

Demo: Decision trees and ensembles

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This is a simple demo notebook that demonstrates a decision tree classifier or an ensemble of decision trees.

Attribution: Parts of this notebook are slightly modified from [this tutorial from “Intro to Data Mining”](#).

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

import sklearn
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier, AdaBoostClassifier
```

```
df = pd.read_csv('http://www.cse.msu.edu/~ptan/dmbook/tutorials/tutorial6/vertebrate.csv')
df
```

	Name	Warm-blooded	Gives Birth	Aquatic Creature	\
0	human	1	1	0	
1	python	0	0	0	
2	salmon	0	0	1	
3	whale	1	1	1	
4	frog	0	0	1	
5	komodo	0	0	0	
6	bat	1	1	0	
7	pigeon	1	0	0	
8	cat	1	1	0	
9	leopard shark	0	1	1	
10	turtle	0	0	1	
11	penguin	1	0	1	
12	porcupine	1	1	0	
13	eel	0	0	1	
14	salamander	0	0	1	

	Aerial Creature	Has Legs	Hibernates	Class
0	0	1	0	mammals
1	0	0	1	reptiles
2	0	0	0	fishes
3	0	0	0	mammals
4	0	1	1	amphibians
5	0	1	0	reptiles
6	1	1	1	mammals
7	1	1	0	birds
8	0	1	0	mammals
9	0	0	0	fishes
10	0	1	0	reptiles
11	0	1	0	birds
12	0	1	1	mammals
13	0	0	0	fishes
14	0	1	1	amphibians

We'll make it a binary classification problem:

```
df['Class'] = df['Class'].replace(['fishes', 'birds', 'amphibians', 'reptiles'], 'non-mammals')
df
```

	Name	Warm-blooded	Gives Birth	Aquatic Creature	\
0	human	1	1	0	
1	python	0	0	0	
2	salmon	0	0	1	
3	whale	1	1	1	
4	frog	0	0	1	
5	komodo	0	0	0	
6	bat	1	1	0	
7	pigeon	1	0	0	
8	cat	1	1	0	
9	leopard shark	0	1	1	
10	turtle	0	0	1	
11	penguin	1	0	1	
12	porcupine	1	1	0	
13	eel	0	0	1	
14	salamander	0	0	1	

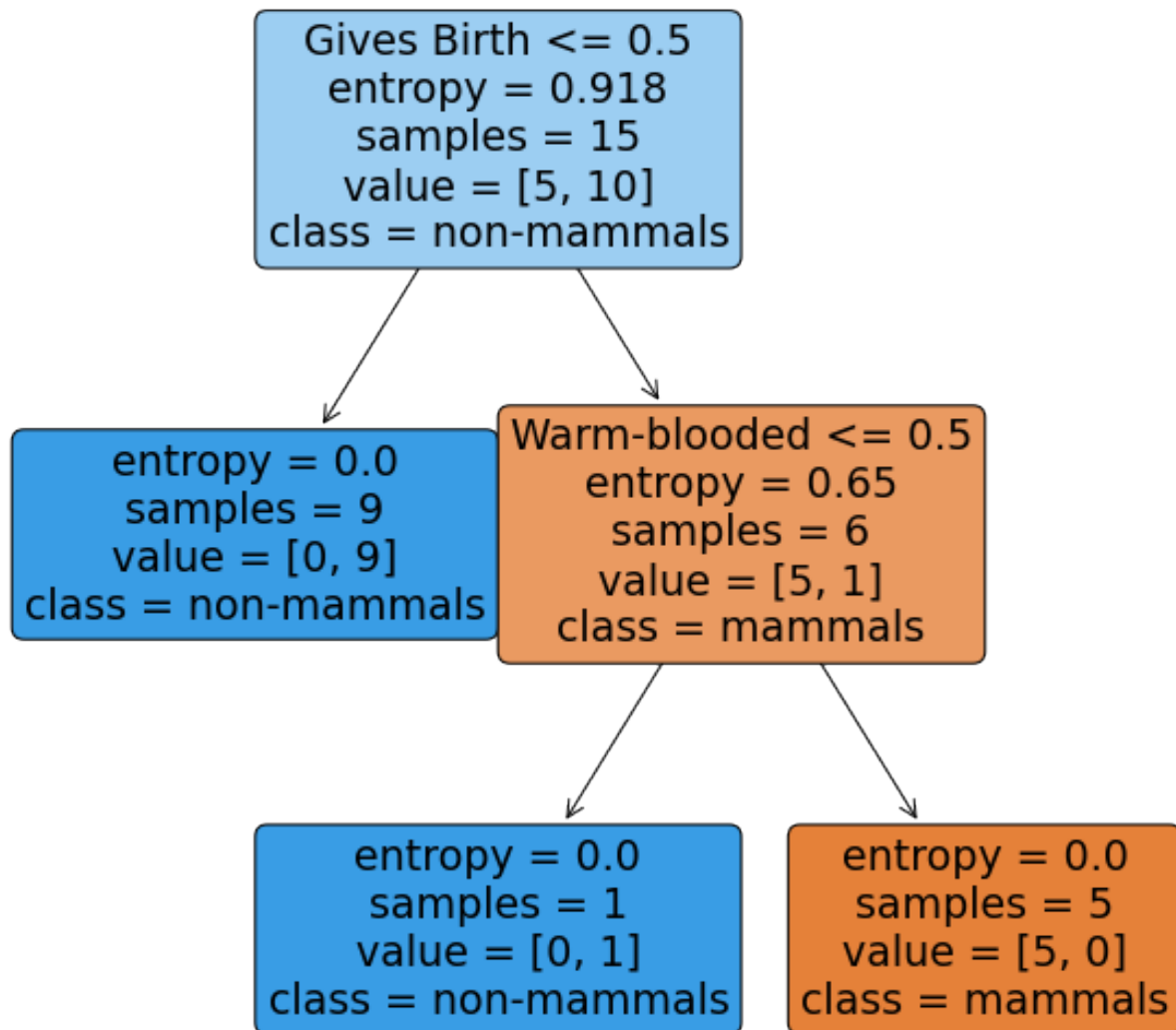
	Aerial Creature	Has Legs	Hibernates	Class
0	0	1	0	mammals
1	0	0	1	non-mammals
2	0	0	0	non-mammals
3	0	0	0	mammals
4	0	1	1	non-mammals
5	0	1	0	non-mammals
6	1	1	1	mammals
7	1	1	0	non-mammals
8	0	1	0	mammals
9	0	0	0	non-mammals
10	0	1	0	non-mammals
11	0	1	0	non-mammals
12	0	1	1	mammals
13	0	0	0	non-mammals
14	0	1	1	non-mammals

Decision tree

