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Bike traffic prediction project

Hello! In this PDF I will go over all my methodological choices, expectations and results. I will also explain my thinking, known issues/bugs, things I would change, and ideas.

This project is split into four parts:

- Data preparation and exploratory analysis
- Model selection, training
- Prediction
- Website

As you read through this report, I recommend having INF161project.py open on the side and watching as I talk through it, it will follow the same order that I do here.

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Data preparation

This project uses data from Statens Vegvesen and Geofysisk institutt. The goal is to create a model that can predict the volume of cyclists at a given time over Nygårdsbroen. For this part, it was all about taking all of that raw data (weather, traffic), and only focusing on what I subjectively decided would be important for the model.

I recognize that throughout the years there have been some times where people might have used the bikes more/less frequently because of certain factors.

- Covid-19 likely kept more people home, especially in peak times. Less people using bicycles to get to work as they had to work from home. Only interested in peak covid-19 times though.

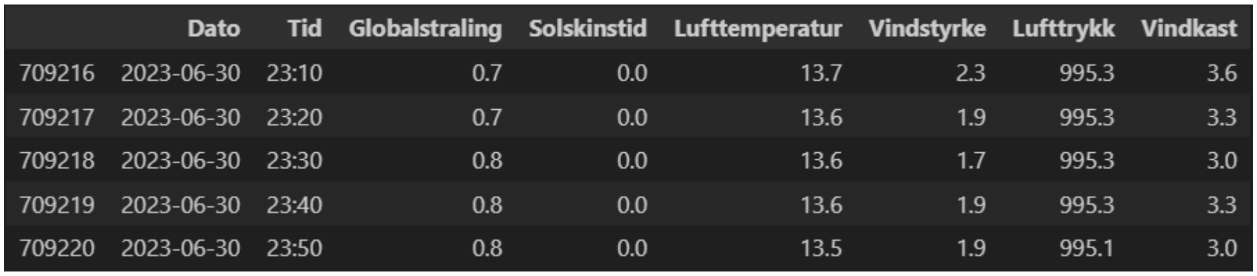
- 2017 UCI Road World Championships. I've checked the routes and don't see that any bikes passed Nygårdsbroen.

We've been given weather data from 2010 all the way to 2023 as well as traffic data from 2015 to 2023. The libraries needed are numpy, pandas, os and matplotlib.pyplot.

I start by defining the directory for all our raw weather data, and I decide that instead of having to write up the names of every single .csv file (they're quite lengthy), I decide to use the power of **os** to create a list of every file in the directory that ends in .csv.

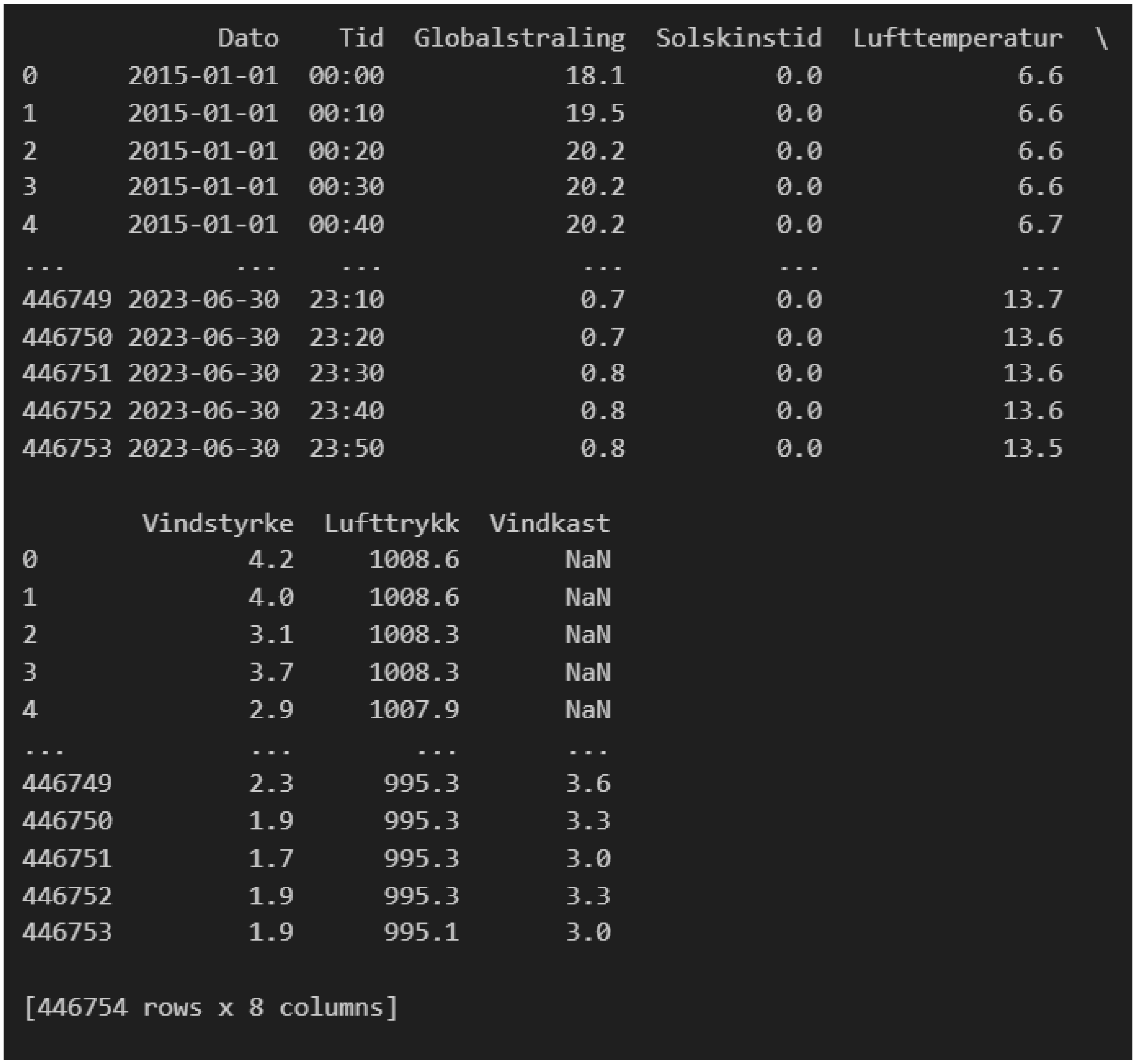
Next I define a list of interesting columns, these are interesting because I decided that I think only these will really have an effect on whether people use their bike that day. In the beginning, I decided to leave "Lufttrykk" and "Vindretning" out, but later when I was trying to get the lowest RMSE possible, I found that "Lufttrykk" really mattered.

Next, we'll append all those datasets in the list, with only the interesting columns into one big dataframe. This dataframe has 709220 rows of data.



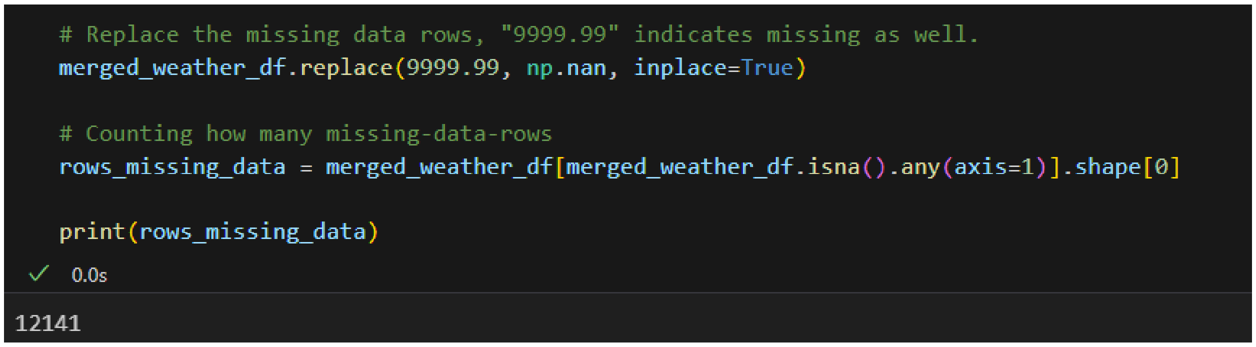
	Dato	Tid	Globalstraling	Solskinstid	Lufttemperatur	Vindstyrke	Lufttrykk	Vindkast
709216	2023-06-30	23:10	0.7	0.0	13.7	2.3	995.3	3.6
709217	2023-06-30	23:20	0.7	0.0	13.6	1.9	995.3	3.3
709218	2023-06-30	23:30	0.8	0.0	13.6	1.7	995.3	3.0
709219	2023-06-30	23:40	0.8	0.0	13.6	1.9	995.3	3.3
709220	2023-06-30	23:50	0.8	0.0	13.5	1.9	995.1	3.0

After this, it is important to realize that because the traffic data only goes from 2015-2023 and the weather data is from 2010-2023, this effectively means we're missing a lot of traffic data for the earlier years. This could be solved in many ways, one way is to impute the data with a median, average, etc.. but I have decided that the best approach here is to simply filter the entire weather data for everything 2015 and later. This results in 446754 rows of data.



```
              Dato    Tid  Globalstraling  Solskinstid  Lufttemperatur  \
0       2015-01-01  00:00            18.1          0.0             6.6   
1       2015-01-01  00:10            19.5          0.0             6.6   
2       2015-01-01  00:20            20.2          0.0             6.6   
3       2015-01-01  00:30            20.2          0.0             6.6   
4       2015-01-01  00:40            20.2          0.0             6.7   
...            ...    ...             ...          ...             ...   
446749  2023-06-30  23:10             0.7          0.0            13.7   
446750  2023-06-30  23:20             0.7          0.0            13.6   
446751  2023-06-30  23:30             0.8          0.0            13.6   
446752  2023-06-30  23:40             0.8          0.0            13.6   
446753  2023-06-30  23:50             0.8          0.0            13.5   

        Vindstyrke  Lufttrykk  Vindkast  
0              4.2     1008.6       NaN  
1              4.0     1008.6       NaN  
2              3.1     1008.3       NaN  
3              3.7     1008.3       NaN  
4              2.9     1007.9       NaN  
...            ...        ...       ...  
446749         2.3      995.3       3.6  
446750         1.9      995.3       3.3  
446751         1.7      995.3       3.0  
446752         1.9      995.3       3.3  
446753         1.9      995.1       3.0  

[446754 rows x 8 columns]
```

