Meet my data

In [28]:
```
from sklearn.datasets import load_iris
iris_dataset = load_iris()
print("Keys of Iris DataSet:\n\t{}".format(iris_dataset.keys()))
```

```
Keys of Iris DataSet:
        dict_keys(['data', 'target', 'target_names', 'DESCR', 'feature_
names'])
```

In [29]:
```
print("\nDescription of Iris Dataset:\n\n{}".format(iris_dataset['DESC
R'][:1180]))
```

```
Description of Iris Dataset:

Iris Plants Database
====================

Notes
-----
Data Set Characteristics:
    :Number of Instances: 150 (50 in each of three classes)
    :Number of Attributes: 4 numeric, predictive attributes and the cla
ss
    :Attribute Information:
        - sepal length in cm
        - sepal width in cm
        - petal length in cm
        - petal width in cm
        - class:
                - Iris-Setosa
                - Iris-Versicolour
                - Iris-Virginica
    :Summary Statistics:
```

```
                ============== ==== ==== ======= ===== ====================
                                Min  Max   Mean    SD   Class Correlation
                ============== ==== ==== ======= ===== ====================
                sepal length:   4.3  7.9   5.84   0.83    0.7826
                sepal width:    2.0  4.4   3.05   0.43   -0.4194
                petal length:   1.0  6.9   3.76   1.76    0.9490  (high!)
                petal width:    0.1  2.5   1.20  0.76     0.9565  (high!)
                ============== ==== ==== ======= ===== ====================

                :Missing Attribute Values: None
                :Class Distribution: 33.3% for each of 3 classes.
                :Creator: R.A. Fisher
                :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)
                :Date: July, 1988
```

In [27]:
```
print("Target Names:\n\t{}".format(iris_dataset['target_names']))
```

```
Target Names:
        ['setosa' 'versicolor' 'virginica']
```

In [30]:
```
print("Feature Names:\n\t{}".format(iris_dataset['feature_names']))
```

```
Feature Names:
        ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)',
'petal width (cm)']
```

In [43]:
```
print("Shape of data:\t{}".format(iris_dataset['data'].shape))
```

```
Shape of data:  (150, 4)
```

In [35]:
```
print("First 5 rows of data:\n\n{}".format(iris_dataset['data'][:5]))
```

```
First 5 rows of data:

[[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]]
```

In [41]:
```
print("Length of target:\t{}".format(len(iris_dataset['target'])))
```

```
Length of target:	150
```

In [150]:
```
print("Target:\n{}".format(iris_dataset['target']))
```

```
Target:
[0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

Measuring Success: Training and Testing Data

In [149]:
```
from sklearn.model_selection import train_test_split as tts

X_train, X_test, y_train, y_test = tts(iris_dataset['data'], iris_datas
et['target'], random_state = 0)

print("Training data set shape: {}".format(X_train.shape))
print("Training target shape: {}".format(y_train.shape))

print("\nTesting data set shape: {}".format(X_test.shape))
print("Testing target shape: {}".format(y_test.shape))
```

```
Training data set shape: (112, 4)
Training target shape: (112,)

Testing data set shape: (38, 4)
Testing target shape: (38,)
```

Look at my data

In [151]:
```
df_column_names = iris_dataset.feature_names
if 'species' not in df_column_names:
    df_column_names.append('species')
print("Dataframe column names:\n{}".format(df_column_names))
```

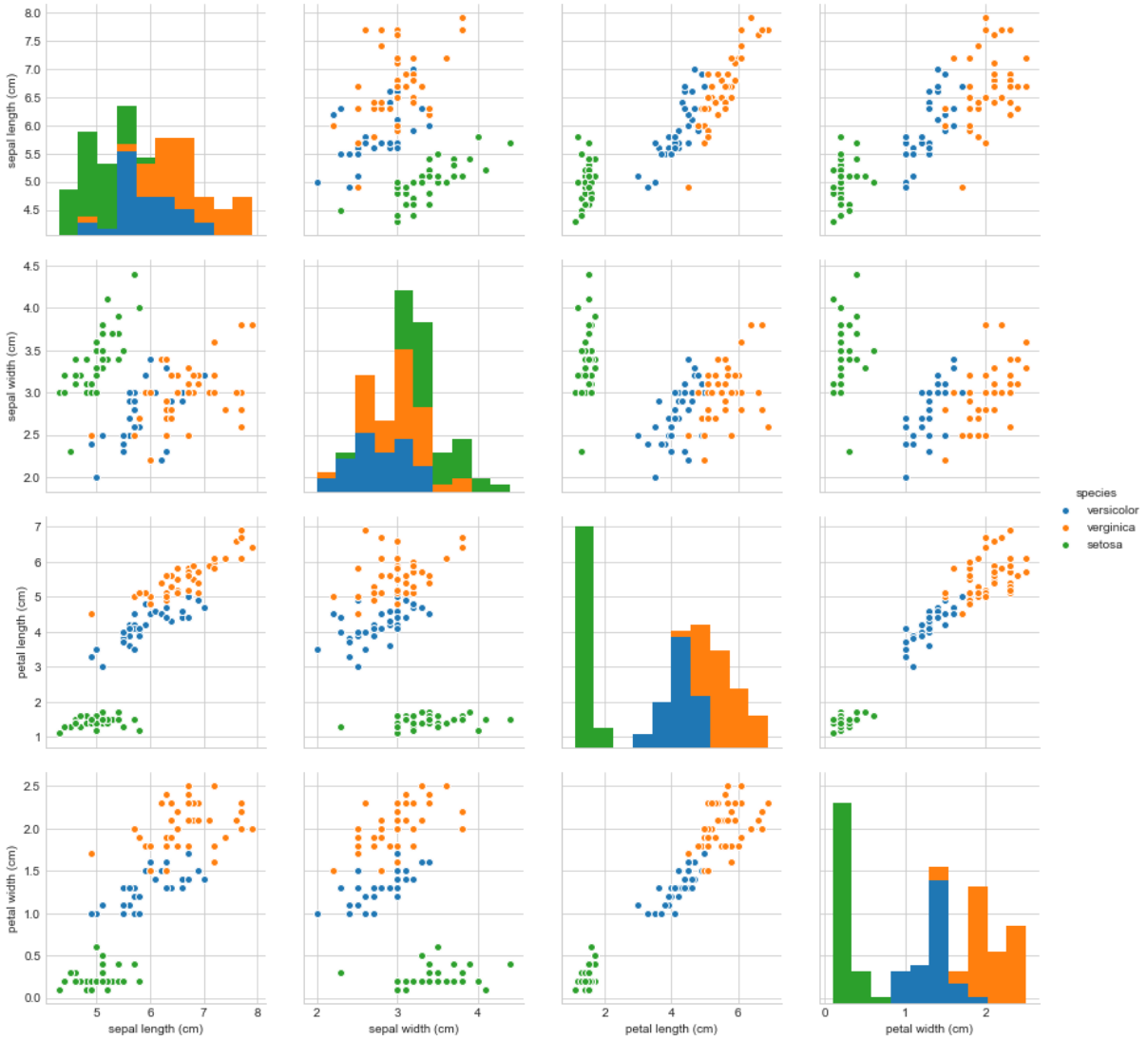
```
Dataframe column names:
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal w
idth (cm)', 'species']
```

In [147]:
```
import pandas as pd
import numpy as np

