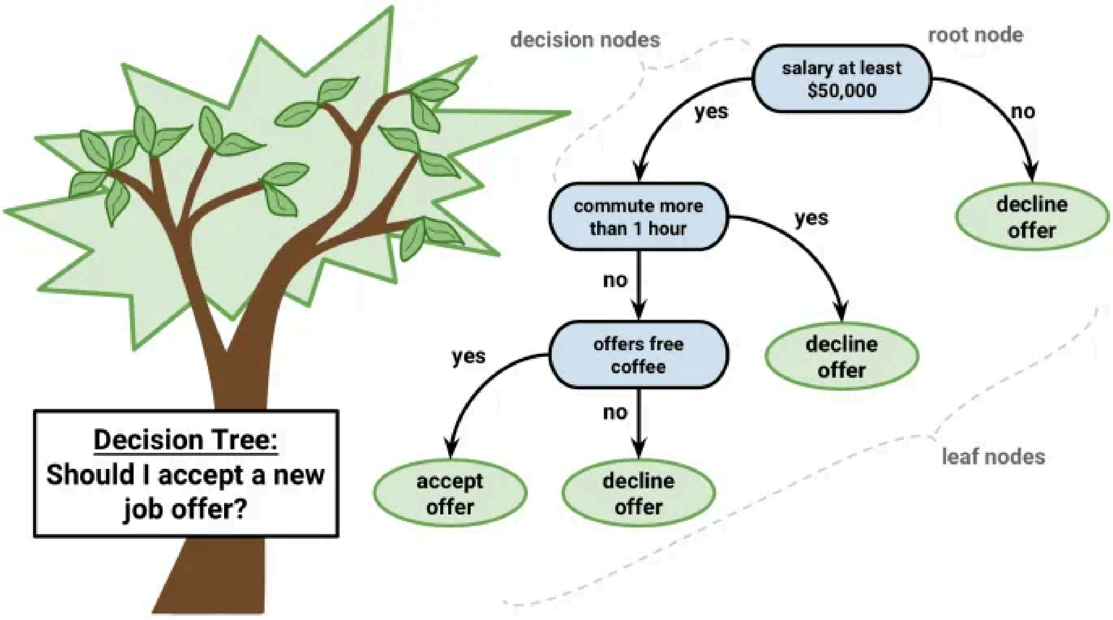
```
In [1]: ls # just for files in current working directory
```

```
 330-students-cilantro.csv   Difference-Between-Mode-and-Median.jp
g
'Decision Tree.ipynb'       'min max.png'
'Decision Tree.webp'
```



```
A decision tree is a type of machine learning model used fo
r classification and regression tasks. It is designed to ma
ke decisions by sequentially splitting data into subsets ba
sed on specific conditions. The decision-making process res
embles a tree structure, with decision nodes representing q
uestions or conditions, branches representing possible outc
omes, and leaf nodes representing the final outcome or clas
s.
```

Key Concepts of Decision Trees

- Root Node:
  - The topmost node in the tree, representing the initial question or split. It's typically chosen based on the feature that best separates the data.
- Decision Nodes:
  - Nodes where a decision is made, leading to different branches based on the condition applied at that node. Each decision node has two or more branches.
- Leaf Nodes:
  - These are the endpoints of the tree, representing a final decision or outcome. In classification, it would be a class label; in regression, it would be a numerical value.
- Splitting Criteria:
  - The condition or question used to split the data at each decision node. Common criteria include Gini impurity, entropy, and information gain for classification, and mean squared error for regression.
- Axis-Parallel Hyperplanes:

    - Decision trees create splits by using axis-parallel hyperplanes, which means each split is aligned with one of the data axes (features). This results in rectangular regions (hypercubes) in the data space.
- Nested If-Else Logic:
    - The tree structure can be represented as a series of nested if-else statements. Each decision node represents a conditional check, and the branches represent the outcomes of those conditions.

Building a Decision Tree

- Data Splitting:
    - A decision tree recursively splits the data based on a chosen splitting criterion. The goal is to maximize the purity of the resulting subsets (for classification) or minimize the variance within subsets (for regression).
- Stopping Criteria:
    - The tree-building process continues until a stopping criterion is met, such as reaching a maximum depth, having a minimum number of samples in a node, or achieving a predefined level of purity.
- Tree Depth and Complexity:
    - The depth of the tree represents the number of levels of decisions. Deeper trees can represent more complex decision boundaries but are more prone to overfitting. Advantages and Disadvantages

Advantages:

- Easy to understand and interpret.
- Can handle both categorical and numerical data.
- Requires little data preprocessing.
- Can model non-linear relationships.
- Works well with large datasets.

Disadvantages:

- Prone to overfitting, especially with deep trees.
- Sensitive to noisy data and outliers.
- May not generalize well with small datasets.
- Does not inherently support multi-class classification without extensions.

