```
In [1]:

1   import pandas as pd
2   import numpy as np
3   import matplotlib.pyplot as plt
4   %matplotlib inline
5   import seaborn as sns
6   from IPython import get_ipython
7   import warnings
8   warnings.filterwarnings("ignore")
```

In [2]:

1 data = pd.read\_csv('rainfall\_aus.csv')

In [3]:

1 data.head()

### Out[3]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustS <sub> </sub>
0	01- 12- 2008	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	02- 12- 2008	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	03- 12- 2008	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	04- 12- 2008	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	05- 12- 2008	Albury	17.5	32.3	1.0	NaN	NaN	W	

5 rows × 23 columns

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In [4]: ▶

```
1 data.tail()
```

#### Out[4]:

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	Wind	
145455	21- 06- 2017	Uluru	2.8	23.4	0.0	NaN	NaN	E		
145456	22- 06- 2017	Uluru	3.6	25.3	0.0	NaN	NaN	NNW		
145457	23- 06- 2017	Uluru	5.4	26.9	0.0	NaN	NaN	N		
145458	24- 06- 2017	Uluru	7.8	27.0	0.0	NaN	NaN	SE		
145459	25- 06- 2017	Uluru	14.9	NaN	0.0	NaN	NaN	NaN		
5 rows × 23 columns										
4									•	

In [5]: ▶

1 data.shape

### Out[5]:

(145460, 23)

In [6]: ▶

1 data.columns

#### Out[6]:

Temp3pm

RainToday

RainTomorrow

dtype: int64

H In [7]: 1 data.duplicated().sum() Out[7]: 0 H In [8]: 1 data.isnull().sum() Out[8]: Date 0 Location 0 1485 MinTemp MaxTemp 1261 Rainfall 3261 Evaporation 62790 Sunshine 69835 WindGustDir 10326 WindGustSpeed 10263 WindDir9am 10566 WindDir3pm 4228 WindSpeed9am 1767 WindSpeed3pm 3062 Humidity9am 2654 Humidity3pm 4507 Pressure9am 15065 Pressure3pm 15028 Cloud9am 55888 Cloud3pm 59358 Temp9am 1767

3609

3261

3267

In [9]:

1 data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 23 columns):

#	Column	Non-Null Count	Dtype
0	Date	145460 non-null	object
1	Location	145460 non-null	object
2	MinTemp	143975 non-null	float64
3	MaxTemp	144199 non-null	float64
4	Rainfall	142199 non-null	float64
5	Evaporation	82670 non-null	float64
6	Sunshine	75625 non-null	float64
7	WindGustDir	135134 non-null	object
8	WindGustSpeed	135197 non-null	float64
9	WindDir9am	134894 non-null	object
10	WindDir3pm	141232 non-null	object
11	WindSpeed9am	143693 non-null	float64
12	WindSpeed3pm	142398 non-null	float64
13	Humidity9am	142806 non-null	float64
14	Humidity3pm	140953 non-null	float64
15	Pressure9am	130395 non-null	float64
16	Pressure3pm	130432 non-null	float64
17	Cloud9am	89572 non-null	float64
18	Cloud3pm	86102 non-null	float64
19	Temp9am	143693 non-null	float64
20	Temp3pm	141851 non-null	float64
21	RainToday	142199 non-null	object
22	RainTomorrow	142193 non-null	object
	C3 + C4 (4 C)		-

dtypes: float64(16), object(7)

memory usage: 25.5+ MB

In [10]: ▶

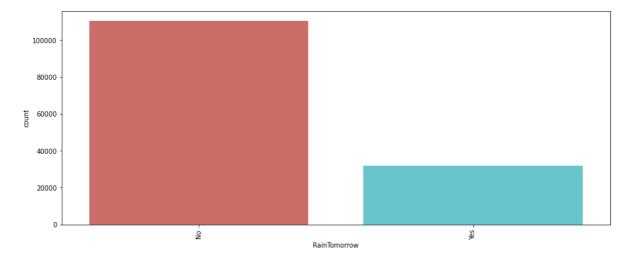
data.describe()

