Mini-project #2

Practice Session 19

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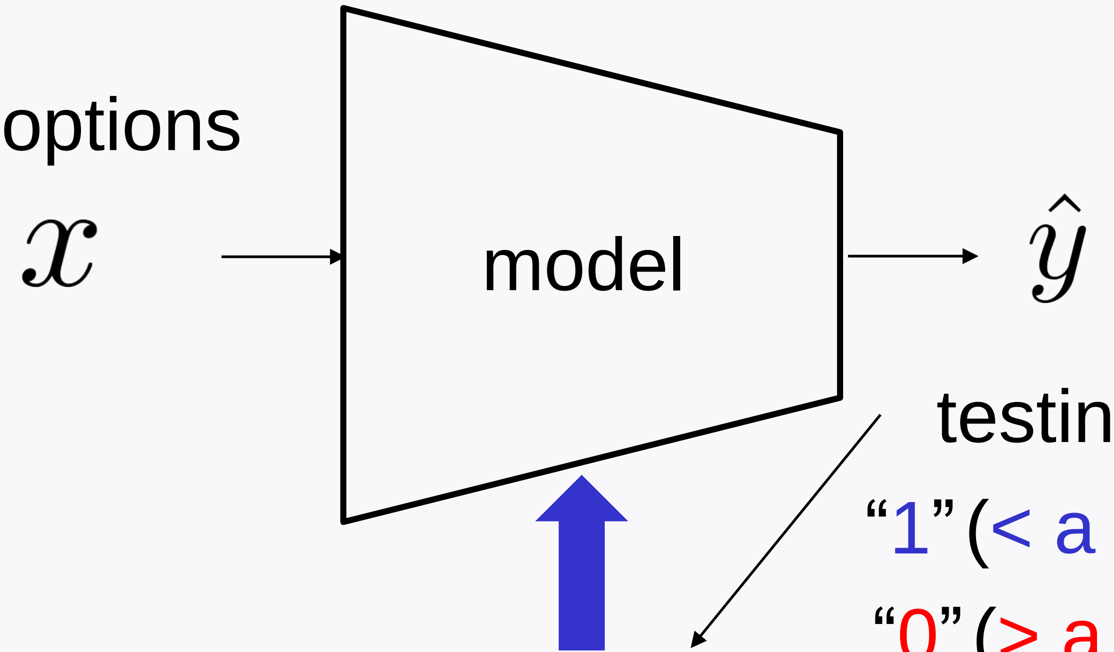
Recap: Mini-project #1

Test-time prediction



testing time:

"1" (< a certain thresh.)

"0" (> a certain thresh.)

$$\{(x^{(i)}, y^{(i)})\}_{i=1}^{m}$$

Mercedes-Benz dataset

Recap: Data organization

Data load:

```
import pandas as pd
data=pd.read_csv("mercedes_test.csv")
```

Pre-processing:

```
# choose categorical data columns
cf = data.select_dtypes(include=['object']).columns
data[cf] = data[cf].astype('category')
data = pd.get_dummies(data)                   # one hot encoding
X_df, y_df = data.drop(['ID', 'y'], axis=1), data['y']
y_df = (y_df<numpy.median(y_df)).astype(float)
```

Recap: Data organization

Transformation to numpy data:

```
X,y = X_df.values, y_df.values
```

Train/test split:

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test =\
train_test_split(X,y,test_size=0.1, stratify=y)
```

Recap: LS hyperparameter search

```
from joblib import dump
from sklearn.model_selection import RandomizedSearchCV
alpha_list = [0.001,0.01,0.1,1,10]
model = RidgeClassifier()
grid = {'alpha':alpha_list)
cv = RandomizedSearchCV(model, grid, n_iter=5, cv=5)
cv.fit(X_train, y_train)
cv.cv_results_  #logs
cv.best_params_ # best alpha
best_model = cv.best_estimator_
dump(best_model,'best_model.joblib')
```

Recap: LR hyperparameter search

