```
import datetime as dt

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

from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report
from sklearn.ensemble import RandomForestRegressor
```

Reading dataset (.csv)

```
forest = pd.read_csv('fire_archive.csv')

forest.head()
```

	latitude	longitude	brightness	scan	track	acq_date	acq_time	satellite	instrument	confidence	version	bright_
0	-11.8070	142.0583	313.0	1.0	1.0	2019-08-01	56	Terra	MODIS	48	6.3	2
1	-11.7924	142.0850	319.3	1.0	1.0	2019-08-01	56	Terra	MODIS	71	6.3	2
2	-12.8398	132.8744	311.6	3.1	1.7	2019-08-01	57	Terra	MODIS	42	6.3	2
						2019-08-						

Data exploration

```
forest.shape
# Here we can see that we have 36011 rows and 15 columns in our dataset, obviously we have to do lot of data cleaning but fi
```

```
(36011, 15)
```

```
forest.columns
```

```
Index(['latitude', 'longitude', 'brightness', 'scan', 'track', 'acq_date',
       'acq_time', 'satellite', 'instrument', 'confidence', 'version',
       'bright_t31', 'frp', 'daynight', 'type'],
      dtype='object')
```

```
forest.isnull().sum()
# Fortunately we don't have any null values in this dataset
```

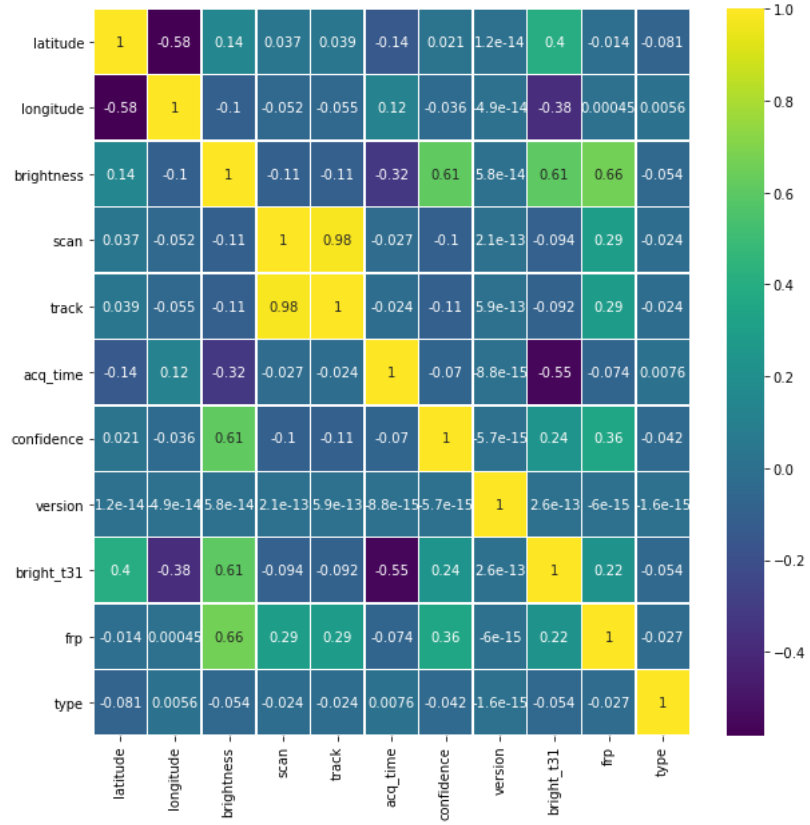
```
latitude      0
longitude     0
brightness    0
scan          0
track         0
acq_date      0
acq_time      0
satellite     0
instrument    0
confidence    0
version       0
bright_t31    0
frp           0
daynight      0
type          0
dtype: int64
```

```
forest.describe()
```

	latitude	longitude	brightness	scan	track	acq_time	confidence	version	bri
count	36011.000000	36011.000000	36011.000000	36011.000000	36011.000000	36011.000000	36011.000000	3.601100e+04	3601
mean	-19.100962	138.931446	328.750696	1.620905	1.215281	600.025798	67.551387	6.300000e+00	30
std	7.265777	9.261400	18.992808	0.813764	0.247852	548.369111	23.179946	3.728625e-12	
min	-42.762800	114.104300	300.000000	1.000000	1.000000	0.000000	0.000000	6.300000e+00	26
25%	-26.370250	131.072250	316.500000	1.100000	1.000000	205.000000	52.000000	6.300000e+00	29
50%	-15.706500	136.738500	326.400000	1.300000	1.100000	424.000000	70.000000	6.300000e+00	30
75%	-13.343600	147.477500	336.700000	1.900000	1.300000	600.000000	86.000000	6.300000e+00	30
max	-10.072600	153.490400	504.400000	4.800000	2.000000	2359.000000	100.000000	6.300000e+00	40

```
plt.figure(figsize=(10, 10))
sns.heatmap(forest.corr(),annot=True,cmap='viridis',linewidths=.5)
```

```
<AxesSubplot:>
```



