Decision Trees and Random Forests

Problem Statement:

Predict next-day rain by training classification models on the target variable RainTomorrow.

We can read the data back preprocessed datasets for training, validation, and testing using `pd.read_parquet`

- Splitting a dataset into training, validation & test sets
- Filling/imputing missing values in numeric columns
- Scaling numeric features to a (0,1) range
- Encoding categorical columns as one-hot vectors

In [1]:
```
import pandas as pd
```

In [2]:
```
train_inputs = pd.read_parquet('train_inputs.parquet')
val_inputs = pd.read_parquet('val_inputs.parquet')
test_inputs = pd.read_parquet('test_inputs.parquet')

train_targets = pd.read_parquet('train_targets.parquet')["RainTomorrow"]
val_targets = pd.read_parquet('val_targets.parquet')["RainTomorrow"]
test_targets = pd.read_parquet('test_targets.parquet')["RainTomorrow"]
```

In [3]:
```
print('train_inputs:', train_inputs.shape)
print('train_targets:', train_targets.shape)
print('val_inputs:', val_inputs.shape)
print('val_targets:', val_targets.shape)
print('test_inputs:', test_inputs.shape)
print('test_targets:', test_targets.shape)
```

```
train_inputs: (9788, 123)
train_targets: (9788,)
val_inputs: (1700, 123)
val_targets: (1700,)
test_inputs: (2591, 123)
test_targets: (2591,)
```

In [4]:
```
train_targets
```

Out[4]:
```
126989     No
40299      No
28288      No
134636     No
130983    Yes
         ...
50356      No
122446    Yes
49288      No
119280     No
118137     No
Name: RainTomorrow, Length: 9788, dtype: object
```

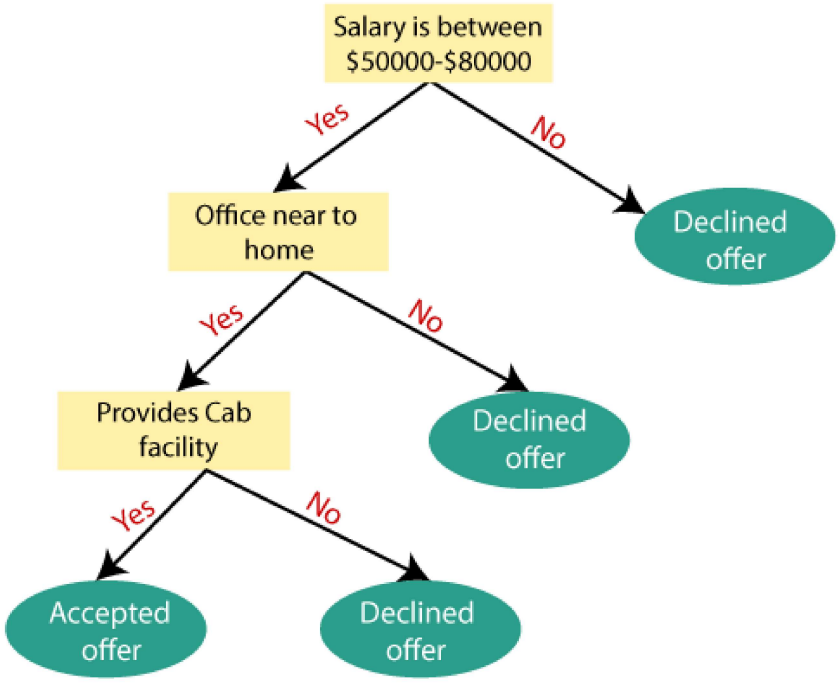
In [5]:
```
test_targets
```

Out[5]:
```
80721      No
```

```
83947      Yes
23750       No
89908       No
93275       No
           ...
143525      No
93147       No
120606     Yes
39511       No
48783       No
Name: RainTomorrow, Length: 2591, dtype: object
```

Training and Visualizing Decision Trees

A decision tree in general parlance represents a hierarchical series of binary decisions:



A decision tree in machine learning works in exactly the same way, and except that we let the computer figure up with criteria manually.

In [6]:
```
train_inputs
```

Out[6]:

	Location	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustDir	WindGustSp
126989	Walpole	0.437824	0.397959	0.031655	0.094322	0.534317	NW	0.190
40299	Williamtown	0.694301	0.932653	0.000000	0.168966	0.895105	WNW	0.427
28288	Richmond	0.634715	0.618367	0.000000	0.094322	0.534317	NNE	0.136
134636	Launceston	0.287565	0.314286	0.021103	0.094322	0.534317	SSW	0.054
130983	Hobart	0.297927	0.467347	0.000000	0.048276	0.272727	NW	0.390
...	...	...	...	...	...	...	...	...
50356	Tuggeranong	0.147668	0.373469	0.000000	0.094322	0.534317	W	0.209
122446	Perth	0.461140	0.483673	0.000000	0.058621	0.223776	N	0.236
49288	Tuggeranong	0.386010	0.455102	0.002878	0.094322	0.534317	NNW	0.327

119280	PerthAirport	0.440415	0.538776	0.000000	0.082759	0.699301	NW	0.290
118137	PerthAirport	0.313472	0.448980	0.000000	0.041379	0.636364	SSW	0.236

9788 rows × 123 columns

In [7]:
```
import numpy as np
```

In [8]:
```
numeric_cols = train_inputs.select_dtypes(include=np.number).columns.tolist()
numeric_cols
```

Out[8]:
```
['MinTemp',
 'MaxTemp',
 'Rainfall',
 'Evaporation',
 'Sunshine',
 'WindGustSpeed',
 'WindSpeed9am',
 'WindSpeed3pm',
 'Humidity9am',
 'Humidity3pm',
 'Pressure9am',
 'Pressure3pm',
 'Cloud9am',
 'Cloud3pm',
 'Temp9am',
 'Temp3pm',
 'Location_Adelaide',
 'Location_Albany',
 'Location_Albury',
 'Location_AliceSprings',
 'Location_BadgerysCreek',
 'Location_Ballarat',
 'Location_Bendigo',
 'Location_Brisbane',
 'Location_Cairns',
 'Location_Canberra',
 'Location_Cobar',
 'Location_CoffsHarbour',
 'Location_Dartmoor',
 'Location_Darwin',
 'Location_GoldCoast',
 'Location_Hobart',
 'Location_Katherine',
 'Location_Launceston',
 'Location_Melbourne',
 'Location_MelbourneAirport',
 'Location_Mildura',
 'Location_Moree',
 'Location_MountGambier',
 'Location_MountGinini',
 'Location_Newcastle',
 'Location_Nhil',
 'Location_NorahHead',
 'Location_NorfolkIsland',
 'Location_Nuriootpa',
 'Location_PearceRAAF',
 'Location_Penrith',
 'Location_Perth',
 'Location_PerthAirport',
 'Location_Portland',
 'Location_Richmond',
```

```
 'Location_Sale',
 'Location_SalmonGums',
 'Location_Sydney',
 'Location_SydneyAirport',
 'Location_Townsville',
 'Location_Tuggeranong',
 'Location_Uluru',
 'Location_WaggaWagga',
 'Location_Walpole',
 'Location_Watsonia',
 'Location_Williamtown',
 'Location_Witchcliffe',
 'Location_Wollongong',
 'Location_Woomera',
 'WindGustDir_E',
 'WindGustDir_ENE',
 'WindGustDir_ESE',
 'WindGustDir_N',
 'WindGustDir_NE',
 'WindGustDir_NNE',
 'WindGustDir_NNW',
 'WindGustDir_NW',
 'WindGustDir_S',
 'WindGustDir_SE',
 'WindGustDir_SSE',
 'WindGustDir_SSW',
 'WindGustDir_SW',
 'WindGustDir_W',
 'WindGustDir_WNW',
 'WindGustDir_WSW',
 'WindGustDir_nan',
 'WindDir9am_E',
 'WindDir9am_ENE',
 'WindDir9am_ESE',
 'WindDir9am_N',
 'WindDir9am_NE',
 'WindDir9am_NNE',
 'WindDir9am_NNW',
 'WindDir9am_NW',
 'WindDir9am_S',
 'WindDir9am_SE',
 'WindDir9am_SSE',
 'WindDir9am_SSW',
 'WindDir9am_SW',
 'WindDir9am_W',
 'WindDir9am_WNW',
 'WindDir9am_WSW',
 'WindDir9am_nan',
 'WindDir3pm_E',
 'WindDir3pm_ENE',
 'WindDir3pm_ESE',
 'WindDir3pm_N',
 'WindDir3pm_NE',
 'WindDir3pm_NNE',
 'WindDir3pm_NNW',
 'WindDir3pm_NW',
 'WindDir3pm_S',
 'WindDir3pm_SE',
 'WindDir3pm_SSE',
 'WindDir3pm_SSW',
 'WindDir3pm_SW',
 'WindDir3pm_W',
 'WindDir3pm_WNW',
 'WindDir3pm_WSW',
 'WindDir3pm_nan',
 'RainToday_No',
 'RainToday_Yes']
```

In [9]:
```
X_train = train_inputs[numeric_cols]
X_val = val_inputs[numeric_cols]
X_test = test_inputs[numeric_cols]
```

In [10]:
```
X_val
```

Out[10]:

	MinTemp	MaxTemp	Rainfall	Evaporation	Sunshine	WindGustSpeed	WindSpeed9am	WindSp
23480	0.595855	0.504082	0.000959	0.082759	0.517483	0.254545	0.292308	
77238	0.461140	0.412245	0.004796	0.003448	0.391608	0.290909	0.261538	
20541	0.712435	0.867347	0.000000	0.094322	0.534317	0.572727	0.461538	
57419	0.251295	0.226531	0.000000	0.094322	0.534317	0.218182	0.338462	
44800	0.567358	0.459184	0.254197	0.094322	0.534317	0.236364	0.200000	
...	...	...	...	...	...	...	...	
2279	0.321244	0.365306	0.000959	0.094322	0.534317	0.118182	0.000000	
5429	0.466321	0.673469	0.000000	0.094322	0.534317	0.154545	0.030769	
83338	0.256477	0.381633	0.000000	0.031034	0.363636	0.327273	0.061538	
72707	0.305699	0.371429	0.006715	0.096552	0.076923	0.372727	0.138462	
54548	0.582902	0.608163	0.000000	0.094322	0.534317	0.472727	0.292308	

1700 rows × 118 columns

Training

We can use `DecisionTreeClassifier` from `sklearn.tree` to train a decision tree.