```
from joblib import dump
from sklearn.model_selection import RandomizedSearchCV
alpha_list = [0.001,0.01,0.1,1,10]
model = LogisticRegression(solver='liblinear,max_iter=10000)
grid = {'alpha':alpha_list)
cv = RandomizedSearchCV(model, grid, n_iter=5, cv=5)
cv.fit(X_train, y_train)
cv.cv_results_  #logs
cv.best_params_ # best alpha
best_model = cv.best_estimator_
dump(best_model,'best_model.joblib')
```

Recap: Regularization & He's initialization

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.regularizers import l2

model_NN = Sequential()
model_NN.add(Dense(128, activation='relu',
                    kernel_regularizer=l2(0.01),
                    bias_regularizer=l2(0.01),
                    kernel_initializer='he_normal'))

model_NN.add(Dense(1, activation='sigmoid',
                    kernel_regularizer=l2(0.01),
                    bias_regularizer=l2(0.01)))

model_NN.compile(optimizer='adam',
                 loss='binary_crossentropy',
                 metrics=['acc'])
```

Recap: Early stopping & learning rate decay

```
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.callbacks import LearningRateScheduler

es_callback = EarlyStopping(monitor='val_acc',patience=20)

 # define scheduling rule
def scheduler(epoch, lr):
    if epoch in [10,20,30]: lr=lr*0.1
    return lr

lrs_callback = LearningRateScheduler(scheduler)

# training w/ callbacks
model_NN.fit(X_train, y_train,
         validation_split=1/9, epochs=100,
         callbacks=[es_callback,lrs_callback])
```

Recap: DNN hyperparameter search

```
from sklearn.model_selection import RandomizedSearchCV
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier

def build_model(lambda_):
    model = Sequential()
    model.add(Dense(128, activation='relu',
              kernel_regulerizer=l2(lambda_),bias_regulerizer=l2(lambda_))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(optimizer='adam',loss='binary_crossentropy',
    metrics=['acc'])
    return model
model = KerasClassifier(build_model)
grid = dict(lambda_=[1e-3, 1e-2, 1e-1, 1, 10])
cv = RandomizedSearchCV(model, grid, n_iter=5, cv=5)
```

Recap: Logging and saving

```
cv.fit(X_train,y_train,epochs=10)
cv.cv_results_  #logs
cv.best_params_ # best alpha
best_model_DNN = cv.best_estimator_
```

```
import pandas as pd
df = pd.DataFrame.from_dict(cv.cv_results_, orient='columns')
df.to_csv('logs_DNN.csv')
```