Applications

```
Decision trees are widely used in various applications, inc
luding finance, healthcare, marketing, and more. They form
the basis for more complex ensemble methods like Random For
ests and Gradient Boosting Machines, which aim to improve t
he performance and stability of single decision trees.
```

Learning objectives

- Explain how a decision tree classifier makes predictions
- Interpret a diagram of a decision tree
- Interpret a decision boundary plot for datasets with 2 numeric features (like the cilantro dataset)
- Appropriately use `fit` , `predict` , and `score in scikit-learn`

- Explain the `max_depth` hyperparameter of `DecisionTreeClasifier`
- Explain the scenario in which a `DecisionTreeClassifier` with `max_depth=None` would not get 100% training accuracy
- Distinguish between parameters and hyperparameters.

Cilantro Dataset

In [23]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['font.size'] = 16

from sklearn.tree import DecisionTreeClassifier
from sklearn.dummy import DummyClassifier

#from plot_classifier import plot_classifier
```

In [24]:

```
import re
import graphviz
from sklearn.tree import export_graphviz

def display_tree(feature_names, tree):
    """ For binary classification only """
    dot = export_graphviz(tree, out_file=None, feature_names=featur
    # adapted from https://stackoverflow.com/questions/44821349/pyt
    dot = re.sub('(\\\\nsamples = [0-9]+)(\\\\nvalue = \[[0-9]+, [0
    dot = re.sub(     '(samples = [0-9]+)(\\\\nvalue = \[[0-9]+, [0
    return graphviz.Source(dot)
```

In [25]:

```
data = pd.read_csv("330-students-cilantro.csv")
```

In [26]:

```
data.head()
```

Out[26]:

	What percentage of days do you typically eat meat or fish?	What percentage grade do you expect to get in this course?	Do you like cilantro?
0	42.0	90	Yes
1	85.0	83	No
2	28.0	83	Yes
3	100.0	80	No
4	100.0	75	No

In [27]:

```
data.columns = ["meat", "grade", "cilantro"] # Just renaming column
```

In [28]:
```
data.head(5) # First five vlaues
```

Out[28]:

	meat	grade	cilantro
0	42.0	90	Yes
1	85.0	83	No
2	28.0	83	Yes
3	100.0	80	No
4	100.0	75	No

In [29]:
```
data.tail(5) # last 5
```

Out[29]:

	meat	grade	cilantro
195	100.0	85	Yes
196	71.0	80	Yes
197	100.0	90	Yes
198	0.0	90	Yes
199	42.0	90	Yes

In [30]:
```
data.sample(5) # 5 Sample values
```

Out[30]:

	meat	grade	cilantro
95	95.0	85	Yes
49	100.0	80	Yes
106	100.0	80	No
111	71.0	90	No
183	100.0	70	No

In [33]:
```
data.duplicated().sum() # showing duplicates
```

Out[33]:
```
88
```

In [34]:
```
data.isnull().sum()
```

Out[34]:
```
meat        0
grade       0
cilantro    0
dtype: int64
```

In [35]:
```
row, columns = data.shape
print("Total no. of Rows: {} ::: Total no. of Columns: {}".format(r
```

```
Total no. of Rows: 200 ::: Total no. of Columns: 3
```

In [36]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 3 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   meat      200 non-null    float64
 1   grade     200 non-null    int64  
 2   cilantro  200 non-null    object 
dtypes: float64(1), int64(1), object(1)
memory usage: 4.8+ KB
```

