Week 7 Homework - Mai Anh Ly - Predicting rain in Seattle

In [67]:
```
# Import packages for data exploration

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import datetime
import calendar

sns.set(context='notebook', style='whitegrid', font_scale=2, rc={'fig
ure.figsize': (20, 10)})
```

About the dataset

In [68]:
```
# Read in Seattle weather file

seattle = pd.read_csv('seattleWeather_1948-2017.csv')
seattle.head()
```

Out[68]:

	DATE	PRCP	TMAX	TMIN	RAIN
0	1948-01-01	0.47	51	42	True
1	1948-01-02	0.59	45	36	True
2	1948-01-03	0.42	45	35	True
3	1948-01-04	0.31	45	34	True
4	1948-01-05	0.17	45	32	True

In [69]:
```
seattle.tail()
```

Out[69]:

	DATE	PRCP	TMAX	TMIN	RAIN
25546	2017-12-10	0.0	49	34	False
25547	2017-12-11	0.0	49	29	False
25548	2017-12-12	0.0	46	32	False
25549	2017-12-13	0.0	48	34	False
25550	2017-12-14	0.0	50	36	False

In [70]:
```
# View dataset info

seattle.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25551 entries, 0 to 25550
Data columns (total 5 columns):
DATE    25551 non-null object
PRCP    25548 non-null float64
TMAX    25551 non-null int64
TMIN    25551 non-null int64
RAIN    25548 non-null object
dtypes: float64(1), int64(2), object(2)
memory usage: 998.2+ KB
```

In [71]:
```
# Count NaN values in dataset

seattle.isnull().sum()
```

Out[71]:
```
DATE    0
PRCP    3
TMAX    0
TMIN    0
RAIN    3
dtype: int64
```

In [72]:
```
# Describe Seattle dataset summary statistics

seattle.describe()
```

Out[72]:

	PRCP	TMAX	TMIN
count	25548.000000	25551.000000	25551.000000
mean	0.106222	59.544206	44.514226
std	0.239031	12.772984	8.892836
min	0.000000	4.000000	0.000000
25%	0.000000	50.000000	38.000000
50%	0.000000	58.000000	45.000000
75%	0.100000	69.000000	52.000000
max	5.020000	103.000000	71.000000

The file `seattleWeather_1948-2017.csv` contains information about the weather in the city of Seattle from 1948 to 2017. The dataset contains the following columns:

- `DATE` -- The date the weather data was collected, in YYYY-MM-DD format
- `PRCP` -- Precipiation in inches
- `TMIN` -- Minimum temperature in Farenheit
- `TMAX` -- Maximum temperature in Farenheit

There also appears to be 3 `NaN` values each in `PRCP` and `RAIN`.

Cleaning up Seattle weather dataset

Checklist:

- Check that RAIN labels are correct:
  - Is PRCP 0 when RAIN is `False`?
  - Is PRCP greater than 0 when RAIN is `True`?
- Convert DATE to `datetime` format and RAIN to `bool` (then `int` after handling NaN values)
- Decide what to do with NaN values
- Split DATE to YEAR, MONTH and DAY numericals since `sklearn` likely isn't able to handle `datetime`
- Check that TMIN is always less then TMAX

In [73]:
```
# Are RAIN labels correct? Check that PRCP is actually 0 when RAIN is
 False

seattle['PRCP'].loc[seattle['RAIN'] == False].sum()
```

Out[73]:
```
0.0
```

In [74]:
```
# Check values for RAIN when PRCP > 0

seattle['RAIN'].loc[seattle['PRCP'] > 0].value_counts()
```

Out[74]:
```
True    10900
Name: RAIN, dtype: int64
```

From the results of the above two cells, it seems the RAIN column does not need to be corrected.

In [75]:
```
# Convert DATE column to datetime format

seattle['DATE'] = pd.to_datetime(seattle['DATE'], format="%Y-%m-%d")
seattle.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25551 entries, 0 to 25550
Data columns (total 5 columns):
DATE    25551 non-null datetime64[ns]
PRCP    25548 non-null float64
TMAX    25551 non-null int64
TMIN    25551 non-null int64
RAIN    25548 non-null object
dtypes: datetime64[ns](1), float64(1), int64(2), object(1)
memory usage: 998.2+ KB
```

In [76]:
```
seattle.head()
```

Out[76]:

	DATE	PRCP	TMAX	TMIN	RAIN
0	1948-01-01	0.47	51	42	True
1	1948-01-02	0.59	45	36	True
2	1948-01-03	0.42	45	35	True
3	1948-01-04	0.31	45	34	True
4	1948-01-05	0.17	45	32	True

In [77]:
```
# Check out NaN values
seattle.loc[(seattle['PRCP'].isnull()) | (seattle['TMIN'].isnull())]
```

Out[77]:

	DATE	PRCP	TMAX	TMIN	RAIN
18415	1998-06-02	NaN	72	52	NaN
18416	1998-06-03	NaN	66	51	NaN
21067	2005-09-05	NaN	70	52	NaN

All 3 `NaN` values for `RAIN` co-occur with the 3 `NaN` values for PRCP. It seems best to simply remove all `NaN` values from the dataset rather than imputing PRCP values from the same day of the year, which means there will be 25548 rows remaining.

In [78]:
```
# Remove NaN values from dataset

seattle_nonull = seattle.dropna()
seattle_nonull.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 25548 entries, 0 to 25550
Data columns (total 5 columns):
DATE    25548 non-null datetime64[ns]
PRCP    25548 non-null float64
TMAX    25548 non-null int64
TMIN    25548 non-null int64
RAIN    25548 non-null object
dtypes: datetime64[ns](1), float64(1), int64(2), object(1)
memory usage: 1.2+ MB
```

In [79]:
```
# Convert RAIN to boolean, then int

seattle_nonull['RAIN'] = seattle_nonull['RAIN'].astype('bool').astype
('int')
```

```
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:3: Setti
ngWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas
-docs/stable/indexing.html#indexing-view-versus-copy
  This is separate from the ipykernel package so we can avoid doing i
mports until
```

In [80]:
```
# Check for TMIN values that are more than TMAX

seattle_nonull.loc[seattle_nonull['TMIN'] > seattle_nonull['TMAX']]
```

Out[80]:

	DATE	PRCP	TMAX	TMIN	RAIN
1419	1951-11-20	0.08	4	39	1

In [81]:
```
# Remove row by inverse selection

seattle_nonull = seattle_nonull.loc[~(seattle_nonull['TMIN'] > seattl
e_nonull['TMAX'])]
```

In [82]:
```
# Check that row 1419 has been removed

seattle_nonull.loc[1418:1421, ]
```

Out[82]:

	DATE	PRCP	TMAX	TMIN	RAIN
1418	1951-11-19	0.06	53	40	1
1420	1951-11-21	0.00	46	33	0
1421	1951-11-22	0.00	43	29	0

Plotting precipitation and temperature in Seattle 1949-2017

In [83]:
```
# Set index as DATE

seattle_indexed = seattle_nonull.set_index('DATE')
```