In [11]:
```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(random_state=42)

model.fit(X_train, train_targets)

# An optimal decision tree has now been created using the training data.
```

Out[11]:
```
DecisionTreeClassifier(random_state=42)
```

Evaluation

Let's evaluate the decision tree using the accuracy score.

In [12]:
```
from sklearn.metrics import accuracy_score, confusion_matrix

train_preds = model.predict(X_train)
train_preds
```

Out[12]:
```
array(['No', 'No', 'No', ..., 'No', 'No', 'No'], dtype=object)
```

In [13]:
```
# returns the count of unique values in the `train_preds` variable.
# It creates a pandas Series object where the unique values in `train_preds` are the index and
pd.value_counts(train_preds)
```

Out[13]:
```
No     7599
Yes    2189
dtype: int64
```

The decision tree also returns probabilities for each prediction.

In [14]:
```
train_probability = model.predict_proba(X_train)
train_probability
```

Out[14]:
```
array([[1., 0.],
       [1., 0.],
       [1., 0.],
       ...,
       [1., 0.],
       [1., 0.],
       [1., 0.]])
```

Seems like the decision tree is quite confident about its predictions.

Let's check the accuracy of its predictions.

In [15]:
```
accuracy_score(train_targets, train_preds)
```

Out[15]:
```
1.0
```

The training set accuracy is 100%! But we can't rely solely on the training set accuracy, we must evaluate the m

We can make predictions and compute accuracy in one step using `model.score`

In [16]:
```
model.score(X_val, val_targets)
```

Out[16]:
```
0.8058823529411765
```

Although the training accuracy is 100%, the accuracy on the validation set is just about 80%, which is only marg

In [17]:
```
val_targets.value_counts() / len(val_targets)
```

Out[17]:
```
No     0.794118
Yes    0.205882
Name: RainTomorrow, dtype: float64
```

It appears that the model has learned the training examples perfect, and doesn't generalize well to previously u overfitting is one of the most important parts of any machine learning project.

Visualization

We can visualize the decision tree *learned* from the training data.

In [18]:
```
from sklearn.tree import plot_tree, export_text
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib
%matplotlib inline
```

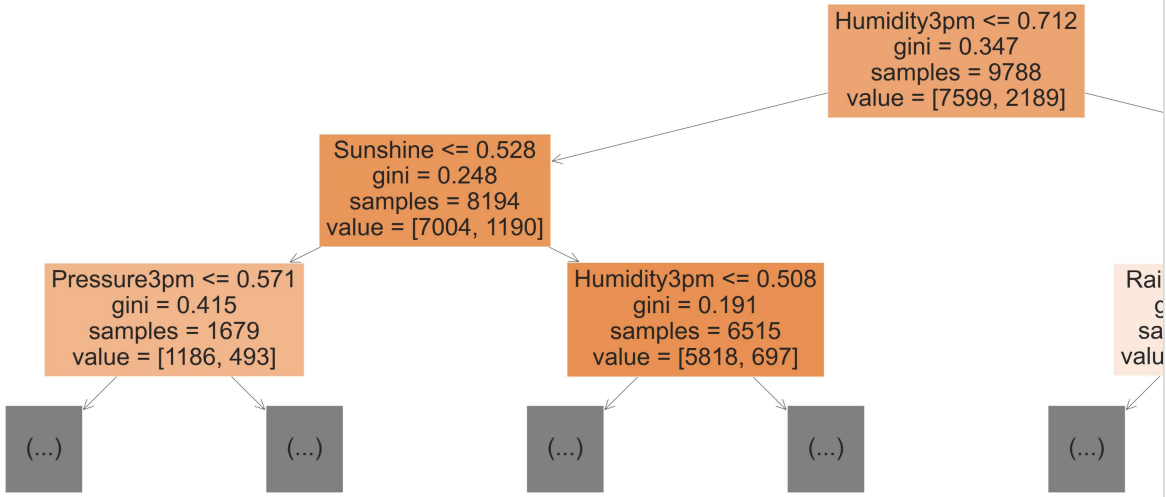
```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', 150)
sns.set_style('darkgrid')
matplotlib.rcParams['font.size'] = 14
matplotlib.rcParams['figure.figsize'] = (10, 6)
matplotlib.rcParams['figure.facecolor'] = '#00000000'
```

In [19]:

```
plt.figure(figsize=(80,20))
plot_tree(model, feature_names= X_train.columns, max_depth=2, filled=True)
```

Out[19]:

```
[Text(0.5, 0.875, 'Humidity3pm <= 0.712\ngini = 0.347\nsamples = 9788\nvalue = [7599, 2189]'),
 Text(0.25, 0.625, 'Sunshine <= 0.528\ngini = 0.248\nsamples = 8194\nvalue = [7004, 1190]'),
 Text(0.125, 0.375, 'Pressure3pm <= 0.571\ngini = 0.415\nsamples = 1679\nvalue = [1186, 493]'),
 Text(0.0625, 0.125, '\n  (...)  \n'),
 Text(0.1875, 0.125, '\n  (...)  \n'),
 Text(0.375, 0.375, 'Humidity3pm <= 0.508\ngini = 0.191\nsamples = 6515\nvalue = [5818, 697]'),
 Text(0.3125, 0.125, '\n  (...)  \n'),
 Text(0.4375, 0.125, '\n  (...)  \n'),
 Text(0.75, 0.625, 'Humidity3pm <= 0.813\ngini = 0.468\nsamples = 1594\nvalue = [595, 999]'),
 Text(0.625, 0.375, 'Rainfall <= 0.013\ngini = 0.496\nsamples = 830\nvalue = [454, 376]'),
 Text(0.5625, 0.125, '\n  (...)  \n'),
 Text(0.6875, 0.125, '\n  (...)  \n'),
 Text(0.875, 0.375, 'Temp9am <= 0.305\ngini = 0.301\nsamples = 764\nvalue = [141, 623]'),
 Text(0.8125, 0.125, '\n  (...)  \n'),
 Text(0.9375, 0.125, '\n  (...)  \n')]
```



Can you see how the model classifies a given input as a series of decisions? The tree is truncated here, but follo "No". Do you see how a decision tree differs from a logistic regression model?

How a Decision Tree is Created

Note the `gini` value in each box. "Gini" is a selection criteria or tree splitting criteria. This is the loss function splitting the data, and at what point the column should be split. "A lower Gini index indicates a better split(resu each side) has a Gini index of 0. If there is 50-50 split then the criteria is least prefered by the model itself beca

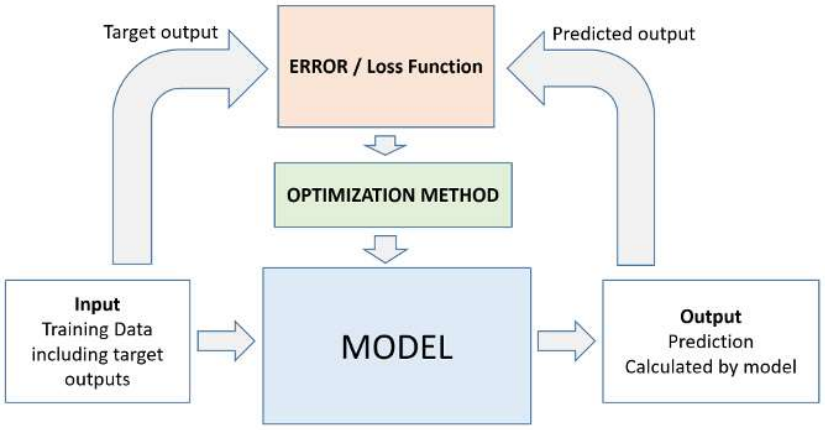
For a mathematical discussion of the Gini Index, watch this video: https://www.youtube.com/watch?v=-W0Dnx

$$\sum_{j=1} P_j$$

p_j: proportion of the samples that belongs to class c for a particular node

Conceptually speaking, while training the models evaluates all possible splits across all possible columns and p two portions. In practice, however, it's very inefficient to check all possible splits, so the model uses a heuristic

The iterative approach of the machine learning workflow in the case of a decision tree involves growing the tre



Let's check the depth of the tree that was created.

In [20]:
```
model.tree_.max_depth
```

Out[20]: 30

We can also display the tree as text, which can be easier to follow for deeper trees.