But, something important here is that we see on the column Vindkast, that there are rows with value NaN. This indicates missing data. There’s also the value “9999.99” which indicates missing data. I want clean, full data, and who knows how many rows are missing data in one or more columns. We’ll replace the 9999.99s with NaN and count this. Let’s find out..



```
# Replace the missing data rows, "9999.99" indicates missing as well.
merged_weather_df.replace(9999.99, np.nan, inplace=True)

# Counting how many missing-data-rows
rows_missing_data = merged_weather_df[merged_weather_df.isna().any(axis=1)].shape[0]

print(rows_missing_data)
```

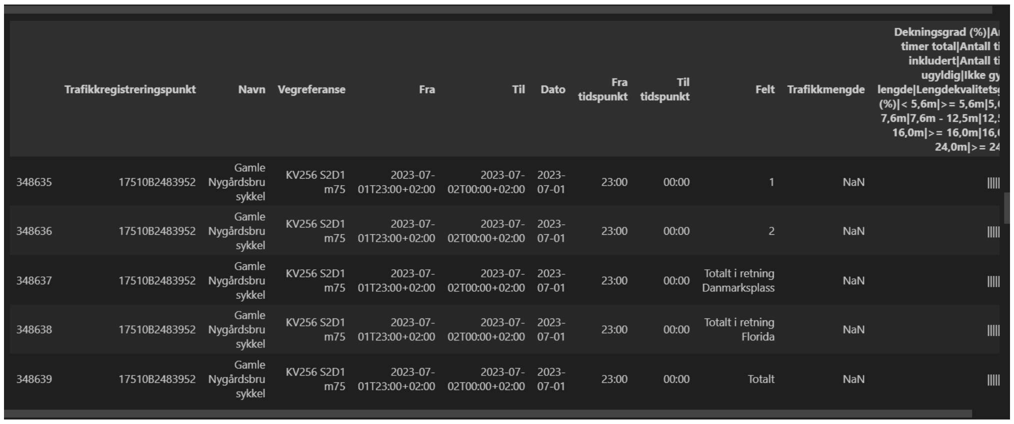
✓ 0.0s

```
12141
```

It appears there are 12141 rows with missing data. Again, we're left with some options on how to handle this, do we impute it or do we delete it? I went with deletion. The reason for this is 11459 only comes out to roughly ~2,7% of the merged dataframe. That is something we can afford to get rid of, and it wouldn't affect the models accuracy *as much*. So we drop them.

The next thing we want to do is convert the two columns, "Dato" and "Tid" to get a single datetime column. The reason for this is because the datetime column will be much easier to work with when we send it to the model, and we're able to pick out individual time features from that object, e.g hour, month, day etc..

Now, it's time to look at the traffic data, and this one is really messy! (a lot of unnecessary information). Reading the csv file for the traffic data and tailing it, gives us this:



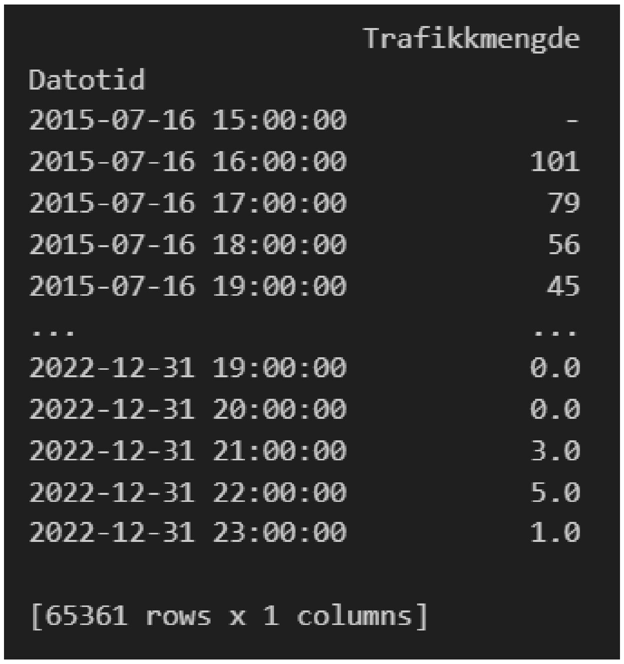
	Trafikkregistreringspunkt	Navn	Vegreferanse	Fra	Til	Dato	Fra tidspunkt	Til tidspunkt	Felt	Trafikkmengde	Dekningsgrad (%)|A timer total|Antall ti inkludert|Antall ti ugyldig|Ikke gy lengde|Lengdekvalitets (%)|< 5,6m|>= 5,6m|5, 7,6m|7,6m - 12,5m|12, 16,0m|>= 16,0m|16, 24,0m|>= 24
348635	17510B2483952	Gamle Nygårdsbru sykkel	KV256 S2D1 m75	2023-07-01T23:00+02:00	2023-07-02T00:00+02:00	2023-07-01	23:00	00:00	1	NaN	|||||
348636	17510B2483952	Gamle Nygårdsbru sykkel	KV256 S2D1 m75	2023-07-01T23:00+02:00	2023-07-02T00:00+02:00	2023-07-01	23:00	00:00	2	NaN	|||||
348637	17510B2483952	Gamle Nygårdsbru sykkel	KV256 S2D1 m75	2023-07-01T23:00+02:00	2023-07-02T00:00+02:00	2023-07-01	23:00	00:00	Totalt i retning Danmarksplass	NaN	|||||
348638	17510B2483952	Gamle Nygårdsbru sykkel	KV256 S2D1 m75	2023-07-01T23:00+02:00	2023-07-02T00:00+02:00	2023-07-01	23:00	00:00	Totalt i retning Florida	NaN	|||||
348639	17510B2483952	Gamle Nygårdsbru sykkel	KV256 S2D1 m75	2023-07-01T23:00+02:00	2023-07-02T00:00+02:00	2023-07-01	23:00	00:00	Totalt	NaN	|||||

.. a mess!

It is clear there is A LOT of information we don't need/want for the project. It is also worth noting that the amount of rows isn't that far away from our weather dataframe, so that is nice.

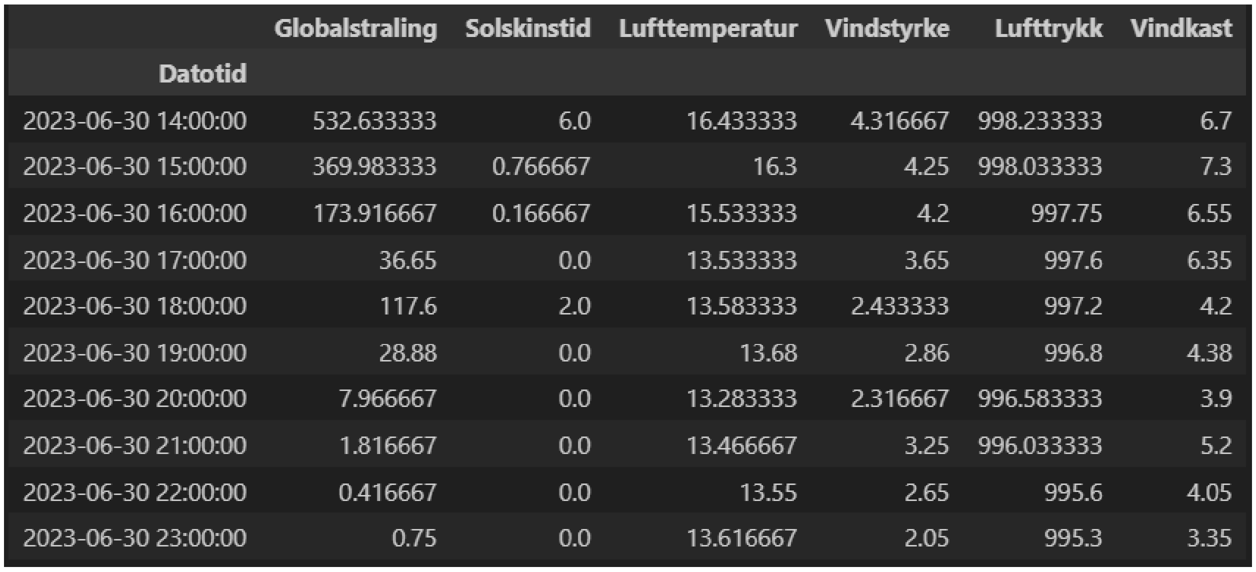
We start by filtering the dataframe where "Felt" == "Totalt". The reason for this is because we want to know the total number of cyclists in each direction. We're not trying to predict the amount of cyclists headed to Florida, we want to know how many pass the bridge. This will allow us to focus on that.

