Data-Science-Practice (/github/um-perez-alvaro/Data-Science-Practice/tree/master)
/ Ensemble Methods (/github/um-perez-alvaro/Data-Science-Practice/tree/master/Ensemble Methods)

In [1]:
```
import pandas as pd
import matplotlib.pyplot as plt
```

Decision Trees

To understand Decision Trees, let's build one and take a look at how it makes prediction.

Example 1: Good versus Evil

In [2]:
```
# load the good vs evil datasets
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
train = pd.read_csv(url, index_col='name')
train
```

Out[2]:

name	sex	mask	cape	tie	ears	smokes	class
batman	0	1	1	0	1	0	good
robin	0	1	1	0	0	0	good
alfred	0	0	0	1	0	0	good
penguin	0	0	0	1	0	1	bad
catwoman	1	1	0	0	1	0	bad
joker	0	0	0	0	0	0	bad

In [3]:
```
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
test  = pd.read_csv(url, index_col='name')
test
```

Out[3]:

name	sex	mask	cape	tie	ears	smokes
batgirl	1	1	1	0	1	0
riddler	0	1	0	0	0	0

goal: identify people as good or bad from their appearance

In [4]:

```
# feature matrix / target vector
X_train = train[['sex','mask','cape','tie','ears','smokes']]
y_train = train['class']
X_test = test
```

The following code trains a **Decision Tree** on the *good or evil* dataset

In [5]:

```
# train a decision tree
from sklearn.tree import DecisionTreeClassifier
tree_clf = DecisionTreeClassifier()
tree_clf.fit(X_train,y_train)
```

Out[5]:

```
DecisionTreeClassifier()
```

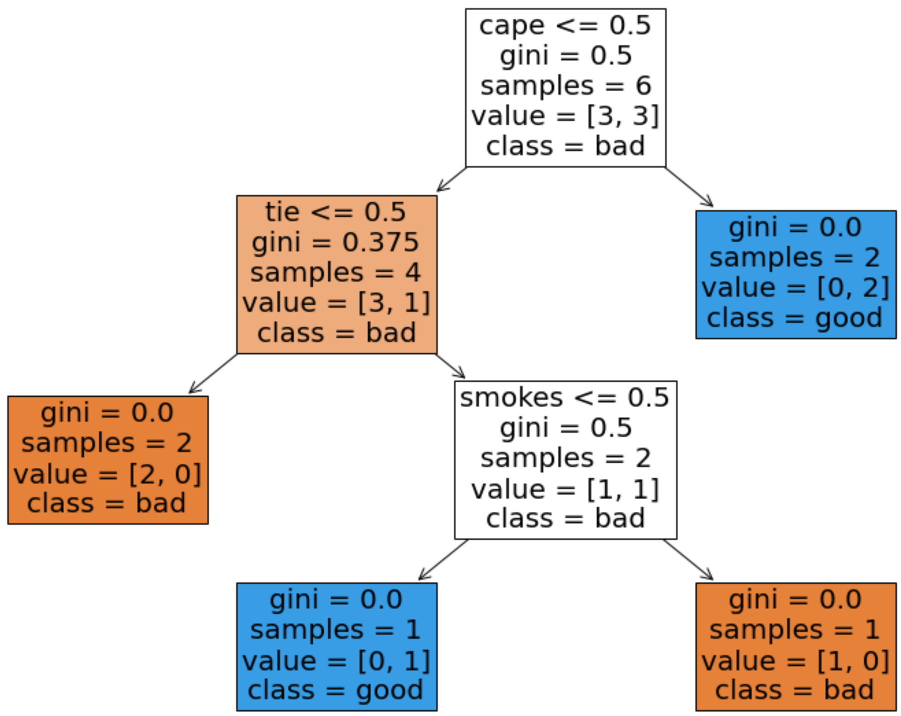
You can visualize the trained Decision Tree by using the **plot_tree** method.

In [6]:

```
# visualize the tree
from sklearn.tree import plot_tree
plt.figure(figsize=(15,10))
plot_tree(tree_clf, feature_names=X_train.columns, class_names =tree_clf.cla
```

Out[6]:

```
[Text(502.20000000000005, 475.65000000000003, 'cape <= 0.5\ngini = 0.5\nsamp
 Text(334.8, 339.75, 'tie <= 0.5\ngini = 0.375\nsamples = 4\nvalue = [3, 1]\
 Text(167.4, 203.85000000000002, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]\nc
 Text(502.20000000000005, 203.85000000000002, 'smokes <= 0.5\ngini = 0.5\nsa
 Text(334.8, 67.94999999999999, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]\ncl
 Text(669.6, 67.94999999999999, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]\ncl
 Text(669.6, 339.75, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]\nclass = good'
```



A **node's samples** attribute counts how many training instances it applies to. A **node's value** attribute tells you how many training instances of each class this done applies to. A **node's gini** attribute measures its *impurity*: a node is "pure" (gini=0) if all training instances it applies to belong to the same class.