logging

```
best_model_DNN.model.save('best_model_DNN')
```

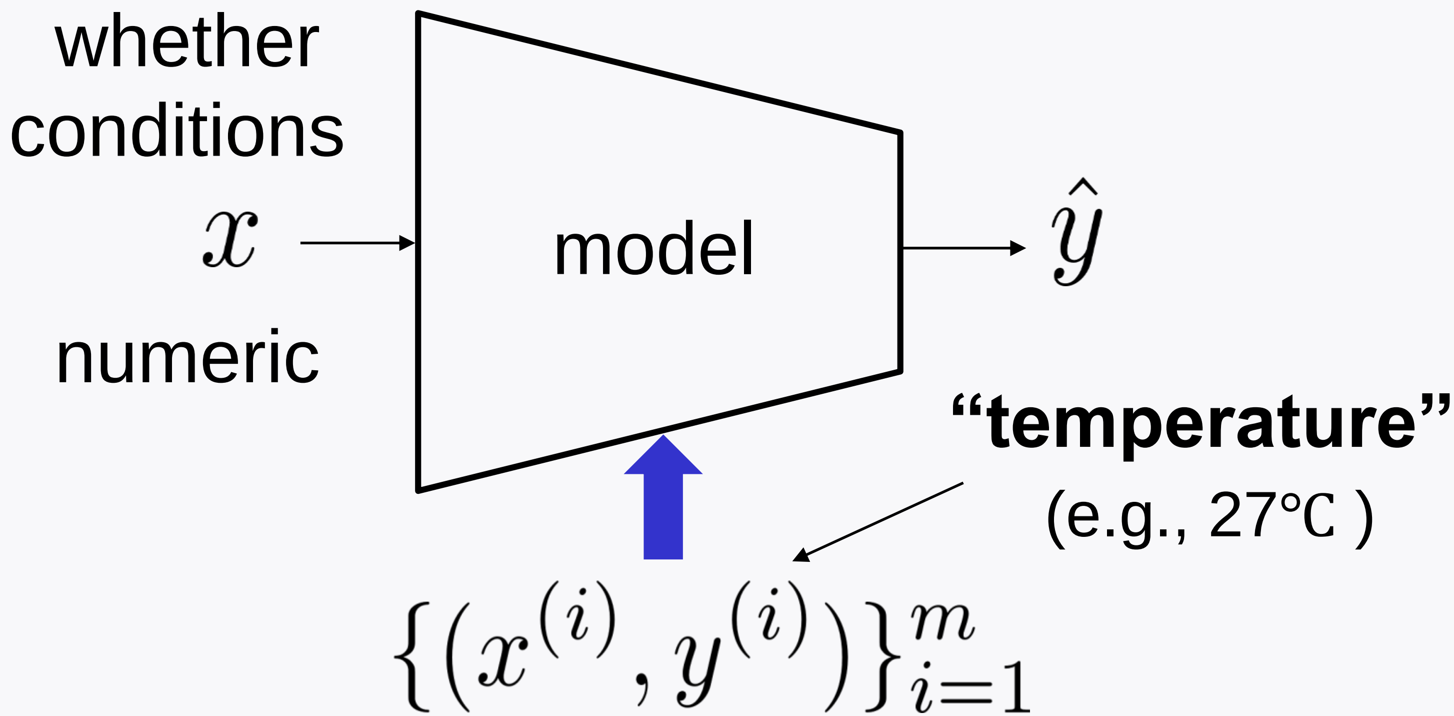
saving the model

Today's contents

Mini-project #2:

Weather prediction using Jena climate dataset

Task: Weather prediction



Jena climate dataset

Data:

weather features $\in \mathbf{R}^{14}$

Example: pressure, humidity, wind speed, …

Label: celcius temperature $\in \mathbf{R}$

Collected in Jena from 2009 to 2016 and measured every 10 minutes:

420,551 samples

Download Jena climate dataset

The dataset is prepared by Max Planck Institute for Biogeochemistry.

Download ‘jena_climate_2009_2016.csv’ from:

https://www.kaggle.com/datasets/mnassrib/jena-climate

Load Jena climate dataset

```python
import pandas as pd
data = pd.read_csv('jena_climate_2009_2016.csv')
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 420551 entries, 0 to 420550
Data columns (total 15 columns):
 #   Column           Non-Null Count   Dtype
---  ------           --------------   -----
 0   Date Time        420551 non-null  object
 1   p (mbar)         420551 non-null  float64
 2   T (degC)         420551 non-null  float64
 3   Tpot (K)         420551 non-null  float64
 4   Tdew (degC)      420551 non-null  float64
 5   rh (%)           420551 non-null  float64
 6   VPmax (mbar)     420551 non-null  float64
 7   VPact (mbar)     420551 non-null  float64
 8   VPdef (mbar)     420551 non-null  float64
 9   sh (g/kg)        420551 non-null  float64
 10  H2OC (mmol/mol)  420551 non-null  float64
 11  rho (g/m**3)     420551 non-null  float64
 12  wv (m/s)         420551 non-null  float64
 13  max. wv (m/s)    420551 non-null  float64
 14  wd (deg)         420551 non-null  float64
dtypes: float64(14), object(1)
memory usage: 48.1+ MB
```

pressure

temperature in celsius

relative humidity

vapor pressure

water vapor concentration

airtight

wind speed

Look at first few examples

```
# Look up the first five examples
data.head(5)
```