We'll also turn "Dato" and "Fra tidspunkt" into a datetime object. We'll drop these two columns afterwards, as well as drop all rows with missing data. This gives us a finished traffic dataframe that looks like this:



```
                    Trafikkmengde
Datotid
2015-07-16 15:00:00             -
2015-07-16 16:00:00           101
2015-07-16 17:00:00            79
2015-07-16 18:00:00            56
2015-07-16 19:00:00            45
...                           ...
2022-12-31 19:00:00           0.0
2022-12-31 20:00:00           0.0
2022-12-31 21:00:00           3.0
2022-12-31 22:00:00           5.0
2022-12-31 23:00:00           1.0

[65361 rows x 1 columns]
```

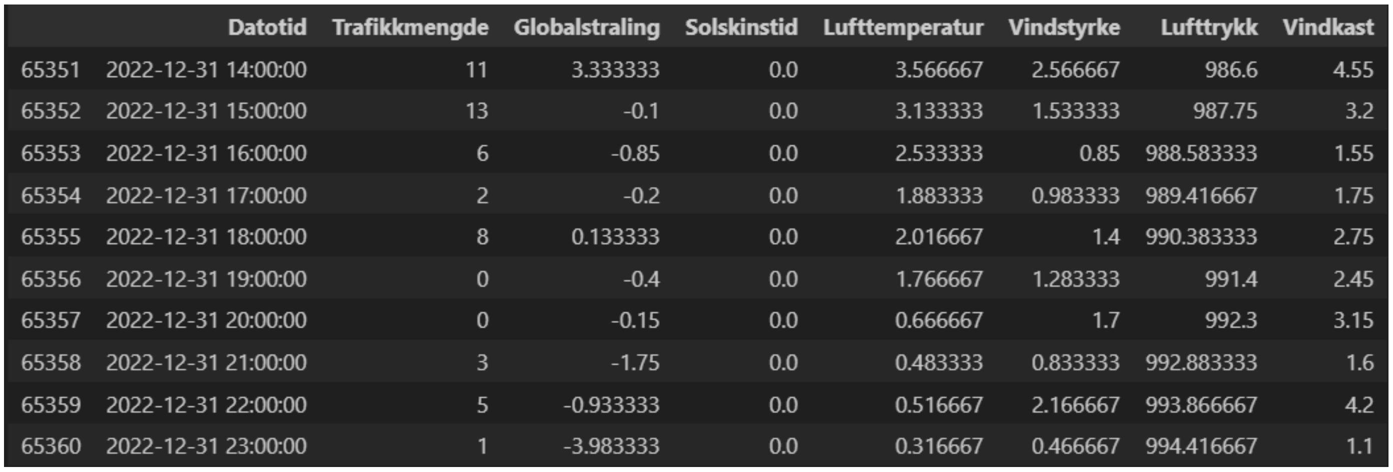
Let's go back to the weather dataframe. We notice here that the weather dataframe is displaying every 10 minutes, while the traffic dataframe is displaying every hour. What should we do here? I decide that the logical answer is to just resample the dataframe into hourly, with the mean. This won't mess up the data either, it'll stay consistent.



	Globalstraling	Solskinstid	Lufttemperatur	Vindstyrke	Lufttrykk	Vindkast
Datotid						
2023-06-30 14:00:00	532.633333	6.0	16.433333	4.316667	998.233333	6.7
2023-06-30 15:00:00	369.983333	0.766667	16.3	4.25	998.033333	7.3
2023-06-30 16:00:00	173.916667	0.166667	15.533333	4.2	997.75	6.55
2023-06-30 17:00:00	36.65	0.0	13.533333	3.65	997.6	6.35
2023-06-30 18:00:00	117.6	2.0	13.583333	2.433333	997.2	4.2
2023-06-30 19:00:00	28.88	0.0	13.68	2.86	996.8	4.38
2023-06-30 20:00:00	7.966667	0.0	13.283333	2.316667	996.583333	3.9
2023-06-30 21:00:00	1.816667	0.0	13.466667	3.25	996.033333	5.2
2023-06-30 22:00:00	0.416667	0.0	13.55	2.65	995.6	4.05
2023-06-30 23:00:00	0.75	0.0	13.616667	2.05	995.3	3.35

Now we're ready to merge them together. I notice Trafikkmengde is currently an object, so I decided to convert it to an integer.

The final dataframe now looks like this:



	Datotid	Trafikkmengde	Globalstraling	Solskinstid	Lufttemperatur	Vindstyrke	Lufttrykk	Vindkast
65351	2022-12-31 14:00:00	11	3.333333	0.0	3.566667	2.566667	986.6	4.55
65352	2022-12-31 15:00:00	13	-0.1	0.0	3.133333	1.533333	987.75	3.2
65353	2022-12-31 16:00:00	6	-0.85	0.0	2.533333	0.85	988.583333	1.55
65354	2022-12-31 17:00:00	2	-0.2	0.0	1.883333	0.983333	989.416667	1.75
65355	2022-12-31 18:00:00	8	0.133333	0.0	2.016667	1.4	990.383333	2.75
65356	2022-12-31 19:00:00	0	-0.4	0.0	1.766667	1.283333	991.4	2.45
65357	2022-12-31 20:00:00	0	-0.15	0.0	0.666667	1.7	992.3	3.15
65358	2022-12-31 21:00:00	3	-1.75	0.0	0.483333	0.833333	992.883333	1.6
65359	2022-12-31 22:00:00	5	-0.933333	0.0	0.516667	2.166667	993.866667	4.2
65360	2022-12-31 23:00:00	1	-3.983333	0.0	0.316667	0.466667	994.416667	1.1

Beautiful..

I was originally worried we wouldn’t have enough data to train on, but it seems with 65360 rows, that is more than enough to get some good predictions!

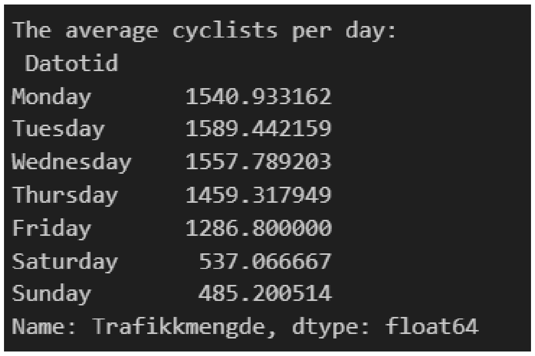
Data exploration

With our dataframe now finally ready, I am curious about a couple things. For example, what's the most popular time of day, and day. What's the best temperature, and the best wind speed?

Let's find out!

We can find the best time by using idxmax() on a list of grouped "Datotid" rows with the mean traffic volumes. idxmax() will return the row label with the maximum value (meaning the most popular time). This is **16:00.** Which makes sense, I sort of expected this considering people are coming home from work..

Now let's find the average cyclists per day. I predict one of the weekend days (where people don't work). We'll find this by resampling the dataframe by days to find the total cyclists per day. Then we can get the average per day of the week using the mean and dayofweek. This is the result:



```
The average cyclists per day:
 Datotid
Monday       1540.933162
Tuesday      1589.442159
Wednesday    1557.789203
Thursday     1459.317949
Friday       1286.800000
Saturday      537.066667
Sunday        485.200514
Name: Trafikkmengde, dtype: float64
```

As predicted.. big surprise! (not)

It is clear that more people leave their bike at home (or at least don't travel over the Nygårdsbroen bridge on Sundays.

We can repeat this method (idxmax and mean) and find the best temperature is 26.7°C. Now this was a surprise, and I think it was because I didn't expect that to be the best temperature. I sort of think that it is a bit too hot to go cycling? Either I've made a mistake here, or there might be some outlier here that brought up this temperature a lot. I wasn't able to pinpoint it. (It wasn't SykkelVM either, that was in September 2017 and this would be too hot for that time of year).

Repeating the method with wind speed we find the best wind speed is 2,28 m/s. This sounds perfectly reasonable to me. Then again, this could simply be similar to the average wind speed and most Norwegians don't really care for the wind speed (unless it's really high). A quick Google search confirms that it is probably the average or something. I don't know how accurate this website is:
https://weatherspark.com/y/52849/Average-Weather-in-Bergen-Norway-Year-Round (in mph, so I had to convert).

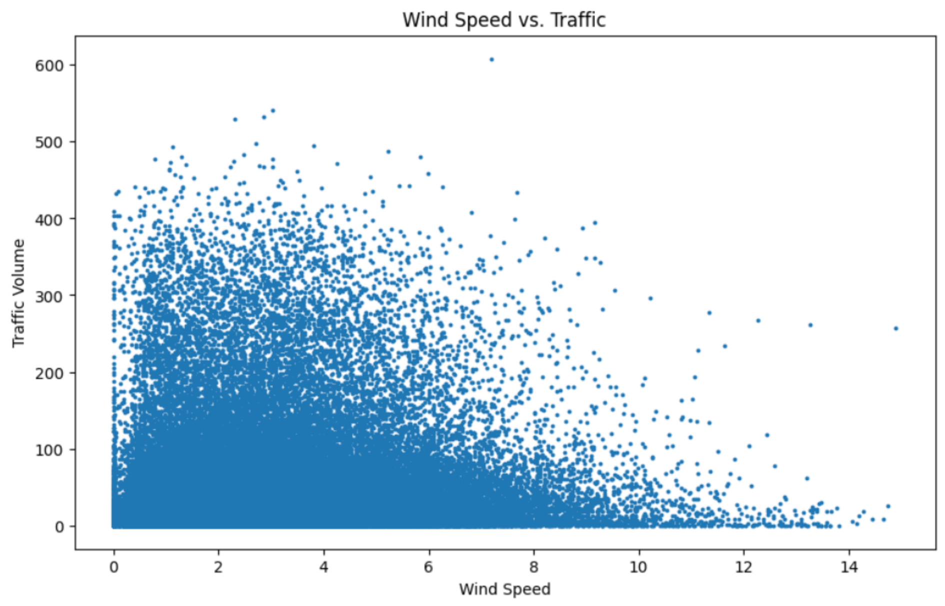
Additionally I also checked for Covid-19 but wasn't happy with my implementation, and I wasn't sure I had done it correctly. The result I found however was:

```
 --------------------------------------------------
Traffic for March-April each year to visualize Covid-19:
 Datotid
2016    238.075163
2017    158.312329
2018    164.756164
2019    185.210959
2020    143.049180
2021    178.216438
2022    617.741667
Name: Trafikkmengde, dtype: float64
```