In [21]:
```
tree_text = export_text(model, max_depth=10, feature_names=list(X_train.columns))
print(tree_text[:5000])
```

```
|--- Humidity3pm <= 0.71
|   |--- Sunshine <= 0.53
|   |   |--- Pressure3pm <= 0.57
|   |   |   |--- Humidity3pm <= 0.56
|   |   |   |   |--- WindGustSpeed <= 0.33
|   |   |   |   |   |--- Location_Albany <= 0.50
|   |   |   |   |   |   |--- Sunshine <= 0.00
|   |   |   |   |   |   |   |--- WindDir3pm_N <= 0.50
|   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |--- WindDir3pm_N >  0.50
|   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |--- Sunshine >  0.00
|   |   |   |   |   |   |   |--- WindDir3pm_nan <= 0.50
|   |   |   |   |   |   |   |   |--- WindSpeed9am <= 0.05
|   |   |   |   |   |   |   |   |   |--- WindDir3pm_NW <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |   |--- WindDir3pm_NW >  0.50
|   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |--- WindSpeed9am >  0.05
|   |   |   |   |   |   |   |   |   |--- WindGustDir_NW <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- Pressure3pm <= 0.41
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 3
|   |   |   |   |   |   |   |   |   |   |--- Pressure3pm >  0.41
```

```
|   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 8
|   |   |   |   |   |   |   |   |   |   |--- WindGustDir_NW >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- Temp9am <= 0.47
|   |   |   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |   |   |   |--- Temp9am >  0.47
|   |   |   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |--- WindDir3pm_nan >  0.50
|   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |--- Location_Albany >  0.50
|   |   |   |   |   |   |   |--- WindSpeed9am <= 0.12
|   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |--- WindSpeed9am >  0.12
|   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |--- WindGustSpeed >  0.33
|   |   |   |   |   |   |--- Location_Portland <= 0.50
|   |   |   |   |   |   |   |--- Pressure9am <= 0.61
|   |   |   |   |   |   |   |   |--- Sunshine <= 0.01
|   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |--- Sunshine >  0.01
|   |   |   |   |   |   |   |   |   |--- Temp3pm <= 0.77
|   |   |   |   |   |   |   |   |   |   |--- MaxTemp <= 0.75
|   |   |   |   |   |   |   |   |   |   |   |--- Location_Dartmoor <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 15
|   |   |   |   |   |   |   |   |   |   |   |--- Location_Dartmoor >  0.50
|   |   |   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |   |   |--- MaxTemp >  0.75
|   |   |   |   |   |   |   |   |   |   |   |--- WindSpeed3pm <= 0.20
|   |   |   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |   |   |   |--- WindSpeed3pm >  0.20
|   |   |   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |   |   |--- Temp3pm >  0.77
|   |   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |--- Pressure9am >  0.61
|   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |--- Location_Portland >  0.50
|   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |--- Humidity3pm >  0.56
|   |   |   |   |   |--- WindGustSpeed <= 0.54
|   |   |   |   |   |   |--- Rainfall <= 0.02
|   |   |   |   |   |   |   |--- Pressure3pm <= 0.36
|   |   |   |   |   |   |   |   |--- MinTemp <= 0.39
|   |   |   |   |   |   |   |   |   |--- Pressure9am <= 0.39
|   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |   |--- Pressure9am >  0.39
|   |   |   |   |   |   |   |   |   |   |--- WindDir9am_NW <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |   |   |--- WindDir9am_NW >  0.50
|   |   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |   |--- MinTemp >  0.39
|   |   |   |   |   |   |   |   |   |   |--- WindSpeed3pm <= 0.16
|   |   |   |   |   |   |   |   |   |   |   |--- class: No
|   |   |   |   |   |   |   |   |   |   |--- WindSpeed3pm >  0.16
|   |   |   |   |   |   |   |   |   |   |   |--- class: Yes
|   |   |   |   |   |   |   |   |--- Pressure3pm >  0.36
|   |   |   |   |   |   |   |   |   |--- WindGustDir_NW <= 0.50
|   |   |   |   |   |   |   |   |   |   |--- WindGustDir_WNW <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |--- MinTemp <= 0.52
|   |   |   |   |   |   |   |   |   |   |   |   |--- MinTemp <= 0.50
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 7
|   |   |   |   |   |   |   |   |   |   |   |   |--- MinTemp >  0.50
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 2
|   |   |   |   |   |   |   |   |   |   |   |--- MinTemp >  0.52
|   |   |   |   |   |   |   |   |   |   |   |   |--- WindGustSpeed <= 0.33
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 10
|   |   |   |   |   |   |   |   |   |   |   |   |--- WindGustSpeed >  0.33
|   |   |   |   |   |   |   |   |   |   |   |   |   |--- truncated branch of depth 5
|   |   |   |   |   |   |   |   |   |   |--- WindGustDir_WNW >  0.50
```

| | | | | |

Why Overfitting or 100% training accuracy?

The training accuracy is 100% because the decision tree has (our model) has literally memorized the entire trai

And when it sees any example other than trainingor which doesn't fit exactly to the training, it tries to categori
DT. That may or may not end up really well because it's going to ultimately boil down to a specific training exa

Feature Importance

Based on the gini index computations, a decision tree assigns an "importance" value to each feature. These val

In [22]:
```
X_train.columns
```

Out[22]:
```
Index(['MinTemp', 'MaxTemp', 'Rainfall', 'Evaporation', 'Sunshine',
       'WindGustSpeed', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am',
       'Humidity3pm',
       ...
       'WindDir3pm_SE', 'WindDir3pm_SSE', 'WindDir3pm_SSW', 'WindDir3pm_SW',
       'WindDir3pm_W', 'WindDir3pm_WNW', 'WindDir3pm_WSW', 'WindDir3pm_nan',
       'RainToday_No', 'RainToday_Yes'],
      dtype='object', length=118)
```

In [23]:
```
model.feature_importances_
```

Out[23]:
```
array([3.49257345e-02, 3.07937151e-02, 4.22748141e-02, 1.86728347e-02,
       5.44097237e-02, 5.15867301e-02, 2.12312331e-02, 2.87536812e-02,
       3.68257188e-02, 2.64559367e-01, 4.61709226e-02, 6.74395647e-02,
       1.73926170e-02, 1.25463339e-02, 3.30940709e-02, 2.81314210e-02,
       2.53636257e-03, 4.88594907e-03, 8.85196443e-05, 5.58347395e-04,
       2.17801237e-03, 1.72048150e-03, 1.79704909e-03, 8.80837628e-04,
       1.85616582e-03, 6.79028712e-04, 5.48664767e-04, 1.60682190e-03,
       3.36763438e-03, 7.65438990e-04, 1.33296623e-03, 1.76337264e-03,
       0.00000000e+00, 2.89718184e-03, 1.15398601e-03, 1.04335506e-03,
       1.42614666e-04, 9.47687991e-04, 8.43648412e-05, 2.30446882e-03,
       6.13116680e-04, 7.75828463e-04, 8.40861880e-04, 3.19148702e-03,
       2.03150657e-03, 1.95633156e-03, 8.01171026e-04, 5.46423397e-04,
       0.00000000e+00, 4.47298844e-03, 1.36814558e-03, 0.00000000e+00,
       1.17777289e-03, 1.32691363e-03, 1.41449744e-03, 1.08994330e-03,
       1.99200741e-03, 5.05498582e-04, 7.28326586e-04, 1.32816124e-03,
       1.86866937e-03, 6.17388159e-04, 1.81192841e-03, 2.20911476e-03,
       0.00000000e+00, 1.83791100e-03, 1.03845236e-03, 7.52022031e-04,
       4.19639250e-03, 2.11818535e-03, 1.83924445e-03, 2.63761456e-03,
       6.51501283e-03, 4.08796835e-03, 4.29656774e-03, 1.08977592e-03,
       1.43907060e-03, 1.91287844e-03, 3.05273200e-03, 3.52894824e-03,
       5.20036521e-03, 7.02232411e-04, 2.10623085e-03, 2.04384088e-03,
       0.00000000e+00, 5.15174436e-03, 4.10503777e-03, 4.36257790e-03,
       5.36214897e-03, 4.57599897e-03, 1.75689777e-03, 1.62553252e-03,
       1.59417504e-03, 4.05762243e-03, 4.86851289e-03, 2.09933276e-03,
       2.76186580e-03, 1.51936939e-03, 1.38712067e-03, 1.53936409e-03,
       3.18368035e-03, 9.87483603e-04, 3.62194595e-03, 2.82413190e-03,
       1.44448964e-03, 4.96895742e-03, 4.35381001e-03, 2.64299215e-03,
       2.84420435e-03, 1.55220559e-03, 2.40836903e-03, 1.29944045e-03,
       4.59302940e-03, 1.16876609e-03, 3.88290293e-03, 1.73375026e-03,
       2.02471991e-03, 6.86496843e-04])
```

Let's turn this into a dataframe and visualize the most important features.

In [24]:
```
importance_df = pd.DataFrame({
    'feature': X_train.columns,
    'importance': model.feature_importances
```

```
}).sort_values('importance', ascending=False)
```

In [25]:
```
importance_df
```

Out[25]:

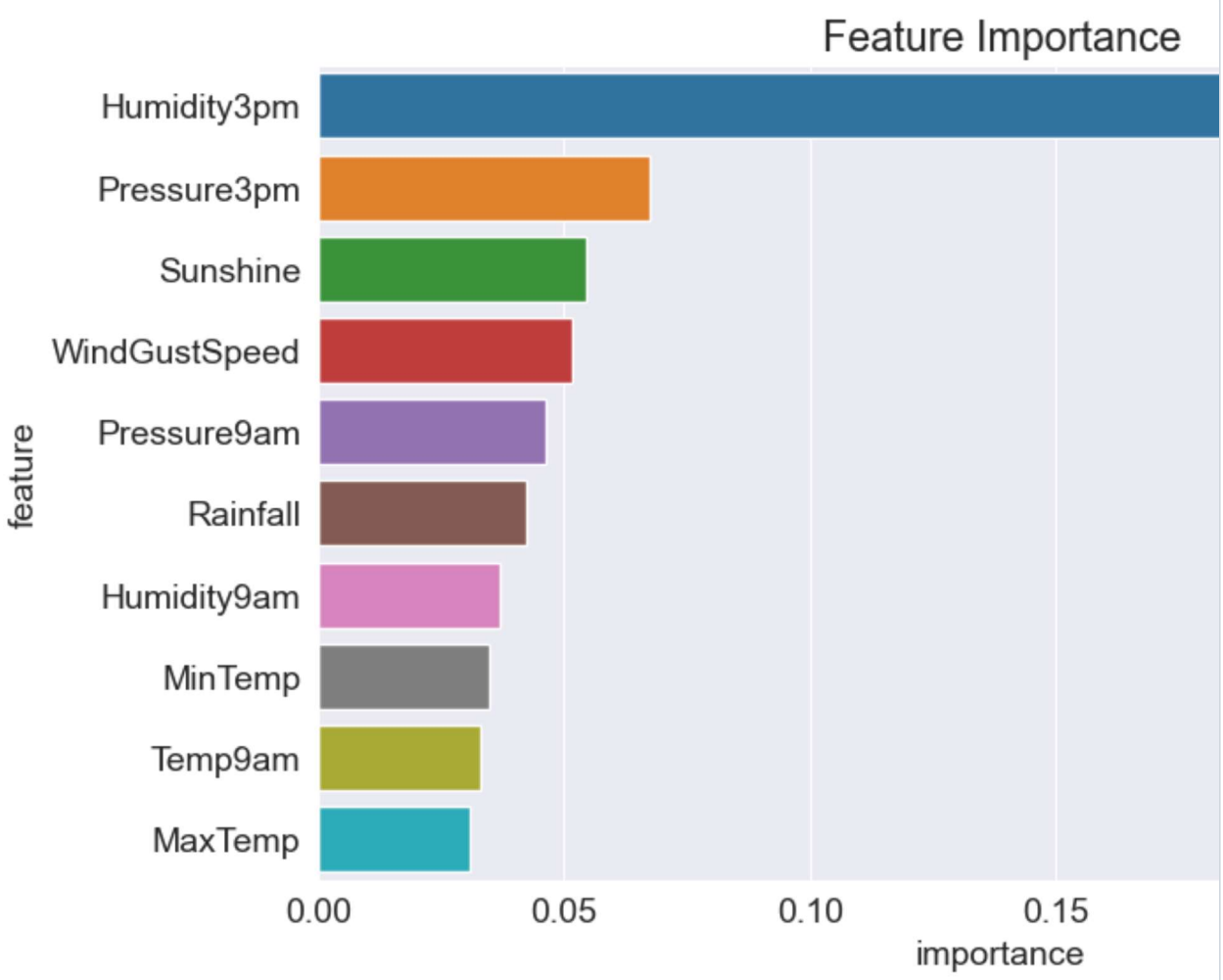
	feature	importance
9	Humidity3pm	0.264559
11	Pressure3pm	0.067440
4	Sunshine	0.054410
5	WindGustSpeed	0.051587
10	Pressure9am	0.046171
2	Rainfall	0.042275
8	Humidity9am	0.036826
0	MinTemp	0.034926
14	Temp9am	0.033094
1	MaxTemp	0.030794
7	WindSpeed3pm	0.028754
15	Temp3pm	0.028131
6	WindSpeed9am	0.021231
3	Evaporation	0.018673
12	Cloud9am	0.017393
13	Cloud3pm	0.012546
72	WindGustDir_NW	0.006515
88	WindDir9am_NNW	0.005362
80	WindGustDir_WSW	0.005200
85	WindDir9am_N	0.005152
105	WindDir3pm_NNW	0.004969
17	Location_Albany	0.004886
94	WindDir9am_SW	0.004869
112	WindDir3pm_W	0.004593
89	WindDir9am_NW	0.004576
49	Location_Portland	0.004473
87	WindDir9am_NNE	0.004363
106	WindDir3pm_NW	0.004354
74	WindGustDir_SE	0.004297
68	WindGustDir_N	0.004196
86	WindDir9am_NE	0.004105
73	WindGustDir_S	0.004088

93	WindDir9am_SSW	0.004058
114	WindDir3pm_WSW	0.003883
102	WindDir3pm_N	0.003622
79	WindGustDir_WNW	0.003529
28	Location_Dartmoor	0.003368
43	Location_NorfolkIsland	0.003191
100	WindDir3pm_ENE	0.003184
78	WindGustDir_W	0.003053
33	Location_Launceston	0.002897
108	WindDir3pm_SE	0.002844
103	WindDir3pm_NE	0.002824
96	WindDir9am_WNW	0.002762
107	WindDir3pm_S	0.002643
71	WindGustDir_NNW	0.002638
16	Location_Adelaide	0.002536
110	WindDir3pm_SSW	0.002408
39	Location_MountGinini	0.002304
63	Location_Wollongong	0.002209
20	Location_BadgerysCreek	0.002178
69	WindGustDir_NE	0.002118
82	WindDir9am_E	0.002106
95	WindDir9am_W	0.002099
83	WindDir9am_ENE	0.002044
44	Location_Nuriootpa	0.002032
116	RainToday_No	0.002025
56	Location_Tuggeranong	0.001992
45	Location_PearceRAAF	0.001956
77	WindGustDir_SW	0.001913
60	Location_Watsonia	0.001869
24	Location_Cairns	0.001856
70	WindGustDir_NNE	0.001839
65	WindGustDir_E	0.001838
62	Location_Witchcliffe	0.001812
22	Location_Bendigo	0.001797
31	Location_Hobart	0.001763
90	WindDir9am_S	0.001757
115	WindDir3pm_nan	0.001734

21	Location_Ballarat	0.001720
91	WindDir9am_SE	0.001626
27	Location_CoffsHarbour	0.001607
92	WindDir9am_SSE	0.001594
109	WindDir3pm_SSE	0.001552
99	WindDir3pm_E	0.001539
97	WindDir9am_WSW	0.001519
104	WindDir3pm_NNE	0.001444
76	WindGustDir_SSW	0.001439
54	Location_SydneyAirport	0.001414
98	WindDir9am_nan	0.001387
50	Location_Richmond	0.001368
30	Location_GoldCoast	0.001333
59	Location_Walpole	0.001328
53	Location_Sydney	0.001327
111	WindDir3pm_SW	0.001299
52	Location_SalmonGums	0.001178
113	WindDir3pm_WNW	0.001169
34	Location_Melbourne	0.001154
55	Location_Townsville	0.001090
75	WindGustDir_SSE	0.001090
35	Location_MelbourneAirport	0.001043
66	WindGustDir_ENE	0.001038
101	WindDir3pm_ESE	0.000987
37	Location_Moree	0.000948
23	Location_Brisbane	0.000881
42	Location_NorahHead	0.000841
46	Location_Penrith	0.000801
41	Location_Nhil	0.000776
29	Location_Darwin	0.000765
67	WindGustDir_ESE	0.000752
58	Location_WaggaWagga	0.000728
81	WindGustDir_nan	0.000702
117	RainToday_Yes	0.000686
25	Location_Canberra	0.000679
61	Location_Williamtown	0.000617

40	Location_Newcastle	0.000613
19	Location_AliceSprings	0.000558
26	Location_Cobar	0.000549
47	Location_Perth	0.000546
57	Location_Uluru	0.000505
36	Location_Mildura	0.000143
18	Location_Albury	0.000089
38	Location_MountGambier	0.000084
84	WindDir9am_ESE	0.000000
48	Location_PerthAirport	0.000000
32	Location_Katherine	0.000000
51	Location_Sale	0.000000
64	Location_Woomera	0.000000

In [26]:
```
plt.title('Feature Importance')
sns.barplot(data=importance_df.head(10), x='importance', y='feature');
```



Hyperparameter Tuning and Overfitting

As we saw in the previous section, our decision tree classifier memorized all training examples, leading to a 10(better than a dumb baseline model. This phenomenon is called overfitting, and in this section, we'll look at son

The `DecisionTreeClassifier` accepts several arguments, some of which can be modified to reduce overfit

These arguments are called hyperparameters because they must be configured manually (as opposed to the pa explore a couple of hyperparameters:

- `max_depth`
- `max_leaf_nodes`

max_depth

By reducing the maximum depth of the decision tree, we can prevent the tree from memorizing all training exa

In [27]:
```
model = DecisionTreeClassifier(max_depth= 3, random_state= 42)

model.fit(X_train, train_targets)
```

Out[27]:
```
DecisionTreeClassifier(max_depth=3, random_state=42)
```

We can compute the accuracy of the model on the training and validation sets using `model.score`

In [28]:
```
print("Training Score: ", model.score(X_train, train_targets))
print("Validation Score: ", model.score(X_val, val_targets))
```

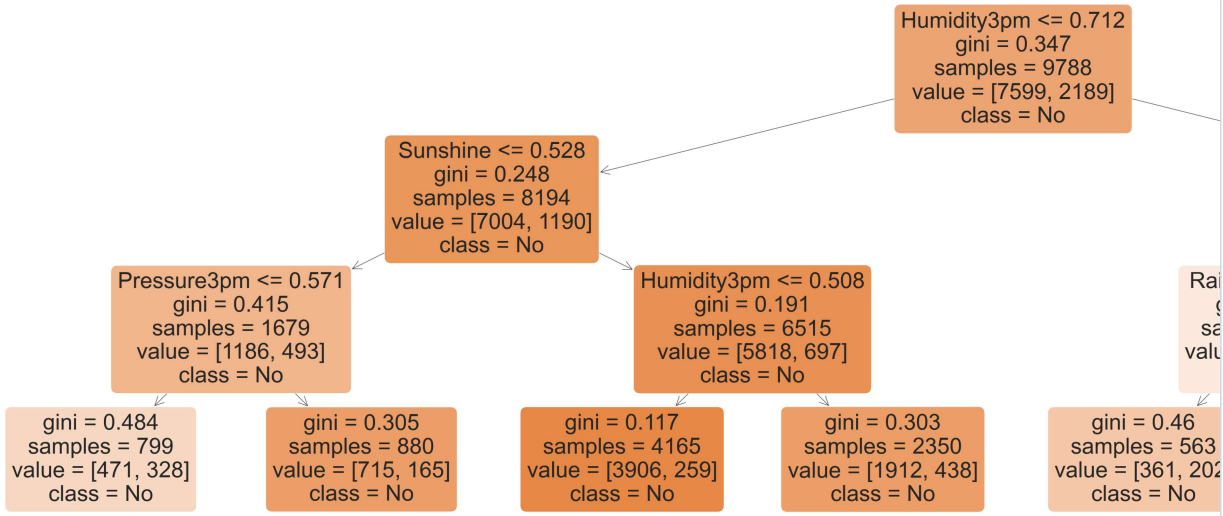
```
Training Score:  0.8338782182263996
Validation Score:  0.8470588235294118
```

Great, while the training accuracy of the model has gone down, the validation accuracy of the model has increa

In [29]:
```
model.classes_
```

Out[29]:
```
array(['No', 'Yes'], dtype=object)
```

In [30]:
```
plt.figure(figsize=(80,20))
plot_tree(model, feature_names=X_train.columns, filled=True, rounded=True, class_names=model.c
```



In [31]:
```
print(export_text(model, feature_names=list(X_train.columns)))
```

```
|--- Humidity3pm <= 0.71
|   |--- Sunshine <= 0.53
|   |   |--- Pressure3pm <= 0.57
|   |   |   |--- class: No
|   |   |--- Pressure3pm >  0.57
|   |   |   |--- class: No
|   |--- Sunshine >  0.53
|   |   |--- Humidity3pm <= 0.51
|   |   |   |--- class: No
|   |   |--- Humidity3pm >  0.51
|   |   |   |--- class: No
|--- Humidity3pm >  0.71
|   |--- Humidity3pm <= 0.81
|   |   |--- Rainfall <= 0.01
|   |   |   |--- class: No
|   |   |--- Rainfall >  0.01
|   |   |   |--- class: Yes
|   |--- Humidity3pm >  0.81
|   |   |--- Temp9am <= 0.30
|   |   |   |--- class: Yes
|   |   |--- Temp9am >  0.30
|   |   |   |--- class: Yes
```

Let's experiment with different depths using a helper function.

