Лабораторная работа №2, Ишков Денис, ИУ5-24М, 2021г.

Краткое описание данных: предлагается поработать над предсказанием погоды в Австралии, будет ли завтра дождь или нет.

Основные признаки:

- Date - Дата наблюдений
- Location - Название локации, в которой расположена метеорологическая станция
- MinTemp - Минимальная температура в градусах цельсия
- MaxTemp - Максимальная температура в градусах цельсия
- Rainfall - Количество осадков, зафиксированных за день в мм
- Evaporation - Так называемое "pan evaporation" класса А (мм) за 24 часа до 9 утра
- Sunshine - Число солнечных часов за день
- WindGustDir - направление самого сильного порыва ветра за последние 24 часа
- WindGustSpeed - скорость (км / ч) самого сильного порыва ветра за последние 24 часа
- WindDir9am - направление ветра в 9 утра

In [ ]:

```
!pip install wldhx.yadisk-direct
!curl -L $(yadisk-direct https://disk.yandex.ru/i/2bePAZi16dhUAg) -o weatherAUS.csv
```

```
Collecting wldhx.yadisk-direct
  Downloading https://files.pythonhosted.org/packages/20/a9/e14d8abec847b8
39d95d131dede68aa03c0bd3ca6485cca406550dfa2a3a/wldhx.yadisk_direct-0.0.6-p
y3-none-any.whl
Requirement already satisfied: requests in /usr/local/lib/python3.7/dist-p
ackages (from wldhx.yadisk-direct) (2.23.0)
Requirement already satisfied: idna<3,>=2.5 in /usr/local/lib/python3.7/di
st-packages (from requests->wldhx.yadisk-direct) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in /usr/local/lib/python
3.7/dist-packages (from requests->wldhx.yadisk-direct) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python
3.7/dist-packages (from requests->wldhx.yadisk-direct) (2020.12.5)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/usr/local/lib/python3.7/dist-packages (from requests->wldhx.yadisk-direc
t) (1.24.3)
Installing collected packages: wldhx.yadisk-direct
Successfully installed wldhx.yadisk-direct-0.0.6
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Cu
rrent
                                 Dload  Upload   Total   Spent    Left  Sp
eed
  0     0    0     0    0     0      0      0 --:--:--  0:00:01 --:--:--
0
100 13.5M  100 13.5M    0     0  3118k      0  0:00:04  0:00:04 --:--:-- 4
897k
```

In [ ]:

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
```

In [ ]:

```
df = pd.read_csv('weatherAUS.csv')
```

In [ ]:

```
df.columns
```

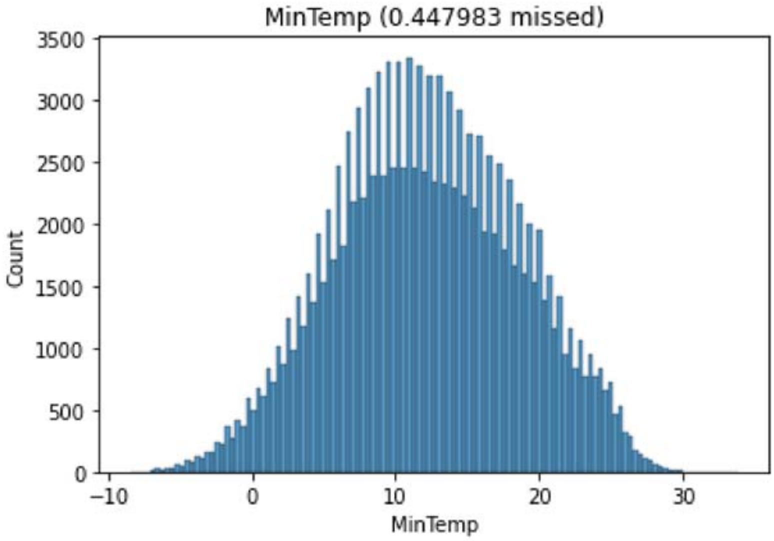
Out[ ]:

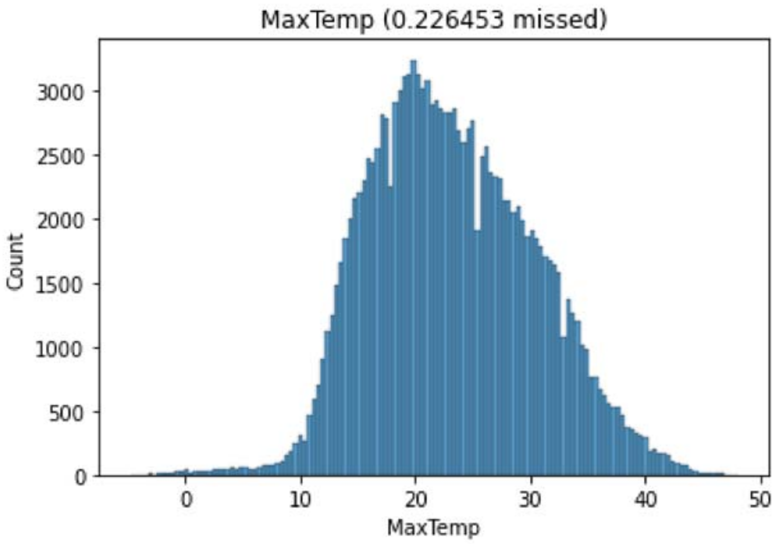
```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporatio
n',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3
pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

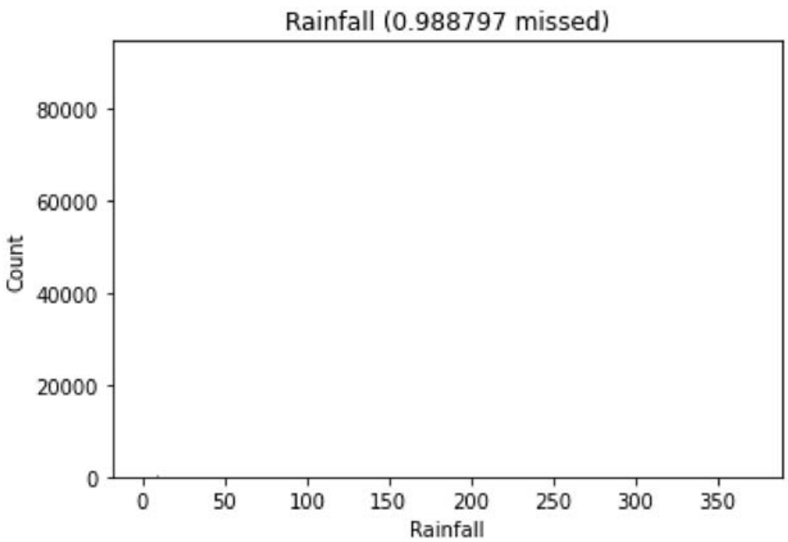
Визуализация признаков

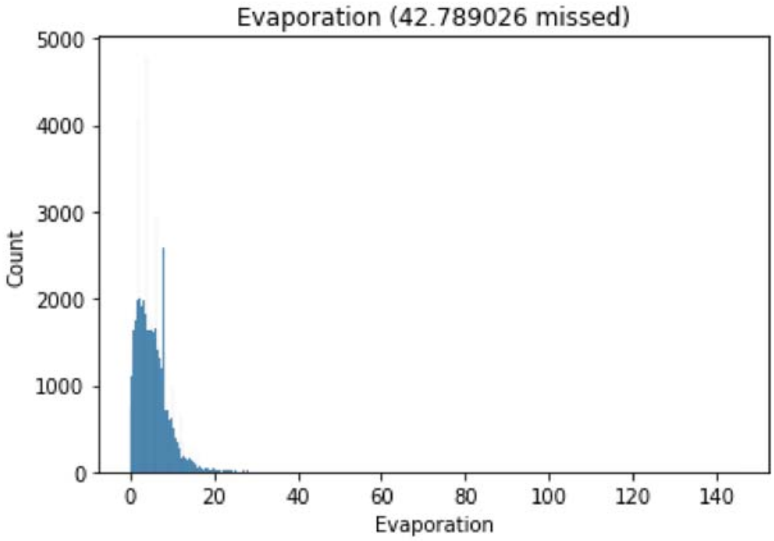
In [ ]:

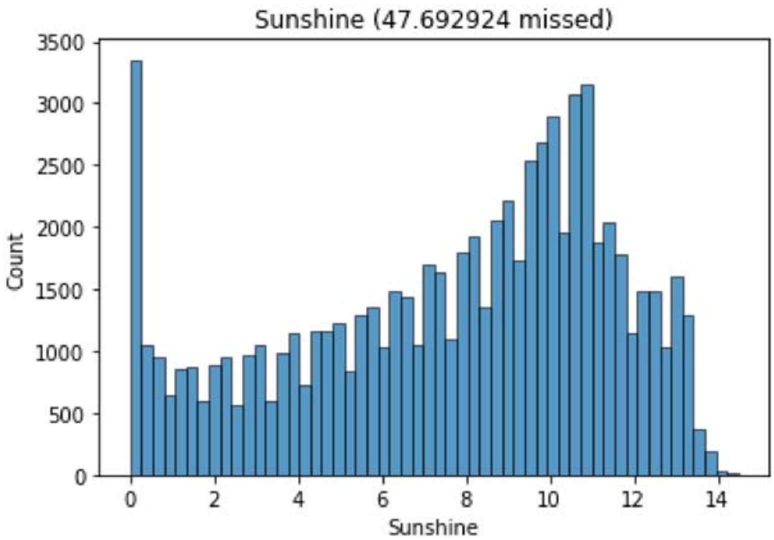
```
for col in df.columns[2:]:
  if df[col].dtype != 'float64':
    if df[col].dtype == 'object':
      df[col].value_counts().plot(kind='bar')
    else:
      continue
  else:
    sns.histplot(df[col])
  plt.title(col+' (%f missed)'%(df[col].isna().mean()*100))
  plt.show()
```