```
y = df['Class']
X = df.drop(['Name', 'Class'], axis=1)
```

```
clf_dt = DecisionTreeClassifier(criterion='entropy')
clf_dt = clf_dt.fit(X, y)
```

```
plt.figure(figsize=(10,10))
sklearn.tree.plot_tree(clf_dt,
                        feature_names = df.columns.drop(['Name', 'Class']),
                        class_names = ["mammals", "non-mammals"],
                        filled=True, rounded=True);
```



Feature importance

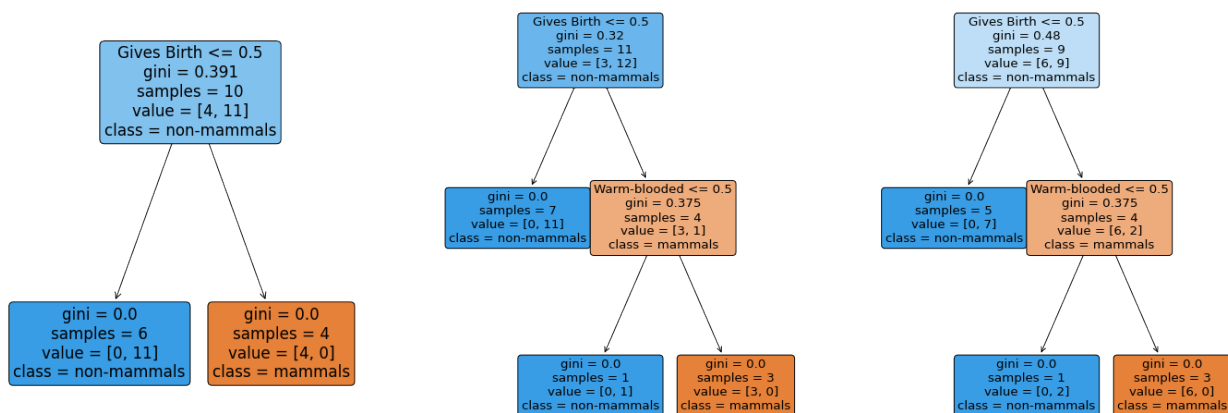
```
df_importance = pd.DataFrame({'feature': df.columns.drop(['Name', 'Class']),
                             'importance': clf_dt.feature_importances_})
df_importance
```

	feature	importance
0	Warm-blooded	0.283143
1	Gives Birth	0.716857
2	Aquatic Creature	0.000000
3	Aerial Creature	0.000000
4	Has Legs	0.000000
5	Hibernates	0.000000

Bagged tree