Let's see how the tree **makes predictions**

- You start at the top node, called the **root note**, (depth 0). This node asks you the question: *does the character wear a cape*.
- If the answer is "yes" (1), you move down to the root's right **child node**. This node is a **leaf node** (it does not have any child nodes). So it does not ask any questions. The tree predicts that the character is good.
- If the answer is "no" (0), you move down to the root's left child node (depth 1), which is not a leaf node. This node asks you another question: *does the character wears a tie?*

- etc

In [7]:
```
X_test
```

Out[7]:

name	sex	mask	cape	tie	ears	smokes
batgirl	1	1	1	0	1	0
riddler	0	1	0	0	0	0

In [8]:
```
# making classification
tree_clf.predict(X_test)
```

Out[8]:
```
array(['good', 'bad'], dtype=object)
```

Scikit-learn uses the *Classification and Regression Tree (CART)* algorithm. At each step, CART searches the "question" that produces the **purest subsets** (weighted by their size).

Example 2: the pima indians diabetes dataset

If left unconstrained, Decision Trees will **overfit** the data (it will adapt itself to the training data, fitting it very closely).

In [9]:
```
# load the data
url = 'https://raw.githubusercontent.com/um-perez-alvaro/Data-Science-Practi
diabetes = pd.read_csv(url)
diabetes.head()
```

Out[9]:

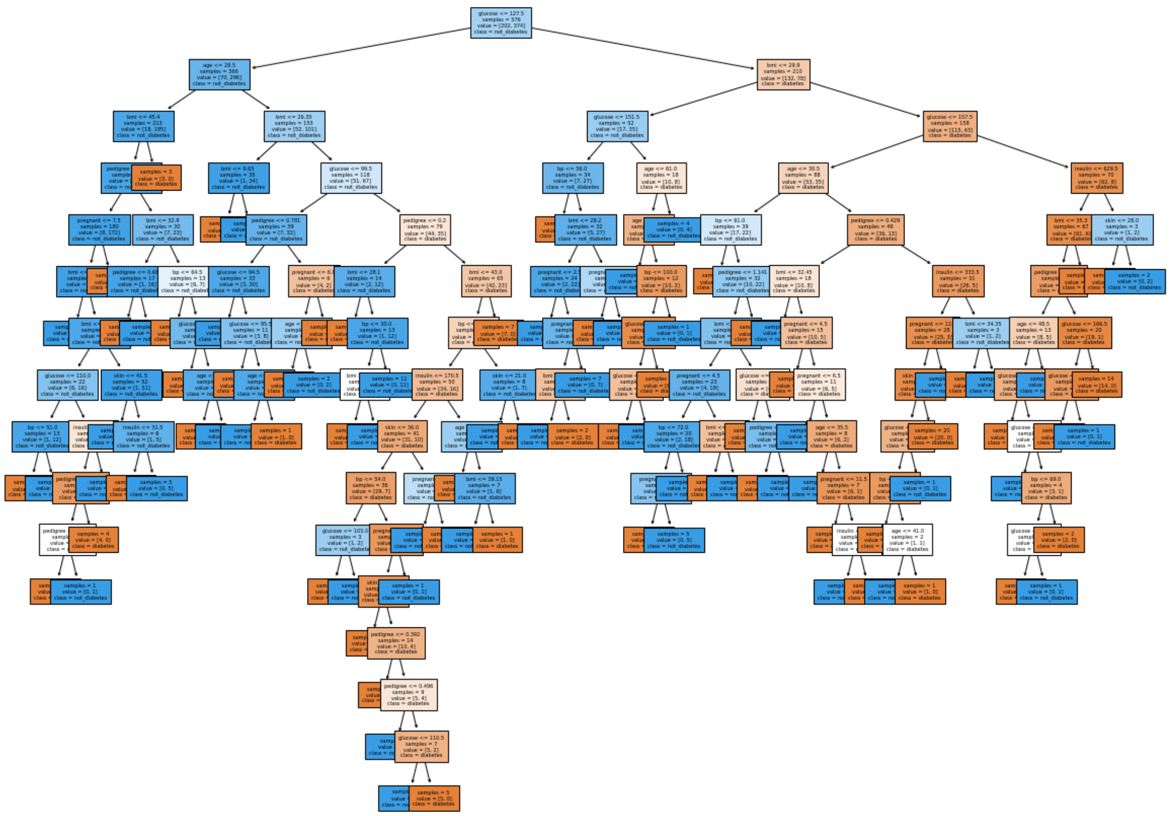
	pregnant	glucose	bp	skin	insulin	bmi	pedigree	age	label
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [10]:
```
X = diabetes.iloc[:,0:8]
y = diabetes.label.replace({1 : 'diabetes', 0 : 'not_diabetes'})
```