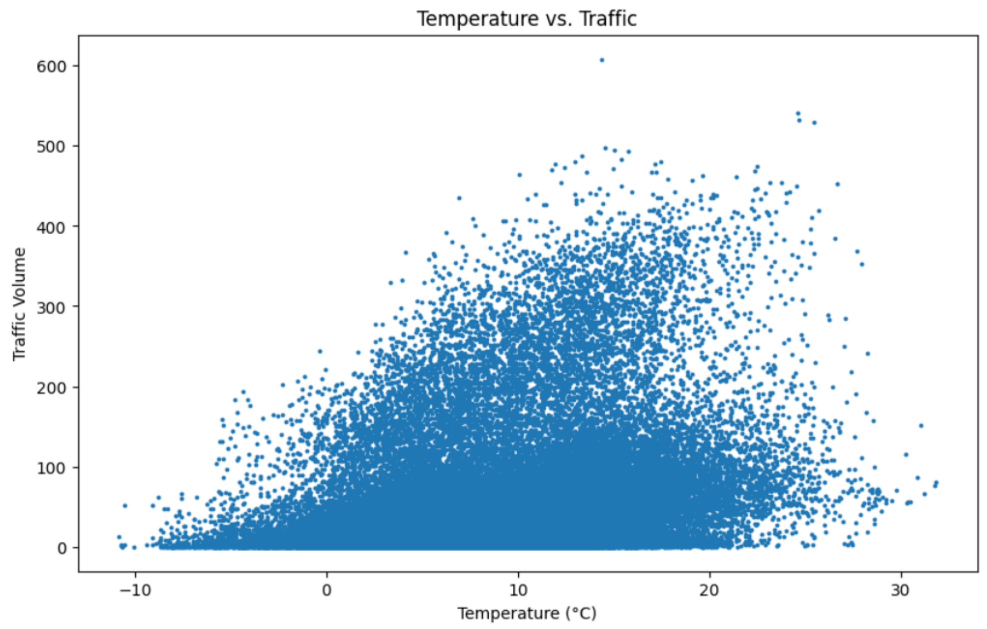
Here's the code as well (not included in my deliverables anymore..)

```python
# Covid-19
march_april_data = ready_df[(ready_df['Datotid'].dt.month.isin([3, 4]))]
daily_bicyclists = march_april_data.resample('D', on='Datotid')['Trafikkmengde'].sum()
avg_bicyclists_per_year = daily_bicyclists.groupby(daily_bicyclists.index.year).mean()
print(avg_bicyclists_per_year)
print("--------------------------------------------------")
```

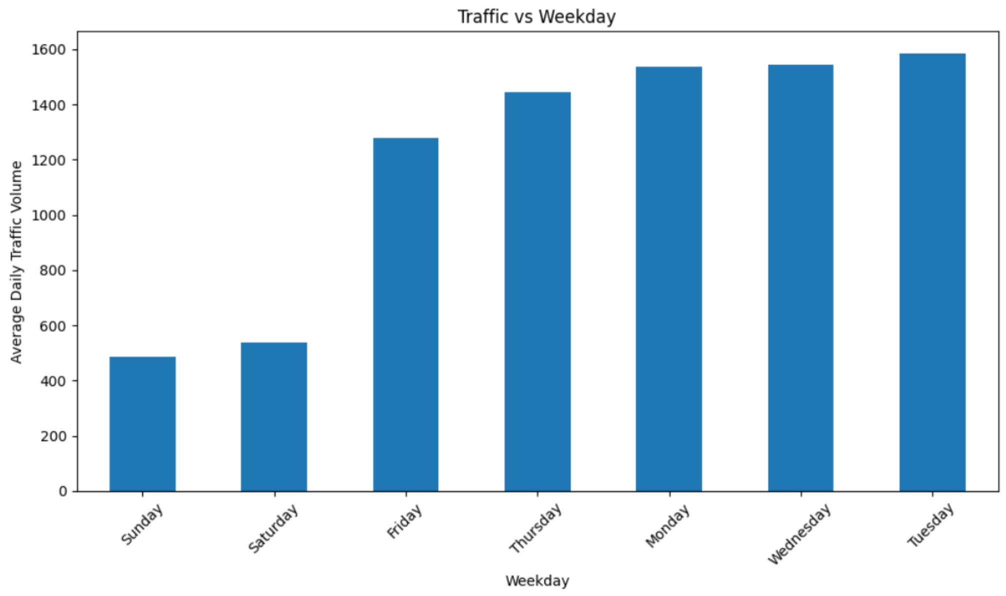
I then write the dataframe to a new file ready_data.csv. But before I end this part, I do some quick visualizations.



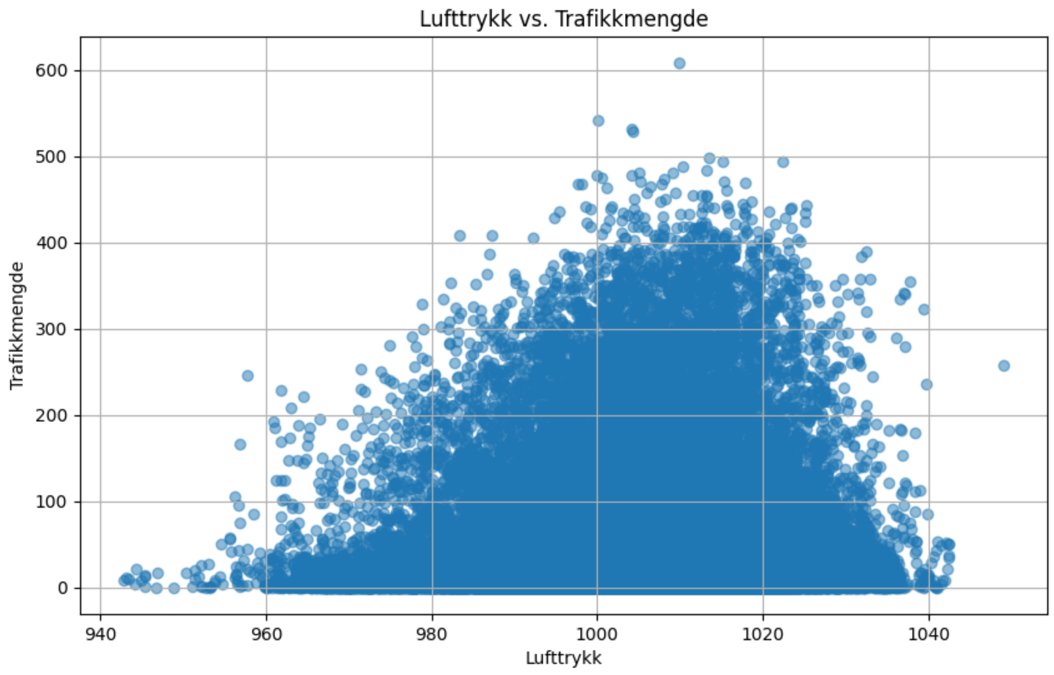
As we can see in the figure above, each point represents a day. It's important to think of the volume of that day as an indicator as to how many people went cycling, and not the amount of points anywhere on the figure. For example, over 14 m/s is a wind speed we rarely get, and hence so little data points. We can count 8 days with more than 14 m/s and 7/8 of those days kept people inside, except one wild day. Majority of people will leave their bike when we get over 8 m/s, which is considered significant.

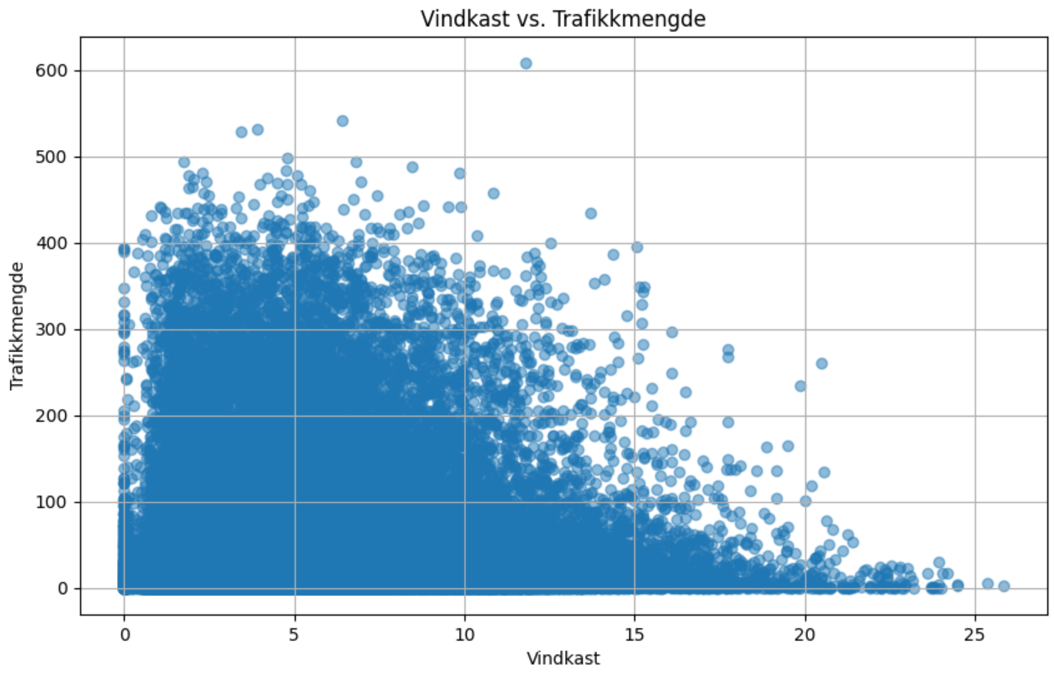


Norway is a pretty cold country, so there's why we see so many data points under 20 celsius. When it's cold, and we're nearing 0 degrees and less, we see a lot less people leaving their bike at home. Especially when we're in -10.