In [39]:
```
def max_depth_error(md):
    model = DecisionTreeClassifier(max_depth=md, random_state=42)
    model.fit(X_train, train_targets)
    train_error = 1 - model.score(X_train, train_targets)
    validation_error = 1 - model.score(X_val, val_targets)
    return {'Max Depth': md, 'Training Error': train_error,
            'Validation Error': validation_error}
```

In [40]:
```
error_df = pd.DataFrame([max_depth_error(md) for md in range (1,21)])
```

In [41]:
```
error_df
```

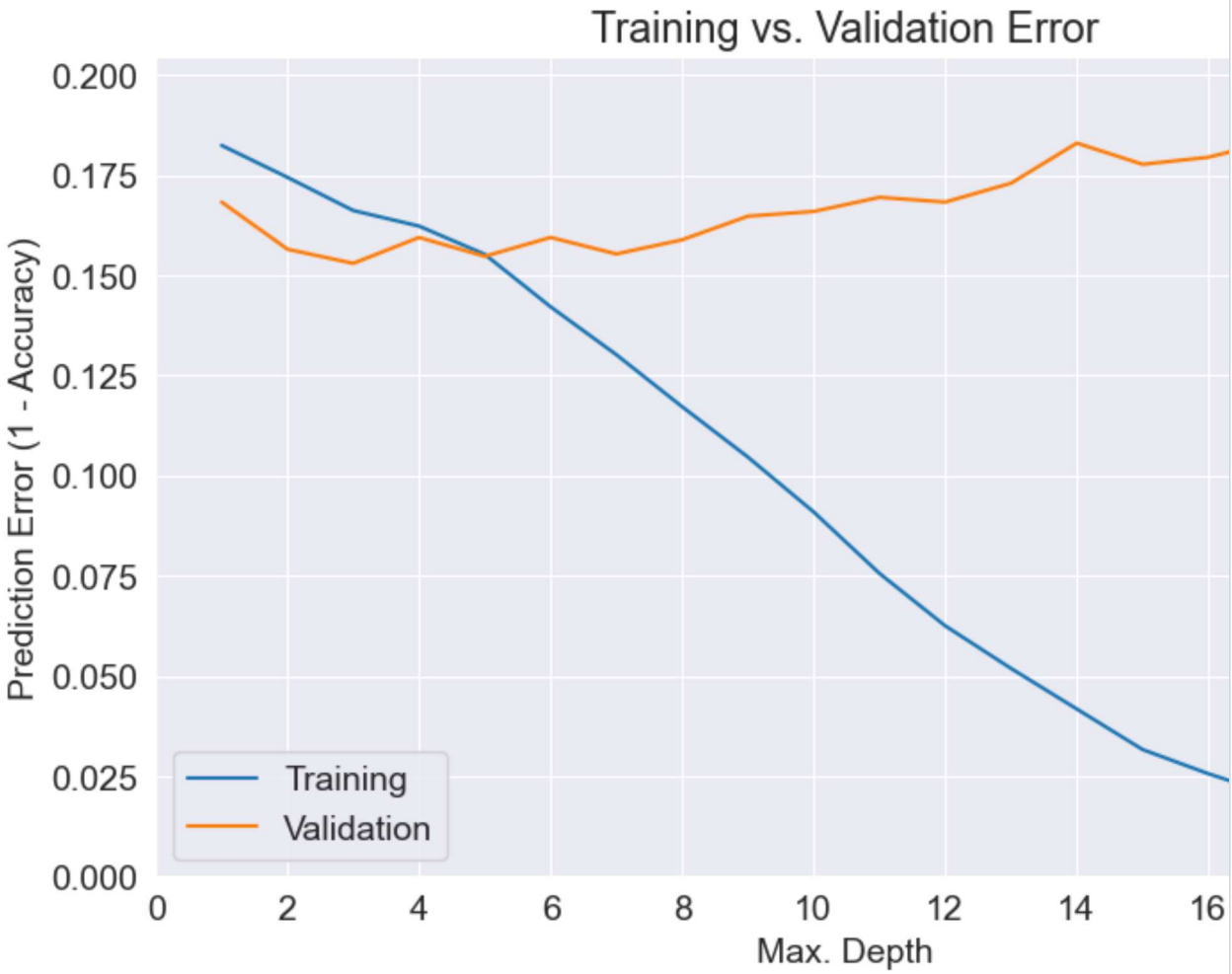
Out[41]:

	Max Depth	Training Error	Validation Error
0	1	0.182366	0.168235
1	2	0.174397	0.156471
2	3	0.166122	0.152941
3	4	0.162239	0.159412
4	5	0.155190	0.154706
5	6	0.142113	0.159412
6	7	0.130159	0.155294
7	8	0.117184	0.158824
8	9	0.104618	0.164706
9	10	0.090928	0.165882
10	11	0.075603	0.169412

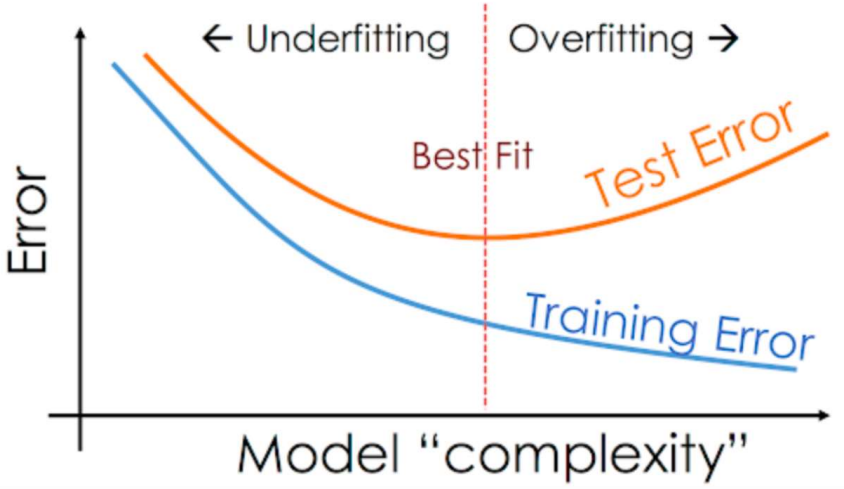
11	12	0.062526	0.168235
12	13	0.051900	0.172941
13	14	0.041786	0.182941
14	15	0.031671	0.177647
15	16	0.025644	0.179412
16	17	0.020331	0.183529
17	18	0.016347	0.192353
18	19	0.013282	0.183529
19	20	0.009195	0.195294

In [35]:
```
plt.figure()
plt.plot(error_df['Max Depth'], error_df['Training Error'])
plt.plot(error_df['Max Depth'], error_df['Validation Error'])
plt.title('Training vs. Validation Error')
plt.xticks(range(0,21, 2))
plt.xlabel('Max. Depth')
plt.ylabel('Prediction Error (1 - Accuracy)')
plt.legend(['Training', 'Validation'])
```

Out[35]: <matplotlib.legend.Legend at 0x1ad38a69940>



This is a common pattern you'll see with all machine learning algorithms:



You'll often need to tune hyperparameters carefully to find the optimal fit. In the above case, it appears that a r

In [42]:
```
model = DecisionTreeClassifier(max_depth=3, random_state= 42).fit(X_train, train_targets)
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[42]:
```
(0.8338782182263996, 0.8470588235294118)
```

In [43]:
```
model = DecisionTreeClassifier(max_depth=5, random_state= 42).fit(X_train, train_targets)
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[43]:
```
(0.8448099713935431, 0.8452941176470589)
```

In [44]:
```
model = DecisionTreeClassifier(max_depth=7, random_state= 42).fit(X_train, train_targets)
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[44]:
```
(0.8698406211687781, 0.8447058823529412)
```

max_leaf_nodes

Another way to control the size of complexity of a decision tree is to limit the number of leaf nodes. This allow

max_leaf_nodes = 2^n

example, 2^7 = 128

In [45]:
```
model = DecisionTreeClassifier(max_leaf_nodes= 8, random_state= 42)
model.fit(X_train, train_targets)
```

Out[45]:
```
DecisionTreeClassifier(max_leaf_nodes=8, random_state=42)
```

In [47]:
```
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[47]:
```
(0.8338782182263996, 0.8470588235294118)
```

In [50]:
```
model.tree_.max_depth
```

Out[50]:
```
4
```

Notice that the model was able to achieve a greater depth of 4 for certain paths while keeping other paths sho

In [53]:
```
model_text = export_text(model, feature_names= list(X_train.columns))
print(model_text[:3000])
```

```
|--- Humidity3pm <= 0.71
|   |--- Sunshine <= 0.53
|   |   |--- Pressure3pm <= 0.57
|   |   |   |--- class: No
|   |   |--- Pressure3pm >  0.57
|   |   |   |--- class: No
|   |--- Sunshine >  0.53
|   |   |--- Humidity3pm <= 0.51
|   |   |   |--- class: No
|   |   |--- Humidity3pm >  0.51
|   |   |   |--- WindGustSpeed <= 0.38
|   |   |   |   |--- class: No
|   |   |   |--- WindGustSpeed >  0.38
|   |   |   |   |--- class: No
|--- Humidity3pm >  0.71
|   |--- Humidity3pm <= 0.81
|   |   |--- Rainfall <= 0.01
|   |   |   |--- class: No
|   |   |--- Rainfall >  0.01
|   |   |   |--- class: Yes
|   |--- Humidity3pm >  0.81
|   |   |--- class: Yes
```

