000
2021-10-31	1990.580645	7.032258	0.000000
2021-11-30	2303.966667	7.133333	0.000000
2021-12-31	2586.879032	8.387097	0.193548

```
lplot(monthly)
```

```
alt.Chart(...)
```

```python
sm.graphics.tsa.plot_acf(monthly.company_sales.squeeze(), lags=12*2);
```



Another way to look at this data is purely by month

```python
dat['month'] = dat.index.month_name()
mdat = dat.groupby('month').mean().filter(['company_sales'])
alt.Chart(mdat.reset_index()).mark_line(point=True).encode(x = 'month', y = 'company_sales
```

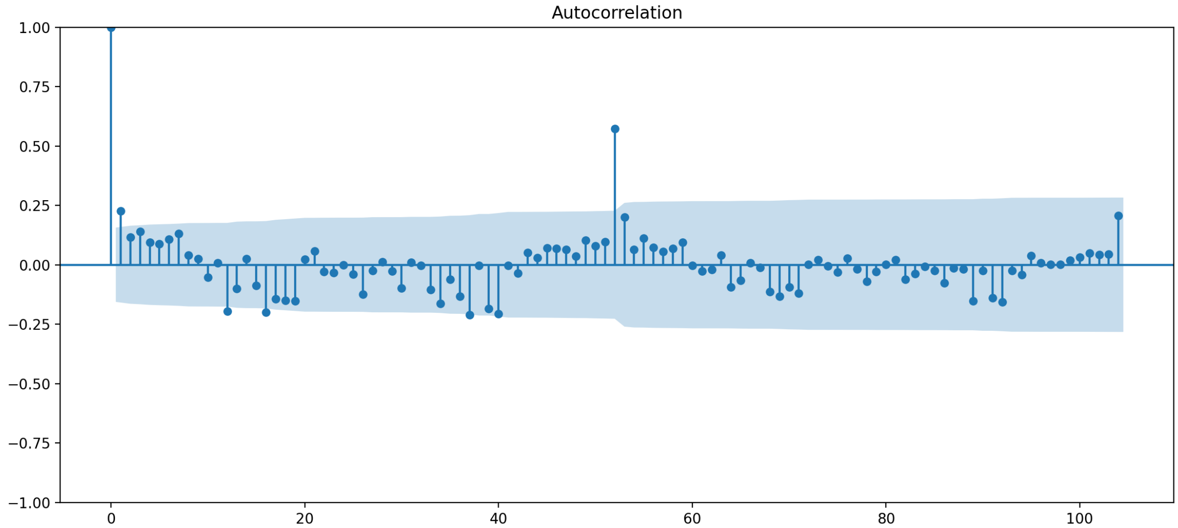
```
alt.Chart(...)
```

```python
weekly = dat.resample('W').mean()
lplot(weekly)
```

```
/var/folders/py/6q30txtn4sx98k_sxsdqgx4w0000gn/T/ipykernel_75519/2980661144.py:1: FutureWarn
  weekly = dat.resample('W').mean()
```

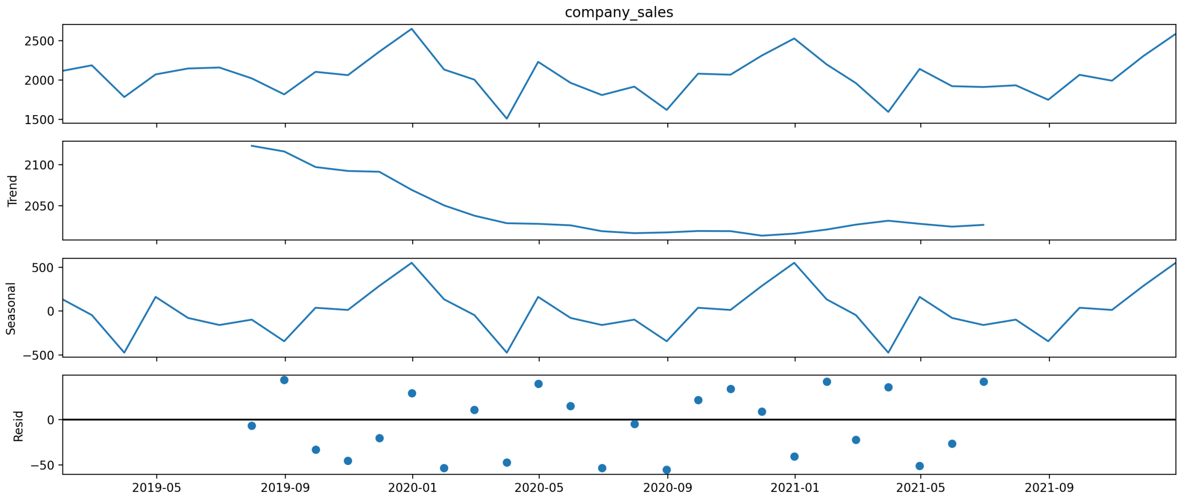
```
alt.Chart(...)
```

```python
sm.graphics.tsa.plot_acf(weekly.company_sales.squeeze(), lags=52*2);
```



Decomposition of Monthly Series

```
monthly_decompose = seasonal_decompose(monthly.company_sales)
monthly_decompose.plot();
```



Average sales per weekday and month

```
dat \
    .filter(['company_sales']) \
    .groupby(pd.Grouper(freq='B')) \
    .mean()
```

	company_sales
date	
2019-01-01	1500.000000
2019-01-02	2000.000000
2019-01-03	4200.000000
2019-01-04	1833.333333
2019-01-07	1200.000000
...	...
2021-12-27	4519.375000
2021-12-28	1648.000000
2021-12-29	1424.000000
2021-12-30	4519.375000
2021-12-31	1606.000000

Exercise B

Exercise B. The second series of the dataset presents the daily sales of a product sold in the store, expressed in units. You are asked: - To visualize the series. - To compute the average daily demand of the product, the coefficient of variation of non-zero demands (CV2), and the average number of time periods between two successive non-zero demands (ADI). - To visualize the empirical distribution of the demand of the product and compute its 5%, 50% and 95% percentiles. - To create and visualize the respective monthly series and comment on its seasonal pattern, if present.