	Date Time	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	rho (g/m**3)	wv (m/s)	max. wv (m/s)	wd (deg)
0	01.01.2009 00:10:00	996.52	-8.02	265.40	-8.90	93.3	3.33	3.11	0.22	1.94	3.12	1307.75	1.03	1.75	152.3
1	01.01.2009 00:20:00	996.57	-8.41	265.01	-9.28	93.4	3.23	3.02	0.21	1.89	3.03	1309.80	0.72	1.50	136.1
2	01.01.2009 00:30:00	996.53	-8.51	264.91	-9.31	93.9	3.21	3.01	0.20	1.88	3.02	1310.24	0.19	0.63	171.6
3	01.01.2009 00:40:00	996.51	-8.31	265.12	-9.07	94.2	3.26	3.07	0.19	1.92	3.08	1309.19	0.34	0.50	198.0
4	01.01.2009 00:50:00	996.51	-8.27	265.15	-9.04	94.1	3.27	3.08	0.19	1.92	3.09	1309.00	0.32	0.63	214.3

Data visualization

```
T_data = data['T (degC)']
date_time = pd.to_datetime(data['Date Time'],format='%d.%m.%Y %H:%M:%S')
```

```
print(T_data)
print(date_time)
```

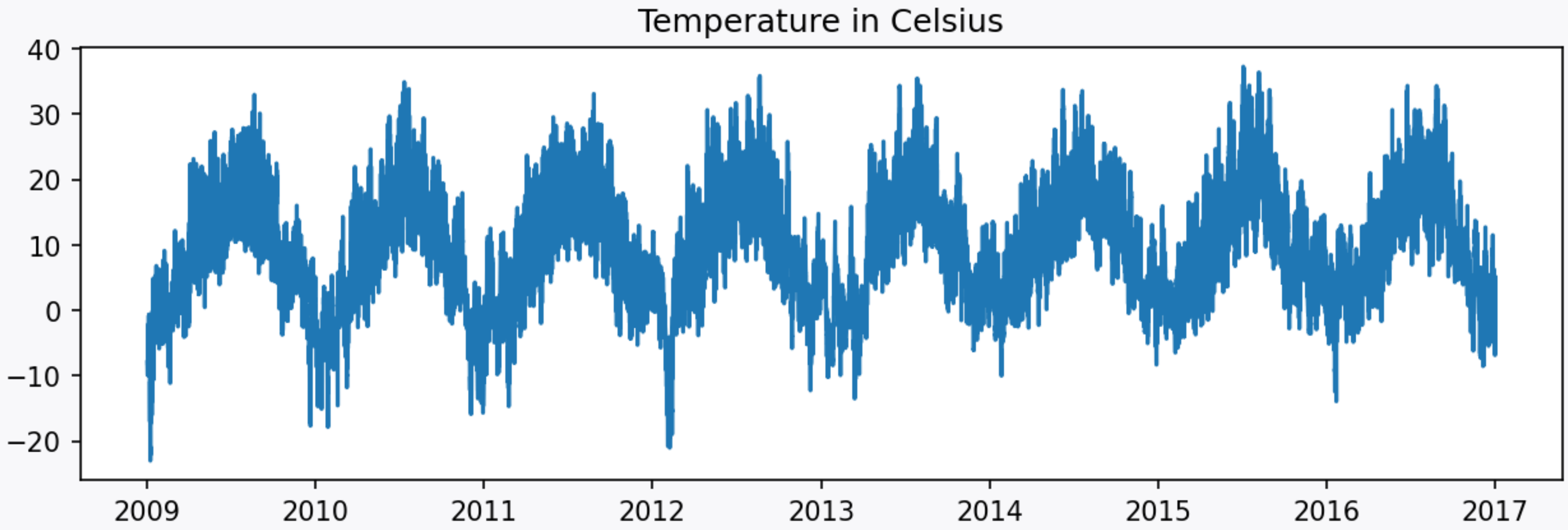
```
0         -8.02
1         -8.41
2         -8.51
3         -8.31
4         -8.27
           ...
420546    -4.05
420547    -3.35
420548    -3.16
420549    -4.23
420550    -4.82
```

```
0         2009-01-01 00:10:00
1         2009-01-01 00:20:00
2         2009-01-01 00:30:00
3         2009-01-01 00:40:00
4         2009-01-01 00:50:00
                  ...
420546    2016-12-31 23:20:00
420547    2016-12-31 23:30:00
420548    2016-12-31 23:40:00
420549    2016-12-31 23:50:00
420550    2017-01-01 00:00:00
```