Let's check the combination of `max_depth` and `max_leaf_nodes` that results in the highest validation accu

In [54]:
```
model = DecisionTreeClassifier(max_depth=3, max_leaf_nodes=8, random_state= 42).fit(X_train, t
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[54]:
```
(0.8338782182263996, 0.8470588235294118)
```

In [55]:
```
model = DecisionTreeClassifier(max_depth=7, max_leaf_nodes= 128, random_state= 42).fit(X_train
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[55]:
```
(0.8698406211687781, 0.8435294117647059)
```

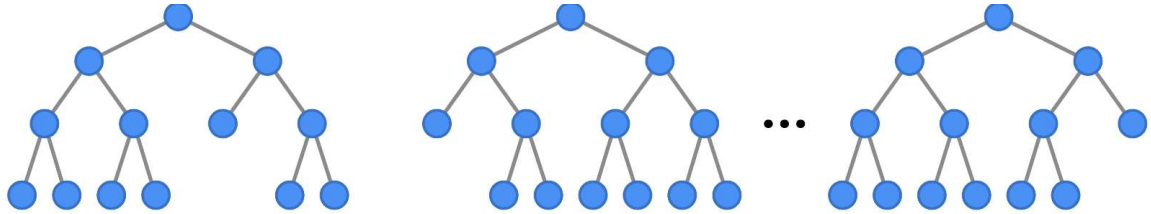
Explore and experiment with other arguments of `DecisionTree` . Refer to the docs for details: https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

Training a Random Forest

While tuning the hyperparameters of a single decision tree may lead to some improvements, a much more effe with slightly different parameters. This is called a random forest model.

The key idea here is that each decision tree in the forest will make different kinds of errors, and upon averagin as the "wisdom of the crowd".

A random forest works by averaging/combining the results of several decision trees:



We'll use the `RandomForestClassifier` class from `sklearn.ensemble`.

In [56]:
```
from sklearn.ensemble import RandomForestClassifier
```

`n_jobs` allows the random forest to use mutiple parallel workers to train decision trees, and `random_state=`

In [57]:
```
model = RandomForestClassifier(n_jobs= -1, random_state= 42)
model.fit(X_train,train_targets)
```

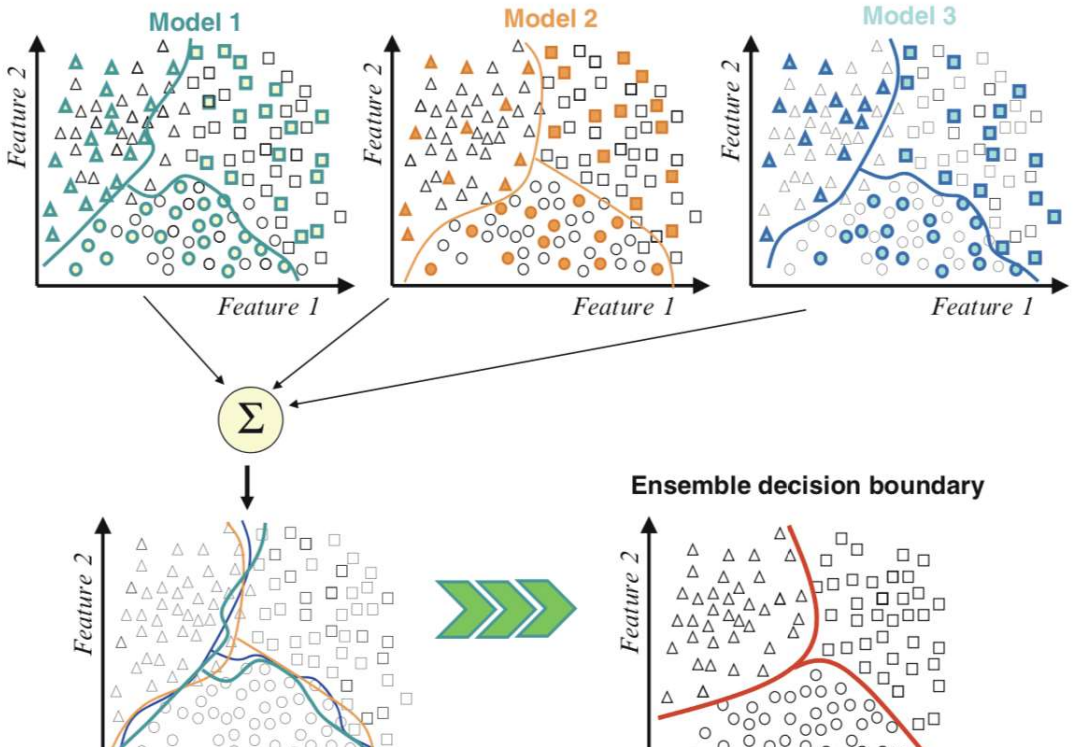
Out[57]:
```
RandomForestClassifier(n_jobs=-1, random_state=42)
```

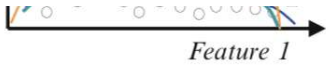
In [59]:
```
model.score(X_train,train_targets), model.score(X_val,val_targets)
```

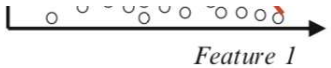
Out[59]:
```
(1.0, 0.8611764705882353)
```

Once again, the training accuracy is almost 100%, but this time the validation accuracy is much better. In fact, i you see the power of random forests?

This general technique of combining the results of many models is called "ensembling", it works because most looks like visually:







We can also look at the probabilities for the predictions. The probability of a class is simply the fraction of trees

In [60]:
```
train_probs  = model.predict_proba(X_train)
train_probs
```

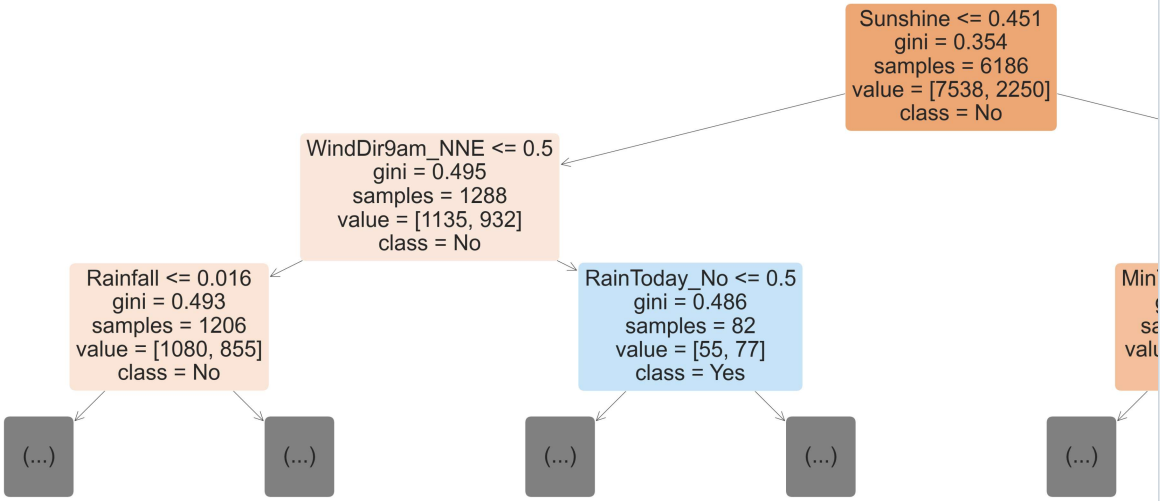
Out[60]:
```
array([[0.87, 0.13],
       [0.88, 0.12],
       [0.98, 0.02],
       ...,
       [0.9 , 0.1 ],
       [0.96, 0.04],
       [0.98, 0.02]])
```

We can can access individual decision trees using `model.estimators_`

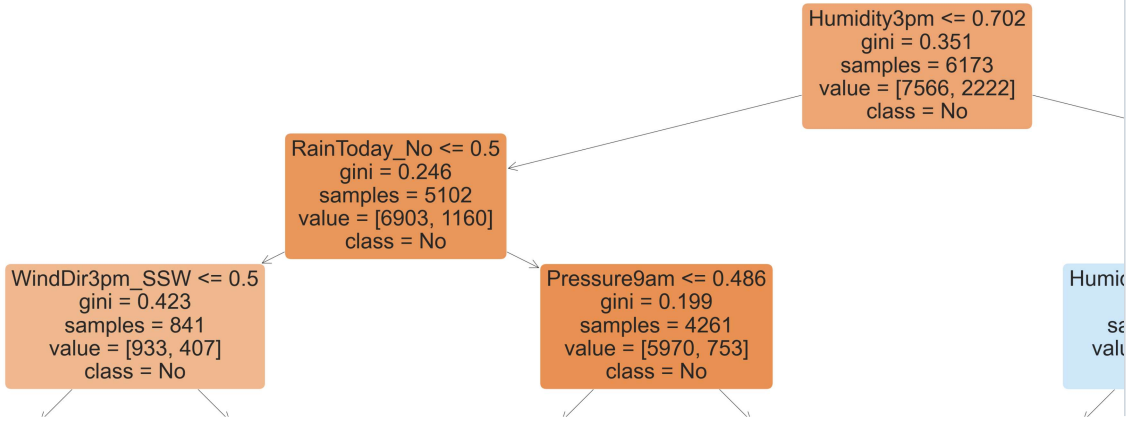
In [62]:
```
model.estimators_[0]
```

Out[62]:
```
DecisionTreeClassifier(max_features='auto', random_state=1608637542)
```

In [63]:
```
plt.figure(figsize=(80,20))
plot_tree(model.estimators_[0], max_depth=2, feature_names=X_train.columns, filled=True, round
```



In [64]:
```
plt.figure(figsize=(80,20))
plot_tree(model.estimators_[15], max_depth=2, feature_names=X_train.columns, filled=True, roun
```



Just like decision tree, random forests also assign an "importance" to each feature, by combining the importan