Daily Product Sales Series

```
alt.Chart(dat.reset_index()).\
    mark_line(point=alt.OverlayMarkDef(filled=False, fill="white")).\
        encode(x = 'date:T', y = 'product_sales:Q', tooltip=['date', 'product_sales']).\
            interactive()
```

```
alt.Chart(...)
```

```
sales = dat.filter(['product_sales']).query('product_sales != 0').reset_index().sort_value
sales["interval"] = sales.date - sales.date.shift(1)
sales
```

	date	product_sales	interval
0	2019-01-01	8	NaT
15	2019-01-02	12	1 days
26	2019-01-03	4	1 days
37	2019-01-04	8	1 days
56	2019-01-05	8	1 days
...	...	...	...
527	2021-12-26	6	3 days
528	2021-12-27	41	1 days
529	2021-12-28	3	1 days
530	2021-12-29	19	1 days
531	2021-12-31	9	2 days

Average daily demand of the product

```
dat.product_sales.mean()
```

```
5.789233576642336
```

Coefficient of variation of non-zero demands (CV2)

```
(np.std(sales.product_sales)/np.mean(sales.product_sales))**2
```

```
0.4825663562393773
```

Average number of time periods between two successive non-zero demands (ADI)

```
sales.interval.mean()
```

```
Timedelta('2 days 01:29:29.491525423')
```

Demand Distribution

```
density_plot = alt.Chart(sales[['product_sales']]).transform_density('product_sales', as_=
                             ).mark_area(color='gray').encode(
    x="Demand:Q",
    y='Density:Q'
)

quantiles = sales['product_sales'].quantile([0.05, 0.5, 0.95]).values

vertical_lines = alt.Chart(pd.DataFrame({'quantiles': quantiles})).mark_rule(color='black'

labels = pd.DataFrame({'quantiles': quantiles, 'labels': [f'Q{q}' for q in [0.05, 0.5, 0.9

labels_text = alt.Chart(labels).mark_text(dy=-10, color='red').encode(
    x='quantiles:Q',
    y=alt.value(0),
    text='labels:N'
)

# Layer density plot and vertical lines
density_plot + vertical_lines + labels_text
```

```
alt.LayerChart(...)
```

Seasonality of Monthly series

Looking at these plots, we can identify the seasonality, particularly using the ACF plot.

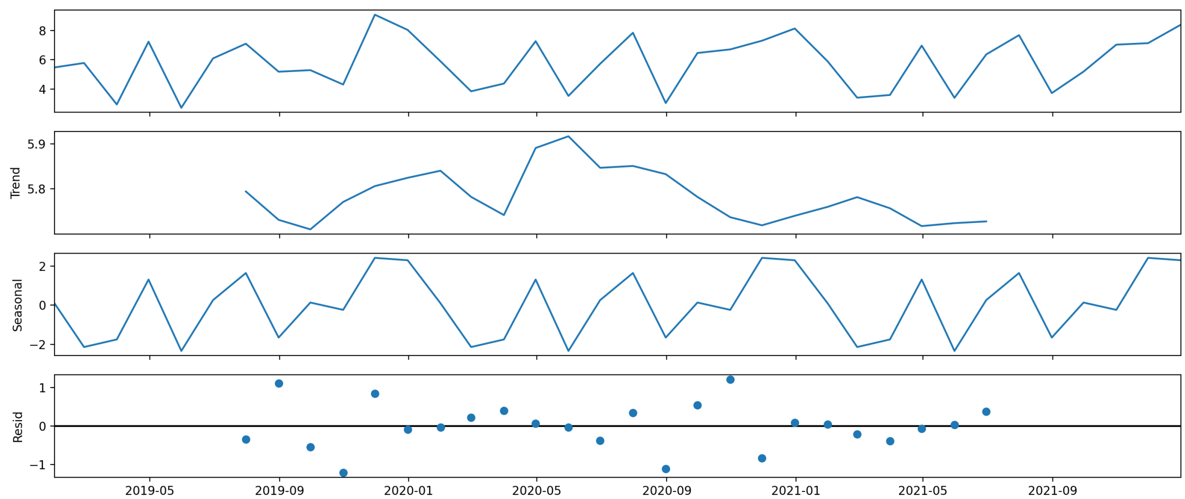
```
monthly_sales = dat[['product_sales']].resample("M").mean().reset_index()
monthly_sales.head()
```

	date	product_sales
0	2019-01-31	5.483871
1	2019-02-28	5.785714
2	2019-03-31	2.967742
3	2019-04-30	7.233333
4	2019-05-31	2.741935

```
alt.Chart(monthly_sales).mark_line().encode(x="date", y="product_sales")
```

alt.Chart(...)

```
monthly_decompose = seasonal_decompose(monthly_sales.set_index('date'))
monthly_decompose.plot();
```




```
sm.graphics.tsa.plot_acf(monthly_sales.product_sales.squeeze(), lags=12*2);
```