Data visualization

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,3), dpi=150)
plt.plot(date_time, T_data)
plt.title('Temperature in Celsius')
plt.show()
```



Correlation analysis

Pearson correlation

$$-1 \leq \rho_{ij} := \frac{\mathsf{cov}(x_i, x_j)}{\sqrt{\mathsf{var}(x_i)\mathsf{var}(x_j)}} \leq 1$$

Correlation analysis

```
data.corr()
```

	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	rho (g/m**3)	wv (m/s)	max. wv (m/s)	wd (deg)
p (mbar)	1.000000	-0.045375	-0.124718	-0.066755	-0.018352	-0.031546	-0.054370	-0.003401	-0.069762	-0.069804	0.307640	-0.005701	-0.007760	-0.063258
T (degC)	-0.045375	1.000000	0.996827	0.895708	-0.572416	0.951113	0.867673	0.761744	0.866755	0.867177	-0.963410	-0.004689	-0.002871	0.038732
Tpot (K)	-0.124718	0.996827	1.000000	0.894911	-0.567127	0.947293	0.866205	0.756962	0.866533	0.866955	-0.981345	-0.004195	-0.002224	0.043599
Tdew (degC)	-0.066755	0.895708	0.894911	1.000000	-0.156615	0.799271	0.968344	0.435752	0.967599	0.968044	-0.885232	-0.008718	-0.009091	0.049877
rh (%)	-0.018352	-0.572416	-0.567127	-0.156615	1.000000	-0.615842	-0.151494	-0.843835	-0.150841	-0.150969	0.514282	-0.005020	-0.009921	-0.015912
VPmax (mbar)	-0.031546	0.951113	0.947293	0.799271	-0.615842	1.000000	0.824865	0.875588	0.824460	0.824493	-0.901536	-0.004018	-0.002213	-0.009583
VPact (mbar)	-0.054370	0.867673	0.866205	0.968344	-0.151494	0.824865	1.000000	0.449154	0.999851	0.999856	-0.850241	-0.009600	-0.010316	0.018418
VPdef (mbar)	-0.003401	0.761744	0.756962	0.435752	-0.843835	0.875588	0.449154	1.000000	0.448641	0.448689	-0.698290	0.001852	0.005317	-0.030881
sh (g/kg)	-0.069762	0.866755	0.866533	0.967599	-0.150841	0.824460	0.999851	0.448641	1.000000	0.999997	-0.853325	-0.009479	-0.010163	0.019376
H2OC (mmol/mol)	-0.069804	0.867177	0.866955	0.968044	-0.150969	0.824493	0.999856	0.448689	0.999997	1.000000	-0.853769	-0.009477	-0.010158	0.019607
rho (g/m**3)	0.307640	-0.963410	-0.981345	-0.885232	0.514282	-0.901536	-0.850241	-0.698290	-0.853325	-0.853769	1.000000	0.003240	0.001086	-0.058072
wv (m/s)	-0.005701	-0.004689	-0.004195	-0.008718	-0.005020	-0.004018	-0.009600	0.001852	-0.009479	-0.009477	0.003240	1.000000	0.948477	-0.015322
max. wv (m/s)	-0.007760	-0.002871	-0.002224	-0.009091	-0.009921	-0.002213	-0.010316	0.005317	-0.010163	-0.010158	0.001086	0.948477	1.000000	-0.014471
wd (deg)	-0.063258	0.038732	0.043599	0.049877	-0.015912	-0.009583	0.018418	-0.030881	0.019376	0.019607	-0.058072	-0.015322	-0.014471	1.000000

Data statistics