In [65]:
```
importance_df = pd.DataFrame({
    'feature': X_train.columns,
    'importance': model.feature_importances_
}).sort_values('importance', ascending=False)

importance_df
```

Out[65]:

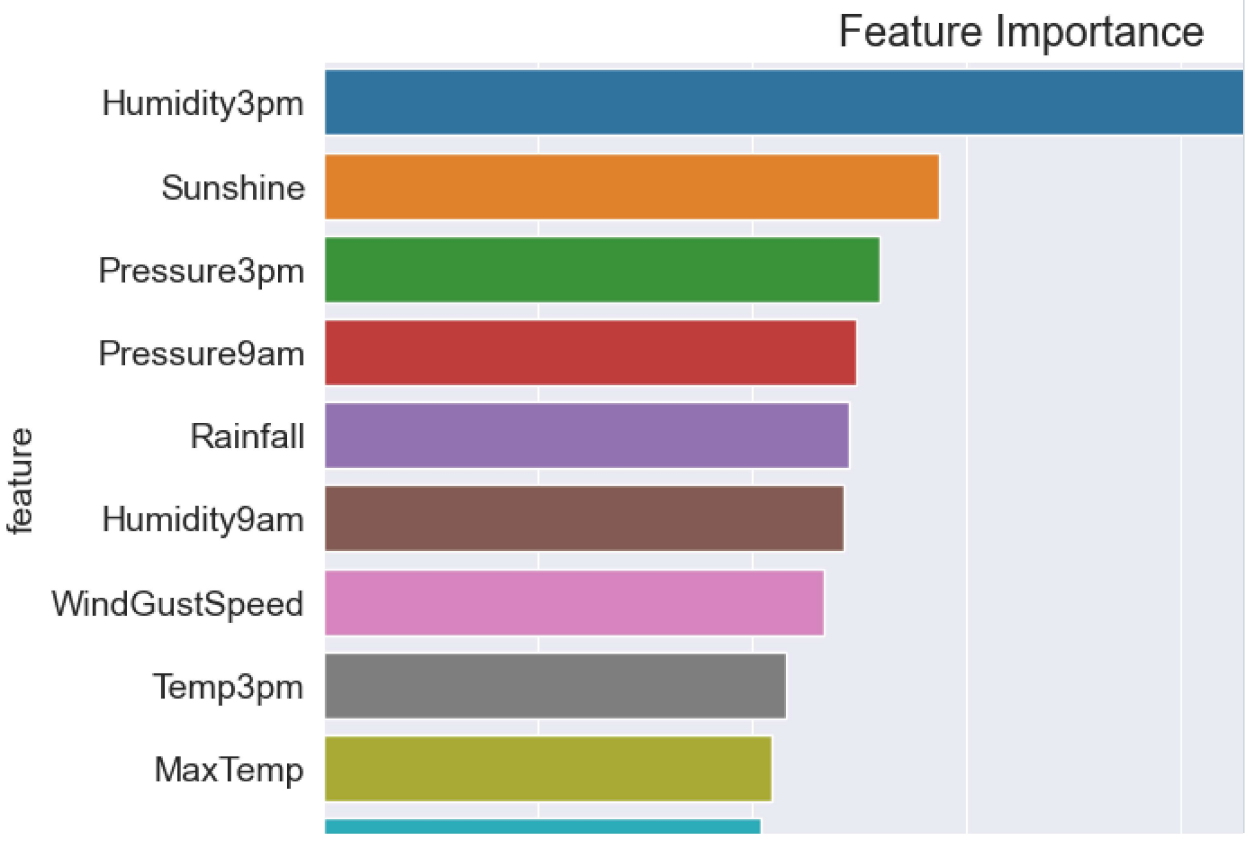
	feature	importance
9	Humidity3pm	0.123956
4	Sunshine	0.057400
11	Pressure3pm	0.051902
10	Pressure9am	0.049768
2	Rainfall	0.049051
8	Humidity9am	0.048557
5	WindGustSpeed	0.046645
15	Temp3pm	0.043211
1	MaxTemp	0.041805
0	MinTemp	0.040839
14	Temp9am	0.038864
13	Cloud3pm	0.036358
7	WindSpeed3pm	0.031184
6	WindSpeed9am	0.029869
3	Evaporation	0.026449
116	RainToday_No	0.023681
12	Cloud9am	0.023680
117	RainToday_Yes	0.014562
85	WindDir9am_N	0.005018
105	WindDir3pm_NNW	0.004133
72	WindGustDir_NW	0.004060
106	WindDir3pm_NW	0.003978
89	WindDir9am_NW	0.003758
88	WindDir9am_NNW	0.003718
62	Location_Witchcliffe	0.003691
96	WindDir9am_WNW	0.003687
87	WindDir9am_NNE	0.003672

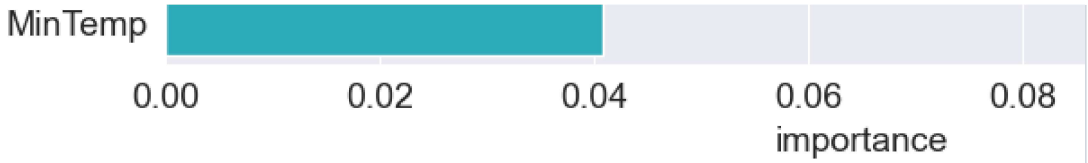
71	WindGustDir_NNW	0.003550
95	WindDir9am_W	0.003440
80	WindGustDir_WSW	0.003407
102	WindDir3pm_N	0.003365
114	WindDir3pm_WSW	0.003365
76	WindGustDir_SSW	0.003347
78	WindGustDir_W	0.003328
107	WindDir3pm_S	0.003321
112	WindDir3pm_W	0.003317
73	WindGustDir_S	0.003292
94	WindDir9am_SW	0.003245
108	WindDir3pm_SE	0.003130
90	WindDir9am_S	0.003095
104	WindDir3pm_NNE	0.003080
79	WindGustDir_WNW	0.003021
113	WindDir3pm_WNW	0.003013
70	WindGustDir_NNE	0.002973
81	WindGustDir_nan	0.002971
111	WindDir3pm_SW	0.002965
77	WindGustDir_SW	0.002887
109	WindDir3pm_SSE	0.002885
74	WindGustDir_SE	0.002799
93	WindDir9am_SSW	0.002797
103	WindDir3pm_NE	0.002753
101	WindDir3pm_ESE	0.002750
68	WindGustDir_N	0.002729
86	WindDir9am_NE	0.002715
110	WindDir3pm_SSW	0.002697
98	WindDir9am_nan	0.002638
97	WindDir9am_WSW	0.002622
75	WindGustDir_SSE	0.002577
92	WindDir9am_SSE	0.002479
91	WindDir9am_SE	0.002362
69	WindGustDir_NE	0.002343
82	WindDir9am_E	0.002319
66	WindGustDir_ENE	0.002307
100	WindDir3pm_ENE	0.002286

99	WindDir3pm_E	0.002218
65	WindGustDir_E	0.002216
83	WindDir9am_ENE	0.002165
17	Location_Albany	0.002146
54	Location_SydneyAirport	0.002106
49	Location_Portland	0.002066
53	Location_Sydney	0.002023
27	Location_CoffsHarbour	0.001928
56	Location_Tuggeranong	0.001890
33	Location_Launceston	0.001840
28	Location_Dartmoor	0.001833
31	Location_Hobart	0.001829
38	Location_MountGambier	0.001818
39	Location_MountGinini	0.001803
59	Location_Walpole	0.001799
67	WindGustDir_ESE	0.001783
60	Location_Watsonia	0.001673
25	Location_Canberra	0.001635
84	WindDir9am_ESE	0.001616
43	Location_NorfolkIsland	0.001609
47	Location_Perth	0.001608
51	Location_Sale	0.001600
30	Location_GoldCoast	0.001575
63	Location_Wollongong	0.001570
16	Location_Adelaide	0.001520
115	WindDir3pm_nan	0.001513
20	Location_BadgerysCreek	0.001486
23	Location_Brisbane	0.001481
21	Location_Ballarat	0.001477
61	Location_Williamtown	0.001456
35	Location_MelbourneAirport	0.001371
36	Location_Mildura	0.001361
24	Location_Cairns	0.001338
34	Location_Melbourne	0.001328
52	Location_SalmonGums	0.001311
48	Location_PerthAirport	0.001298

22	Location_Bendigo	0.001283
50	Location_Richmond	0.001249
45	Location_PearceRAAF	0.001235
18	Location_Albury	0.001214
40	Location_Newcastle	0.001204
58	Location_WaggaWagga	0.001189
37	Location_Moree	0.001175
42	Location_NorahHead	0.001149
44	Location_Nuriootpa	0.001005
29	Location_Darwin	0.000981
46	Location_Penrith	0.000886
64	Location_Woomera	0.000829
26	Location_Cobar	0.000780
41	Location_Nhil	0.000764
55	Location_Townsville	0.000748
19	Location_AliceSprings	0.000628
32	Location_Katherine	0.000392
57	Location_Uluru	0.000336

In [68]:
```
plt.title('Feature Importance')
sns.barplot(data=importance_df.head(10), x='importance', y='feature');
```





Notice that the distribution is a lot less skewed than that for a single decision tree.

Hyperparameter Tuning with Random Forests

Just like decision trees, random forests also have several hyperparameters. In fact many of these hyperparamet

Let's study some the hyperparameters for random forests. You can learn more about them here: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

Let's create a base model with which we can compare models with tuned hyperparameters.

In [69]:
```
base_model = RandomForestClassifier(random_state=42, n_jobs=-1).fit(X_train, train_targets)
base_train_accuracy = base_model.score(X_train, train_targets)
base_val_accuracy = base_model.score(X_val, val_targets)
base_accuracies = base_train_accuracy, base_val_accuracy
base_accuracies
```

Out[69]: (1.0, 0.8611764705882353)

We can use this as a benchmark for hyperparmeter tuning.

n_estimators

This argument controls the number of decision trees in the random forest. The default value is 100. For larger d rule, try to have as few estimators as needed.