# Out[10]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSp
count	143975.000000	144199.000000	142199.000000	82670.000000	75625.000000	135197.000
mean	12.194034	23.221348	2.360918	5.468232	7.611178	40.035
std	6.398495	7.119049	8.478060	4.193704	3.785483	13.607
min	-8.500000	-4.800000	0.000000	0.000000	0.000000	6.000
25%	7.600000	17.900000	0.000000	2.600000	4.800000	31.000
50%	12.000000	22.600000	0.000000	4.800000	8.400000	39.000
75%	16.900000	28.200000	0.800000	7.400000	10.600000	48.000
max	33.900000	48.100000	371.000000	145.000000	14.500000	135.000
4						<b>•</b>

In [11]:

```
plt.figure(figsize=(15,6))
sns.countplot(x= data["RainTomorrow"], data = data, palette='hls')
plt.xticks(rotation = 90)
plt.show()
```



In [13]:

```
1 corrmat = data.corr()
2 corrmat
```

# Out[13]:

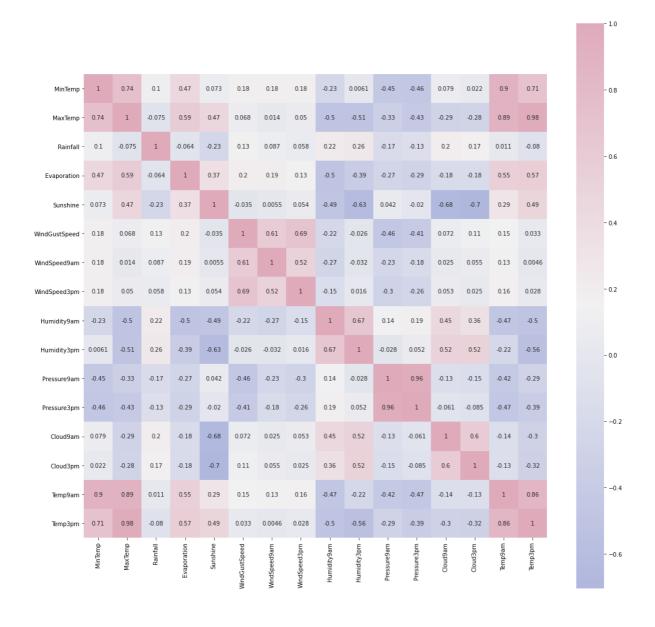
	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindS
MinTemp	1.000000	0.736555	0.103938	0.466993	0.072586	0.177415	
MaxTemp	0.736555	1.000000	-0.074992	0.587932	0.470156	0.067615	
Rainfall	0.103938	-0.074992	1.000000	-0.064351	-0.227549	0.133659	
Evaporation	0.466993	0.587932	-0.064351	1.000000	0.365602	0.203021	
Sunshine	0.072586	0.470156	-0.227549	0.365602	1.000000	-0.034750	
WindGustSpeed	0.177415	0.067615	0.133659	0.203021	-0.034750	1.000000	
WindSpeed9am	0.175064	0.014450	0.087338	0.193084	0.005499	0.605303	
WindSpeed3pm	0.175173	0.050300	0.057887	0.129400	0.053834	0.686307	
Humidity9am	-0.232899	-0.504110	0.224405	-0.504092	-0.490819	-0.215070	-
Humidity3pm	0.006089	-0.508855	0.255755	-0.390243	-0.629130	-0.026327	-
Pressure9am	-0.450970	-0.332061	-0.168154	-0.270362	0.041970	-0.458744	-
Pressure3pm	-0.461292	-0.427167	-0.126534	-0.293581	-0.019719	-0.413749	-
Cloud9am	0.078754	-0.289370	0.198528	-0.183793	-0.675323	0.071736	
Cloud3pm	0.021605	-0.277921	0.172403	-0.182618	-0.703930	0.109168	
Temp9am	0.901821	0.887210	0.011192	0.545115	0.291188	0.150150	
Temp3pm	0.708906	0.984503	-0.079657	0.572893	0.490501	0.032748	
4							<b>&gt;</b>

In [14]: ▶

- 1 cmap = sns.diverging\_palette(260,-10,s=50, l=75, n=6, as\_cmap=True)
- plt.subplots(figsize=(18,18))
- sns.heatmap(corrmat,cmap= cmap,annot=True, square=True)