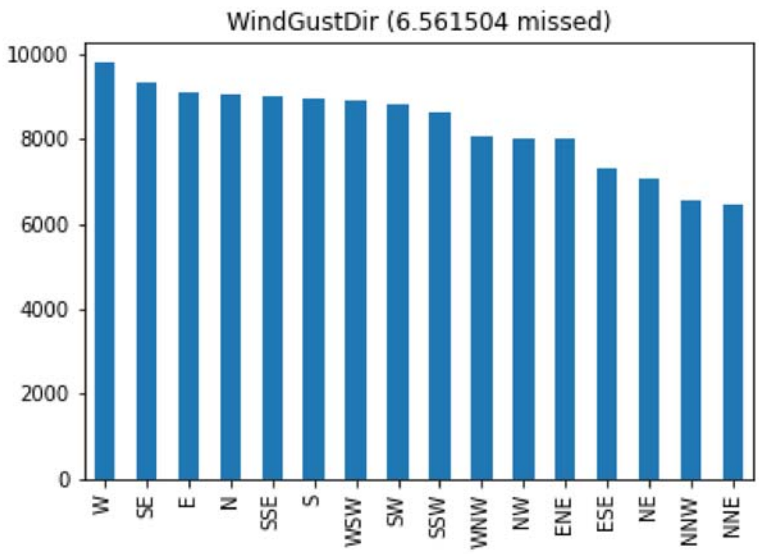

MinTemp (0.447983 missed)
Count
MinTemp
0
500
1000
1500
2000
2500
3000
3500
−10
0
10
20
30

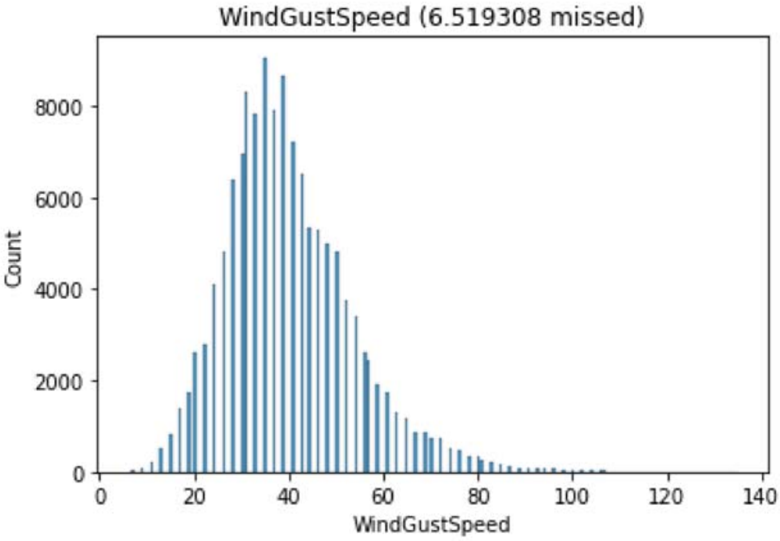

MaxTemp (0.226453 missed)
Count
MaxTemp
0
500
1000
1500
2000
2500
3000
0
10
20
30
40
50

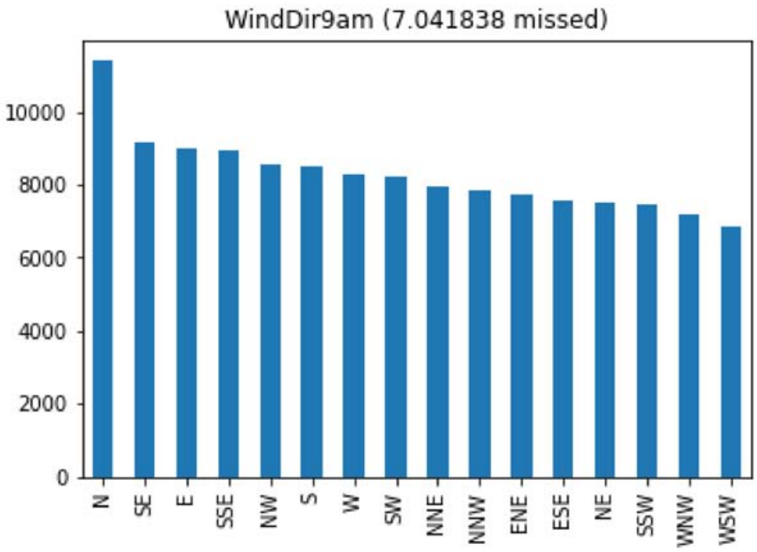

Rainfall (0.988797 missed)
Count
Rainfall
0
20000
40000
60000
80000
0
50
100
150
200
250
300
350

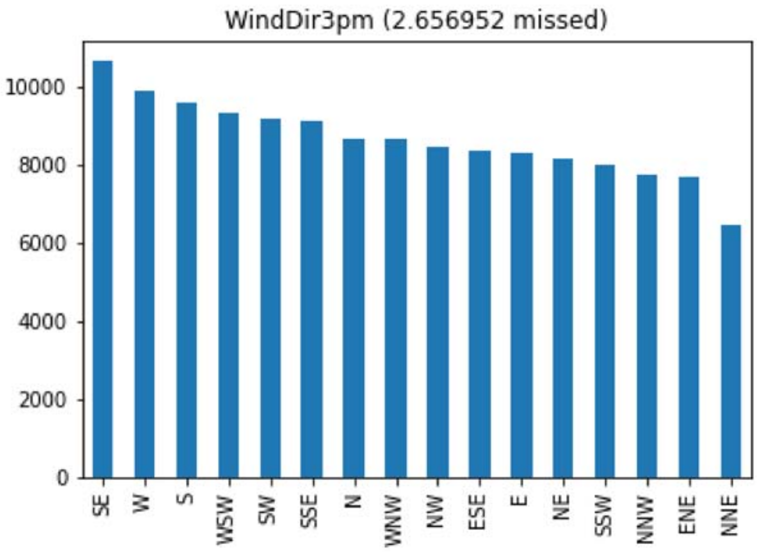

Evaporation (42.789026 missed)
Count
Evaporation
0
1000
2000
3000
4000
5000
0
20
40
60
80
100
120
140

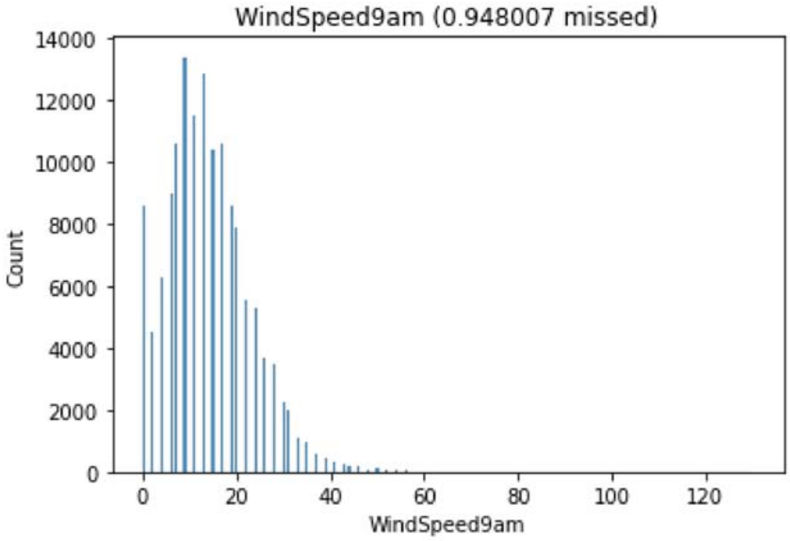

Sunshine (47.692924 missed)
Count
Sunshine
0
500
1000
1500
2000
2500
3000
3500
0
2
4
6
8
10
12
14

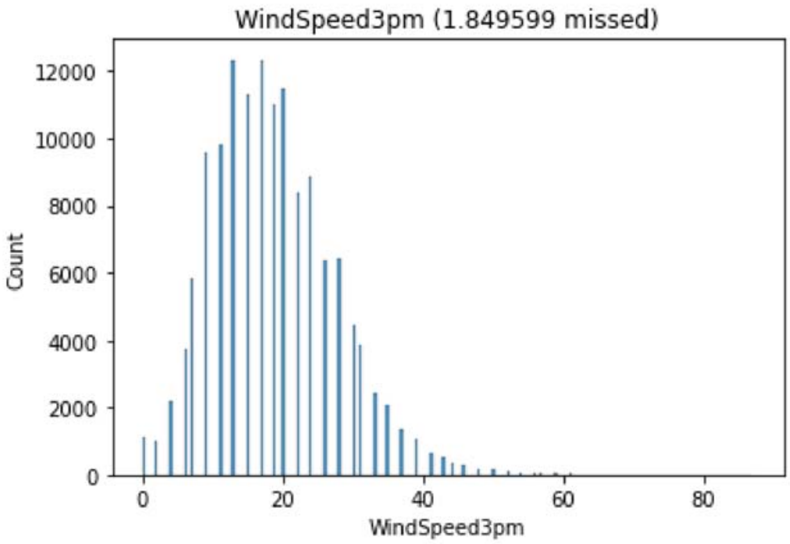

WindGustDir (6.561504 missed)
0
2000
4000
6000
8000
10000
W
SE
E
N
SSE
S
WSW
SW
SSW
WNW
NW
ENE
ESE
NE
NNW
NNE