```
data.describe()
```

1st quartile (Q1) 2nd quartile 3rd quartile

	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)
count	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000
mean	989.212776	9.450147	283.492743	4.955854	76.008259	13.576251	9.533756
std	8.358481	8.423365	8.504471	6.730674	16.476175	7.739020	4.184164
min	913.600000	-23.010000	250.600000	-25.010000	12.950000	0.950000	0.790000
25%	984.200000	3.360000	277.430000	0.240000	65.210000	7.780000	6.210000
50%	989.580000	9.420000	283.470000	5.220000	79.300000	11.820000	8.860000
75%	994.720000	15.470000	289.530000	10.070000	89.400000	17.600000	12.350000
max	1015.350000	37.280000	311.340000	23.110000	100.000000	63.770000	28.320000

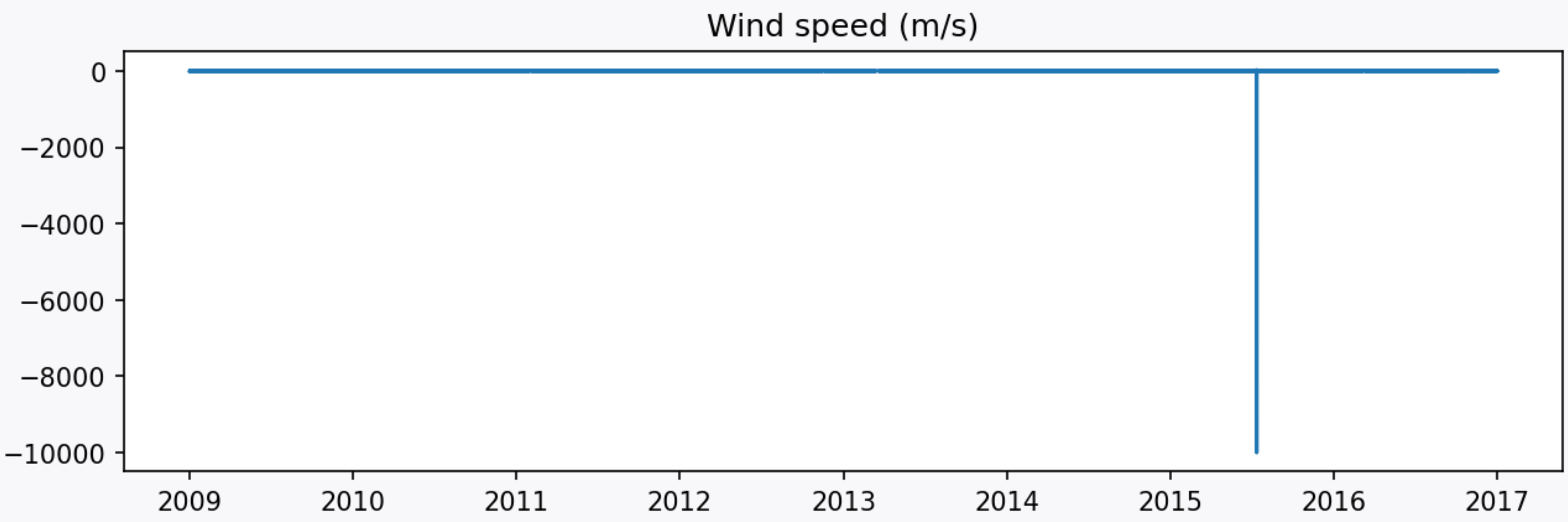
	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	rho (g/m**3)	wv (m/s)	max. wv (m/s)	wd (deg)
count	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000
mean	4.042412	6.022408	9.640223	1216.062748	1.702224	3.056555	174.743738
std	4.896851	2.656139	4.235395	39.975208	65.446714	69.016932	86.681693
min	0.000000	0.500000	0.800000	1059.450000	-9999.000000	-9999.000000	0.000000
25%	0.870000	3.920000	6.290000	1187.490000	0.990000	1.760000	124.900000
50%	2.190000	5.590000	8.960000	1213.790000	1.760000	2.960000	198.100000
75%	5.300000	7.800000	12.490000	1242.770000	2.860000	4.740000	234.100000
max	46.010000	18.130000	28.820000	1393.540000	28.490000	23.500000	360.000000

missing entries

Missing entries in wind speed

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,3), dpi=150)
wv = data['wv (m/s)']
plt.plot(date_time, wv)
plt.title('Wind speed (m/s)')
plt.show()
```