#### Out[14]:

#### <AxesSubplot:>



```
In [15]:
                                                                                                   H
 1 lengths = data["Date"].str.len()
 2 lengths.value_counts()
Out[15]:
10
      145460
Name: Date, dtype: int64
In [16]:
                                                                                                   H
    data['Date'] = pd.to_datetime(data["Date"])
    data['year'] = data.Date.dt.year
 3
    def encode(data, col, max_val):
         data[col + '_sin'] = np.sin(2 * np.pi * data[col]/max_val)
data[col + '_cos'] = np.cos(2 * np.pi * data[col]/max_val)
 5
 6
 7
         return data
 8
 9
    data['month'] = data.Date.dt.month
10
    data = encode(data, 'month', 12)
11
12 data['day'] = data.Date.dt.day
13
    data = encode(data, 'day', 31)
```

#### Out[16]:

data.head()

14 15

	Date	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustS
0	2008- 01-12	Albury	13.4	22.9	0.6	NaN	NaN	W	
1	2008- 02-12	Albury	7.4	25.1	0.0	NaN	NaN	WNW	
2	2008- 03-12	Albury	12.9	25.7	0.0	NaN	NaN	WSW	
3	2008- 04-12	Albury	9.2	28.0	0.0	NaN	NaN	NE	
4	2008- 05-12	Albury	17.5	32.3	1.0	NaN	NaN	W	
5 rows × 30 columns									

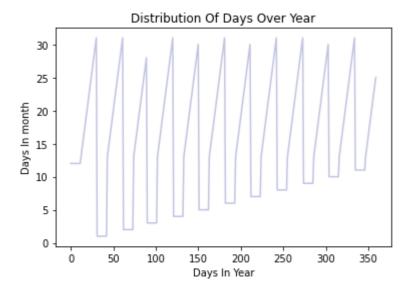
localhost:8888/notebooks/Rainfall Prediction using Deep Learning.ipynb

In [17]: ▶

```
section = data[:360]
tm = section["day"].plot(color="#C2C4E2")
tm.set_title("Distribution Of Days Over Year")
tm.set_ylabel("Days In month")
tm.set_xlabel("Days In Year")
```

## Out[17]:

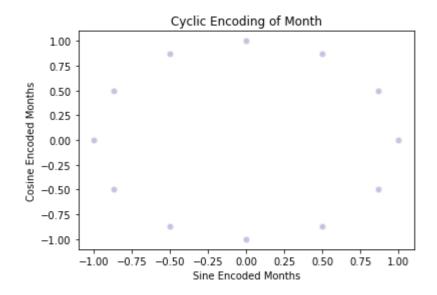
Text(0.5, 0, 'Days In Year')



In [18]:

#### Out[18]:

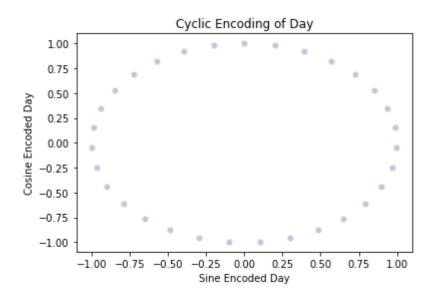
Text(0.5, 0, 'Sine Encoded Months')



```
In [19]: ▶
```

## Out[19]:

Text(0.5, 0, 'Sine Encoded Day')



```
In [20]:
    s = (data.dtypes == "object")
 2
    object_cols = list(s[s].index)
 3
 4 print("Categorical variables:")
  5 print(object_cols)
Categorical variables:
['Location', 'WindGustDir', 'WindDir9am', 'WindDir3pm', 'RainToday', 'Rain
Tomorrow']
In [21]:
                                                                                               H
 1 | for i in object cols:
         print(i, data[i].isnull().sum())
 2
Location 0
WindGustDir 10326
WindDir9am 10566
WindDir3pm 4228
RainToday 3261
RainTomorrow 3267
In [22]:
                                                                                               H
 1 | for i in object cols:
         data[i].fillna(data[i].mode()[0], inplace=True)
                                                                                                H
In [23]:
 1 t = (data.dtypes == "float64")
    num_cols = list(t[t].index)
 3
 4 print("Neumeric variables:")
    print(num_cols)
Neumeric variables:
['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustSpe
ed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am', 'Temp3pm', 'mont
h_sin', 'month_cos', 'day_sin', 'day_cos']
```