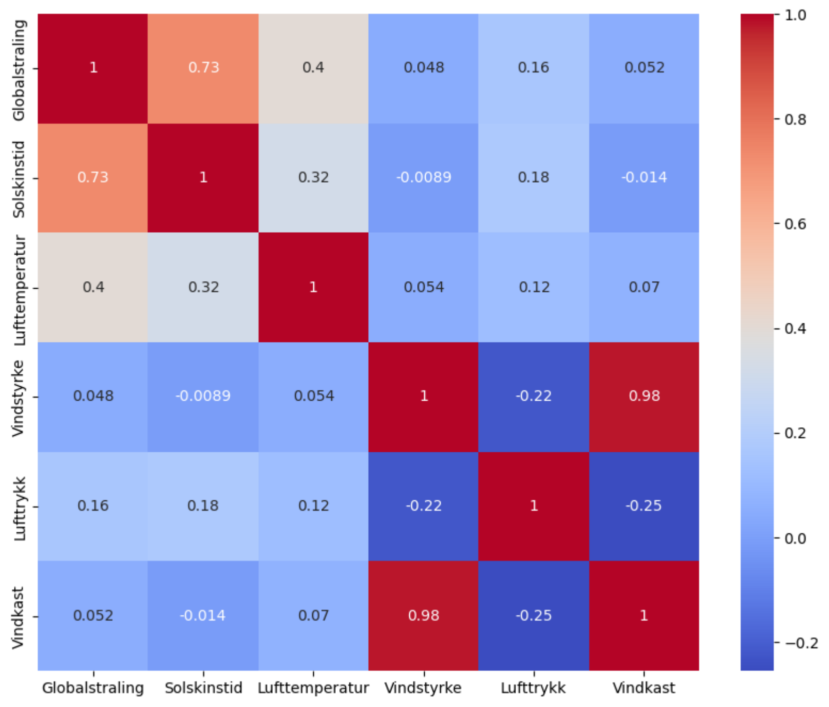


Sunday being the least popular day wasn't a big surprise anywhere.

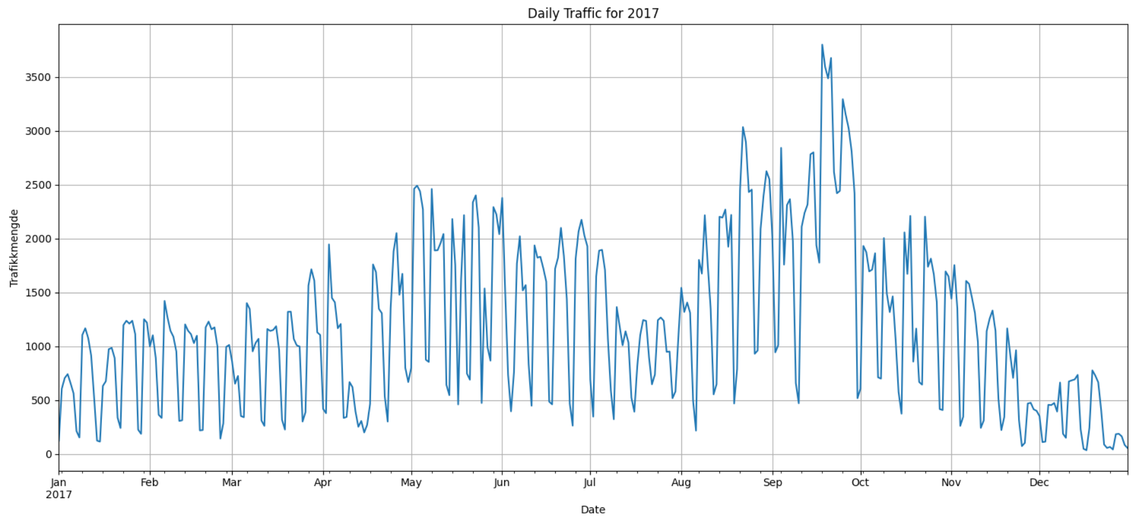




We notice on the second figure, "Vindkast vs. Trafikkmengde" that it looks really similar to our "Windspeed vs. Traffic Volume" figure further up. This looks like it correlates a lot! We can check this with a correlation matrix:



As I said, Vindstyrke and Vindkast correlate at 98%. This makes me rethink whether or not to include it. Edit: I have since removed Vindkast from my interesting columns list, and the reported RMSE value is: 22.678 and hence I am happy with my choice.



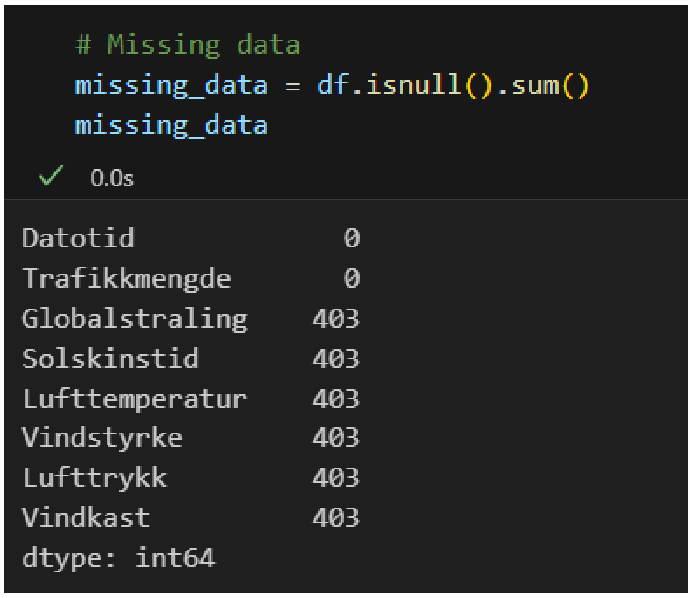
Now, regarding SykkelVM, it is clear there is a change there, but it isn't as substantial as I originally thought, and I plan to leave it alone.

Model selection and training

This part is all about using the dataset we've created in the previous part and training a model on this data, finding the best possible model (both efficiency and root mean squared error), and finding the best hyperparameters.

We start by defining the location of our ready_data.csv file. We'll read the csv file into a dataframe using pandas (so we import pandas).

Before we continue, I decided to check for missing data one more time, and found some missing data again (I thought I got rid of it all).



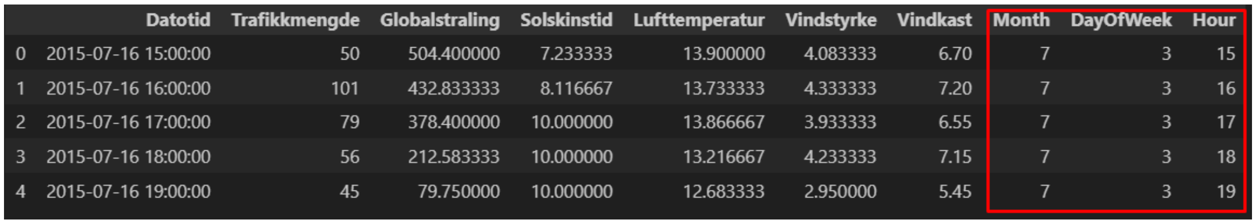
```
# Missing data
missing_data = df.isnull().sum()
missing_data
```

```
✓ 0.0s
```

```
Datotid             0
Trafikkmengde       0
Globalstraling    403
Solskinstid       403
Lufttemperatur    403
Vindstyrke        403
Lufttrykk         403
Vindkast          403
dtype: int64
```

Regarding these missing values, we're gonna fix this by imputing them with the median because the median is less sensitive to outliers. This will artificially impute these missing values with the median of the other values so it's sort of accurate. There are other strategies to do this, and they're not necessarily false either, but this is the way I'm doing it, plus it has worked earlier.

Now, on this next part, it is all about getting a lower and lower RMSE reading. With just using the Month, DayOfWeek, Hour extra columns I was able to get an RMSE of about 25-27 depending on the parameters.



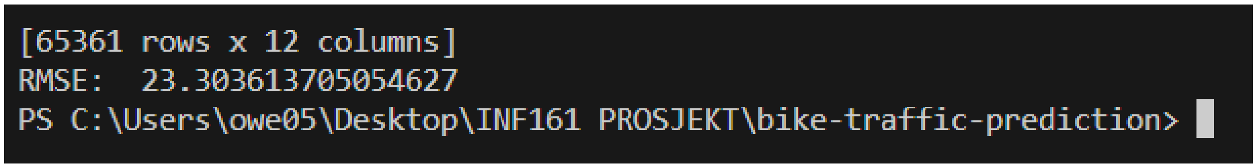
	Datotid	Trafikkmengde	Globalstraling	Solskinstid	Lufttemperatur	Vindstyrke	Vindkast	Month	DayOfWeek	Hour
0	2015-07-16 15:00:00	50	504.400000	7.233333	13.900000	4.083333	6.70	7	3	15
1	2015-07-16 16:00:00	101	432.833333	8.116667	13.733333	4.333333	7.20	7	3	16
2	2015-07-16 17:00:00	79	378.400000	10.000000	13.866667	3.933333	6.55	7	3	17
3	2015-07-16 18:00:00	56	212.583333	10.000000	13.216667	4.233333	7.15	7	3	18
4	2015-07-16 19:00:00	45	79.750000	10.000000	12.683333	2.950000	5.45	7	3	19

Lufttrykk is missing from this figure because the screenshot is from before I added it to the data.

Then I did some thinking, went over everything I could think of that could affect the accuracy of the model. Even asked my girlfriend for tips and she had some good points.

I started by importing the holidays package (for simplicity and it was mentioned in the Discord server it would be permitted. We then create a new column in the data set *IsHoliday* which will have the value True if that time is within a public holiday (Not autumn or winter vacation), and False if it isn’t. I had already at this point tested 5 or 6 or so models and wasn’t expecting that much, maybe a minor decrease.