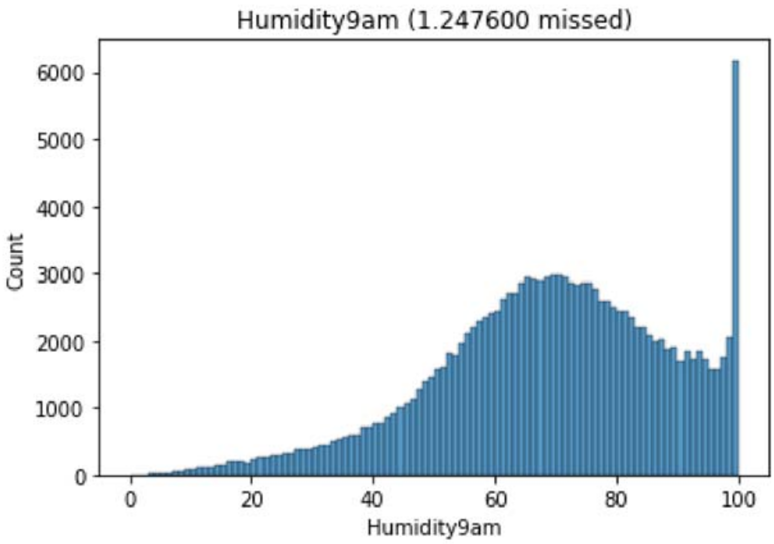

WindGustSpeed (6.519308 missed)
Count
0
2000
4000
6000
8000
0
20
40
60
80
100
120
140
WindGustSpeed

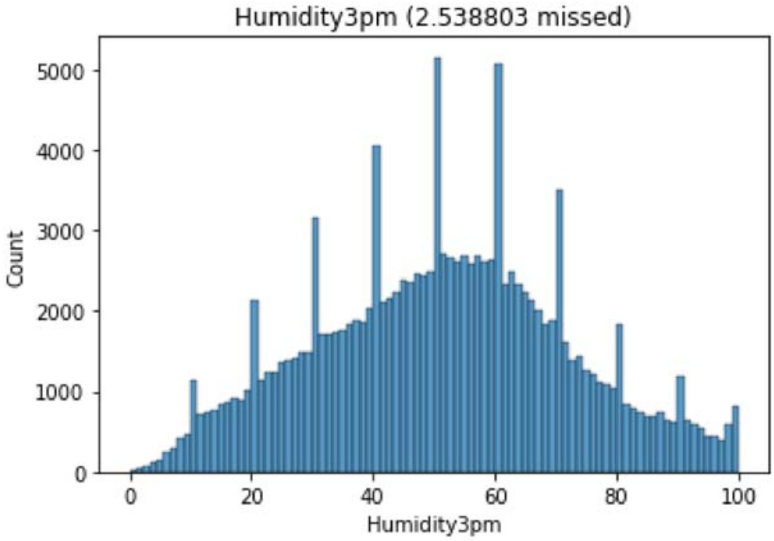

WindDir9am (7.041838 missed)
0
2000
4000
6000
8000
10000
N
SE
E
SSE
NW
S
W
SW
NNE
NNW
ENE
ESE
NE
SSW
WNW
WSW

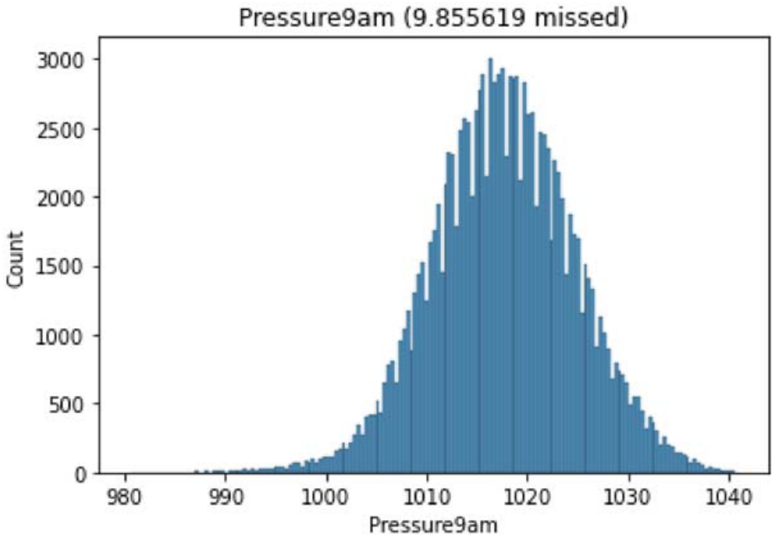

WindDir3pm (2.656952 missed)
0
2000
4000
6000
8000
10000
SE
W
S
WSW
SW
SSE
N
WNW
NW
ESE
E
NE
SSW
NNW
ENE
NNE

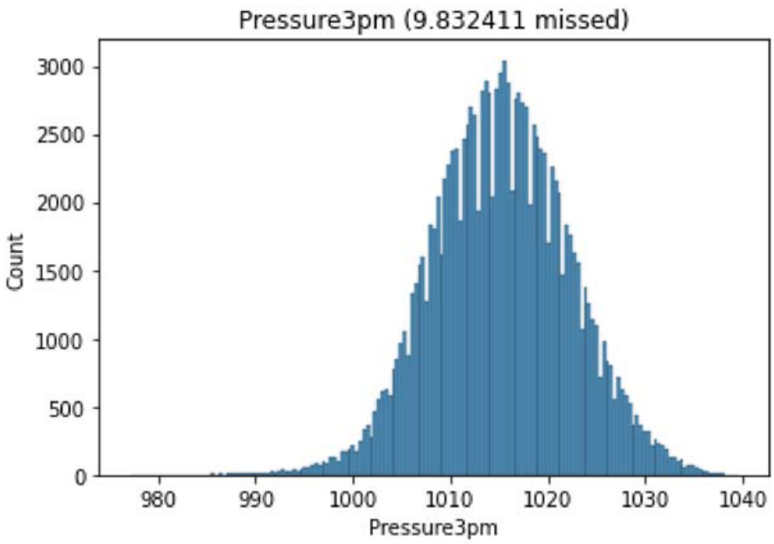

WindSpeed9am (0.948007 missed)
Count
WindSpeed9am
0
2000
4000
6000
8000
10000
12000
14000
0
20
40
60
80
100
120

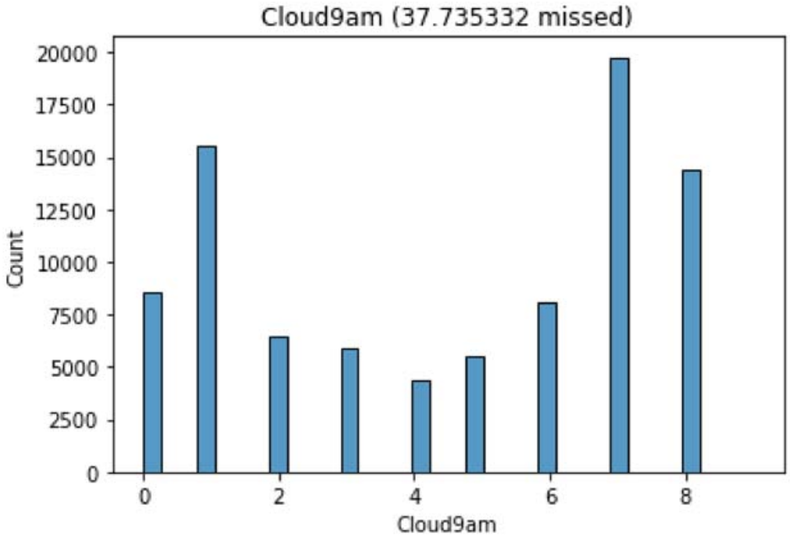

WindSpeed3pm (1.849599 missed)
Count
WindSpeed3pm
0
2000
4000
6000
8000
10000
12000
0
20
40
60
80

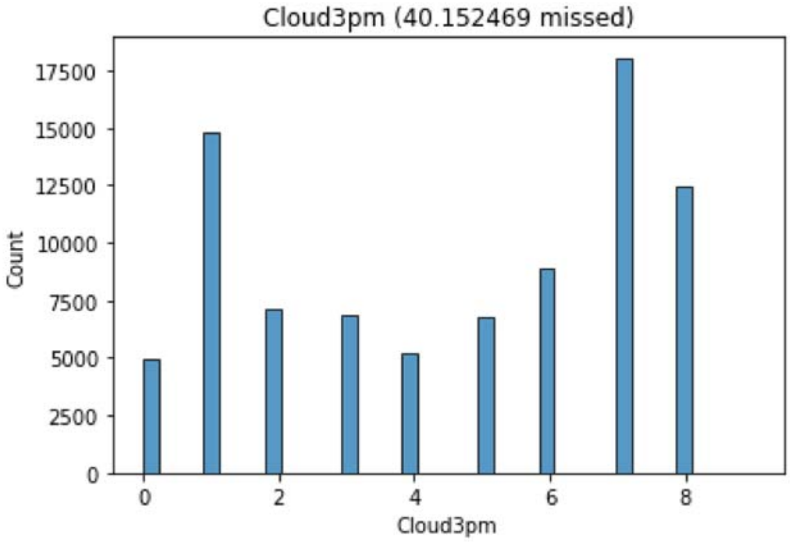

Humidity9am (1.247600 missed)
Count
Humidity9am
0
1000
2000
3000
4000
5000
6000
0
20
40
60
80
100