In [24]: ▶

```
for i in num_cols:
    print(i, data[i].isnull().sum())
```

MinTemp 1485 MaxTemp 1261 Rainfall 3261 Evaporation 62790 Sunshine 69835 WindGustSpeed 10263 WindSpeed9am 1767 WindSpeed3pm 3062 Humidity9am 2654 Humidity3pm 4507 Pressure9am 15065 Pressure3pm 15028 Cloud9am 55888 Cloud3pm 59358 Temp9am 1767 Temp3pm 3609 month\_sin 0 month\_cos 0 day\_sin 0 day\_cos 0

In [25]: ▶

```
for i in num_cols:
    data[i].fillna(data[i].median(), inplace=True)

data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 30 columns):
#
    Column
                   Non-Null Count
                                    Dtype
---
                   _____
0
    Date
                   145460 non-null datetime64[ns]
1
    Location
                   145460 non-null object
                   145460 non-null float64
2
    MinTemp
3
    MaxTemp
                   145460 non-null float64
4
    Rainfall
                   145460 non-null float64
5
    Evaporation
                   145460 non-null float64
6
    Sunshine
                   145460 non-null float64
7
                   145460 non-null object
    WindGustDir
8
    WindGustSpeed
                   145460 non-null float64
9
    WindDir9am
                   145460 non-null object
10
    WindDir3pm
                   145460 non-null object
11
    WindSpeed9am
                   145460 non-null float64
12
    WindSpeed3pm
                   145460 non-null float64
13
    Humidity9am
                   145460 non-null float64
    Humidity3pm
                   145460 non-null float64
15
    Pressure9am
                   145460 non-null float64
    Pressure3pm
                   145460 non-null float64
    Cloud9am
17
                   145460 non-null float64
    Cloud3pm
                   145460 non-null float64
18
    Temp9am
                   145460 non-null float64
19
20
    Temp3pm
                   145460 non-null float64
                   145460 non-null object
21
    RainToday
22
    RainTomorrow
                   145460 non-null object
23
    year
                   145460 non-null
                                   int64
24
                   145460 non-null int64
    month
25
    month sin
                   145460 non-null float64
                   145460 non-null float64
26
    month cos
27
    day
                   145460 non-null int64
28
    day_sin
                   145460 non-null float64
29
    day cos
                   145460 non-null float64
dtypes: datetime64[ns](1), float64(20), int64(3), object(6)
memory usage: 33.3+ MB
```

In [27]: ▶

```
import datetime
from sklearn.preprocessing import LabelEncoder
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from keras.layers import Dense, BatchNormalization, Dropout, LSTM
from keras.models import Sequential
from keras.utils import to_categorical
from keras.optimizers import Adam
from tensorflow.keras import regularizers
from sklearn.metrics import precision_score, recall_score, confusion_matrix, classiform keras import callbacks
```

H In [28]:

```
label encoder = LabelEncoder()
1
  for i in object_cols:
2
       data[i] = label_encoder.fit_transform(data[i])
3
4
5
  data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 145460 entries, 0 to 145459
Data columns (total 30 columns):
     Column
                    Non-Null Count
                                     Dtype
```

```
____
                  _____
0
    Date
                  145460 non-null datetime64[ns]
                  145460 non-null int32
1
   Location
2
   MinTemp
                  145460 non-null float64
                  145460 non-null float64
3
   MaxTemp
4
   Rainfall
                  145460 non-null float64
5
                  145460 non-null float64
   Evaporation
   Sunshine
                  145460 non-null float64
6
7
   WindGustDir
                  145460 non-null int32
8
   WindGustSpeed
                  145460 non-null float64
9
   WindDir9am
                  145460 non-null int32
10 WindDir3pm
                  145460 non-null int32
11
   WindSpeed9am
                  145460 non-null float64
12
   WindSpeed3pm
                  145460 non-null float64
13
   Humidity9am
                  145460 non-null float64
14
   Humidity3pm
                  145460 non-null float64
15
   Pressure9am
                  145460 non-null float64
16 Pressure3pm
                  145460 non-null float64
   Cloud9am
                  145460 non-null float64
17
18 Cloud3pm
                  145460 non-null float64
19
   Temp9am
                  145460 non-null float64
20
   Temp3pm
                  145460 non-null float64
21
   RainToday
                  145460 non-null int32
22
   RainTomorrow
                  145460 non-null int32
23
                  145460 non-null int64
   year
24
   month
                  145460 non-null int64
25
   month sin
                  145460 non-null float64
26
   month_cos
                  145460 non-null float64
27
   day
                  145460 non-null int64
                  145460 non-null float64
28
   day_sin
                  145460 non-null float64
29
   day cos
```