X_y_train = np.concatenate((X_train,y_train[:,np.newaxis]),axis=1)
iris_df = pd.DataFrame(X_y_train, columns = df_column_names)

iris_df["species"] = iris_df["species"].map({0.: "setosa", 1.0: "versic
olor", 2.0: "verginica"})
iris_df.head()
```

Out[147]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	species
0	5.9	3.0	4.2	1.5	versicolor
1	5.8	2.6	4.0	1.2	versicolor
2	6.8	3.0	5.5	2.1	verginica
3	4.7	3.2	1.3	0.2	setosa
4	6.9	3.1	5.1	2.3	verginica

In [152]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("whitegrid");
sns.pairplot(iris_df, hue = "species", size = 3);
plt.show()
```



From the plots, we can see that the 3 classes seem to be relatively well seperated using the sepal and petal measurements. This means that a machine learning model will likely be able to learn to seperate them.

Building my Model: k-Nearest Neighbors

In [63]:
```
from sklearn.neighbors import KNeighborsClassifier as knc
knn = knc(n_neighbors = 1)
knn.fit(X_train, y_train)
```

Out[63]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
                     metric_params=None, n_jobs=1, n_neighbors=1, p=2,
                     weights='uniform')
```

Making Predictions

In [144]:
```
test_sample = X_test[:1]
prediction = knn.predict(test_sample)
print("Test Sample:\t{}".format(test_sample[0]))
print("Prediction:\t{}".format(prediction[0]))
print("Predicted Target Name:\t{}".format(iris_dataset['target_names'][
prediction][0]))
print("Actual Target Name:\t{}".format(iris_dataset['target_names'][y_t
est[0]]))
```

```
Test Sample:    [5.8 2.8 5.1 2.4]
Prediction:     2
Predicted Target Name:  virginica
Actual Target Name:     virginica
```

Evaluating the model

In [153]:
```
y_pred = knn.predict(X_test)
print("Test set prediction:\n\n{}".format(y_pred))
print("\nTesting Target:\n\n{}".format(y_test))
print("\nTesting Data for which prediction failed:\n\n{}".format(X_test
[y_pred != y_test][0]))
```

```
Test set prediction:

[2 1 0 2 0 2 0 1 1 1 2 1 1 1 1 0 1 1 0 0 2 1 0 0 2 0 0 1 1 0 2 1 0 2 2
```

```
1 0
 2]

Testing Target:

[2 1 0 2 0 2 0 1 1 1 2 1 1 1 1 0 1 1 0 0 2 1 0 0 2 0 0 1 1 0 2 1 0 2 2
1 0
 1]

Testing Data for which prediction failed:

[6.  2.7 5.1 1.6]
```

In [78]:
```
print("Test set score:\t{:.2f}".format(np.mean(y_pred == y_test)))
```

```
Test set score: 0.97
```

In [79]:
```
print("Test set score:\t{:.2f}".format(knn.score(X_test, y_test)))
```

```
Test set score: 0.97
```

Conclusion

For this model, the test accuracy is about 0.97, which means we made right prediction for 97% of iris flowers in the test set. This high level of accuracy means that our model may be trustworthy enough to use for our hobby botanist application.