In [84]:
```
# Define function to categorise dates into seasons

def apply_season(date):
    if date.month in [3, 4, 5]:
        return 'Spring'
    elif date.month in [6, 7, 8]:
        return 'Summer'
    elif date.month in [9, 10, 11]:
        return 'Autumn'
    else:
        return 'Winter'
```

In [85]:
```
# Map date to season

seattle_indexed['SEASON'] = seattle_indexed.index.map(apply_season)

# Format SEASON as category in chronological order

seattle_indexed['SEASON'] = pd.Categorical(seattle_indexed['SEASON'],
                                           ['Winter', 'Spring', 'Summ
er', 'Autumn'])

# Check values of SEASON column

seattle_indexed['SEASON'].value_counts()
```

Out[85]:
```
Spring    6440
Summer    6438
Autumn    6368
Winter    6301
Name: SEASON, dtype: int64
```

In [86]:
```
# Extract month name from index

seattle_indexed['MONTH NAME'] = seattle_indexed.index.map(lambda x: c
alendar.month_name[x.month])

# Format MONTH NAME column as category with months in chronological o
rder

seattle_indexed['MONTH NAME'] = pd.Categorical(seattle_indexed['MONTH
 NAME'],
                                            ['January', 'February', 'Ma
rch',
                                             'April', 'May', 'June', 'J
uly',
                                             'August', 'September', 'Oc
tober',
                                             'November', 'December'])

# Check values of MONTH NAME

seattle_indexed['MONTH NAME'].value_counts()
```

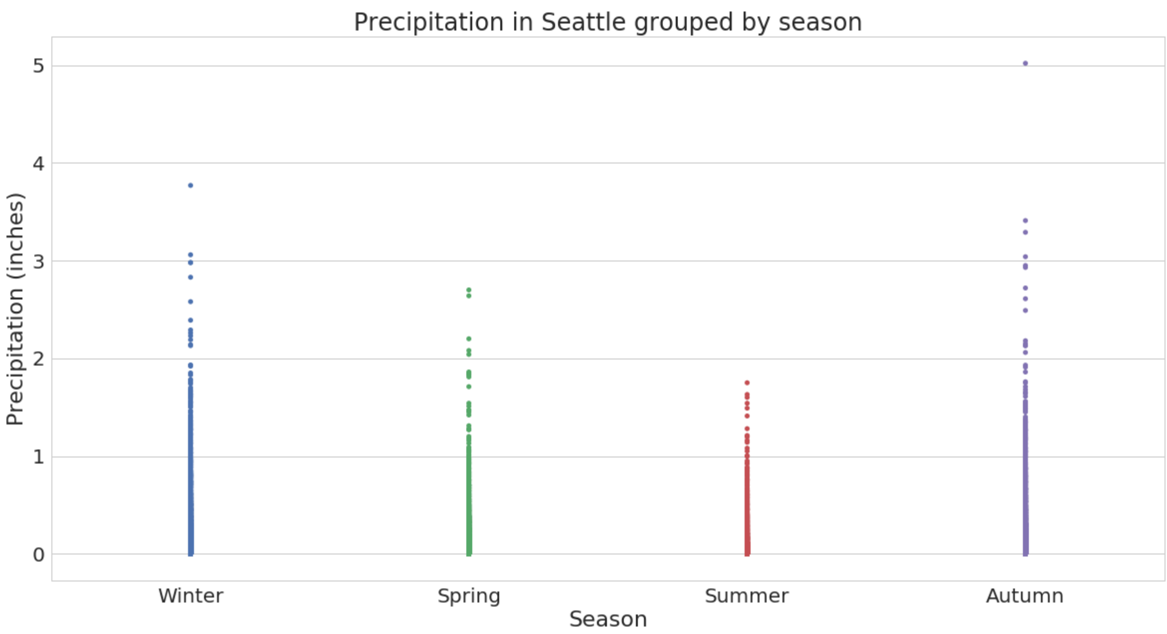
Out[86]:
```
October      2170
August       2170
July         2170
May          2170
March        2170
January      2170
December     2153
April        2100
November     2099
September    2099
June         2098
February     1978
Name: MONTH NAME, dtype: int64
```

In [87]:
```
# Extract year, month and day from index to create YEAR, MONTH and DA
Y numerical column

seattle_indexed['YEAR'] = seattle_indexed.index.map(lambda x: x.year)
seattle_indexed['MONTH'] = seattle_indexed.index.map(lambda x: x.mont
h)
seattle_indexed['DAY'] = seattle_indexed.index.map(lambda x: x.day)
seattle_indexed = seattle_indexed[['YEAR', 'MONTH', 'DAY', 'MONTH NAM
E', 'SEASON', 'TMIN', 'TMAX', 'PRCP', 'RAIN']]
seattle_indexed.head()
```

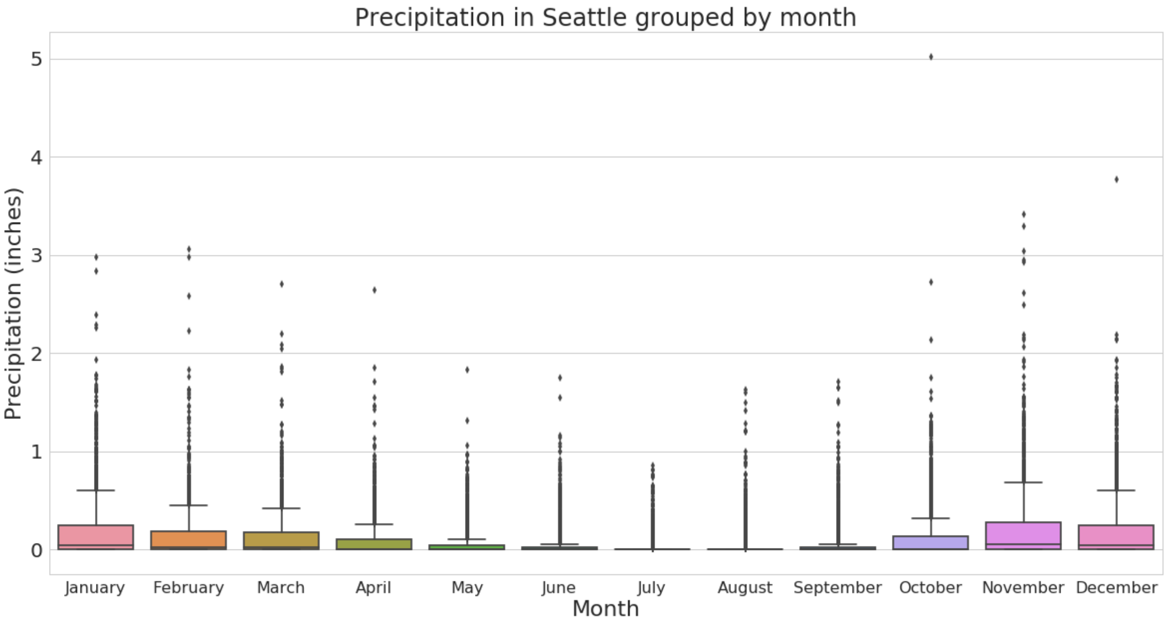
Out[87]:

	YEAR	MONTH	DAY	MONTH NAME	SEASON	TMIN	TMAX	PRCP	RAIN
DATE									
1948-01-01	1948	1	1	January	Winter	42	51	0.47	1
1948-01-02	1948	1	2	January	Winter	36	45	0.59	1
1948-01-03	1948	1	3	January	Winter	35	45	0.42	1
1948-01-04	1948	1	4	January	Winter	34	45	0.31	1
1948-01-05	1948	1	5	January	Winter	32	45	0.17	1

In [88]:
```
# Draw boxplot for precipitation against season

sns.stripplot(data=seattle_indexed, x='SEASON', y='PRCP')
plt.xlabel('Season')
plt.ylabel('Precipitation (inches)')
plt.title('Precipitation in Seattle grouped by season')
plt.show()
```



In [89]:
```
# Draw boxplot of precipitation according to month

sns.boxplot(data=seattle_indexed, x='MONTH NAME', y='PRCP')
plt.xlabel('Month')
plt.xticks(fontsize=16)
plt.ylabel('Precipitation (inches)')
plt.title('Precipitation in Seattle grouped by month')
plt.show()
```

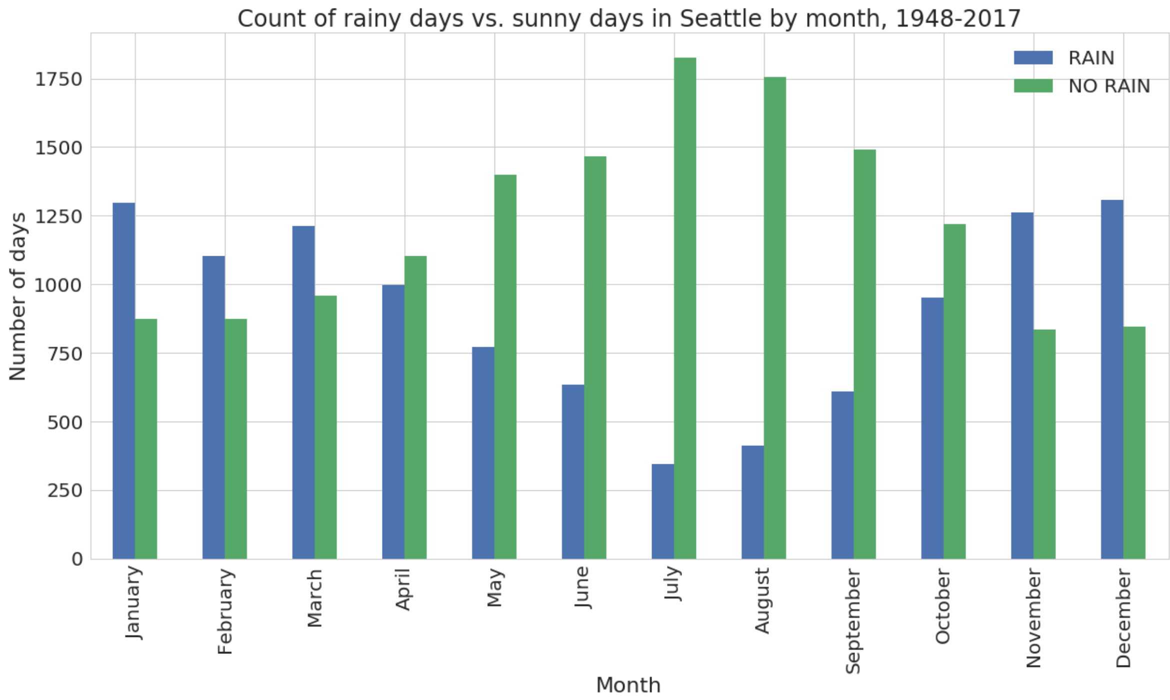


In [90]:
```
# Plot rainy days by month

rain_month_count = seattle_indexed.groupby('MONTH NAME')['RAIN'].sum
().reset_index()
rain_month_count = pd.merge(rain_month_count,  seattle_indexed['MONTH
 NAME'].value_counts().reset_index(),
                            left_on='MONTH NAME', right_on='index')
del rain_month_count['index']
rain_month_count = rain_month_count.rename(columns={'MONTH NAME_x':
'MONTH NAME', 'MONTH NAME_y': 'TOTAL DAYS'})
rain_month_count['NO RAIN'] = rain_month_count['TOTAL DAYS'] - rain_m
onth_count['RAIN']
rain_month_count.set_index('MONTH NAME', inplace=True)

rain_month_count.head()
```

Out[90]:

	RAIN	TOTAL DAYS	NO RAIN
MONTH NAME			
January	1298	2170	872
February	1103	1978	875
March	1212	2170	958
April	998	2100	1102
May	771	2170	1399

In [91]:
```
# Plot count of rain vs no rain per month

rain_month_count[['RAIN', 'NO RAIN']].plot(kind='bar')
plt.ylabel('Number of days')
plt.xlabel('Month')
plt.title('Count of rainy days vs. sunny days in Seattle by month, 19
48-2017')
plt.show()
```