Preprocessing

Fill up the missing entries with the mean:

```
wv = data['wv (m/s)']
wv_missing_idx = (wv == -9999.00)
wv_mean = wv[~wv_missing_idx].mean()
wv[wv_missing_idx] = wv_mean
```

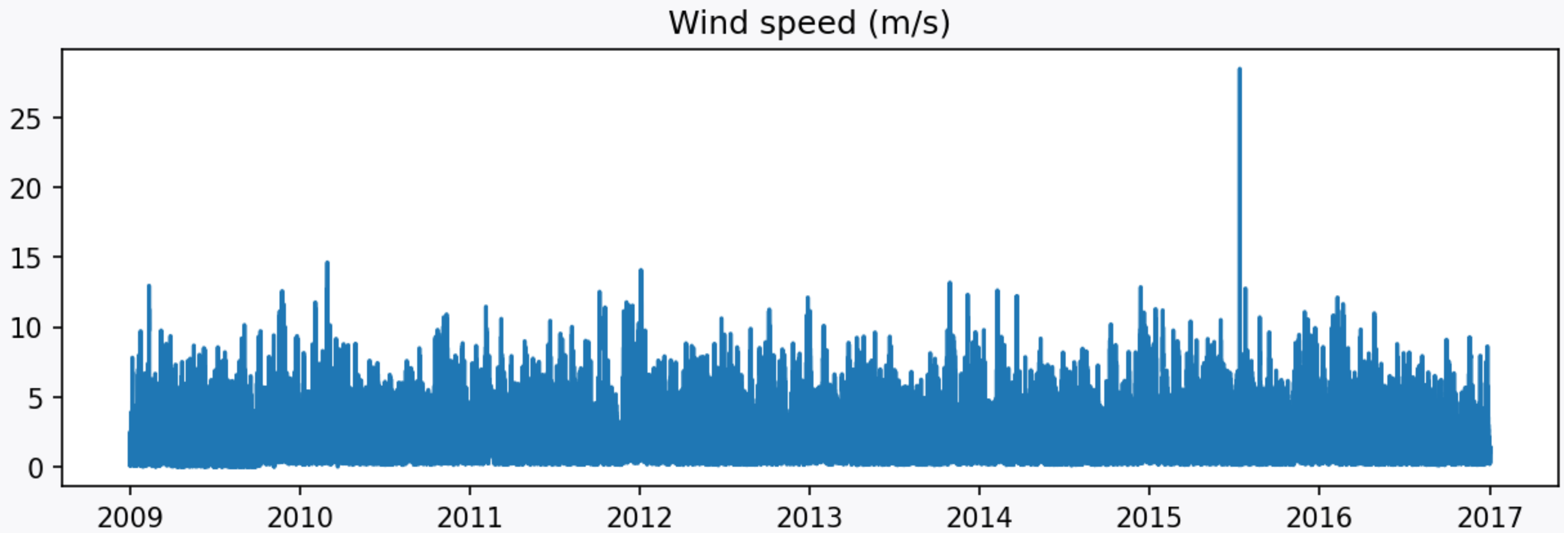
returns corresponding indices

```
max_wv = data['max. wv (m/s)']
missing_idx = (max_wv == -9999.00)
max_wv_mean = max_wv[~missing_idx].mean()
max_wv[missing_idx] = max_wv_mean
```