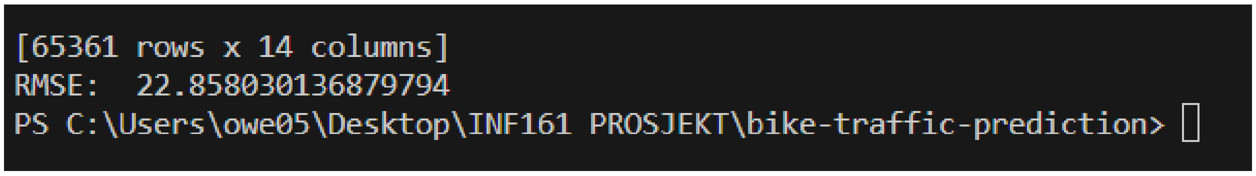
However, this gave me an RMSE of **~23,3**



```
[65361 rows x 12 columns]
RMSE:  23.303613705054627
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

Surprisingly, this was more than I thought it would be, but looking over it, it makes sense. People tend to not ride their bikes during a public holiday.

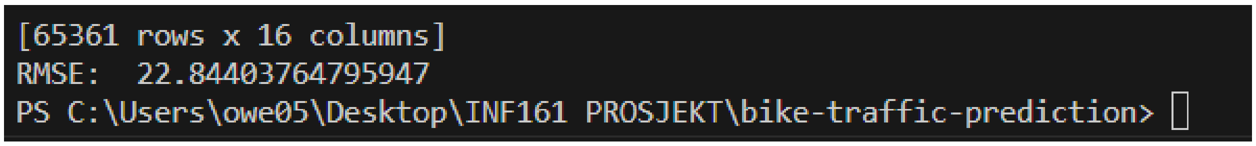
Next move was to add two more columns, one that checks for weekends, and one that checks whether or not it is “rush hour”. My thoughts behind this was that the model is likely to be more accurate when it knows which days are weekends (people stay home and don’t work). The rush hour part was a bit more tricky. I had some issues identifying what was “rush hour” times. I tried 6,7,8,9, 15,16,17 and many different combinations of these. I found [7,8,15,16,17] to be the values giving the lowest RMSE. I had high hopes with this one since my previous move gave a huge decrease in RMSE. This however, gave RMSE: **~22,85.**



```
[65361 rows x 14 columns]
RMSE:  22.858030136879794
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

I was a bit disappointed here, of course it was better, but not as much as I was expecting.

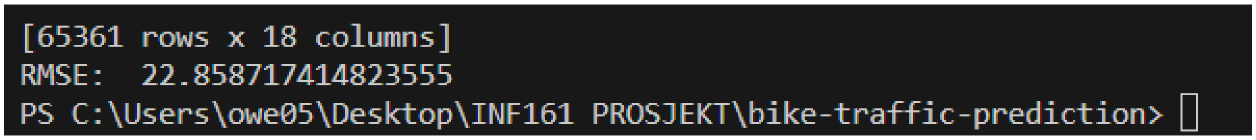
For my next number, I decided to define two new columns, one for the winter holiday we have in February, and one for the autumn holiday in October. I had high hopes for this, but the result was RMSE: **~22,84**



```
[65361 rows x 16 columns]
RMSE:  22.84403764795947
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

So I decided to scrap this one.

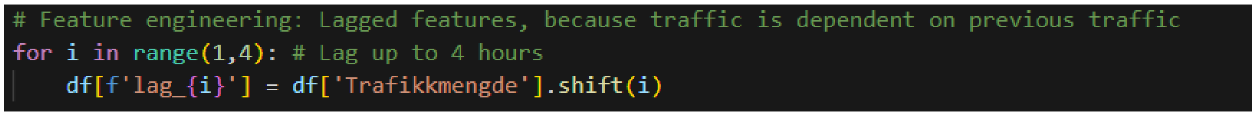
I didn’t give up and kept looking for other ideas. I wanted to try out having four columns, Summer, Winter, Spring, Autumn. This gave an RMSE: **~22,85**



```
[65361 rows x 18 columns]
RMSE:  22.858717414823555
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

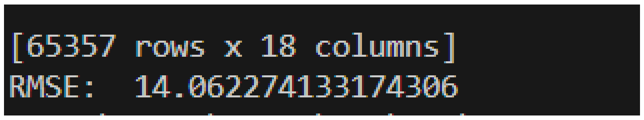
This only made it worse.

I decided to ask ChatGPT for some ideas, and was pointed in the direction of “lagged features”. I found this article which covered the basic idea of how it works:
https://hackernoon.com/must-know-base-tips-for-feature-engineering-with-time-series-data



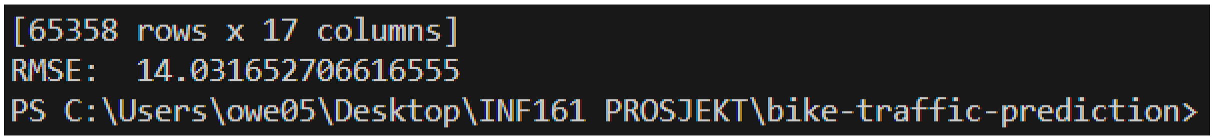
```
# Feature engineering: Lagged features, because traffic is dependent on previous traffic
for i in range(1,4): # Lag up to 4 hours
    df[f'lag_{i}'] = df['Trafikkmengde'].shift(i)
```

The idea of it is to have the model learn patterns from past events to try and predict the future. I started by trying to lag it by 1 to 4 hours. I figured anything more than 4 and it’s too much of a difference to be noteworthy. This dropped the RMSE to **~14.06!!** This created four columns, lag_1, lag_2, lag_3, lag_4.



```
[65357 rows x 18 columns]
RMSE:  14.062274133174306
```

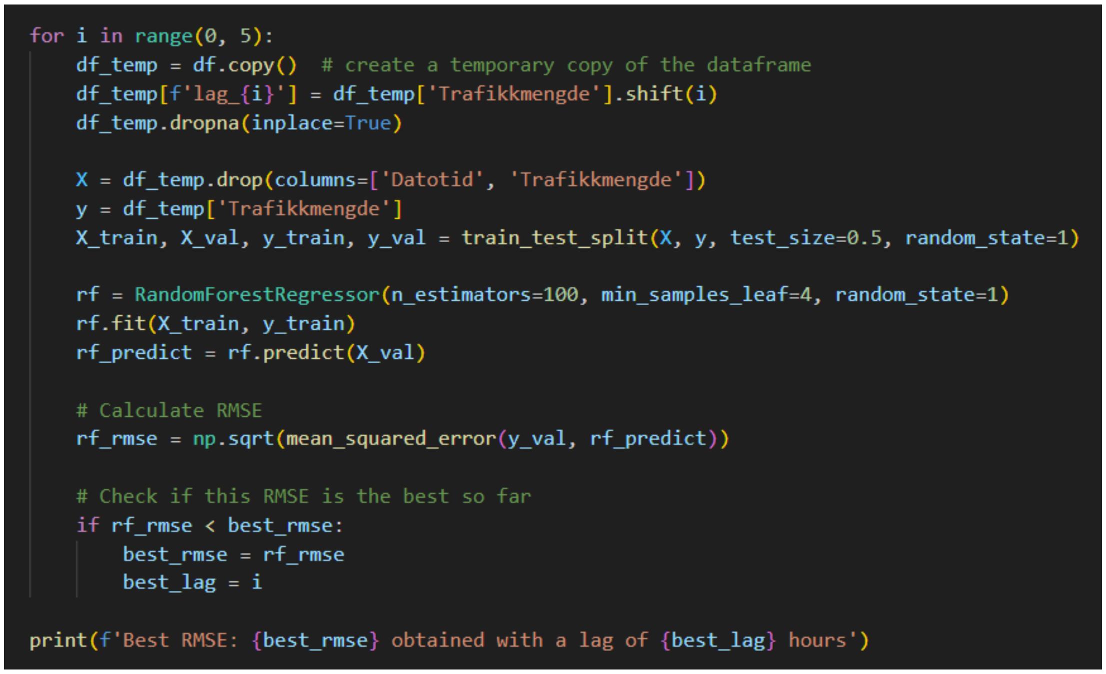
At this point I was struggling to see how much of a difference lagged features really do for the model. I tried to lag it for up to three hours.



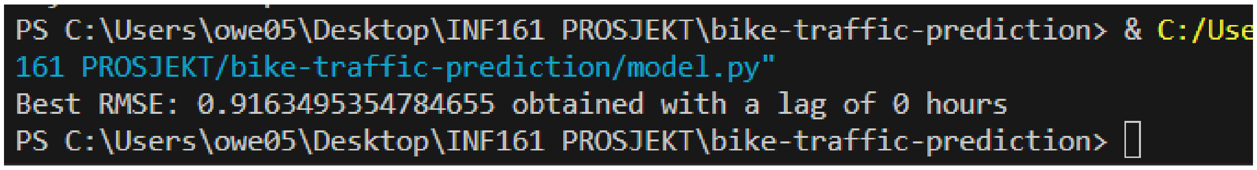
```
[65358 rows x 17 columns]
RMSE:  14.031652706616555
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

Small decrease.

At this point, I wanted to find the perfect amount of hours to lag it by, so I created a loop which would find the RMSE of every number of hours we lag it by. (0 to 5).



```python
for i in range(0, 5):
    df_temp = df.copy()  # create a temporary copy of the dataframe
    df_temp[f'lag_{i}'] = df_temp['Trafikkmengde'].shift(i)
    df_temp.dropna(inplace=True)

    X = df_temp.drop(columns=['Datotid', 'Trafikkmengde'])
    y = df_temp['Trafikkmengde']
    X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.5, random_state=1)

    rf = RandomForestRegressor(n_estimators=100, min_samples_leaf=4, random_state=1)
    rf.fit(X_train, y_train)
    rf_predict = rf.predict(X_val)

    # Calculate RMSE
    rf_rmse = np.sqrt(mean_squared_error(y_val, rf_predict))

    # Check if this RMSE is the best so far
    if rf_rmse < best_rmse:
        best_rmse = rf_rmse
        best_lag = i

print(f'Best RMSE: {best_rmse} obtained with a lag of {best_lag} hours')
```

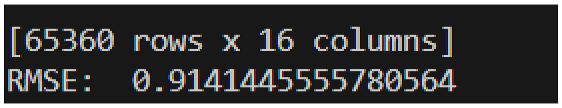


```
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction> & C:/Use
161 PROSJEKT/bike-traffic-prediction/model.py"
Best RMSE: 0.9163495354784655 obtained with a lag of 0 hours
PS C:\Users\owe05\Desktop\INF161 PROSJEKT\bike-traffic-prediction>
```

I was shocked. **~0.916 RMSE! (Keep in mind this is range(0,1) hours)**

At this point it has become a personal challenge for me to see if I can get it lower, and lower, which becomes harder and harder. I thought, okay if 0 is the best number of hours to lag it by, what if we do 0 to n hours? We already know 0 to 0 (0) is 0.916 RMSE.

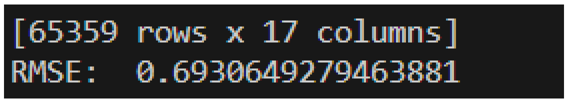
What about range(0,2) hours?



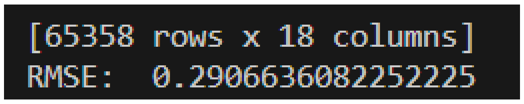
```
[65360 rows x 16 columns]
RMSE:  0.9141445555780564
```

A little better..

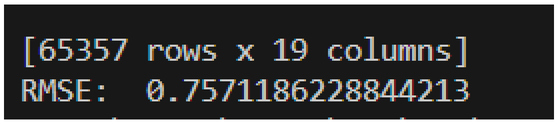
range(0,3)?