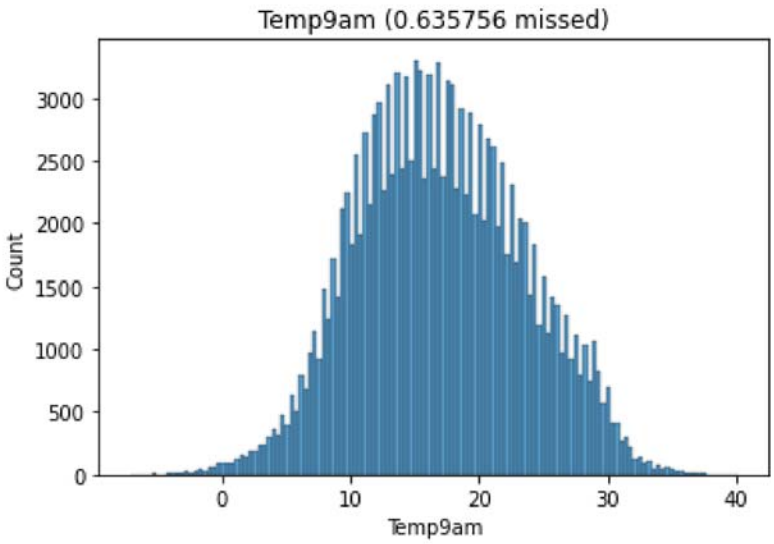

Humidity3pm (2.538803 missed)
Count
Humidity3pm

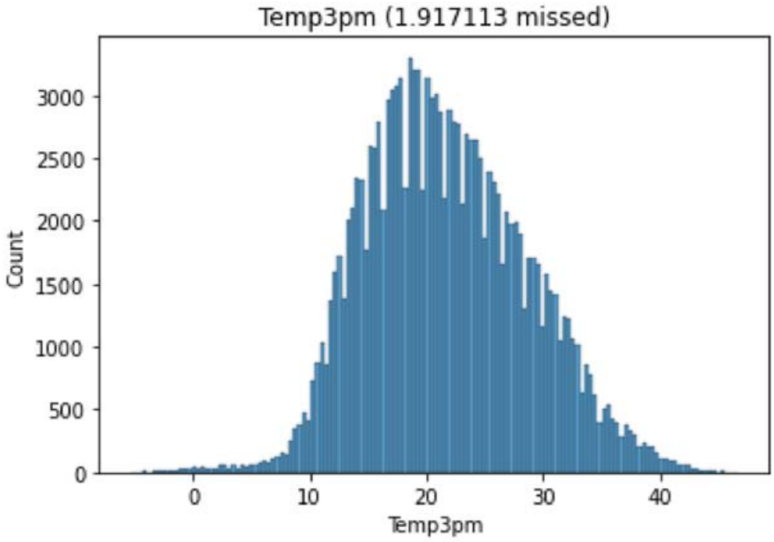

Pressure9am (9.855619 missed)
Count
Pressure9am

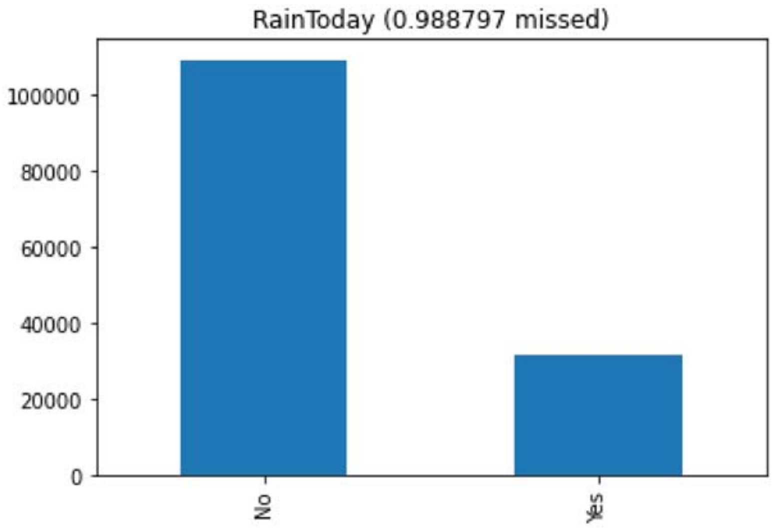

Pressure3pm (9.832411 missed)
Count
Pressure3pm

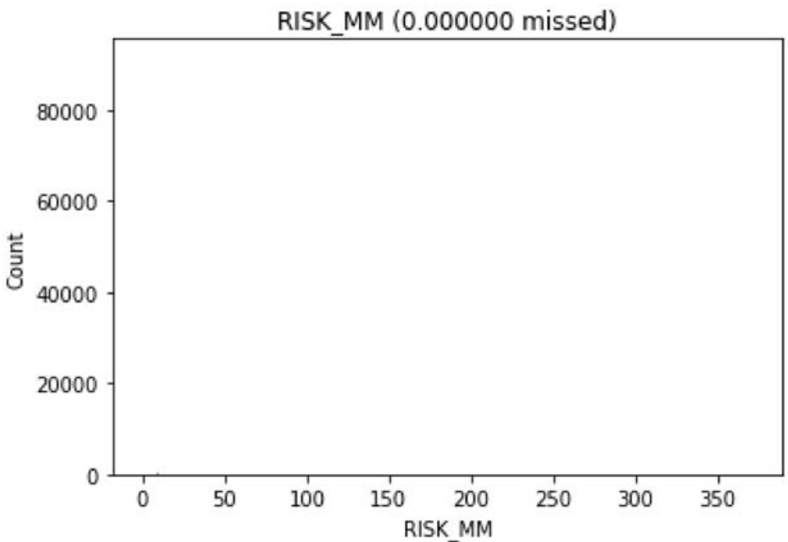

Cloud9am (37.735332 missed)
Count
Cloud9am

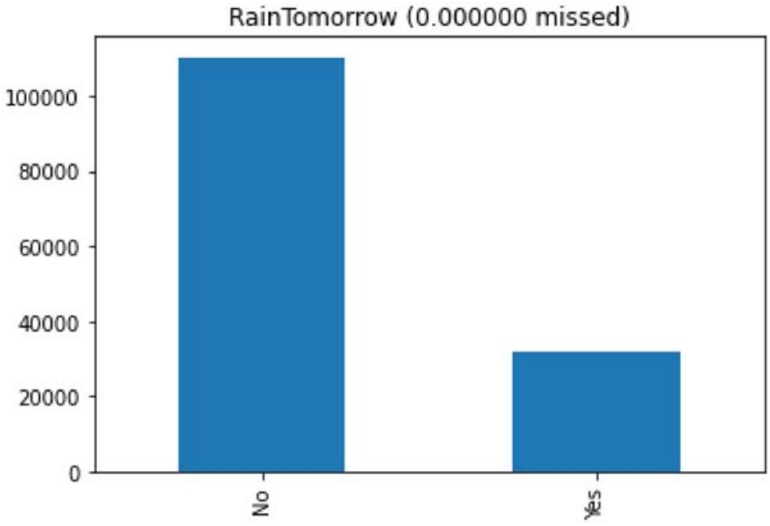

Cloud3pm (40.152469 missed)
Count
Cloud3pm


Temp9am (0.635756 missed)
Count
Temp9am


Temp3pm (1.917113 missed)
Count
3000
2500
2000
1500
1000
500
0
0
10
20
30
40
Temp3pm


RainToday (0.988797 missed)
100000
80000
60000
40000
20000
0
No
Yes


RISK_MM (0.000000 missed)
Count
80000
60000
40000
20000
0
0
50
100
150
200
250
300
350
RISK_MM



In [ ]:

```
train_part = df.RainTomorrow.size*75//100
df_train = df.iloc[:train_part].copy()
df_test = df.iloc[train_part:].copy()
del df
```

Изучение процентна пропущенных значений

In [ ]:

```
colmiss = dict()
for col in df_train.columns[2:]:
  result = [col.strip()]
  for h, d in [('train', df_train),
             ('test', df_test)]:
      result.append('\t\t{}: ({:.1f}% missed)\t'.format(h, d[col].isna().mean()*100))
  colmiss[col] = d[col].isna().mean()*100
  print(''.join(result))
```

```
MinTemp         train: (0.5% missed)                    test: (0.4% misse
d)
MaxTemp         train: (0.2% missed)                    test: (0.3% misse
d)
Rainfall                train: (1.1% missed)                    test: (0.
8% missed)
Evaporation             train: (41.6% missed)                   test: (46.
5% missed)
Sunshine                train: (48.7% missed)                   test: (44.
7% missed)
WindGustDir             train: (6.1% missed)                    test: (7.
9% missed)
WindGustSpeed           train: (6.1% missed)                    test: (7.
8% missed)
WindDir9am              train: (7.7% missed)                    test: (5.
2% missed)
WindDir3pm              train: (2.6% missed)                    test: (2.
9% missed)
WindSpeed9am            train: (1.1% missed)                    test: (0.
4% missed)
WindSpeed3pm            train: (1.7% missed)                    test: (2.
3% missed)
Humidity9am             train: (1.2% missed)                    test: (1.
3% missed)
Humidity3pm             train: (1.7% missed)                    test: (5.
2% missed)
Pressure9am             train: (9.1% missed)                    test: (12.
0% missed)
Pressure3pm             train: (9.1% missed)                    test: (12.
1% missed)
Cloud9am                train: (36.5% missed)                   test: (41.
4% missed)
Cloud3pm                train: (38.4% missed)                   test: (45.
3% missed)
Temp9am         train: (0.8% missed)                    test: (0.3% misse
d)
Temp3pm         train: (1.2% missed)                    test: (4.1% misse
d)
RainToday               train: (1.1% missed)                    test: (0.
8% missed)
RISK_MM         train: (0.0% missed)                    test: (0.0% misse
d)
RainTomorrow            train: (0.0% missed)                    test: (0.
0% missed)
```