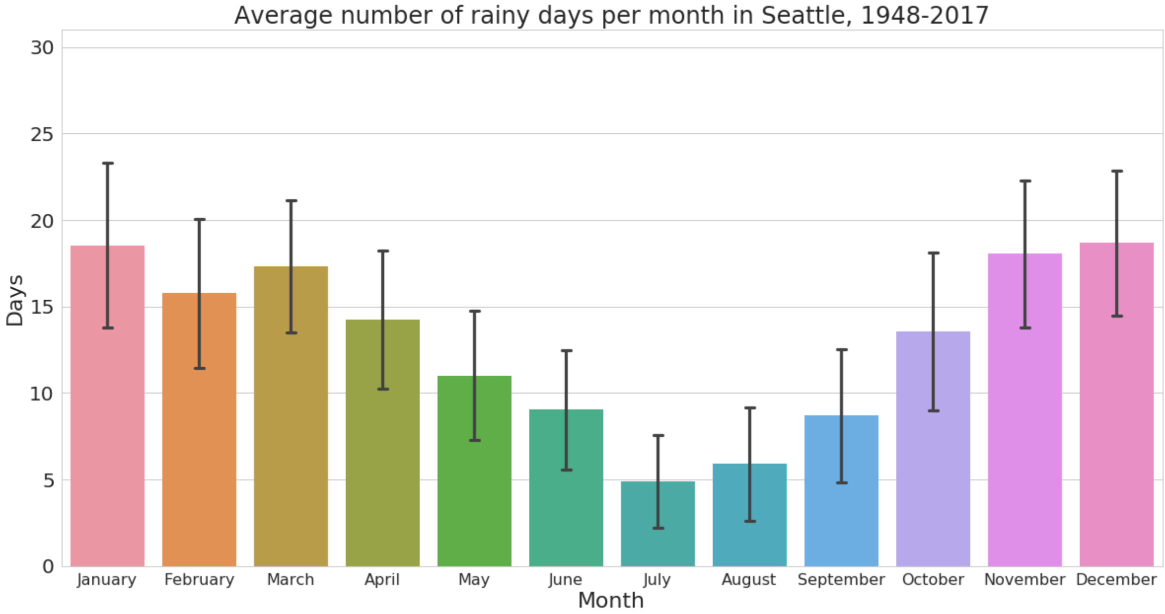


In [92]:
```
# Count number of rainy days vs sunny days every month-year pair

rain_month_year_count = seattle_indexed.groupby(['YEAR', 'MONTH NAME'
])\
                        ['RAIN', 'TMAX'].agg({'RAIN': 'sum', 'TMAX':
'count'}).\
                        reset_index().rename(columns={'TMAX': 'TOTAL
 DAYS'})

rain_month_year_count['NO RAIN'] = rain_month_year_count['TOTAL DAYS'
] - rain_month_year_count['RAIN']
rain_month_year_count.head()
```

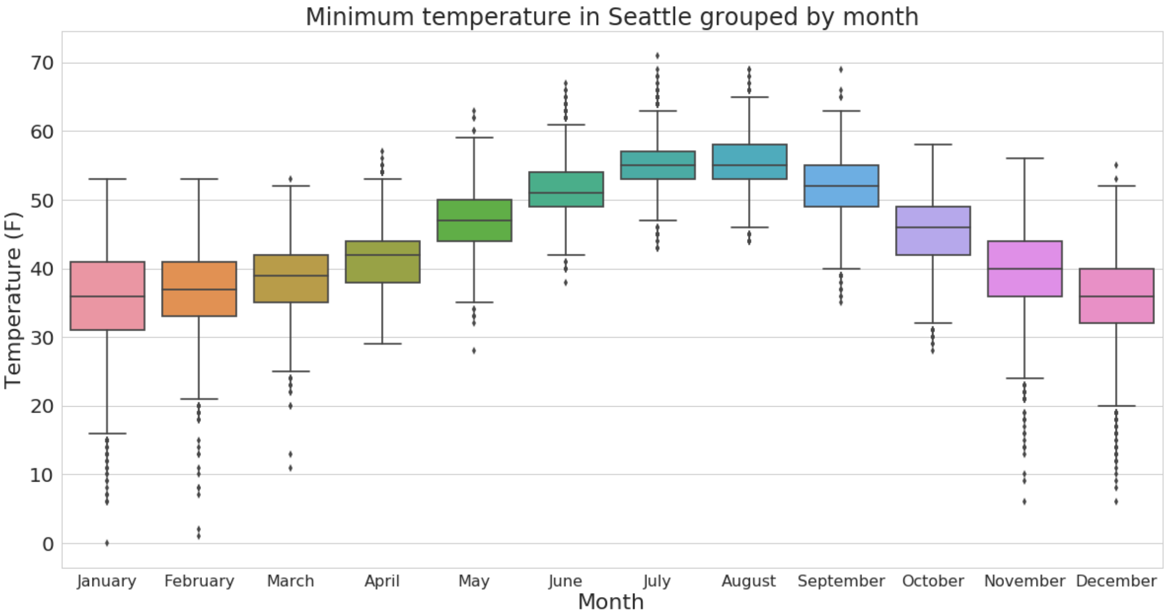
Out[92]:

	YEAR	MONTH NAME	TOTAL DAYS	RAIN	NO RAIN
0	1948	January	31	16	15
1	1948	February	29	16	13
2	1948	March	31	14	17
3	1948	April	30	20	10
4	1948	May	31	16	15

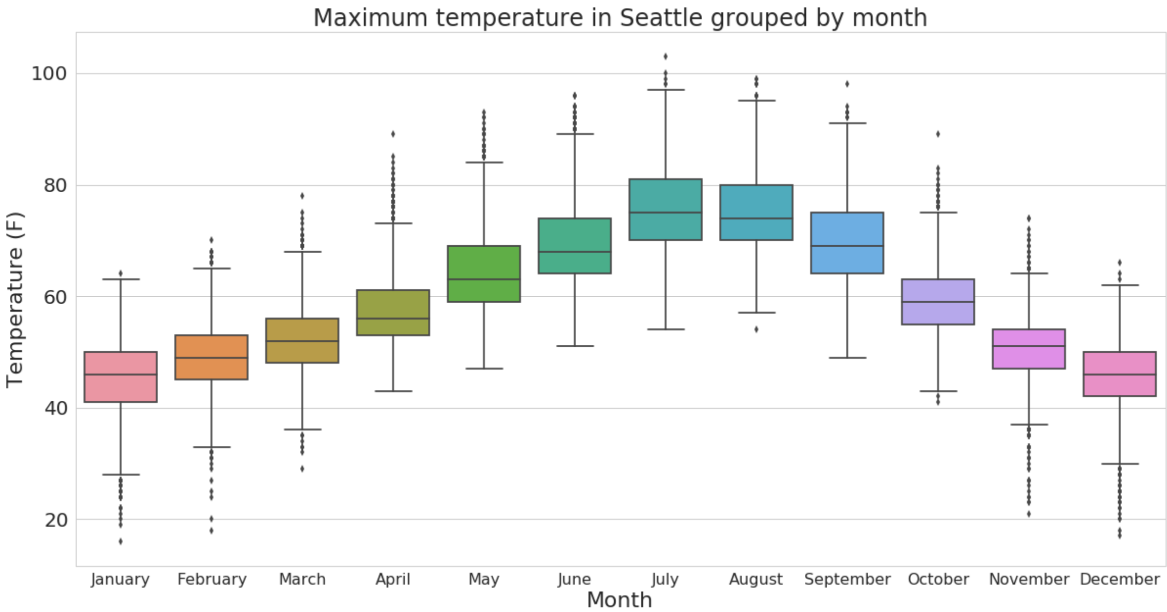
In [93]:
```
# Plot average number of rainy days per month

sns.barplot(data=rain_month_year_count, x='MONTH NAME', y='RAIN', ci=
'sd', capsize=0.1)
plt.ylabel('Days')
plt.ylim(0, 31)
plt.xlabel('Month')
plt.xticks(fontsize=16)
plt.title('Average number of rainy days per month in Seattle, 1948-20
17')
plt.show()
```