Data cleaning

```
forest = forest.drop(['track'], axis = 1)
```

```
# By the way from the the dataset we are not finding if the forest fire happens or not, we are trying to find the confidence
# fire happening. They may seem to be the same thing but there is a very small difference between them, try to find that :)
```

```
# Finding categorical data
print("The scan column")
print(forest['scan'].value_counts())
print()
print("The aqc_time column")
print(forest['acq_time'].value_counts())
print()
print("The satellite column")
```

```
print(forest['satellite'].value_counts())
print()
print("The instrument column")
print(forest['instrument'].value_counts())
print()
print("The version column")
print(forest['version'].value_counts())
print()
print("The daynight column")
print(forest['daynight'].value_counts())
print()
```

```
2.4     433
2.8     422
3.0     402
2.7     366
2.9     361
2.6     347
3.1     259
3.2     244
3.6     219
3.4     203
3.3     203
3.8     189
3.9     156
4.7     149
4.3     137
3.5     134
3.7     134
4.1     120
4.6     118
4.5     116
4.2     108
4.0     103
4.4     100
4.8      70
Name: scan, dtype: int64

The aqc_time column
506     851
454     631
122     612
423     574
448     563
       ...
1558      1
635       1
1153      1
302       1
1519      1
Name: acq_time, Length: 662, dtype: int64

The satellite column
Aqua     20541
Terra    15470
Name: satellite, dtype: int64

The instrument column
MODIS    36011
Name: instrument, dtype: int64

The version column
6.3    36011
Name: version, dtype: int64

The daynight column
D    28203
N     7808
Name: daynight, dtype: int64
```

```
# From the above data we can see that some columns have just one value reccurring in them, meaning they are not valuable to
# So we will drop them altogether.
# Thus only satellite and daynight column are the only categorical type.
```

```
# But we can even use the scan column to restructure it into a categorical data type column. Which we will be doing in just
```

```
forest = forest.drop(['instrument', 'version'], axis = 1)

forest.head()
```

	latitude	longitude	brightness	scan	acq_date	acq_time	satellite	confidence	bright_t31	frp	daynight	type
0	-11.8070	142.0583	313.0	1.0	2019-08-01	56	Terra	48	297.3	6.6	D	0
1	-11.7924	142.0850	319.3	1.0	2019-08-01	56	Terra	71	297.3	11.3	D	0
2	-12.8398	132.8744	311.6	3.1	2019-08-01	57	Terra	42	298.7	23.1	D	0
3	-14.4306	143.3035	310.1	1.1	2019-08-01	57	Terra	33	296.1	6.5	D	0
4	-12.4953	131.4897	310.3	4.0	2019-08-01	57	Terra	36	298.8	27.6	D	0

```
daynight_map = {"D": 1, "N": 0}
satellite_map = {"Terra": 1, "Aqua": 0}

forest['daynight'] = forest['daynight'].map(daynight_map)
forest['satellite'] = forest['satellite'].map(satellite_map)

forest.head()
```

	latitude	longitude	brightness	scan	acq_date	acq_time	satellite	conf
0	-11.8070	142.0583	313.0	1.0	2019-08-01	56	1	
1	-11.7924	142.0850	319.3	1.0	2019-08-01	56	1	
2	-12.8398	132.8744	311.6	3.1	2019-08-01	57	1	

```
# Looking at another columns type
forest['type'].value_counts()
```

```
0    35666
2      335
3       10
Name: type, dtype: int64
```

```
types = pd.get_dummies(forest['type'])
forest = pd.concat([forest, types], axis=1)

forest = forest.drop(['type'], axis = 1)
forest.head()
```

	latitude	longitude	brightness	scan	acq_date	acq_time	satellite	confidence	bright_t31	frp	daynight	0	2	3
0	-11.8070	142.0583	313.0	1.0	2019-08-01	56	1	48	297.3	6.6	1	1	0	0
1	-11.7924	142.0850	319.3	1.0	2019-08-01	56	1	71	297.3	11.3	1	1	0	0
2	-12.8398	132.8744	311.6	3.1	2019-08-01	57	1	42	298.7	23.1	1	1	0	0

```
# Renaming columns for better understanding

forest = forest.rename(columns={0: 'type_0', 2: 'type_2', 3: 'type_3'})
```

```
# Now I mentioned we will be converting scan column to categorical type, we will be doing this using binning method.
# Range for this columns was 1 to 4.8

bins = [0, 1, 2, 3, 4, 5]
```

```
labels = [1,2,3,4,5]
forest['scan_binned'] = pd.cut(forest['scan'], bins=bins, labels=labels)

forest.head()
```