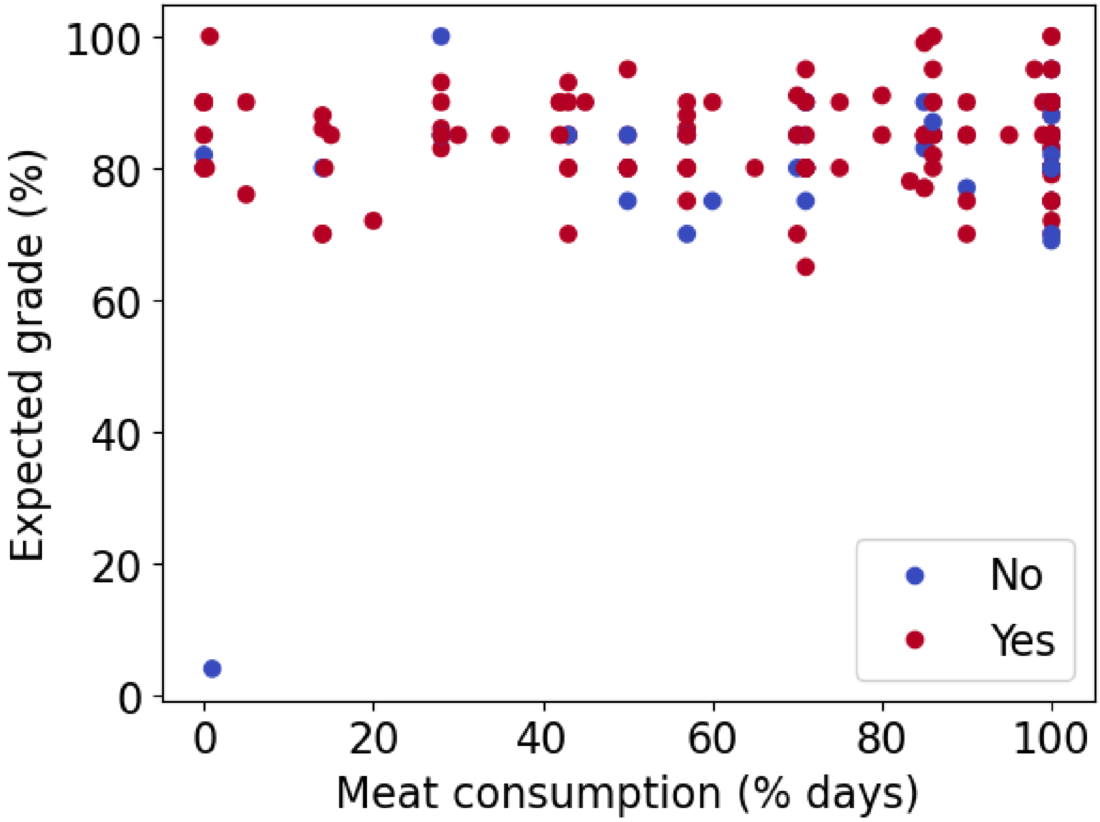
In [37]:

```
data.describe()
```

Out[37]:

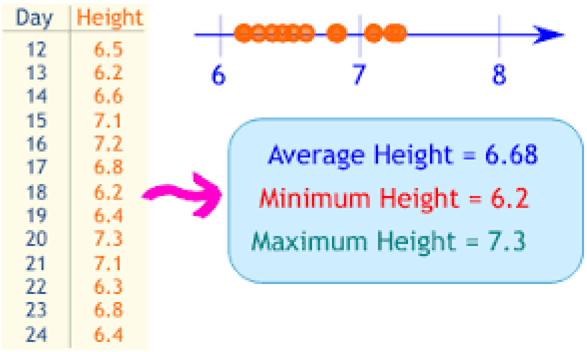
	meat	grade
count	200.000000	200.000000
mean	72.812850	83.440000
std	31.605226	8.633603
min	0.000000	4.000000
25%	50.000000	80.000000
50%	86.000000	85.000000
75%	100.000000	90.000000
max	100.000000	100.000000

In [38]:
```
scatter = plt.scatter(data["meat"], data["grade"], c=data["cilantro
plt.xlabel("Meat consumption (% days)");
plt.ylabel("Expected grade (%)");
plt.legend(scatter.legend_elements()[0], ["No", "Yes"]);
```



In [39]:
```
data["cilantro"].value_counts() # counting values of "Cilantro"==Ye
```

Out[39]:
```
cilantro
Yes    144
No      56
Name: count, dtype: int64
```



Day	Height
12	6.5
13	6.2
14	6.6
15	7.1
16	7.2
17	6.8
18	6.2
19	6.4
20	7.3
21	7.1
22	6.3
23	6.8
24	6.4

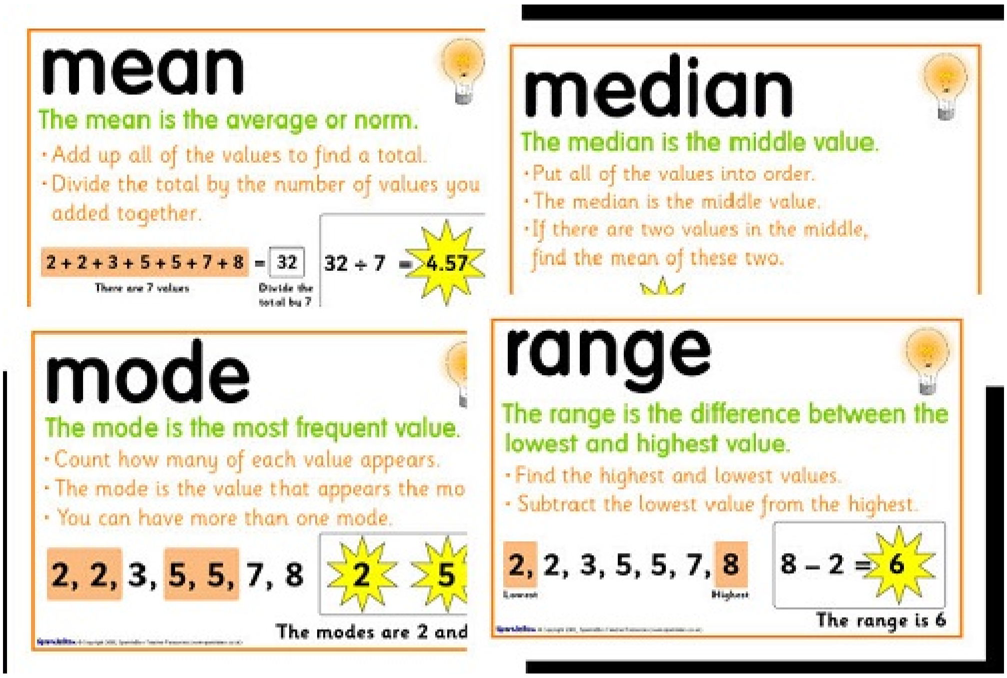
Average Height = 6.68
Minimum Height = 6.2
Maximum Height = 7.3