In [ ]:

```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 106644 entries, 0 to 106643
Data columns (total 24 columns):
 #   Column         Non-Null Count   Dtype  
---  ------         --------------   -----  
 0   Date           106644 non-null  object 
 1   Location       106644 non-null  object 
 2   MinTemp        106162 non-null  float64
 3   MaxTemp        106414 non-null  float64
 4   Rainfall       105517 non-null  float64
 5   Evaporation    62333 non-null   float64
 6   Sunshine       54707 non-null   float64
 7   WindGustDir    100137 non-null  object 
 8   WindGustSpeed  100160 non-null  float64
 9   WindDir9am     98485 non-null   object 
 10  WindDir3pm     103893 non-null  object 
 11  WindSpeed9am   105454 non-null  float64
 12  WindSpeed3pm   104838 non-null  float64
 13  Humidity9am    105316 non-null  float64
 14  Humidity3pm    104883 non-null  float64
 15  Pressure9am    96912 non-null   float64
 16  Pressure3pm    96956 non-null   float64
 17  Cloud9am       67720 non-null   float64
 18  Cloud3pm       65645 non-null   float64
 19  Temp9am        105844 non-null  float64
 20  Temp3pm        105365 non-null  float64
 21  RainToday      105517 non-null  object 
 22  RISK_MM        106644 non-null  float64
 23  RainTomorrow   106644 non-null  object 
dtypes: float64(17), object(7)
memory usage: 19.5+ MB
```

In [ ]:

```
df_train_nonmissed = df_train[~df_train.isna().apply(lambda row: row.values.any(), axis
=1)].copy()
df_train_nonmissed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 43258 entries, 5939 to 105940
Data columns (total 24 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Date           43258 non-null  object 
 1   Location       43258 non-null  object 
 2   MinTemp        43258 non-null  float64
 3   MaxTemp        43258 non-null  float64
 4   Rainfall       43258 non-null  float64
 5   Evaporation    43258 non-null  float64
 6   Sunshine       43258 non-null  float64
 7   WindGustDir    43258 non-null  object 
 8   WindGustSpeed  43258 non-null  float64
 9   WindDir9am     43258 non-null  object 
 10  WindDir3pm     43258 non-null  object 
 11  WindSpeed9am   43258 non-null  float64
 12  WindSpeed3pm   43258 non-null  float64
 13  Humidity9am    43258 non-null  float64
 14  Humidity3pm    43258 non-null  float64
 15  Pressure9am    43258 non-null  float64
 16  Pressure3pm    43258 non-null  float64
 17  Cloud9am       43258 non-null  float64
 18  Cloud3pm       43258 non-null  float64
 19  Temp9am        43258 non-null  float64
 20  Temp3pm        43258 non-null  float64
 21  RainToday      43258 non-null  object 
 22  RISK_MM        43258 non-null  float64
 23  RainTomorrow   43258 non-null  object 
dtypes: float64(17), object(7)
memory usage: 8.3+ MB
```

In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
```

In [ ]:

```
cols = df_train_nonmissed.columns
cols
```

Out[ ]:

```
Index(['Date', 'Location', 'MinTemp', 'MaxTemp', 'Rainfall', 'Evaporatio
n',
       'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3
pm',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'RISK_MM', 'RainTomorrow'],
      dtype='object')
```

Добавление координат о районах и направлении ветра

In [ ]:

```
coordinates_latitude = dict(Cobar=31.4958,
                            CoffsHarbour=30.2986,
                            Moree=29.4658,
                            NorfolkIsland=29.0408,
                            Sydney=33.8688,
                            SydneyAirport=33.9399,
                            WaggaWagga=35.1082,
                            Williamtown=32.8150,
                            Canberra=35.2809,
                            Sale=38.1026,
                            MelbourneAirport=37.6690,
                            Melbourne=37.8136,
                            Mildura=34.2080,
                            Portland=45.5051,
                            Watsonia=37.7080,
                            Brisbane=27.4705,
                            Cairns=16.9186,
                            Townsville=19.2590,
                            MountGambier=37.8284,
                            Nuriootpa=34.4666,
                            Woomera=31.1656)
coordinates_longitude = dict(Cobar=145.8389,
                            CoffsHarbour=153.1094,
                            Moree=149.8339,
                            NorfolkIsland=167.9547,
                            Sydney=151.2093,
                            SydneyAirport=151.1753,
                            WaggaWagga=147.3598,
                            Williamtown=151.8428,
                            Canberra=149.1300,
                            Sale=147.0730,
                            MelbourneAirport=144.8410,
                            Melbourne=144.9631,
                            Mildura=142.1246,
                            Portland=122.6750,
                            Watsonia=145.0830,
                            Brisbane=153.0260,
                            Cairns=145.7781,
                            Townsville=146.8169,
                            MountGambier=140.7804,
                            Nuriootpa=138.9917,
                            Woomera=136.8193)
```

In [ ]:

```
# wind direction
# http://snowfence.umn.edu/Components/winddirectionanddegrees.htm
# N 348.75 - 11.25
# NNE 11.25 - 33.75
# NE 33.75 - 56.25
# ENE 56.25 - 78.75
# E 78.75 - 101.25
# ESE 101.25 - 123.75
# SE 123.75 - 146.25
# SSE 146.25 - 168.75
# S 168.75 - 191.25
# SE 123.75 - 146.25
# SSE 146.25 - 168.75
# SSW 191.25 - 213.75
# SW 213.75 - 236.25
# WSW 236.25 - 258.75
# W 258.75 - 281.25
# WNW 281.25 - 303.75
# NW 303.75 - 326.25
# NNW 326.25 - 348.75


map_direction = dict(E=90, ENE=67.5, ESE=110, N=0, NE=45,
                     NNE=20, NNW=335, NW=315, S=180, SE=135,
                     SSE=155, SSW=200, SW=225, W=270,
                     WNW=290, WSW=245)
```

In [ ]:

```
cols_directions = ['WindGustDir', 'WindDir9am', 'WindDir3pm']
for col in cols_directions:
    df_train_nonmissed[col+'Degrees'] = df_train_nonmissed[col].apply(lambda x: map_dir
ection[x])
    df_train_nonmissed[col+'Sin'] = np.sin(df_train_nonmissed[col+'Degrees']*np.pi/180)
    df_train_nonmissed[col+'Cos'] = np.cos(df_train_nonmissed[col+'Degrees']*np.pi/180)
if cols_directions[0]+'Degrees' not in cols:
    cols = list(map(lambda x: x+'Degrees', cols_directions)) + list(filter(lambda x: x
not in cols_directions, cols))
if cols_directions[0]+'Sin' not in cols:
    cols = list(map(lambda x: x+'Sin', cols_directions)) + list(filter(lambda x: x not
in cols_directions, cols))
if cols_directions[0]+'Cos' not in cols:
    cols = list(map(lambda x: x+'Cos', cols_directions)) + list(filter(lambda x: x not
in cols_directions, cols))
```

In [ ]:

```
missed_columns = [df_train[col.split('Degrees')[0].split('Cos')[0].split('Sin')[0]].isn
a().any() for col in cols]
missed_columns
```

Out[ ]:

```
[True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 False,
 False,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 True,
 False,
 False]
```

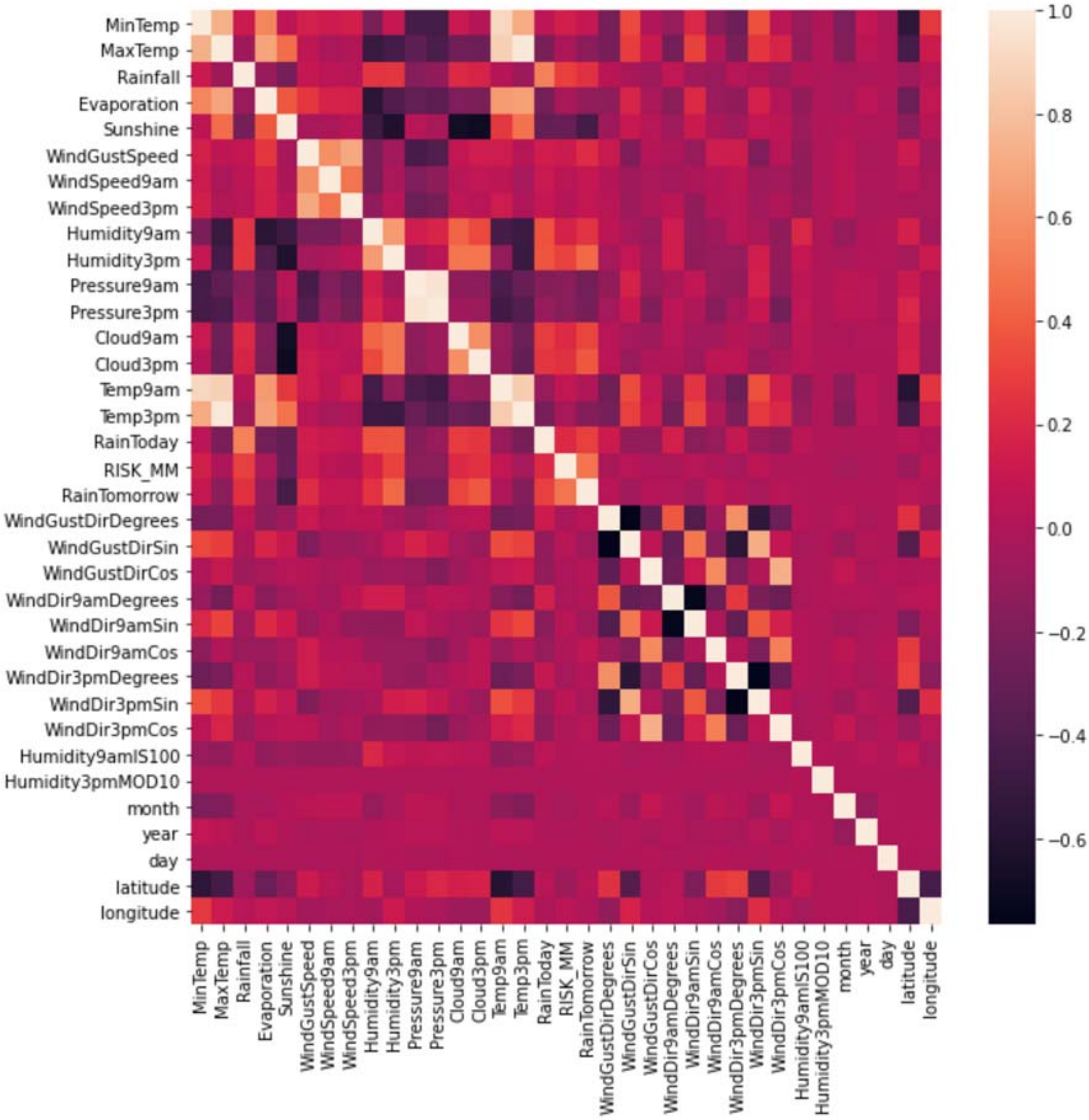
Некоторые другие созданные признаки + матрица корреляций

In [ ]:

```
data_x = df_train_nonmissed.copy()
# box-cox
for col in ['Evaporation', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm']:
    data_x[col] = np.log(1+data_x[col])
# humidity features
data_x['Humidity9amIS100'] = data_x['Humidity9am'] == 100
data_x['Humidity3pmMOD10'] = data_x['Humidity3pm'] % 10 == 0
# encode target
data_x['RainToday'] = pd.get_dummies(data_x.RainToday, drop_first=True)
data_x['RainTomorrow'] = pd.get_dummies(data_x.RainTomorrow, drop_first=True)
# season features
data_x['month'] = pd.to_datetime(data_x['Date']).dt.month
data_x['year'] = pd.to_datetime(data_x['Date']).dt.year
data_x['day'] = pd.to_datetime(data_x['Date']).dt.day
# coordinates features
data_x['latitude'] = data_x['Location'].apply(lambda x: coordinates_latitude[x])
data_x['longitude'] = data_x['Location'].apply(lambda x: coordinates_longitude[x])
data_x.drop(columns=['Date', 'Location'], inplace=True)
plt.figure(figsize=(10, 10))
sns.heatmap(data_x.corr(), )
```

Out[ ]:

<matplotlib.axes._subplots.AxesSubplot at 0x7f1708d89d50>



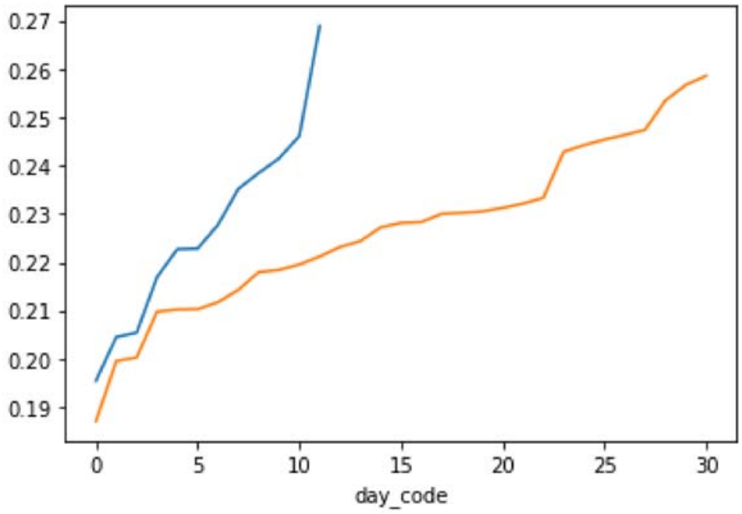
Переобозначение месяцев и дней для повышения корреляции с целевым признаком

In [ ]:

```
month_indexes = data_x.groupby('month').RainTomorrow.agg('mean').sort_values().reset_in
dex().month.values
data_x['month_code'] = data_x.month.apply(lambda x: np.argmax(x==month_indexes))
data_x.groupby('month_code').RainTomorrow.agg('mean').plot()
day_indexes = data_x.groupby('day').RainTomorrow.agg('mean').sort_values().reset_index
().day.values
data_x['day_code'] = data_x.day.apply(lambda x: np.argmax(x==day_indexes))
data_x.groupby('day_code').RainTomorrow.agg('mean').plot()
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16ebb35450>
```



Масштабирование признаков в неотрицательный диапазон

In [ ]:

```
train_cols = ['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed',
       'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm',
       'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am',
       'Temp3pm', 'RainToday', 'WindGustDirDegrees',
       'WindGustDirSin', 'WindGustDirCos', 'WindDir9amDegrees',
       'WindDir9amSin', 'WindDir9amCos', 'WindDir3pmDegrees', 'WindDir3pmSin',
       'WindDir3pmCos', 'Humidity9amIS100', 'Humidity3pmMOD10',
       'year', 'latitude', 'longitude', 'month_code', 'day_code']
target_cols = ['RainTomorrow',]
scaler = MinMaxScaler().fit(data_x[train_cols])
data_x_p = scaler.transform(data_x[train_cols])
data_y = data_x[target_cols]
```

Поиск лучших параметров для факторизации

In [ ]:

```
for col in train_cols:
    for col2 in filter(lambda x: x!=col, train_cols):
        if col2.startswith(col):
            print(col, col2, colmiss[col])
```

```
Humidity9am Humidity9amIS100 1.2546063180398885
Humidity3pm Humidity3pmMOD10 5.201271484429942
```

In [ ]:

```
missprobs = []
for col in train_cols:
    if col in ['WindGustDirDegrees',
               'WindGustDirSin',
               'WindGustDirCos',
               'WindDir9amDegrees',
               'WindDir9amSin',
               'WindDir9amCos',
               'WindDir3pmDegrees',
               'WindDir3pmSin',
               'WindDir3pmCos',
               'Humidity9amIS100',
               'Humidity3pmMOD10',
               'year',
               'latitude',
               'longitude',
               'month_code',
               'day_code']:
      missprobs.append(0.0)
    else:
      missprobs.append(colmiss[col])
missprobs
```

Out[ ]:

```
[0.436017890798616,
 0.2587977158288559,
 0.7848322034375087,
 46.504824326985286,
 44.66792314833047,
 7.837069959773833,
 0.444456946749557,
 2.3179273678584487,
 1.2546063180398885,
 5.201271484429942,
 12.045345860643057,
 12.076289065796507,
 41.44420377507103,
 45.27553517679822,
 0.2925539396326198,
 4.070437987003854,
 0.7848322034375087,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0,
 0.0]
```

In [ ]:

```
((.sum(axis=-1) > 0).mean()
```

Out[ ]:

0.9431550233482824

In [ ]:

```
def get_missed_data(d, missprobs):
   '''Get clean data as input and zeroes values in every column
   by given probability matrix'''
   d = d.copy()
   mask = np.random.uniform(0, 100, size=d.shape)
   d[(mask - np.array(missprobs)) < 0] = 0.0
   return d
```

In [ ]:

```
from sklearn.decomposition import NMF
from sklearn.model_selection import KFold
from sklearn.metrics import r2_score, mean_squared_error
from tqdm.notebook import tqdm

pbar = tqdm()
kfold = KFold(shuffle=True, n_splits=3, random_state=69)
history = {}
for alpha in [0.0, 0.1, 0.25, 0.5]:
    for l1_ratio in [0.0, 0.5, 1.0]:
        for n_components in range(3, 25, 4):
            metrics = []
            for train_ind, test_ind in kfold.split(data_x_p):
                nmf = NMF(alpha=alpha,
                          n_components=n_components,
                          l1_ratio=l1_ratio,
                          random_state=69,
                          verbose=0).fit(data_x_p[train_ind])
                for _ in range(5):
                    metrics.append(r2_score(data_x_p[test_ind],
                                            nmf.inverse_transform(nmf.transform(
                                                get_missed_data(data_x_p[test_ind],
                                                                missprobs)))))
            history[(alpha, l1_ratio, n_components)] = np.mean(metrics)
            pbar.update(1)
```

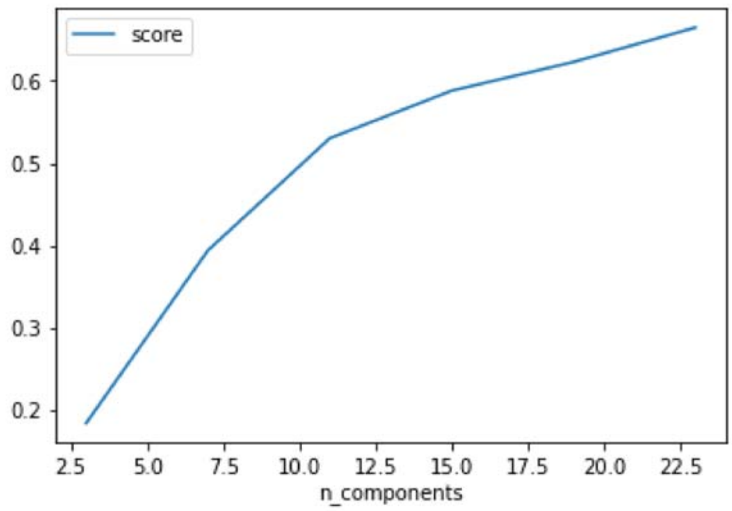
In [ ]:

```
history_dat = [(alpha, l1_ratio, n_components, score) for (alpha, l1_ratio, n_component
s), score in history.items()]
history_df = pd.DataFrame(history_dat)
history_df.columns = ['alpha', 'l1_ratio', 'n_components', 'score']
print(history_df.sort_values(by=['score'], ascending=False).head(10))
history_df.groupby(['alpha', 'l1_ratio']).score.agg('max')
history_df.groupby(['n_components']).score.agg('max').reset_index().plot(x='n_component
s', y='score')
```

```
    alpha  l1_ratio  n_components     score
47   0.25       0.5            23  0.664608
65   0.50       0.5            23  0.659560
53   0.25       1.0            23  0.650397
59   0.50       0.0            23  0.649362
35   0.10       1.0            23  0.649315
29   0.10       0.5            23  0.646778
41   0.25       0.0            23  0.634021
23   0.10       0.0            23  0.626976
40   0.25       0.0            19  0.622795
58   0.50       0.0            19  0.622672
```

Out[ ]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f16f0c63390>
```