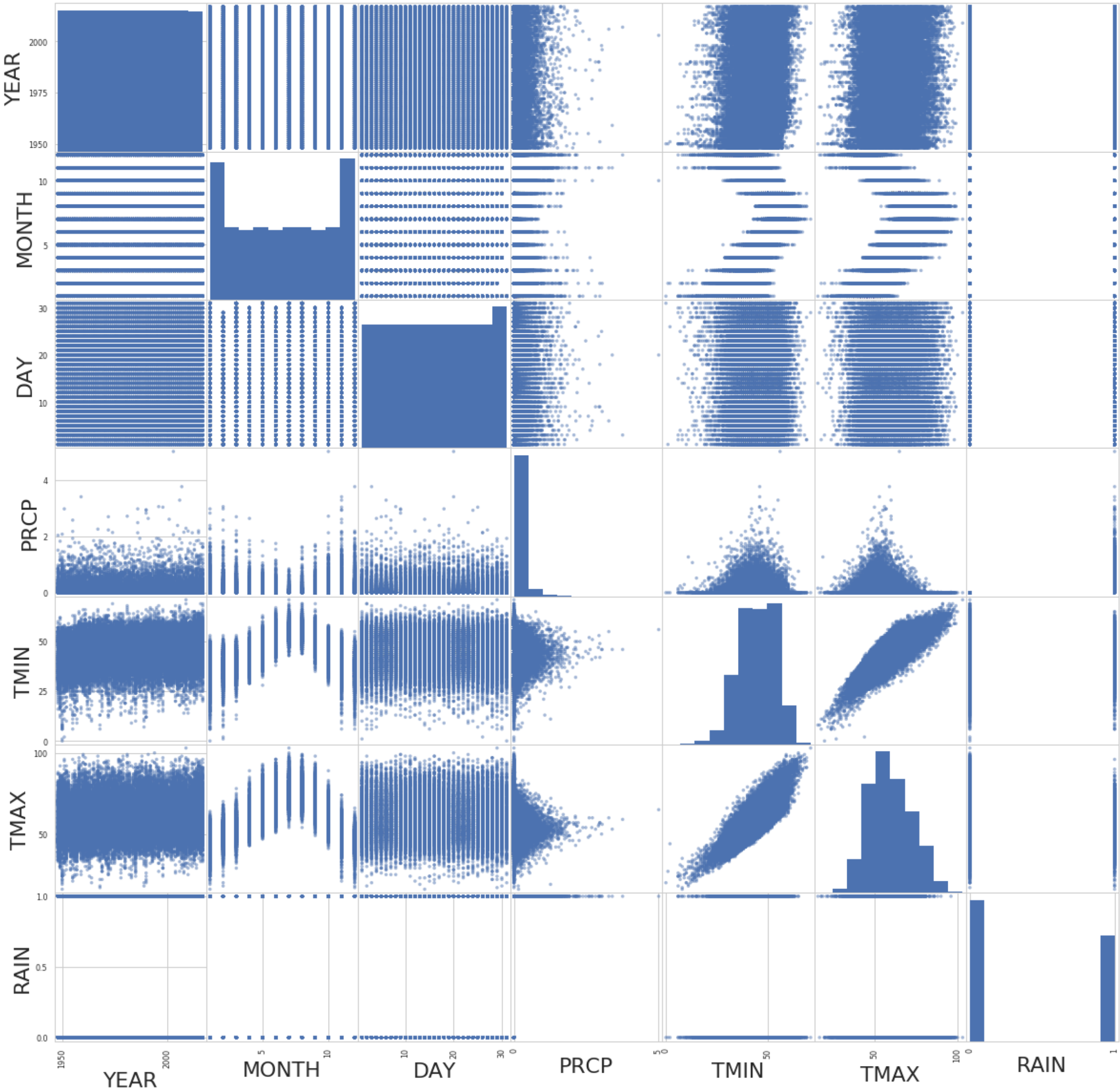
In [94]:
```
# Plot TMIN by month

sns.boxplot(data=seattle_indexed, x='MONTH NAME', y='TMIN')
plt.xlabel('Month')
plt.xticks(fontsize=16)
plt.ylabel('Temperature (F)')
plt.title('Minimum temperature in Seattle grouped by month')
plt.show()
```



In [95]:
```
# Plot TMAX by month

sns.boxplot(data=seattle_indexed, x='MONTH NAME', y='TMAX')
plt.xlabel('Month')
plt.xticks(fontsize=16)
plt.ylabel('Temperature (F)')
plt.title('Maximum temperature in Seattle grouped by month')
plt.show()
```



In [96]:
```
seattle_scatter = seattle_indexed.loc[:, ['YEAR', 'MONTH', 'DAY', 'PR
CP', 'TMIN', 'TMAX', 'RAIN']]

pd.plotting.scatter_matrix(seattle_scatter, figsize=(20, 20))
plt.show()
```



Generally:

- Daily average PCRP is low during the summer months (June, July, August) compared to the rest of the year.
- Consequently, the same period has the least average number of days where RAIN is True.
- Daily TMIN and TMAX is higher during the summer and at the lowest during the winter (December, January)
- TMIN and TMAX appear to be highly co-linear and one of the two should be excluded as a feature in a logistic regresion model

Selecting an extra feature

A useful extra feature could be: *Did it rain the previous day?*

In [97]:

```
# View Seattle dataset again

seattle_indexed = seattle_indexed.reset_index()

seattle_indexed.head(10)
```

Out[97]:

	DATE	YEAR	MONTH	DAY	MONTH NAME	SEASON	TMIN	TMAX	PRCP	RAIN
0	1948-01-01	1948	1	1	January	Winter	42	51	0.47	1
1	1948-01-02	1948	1	2	January	Winter	36	45	0.59	1
2	1948-01-03	1948	1	3	January	Winter	35	45	0.42	1
3	1948-01-04	1948	1	4	January	Winter	34	45	0.31	1
4	1948-01-05	1948	1	5	January	Winter	32	45	0.17	1
5	1948-01-06	1948	1	6	January	Winter	39	48	0.44	1
6	1948-01-07	1948	1	7	January	Winter	40	50	0.41	1
7	1948-01-08	1948	1	8	January	Winter	35	48	0.04	1
8	1948-01-09	1948	1	9	January	Winter	31	50	0.12	1
9	1948-01-10	1948	1	10	January	Winter	34	43	0.74	1

In [98]:

```
# Initialise RAIN_YESTERDAY as NaNs

seattle_indexed['RAIN_YESTERDAY'] = np.nan

# Set RAIN_YESTERDAY as previous row value for RAIN

for i in range(1, len(seattle_indexed)):
    seattle_indexed.loc[i, 'RAIN_YESTERDAY'] = seattle_indexed.loc[i-
1, 'RAIN']

# Check new dataframe

seattle_indexed.head(15)
```

Out[98]:

	DATE	YEAR	MONTH	DAY	MONTH NAME	SEASON	TMIN	TMAX	PRCP	RAIN	RAIN_Y
0	1948-01-01	1948	1	1	January	Winter	42	51	0.47	1	NaN
1	1948-01-02	1948	1	2	January	Winter	36	45	0.59	1	1.0
2	1948-01-03	1948	1	3	January	Winter	35	45	0.42	1	1.0
3	1948-01-04	1948	1	4	January	Winter	34	45	0.31	1	1.0
4	1948-01-05	1948	1	5	January	Winter	32	45	0.17	1	1.0
5	1948-01-06	1948	1	6	January	Winter	39	48	0.44	1	1.0
6	1948-01-07	1948	1	7	January	Winter	40	50	0.41	1	1.0
7	1948-01-08	1948	1	8	January	Winter	35	48	0.04	1	1.0
8	1948-01-09	1948	1	9	January	Winter	31	50	0.12	1	1.0
9	1948-01-10	1948	1	10	January	Winter	34	43	0.74	1	1.0
10	1948-01-11	1948	1	11	January	Winter	32	42	0.01	1	1.0
11	1948-01-12	1948	1	12	January	Winter	26	41	0.00	0	1.0
12	1948-01-13	1948	1	13	January	Winter	29	45	0.00	0	0.0
13	1948-01-14	1948	1	14	January	Winter	26	38	0.00	0	0.0
14	1948-01-15	1948	1	15	January	Winter	31	34	0.00	0	0.0

Logistic regression model for predicting rain in Seattle

In [128]:

```
# Import packages for machine learning

import itertools

from sklearn import model_selection
from sklearn.preprocessing import binarize
from sklearn.linear_model import LogisticRegressionCV, LogisticRegres
sion
from sklearn.metrics import confusion_matrix, precision_score, recall
_score
from sklearn import svm, datasets, metrics
from sklearn.dummy import DummyClassifier
```

In [100]:

```
# Define function for confusion matrix

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[
1])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [101]:

```
# Split dataset into training and validation

seattle_training = seattle_indexed.loc[(seattle_indexed['YEAR'] >= 19
50) &
                                       (seattle_indexed['YEAR'] <= 20
09)]

seattle_val = seattle_indexed.loc[seattle_indexed['YEAR'] >= 2010]

# Convert RAIN YESTERDAY column from float to int

seattle_training['RAIN_YESTERDAY'] = seattle_training['RAIN_YESTERDA
Y'].astype('int')
seattle_val['RAIN_YESTERDAY'] = seattle_val['RAIN_YESTERDAY'].astype(
'int')

# View seattle_training

seattle_training.head()
```

```
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:10: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas
-docs/stable/indexing.html#indexing-view-versus-copy
  # Remove the CWD from sys.path while we load stuff.
/usr/local/lib/python3.5/dist-packages/ipykernel_launcher.py:11: Sett
ingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas
-docs/stable/indexing.html#indexing-view-versus-copy
  # This is added back by InteractiveShellApp.init_path()
```

Out[101]:

	DATE	YEAR	MONTH	DAY	MONTH NAME	SEASON	TMIN	TMAX	PRCP	RAIN	RAIN_
731	1950-01-01	1950	1	1	January	Winter	24	32	0.25	1	1
732	1950-01-02	1950	1	2	January	Winter	6	24	0.01	1	1
733	1950-01-03	1950	1	3	January	Winter	6	26	0.10	1	1
734	1950-01-04	1950	1	4	January	Winter	14	28	0.00	0	1
735	1950-01-05	1950	1	5	January	Winter	22	38	0.08	1	0

In [102]:
```
seattle_training.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 21911 entries, 731 to 22641
Data columns (total 11 columns):
DATE              21911 non-null datetime64[ns]
YEAR              21911 non-null int64
MONTH             21911 non-null int64
DAY               21911 non-null int64
MONTH NAME        21911 non-null category
SEASON            21911 non-null category
TMIN              21911 non-null int64
TMAX              21911 non-null int64
PRCP              21911 non-null float64
RAIN              21911 non-null int64
RAIN_YESTERDAY    21911 non-null int64
dtypes: category(2), datetime64[ns](1), float64(1), int64(7)
memory usage: 1.7 MB
```

Test PRCP only

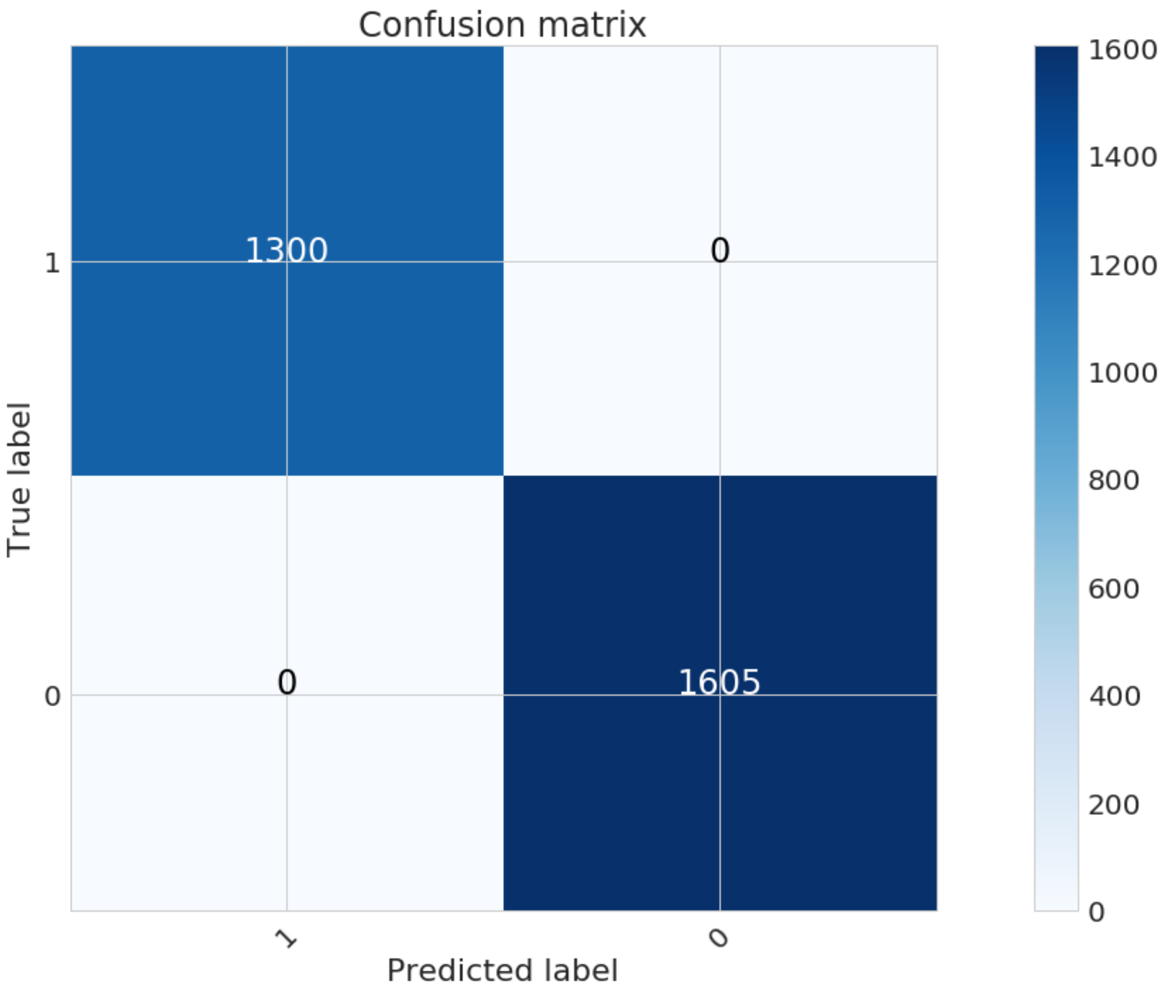
Accuracy score should be 1, as PRCP being more than 0 determines whether RAIN is True/1.

In [103]:
```
# Choose variables

feature_cols = ['PRCP']