dtypes: datetime64[ns](1), float64(20), int32(6), int64(3)

memory usage: 30.0 MB

In [29]: ▶

```
features = data.drop(['RainTomorrow', 'Date','day', 'month'], axis=1) # dropping ta

target = data['RainTomorrow']

col_names = list(features.columns)
s_scaler = preprocessing.StandardScaler()
features = s_scaler.fit_transform(features)
features = pd.DataFrame(features, columns=col_names)

features.describe().T
```

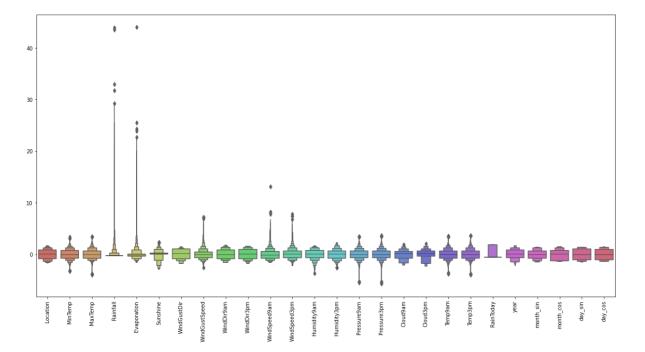
## Out[29]:

	count	mean	std	min	25%	50%	75%
Location	145460.0	7.815677e- 18	1.000003	-1.672228	-0.899139	0.014511	0.857881
MinTemp	145460.0	-4.501830e- 16	1.000003	-3.250525	-0.705659	-0.030170	0.723865
MaxTemp	145460.0	3.001220e- 16	1.000003	-3.952405	-0.735852	-0.086898	0.703133
Rainfall	145460.0	7.815677e- 18	1.000003	-0.275097	-0.275097	-0.275097	-0.203581
Evaporation	145460.0	-3.282584e- 17	1.000003	-1.629472	-0.371139	-0.119472	0.006361
Sunshine	145460.0	-5.424080e- 16	1.000003	-2.897217	0.076188	0.148710	0.257494
WindGustDir	145460.0	6.252542e- 18	1.000003	-1.724209	-0.872075	0.193094	1.045228
WindGustSpeed	145460.0	1.824961e- 16	1.000003	-2.588407	-0.683048	-0.073333	0.460168
WindDir9am	145460.0	7.190423e- 17	1.000003	-1.550000	-0.885669	0.000105	0.885879
WindDir3pm	145460.0	8.284618e- 17	1.000003	-1.718521	-0.837098	0.044324	0.925747
WindSpeed9am	145460.0	5.627287e- 17	1.000003	-1.583291	-0.793380	-0.116314	0.560752
WindSpeed3pm	145460.0	6.565169e- 17	1.000003	-2.141841	-0.650449	0.037886	0.611499
Humidity9am	145460.0	2.250915e- 16	1.000003	-3.654212	-0.631189	0.058273	0.747734
Humidity3pm	145460.0	-8.440931e- 17	1.000003	-2.518329	-0.710918	0.021816	0.656852
Pressure9am	145460.0	-4.314254e- 16	1.000003	-5.520544	-0.616005	-0.006653	0.617561
Pressure3pm	145460.0	5.027043e- 15	1.000003	-5.724832	-0.622769	-0.007520	0.622735
Cloud9am	145460.0	-1.016038e- 16	1.000003	-2.042425	-0.727490	0.149133	0.587445