In [40]:
```
 data["meat"].min() # Minimum value of meat consumption
```

Out[40]:
```
0.0
```

In [41]:
```
data["meat"].max() # Maximum value of meat consumption
```

Out[41]:
```
100.0
```



mean

The mean is the average or norm.

·Add up all of the values to find a total.

·Divide the total by the number of values you added together.

2 + 2 + 3 + 5 + 5 + 7 + 8 = 32 32 ÷ 7 = 4.57

There are 7 values

Divide the total by 7

median

The median is the middle value.

·Put all of the values into order.

·The median is the middle value.

·If there are two values in the middle, find the mean of these two.

mode

The mode is the most frequent value.

·Count how many of each value appears.

·The mode is the value that appears the mo

·You can have more than one mode.

2, 2, 3, 5, 5, 7, 8 2 5

The modes are 2 and

range

The range is the difference between the lowest and highest value.

·Find the highest and lowest values.

·Subtract the lowest value from the highest.

2, 2, 3, 5, 5, 7, 8 8 – 2 = 6

Lowest

Highest

The range is 6

In [42]:
```
data["meat"].mode()
```

Out[42]:
```
0    100.0
Name: meat, dtype: float64
```

In [43]:
```
data["meat"].median()
```

Out[43]:
```
86.0
```

In [44]:
```
data["meat"].sum() / len(data.meat)
```

Out[44]:
```
72.81285
```

In [45]:
```
data["meat"].mean()
```

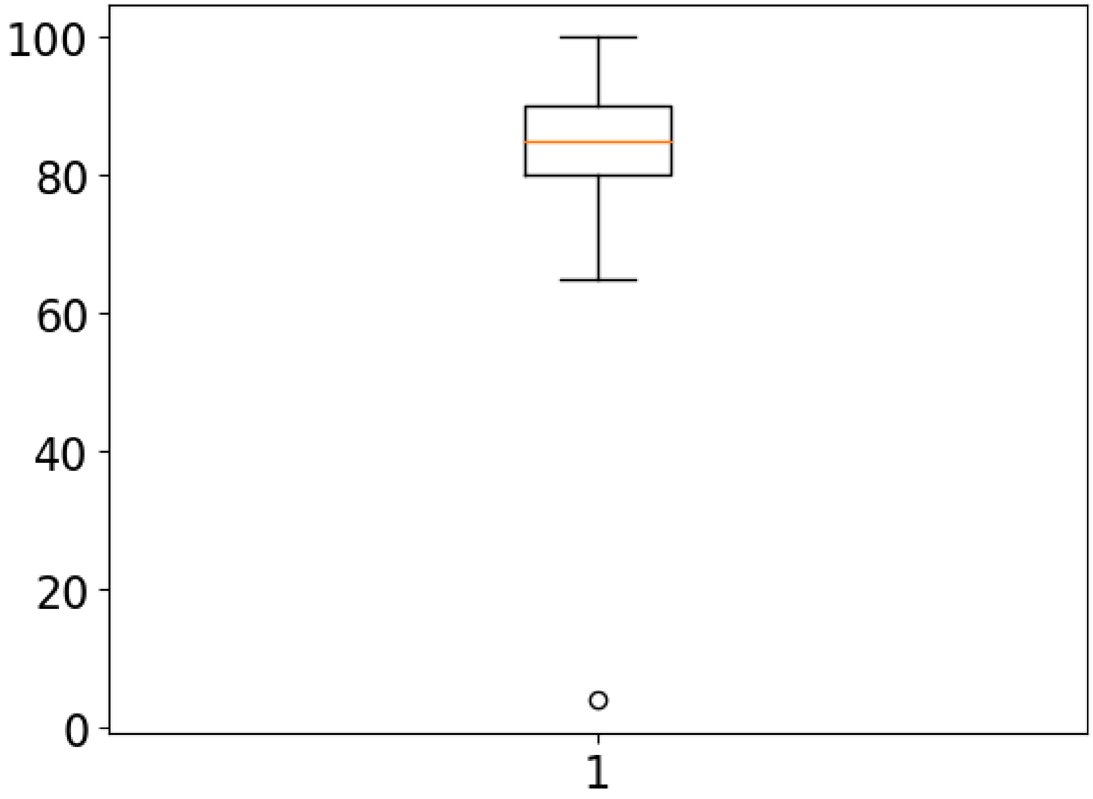
Out[45]:
```
72.81285
```

In [46]:
```
range_of_data = data["meat"].max()-data["meat"].min()
```

In [47]:
```
range_of_data
```

Out[47]:
```
100.0
```

In [48]:
```
plt.boxplot(data["grade"])
plt.show()
```



In [49]:
```
X = data[["meat","grade"]]
```

In [50]:
```
X
```

Out[50]:

	meat	grade
0	42.0	90
1	85.0	83
2	28.0	83
3	100.0	80
4	100.0	75
...	...	...
195	100.0	85
196	71.0	80
197	100.0	90
198	0.0	90
199	42.0	90

200 rows × 2 columns

In [51]:
```
y = data["cilantro"]
```

In [52]:
```
y.dtypes
```

Out[52]:
```
dtype('O')
```

In [53]:
```
y.head()
```

Out[53]:
```
0    Yes
1     No
2    Yes
3     No
4     No
Name: cilantro, dtype: object
```

In [54]:
```
y.value_counts()
```

Out[54]:
```
cilantro
Yes    144
No      56
Name: count, dtype: int64
```

In [55]:
```
dc = DummyClassifier(strategy="prior") # It predicts more common cl
```

In [56]:
```
dc.fit(X,y) # Pick data and learning but not very interesting learn
```

Out[56]:
```