```
n_tree = 3
clf_bag = BaggingClassifier(n_estimators=n_tree)
clf_bag = clf_bag.fit(X, y)
```

```
plt.figure(figsize=(n_tree*8, 10))
for idx, clf_t in enumerate(clf_bag.estimators_):
    plt.subplot(1, n_tree, idx+1)
    sklearn.tree.plot_tree(clf_t,
                           feature_names = df.columns.drop(['Name', 'Class']),
                           class_names = ["mammals", "non-mammals"],
                           filled=True, rounded=True)
```



Notice the similarities! The bagged trees are highly correlated.

Let's look at the bootstrap sets each tree was trained on:

```
for samples in clf_bag.estimators_samples_:
    print(df.iloc[samples])
```

	Name	Warm-blooded	Gives Birth	Aquatic Creature	Aerial Creature	\
13	eel	0	0	1	0	
6	bat	1	1	0	1	
7	pigeon	1	0	0	1	
14	salamander	0	0	1	0	
14	salamander	0	0	1	0	
12	porcupine	1	1	0	0	
2	salmon	0	0	1	0	
3	whale	1	1	1	0	
2	salmon	0	0	1	0	
10	turtle	0	0	1	0	
11	penguin	1	0	1	0	
10	turtle	0	0	1	0	
13	eel	0	0	1	0	
7	pigeon	1	0	0	1	
8	cat	1	1	0	0	

	Has Legs	Hibernates	Class
13	0	0	non-mammals
6	1	1	mammals
7	1	0	non-mammals
14	1	1	non-mammals
14	1	1	non-mammals
12	1	1	mammals
2	0	0	non-mammals
3	0	0	mammals
2	0	0	non-mammals
10	1	0	non-mammals
11	1	0	non-mammals
10	1	0	non-mammals
13	0	0	non-mammals
7	1	0	non-mammals
8	1	0	mammals

	Name	Warm-blooded	Gives Birth	Aquatic Creature	\
10	turtle	0	0	1	
0	human	1	1	0	
14	salamander	0	0	1	
3	whale	1	1	1	
9	leopard shark	0	1	1	
11	penguin	1	0	1	
1	python	0	0	0	
2	salmon	0	0	1	
14	salamander	0	0	1	
13	eel	0	0	1	
7	pigeon	1	0	0	
11	penguin	1	0	1	
8	cat	1	1	0	
1	python	0	0	0	
10	turtle	0	0	1	

	Aerial Creature	Has Legs	Hibernates	Class
10	0	1	0	non-mammals
0	0	1	0	mammals
14	0	1	1	non-mammals
3	0	0	0	mammals
9	0	0	0	non-mammals
11	0	1	0	non-mammals
1	0	0	1	non-mammals
2	0	0	0	non-mammals
14	0	1	1	non-mammals
13	0	0	0	non-mammals
7	1	1	0	non-mammals
11	0	1	0	non-mammals
8	0	1	0	mammals
1	0	0	1	non-mammals
10	0	1	0	non-mammals

	Name	Warm-blooded	Gives Birth	Aquatic Creature	\
0	human	1	1	0	
13	eel	0	0	1	
9	leopard shark	0	1	1	

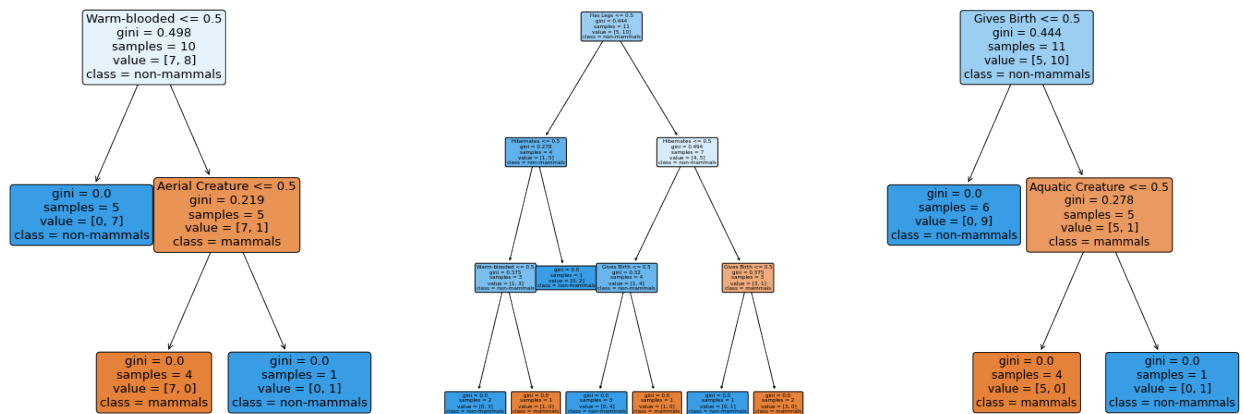
11	penguin	1	0	1
3	whale	1	1	1
2	salmon	0	0	1
5	komodo	0	0	0
3	whale	1	1	1
6	bat	1	1	0
6	bat	1	1	0
13	eel	0	0	1
7	pigeon	1	0	0
11	penguin	1	0	1
9	leopard shark	0	1	1
0	human	1	1	0

	Aerial Creature	Has Legs	Hibernates	Class
0	0	1	0	mammals
13	0	0	0	non-mammals
9	0	0	0	non-mammals
11	0	1	0	non-mammals
3	0	0	0	mammals
2	0	0	0	non-mammals
5	0	1	0	non-mammals
3	0	0	0	mammals
6	1	1	1	mammals
6	1	1	1	mammals
13	0	0	0	non-mammals
7	1	1	0	non-mammals
11	0	1	0	non-mammals
9	0	0	0	non-mammals
0	0	1	0	mammals

Random forest