count	mean	std	min	25%	50%	75%
145460.0	7.346736e- 17	1.000003	-2.235619	-0.336969	0.137693	0.612356
145460.0	7.503050e- 17	1.000003	-3.750358	-0.726764	-0.044517	0.699753
145460.0	-6.877796e- 17	1.000003	-3.951301	-0.725322	-0.083046	0.661411
145460.0	-8.988029e- 18	1.000003	-0.529795	-0.529795	-0.529795	-0.529795
145460.0	2.080221e- 14	1.000003	-2.273637	-0.697391	0.090732	0.878855
145460.0	-8.011069e- 18	1.000003	-1.424382	-0.715973	-0.007564	0.700845
145460.0	9.735403e- 17	1.000003	-1.397692	-1.208546	0.014112	0.720014
145460.0	-2.165187e- 17	1.000003	-1.403031	-1.018734	-0.001896	1.014942
145460.0	6.375883e- 17	1.000003	-1.402828	-1.066146	-0.056419	0.998236
	145460.0 145460.0 145460.0 145460.0 145460.0 145460.0	145460.0       7.346736e-17         145460.0       7.503050e-17         145460.0       -6.877796e-17         145460.0       -8.988029e-18         145460.0       2.080221e-14         145460.0       -8.011069e-18         145460.0       9.735403e-17         145460.0       -2.165187e-17         145460.0       6.375883e-18	145460.0       7.346736e-17       1.000003         145460.0       7.503050e-17       1.000003         145460.0       -6.877796e-17       1.000003         145460.0       -8.988029e-18       1.000003         145460.0       2.080221e-18       1.000003         145460.0       -8.011069e-18       1.000003         145460.0       9.735403e-17       1.000003         145460.0       -2.165187e-17       1.000003         145460.0       6.375883e-1       1.000003	145460.0       7.346736e-17       1.000003       -2.235619         145460.0       7.503050e-17       1.000003       -3.750358         145460.0       -6.877796e-17       1.000003       -3.951301         145460.0       -8.988029e-18       1.000003       -0.529795         145460.0       -8.011069e-18       1.000003       -1.424382         145460.0       9.735403e-17       1.000003       -1.397692         145460.0       -2.165187e-17       1.000003       -1.403031         145460.0       6.375883e-1000003       -1.402828	145460.0       7.346736e-17       1.000003       -2.235619       -0.336969         145460.0       7.503050e-17       1.000003       -3.750358       -0.726764         145460.0       -6.877796e-17       1.000003       -3.951301       -0.725322         145460.0       -8.988029e-18       1.000003       -0.529795       -0.529795         145460.0       -8.011069e-18       1.000003       -1.424382       -0.715973         145460.0       9.735403e-17       1.000003       -1.397692       -1.208546         145460.0       -2.165187e-17       1.000003       -1.403031       -1.018734         145460.0       6.375883e-17       1.000003       -1.402828       -1.066146	145460.0       7.346736e-17       1.000003       -2.235619       -0.336969       0.137693         145460.0       7.503050e-17       1.000003       -3.750358       -0.726764       -0.044517         145460.0       -6.877796e-17       1.000003       -3.951301       -0.725322       -0.083046         145460.0       -8.988029e-18       1.000003       -0.529795       -0.529795       -0.529795         145460.0       -8.011069e-14       1.000003       -2.273637       -0.697391       0.090732         145460.0       9.735403e-17       1.000003       -1.424382       -0.715973       -0.007564         145460.0       -2.165187e-17       1.000003       -1.403031       -1.018734       -0.001896         145460.0       6.375883e-1000003       -1.402828       -1.066146       -0.056419

In [30]: ▶

```
plt.figure(figsize=(20,10))
sns.boxenplot(data = features, palette = 'hls')
plt.xticks(rotation=90)
plt.show()
```



In [31]:

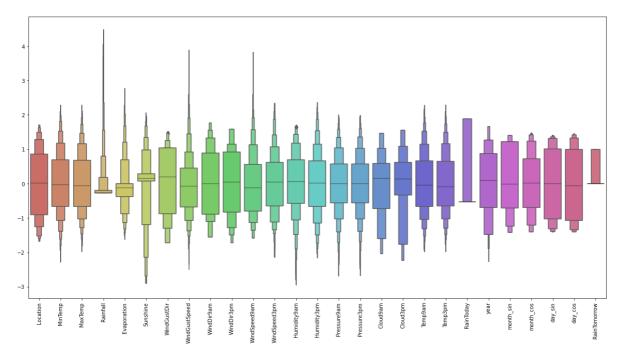
```
1
    features["RainTomorrow"] = target
 2
   features = features[(features["MinTemp"]<2.3)&(features["MinTemp"]>-2.3)]
 3
   features = features[(features["MaxTemp"]<2.3)&(features["MaxTemp"]>-2)]
   features = features[(features["Rainfall"]<4.5)]</pre>
 5
 6 | features = features[(features["Evaporation"]<2.8)]</pre>
   features = features[(features["Sunshine"]<2.1)]</pre>
   features = features[(features["WindGustSpeed"]<4)&(features["WindGustSpeed"]>-4)]
 9 features = features[(features["WindSpeed9am"]<4)]</pre>
10 | features = features[(features["WindSpeed3pm"]<2.5)]
   features = features[(features["Humidity9am"]>-3)]
11
12 | features = features[(features["Humidity3pm"]>-2.2)]
13 | features = features[(features["Pressure9am"] < 2)&(features["Pressure9am"] > -2.7)]
14 | features = features[(features["Pressure3pm"]< 2)&(features["Pressure3pm"]>-2.7)]
features = features[(features["Cloud9am"]<1.8)]</pre>
16 | features = features[(features["Cloud3pm"]<2)]</pre>
17 | features = features[(features["Temp9am"]<2.3)&(features["Temp9am"]>-2)]
   features = features[(features["Temp3pm"]<2.3)&(features["Temp3pm"]>-2)]
19
20
   features.shape
```

#### Out[31]:

(127536, 27)

```
In [32]: ▶
```

```
plt.figure(figsize=(20,10))
sns.boxenplot(data = features,palette = 'hls')
plt.xticks(rotation=90)
plt.show()
```



#### Out[33]:

(127536, 26)

In [34]:

```
early_stopping = callbacks.EarlyStopping(
 1
 2
       min_delta=0.001,
 3
       patience=20,
 4
       restore best weights=True,
 5
   )
 6
 7
   model = Sequential()
 8
   model.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu', in
 9
   model.add(Dense(units = 32, kernel_initializer = 'uniform', activation = 'relu'))
10
   model.add(Dense(units = 16, kernel_initializer = 'uniform', activation = 'relu'))
11
   model.add(Dropout(0.25))
12
   model.add(Dense(units = 8, kernel_initializer = 'uniform', activation = 'relu'))
13
14
   model.add(Dropout(0.5))
   model.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))
15
16
17
   opt = Adam(learning rate=0.00009)
   model.compile(optimizer = opt, loss = 'binary_crossentropy', metrics = ['accuracy']
18
19
20
   history = model.fit(X_train, y_train, batch_size = 32,
21
                       epochs = 20, callbacks=[early_stopping],
22
                        validation split=0.2)
```

```
Epoch 1/20
2551/2551 [=============== ] - 5s 2ms/step - loss: 0.4700 -
accuracy: 0.7841 - val_loss: 0.3908 - val_accuracy: 0.7860
Epoch 2/20
accuracy: 0.8106 - val_loss: 0.3823 - val_accuracy: 0.8413
Epoch 3/20
accuracy: 0.8120 - val_loss: 0.3765 - val_accuracy: 0.8424
Epoch 4/20
accuracy: 0.8131 - val_loss: 0.3721 - val_accuracy: 0.8437
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3981 -
accuracy: 0.8131 - val_loss: 0.3697 - val_accuracy: 0.8450
Epoch 6/20
accuracy: 0.8148 - val_loss: 0.3685 - val_accuracy: 0.8450
Epoch 7/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3942 -
accuracy: 0.8163 - val_loss: 0.3668 - val_accuracy: 0.8451
Epoch 8/20
accuracy: 0.8140 - val_loss: 0.3666 - val_accuracy: 0.8448
Epoch 9/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3927 -
accuracy: 0.8157 - val loss: 0.3652 - val accuracy: 0.8456
Epoch 10/20
accuracy: 0.8145 - val_loss: 0.3648 - val_accuracy: 0.8463
Epoch 11/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3912 -
accuracy: 0.8177 - val_loss: 0.3639 - val_accuracy: 0.8464
Epoch 12/20
```

```
accuracy: 0.8163 - val_loss: 0.3638 - val_accuracy: 0.8455
Epoch 13/20
2551/2551 [============== ] - 4s 2ms/step - loss: 0.3903 -
accuracy: 0.8170 - val loss: 0.3630 - val accuracy: 0.8459
Epoch 14/20
accuracy: 0.8156 - val_loss: 0.3631 - val_accuracy: 0.8452
Epoch 15/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3891 -
accuracy: 0.8163 - val_loss: 0.3624 - val_accuracy: 0.8449
Epoch 16/20
accuracy: 0.8164 - val_loss: 0.3618 - val_accuracy: 0.8455
Epoch 17/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3886 -
accuracy: 0.8169 - val_loss: 0.3613 - val_accuracy: 0.8458
Epoch 18/20
accuracy: 0.8182 - val_loss: 0.3609 - val_accuracy: 0.8450
Epoch 19/20
2551/2551 [=============== ] - 4s 2ms/step - loss: 0.3879 -
accuracy: 0.8172 - val_loss: 0.3609 - val_accuracy: 0.8450
Epoch 20/20
accuracy: 0.8170 - val_loss: 0.3608 - val_accuracy: 0.8444
```