▾ DummyClassifier
DummyClassifier()
```

In [57]:
```
dc.score(X,y)
```

Out[57]:
```
0.72
```

In [58]:
```
y.value_counts()/len(y) # verifc=ication of above
```

Out[58]:
```
cilantro
Yes    0.72
No     0.28
Name: count, dtype: float64
```

Decision Tree

- Our first approach to supervised learning: decision trees.
- Basic idea: ask a bunch of yes/no questions until you end up at a prediction.
- E.g. for our cilantro dataset,
  - If you eat meat <5% of the time, predict "Yes"
  - Otherwise, if you eat meat >95% of the time, predict "No"
  - Otherwise, if you expect to fail the course, predict "No"
  - Otherwise, predict "Yes"
- This "series of questions" approach can be drawn as a tree:

```
        Eats meat <5% of the time
            /          \
           / True       \  False
          /              \
         Yes           Eats meat >95% of the time
                        /      \
                  True /        \ False
                      /          \
                    No         Expects to fail the course
(<50%)
                                 /           \
                                / True        \ False
                               /               \
                              No              Yes
```

- The decision tree algorithm automatically learns a tree like this, based on the data set!
  - We would go through how it does this
  - But it's worth noting that it support two types of inputs:

1. Categorical (e.g., Yes/No or more options)
2. Numeric (a number) In the numeric case, the decision tree algorithm also picks the

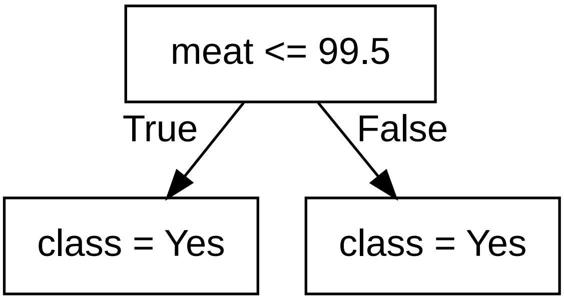
In [59]:
```
tree = DecisionTreeClassifier(max_depth=1)
```

- Here, we create a DecisionTreeClassifier object from scikit-learn.
- We pass in parameters - these are called **hyperparameters** - in this case `max_depth=1` which means the tree can only have depth 1.
- Next we fit to the data using .fit().
- The semicolon `;` is just cosmetic, otherwise some junk gets printed out.

In [60]:
```
tree.fit(X,y);
```

In [61]:
```
display_tree(data.columns[:-1],tree)
```

Out[61]:



- This is a totally useless decision tree that predicts "Yes" for any feature.
- This happens sometimes. Let's roll with it for the moment.

- This is doing the same thing as DummyClassifier so we get the same score.