```
[65359 rows x 17 columns]
RMSE:  0.6930649279463881
```
Wow! That's again a huge increase if you look at it in percentage.

range(0,4)?


```
[65358 rows x 18 columns]
RMSE:  0.2906636082252225
```
Again, it's a lot sharper now!

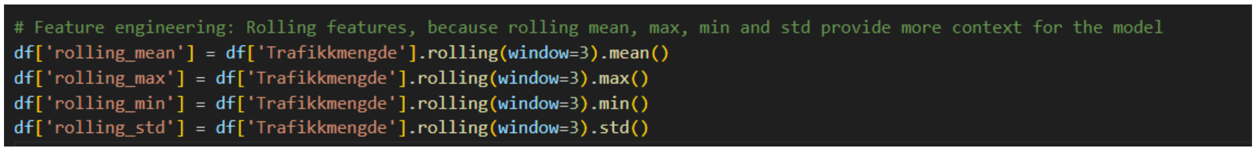
range(0,5)?


```
[65357 rows x 19 columns]
RMSE:  0.7571186228844213
```
This was a little worse.

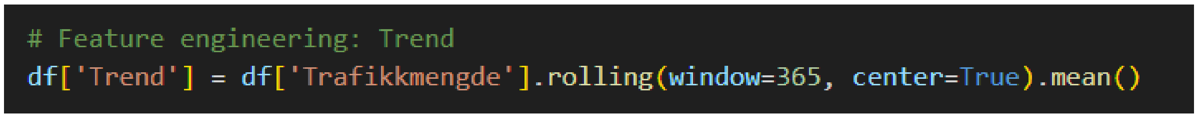
I kept testing a bit further, 6,7,8 but it wasn't giving a result quite like **4.** The reason for this feature performing so well is because traffic is actually dependent on previous traffic, *historically.* For example, let's assume we wish to predict what the traffic will be on 05.02.2025 10:00 AM (random). If the model knows what the historical data for that day, and time (0, -1,-2,-3 | shifted) it is likely that 10 AM on that day will be similar historically to 9 AM for example before. The context of how many bikes at one time affects how many will bike later (within reason, in our example more than 4 was detrimental).

I attempted to use some rolling features to add more context for the model with a 3 hour window. (Essentially how this works is to give the model the mean, max, min, standard deviation for the last three hours to provide context). These did give me a lower RMSE value earlier, before I added the lagged features. However, now with the lagged features, these were either worse, or the same. (Likely due to overfitting).

Here's the code for them, nonetheless:


```python
# Feature engineering: Rolling features, because rolling mean, max, min and std provide more context for the model
df['rolling_mean'] = df['Trafikkmengde'].rolling(window=3).mean()
df['rolling_max'] = df['Trafikkmengde'].rolling(window=3).max()
df['rolling_min'] = df['Trafikkmengde'].rolling(window=3).min()
df['rolling_std'] = df['Trafikkmengde'].rolling(window=3).std()
```

I also tried to implement a yearly trend, but this one as well wasn't doing me any favors.


```python
# Feature engineering: Trend
df['Trend'] = df['Trafikkmengde'].rolling(window=365, center=True).mean()
```

I decided to end it with a RMSE of ~**0.2906.**

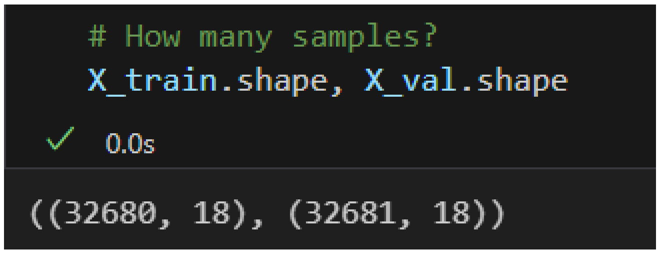
Then I started working on my predictions, and when I saw that I was trying to predict traffic without having any traffic to create lagged features with, I realized I would have to scrap most of this and go back to before I started to model the model on the actual traffic. This was a bit of a bummer for me.

I went back and ended up sticking with: Month, DayOfWeek, Hour, IsHoliday, IsWeekend, IsRushhour, Summer, Winter, Spring, Autumn, IsNight. These are the features I have added for accuracy.

Now that our data is clean, and *really ready*, we can start with data splitting. This essentially follows what I've been doing in the lab04 assignment. We'll need an additional library from this so we **import train_test_split** from **sklearn.model_selection**.

We're going to define two variables here, X and y. X is gonna be the entire dataframe, except "Datotid" (obsolete now), and "Trafikkmengde". This means that X now contains Month, DayOfWeek, Hour as well as our additional features, and all the weather information. Next, y is gonna be only "Trafikkmengde".

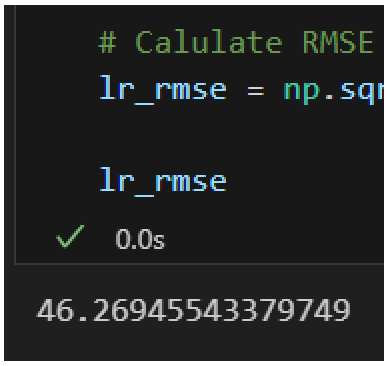
Once this is done, we're gonna define four variables here, X_train, X_val, y_train, y_val. These are split into two equal (0.5 test size) sets of data where one is training set and the other one validation. The training set contains 32,680 samples and the validation set contains 32,681 samples.



```
# How many samples?
X_train.shape, X_val.shape
✓ 0.0s

((32680, 18), (32681, 18))
```

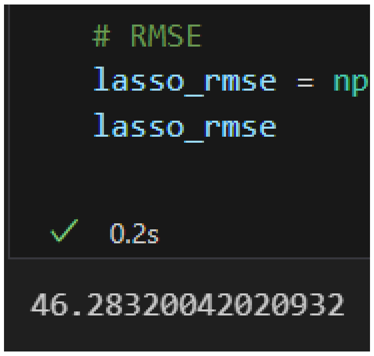
Next, we need to select a model, and we'll need to import numpy, as well as the first model and MSE. We already know the RMSE from RandomForest: **23,80.** Our goal is to find a model that beats this.

Contender 1: LinearRegression.



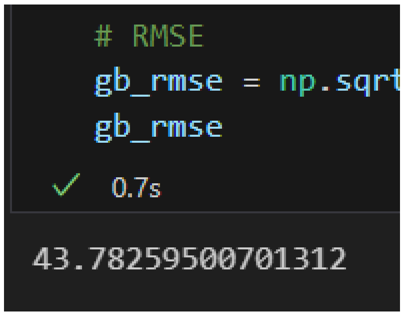
```
# Calulate RMSE
lr_rmse = np.sq

lr_rmse
✓ 0.0s

46.26945543379749
```

Contender 2: Lasso.



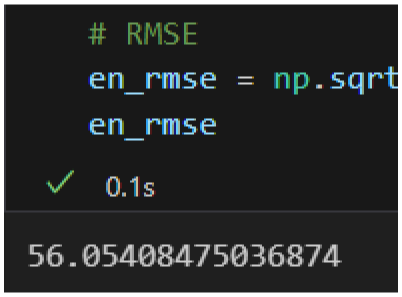
```
# RMSE
lasso_rmse = np
lasso_rmse

✓ 0.2s

46.28320042020932
```

Contender 3: GradientBoostingRegressor.



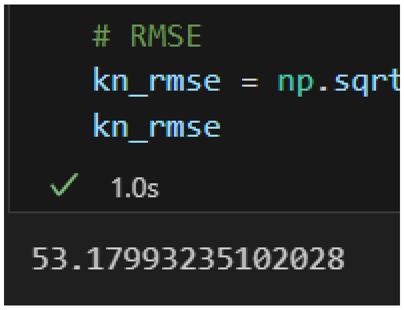
```
# RMSE
gb_rmse = np.sqrt
gb_rmse
✓ 0.7s

43.78259500701312
```

Contender 4: ElasticNet.



```
# RMSE
en_rmse = np.sqrt
en_rmse
✓ 0.1s

56.05408475036874
```

Contender 5: KNeighborsRegressor.

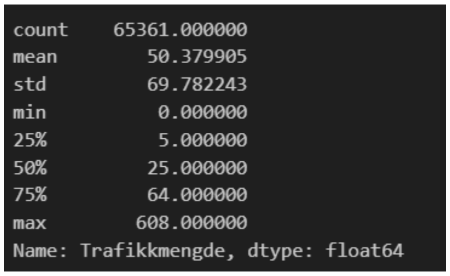


```
# RMSE
kn_rmse = np.sqrt
kn_rmse
✓ 1.0s

53.17993235102028
```

RMSE for every model with these features:
LinearRegression = **46.27**
Lasso = **46.28**
RandomForestRegressor = **23.80**
GradientBoostingRegressor = **43.78**
ElasticNet = **56.05**
KNeighborsRegressor = **53.17**

RandomForest wins, and before GridSearchCV, **RMSE = 23.80** which I think is still fairly good!

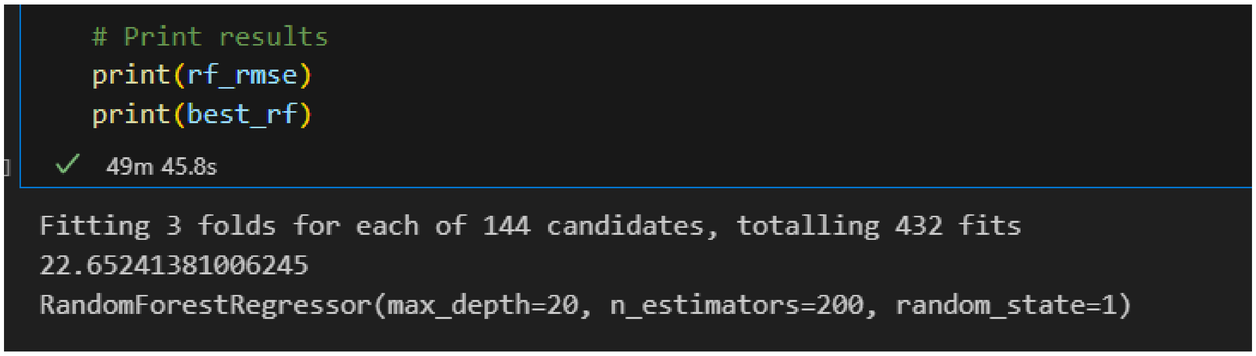
Before we continue, I wish to stop and look at how good of a RMSE this actually is. So we can check the cycle stats, and we see the mean is around 50.37, and the upper 75% is 64. Our RMSE is okay.