	latitude	longitude	brightness	scan	acq_date	acq_time	satellite	confidence	bright_t31	frp	daynight	type_0
0	-11.8070	142.0583	313.0	1.0	2019-08-01	56	1	48	297.3	6.6	1	1
1	-11.7924	142.0850	319.3	1.0	2019-08-01	56	1	71	297.3	11.3	1	1
2	-12.8398	132.8744	311.6	3.1	2019-08-01	57	1	42	298.7	23.1	1	1

```
# Converting the datatype to datetype from string or numpy.

forest['acq_date'] = pd.to_datetime(forest['acq_date'])
```

```
# Now we will be dropping scan column and handle date type data - we can extract useful information from these datatypes
# just like we do with categorical data.

forest = forest.drop(['scan'], axis = 1)
```

```
forest['year'] = forest['acq_date'].dt.year

forest.head()
```

	latitude	longitude	brightness	acq_date	acq_time	satellite	confidence	bright_t31	frp	daynight	type_0	type_
0	-11.8070	142.0583	313.0	2019-08-01	56	1	48	297.3	6.6	1	1	
1	-11.7924	142.0850	319.3	2019-08-01	56	1	71	297.3	11.3	1	1	
2	-12.8398	132.8744	311.6	2019-08-01	57	1	42	298.7	23.1	1	1	

```
forest['month'] = forest['acq_date'].dt.month
forest['day'] = forest['acq_date'].dt.day
```

```
forest.shape
```

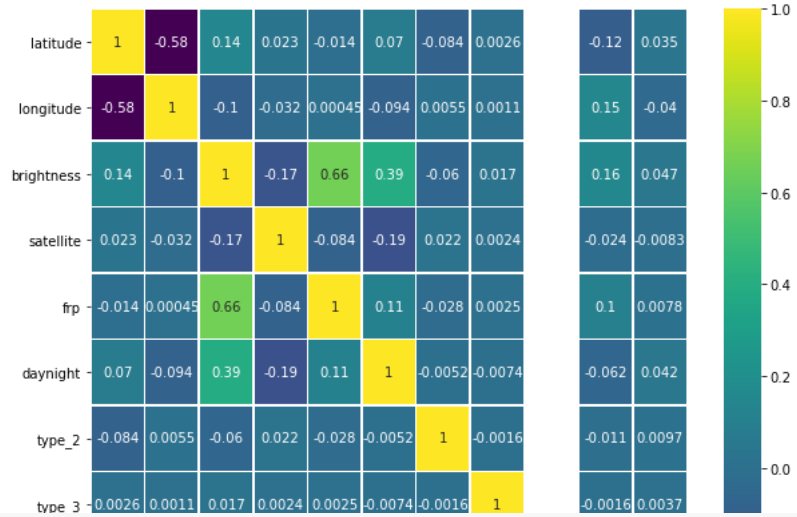
```
(36011, 17)
```

```
# Separating our target varibale:

y = forest['confidence']
fin = forest.drop(['confidence', 'acq_date', 'acq_time', 'bright_t31', 'type_0'], axis = 1)
```

```
plt.figure(figsize=(10, 10))
sns.heatmap(fin.corr(),annot=True,cmap='viridis',linewidths=.5)
```

```
<AxesSubplot:>
```




```
fin.head()
```

	latitude	longitude	brightness	satellite	frp	daynight	type_2	type_3	scan_binned	year	month	day
0	-11.8070	142.0583	313.0	1	6.6	1	0	0	1	2019	8	1
1	-11.7924	142.0850	319.3	1	11.3	1	0	0	1	2019	8	1
2	-12.8398	132.8744	311.6	1	23.1	1	0	0	4	2019	8	1
3	-14.4306	143.3035	310.1	1	6.5	1	0	0	2	2019	8	1
4	-12.4953	131.4897	310.3	1	27.6	1	0	0	4	2019	8	1

Splitting the clean data into training and testing dataset

```
Xtrain, Xtest, ytrain, ytest = train_test_split(fin.iloc[:, :500], y, test_size=0.2)
```

Using RandomForestRegressor for model building

```
random_model = RandomForestRegressor(n_estimators=300, random_state = 42, n_jobs = -1)
```

```
#Fit
random_model.fit(Xtrain, ytrain)

y_pred = random_model.predict(Xtest)

#Checking the accuracy
random_model_accuracy = round(random_model.score(Xtrain, ytrain)*100,2)
print(round(random_model_accuracy, 2), '%')
```

```
95.32 %
```

```
#Checking the accuracy
random_model_accuracy1 = round(random_model.score(Xtest, ytest)*100,2)
print(round(random_model_accuracy1, 2), '%')
```

```
65.32 %
```

```
# Save the trained model as a pickle string.
import pickle

saved_model = pickle.dump(random_model, open('ForestModelOld.pickle','wb'))
```