- We can verify this using .predict()

In [62]:
```
X = X.astype(float)  # Convert to floats
```

In [63]:
```
tree.score(X,y)
```

Out[63]:
```
0.72
```

In [64]:
```
X.dtypes
```

Out[64]:
```
meat     float64
grade    float64
dtype: object
```

In [65]:
```
tree.predict([[50,50]]) # user input
```

```
/home/chattha/anaconda3/lib/python3.11/site-packages/sklearn/base.
py:464: UserWarning: X does not have valid feature names, but Deci
sionTreeClassifier was fitted with feature names
  warnings.warn(
```

Out[65]:
```
array(['Yes'], dtype=object)
```

In [66]:
```
tree.predict([[99,99]])
```

```
/home/chattha/anaconda3/lib/python3.11/site-packages/sklearn/base.
py:464: UserWarning: X does not have valid feature names, but Deci
sionTreeClassifier was fitted with feature names
  warnings.warn(
```

Out[66]:
```
array(['Yes'], dtype=object)
```

In [67]:
```
tree.predict([[10,10]])
```

```
/home/chattha/anaconda3/lib/python3.11/site-packages/sklearn/base.
py:464: UserWarning: X does not have valid feature names, but Deci
sionTreeClassifier was fitted with feature names
  warnings.warn(
```

Out[67]:
```
array(['Yes'], dtype=object)
```

In [68]:
```
tree.predict(X) # all input from data set
```

Out[68]:
```
array(['Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes'], dtype=object)
```

In [69]:
```
# Show One because of Depth=1
```

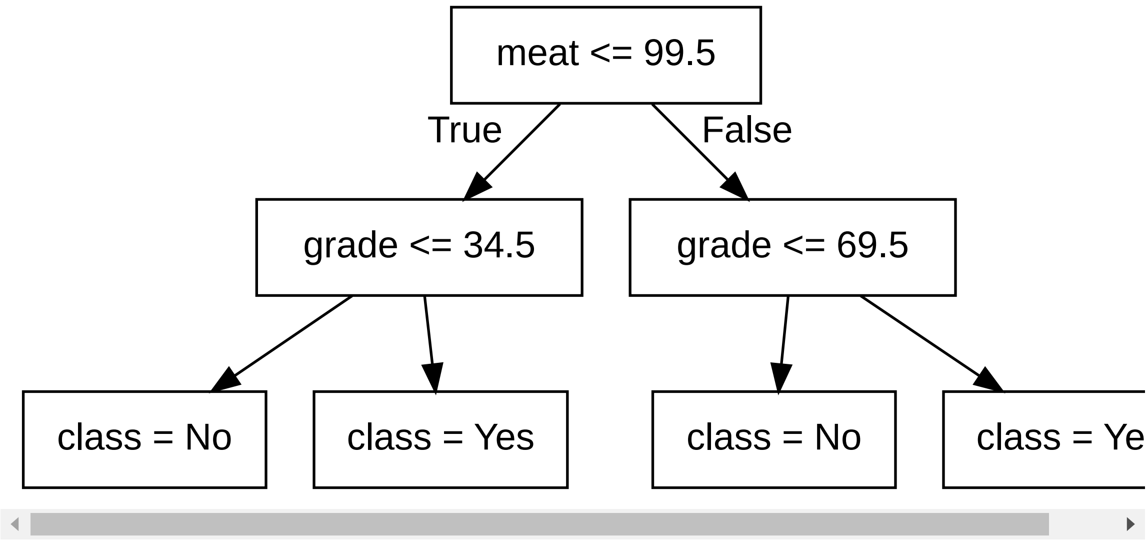
In [70]:
```
tree = DecisionTreeClassifier(max_depth=2)
```

In [71]:
```
tree.fit(X,y)
```

Out[71]:
```
▾       DecisionTreeClassifier
DecisionTreeClassifier(max_depth=2)
```

In [72]:
```
display_tree(data.columns[:-1], tree)
```

Out[72]:



In [73]:
```
tree.predict(X)
```

Out[73]:
```
array(['Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes'], dtype=object)
```

In [74]:
```
tree= DecisionTreeClassifier(max_depth=30)
```

In [75]:
```
tree.fit(X,y)
```

Out[75]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier(max_depth=30)
```

```
In [76]: display_tree(data.columns[:-1], tree) # for not last column name
```

```
Out[76]:
```

In [77]:
```
tree.predict(X)
```

Out[77]:
```
array(['Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'N
o',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'N
o', 'No',
       'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Ye
s', 'No',
       'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'N
o', 'Yes',
       'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'N
o', 'Yes',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'Yes', 'No',
'Yes',
       'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'No', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s', 'No',
       'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'No', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Yes', 'Ye
s',
       'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes', 'No', 'No', 'Yes',
'Yes',
       'Yes', 'No', 'Yes', 'Yes', 'No', 'Yes', 'No', 'Yes', 'Yes',
'Yes',
       'Yes', 'Yes', 'Yes'], dtype=object)
```

In [78]:
```
# As the Depth increase see changes in Tree structure
```

In [79]:
```
tree.score(X, y)
```

Out[79]:
```
0.805
```

Why Not 100 Accuracy??

Instances of duplicate features

In [80]:

```
# If two person have same thing the job is to find They like or not
# If you have same both features but different labels there's no wa
# Decision tree can get them both right that why giving 80%
```

In [81]:

```
it's OK if you don't understand this line
Here I'm showing duplicate
ata.loc[data.duplicated(subset=data.columns[:-1], keep=False)].sort_
```

Out[81]:

	meat	grade	cilantro
19	0.0	80	Yes
62	0.0	80	Yes
100	0.0	80	Yes
143	0.0	90	Yes
170	0.0	90	Yes
198	0.0	90	Yes
69	14.0	70	Yes
130	14.0	70	Yes
31	28.0	85	No
162	28.0	85	No
178	28.0	85	Yes
0	42.0	90	Yes
199	42.0	90	Yes
145	43.0	80	Yes
158	43.0	80	Yes
179	43.0	85	No
147	43.0	85	Yes
150	43.0	85	Yes
88	50.0	80	No
51	50.0	80	Yes

See 162 and 178 same meat same grade and different cilantro

If we remove duplicate then 100% accuracy

In [82]:

```
# it's OK if you don't understand this line Actually I'm dropping d
data_nodup = data.sort_values(by="cilantro").drop_duplicates(subset
```

In [83]:
```
data_nodup
```

Out[83]:

	meat	grade	cilantro
0	100.0	90	No
1	100.0	83	No
2	70.0	80	No
3	57.0	85	No
4	57.0	70	No
...	...	...	...
90	15.0	85	Yes
91	100.0	72	Yes
92	57.0	75	Yes
93	30.0	85	Yes
94	86.0	95	Yes

95 rows × 3 columns

In [84]:
```
data_nodup.shape
```

Out[84]:
```
(95, 3)
```

In [85]:
```
X_nodup = data_nodup.iloc[:,:2]
y_nodup = data_nodup.iloc[:,-1]
```

In [86]:
```
tree_nodup = DecisionTreeClassifier() # default is max_depth=None
```

In [87]:
```
tree_nodup.fit(X_nodup, y_nodup);
```

In [88]:
```
tree_nodup.score(X_nodup, y_nodup) # 100 Accuracy
```

Out[88]:
```
1.0
```

ML model parameters and hyperparameters

- When you call `fit` , a bunch of values get set, like the split variables and split thresholds.
- These are called **parameters**.
- But even before calling `fit` on a specific data set, we can set some "knobs" that control the learning, e.g. `max_depth` .
- These are called **hyperparameters**.

In scikit-learn, hyperparameters are set in the constructor:

Run what you can do in Decision Tree Classifer

In [89]:

```
?DecisionTreeClassifier
```

In [90]:

```
tree = DecisionTreeClassifier(max_depth=3)
tree.fit(X, y);
```

Here, `max_depth` is a hyperparameter. There are many, many more! See here (https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html).

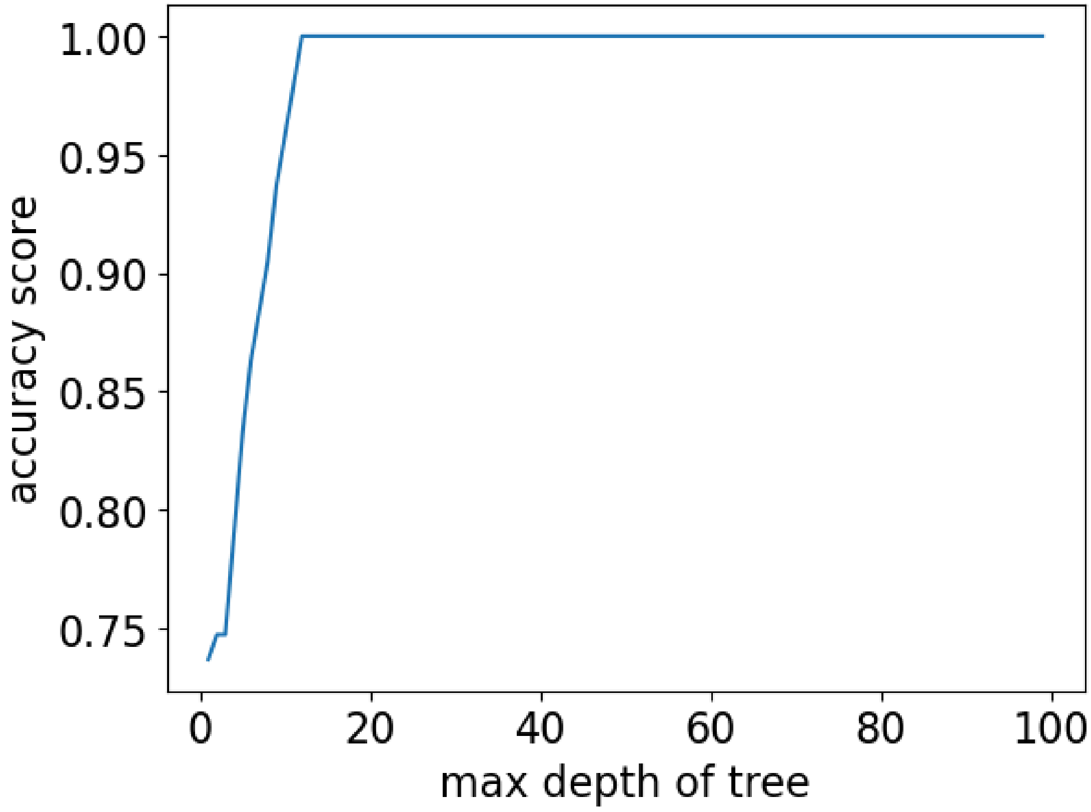
To summarize:

- **parameters** are automatically learned by the algorithm during training (`fit`)
- **hyperparameters** are specified by the human, before `fit` , based on:
  - expert knowledge
  - heuristics, or
  - systematic/automated optimization (more on that later on)

Important question: how does accuracy change vs. max_depth?

In [91]:

```
# it would be good to understand this code, but not that urgent
# I am using a list comprehension but you might find it easier to u
max_depths = np.arange(1, 100)
scores = [DecisionTreeClassifier(max_depth=max_depth).fit(X_nodup, 
plt.plot(max_depths, scores);
plt.xlabel("max depth of tree");
plt.ylabel("accuracy score");
```



- Why not just use a very deep decision tree for every supervised learning problem and get super high accuracy?

- Well, the goal of supervised learning is to predict unseen/new data...
    - The above decision tree has 100% accuracy on the training data **where we already know the answer**.
    - It perfectly labels the data we used to make the tree...
    - But we want to know how our model performs on data not used in training.
    - We will split our original dataset into two parts, one for "training" and one for "testing".

In [92]:

```
from sklearn.model_selection import train_test_split
```

In [93]:

```
df_train, df_test = train_test_split(df_nodup)
```

```
------------------------------------------------------------------
---------
NameError                                 Traceback (most recent c
all last)
Cell In[93], line 1
----> 1 df_train, df_test = train_test_split(df_nodup)

NameError: name 'df_nodup' is not defined
```

In [94]:

```
scatter = plt.scatter(df_train["meat"], df_train["grade"], c=df_tra
plt.xlabel("Meat consumption (% days)");
plt.ylabel("Expected grade (%)");
plt.legend(scatter.legend_elements()[0], ["No", "Yes"]);
```

```
------------------------------------------------------------------
---------
NameError                                 Traceback (most recent c
all last)
Cell In[94], line 1
----> 1 scatter = plt.scatter(df_train["meat"], df_train["grade"],
c=df_train["cilantro"]=="Yes", cmap=plt.cm.coolwarm);
      2 plt.xlabel("Meat consumption (% days)");
      3 plt.ylabel("Expected grade (%)");

NameError: name 'df_train' is not defined
```

In [95]:

```
scatter = plt.scatter(df_test["meat"], df_test["grade"], c=df_test[
plt.xlabel("Meat consumption (% days)");
plt.ylabel("Expected grade (%)");
plt.xlim((0,100));
plt.ylim((0,100));
plt.legend(scatter.legend_elements()[0], ["No", "Yes"]);
```

```
-------------------------------------------------------------------
---------
NameError                                 Traceback (most recent c
all last)
Cell In[95], line 1
----> 1 scatter = plt.scatter(df_test["meat"], df_test["grade"], c
=df_test["cilantro"]=="Yes", cmap=plt.cm.coolwarm);
      2 plt.xlabel("Meat consumption (% days)");
      3 plt.ylabel("Expected grade (%)");

NameError: name 'df_test' is not defined
```

Summary

- Cilantro dataset: predict whether a CPSC 330 student likes cilantro (yes/no) from their meat consumption and expected grade (numeric features)
- Decision trees: a classifier that makes predictions by sequentially looking at features and checking whether they are above/below a threshold
- Decision trees learn axis-aligned decision boundaries (vertical and horizontal lines with 2 features)
- `fit(X,y)` : train classifier from training data
- `predict(X)` : make one or more predictions given a trained classifier
- `score(X,y)` : makes predictions with `predict()` and compares them to the true answers passed in as `y`
- Classifiers have hyperparameters, which are set before calling `fit`
  - Often set by humans, but not always (see later lecture)
- `max_depth` is a hyperparameter of `DecisionTreeClassifier` that controls the maximum depth of the learned tree
- larger `max_depth` -> larger accuracy on training data
- `DecisionTreeClassifier` with `max_depth=None` not getting 100% training accuracy when two students have the same features but different target values

-----------------------------End Of Lecture-----------------------------

In [ ]:

```
```

In [ ]:

```
```