X = seattle_training[feature_cols]
y = seattle_training.RAIN

X_val = seattle_val[feature_cols]
y_val = seattle_val.RAIN

# Fit logistic regression model

logreg_cv = LogisticRegressionCV(cv=model_selection.KFold(20, shuffle
=True, random_state=1), max_iter=100)
logreg_cv.fit(X, y)

# Predict with test data

y_pred_class = logreg_cv.predict(X_val)
print (metrics.accuracy_score(y_val, y_pred_class))
```

```
1.0
```

In [104]:
```
# plot confusion matrix
cnf_mat = metrics.confusion_matrix(y_val, y_pred_class, labels = seat
tle_training.RAIN.unique())
class_labels = seattle_training.RAIN.unique()
plt.figure()
plot_confusion_matrix(cnf_mat, class_labels,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues)
plt.show()
```

```
Confusion matrix, without normalization
[[1300    0]
 [   0 1605]]
```



Model without PRCP

If a model is to be used for predicting rain, PRCP will have to be excluded as a feature.

In [105]:
```
# Choose variables

feature_cols = ['YEAR', 'MONTH', 'DAY', 'TMIN', 'RAIN_YESTERDAY']

X = seattle_training[feature_cols]
y = seattle_training.RAIN

X_val = seattle_val[feature_cols]
y_val = seattle_val.RAIN
```

In [106]:
```
# Calculate null accuracy

dumb = DummyClassifier(strategy='most_frequent')
dumb.fit(X, y)
y_dumb_class = dumb.predict(X_val)
print ('Null accuracy is', metrics.accuracy_score(y_val, y_dumb_class
))
```

```
Null accuracy is 0.5524956970740104
```

In [107]:
```
# Fit logistic regression model with KFold validation where K = 20

logreg_cv = LogisticRegressionCV(cv=model_selection.KFold(20, shuffle
=True, random_state=1), max_iter=100)
logreg_cv.fit(X, y)

# Predict with test data

y_pred_class = logreg_cv.predict(X_val)
print ('Accuracy of model (prediction with X_val)', metrics.accuracy_
score(y_val, y_pred_class))
```

```
Accuracy of model (prediction with X_val) 0.7201376936316696
```

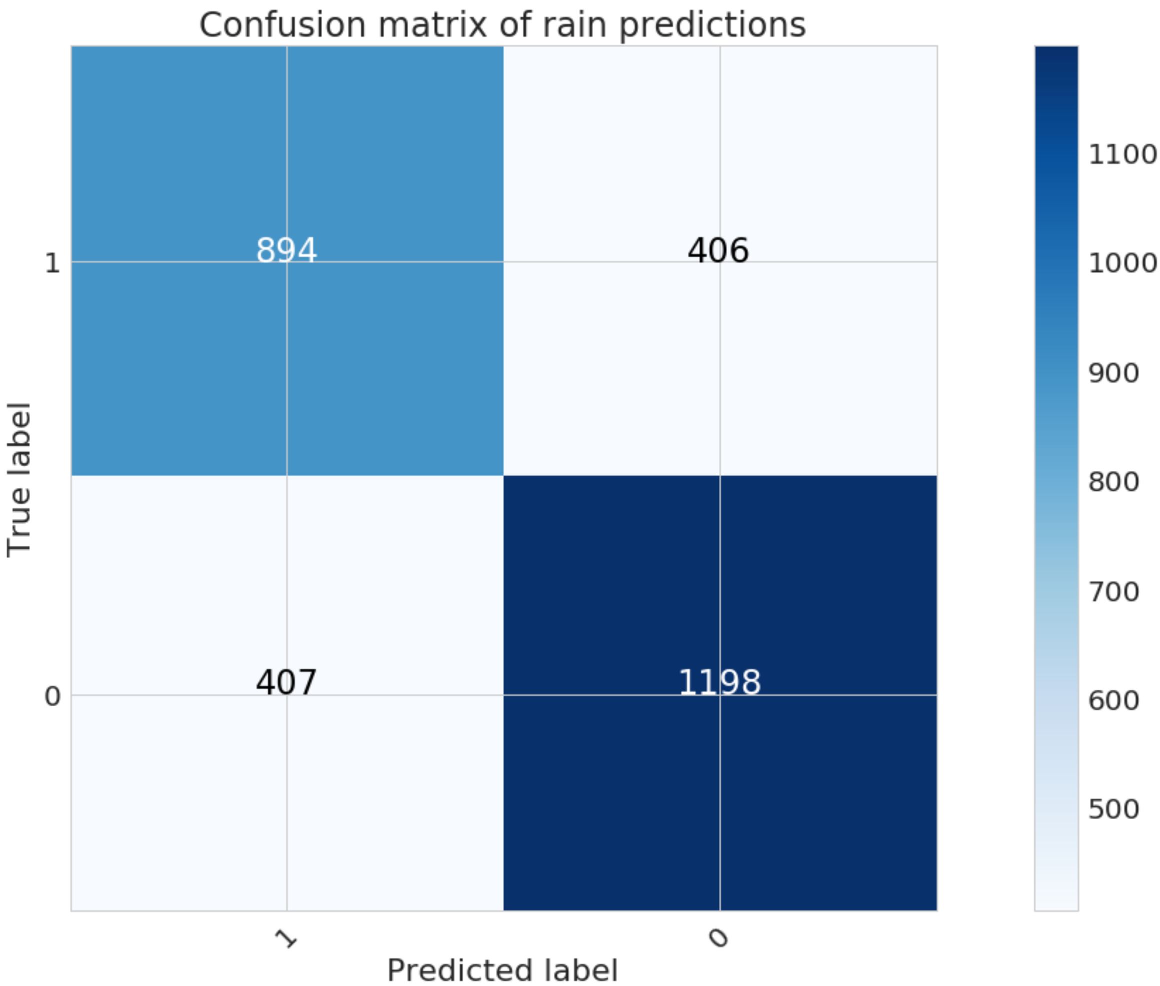
The accuracy of the model in correctly predicting rainy days in 2009-2017 is 0.15 higher than the null accuracy.

In [122]:
```
# Print co-efficients and intercept

print('Coefficients:', list(zip(feature_cols, logreg_cv.coef_[0])))
print('Intercept:', logreg_cv.intercept_)
```

