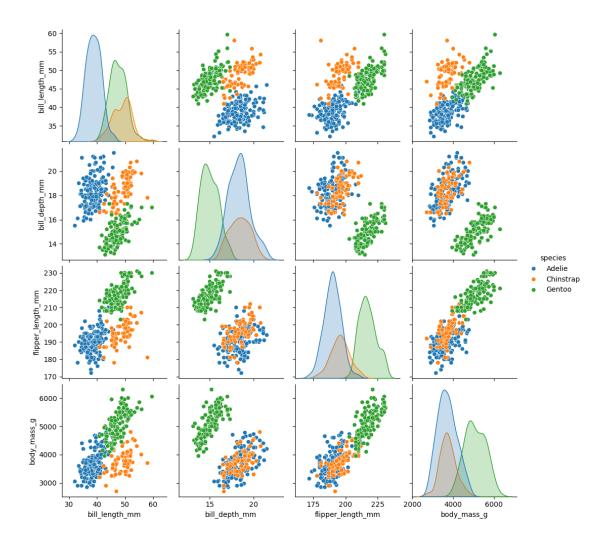
palmer_penguins

April 4, 2025

```
[1]: #Import all packages to be used
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn as sk
[2]: penguinData = sns.load_dataset('penguins')
[3]: #Pairplot to get an overview of how each species compares
sns.pairplot(penguinData, hue='species')
```

[3]: <seaborn.axisgrid.PairGrid at 0x25776eafa10>



0.1 The Problem

We have plenty of data about each species, but we are missing values for some instances, as seen here.

[4]: penguinData[penguinData.isna().any(axis=1)]

[4]:		species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	\
	3	Adelie	Torgersen	NaN	NaN	NaN	
	8	Adelie	Torgersen	34.1	18.1	193.0	
	9	Adelie	Torgersen	42.0	20.2	190.0	
	10	Adelie	Torgersen	37.8	17.1	186.0	
	11	Adelie	Torgersen	37.8	17.3	180.0	
	47	Adelie	Dream	37.5	18.9	179.0	
	246	Gentoo	Biscoe	44.5	14.3	216.0	
	286	Gentoo	Biscoe	46.2	14.4	214.0	
	324	Gentoo	Biscoe	47.3	13.8	216.0	

336 339		Biscoe Biscoe	44.5 NaN	15.7 NaN	217.0 NaN
3 8 9 10 11 47 246 286	body_mass_g NaN 3475.0 4250.0 3300.0 3700.0 2975.0 4100.0	NaN			
324	4725.0				
336	4875.0				
339	NaN	NaN			

The observations indexed 3 and 339 are missing all values besides the species and island, so we will ignore them for the purposes of our analysis.

```
penguinData = penguinData.drop(axis=1, index=[3,339])
[6]:
     penguinData[penguinData.isna().any(axis=1)]
[6]:
                                                                 flipper_length_mm
         species
                       island
                               bill_length_mm
                                                 bill_depth_mm
     8
           Adelie
                   Torgersen
                                          34.1
                                                           18.1
                                                                               193.0
     9
                   Torgersen
                                          42.0
                                                           20.2
                                                                               190.0
          Adelie
     10
          Adelie
                   Torgersen
                                          37.8
                                                           17.1
                                                                               186.0
          Adelie
                                          37.8
                                                           17.3
                                                                               180.0
     11
                   Torgersen
     47
           Adelie
                        Dream
                                          37.5
                                                           18.9
                                                                               179.0
     246
          Gentoo
                                          44.5
                                                           14.3
                                                                               216.0
                       Biscoe
     286
          Gentoo
                       Biscoe
                                          46.2
                                                           14.4
                                                                               214.0
     324
          Gentoo
                       Biscoe
                                          47.3
                                                           13.8
                                                                               216.0
     336
          Gentoo
                       Biscoe
                                          44.5
                                                           15.7
                                                                               217.0
          body_mass_g
                         sex
     8
                3475.0
                         NaN
     9
                4250.0
                         NaN
     10
                3300.0
                         NaN
                3700.0
     11
                         NaN
     47
                2975.0
                         NaN
     246
                4100.0
                         NaN
     286
                4650.0
                         NaN
```

We can see here that the only other missing values are sex. We can use some classification algorithms to try and predict the sex of these penguins. We will explore a few methods.

324

336

4725.0

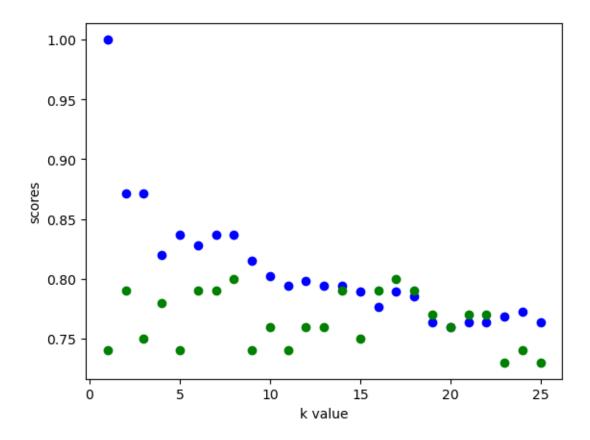
4875.0

NaN

NaN

0.2 KNeighbors

```
[7]: # Initialize the Model
     from sklearn.neighbors import KNeighborsClassifier
     knm = KNeighborsClassifier(n_neighbors = 5)
 [8]: X = penguinData.dropna()[['bill_length_mm', 'bill_depth_mm', u
      y = penguinData.dropna()['sex'].values
     knm = knm.fit(X, np.ravel(y))
 [9]: knm.predict([penguinData.iloc[8, 2:6]])[0]
     penguinData.iloc[8,6]
 [9]: nan
[10]: from sklearn.model_selection import train_test_split
[11]: K = []
     training = []
     test = []
     scores = {}
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,_
       →random_state=0)
     for k in range(1,26):
         knm = KNeighborsClassifier(n_neighbors = k)
         knm.fit(X_train, y_train)
         training_score = knm.score(X_train, y_train)
         test_score = knm.score(X_test, y_test)
         K.append(k)
         training.append(training_score)
         test.append(test_score)
         scores[k] = [training_score, test_score]
[12]: plt.scatter(K, training, color = 'b')
     plt.scatter(K, test, color = 'g')
     plt.xlabel('k value')
     plt.ylabel('scores')
     plt.show()
```



```
['Male']
```

['Female']

['Female']

['Female']

['Male']

['Female']

['Female']

['Female']

So using a very simple model we were able to provide preedictions for the sex of the penguins who had a missing entry.