# In [35]:

```
history_df = pd.DataFrame(history.history)

plt.plot(history_df.loc[:, ['loss']], "#BDE2E2", label='Training loss')

plt.plot(history_df.loc[:, ['val_loss']], "#C2C4E2", label='Validation loss')

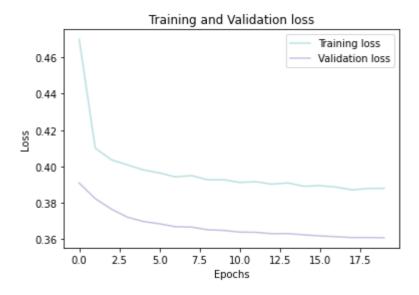
plt.title('Training and Validation loss')

plt.xlabel('Epochs')

plt.ylabel('Loss')

plt.legend(loc="best")

plt.show()
```



H

In [36]: ▶

```
history_df = pd.DataFrame(history.history)

plt.plot(history_df.loc[:, ['accuracy']], "#BDE2E2", label='Training accuracy')
plt.plot(history_df.loc[:, ['val_accuracy']], "#C2C4E2", label='Validation accuracy

plt.title('Training and Validation accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

## Training and Validation accuracy 0.84 0.83 0.82 0.81 0.80 Training accuracy 0.79 Validation accuracy 0.0 2.5 5.0 7.5 10.0 12.5 15.0 17.5 Epochs

```
In [37]:

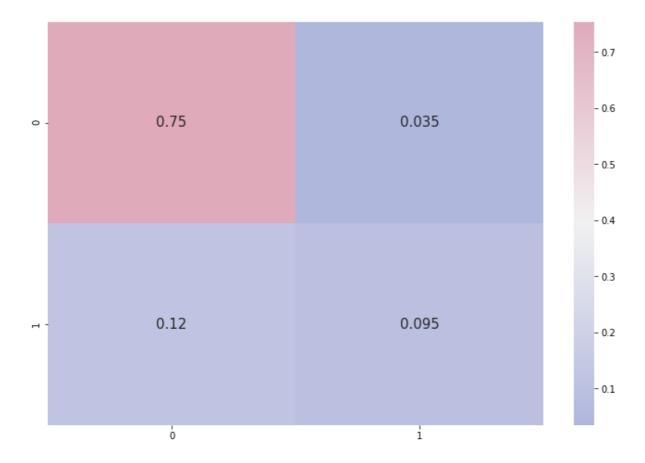
1  y_pred = model.predict(X_test)
2  y_pred = (y_pred > 0.5)
```

In [38]: ▶

```
cmap1 = sns.diverging_palette(260,-10,s=50, l=75, n=5, as_cmap=True)
plt.subplots(figsize=(12,8))
cf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(cf_matrix/np.sum(cf_matrix), cmap = cmap1, annot = True,
annot_kws = {'size':15})
```

# Out[38]:

### <AxesSubplot:>



In [39]:

print(classification\_report(y\_test, y\_pred))

	precision	recall	f1-score	support
0 1	0.87 0.73	0.96 0.45	0.91 0.56	20110 5398
accuracy macro avg weighted avg	0.80 0.84	0.70 0.85	0.85 0.73 0.83	25508 25508 25508