```
count    65361.000000
mean        50.379905
std         69.782243
min          0.000000
25%          5.000000
50%         25.000000
75%         64.000000
max        608.000000
Name: Trafikkmengde, dtype: float64
```

Note: had it been allowed in the project description, I would probably try out some other libraries as well e.g XGBoost or some neural networks e.g Keras.

The next logical step is to find the best parameters to use with LinearRegression. To achieve this, we can use GridSearchCV. This lets us specify a model, and a parameter grid, and it will run on every single combination of parameters until it finds the best estimators, and best params. Since RandomForest is a tree-based model, this will be especially good, but will take a really long time.



```
# Print results
print(rf_rmse)
print(best_rf)
```

✓ 49m 45.8s

```
Fitting 3 folds for each of 144 candidates, totalling 432 fits
22.65241381006245
RandomForestRegressor(max_depth=20, n_estimators=200, random_state=1)
```

After 49 minutes and 45 seconds, we see the RMSE with the best parameters.

Prediction

Now that we’ve successfully found our model and its parameters, it is time to do the next part of this project. That is, we give the model the weather data from 01.01.2023 to 01.07.2023 and have it predict traffic volume given the weather data.

To do this, we’ll start by importing pandas, numpy and the model.

We’ll have two variables for the paths to the input data, and output data. We will read the *Florida_2023-01-01_2023-07-01_1688719120.csv* file into a dataframe. Now, we’ll have to repeat some steps from the preparation part, for example converting the two “Dato” and “Tid” columns into one “Datotid” column and also have it be a datetime object.

We’ll then drop the obsolete columns “Dato” and “Tid”.

Then we’ll move the “Datotid” column to make it the leftmost column. Note that this isn’t really necessary, but I still choose to do it for visualization where I might want to look at the dataframe. It is much cleaner and tidier when the first column you see is that. (I have to do this at the end anyways because the project description is asking for the columns in that order).

Now, this weather dataframe, just like the others, have missing data. So let’s replace all “9999.99” values with NaN and fill them all with the median of that column (we can’t drop them here, we need to predict on each timestamp).

Then, we remember the weather dataset had a bunch of columns that weren’t necessary and the model won’t look at them for predictions, in fact it will crash if we have it predicted with them included. So we will define a variable interesting_cols which contains all the columns that the model needs. We’ll also remember that we need to extract the month, dayofweek and hour from “Datotid” and create new columns of those, then drop the “Datotid” column. (The model needs these three to predict).

Then.. we give the model the data and use predict(). We create a new column “Prediksjon” and set it to be the predicted data. Then because the assignment description only asks for the date, time and prediction columns, we have to retain only those. We’ll also have to split the “Datotid” column back into “Dato” and “Tid” as per the description, then reorder them.

We save the dataframe to predictions.csv and voila! It is done. I have looked at the predictions, and they seem realistic as well. So I believe it has worked.

Website

The last part, which I found the most fun, is to create a website (hosted locally) that lets a user fill in a date and time, as well as optional weather data, then get a prediction on their screen of how many cyclists are predicted at that time.

All of the files for this can be found in the .zip file website.zip. You'll see that it contains in the main directory: app.py, model.py and three directories: static, templates and ready_data.

We'll start with the simplest one, model.py.

Model.py is like the name suggests, literally just a copy of the model we've found and trained earlier. It is done this way because it was asked for the website files to be zipped, and all required files needed to run the server needed to be included. I'm not going to explain it any further since I have already done so earlier. The TLDR: app.py calls for the model when receiving requests. Keep in mind, the parameters are tuned so that the server starts faster, the accuracy isn't too different.

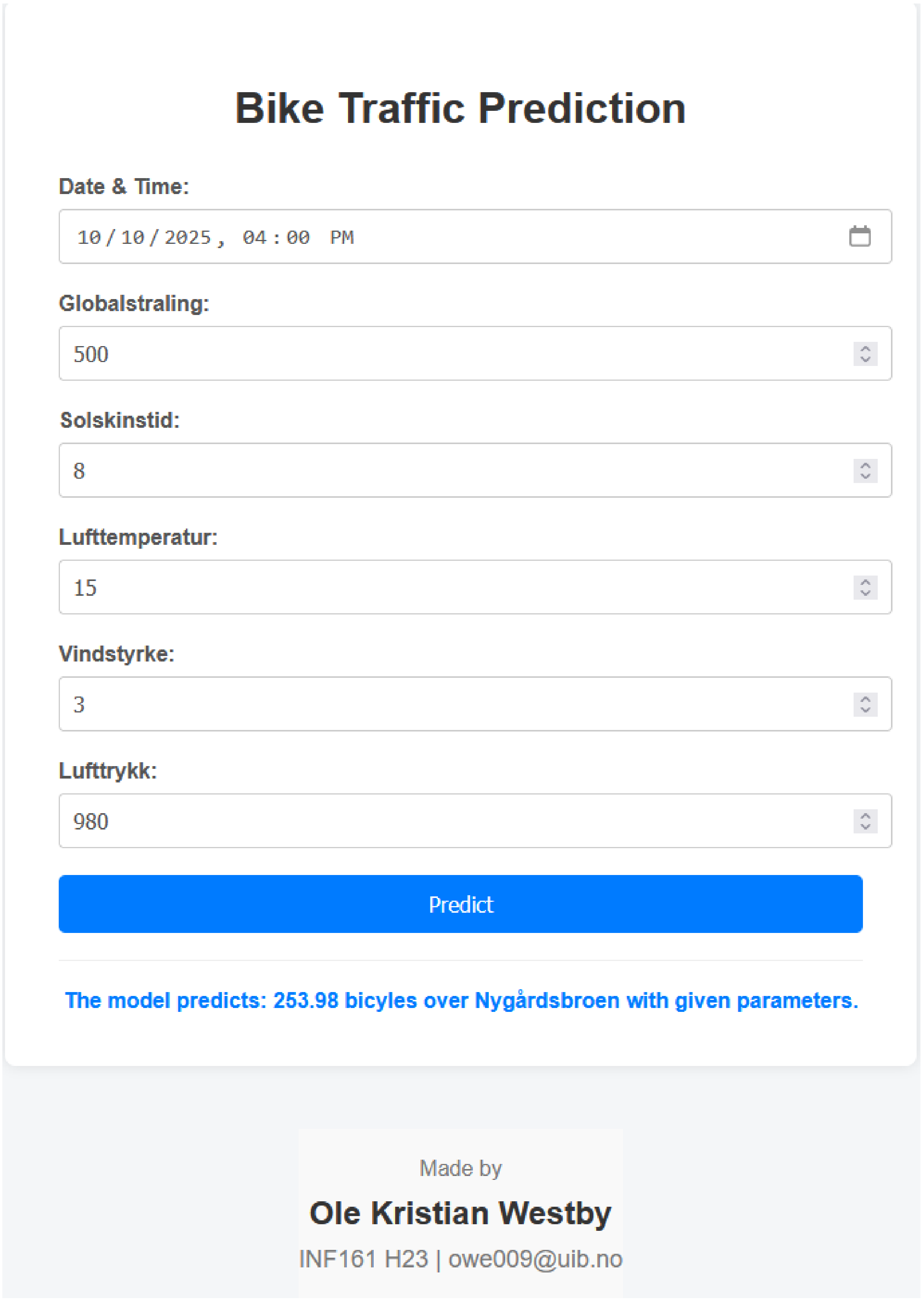
App.py is our flask server. You'll immediately notice an interesting function get_or_default(). This function takes three parameters: field, form, default_value. It basically does this: whenever the user sends in a request for prediction, it will check every single field. If the user has given a value, we will **get** that value *value = form.get(field)* and return the float version of the value if it exists, if not it will return the default_value, in this case: median. Let's say the user is sending in a request but leaves Globalstraling empty. The function will be called and since the field is empty, *else statement*, it will default to the median version instead. If however, the user does decide to input something, it will simply stay as the float version of that. The rest of this file is simple, we save all the input data as input_data, feed it to our model, and round it (the user is probably not interested in 500 decimal points), then return it to the user. I have also made some changes with app.run() to force it to run on localhost:8080, although it should run on all local addresses anyways. Make sure the 8080 port is open on your network!

static/styles.css contains styling. I made this file with an online editor to save some time, figured it was fine because it was only the styling and it is my work regardless.

templates/index.html contains the website. It is pretty self explanatory, but basically we've created a bunch of input-groups. We've also made sure to make the date and time a required form, but other fields are optional.

ready_data/ready_data.csv is just the dataset that the model is trained on, and is necessary for the model to work.

Lastly, you will see a picture of the webpage on the next page.
PS: This was probably my favorite project since I started my degree in 2020, kudos.



Bike Traffic Prediction

Date & Time:

10/10/2025, 04:00 PM

Globalstraling:

500

Solskinstid:

8

Lufttemperatur:

15

Vindstyrke:

3

Lufttrykk:

980

The model predicts: 253.98 bicyles over Nygårdsbroen with given parameters.

Made by

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