Model Tuning

```
# The accuracy is not so great, plus the model is overfitting
# So we use RandomCV
```

```
random_model.get_params()
```

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'criterion': 'mse',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 300,
 'n_jobs': -1,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

```
"""
n_estimators = number of trees in the foreset
max_features = max number of features considered for splitting a node
max_depth = max number of levels in each decision tree
min_samples_split = min number of data points placed in a node before the node is split
min_samples_leaf = min number of data points allowed in a leaf node
bootstrap = method for sampling data points (with or without replacement)
"""

from sklearn.model_selection import RandomizedSearchCV
```

```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 300, stop = 500, num = 20)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(15, 35, num = 7)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 3, 5]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
                }
print(random_grid)
```

```
{'n_estimators': [300, 310, 321, 331, 342, 352, 363, 373, 384, 394, 405, 415, 426, 436, 447, 457, 468, 478, 489, 500],
```

```
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores

# n_iter, which controls the number of different combinations to try, and cv which is the number of folds to use for cross v
rf_random = RandomizedSearchCV(estimator = random_model, param_distributions = random_grid, n_iter = 50, cv = 3, verbose=2,
# Fit the random search model
rf_random.fit(Xtrain, ytrain)
```

```
Fitting 3 folds for each of 50 candidates, totalling 150 fits
[CV] n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV]  n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18, total=  32.6s
[CV] n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:   32.5s remaining:    0.0s
[CV]  n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18, total=  27.3s
[CV] n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18
[CV]  n_estimators=415, min_samples_split=5, min_samples_leaf=2, max_features=auto, max_depth=18, total=  29.7s
[CV] n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28
[CV]  n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28, total=  36.1s
[CV] n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28
[CV]  n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28, total=  34.7s
[CV] n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28
[CV]  n_estimators=436, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=28, total=  35.9s
[CV] n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35
[CV]  n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35, total=  14.7s
[CV] n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35
[CV]  n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35, total=  14.5s
[CV] n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35
[CV]  n_estimators=478, min_samples_split=3, min_samples_leaf=1, max_features=sqrt, max_depth=35, total=  14.9s
[CV] n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28
[CV]  n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28, total=  19.3s
[CV] n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28
[CV]  n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28, total=  19.1s
[CV] n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28
[CV]  n_estimators=310, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=28, total=  19.4s
[CV] n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25, total=  36.2s
[CV] n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25, total=  37.2s
[CV] n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=447, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=25, total=  35.7s
[CV] n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25
[CV]  n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25, total=  29.2s
[CV] n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25
[CV]  n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25, total=  27.8s
[CV] n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25
[CV]  n_estimators=457, min_samples_split=5, min_samples_leaf=4, max_features=auto, max_depth=25, total=  29.8s
[CV] n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25, total=  34.3s
[CV] n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25, total=  40.8s
[CV] n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25
[CV]  n_estimators=384, min_samples_split=5, min_samples_leaf=1, max_features=auto, max_depth=25, total=  28.1s
[CV] n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35
[CV]  n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35, total=  41.1s
[CV] n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35
[CV]  n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35, total=  32.6s
[CV] n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35
[CV]  n_estimators=426, min_samples_split=3, min_samples_leaf=2, max_features=auto, max_depth=35, total=  42.3s
[CV] n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21
[CV]  n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21, total=  11.6s
[CV] n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21
[CV]  n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21, total=  12.5s
[CV] n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21
[CV]  n_estimators=352, min_samples_split=5, min_samples_leaf=1, max_features=sqrt, max_depth=21, total=  12.0s
[CV] n_estimators=300, min_samples_split=2, min_samples_leaf=1, max_features=auto, max_depth=31
```

```
rf_random.best_params_
```

```
{'n_estimators': 394,
 'min_samples_split': 2,
 'min_samples_leaf': 1,
 'max_features': 'sqrt',
 'max_depth': 25}
```

```
random_new = RandomForestRegressor(n_estimators = 394, min_samples_split = 2, min_samples_leaf = 1, max_features = 'sqrt',
                                   max_depth = 25, bootstrap = True)
```

```
#Fit
random_new.fit(Xtrain, ytrain)

y_pred1 = random_new.predict(Xtest)
```

```
#Checking the accuracy
random_model_accuracy1 = round(random_new.score(Xtrain, ytrain)*100,2)
print(round(random_model_accuracy1, 2), '%')
```

```
95.31 %
```

```
#Checking the accuracy
random_model_accuracy2 = round(random_new.score(Xtest, ytest)*100,2)
print(round(random_model_accuracy2, 2), '%')
```

```
67.39 %
```