Note: Randomness helps reduce overfitting. More randomness, less overfitting.

10 estimators

In [70]:
```
model = RandomForestClassifier(random_state= 42, n_jobs= -1, n_estimators=10)
model.fit(X_train, train_targets)
```

Out[70]: RandomForestClassifier(n_estimators=10, n_jobs=-1, random_state=42)

In [73]:
```
print(base_accuracies)
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

(1.0, 0.8611764705882353)

Out[73]: (0.9871270944013077, 0.8470588235294118)

500 estimators

In [74]:
```
model = RandomForestClassifier(random_state= 42, n_jobs= -1, n_estimators=500)
model.fit(X_train, train_targets)
```

Out[74]: RandomForestClassifier(n_estimators=500, n_jobs=-1, random_state=42)

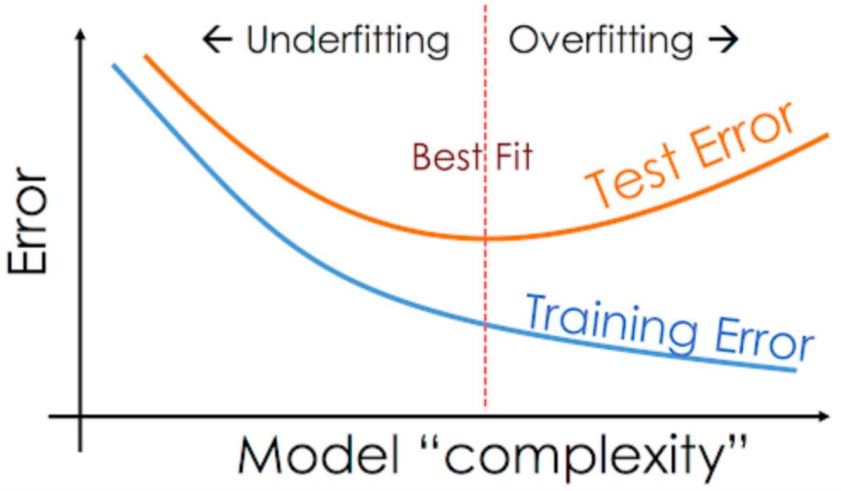
In [75]:
```
print(base_accuracies)
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

```
(1.0, 0.8611764705882353)
```

Out[75]: (1.0, 0.8641176470588235)

max_depth and max_leaf_nodes

These arguments are passed directly to each decision tree, and control the maximum depth and max. no leaf n specified, which is why each tree has a training accuracy of 100%. You can specify a `max_depth` to reduce ove



Let's define a helper function `test_params` to make it easy to test hyperparameters.

In [76]:
```
def test_params(**params):
    model = RandomForestClassifier(random_state=42, n_jobs=-1, **params).fit(X_train, train_ta
    return model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Let's test a few values of `max_depth` and `max_leaf_nodes`.

In [78]:
```
test_params(max_depth = 5)
```

Out[78]: (0.8314262362076011, 0.8370588235294117)

In [80]:
```
test_params(max_depth = 26)
```

Out[80]: (0.9989783408255006, 0.8658823529411764)

In [81]:
```
test_params(max_leaf_nodes=2**5)
```

Out[81]: (0.8400081732733959, 0.84)

In [82]:
```
test_params(max_leaf_nodes=2**20)
```

Out[82]: (1.0, 0.8647058823529412)

In [83]:
```
test_params(max_depth = 26, max_leaf_nodes = 2**20)
```

Out[83]: (0.998467511238251, 0.8658823529411764)

In [84]:
```
base_accuracies # no max depth or max leaf nodes
```

Out[84]: (1.0, 0.8611764705882353)

The optimal values of `max_depth` and `max_leaf_nodes` lies somewhere between 0 and unbounded.

max_features

Instead of picking all features (columns) for every split, we can specify that only a fraction of features be chose

max_features : *{"auto", "sqrt", "log2"}, int or float, default="auto"*
The number of features to consider when looking for the best split:

- If int, then consider `max_features` features at each split.
- If float, then `max_features` is a fraction and `round(max_features * n_features)` features are consid-ered at each split.
- If "auto", then `max_features=sqrt(n_features)`.
- If "sqrt", then `max_features=sqrt(n_features)` (same as "auto").
- If "log2", then `max_features=log2(n_features)`.
- If None, then `max_features=n_features`.

Note: the search for a split does not stop until at least one valid partition of the node samples is found, eve if it requires to effectively inspect more than `max_features` features.

Notice that the default value `auto` causes only $\sqrt{n}$ out of total features (n) to be chosen randomly at each s it may seem counterintuitive, choosing all features for every split of every tree will lead to identical trees, so the

In [85]:
```
test_params(max_features = 'log2')
```

Out[85]: (1.0, 0.8558823529411764)

In [86]:
```
test_params(max_features=3)
```

Out[86]: (1.0, 0.8564705882352941)

In [93]:
```
test_params(max_features=10)
```

Out[93]: (1.0, 0.8611764705882353)

In [88]:
```
base_accuracies
```

Out[88]: (1.0, 0.8611764705882353)

In [98]:
```
test_params(min_samples_split=2)
```

Out[98]: (1.0, 0.8611764705882353)

min_impurity_decrease

This argument is used to control the threshold for splitting nodes. A node will be split if this split induces a dec
default value is 0, and you can increase it to reduce overfitting.

In [99]:
```
test_params(min_impurity_decrease = 1e-7)
```

Out[99]: (1.0, 0.861764705882353)

In [106…
```
test_params(min_impurity_decrease = 1e-9)
```

Out[106… (1.0, 0.8629411764705882)

bootstrap , max_samples

By default, a random forest doesn't use the entire dataset for training each decision tree. Instead it applies a te
picked one by one randomly, with replacement i.e. some rows may not show up at all, while some rows may sh

bootstrap : *bool, default=True*
Whether bootstrap samples are used when building trees. If False, the whole dataset is used to build each tree.

Bootstrapping helps the random forest generalize better, because each decision tree only sees a fraction of th
others.

In [107…
```
test_params(bootstrap = False)
```

Out[107… (1.0, 0.8582352941176471)

When bootstrapping is enabled, you can also control the number or fraction of rows to be considered for each

max_samples : *int or float, default=None*
If bootstrap is True, the number of samples to draw from X to train each base estimator.

- If None (default), then draw `X.shape[0]` samples.
- If int, then draw `max_samples` samples.
- If float, then draw `max_samples * X.shape[0]` samples. Thus, `max_samples` should be in the interval `(0, 1)`.

In [110…
```
test_params(max_samples = .9)
```

Out[110… (1.0, 0.8635294117647059)

Learn more about bootstrapping here: https://towardsdatascience.com/what-is-out-of-bag-oob-score-in-rand

class_weight

In [111…
```
model.classes_
```

Out[111… array(['No', 'Yes'], dtype=object)

In [112…
```
test_params(class_weight='balanced')
```

Out[112… (1.0, 0.8570588235294118)

In [113…
```
test_params(class_weight={'No': 1, 'Yes': 2})
```

Out[113… (1.0, 0.8611764705882353)

Strategy for Tuning Hyperparameters

Here's a good strategy for tuning hyperparameters:

1. Tune the most important/impactful hyperparameter first e.g. n_estimators
2. With the best value of the first hyperparameter, tune the next most impactful hyperparameter
3. And so on, keep training the next most impactful parameters with the best values for previous parameters
4. Then, go back to the top and further tune each parameter again for further marginal gains

Keep your ideas and experiments organized using a google or excel sheet.

Your first objective should be make the training loss as low as possible (even if the validation loss is very large), loss while increasing the training loss.

Putting it together

Let's train a random forest with customized hyperparameters based on our learnings. Of course, different hype

In [119…
```
model = RandomForestClassifier(n_jobs=-1,
                               random_state=42,
                               n_estimators=500,
                               max_features=10,
                               max_depth=26,
                               class_weight={'No': 1, 'Yes': 1.5})
```

In [120…
```
model.fit(X_train, train_targets)
```

Out[120…
```
RandomForestClassifier(class_weight={'No': 1, 'Yes': 1.5}, max_depth=26,
                       max_features=10, n_estimators=500, n_jobs=-1,
                       random_state=42)
```

In [121…
```
model.score(X_train, train_targets), model.score(X_val, val_targets)
```

Out[121… (0.9996935022476502, 0.8623529411764705)

In [118…
```
base_accuracies
```

Out[118… (1.0, 0.8611764705882353)

We've increased the accuracy from 80.58% with a single decision tree to 86.23% with a well-tuned random fore not a see a significant improvement with hyperparameter tuning.

There are several possible reasons for the observed limitations in our model's performance:

- We might not have identified the optimal combination of hyperparameters to effectively regularize the mo warranted.
- The current modeling technique, Random Forests, may have reached its effectiveness limits. Exploring alte results.
- Insufficient data might be a limiting factor. Acquiring more data could potentially enhance the model's pre
- The predictive accuracy may be constrained by the available features. Considering additional features or e
- Predicting whether it will rain tomorrow could be inherently challenging due to the inherent randomness o fundamental limit on the accuracy achievable with the given data and modeling techniques.

It's important to acknowledge that no model is perfect. If you can rely on the model we've created today to ma though it may sometimes be wrong.

Finally, let's also compute the accuracy of our model on the test set.

In [122…
```
model.score(X_test, test_targets)
```

Out[122…
```
0.8340409108452335
```

Notice that the test accuracy is lower

Saving and Loading Trained Models

We can save the parameters (weights and biases) of our trained model to disk, so that we needn't retrain the m it's also important to save imputers, scalers, encoders and even column names. Anything that will be required v

We can use the `joblib` module to save and load Python objects on the disk.

Summary and References

The following topics were covered in this tutorial:

- Downloading a real-world dataset
- Preparing a dataset for training
- Training and interpreting decision trees
- Training and interpreting random forests
- Overfitting & hyperparameter tuning
- Making predictions on single inputs

We also introduced the following terms:

- Decision tree
- Random forest
- Overfitting
- Hyperparameter
- Hyperparameter tuning
- Ensembling
- Generalization
- Bootstrapping