In [ ]:

```
nmf = NMF(alpha=0.25, n_components=19,
          l1_ratio=0.0,
          random_state=69,
          verbose=0).fit(data_x_p)
```

Заполнение пропусков в первоначальных данных

Заполнение пропусков средним значением и модой для категориальных признаков

In [ ]:

```
data_test = df_test.copy()
data_train = df_train.copy()
datas = [data_train, data_test]
for i, d in enumerate(datas):
    #missing value imputation
    for col in d.columns[2:]:
      if d[col].isna().mean() == 0:
          continue
      if d[col].dtype != 'float64':
        if d[col].dtype == 'object':
          # fill with moda
          print(col, d[col].value_counts().reset_index().values[0, 0])
          datas[i].loc[d[col].isna(), col] = d.loc[~d[col].isna(), col].value_counts
().reset_index().values[0, 0]
        else:
          print(col)
      else:
        # fill with mean
        print(col, d[col].mean())
        datas[i].loc[d[col].isna(), col] = d.loc[~d[col].isna(), col].mean()
      print('After imputation', col, d[col].isna().mean())

    # directions encoding
    for col in cols_directions:
        datas[i][col+'Degrees'] = d[col].apply(lambda x: map_direction[x])
        datas[i][col+'Sin'] = np.sin(d[col+'Degrees']*np.pi/180)
        datas[i][col+'Cos'] = np.cos(d[col+'Degrees']*np.pi/180)
    # box-cox
    for col in ['Evaporation', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm']:
        datas[i][col] = np.log(1+d[col])
    # humidity features
    datas[i]['Humidity9amIS100'] = d['Humidity9am'] == 100
    datas[i]['Humidity3pmMOD10'] = d['Humidity3pm'] % 10 == 0
    # encode target
    datas[i]['RainToday'] = pd.get_dummies(d.RainToday, drop_first=True)
    datas[i]['RainTomorrow'] = pd.get_dummies(d.RainTomorrow, drop_first=True)
    # season features
    datas[i]['month'] = pd.to_datetime(d['Date']).dt.month
    datas[i]['year'] = pd.to_datetime(d['Date']).dt.year
    datas[i]['day'] = pd.to_datetime(d['Date']).dt.day
    datas[i]['month_code'] = d.month.apply(lambda x: np.argmax(x==month_indexes))
    datas[i]['day_code'] = d.day.apply(lambda x: np.argmax(x==day_indexes))
    # coordinates features
    datas[i]['latitude'] = d['Location'].apply(lambda x: coordinates_latitude.get(x, 2
5.2744))# default australian coordinates
    datas[i]['longitude'] = d['Location'].apply(lambda x: coordinates_longitude.get(x,
133.7751))# default australian coordinates
    datas[i].drop(columns=['Date', 'Location'], inplace=True)
```

```
MinTemp 11.96442512386722
After imputation MinTemp 0.0
MaxTemp 22.7381096472271
After imputation MaxTemp 0.0
Rainfall 2.4116483599802083
After imputation Rainfall 0.0
Evaporation 5.33922801726212
After imputation Evaporation 0.0
Sunshine 7.382788308625942
After imputation Sunshine 0.0
WindGustDir W
After imputation WindGustDir 0.0
WindGustSpeed 39.797633785942494
After imputation WindGustSpeed 0.0
WindDir9am N
After imputation WindDir9am 0.0
WindDir3pm W
After imputation WindDir3pm 0.0
WindSpeed9am 13.92605306579172
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.768929205059234
After imputation WindSpeed3pm 0.0
Humidity9am 70.42160735310874
After imputation Humidity9am 0.0
Humidity3pm 52.69115109216937
After imputation Humidity3pm 0.0
Pressure9am 1018.0428244180362
After imputation Pressure9am 0.0
Pressure3pm 1015.6959712859581
After imputation Pressure3pm 0.0
Cloud9am 4.597829297105729
After imputation Cloud9am 0.0
Cloud3pm 4.65576967019575
After imputation Cloud3pm 0.0
Temp9am 16.536189108499293
After imputation Temp9am 0.0
Temp3pm 21.253259621316268
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
MinTemp 12.852198112674518
After imputation MinTemp 0.0
MaxTemp 24.69340045689145
After imputation MaxTemp 0.0
Rainfall 2.1654635667705837
After imputation Rainfall 0.0
Evaporation 5.897886101908847
After imputation Evaporation 0.0
Sunshine 8.298093543467216
After imputation Sunshine 0.0
WindGustDir E
After imputation WindGustDir 0.0
WindGustSpeed 40.554924762689616
After imputation WindGustSpeed 0.0
WindDir9am E
After imputation WindDir9am 0.0
WindDir3pm SE
After imputation WindDir3pm 0.0
WindSpeed9am 14.228250120087027
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.24100791936645
```

```
After imputation WindSpeed3pm 0.0
Humidity9am 64.1101045494687
After imputation Humidity9am 0.0
Humidity3pm 47.7213056379822
After imputation Humidity3pm 0.0
Pressure9am 1016.4478491700535
After imputation Pressure9am 0.0
Pressure3pm 1013.9002495520838
After imputation Pressure3pm 0.0
Cloud9am 3.914584934665642
After imputation Cloud9am 0.0
Cloud3pm 3.98822864192454
After imputation Cloud3pm 0.0
Temp9am 18.335215122020145
After imputation Temp9am 0.0
Temp3pm 23.028089261626775
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
```

Заполнение пропусков константой

In [ ]:

```
data_test = df_test.copy()
data_train = df_train.copy()
datas2 = [data_train, data_test]
for i, d in enumerate(datas2):
    #missing value imputation
    for col in d.columns[2:]:
      if d[col].isna().mean() == 0:
          continue
      if d[col].dtype != 'float64':
        if d[col].dtype == 'object':
            # fill with moda
            print(col, d[col].value_counts().reset_index().values[0, 0])
            datas2[i].loc[d[col].isna(), col] = 1e7
        else:
            print(col)
      else:
        # fill with mean
        print(col, d[col].mean())
        datas2[i].loc[d[col].isna(), col] = 1e7
      print('After imputation', col, d[col].isna().mean())

    # directions encoding
    for col in cols_directions:
        datas2[i][col+'Degrees'] = d[col].apply(lambda x: map_direction.get(x, 1000))
        datas2[i][col+'Sin'] = np.sin(d[col+'Degrees']*np.pi/180)
        datas2[i][col+'Cos'] = np.cos(d[col+'Degrees']*np.pi/180)
    # box-cox
    for col in ['Evaporation', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm']:
        datas2[i][col] = np.log(1+d[col])
    # humidity features
    datas2[i]['Humidity9amIS100'] = d['Humidity9am'] == 100
    datas2[i]['Humidity3pmMOD10'] = d['Humidity3pm'] % 10 == 0
    # encode target
    datas2[i]['RainToday'] = pd.get_dummies(d.RainToday, drop_first=True)
    datas2[i]['RainTomorrow'] = pd.get_dummies(d.RainTomorrow, drop_first=True)
    # season features
    datas2[i]['month'] = pd.to_datetime(d['Date']).dt.month
    datas2[i]['year'] = pd.to_datetime(d['Date']).dt.year
    datas2[i]['day'] = pd.to_datetime(d['Date']).dt.day
    datas2[i]['month_code'] = d.month.apply(lambda x: np.argmax(x==month_indexes))
    datas2[i]['day_code'] = d.day.apply(lambda x: np.argmax(x==day_indexes))
    # coordinates features
    datas2[i]['latitude'] = d['Location'].apply(lambda x: coordinates_latitude.get(x, 2
5.2744))# default australian coordinates
    datas2[i]['longitude'] = d['Location'].apply(lambda x: coordinates_longitude.get(x,
133.7751))# default australian coordinates
    datas2[i].drop(columns=['Date', 'Location'], inplace=True)
```

```
MinTemp 11.96442512386722
After imputation MinTemp 0.0
MaxTemp 22.7381096472271
After imputation MaxTemp 0.0
Rainfall 2.4116483599802083
After imputation Rainfall 0.0
Evaporation 5.33922801726212
After imputation Evaporation 0.0
Sunshine 7.382788308625942
After imputation Sunshine 0.0
WindGustDir W
After imputation WindGustDir 0.0
WindGustSpeed 39.797633785942494
After imputation WindGustSpeed 0.0
WindDir9am N
After imputation WindDir9am 0.0
WindDir3pm W
After imputation WindDir3pm 0.0
WindSpeed9am 13.92605306579172
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.768929205059234
After imputation WindSpeed3pm 0.0
Humidity9am 70.42160735310874
After imputation Humidity9am 0.0
Humidity3pm 52.69115109216937
After imputation Humidity3pm 0.0
Pressure9am 1018.0428244180362
After imputation Pressure9am 0.0
Pressure3pm 1015.6959712859581
After imputation Pressure3pm 0.0
Cloud9am 4.597829297105729
After imputation Cloud9am 0.0
Cloud3pm 4.65576967019575
After imputation Cloud3pm 0.0
Temp9am 16.536189108499293
After imputation Temp9am 0.0
Temp3pm 21.253259621316268
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
MinTemp 12.852198112674518
After imputation MinTemp 0.0
MaxTemp 24.69340045689145
After imputation MaxTemp 0.0
Rainfall 2.1654635667705837
After imputation Rainfall 0.0
Evaporation 5.897886101908847
After imputation Evaporation 0.0
Sunshine 8.298093543467216
After imputation Sunshine 0.0
WindGustDir E
After imputation WindGustDir 0.0
WindGustSpeed 40.554924762689616
After imputation WindGustSpeed 0.0
WindDir9am E
After imputation WindDir9am 0.0
WindDir3pm SE
After imputation WindDir3pm 0.0
WindSpeed9am 14.228250120087027
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.24100791936645
```

```
After imputation WindSpeed3pm 0.0
Humidity9am 64.1101045494687
After imputation Humidity9am 0.0
Humidity3pm 47.7213056379822
After imputation Humidity3pm 0.0
Pressure9am 1016.4478491700535
After imputation Pressure9am 0.0
Pressure3pm 1013.9002495520838
After imputation Pressure3pm 0.0
Cloud9am 3.914584934665642
After imputation Cloud9am 0.0
Cloud3pm 3.98822864192454
After imputation Cloud3pm 0.0
Temp9am 18.335215122020145
After imputation Temp9am 0.0
Temp3pm 23.028089261626775
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
```