The processed wind speed

```
import matplotlib.pyplot as plt

plt.figure(figsize=(10,3), dpi=150)
plt.plot(date_time, wv)
plt.title('Wind speed (m/s)')
plt.show()
```



Check if missing entries are filled up

```
data.describe()
```

	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)
count	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000
mean	989.212776	9.450147	283.492743	4.955854	76.008259	13.576251	9.533756
std	8.358481	8.423365	8.504471	6.730674	16.476175	7.739020	4.184164
min	913.600000	-23.010000	250.600000	-25.010000	12.950000	0.950000	0.790000
25%	984.200000	3.360000	277.430000	0.240000	65.210000	7.780000	6.210000
50%	989.580000	9.420000	283.470000	5.220000	79.300000	11.820000	8.860000
75%	994.720000	15.470000	289.530000	10.070000	89.400000	17.600000	12.350000
max	1015.350000	37.280000	311.340000	23.110000	100.000000	63.770000	28.320000

	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	rho (g/m**3)	wv (m/s)	max. wv (m/s)	wd (deg)
count	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000	420551.000000
mean	4.042412	6.022408	9.640223	1216.062748	2.130282	3.532242	174.743738
std	4.896851	2.656139	4.235395	39.975208	1.542271	2.340355	86.681693
min	0.000000	0.500000	0.800000	1059.450000	0.000000	0.000000	0.000000
25%	0.870000	3.920000	6.290000	1187.490000	0.990000	1.760000	124.900000
50%	2.190000	5.590000	8.960000	1213.790000	1.760000	2.960000	198.100000
75%	5.300000	7.800000	12.490000	1242.770000	2.860000	4.740000	234.100000
max	46.010000	18.130000	28.820000	1393.540000	28.490000	23.500000	360.000000

Remove ‘date_time’ column

```
data.pop('Date Time')
data
```

	p (mbar)	T (degC)	Tpot (K)	Tdew (degC)	rh (%)	VPmax (mbar)	VPact (mbar)	VPdef (mbar)	sh (g/kg)	H2OC (mmol/mol)	rho (g/m**3)	wv (m/s)	max. wv (m/s)	wd (deg)
0	996.52	-8.02	265.40	-8.90	93.30	3.33	3.11	0.22	1.94	3.12	1307.75	1.03	1.75	152.3
1	996.57	-8.41	265.01	-9.28	93.40	3.23	3.02	0.21	1.89	3.03	1309.80	0.72	1.50	136.1
2	996.53	-8.51	264.91	-9.31	93.90	3.21	3.01	0.20	1.88	3.02	1310.24	0.19	0.63	171.6
3	996.51	-8.31	265.12	-9.07	94.20	3.26	3.07	0.19	1.92	3.08	1309.19	0.34	0.50	198.0
4	996.51	-8.27	265.15	-9.04	94.10	3.27	3.08	0.19	1.92	3.09	1309.00	0.32	0.63	214.3
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
420546	1000.07	-4.05	269.10	-8.13	73.10	4.52	3.30	1.22	2.06	3.30	1292.98	0.67	1.52	240.0
420547	999.93	-3.35	269.81	-8.06	69.71	4.77	3.32	1.44	2.07	3.32	1289.44	1.14	1.92	234.3
420548	999.82	-3.16	270.01	-8.21	67.91	4.84	3.28	1.55	2.05	3.28	1288.39	1.08	2.00	215.2
420549	999.81	-4.23	268.94	-8.53	71.80	4.46	3.20	1.26	1.99	3.20	1293.56	1.49	2.16	225.8
420550	999.82	-4.82	268.36	-8.42	75.70	4.27	3.23	1.04	2.01	3.23	1296.38	1.23	1.96	184.9

Look ahead

Will preprocess data further.