```
n_tree = 3
clf_rf = RandomForestClassifier(n_estimators=n_tree, )
clf_rf = clf_rf.fit(X, y)
```

```
plt.figure(figsize=(n_tree*8, 10))
for idx, clf_t in enumerate(clf_rf.estimators_):
    plt.subplot(1, n_tree, idx+1)
    sklearn.tree.plot_tree(clf_t,
                           feature_names = df.columns.drop(['Name', 'Class']),
                           class_names = ["mammals", "non-mammals"],
                           filled=True, rounded=True)
```

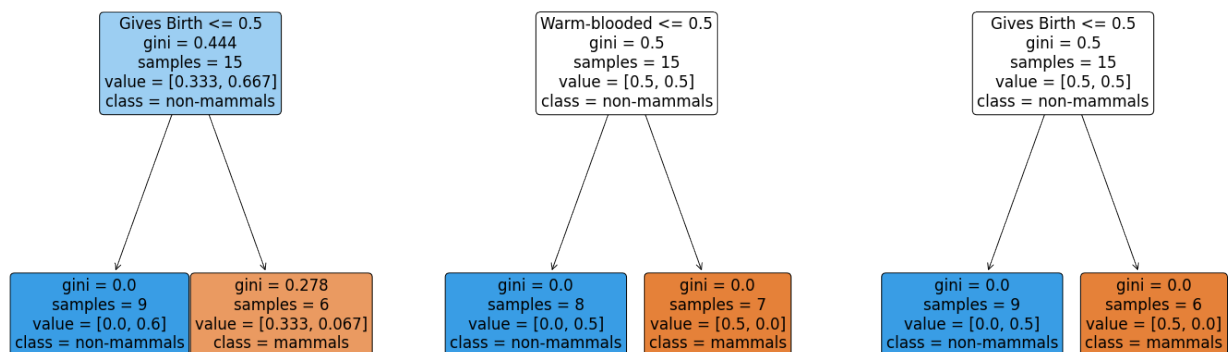


These trees are much less correlated.

AdaBoost

```
n_tree = 3
clf_ab = AdaBoostClassifier(n_estimators=n_tree)
clf_ab = clf_ab.fit(X, y)
```

```
plt.figure(figsize=(n_tree*8, 10))
for idx, clf_t in enumerate(clf_ab.estimators_):
    plt.subplot(1, n_tree, idx+1)
    sklearn.tree.plot_tree(clf_t,
                           feature_names = df.columns.drop(['Name', 'Class']),
                           class_names = ["mammals", "non-mammals"],
                           filled=True, rounded=True)
```



The output will be a weighted average of the predictions of all three trees.

As we add more trees, the ensemble accuracy increases:

```
for p in clf_ab.staged_predict(X):  
    print(np.mean(p==y))
```

```
0.9333333333333333
```

```
1.0
```

```
1.0
```