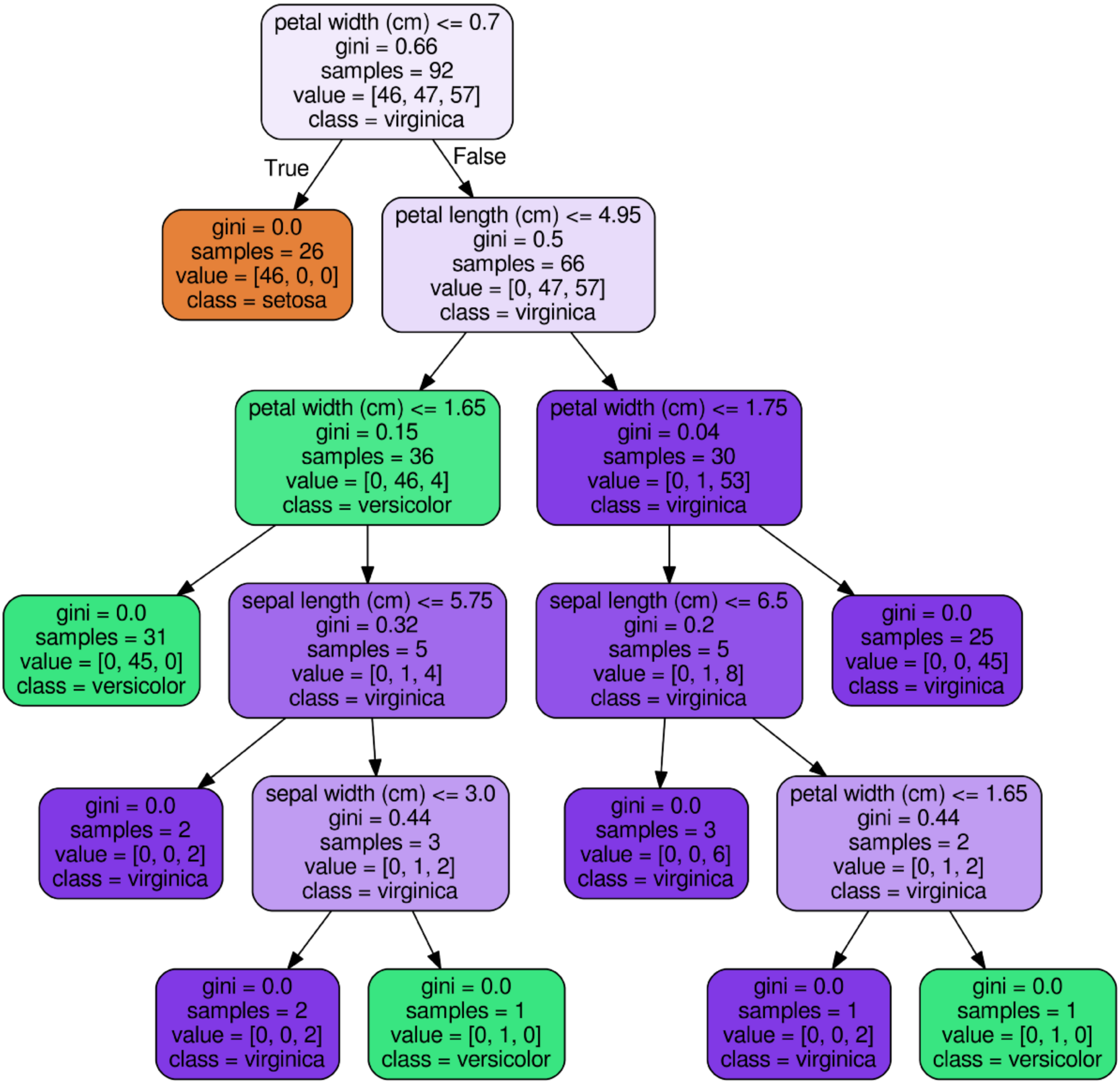
```python
from sklearn.datasets import load_iris
iris = load_iris()

# Model (can also use single decision tree)
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10)

# Train
model.fit(iris.data, iris.target)
# Extract single tree
estimator = model.estimators_[5]

from sklearn.tree import export_graphviz
# Export as dot file
export_graphviz(estimator, out_file='tree.dot',
                feature_names = iris.feature_names,
                class_names = iris.target_names,
                rounded = True, proportion = False,
```

Code to visualize a decision tree and save as png (on GitHub here).

The final result is a complete decision tree as an image.



Decision Tree for Iris Dataset

Explanation of code

1. **Create a model train and extract:** we could use a single decision tree, but since I often employ the random forest for modeling it's used in this example. (The trees will be slightly different from one another!).

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10)

# Train
model.fit(iris.data, iris.target)
# Extract single tree
estimator = model.estimators_[5]
```

2. Export Tree as .dot File: This makes use of the `export_graphviz` function in Scikit-Learn. There are many parameters here that control the look and information displayed. Take a look at the documentation for specifics.

```
from sklearn.tree import export_graphviz

# Export as dot file
export_graphviz(estimator_limited,
                out_file='tree.dot',
                feature_names = iris.feature_names,
                class_names = iris.target_names,
                rounded = True, proportion = False,
                precision = 2, filled = True)
```

3. Convert `dot` to `png` using a system command: running system commands in Python can be handy for carrying out simple tasks. This requires installation of graphviz which includes the dot utility. For the complete options for conversion, take a look at the documentation.

```
# Convert to png
from subprocess import call
call(['dot', '-Tpng', 'tree.dot', '-o', 'tree.png', '-
Gdpi=600'])
```

4. Visualize: the best visualizations appear in the Jupyter Notebook. (Equivalently you can use `matplotlib` to show images).

```
# Display in jupyter notebook
from IPython.display import Image
Image(filename = 'tree.png')
```

Considerations

With a random forest, every tree will be built differently. I use these images to display the reasoning behind a decision tree (and subsequently a random forest) rather than for specific details.

It's helpful to limit maximum depth in your trees when you have a lot of features. Otherwise, you end up with massive trees, which look impressive, but cannot be interpreted at all! Here's a full example with 50 features.

Full decision tree from a real problem (see here).

Conclusions

Machine learning still suffers from a black box problem, and one image is not going to solve the issue! Nonetheless, looking at an individual decision tree shows us this model (and a random forest) is not an unexplainable method, but a sequence of logical questions and answers —much as we would form when making predictions. Feel free to use and adapt this code for your data.

As always, I welcome feedback, constructive criticism, and hearing about your data science projects. I can be reached on Twitter @koehrsen_will