```
Coefficients: [('YEAR', -4.977335818707858e-05), ('MONTH', -0.0099826
97054080199), ('DAY', -0.0010406500904158035), ('TMIN', -0.0177571263
8867668), ('RAIN_YESTERDAY', 1.4657939529805413)]
Intercept: [0.00175042]
```

In [123]:
```
# Plot confusion matrix
cnf_mat = metrics.confusion_matrix(y_val, y_pred_class, labels = seat
tle_val.RAIN.unique())
class_labels = seattle_val.RAIN.unique()
plt.figure()
plot_confusion_matrix(cnf_mat, class_labels,
                          normalize=False,
                          title='Confusion matrix of rain prediction
s',
                          cmap=plt.cm.Blues)
plt.show()
```

```
Confusion matrix, without normalization
[[ 894  406]
 [ 407 1198]]
```



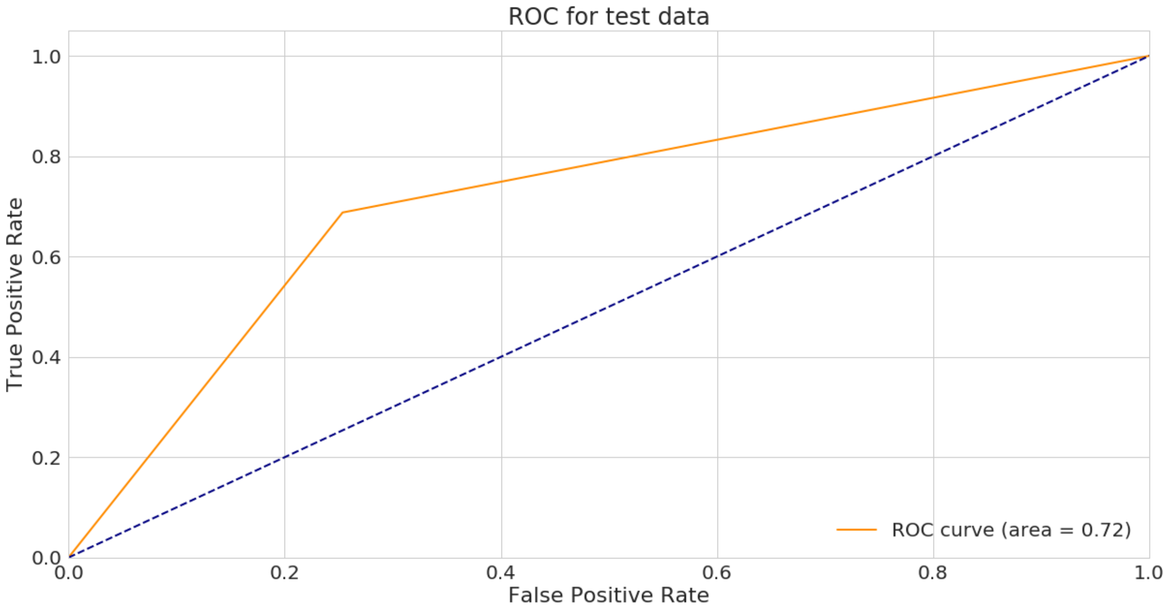
In [119]:
```
# Calculate TPR and TNR

print('True positive rate is', precision_score(y_val, y_pred_class))
print('True negative rate is', 1198/(1198+407))
```

```
True positive rate is 0.6871637202152191
True negative rate is 0.746417445482866
```

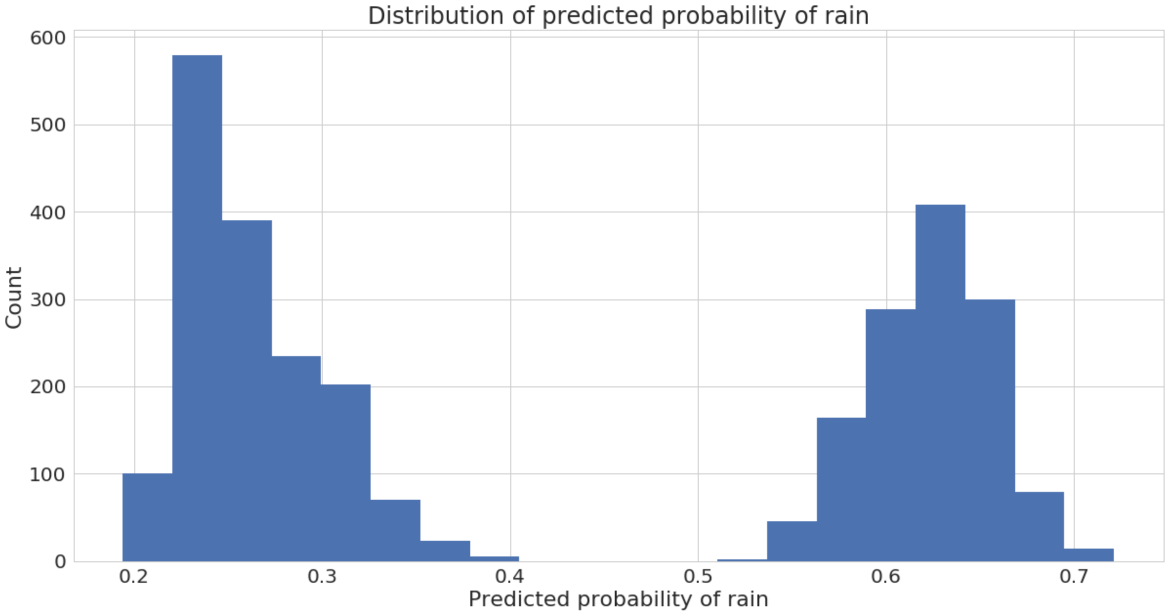
The model correctly predicts when there will be no rain - given the date, minimum temperature and whether it rained yesterday - 75% of the period between 2009-2017, while correctly predicting for rain 69% of the time.

In [124]:

```
# get FPR and TPR for holdout data
fpr, tpr, _ = metrics.roc_curve(y_val, y_pred_class)

# Store the Area Under the Curve (AUC)
roc_auc = metrics.auc(fpr,tpr)

# Plot the ROC Curve
plt.figure()
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC for test data')
plt.legend(loc="lower right")
plt.show()
```



In [127]:
```
# Generate the prediction values for each of the test observations
preds = logreg_cv.predict_proba(X_val)[:,1]

plt.hist(preds, bins=20)
plt.title('Distribution of predicted probability of rain')
plt.xlabel('Predicted probability of rain')
plt.ylabel('Count')
plt.show()
```



The distribution of probability estimates shows two distinct groups: one where P is 0.2-0.45 and another where P is 0.5-0.7. The total count of the group where P < 0.45 seems roughly equal to the number of total negatives (where `RAIN` is `False`), while the other group seems roughly equal to the number of total positives (where `RAIN` is `True`).