In [11]:
```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test = train_test_split(X,y)
```

In [12]:
```
tree_clf.fit(X_train,y_train)
```
Out[12]:
```
DecisionTreeClassifier()
```

In [13]:
```
# an overly complicated model
fig = plt.figure(figsize=(20,15))
_ = plot_tree(tree_clf, feature_names=X_train.columns, class_names =tree_clf
```



An overfitted model:

- performs well on the training data
- performs poorly on the test data

In [14]:
```
from sklearn.metrics import accuracy_score
y_train_pred = tree_clf.predict(X_train)
y_test_pred = tree_clf.predict(X_test)
```

In [15]:
```
accuracy_score(y_train,y_train_pred)
```
Out[15]:
```
1.0
```

In [16]:
```
accuracy_score(y_test, y_test_pred)
```
Out[16]:
```
0.6302083333333334
```

To avoid overfitting, we need to restrict the Decision Tree's freedom during training. This is controlled by the **max_depth** hyperparameter (by default, unlimited). Reducing max_depth will reduce the risk of overfitting.

In [17]:

```
depths = list(range(1,20))
accuracy_train = []
accuracy_test = []
for depth in depths:
    tree_clf = DecisionTreeClassifier(max_depth=depth)
    tree_clf.fit(X_train,y_train)
    y_train_pred = tree_clf.predict(X_train)
    y_test_pred = tree_clf.predict(X_test)
    accuracy_train.append(accuracy_score(y_train,y_train_pred))
    accuracy_test.append(accuracy_score(y_test,y_test_pred))
```

In [18]:

```
# change matplotlib style (only if you know and like XKCD comics)
plt.xkcd()
```

Out[18]:

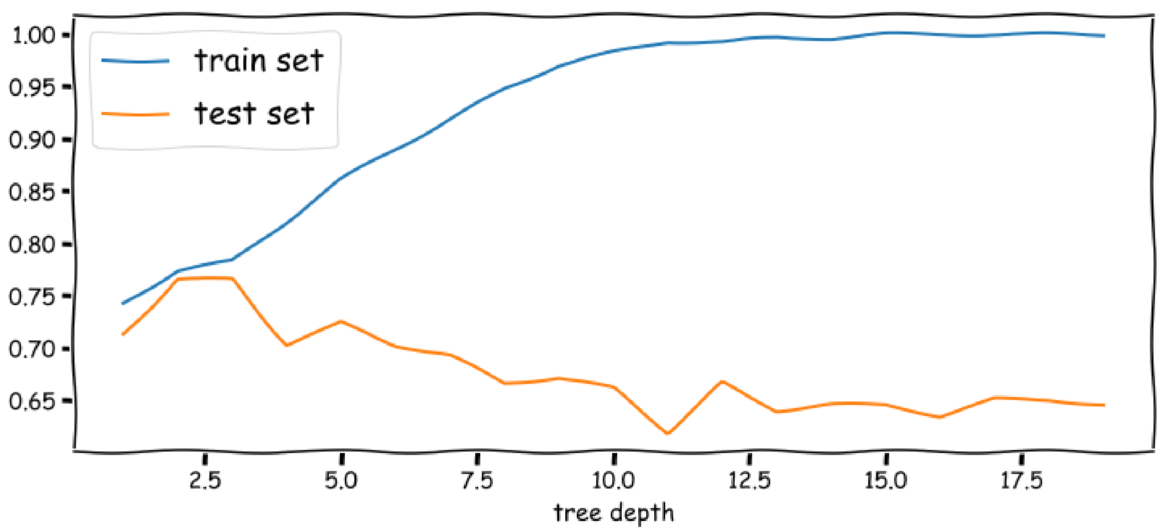
```
<matplotlib.rc_context at 0x2a65b1dbf10>
```

In [19]:

```
plt.figure(figsize=(12,5))
plt.plot(depths,accuracy_train, label='train set')
plt.plot(depths,accuracy_test, label='test set')
plt.xlabel('tree depth',fontsize=15)
plt.legend(fontsize=20)
```

Out[19]:

```
<matplotlib.legend.Legend at 0x2a65b1e63a0>
```



Decision Trees have other hyperparameters that restric the complexity of the tree:

- min_samples_split (the minimum number of samples a node must have before it can be split)
- min_sample_leaf (the minimum number of sample a leaf node must have)
- max_leaf_nodes (the maximum number of leaf nodes)
- max_features (the maximum number of features that are evaluated for splitting at each node)