Заполнение пропусков обратной трансформаицией от NMF

In [ ]:

```
data_test = df_test.copy()
data_train = df_train.copy()
datas3 = [data_train, data_test]
for i, d in enumerate(datas3):
    #missing value imputation
    for col in d.columns[2:]:
      datas3[i][col+'isna'] = d[col].isna()
      if d[col].isna().mean() == 0:
          continue
      if d[col].dtype != 'float64':
        if d[col].dtype == 'object':
            # fill with moda
            print(col, d[col].value_counts().reset_index().values[0, 0])
            datas3[i].loc[d[col].isna(), col] = datas3[i].loc[~d[col].isna(), col].uniq
ue()[0]
        else:
            print(col)
      else:
          # fill with mean
          print(col, d[col].mean())
          datas3[i].loc[d[col].isna(), col] = datas3[i].loc[~d[col].isna(), col].mean()

      print('After imputation', col, d[col].isna().mean())

    # directions encoding
    for col in cols_directions:
        datas3[i][col+'Degrees'] = d[col].apply(lambda x: map_direction.get(x, 0))
        datas3[i][col+'Sin'] = np.sin(d[col+'Degrees']*np.pi/180)
        datas3[i][col+'Cos'] = np.cos(d[col+'Degrees']*np.pi/180)
        datas3[i][col+'Degrees'+'isna'] = d[col+'isna']
        datas3[i][col+'Sin'+'isna'] = d[col+'isna']
        datas3[i][col+'Cos'+'isna'] = d[col+'isna']
    # box-cox
    for col in ['Evaporation', 'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm']:
        datas3[i][col] = np.log(1+d[col])
    # humidity features
    datas3[i]['Humidity9amIS100'] = d['Humidity9am'] == 100
    datas3[i]['Humidity9amIS100'+'isna'] = d['Humidity9amisna']
    datas3[i]['Humidity3pmMOD10'] = d['Humidity3pm'] % 10 == 0
    datas3[i]['Humidity3pmMOD10isna'] = d['Humidity3pmisna']
    # encode target
    datas3[i]['RainToday'] = pd.get_dummies(d.RainToday, drop_first=True)
    datas3[i]['RainTomorrow'] = pd.get_dummies(d.RainTomorrow, drop_first=True)
    # season features
    datas3[i]['month'] = pd.to_datetime(d['Date']).dt.month
    datas3[i]['year'] = pd.to_datetime(d['Date']).dt.year
    datas3[i]['day'] = pd.to_datetime(d['Date']).dt.day
    datas3[i]['month_code'] = d.month.apply(lambda x: np.argmax(x==month_indexes))
    datas3[i]['day_code'] = d.day.apply(lambda x: np.argmax(x==day_indexes))

    # coordinates features
    datas3[i]['latitude'] = d['Location'].apply(lambda x: coordinates_latitude.get(x, 0
))
    datas3[i]['longitude'] = d['Location'].apply(lambda x: coordinates_longitude.get(x,
0))
    datas3[i]['latitude'+'isna'] = False
    datas3[i]['longitude'+'isna'] = False
    datas3[i]['day_code'+'isna'] = False
    datas3[i]['month_code'+'isna'] = False
```

```
    datas3[i]['year'+'isna'] = False
    datas3[i].drop(columns=['Date', 'Location'], inplace=True)
```

```
MinTemp 11.96442512386722
After imputation MinTemp 0.0
MaxTemp 22.7381096472271
After imputation MaxTemp 0.0
Rainfall 2.4116483599802083
After imputation Rainfall 0.0
Evaporation 5.33922801726212
After imputation Evaporation 0.0
Sunshine 7.382788308625942
After imputation Sunshine 0.0
WindGustDir W
After imputation WindGustDir 0.0
WindGustSpeed 39.797633785942494
After imputation WindGustSpeed 0.0
WindDir9am N
After imputation WindDir9am 0.0
WindDir3pm W
After imputation WindDir3pm 0.0
WindSpeed9am 13.92605306579172
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.768929205059234
After imputation WindSpeed3pm 0.0
Humidity9am 70.42160735310874
After imputation Humidity9am 0.0
Humidity3pm 52.69115109216937
After imputation Humidity3pm 0.0
Pressure9am 1018.0428244180362
After imputation Pressure9am 0.0
Pressure3pm 1015.6959712859581
After imputation Pressure3pm 0.0
Cloud9am 4.597829297105729
After imputation Cloud9am 0.0
Cloud3pm 4.65576967019575
After imputation Cloud3pm 0.0
Temp9am 16.536189108499293
After imputation Temp9am 0.0
Temp3pm 21.253259621316268
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
MinTemp 12.852198112674518
After imputation MinTemp 0.0
MaxTemp 24.69340045689145
After imputation MaxTemp 0.0
Rainfall 2.1654635667705837
After imputation Rainfall 0.0
Evaporation 5.897886101908847
After imputation Evaporation 0.0
Sunshine 8.298093543467216
After imputation Sunshine 0.0
WindGustDir E
After imputation WindGustDir 0.0
WindGustSpeed 40.554924762689616
After imputation WindGustSpeed 0.0
WindDir9am E
After imputation WindDir9am 0.0
WindDir3pm SE
After imputation WindDir3pm 0.0
WindSpeed9am 14.228250120087027
After imputation WindSpeed9am 0.0
WindSpeed3pm 18.24100791936645
```

```
After imputation WindSpeed3pm 0.0
Humidity9am 64.1101045494687
After imputation Humidity9am 0.0
Humidity3pm 47.7213056379822
After imputation Humidity3pm 0.0
Pressure9am 1016.4478491700535
After imputation Pressure9am 0.0
Pressure3pm 1013.9002495520838
After imputation Pressure3pm 0.0
Cloud9am 3.914584934665642
After imputation Cloud9am 0.0
Cloud3pm 3.98822864192454
After imputation Cloud3pm 0.0
Temp9am 18.335215122020145
After imputation Temp9am 0.0
Temp3pm 23.028089261626775
After imputation Temp3pm 0.0
RainToday No
After imputation RainToday 0.0
```

In [ ]:

```
for i, d in enumerate(datas3):
    mask = datas3[i][list(map(lambda x: x+'isna', train_cols))].values
    values = datas3[i][train_cols].values
    values_p = scaler.transform(values)
    values_p[mask] = 0.0
    values_p = np.clip(values_p, 0.0, 1.0)
    values_p = nmf.inverse_transform(nmf.transform(values_p))
    values_r = scaler.inverse_transform(values_p)
    values[mask] = values_r[mask]
    for j, col in enumerate(train_cols):
        datas3[i][col] = values[:, j]
```

Проверка импутаций на качество моделей

In [ ]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV, KFold
from sklearn.metrics import classification_report

ddd = [[data_x[train_cols], data_y],
[datas[0][train_cols], datas[0][target_cols]],
[datas2[0][train_cols], datas2[0][target_cols]],
[datas3[0][train_cols], datas3[0][target_cols]],]

ddd_test = [[datas[1][train_cols], datas[1][target_cols]],
[datas[1][train_cols], datas[1][target_cols]],
[datas2[1][train_cols], datas2[1][target_cols]],
[datas3[1][train_cols], datas3[1][target_cols]],]

metainfo = ['dropped', 'meanandmoda', 'constant', 'nmf']

for ((x, y), (xt, yt), info) in zip(ddd, ddd_test, metainfo):
    dt = RandomForestClassifier(max_depth=1, random_state=69)

    params = {'max_depth': [5, 7, 8, 10],
              'n_estimators': [50, 100, 150]}
    kfold = KFold(n_splits=4, shuffle=True, random_state=69)
    dt = GridSearchCV(dt, params,
                      scoring='roc_auc', cv=kfold,
                      verbose=False).fit(x, y.values[:, 0])
    print(info)
    print(classification_report(yt, dt.predict(xt)))
    print('-'*50)
```

```
dropped
              precision    recall  f1-score   support

           0       0.84      0.98      0.90     27882
           1       0.81      0.31      0.45      7667

    accuracy                           0.84     35549
   macro avg       0.83      0.65      0.68     35549
weighted avg       0.83      0.84      0.81     35549

--------------------------------------------------
meanandmoda
              precision    recall  f1-score   support

           0       0.85      0.98      0.91     27882
           1       0.81      0.36      0.50      7667

    accuracy                           0.84     35549
   macro avg       0.83      0.67      0.70     35549
weighted avg       0.84      0.84      0.82     35549

--------------------------------------------------
constant
              precision    recall  f1-score   support

           0       0.86      0.97      0.91     27882
           1       0.78      0.41      0.54      7667

    accuracy                           0.85     35549
   macro avg       0.82      0.69      0.72     35549
weighted avg       0.84      0.85      0.83     35549

--------------------------------------------------
nmf
              precision    recall  f1-score   support

           0       0.85      0.98      0.91     27882
           1       0.81      0.36      0.50      7667

    accuracy                           0.84     35549
   macro avg       0.83      0.67      0.70     35549
weighted avg       0.84      0.84      0.82     35549

--------------------------------------------------
```

In [ ]: