Q6. Use Simple Kmeans, DBScan, Hierachical clustering algorithms for clustering. Compare the performance of clusters by changing the parameters involved in the algorithms.

```
from google.colab import drive
drive.mount('/content/gdrive')
```

Drive already mounted at /content/gdrive; to attempt to forcibly remount, call drive.mou

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.cluster import hierarchical
from sklearn.cluster import DBSCAN
from sklearn import preprocessing
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

```
iris=pd.read_csv('/content/gdrive/MyDrive/iris.csv')
print(iris)
#print(iris.keys())
```

		sepal length	sepal width	petal_length	petal_width	species
				1.4	0.2	setosa
	Saving		×	1.4	0.2	setosa
L		1.,	J.2	1.3	0.2	setosa
	3	4.6	3.1	1.5	0.2	setosa
	4	5.0	3.6	1.4	0.2	setosa
	• •	• • •	• • •			
	145	6.7	3.0	5.2	2.3	virginica
	146	6.3	2.5	5.0	1.9	virginica
	147	6.5	3.0	5.2	2.0	virginica
	148	6.2	3.4	5.4	2.3	virginica
	149	5.9	3.0	5.1	1.8	virginica

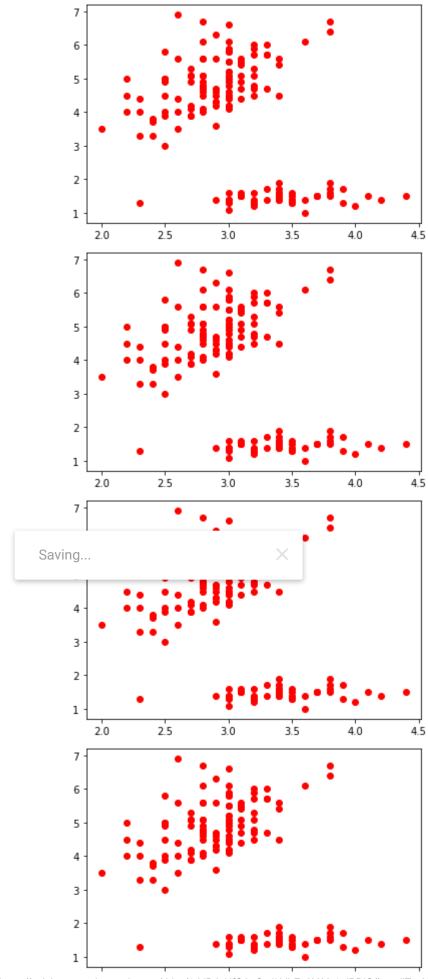
[150 rows x 5 columns]

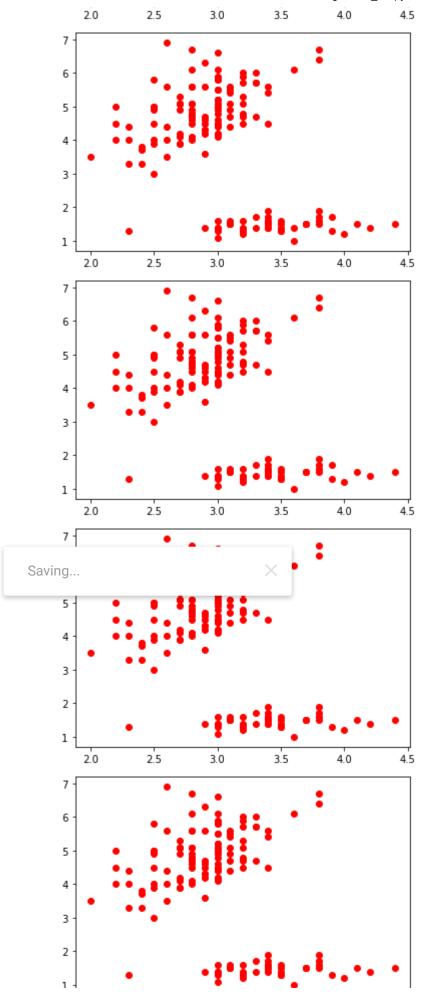
```
sep_l=iris.values[:,0]
print(sep_l)
#print(len(sep_l))
sep_w=iris.values[:,1]
print(sep_w)
#print(len(sep_w))
pet_l=iris.values[:,2]
print(pet_l)
#print(len(pet_l))
pet w=iris.values[:.3]
```

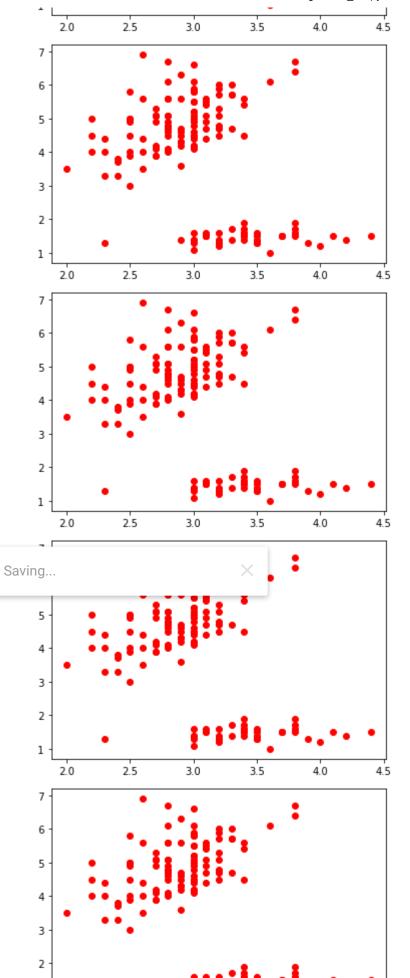
```
print(pet_w)
#print(len(pet w))
     [5.1 4.9 4.7 4.6 5.0 5.4 4.6 5.0 4.4 4.9 5.4 4.8 4.8 4.3 5.8 5.7 5.4 5.1
      5.7 5.1 5.4 5.1 4.6 5.1 4.8 5.0 5.0 5.2 5.2 4.7 4.8 5.4 5.2 5.5 4.9 5.0
      5.5 4.9 4.4 5.1 5.0 4.5 4.4 5.0 5.1 4.8 5.1 4.6 5.3 5.0 7.0 6.4 6.9 5.5
      6.5 5.7 6.3 4.9 6.6 5.2 5.0 5.9 6.0 6.1 5.6 6.7 5.6 5.8 6.2 5.6 5.9 6.1
      6.3 6.1 6.4 6.6 6.8 6.7 6.0 5.7 5.5 5.5 5.8 6.0 5.4 6.0 6.7 6.3 5.6 5.5
      5.5 6.1 5.8 5.0 5.6 5.7 5.7 6.2 5.1 5.7 6.3 5.8 7.1 6.3 6.5 7.6 4.9 7.3
      6.7 7.2 6.5 6.4 6.8 5.7 5.8 6.4 6.5 7.7 7.7 6.0 6.9 5.6 7.7 6.3 6.7 7.2
      6.2 6.1 6.4 7.2 7.4 7.9 6.4 6.3 6.1 7.7 6.3 6.4 6.0 6.9 6.7 6.9 5.8 6.8
      6.7 6.7 6.3 6.5 6.2 5.9]
     [3.5 3.0 3.2 3.1 3.6 3.9 3.4 3.4 2.9 3.1 3.7 3.4 3.0 3.0 4.0 4.4 3.9 3.5
      3.8 3.8 3.4 3.7 3.6 3.3 3.4 3.0 3.4 3.5 3.4 3.2 3.1 3.4 4.1 4.2 3.1 3.2
      3.5 3.1 3.0 3.4 3.5 2.3 3.2 3.5 3.8 3.0 3.8 3.2 3.7 3.3 3.2 3.2 3.1 2.3
      2.8 2.8 3.3 2.4 2.9 2.7 2.0 3.0 2.2 2.9 2.9 3.1 3.0 2.7 2.2 2.5 3.2 2.8
      2.5 2.8 2.9 3.0 2.8 3.0 2.9 2.6 2.4 2.4 2.7 2.7 3.0 3.4 3.1 2.3 3.0 2.5
      2.6 3.0 2.6 2.3 2.7 3.0 2.9 2.9 2.5 2.8 3.3 2.7 3.0 2.9 3.0 3.0 2.5 2.9
      2.5 3.6 3.2 2.7 3.0 2.5 2.8 3.2 3.0 3.8 2.6 2.2 3.2 2.8 2.8 2.7 3.3 3.2
      2.8 3.0 2.8 3.0 2.8 3.8 2.8 2.8 2.6 3.0 3.4 3.1 3.0 3.1 3.1 3.1 2.7 3.2
      3.3 3.0 2.5 3.0 3.4 3.0]
     [1.4 1.4 1.3 1.5 1.4 1.7 1.4 1.5 1.4 1.5 1.6 1.4 1.1 1.2 1.5 1.3 1.4
      1.7 1.5 1.7 1.5 1.0 1.7 1.9 1.6 1.6 1.5 1.4 1.6 1.6 1.5 1.5 1.4 1.5 1.2
      1.3 1.5 1.3 1.5 1.3 1.3 1.3 1.6 1.9 1.4 1.6 1.4 1.5 1.4 4.7 4.5 4.9 4.0
      4.6 4.5 4.7 3.3 4.6 3.9 3.5 4.2 4.0 4.7 3.6 4.4 4.5 4.1 4.5 3.9 4.8 4.0
      4.9 4.7 4.3 4.4 4.8 5.0 4.5 3.5 3.8 3.7 3.9 5.1 4.5 4.5 4.7 4.4 4.1 4.0
      4.4 4.6 4.0 3.3 4.2 4.2 4.2 4.3 3.0 4.1 6.0 5.1 5.9 5.6 5.8 6.6 4.5 6.3
      5.8 6.1 5.1 5.3 5.5 5.0 5.1 5.3 5.5 6.7 6.9 5.0 5.7 4.9 6.7 4.9 5.7 6.0
      4.8 4.9 5.6 5.8 6.1 6.4 5.6 5.1 5.6 6.1 5.6 5.5 4.8 5.4 5.6 5.1 5.1 5.9
      5.7 5.2 5.0 5.2 5.4 5.1]
     [0.2 0.2 0.2 0.2 0.2 0.4 0.3 0.2 0.2 0.1 0.2 0.2 0.1 0.1 0.2 0.4 0.4 0.3
                                    2 0.4 0.2 0.2 0.2 0.2 0.4 0.1 0.2 0.1 0.2
 Saving...
                                    6 0.4 0.3 0.2 0.2 0.2 0.2 1.4 1.5 1.5 1.3
                                    5 1.0 1.4 1.3 1.4 1.5 1.0 1.5 1.1 1.8 1.3
      1.5 1.2 1.3 1.4 1.4 1.7 1.5 1.0 1.1 1.0 1.2 1.6 1.5 1.6 1.5 1.3 1.3 1.3
      1.2 1.4 1.2 1.0 1.3 1.2 1.3 1.3 1.1 1.3 2.5 1.9 2.1 1.8 2.2 2.1 1.7 1.8
      1.8 2.5 2.0 1.9 2.1 2.0 2.4 2.3 1.8 2.2 2.3 1.5 2.3 2.0 2.0 1.8 2.1 1.8
      1.8 1.8 2.1 1.6 1.9 2.0 2.2 1.5 1.4 2.3 2.4 1.8 1.8 2.1 2.4 2.3 1.9 2.3
      2.5 2.3 1.9 2.0 2.3 1.8]
```

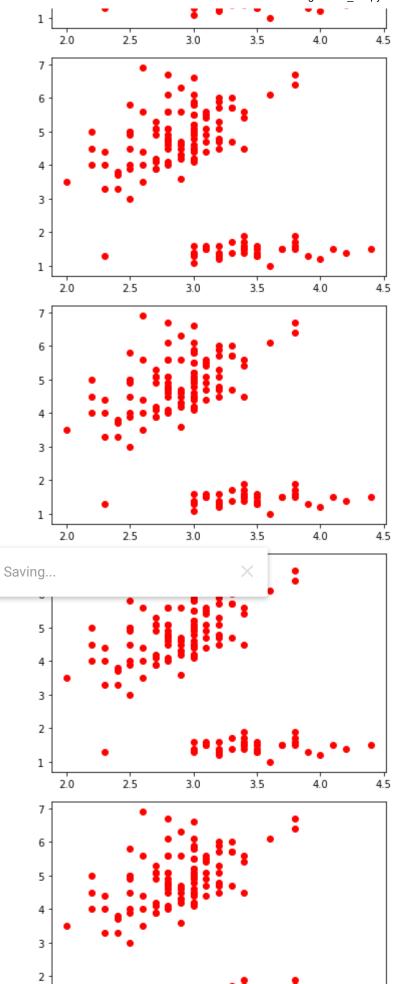
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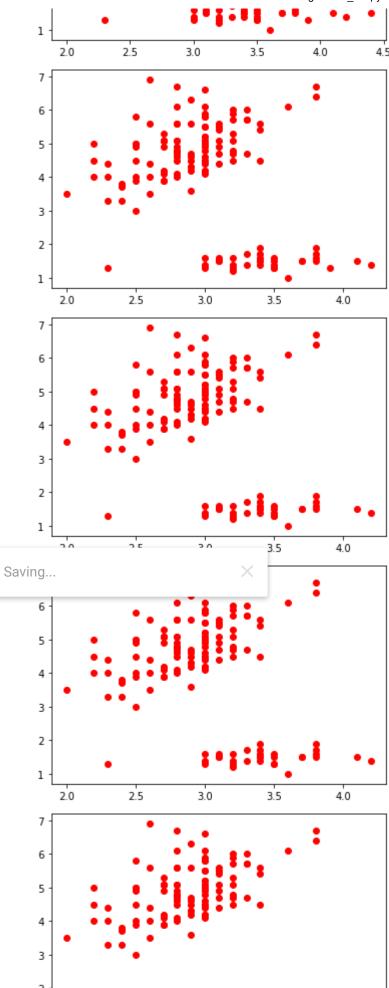
```
for i in range(150):
    if i<=49:
        plt.plot(iris.values[i:,1],iris.values[i:,2],'ro')
    if i>49 and i<=99:
        plt.plot(iris.values[i:,1],iris.values[i:,2],'bo')
    if i>99:
        plt.plot(iris.values[i:,1],iris.values[i:,2],'go')
    plt.show()
```

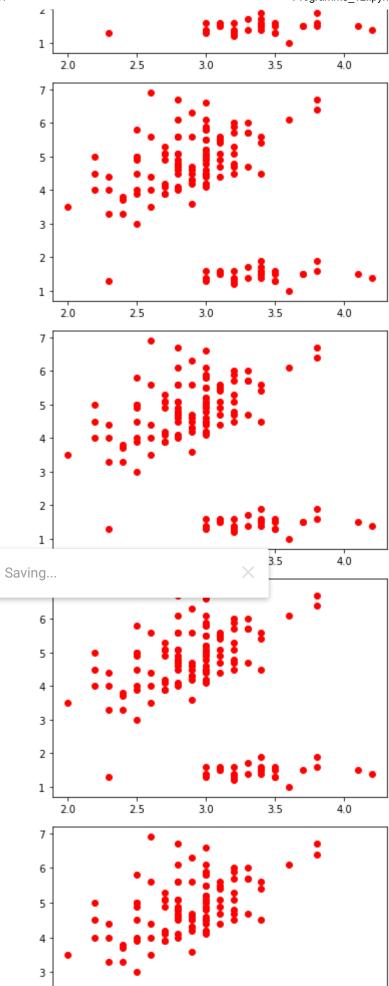


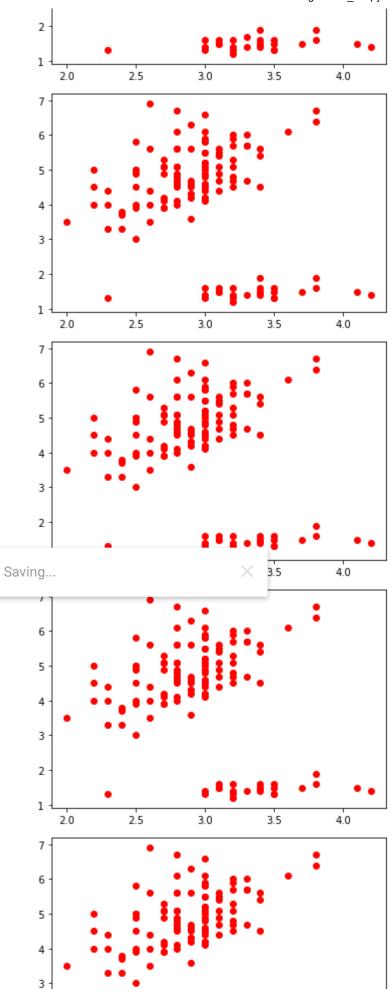


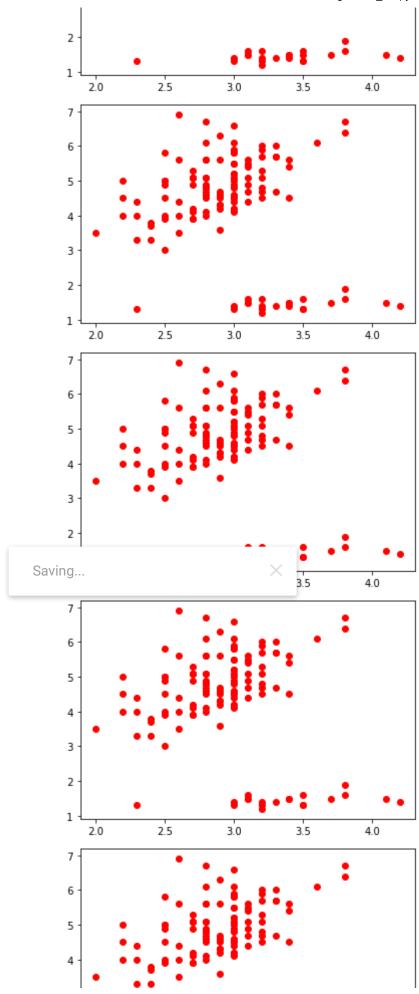


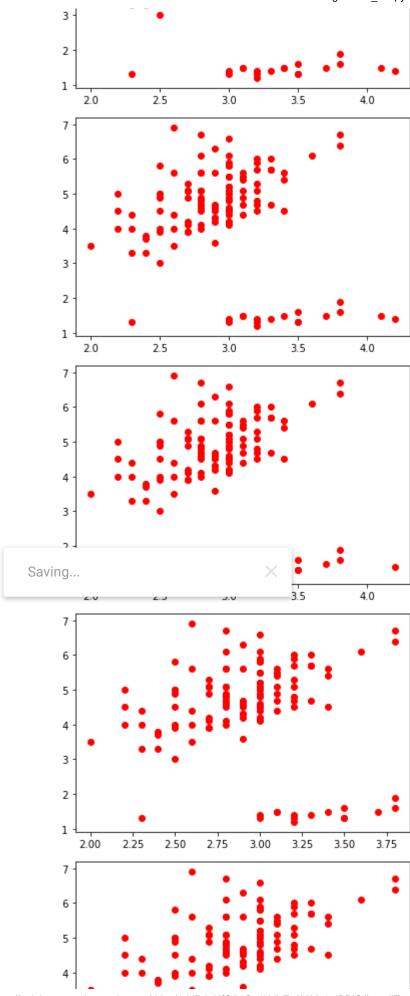


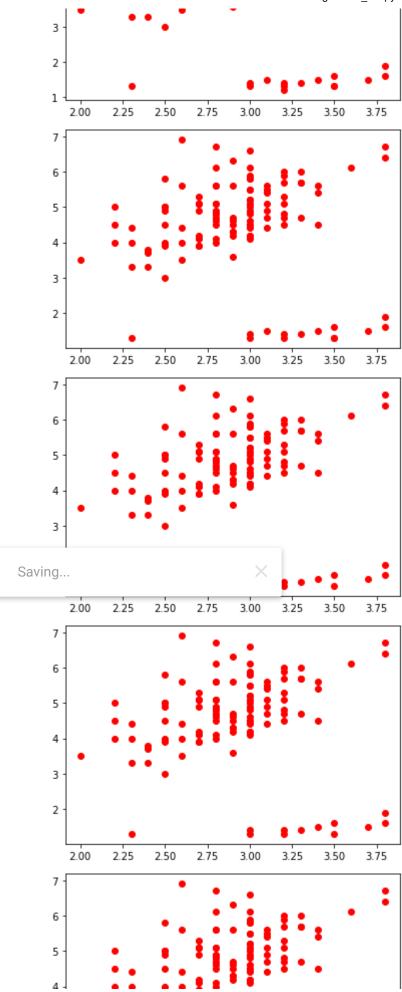


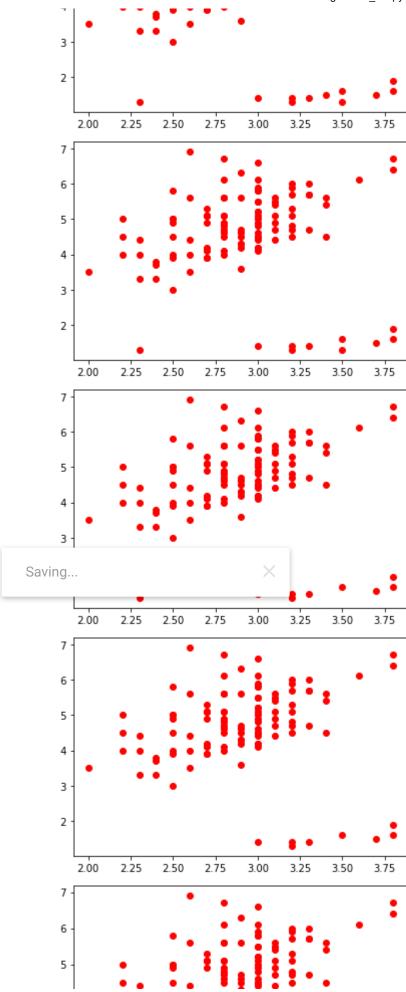


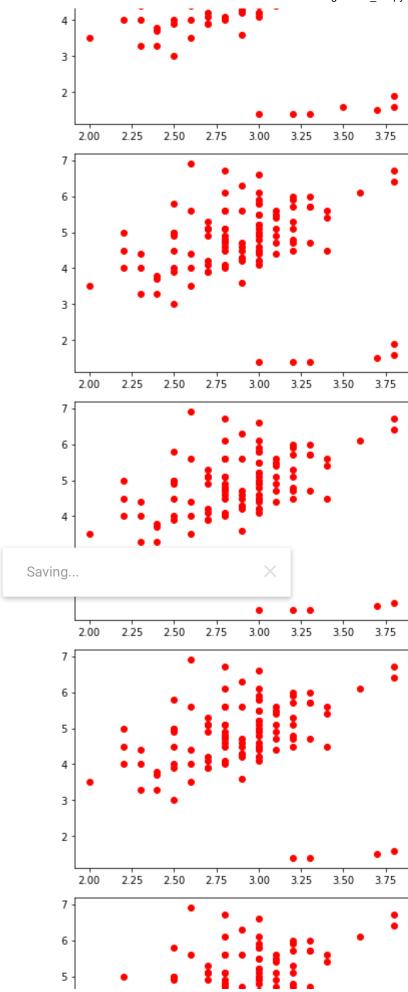


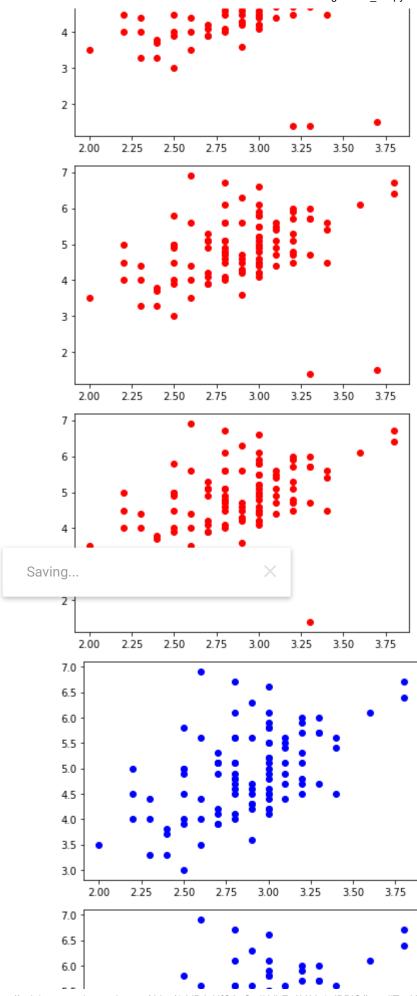


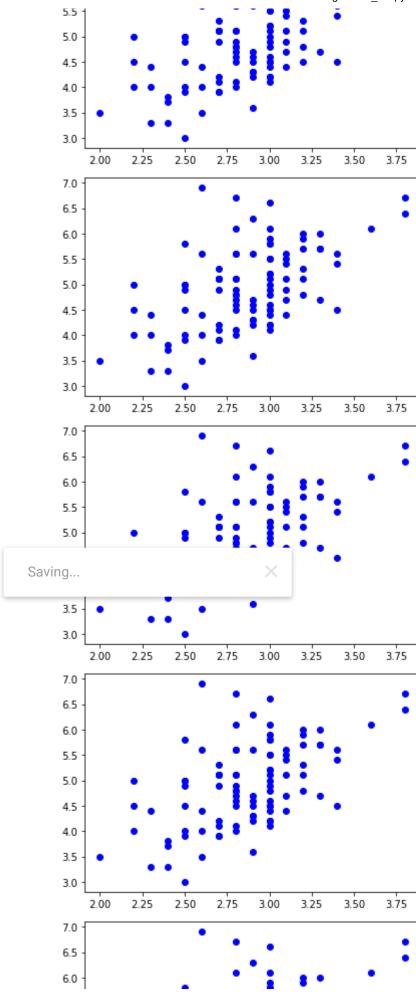


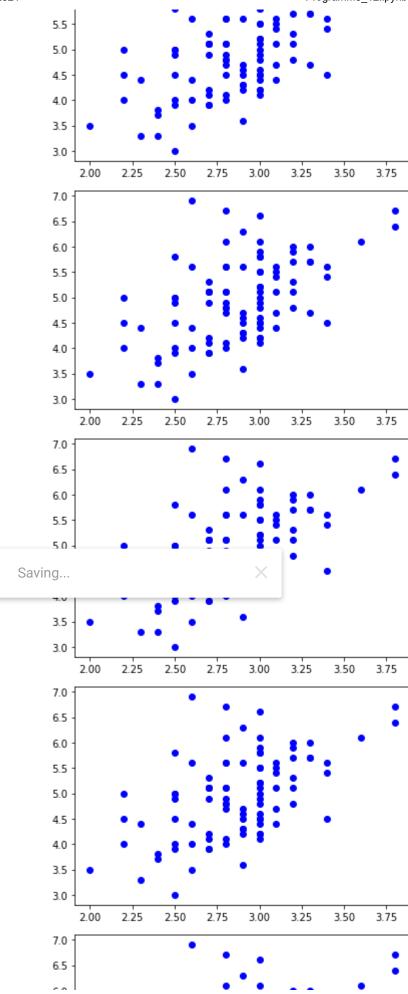


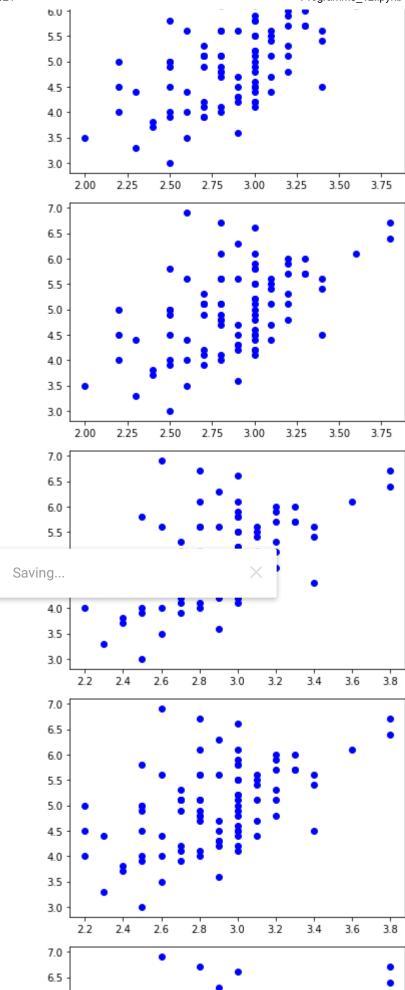


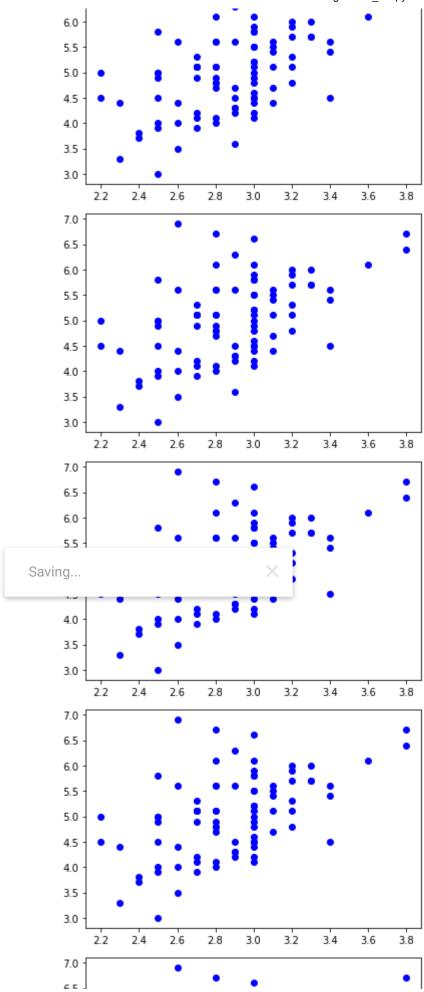


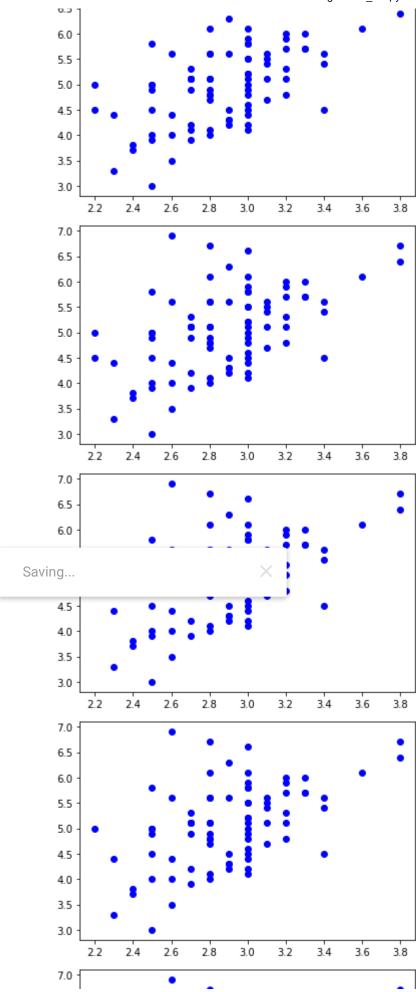


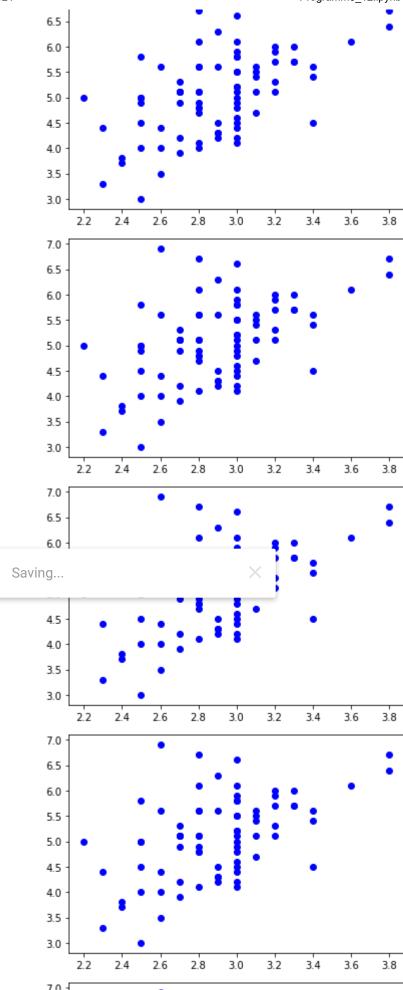


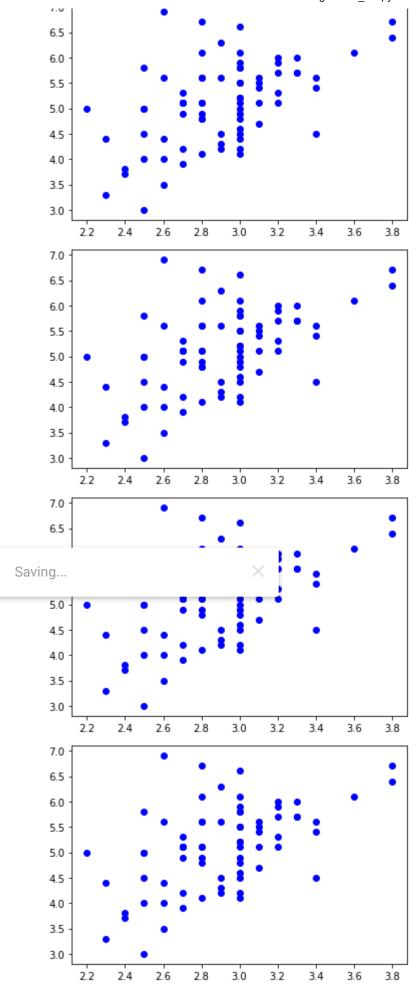


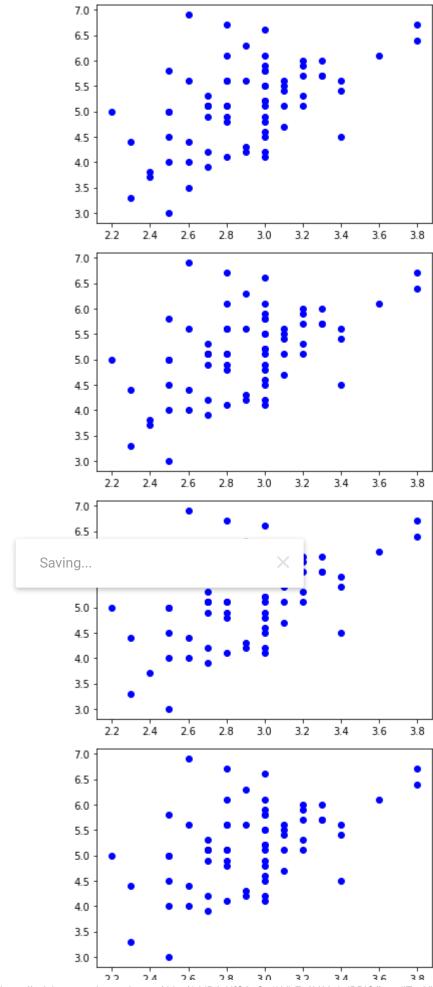


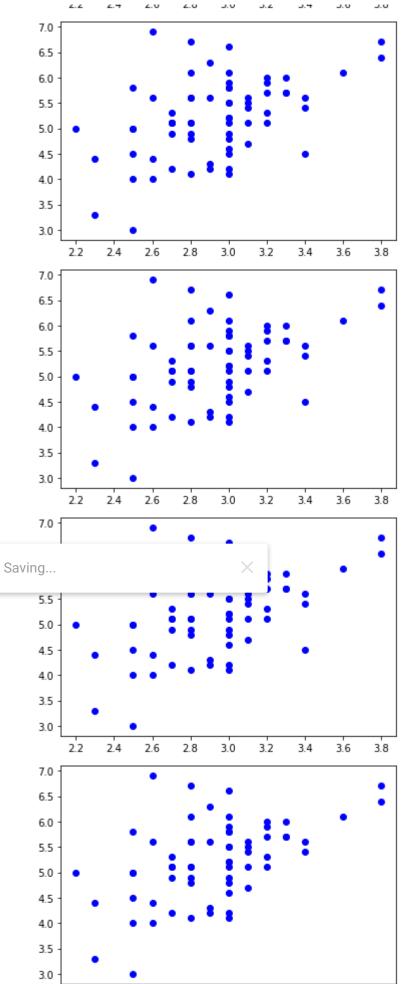


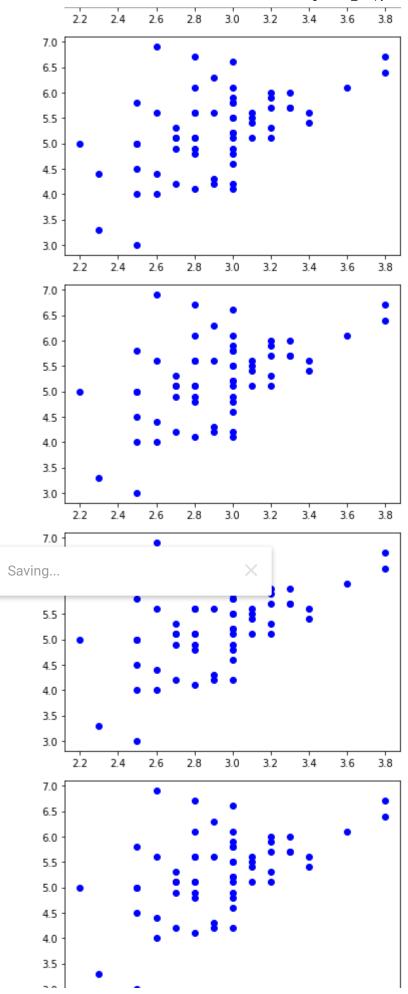


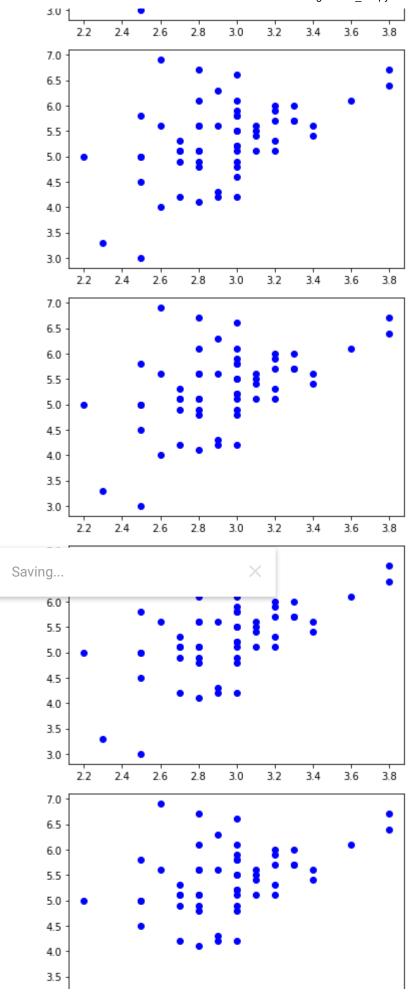


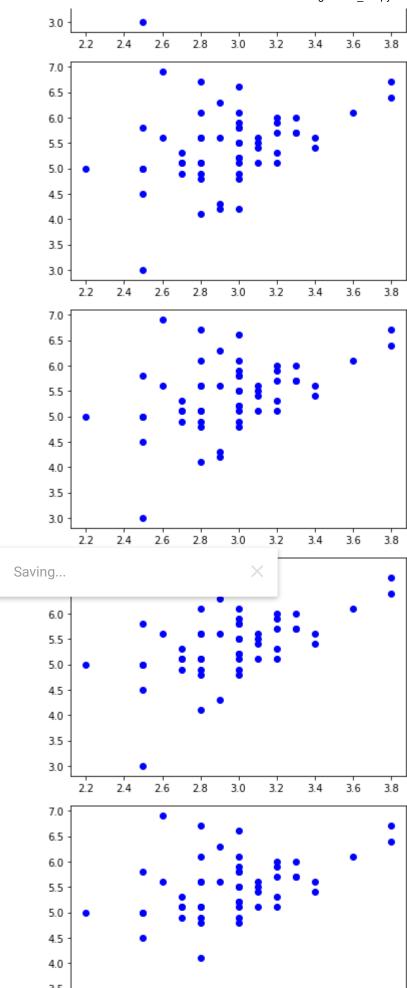


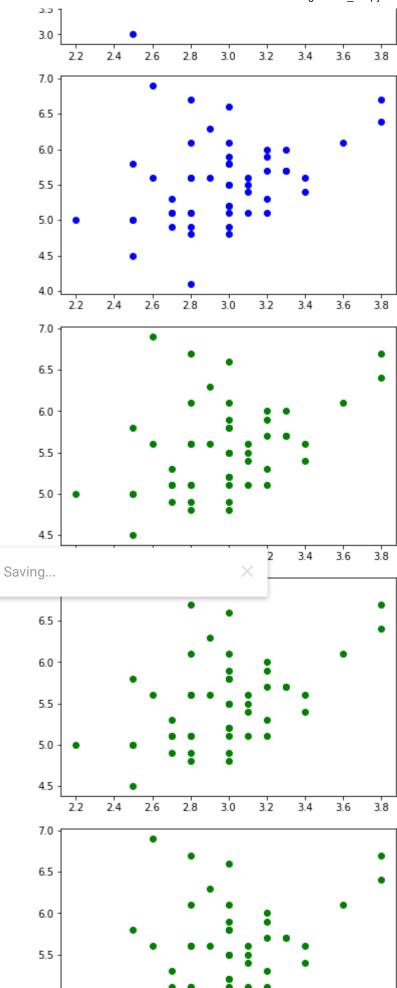


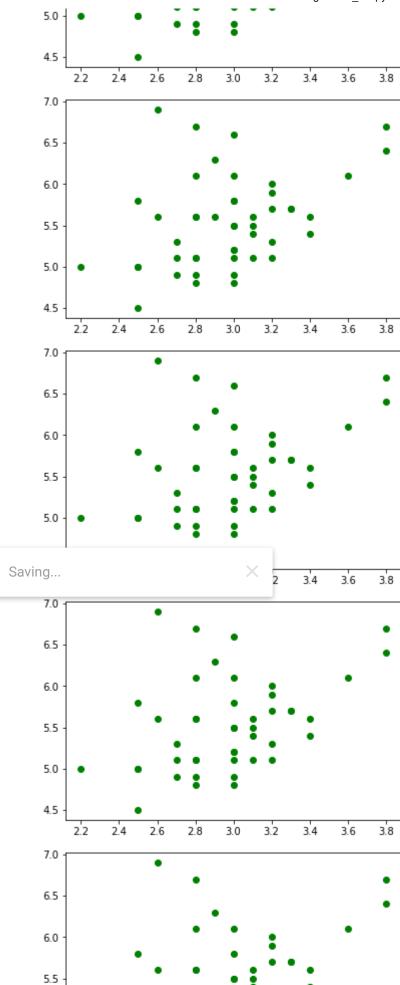


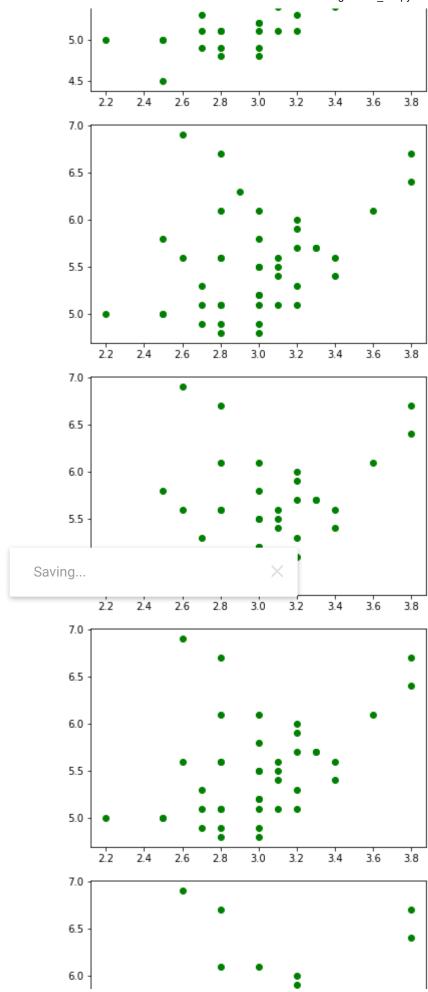


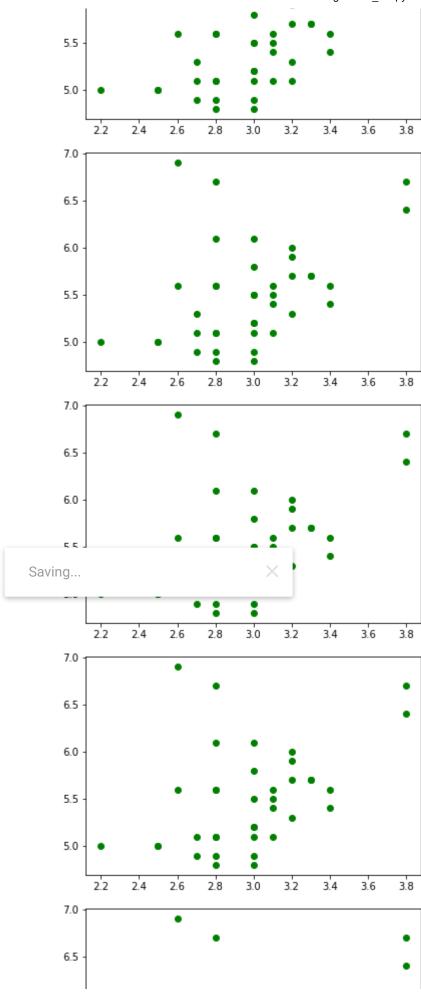


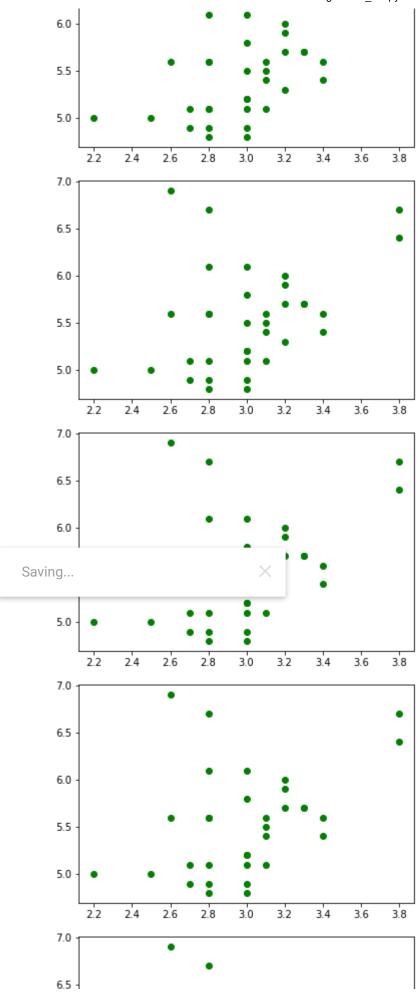


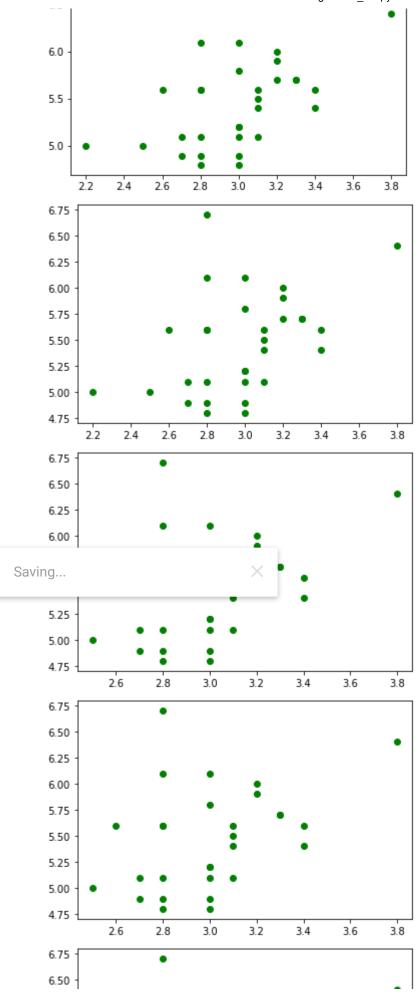


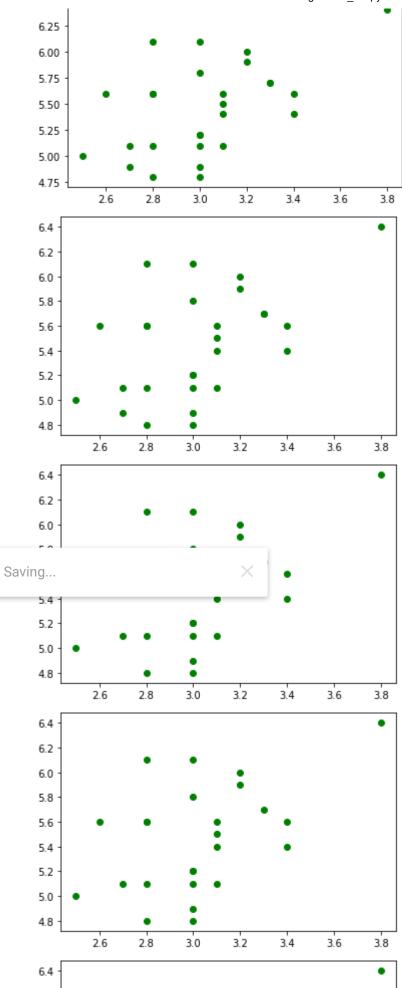


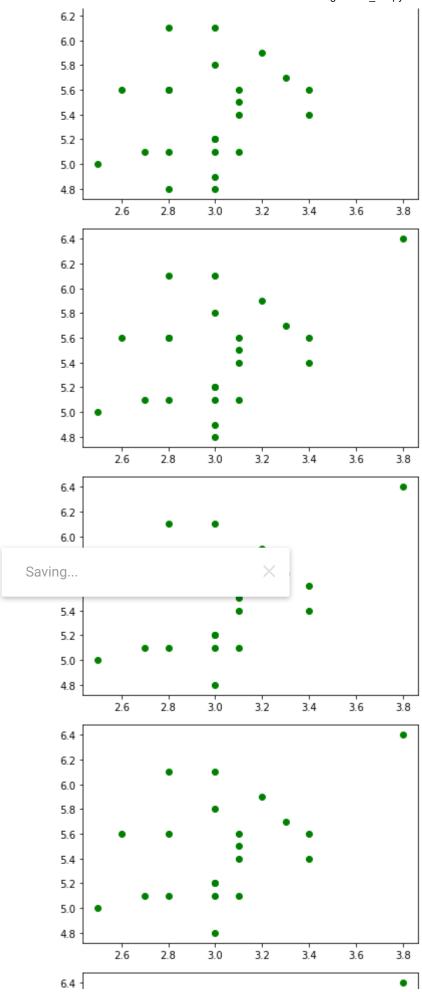


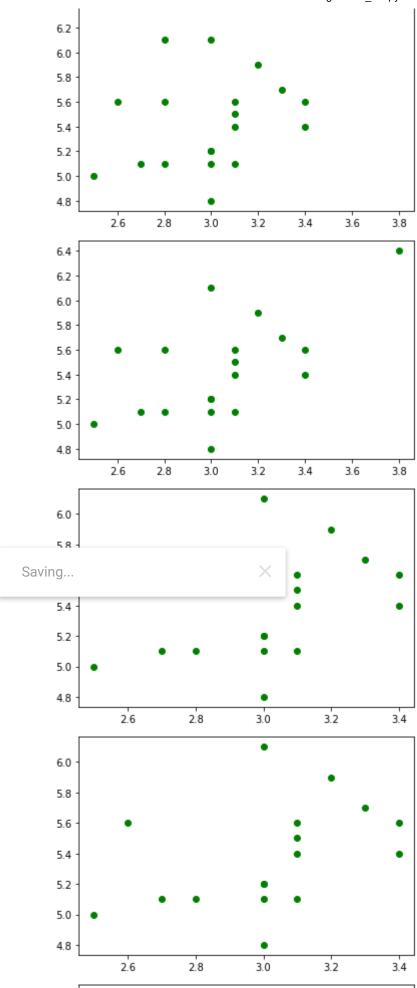


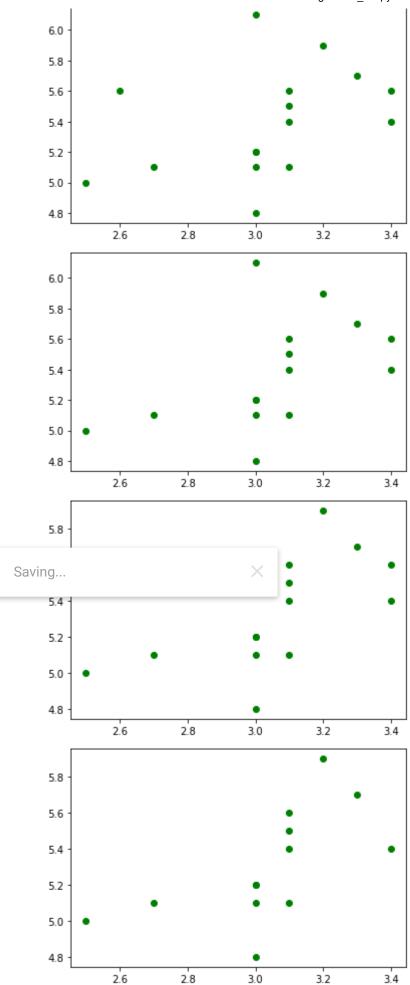


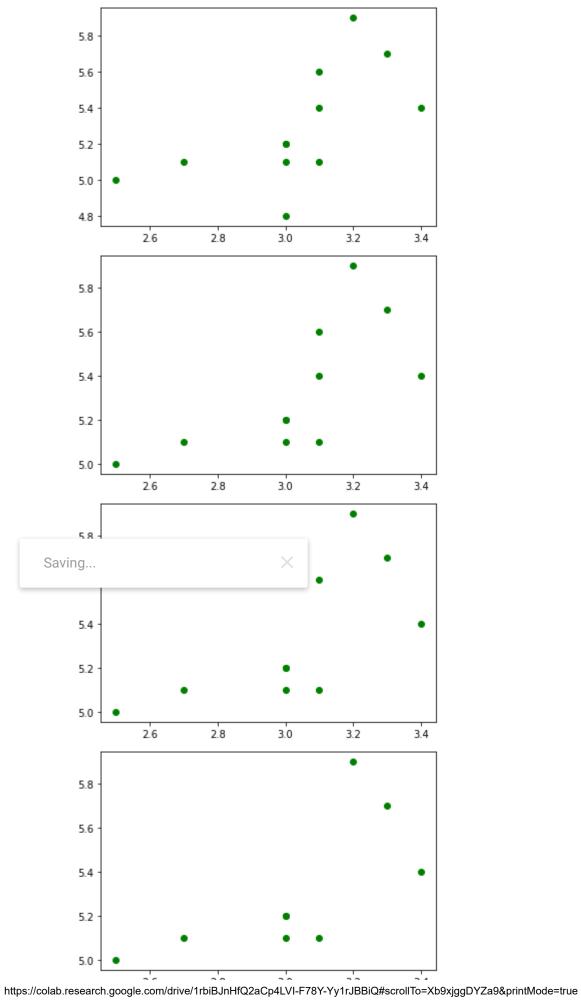


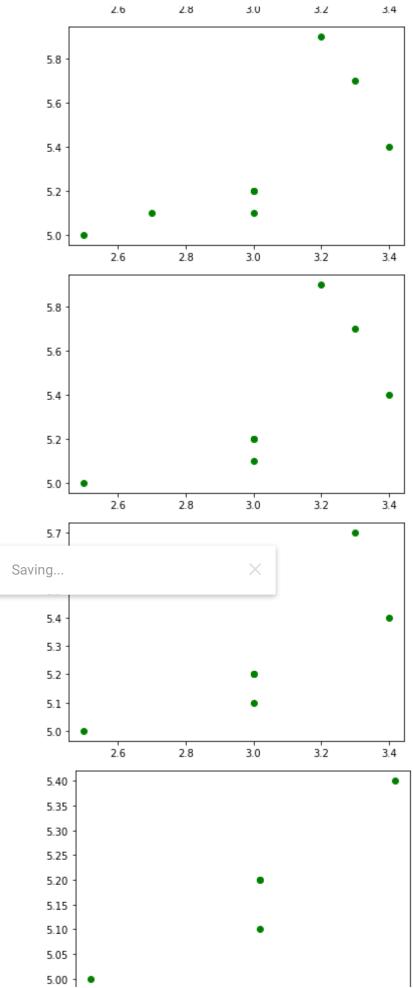


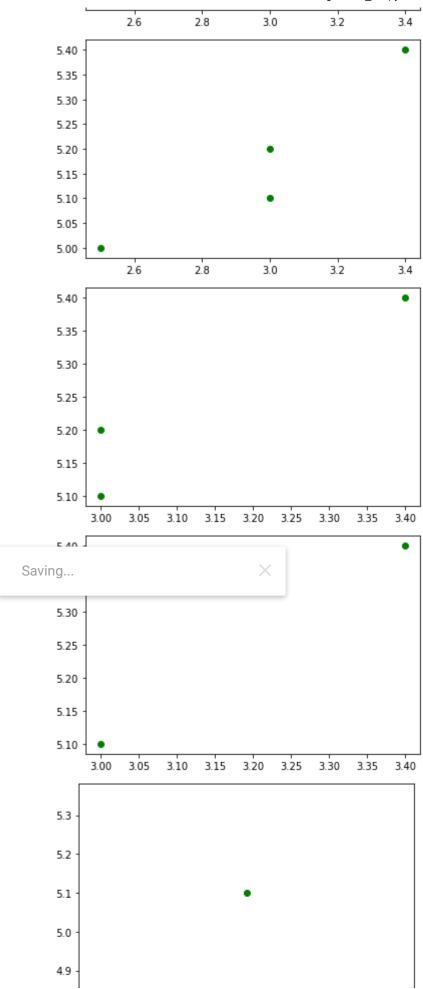








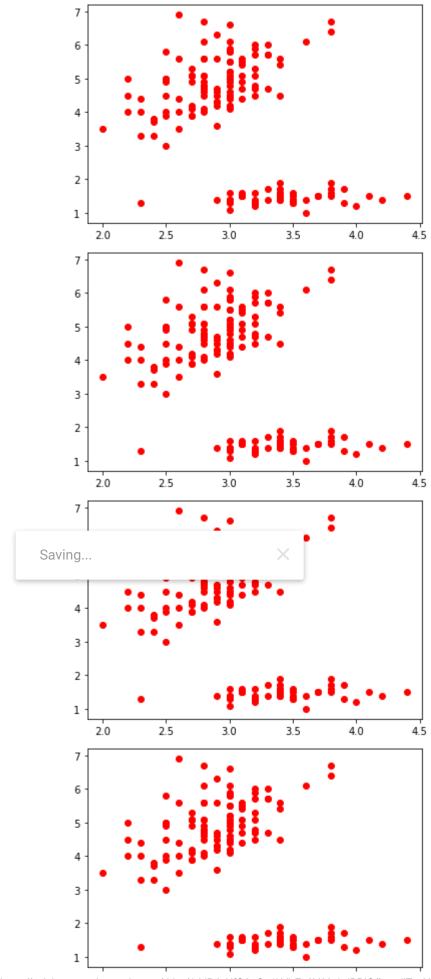


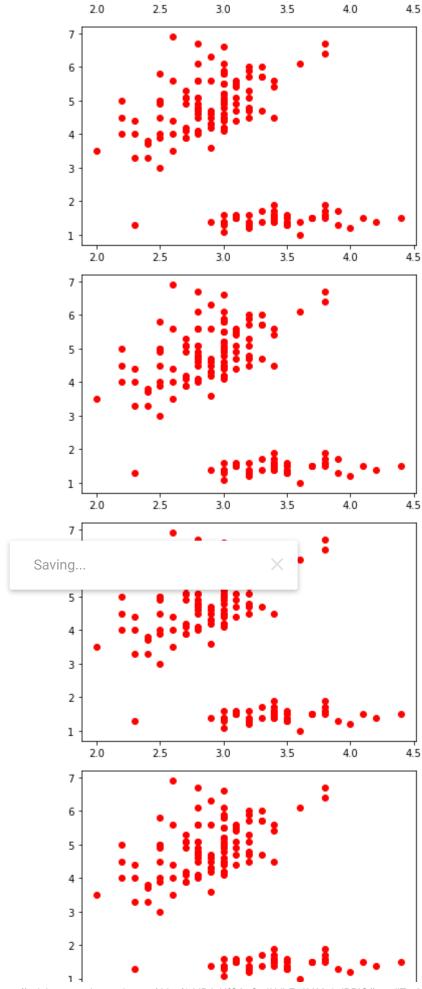


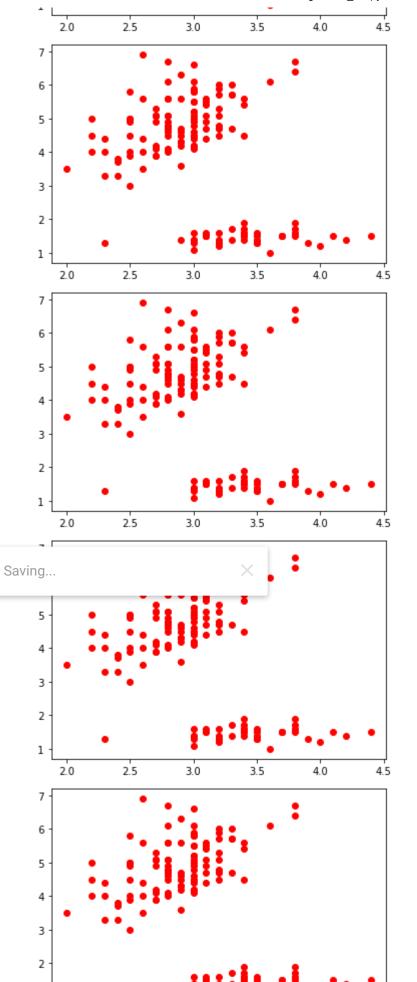
Taking Sepal Width and Petal Length as our two features for clustering

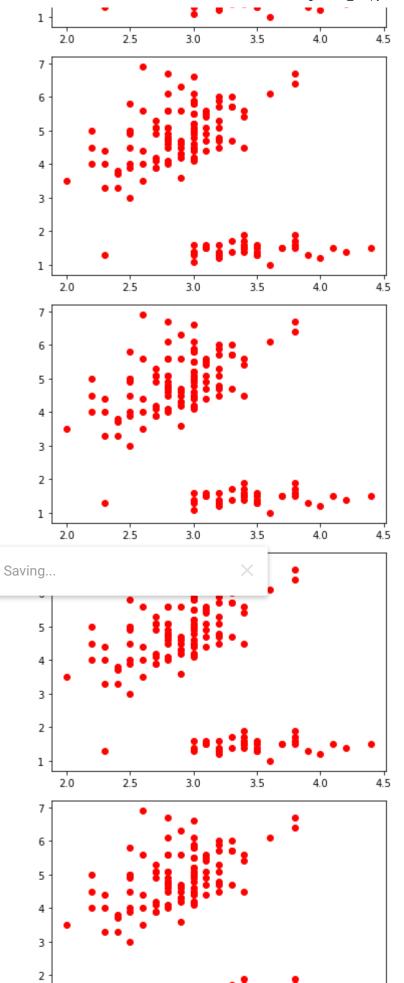
```
for i in range(150):
    if i<=49:
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    if i>49 and i<=99:
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    if i>99:
        plt.plot(iris.values[i:,1],iris.values[i:,2],'go')
    plt.show()
```

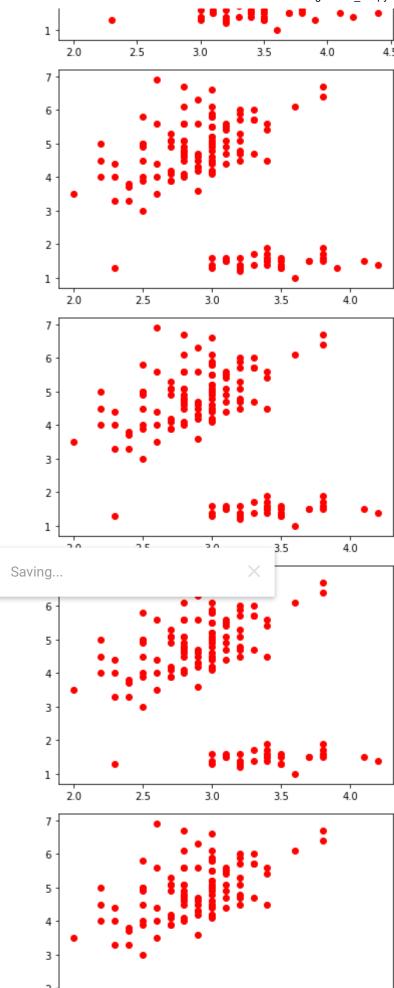
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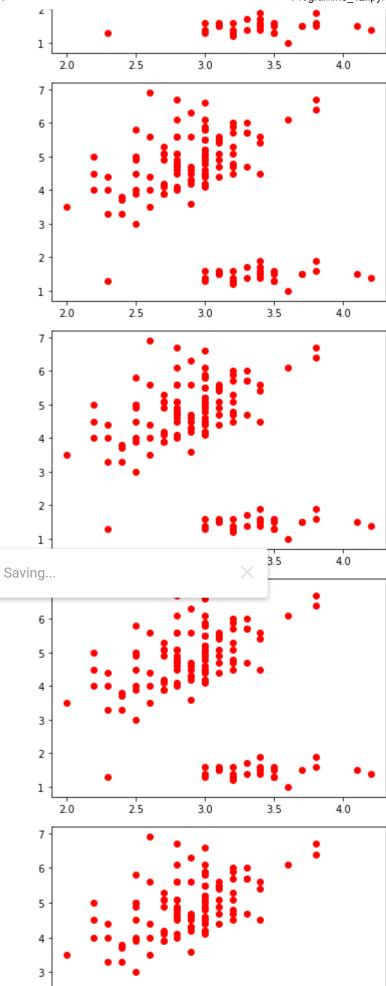


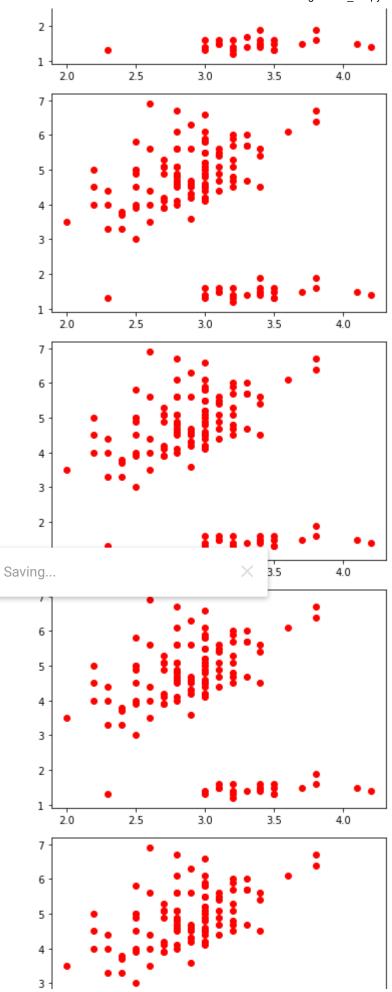


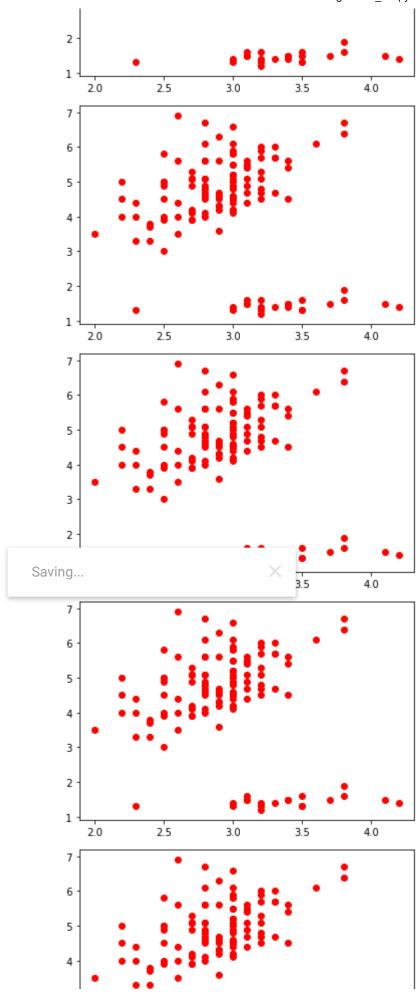


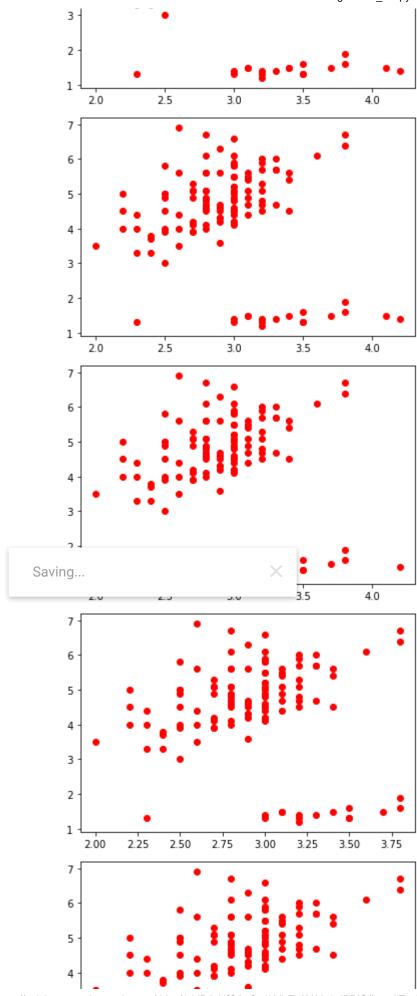


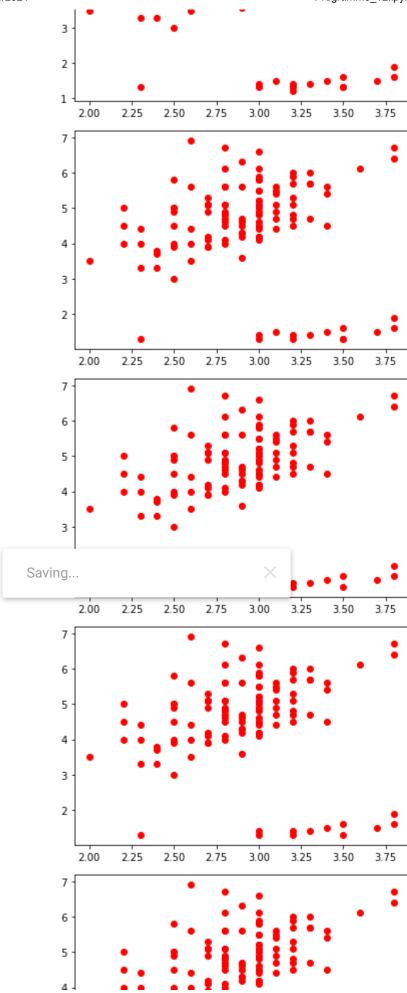


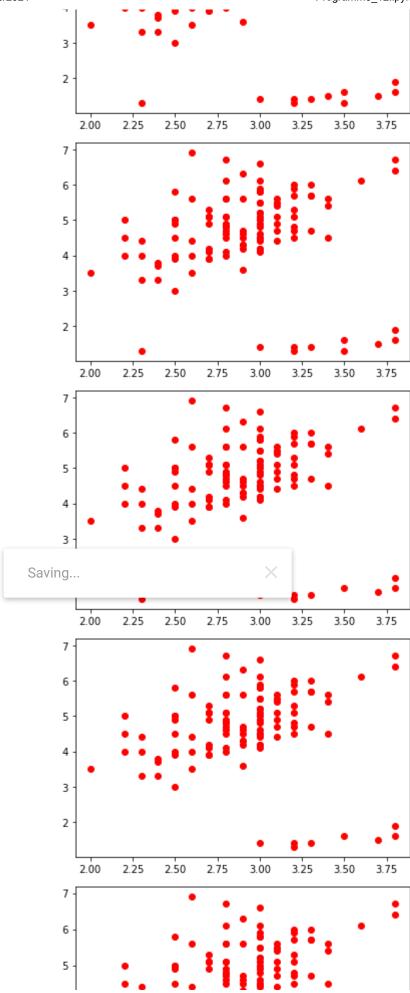


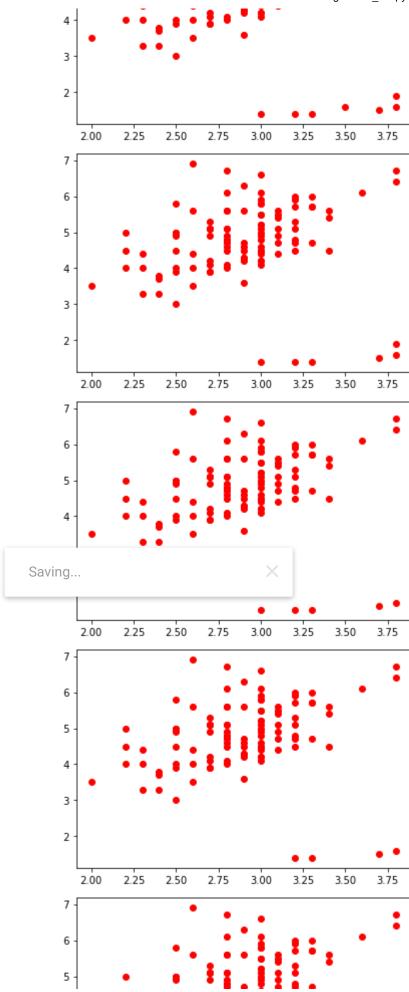


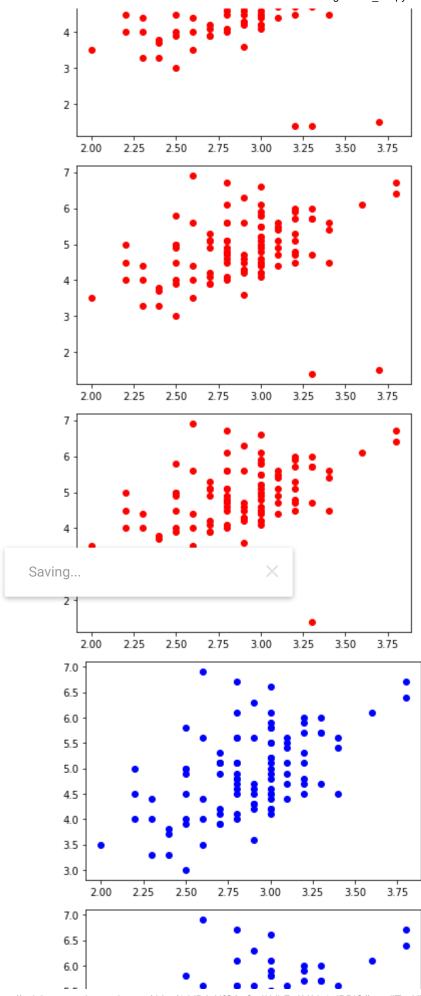


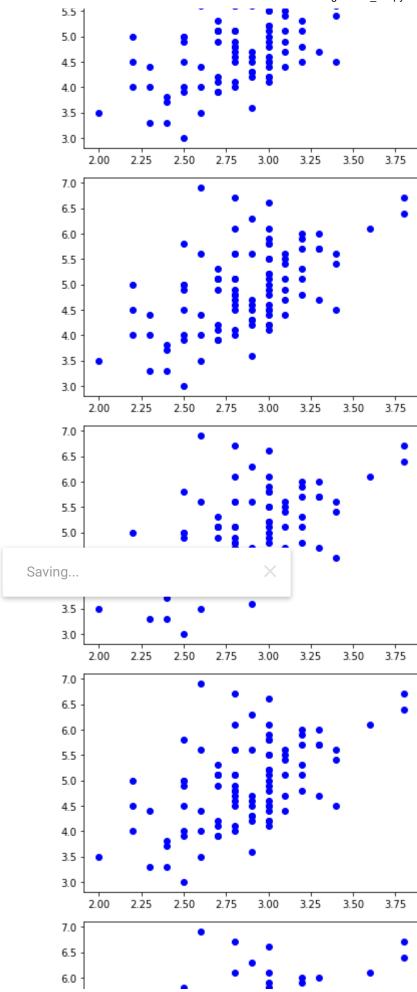


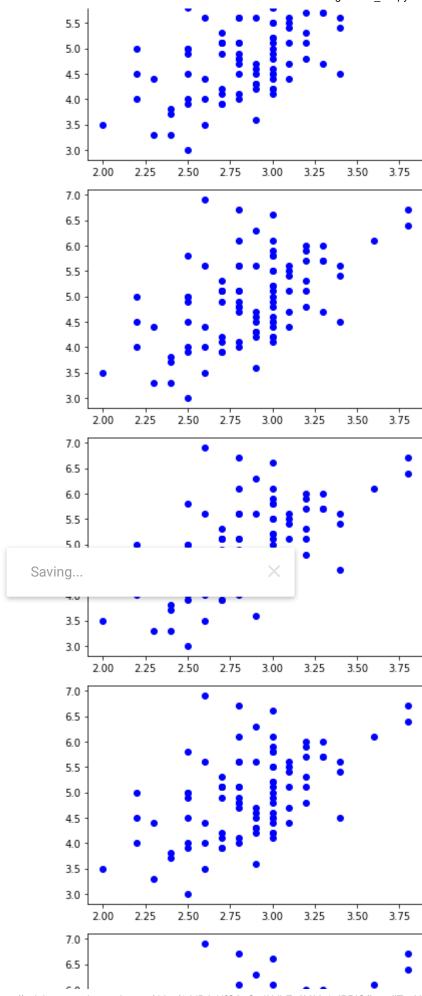


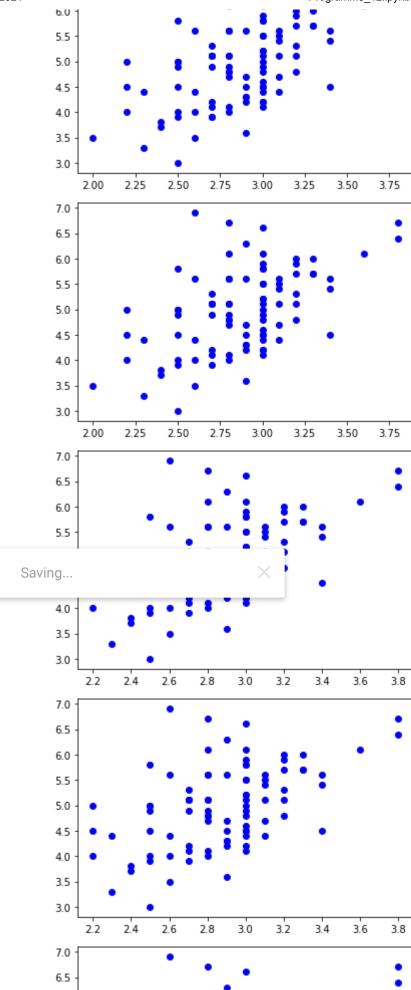


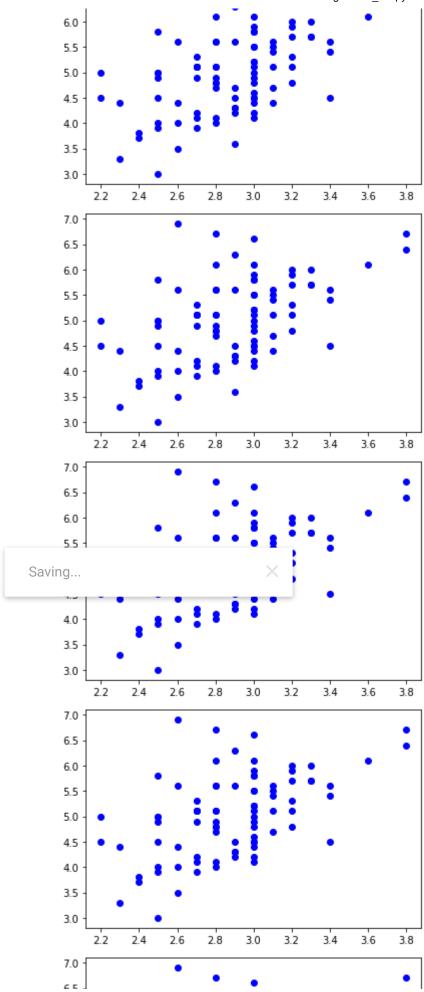


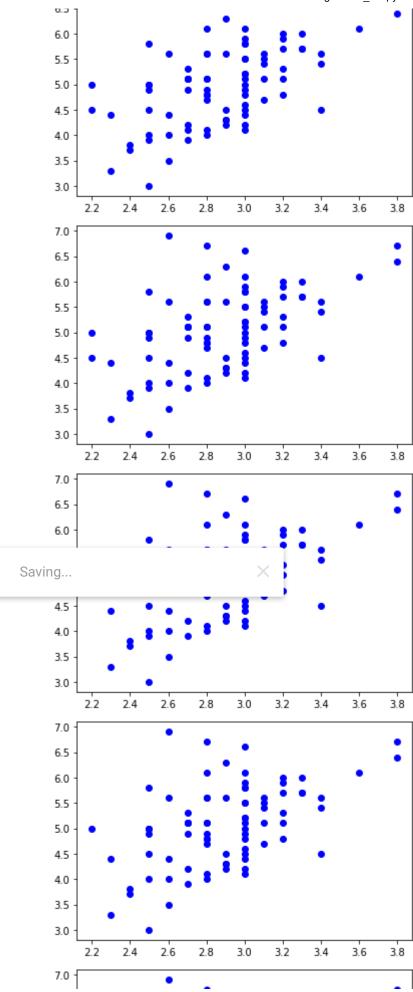


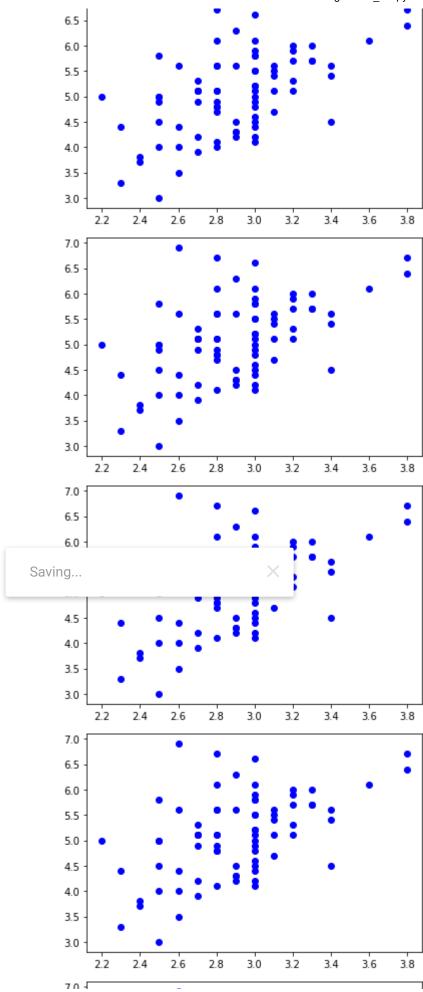


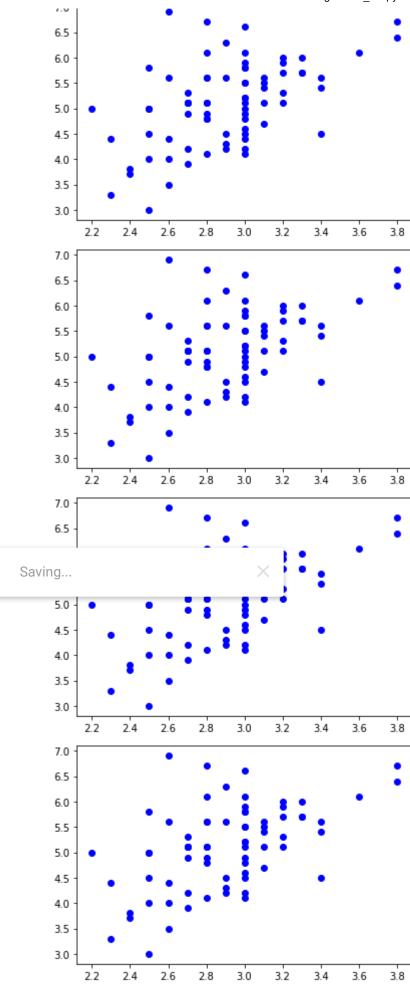


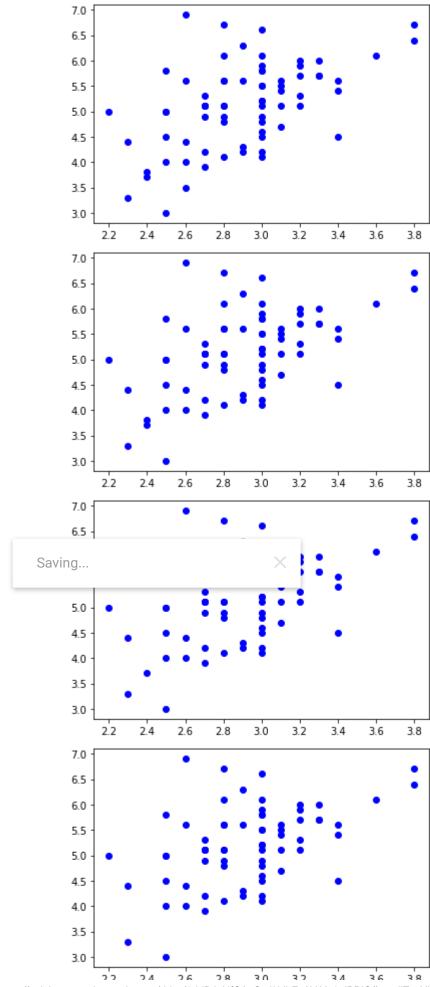


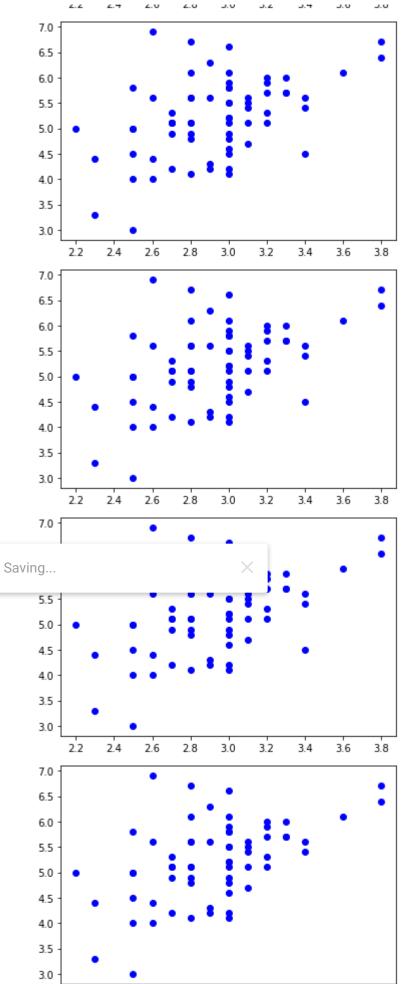


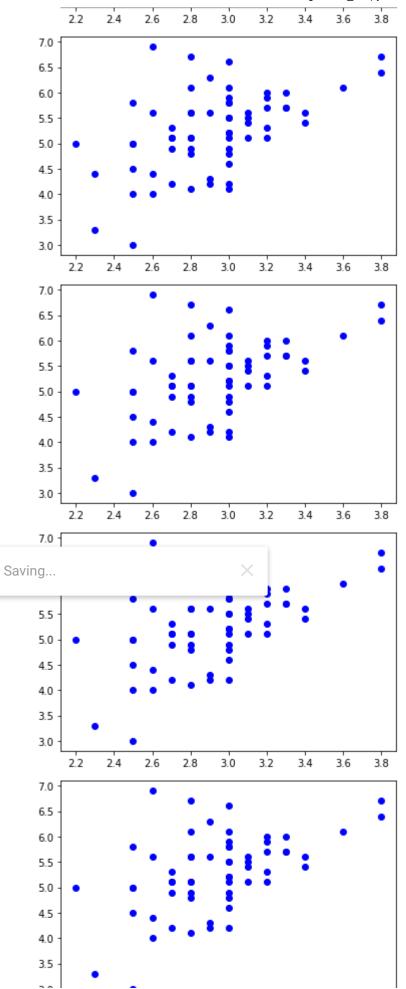


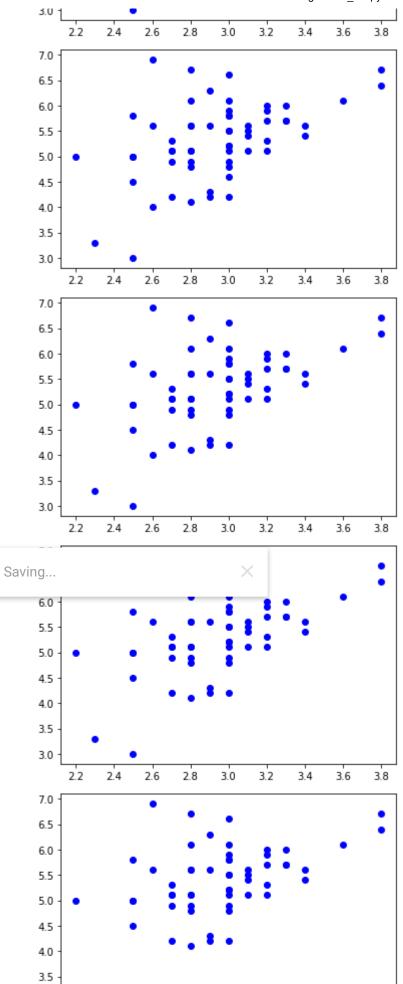


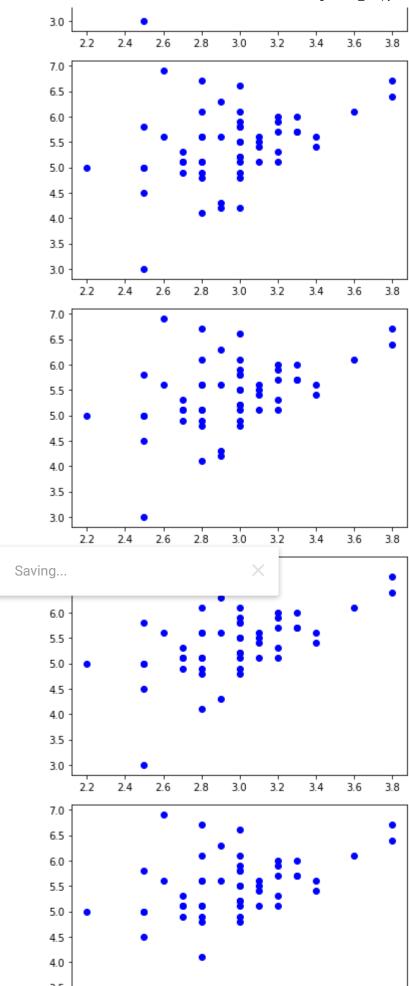


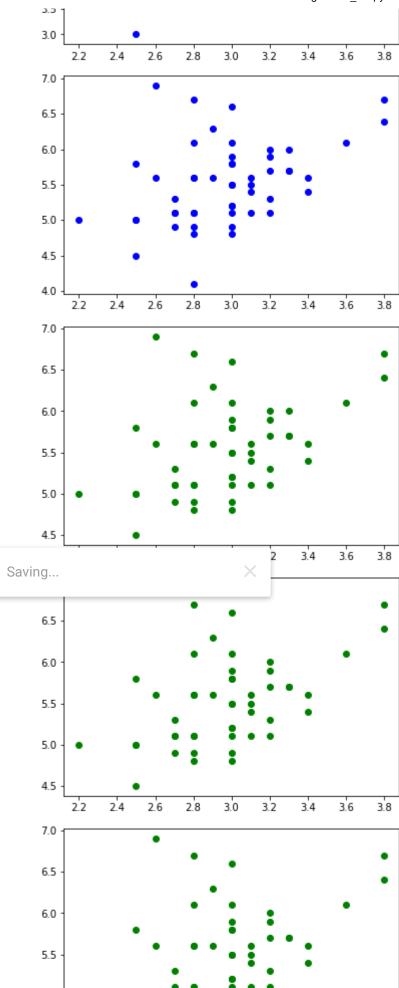


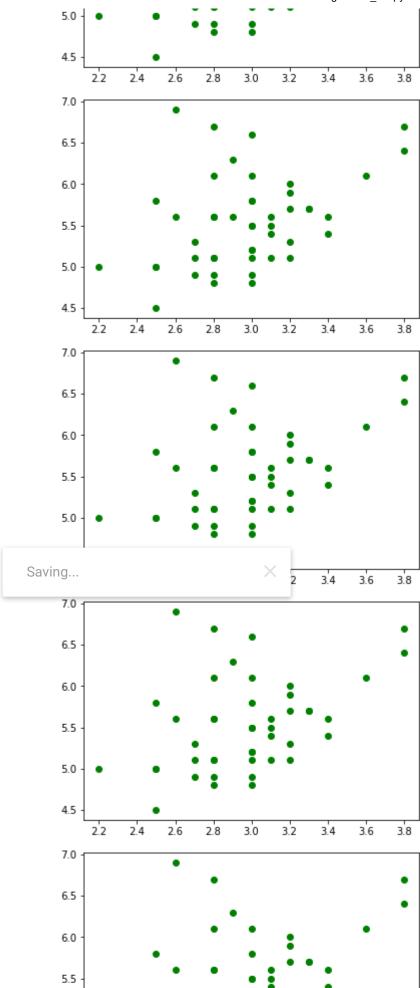


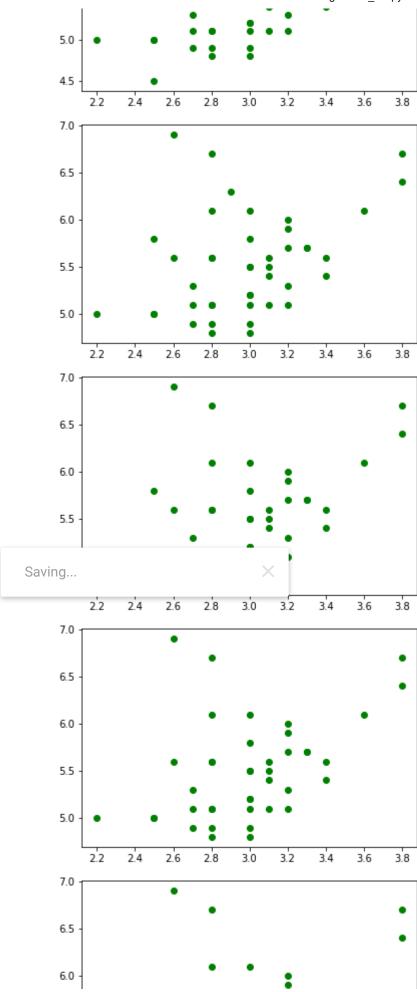


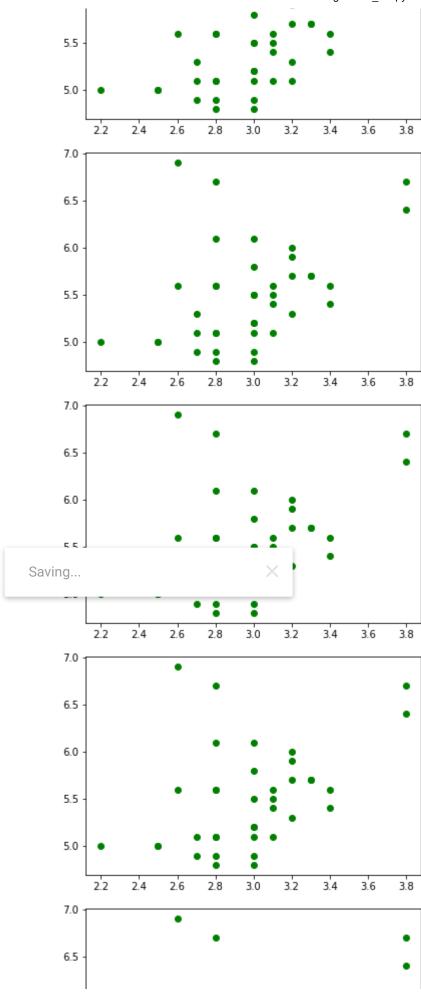


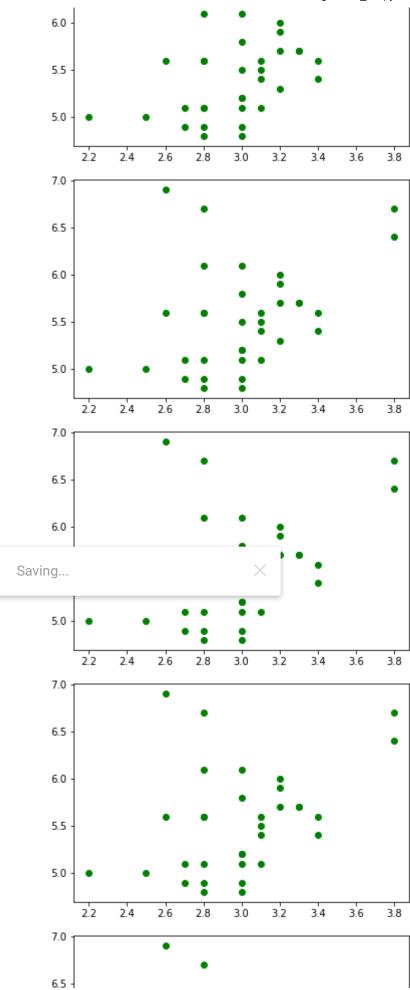


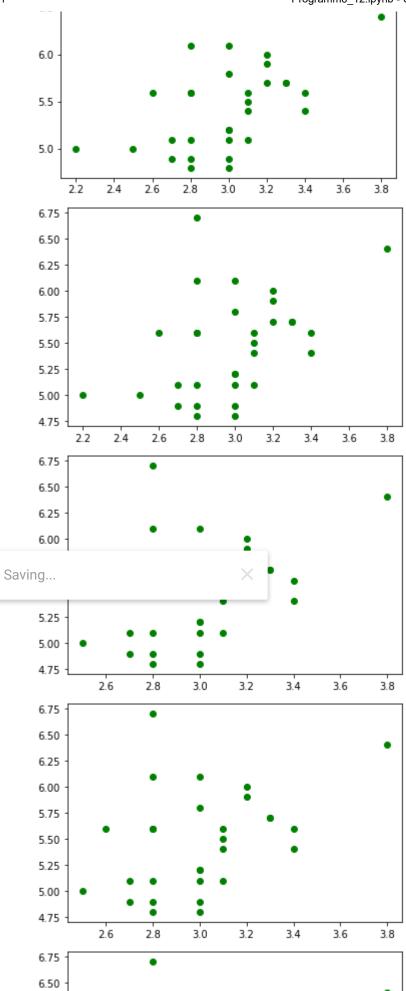


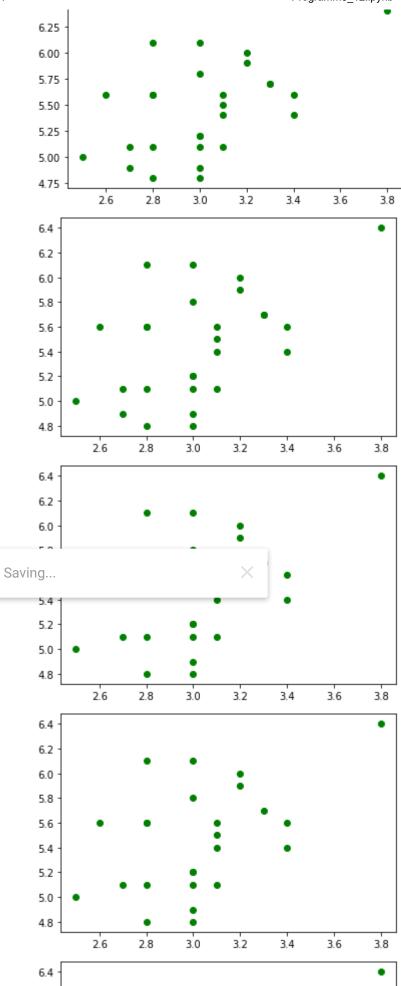


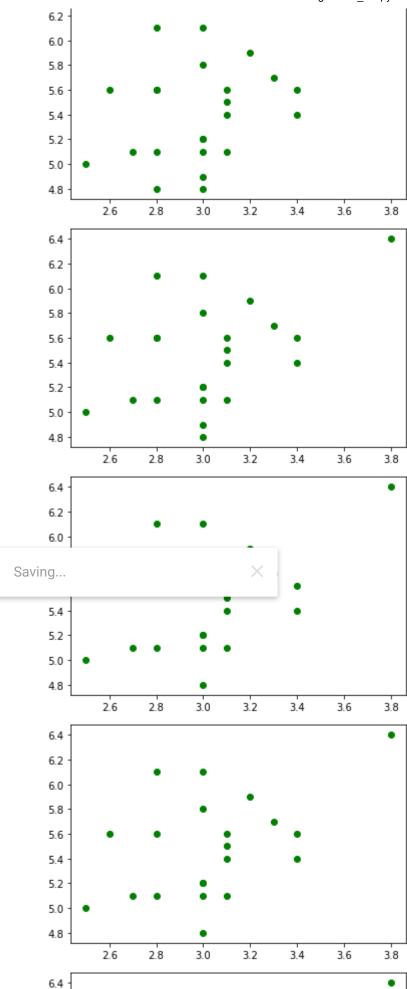


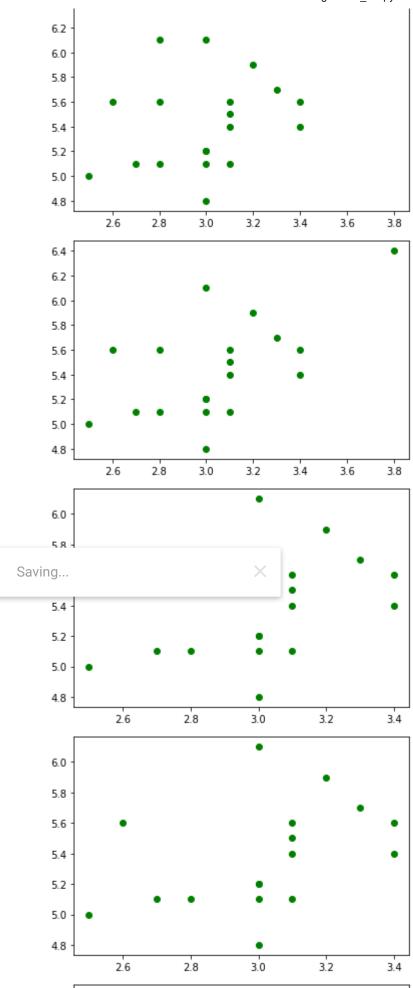


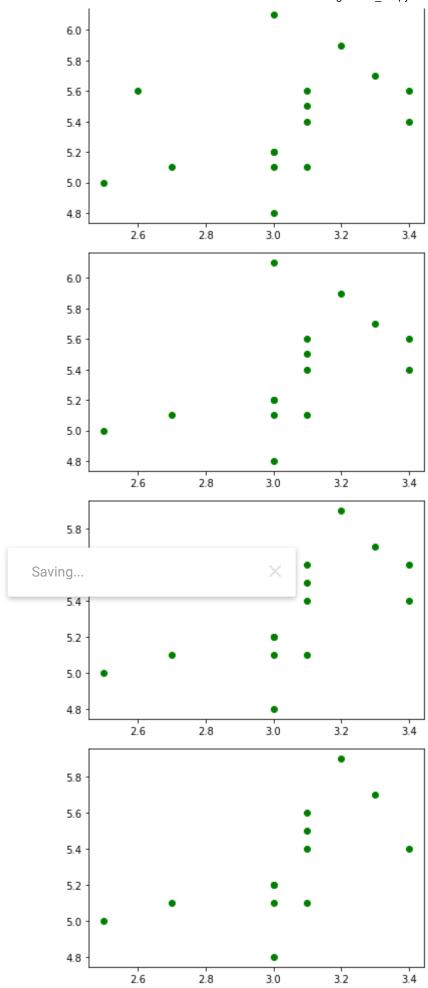


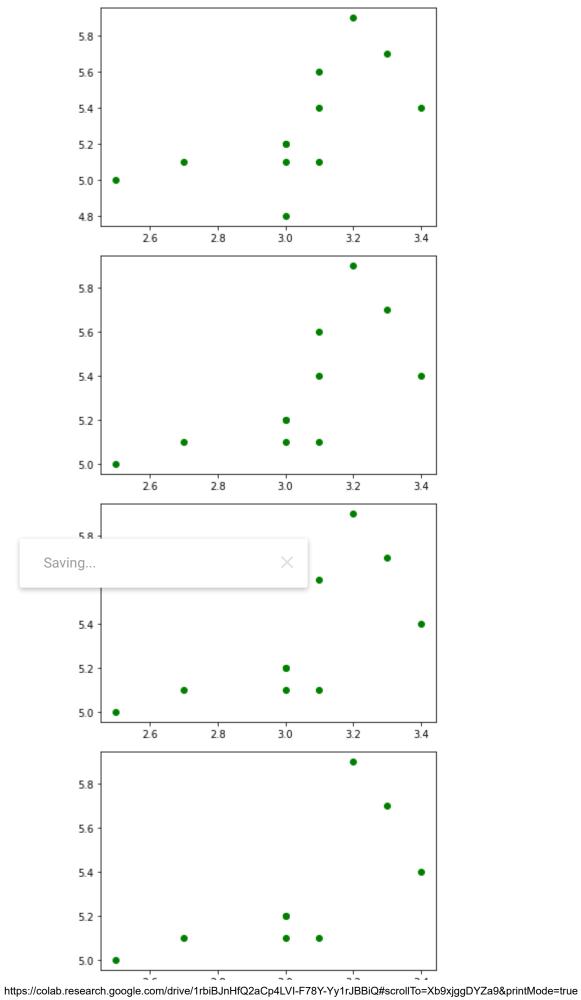


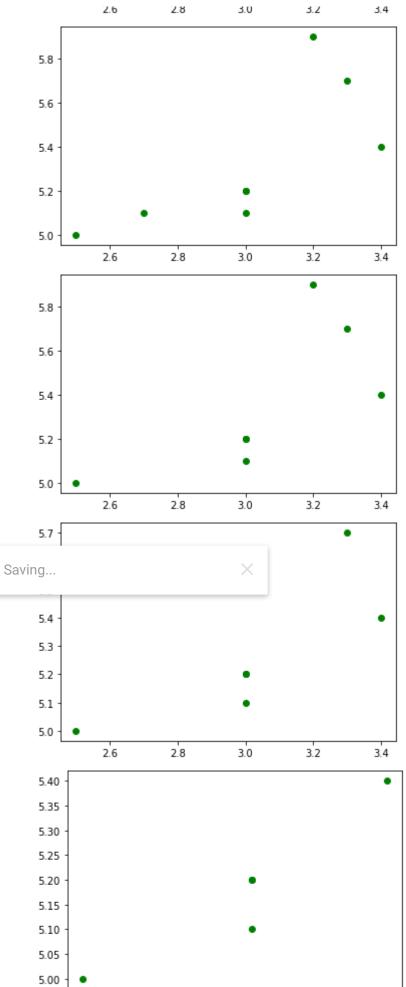


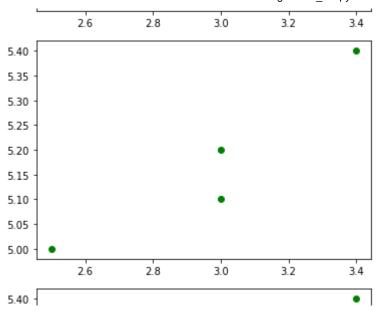






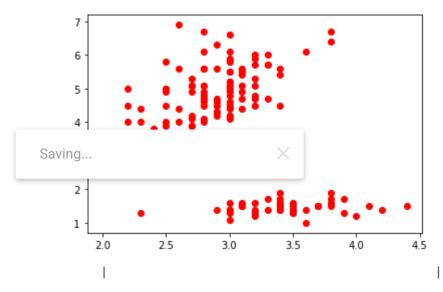






Plotting unlabelized iris data set

```
plt.plot(iris.values[:,1],iris.values[:,2],'ro')
plt.show()
```



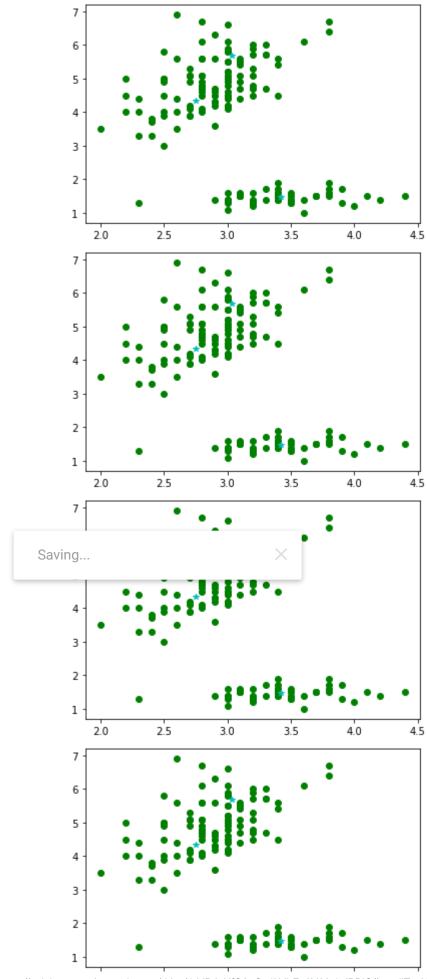
Clustering using KMeans Clustering Algorithm

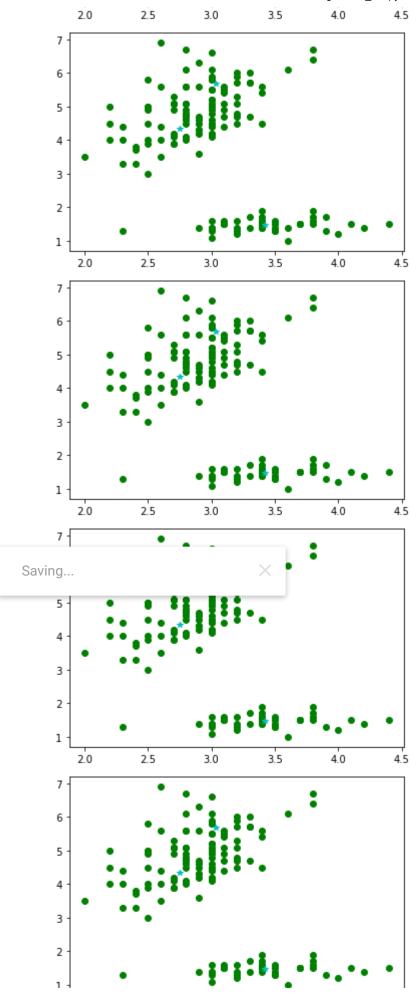
Plotting Clustered data points using K_Means with 3 clusters

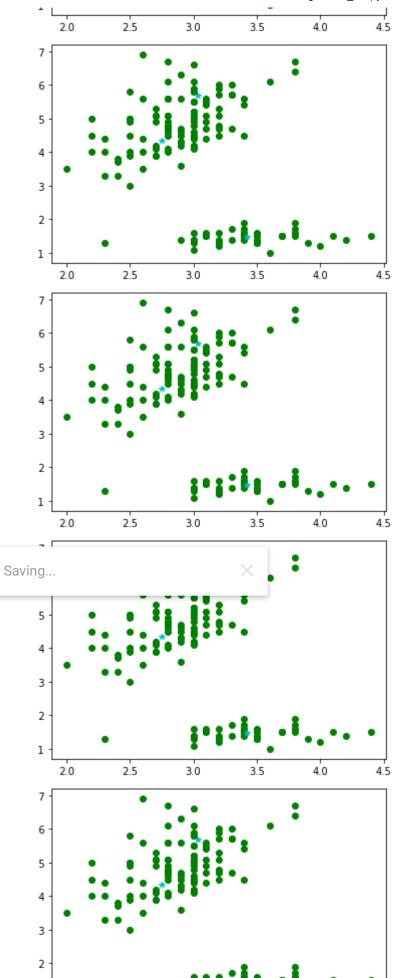
```
for i in range(150):
  if estimate1.labels [i]==0:
```

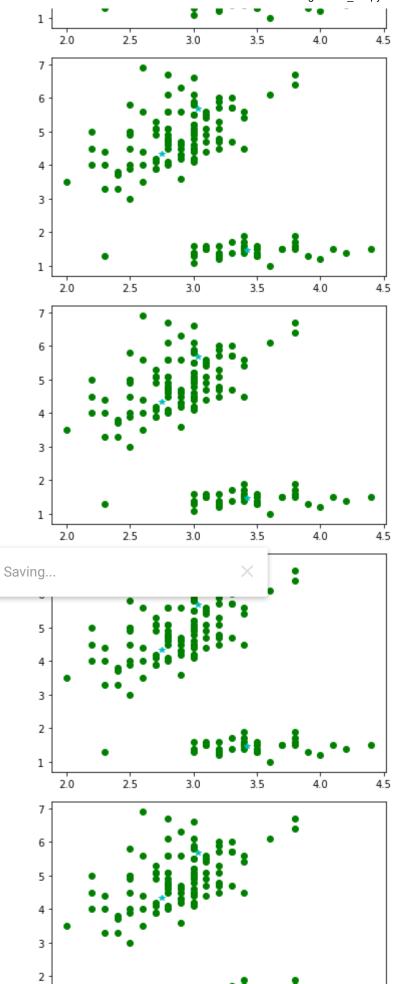
```
plt.plot(iris.values[i:,1],iris.values[i:,2],'go')
plt.plot(estimate1.cluster_centers_[:,0],estimate1.cluster_centers_[:,1],'c*')
elif estimate1.labels_[i]==1:
  plt.plot(iris.values[i:,1],iris.values[i:,2],'ro')
  plt.plot(estimate1.cluster_centers_[:,0],estimate1.cluster_centers_[:,1],'c*')
elif estimate1.labels_[i]==2:
  plt.plot(iris.values[i:,1],iris.values[i:,2],'bo')
  plt.plot(estimate1.cluster_centers_[:,0],estimate1.cluster_centers_[:,1],'c*')
plt.show()
```

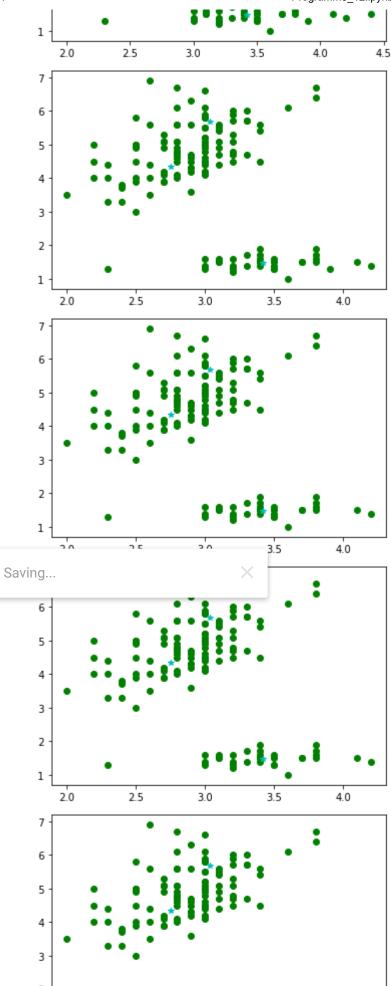
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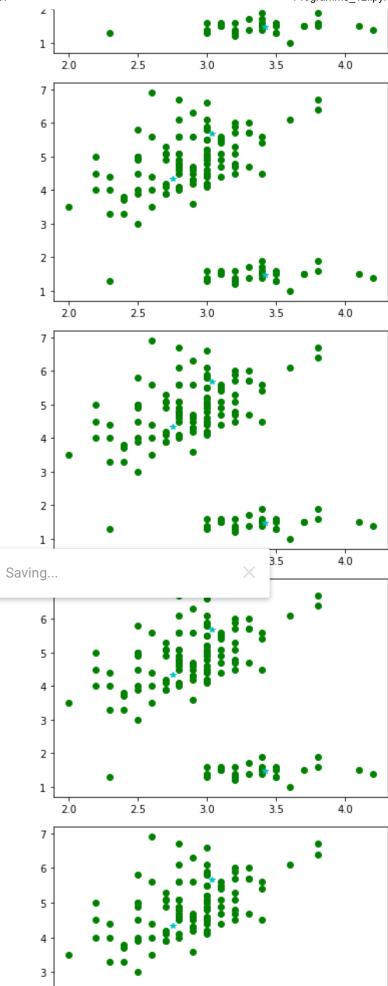


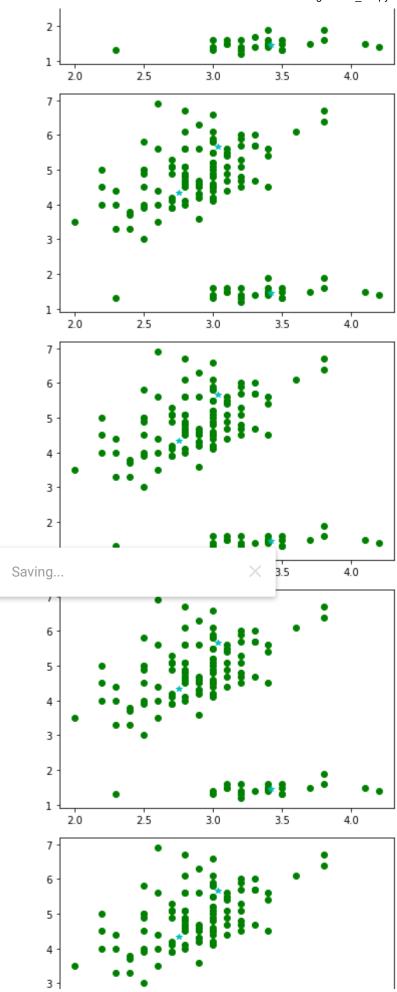


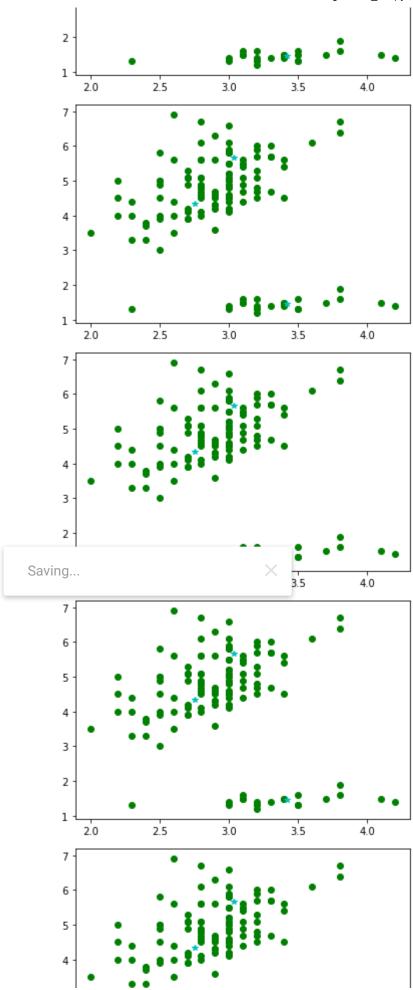


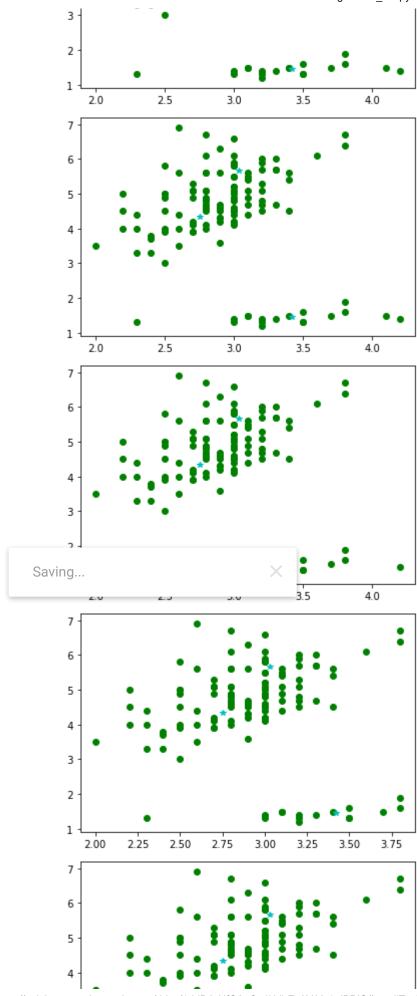


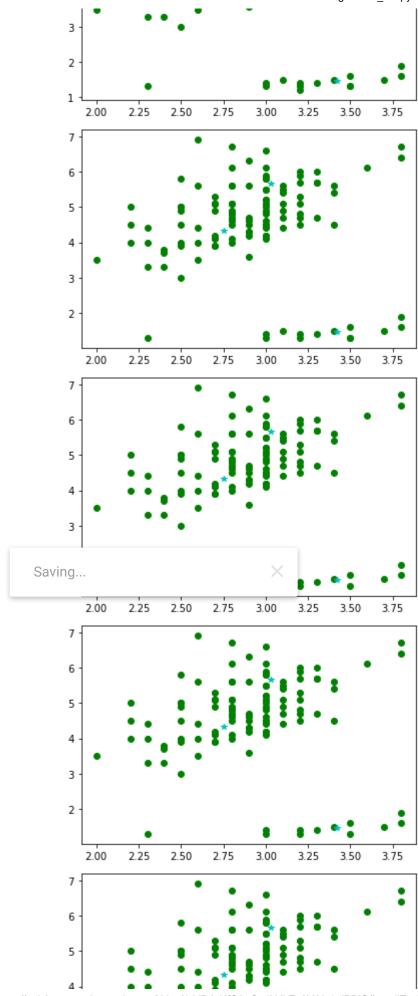


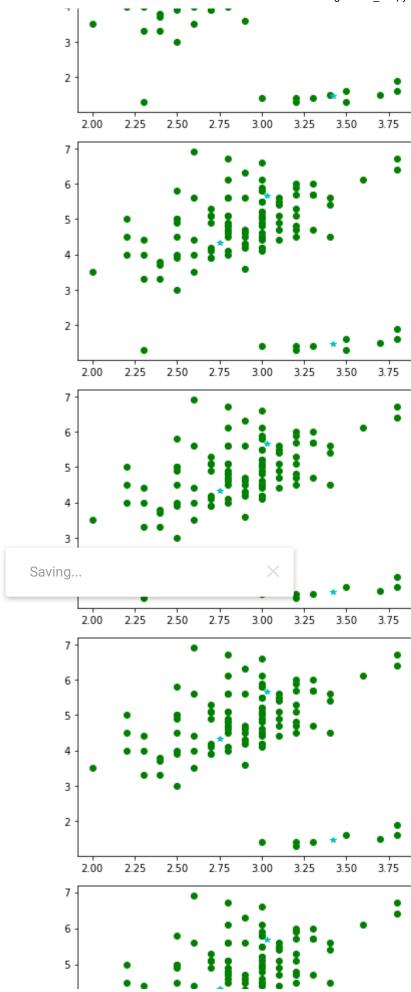


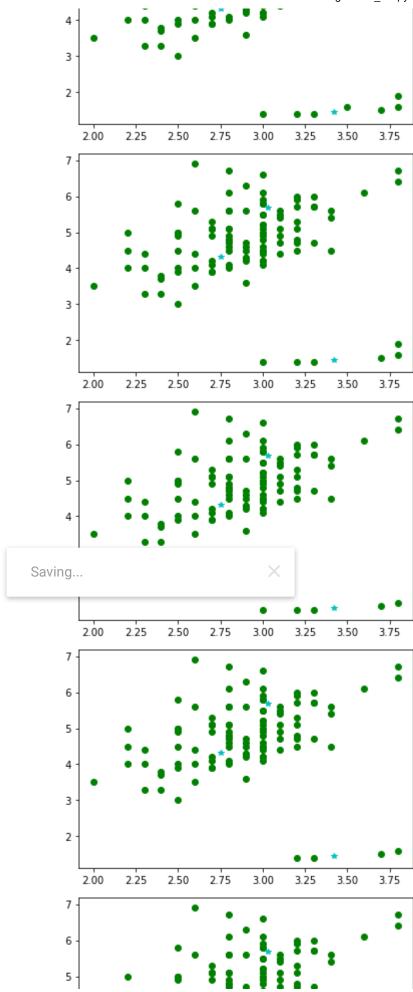


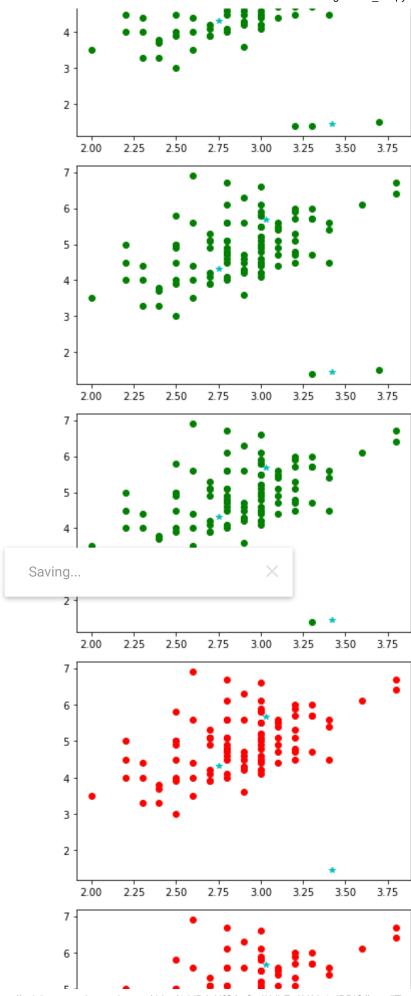


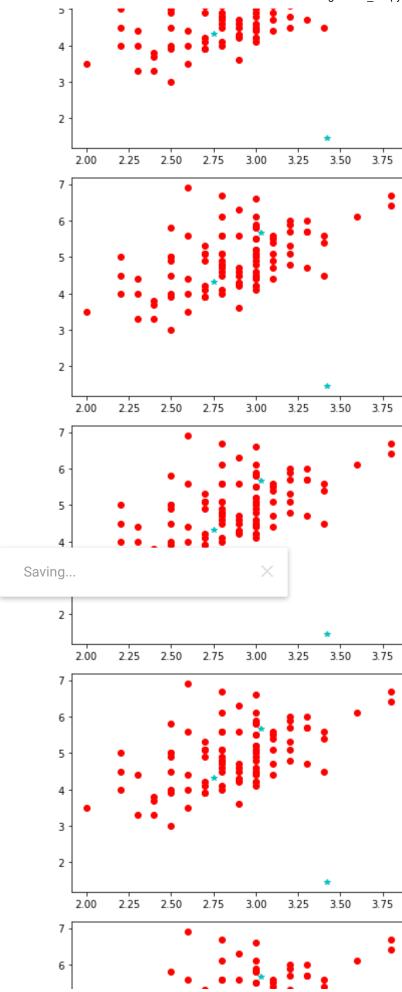


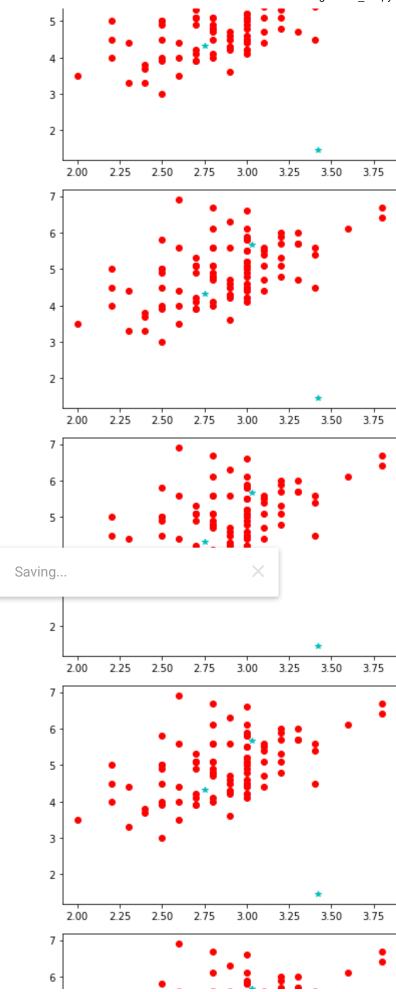


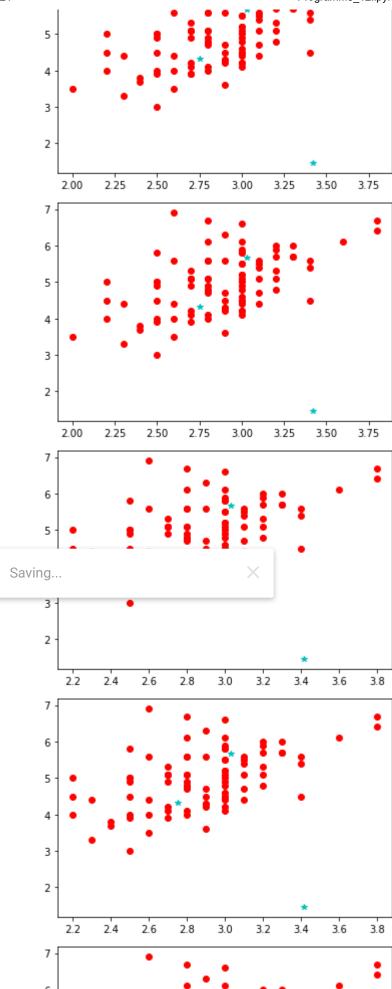


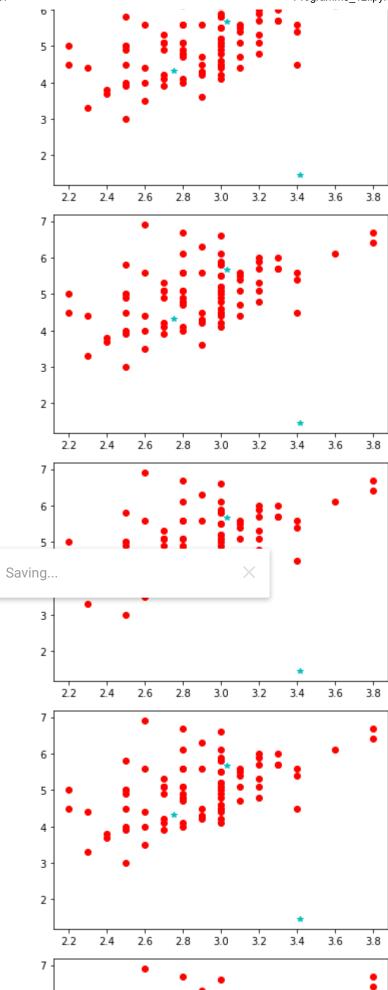


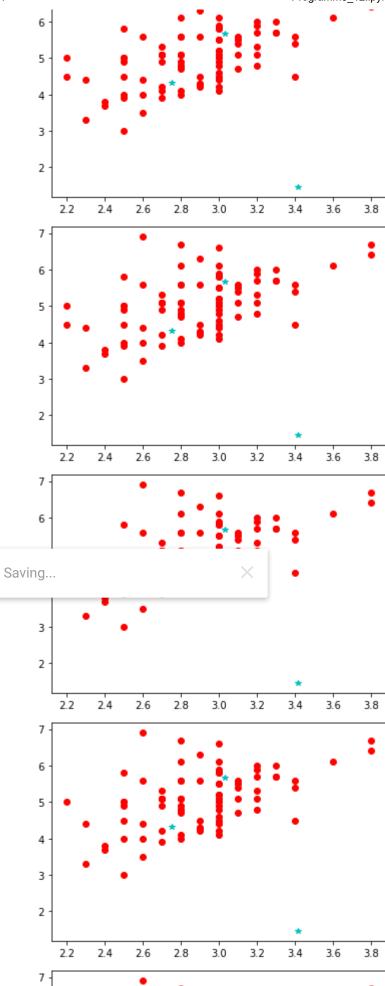


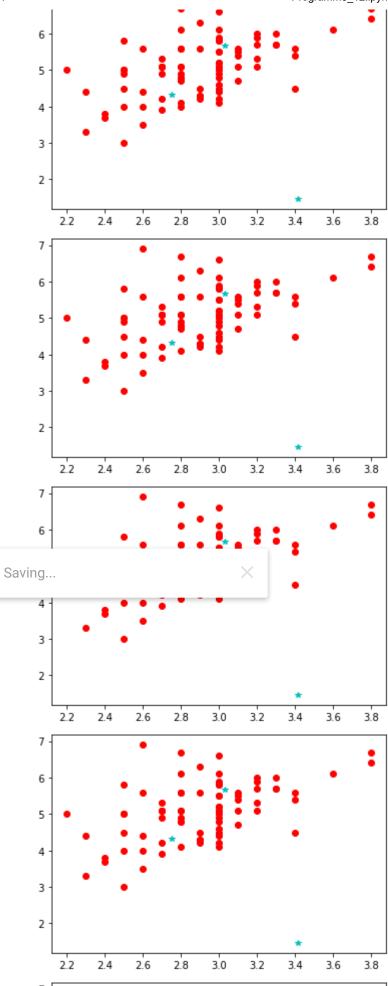


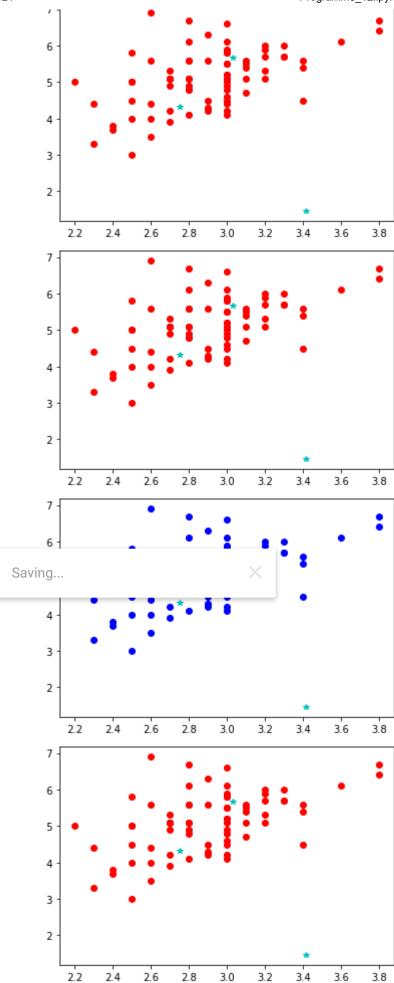


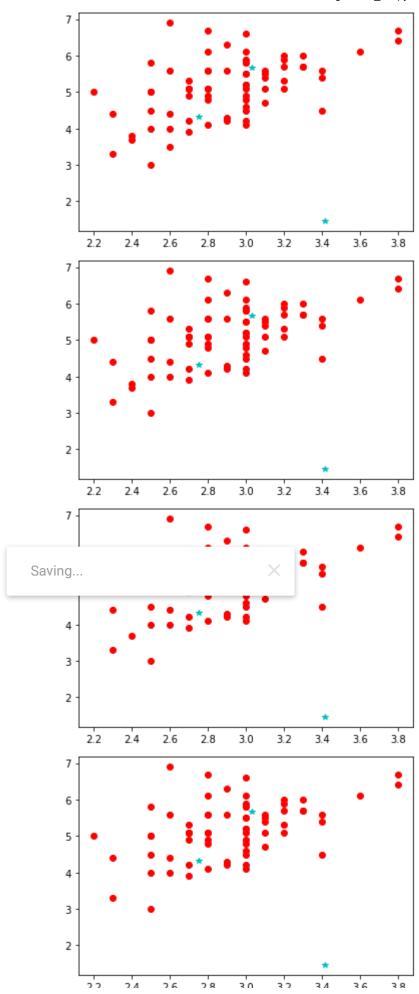


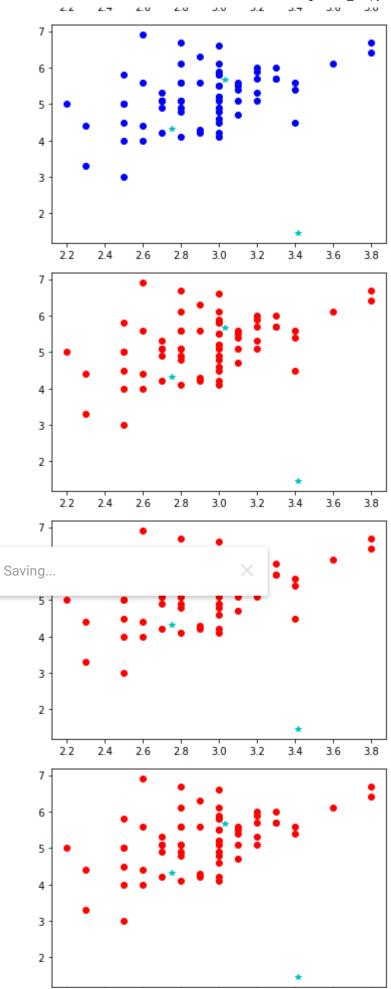


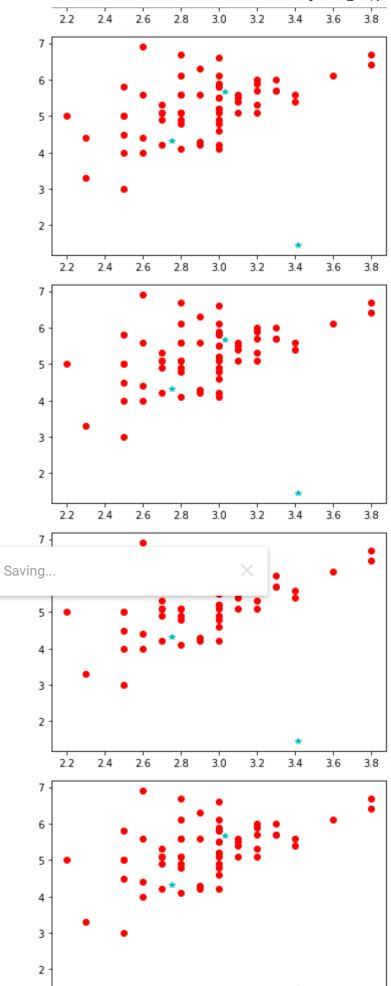


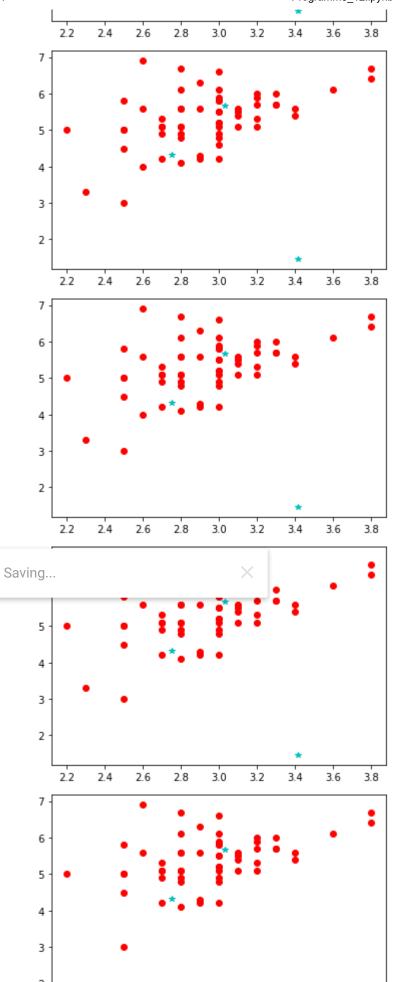


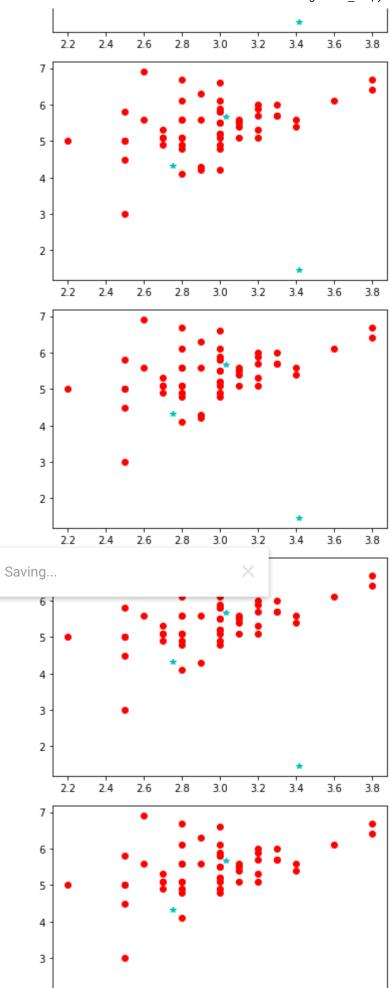


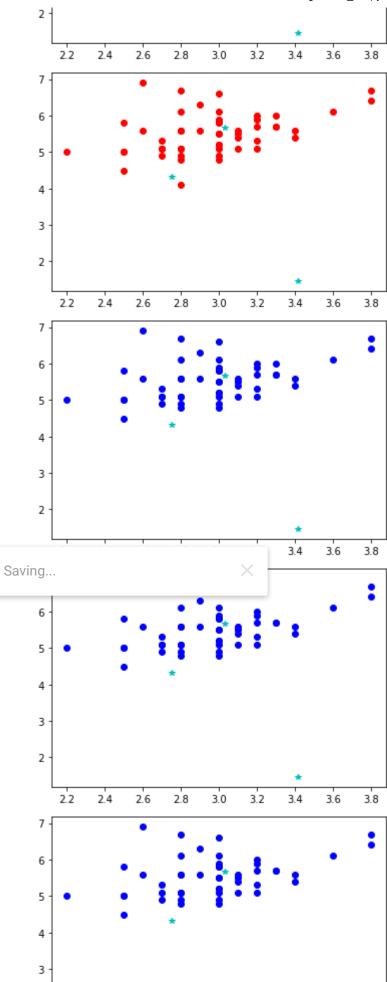


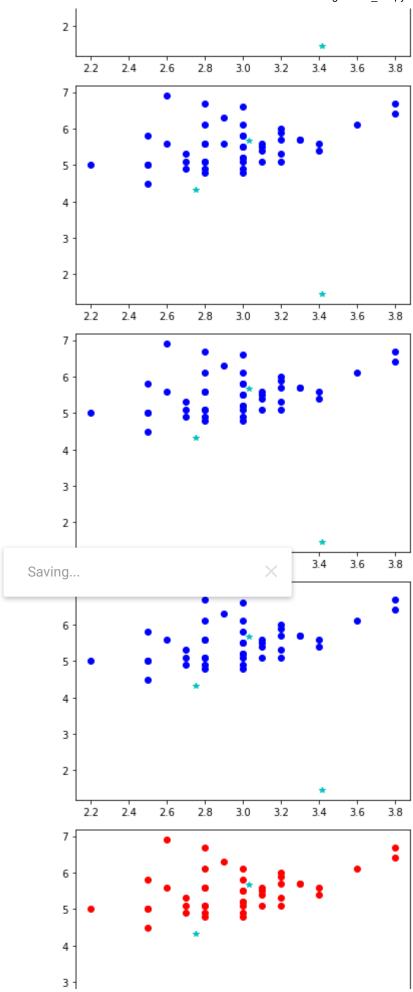


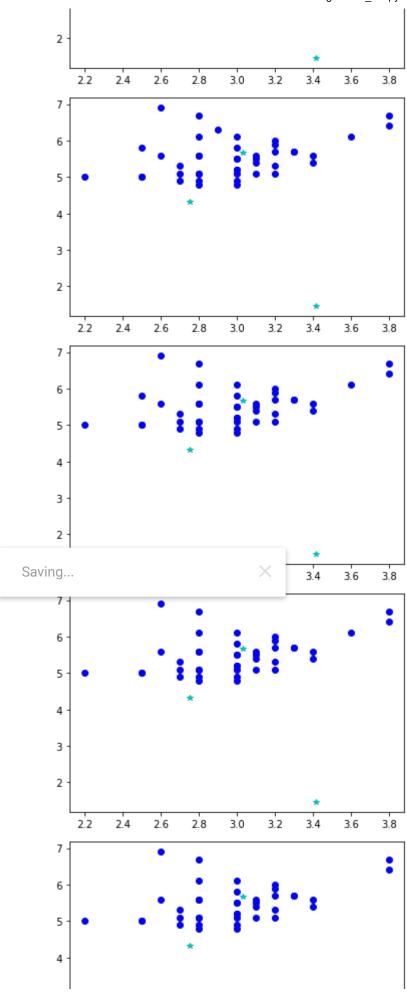


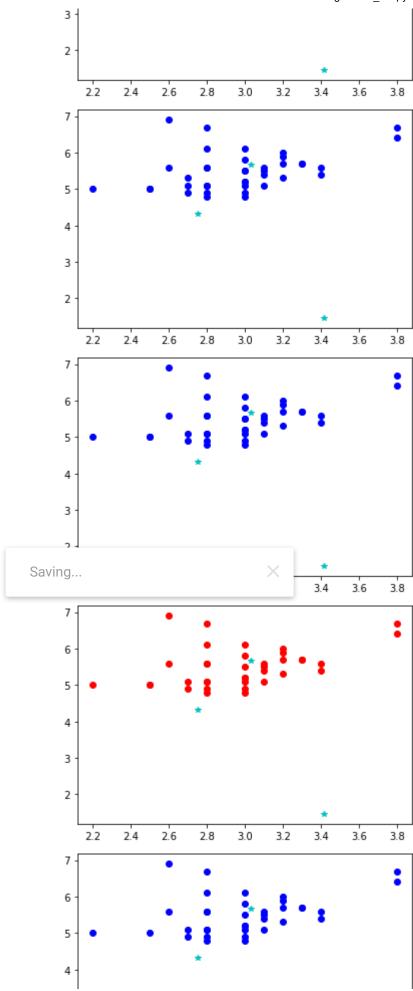


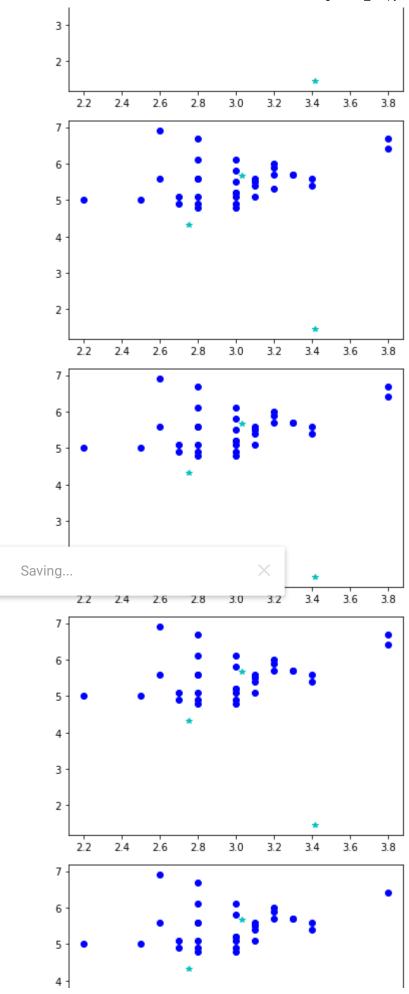


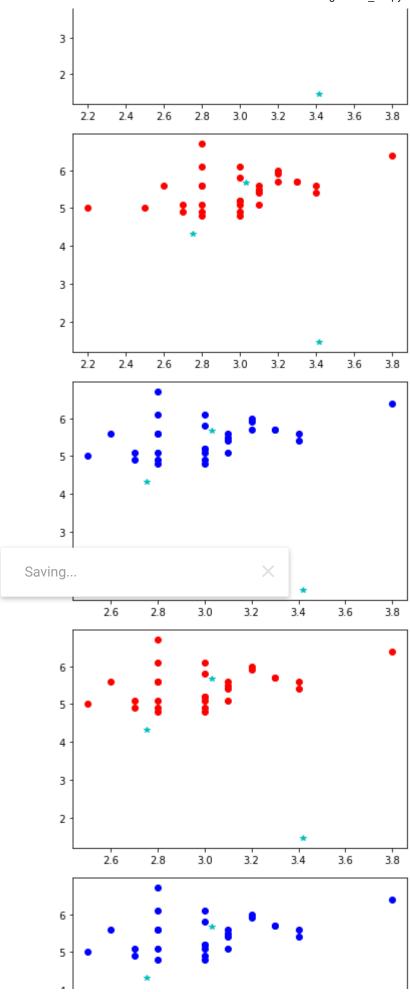


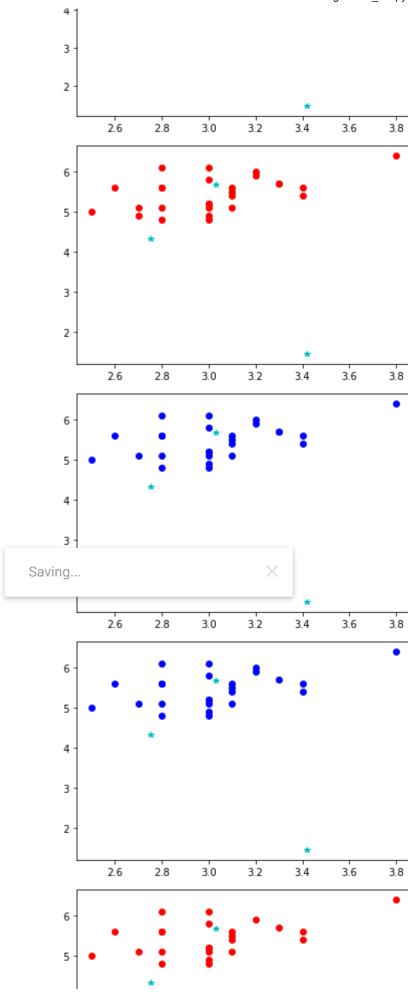


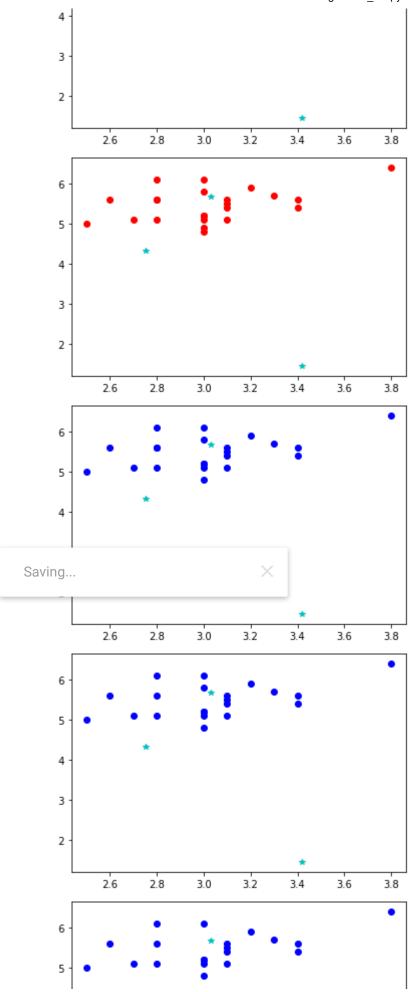


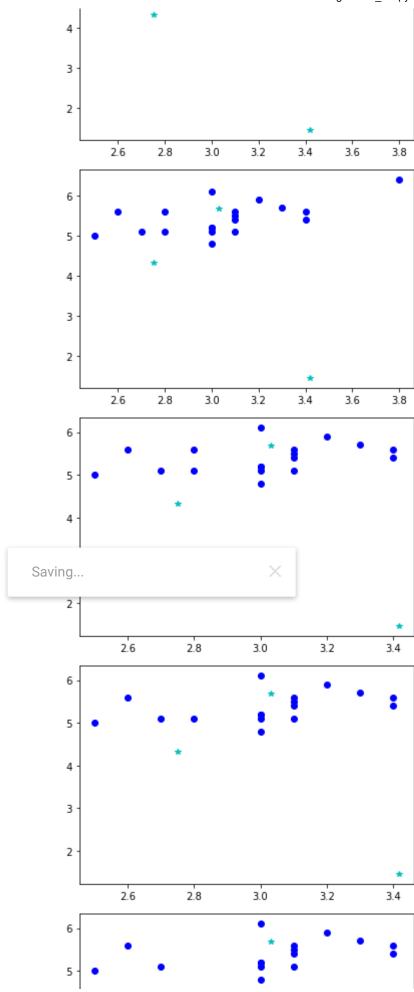


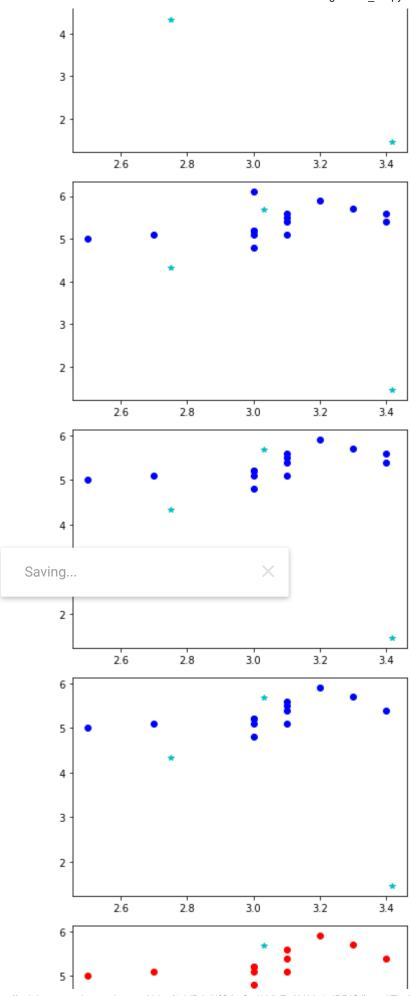


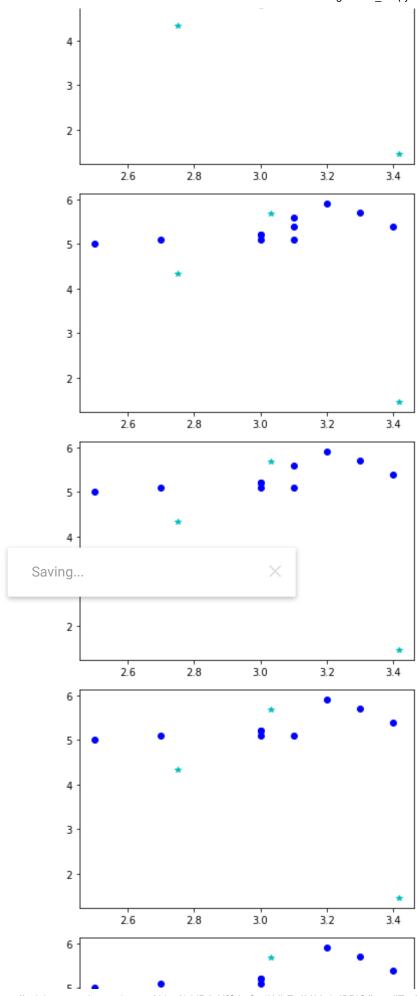


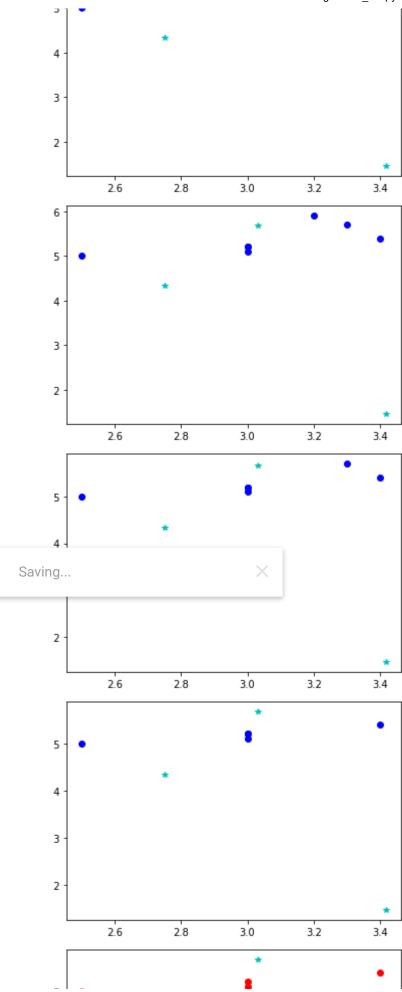












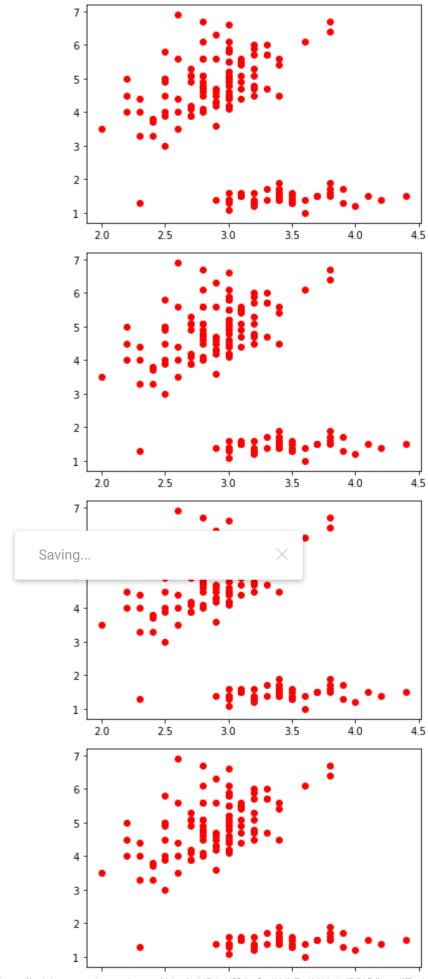


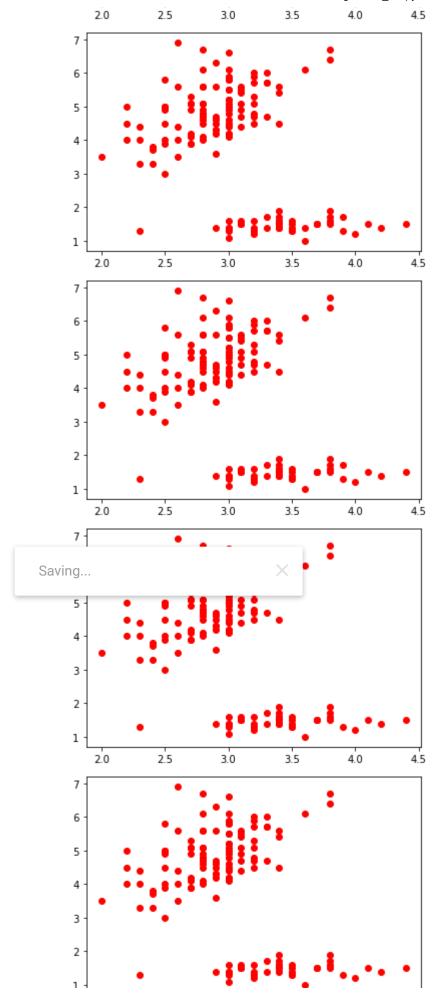
Clustering using Hierarchical Clustering Algorithm

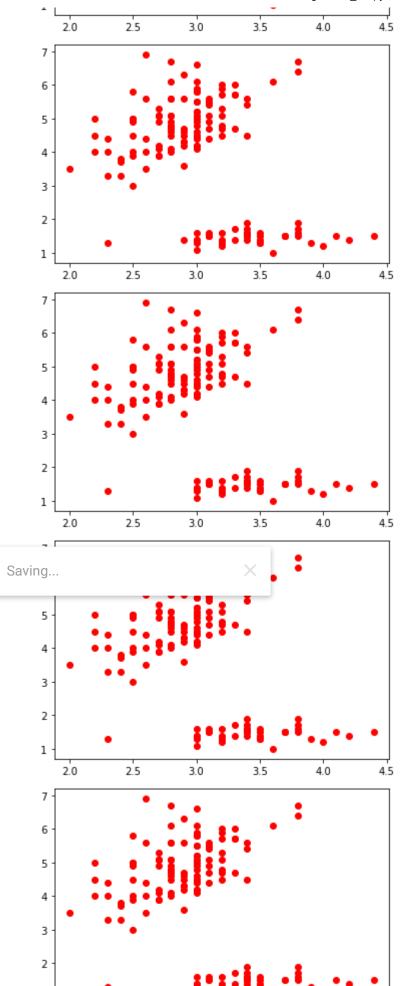
```
estimate2 = hierarchical.AgglomerativeClustering(n_clusters=3)
estimate2.fit(iris.values[:,1:3])

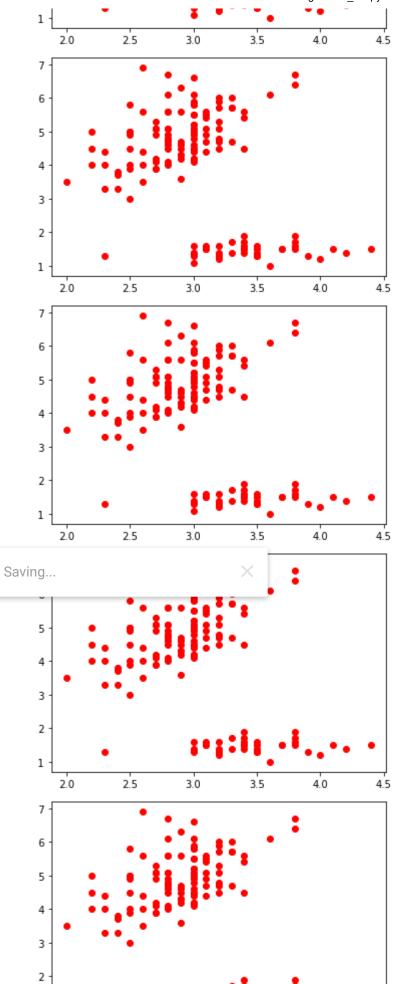
for i in range(150):
   if estimate2.labels_[i]==0:
      plt.plot(iris.values[i:,1],iris.values[i:,2],'go')
   elif estimate2.labels_[i]==1:
      plt.plot(iris.values[i:,1],iris.values[i:,2],'ro')
   elif estimate2.labels_[i]==2:
      plt.plot(iris.values[i:,1],iris.values[i:,2],'bo')
   plt.show()
   #pairplot
```

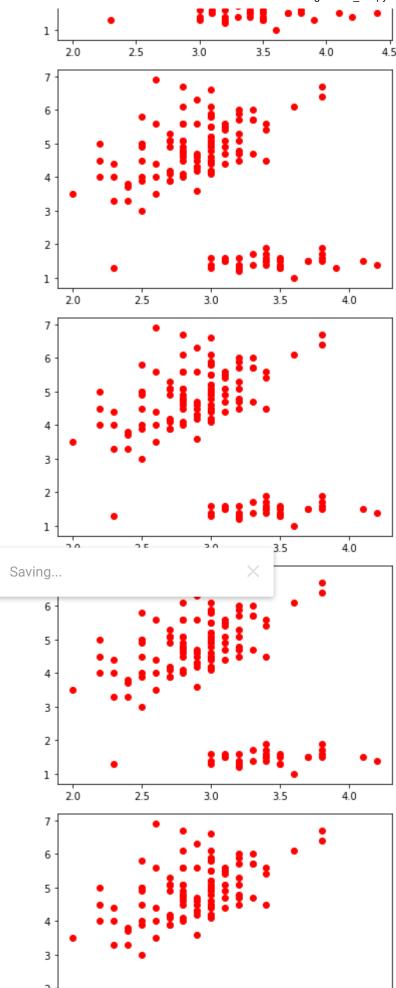
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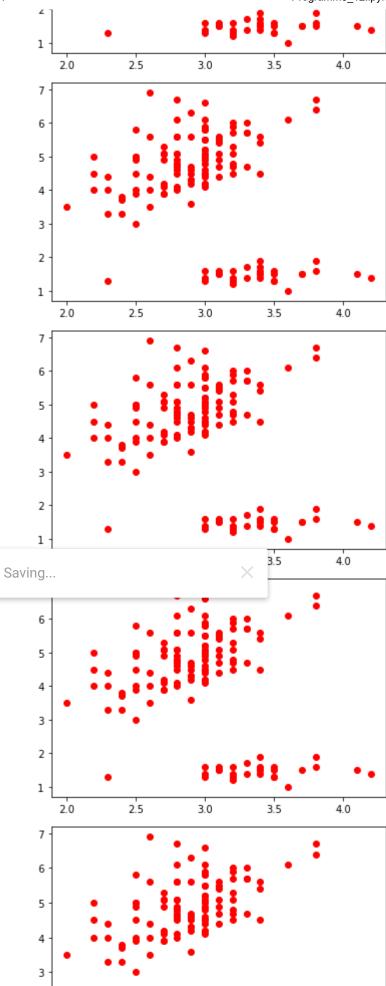


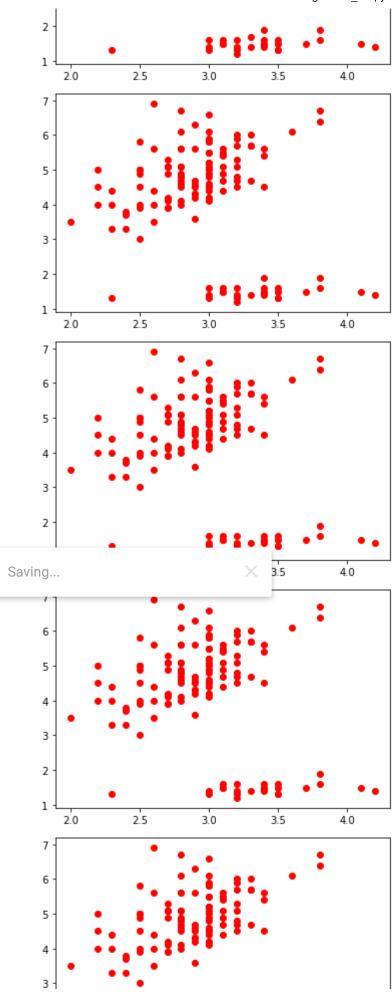


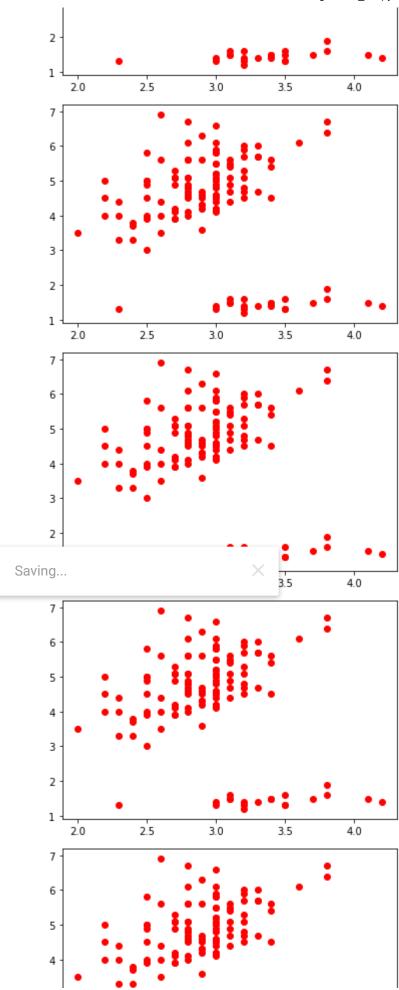


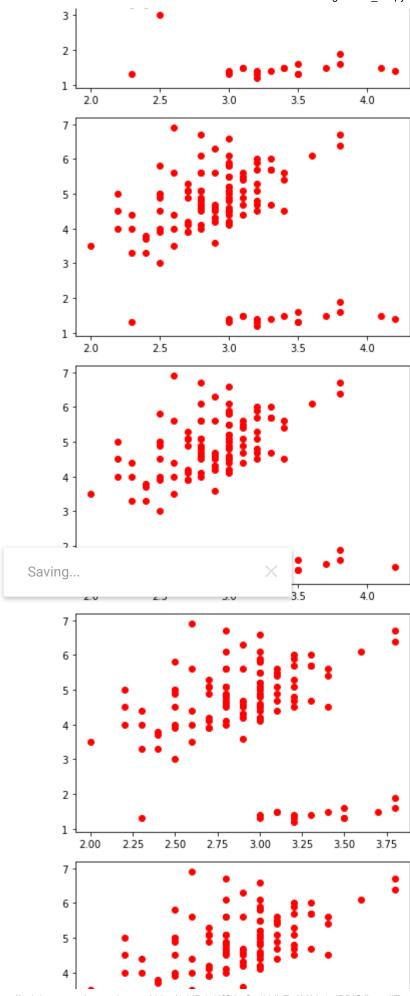


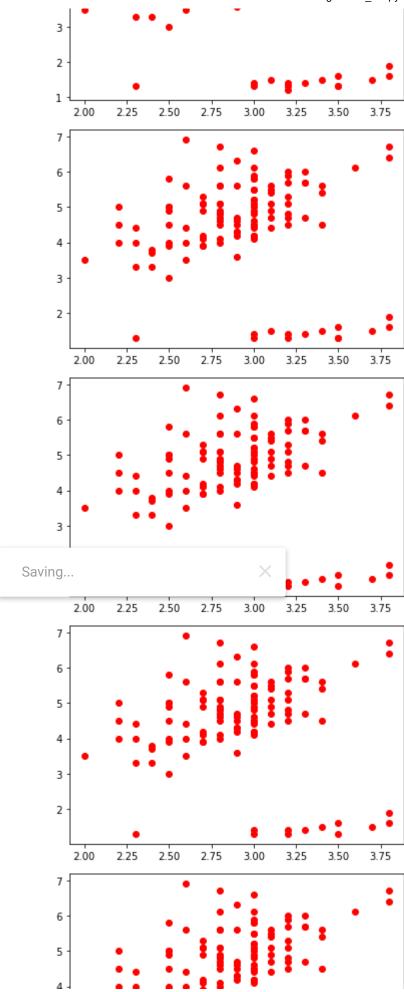


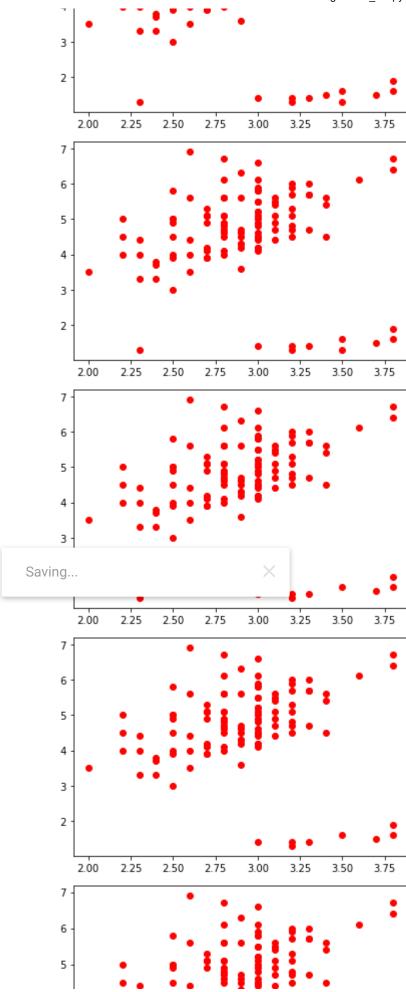


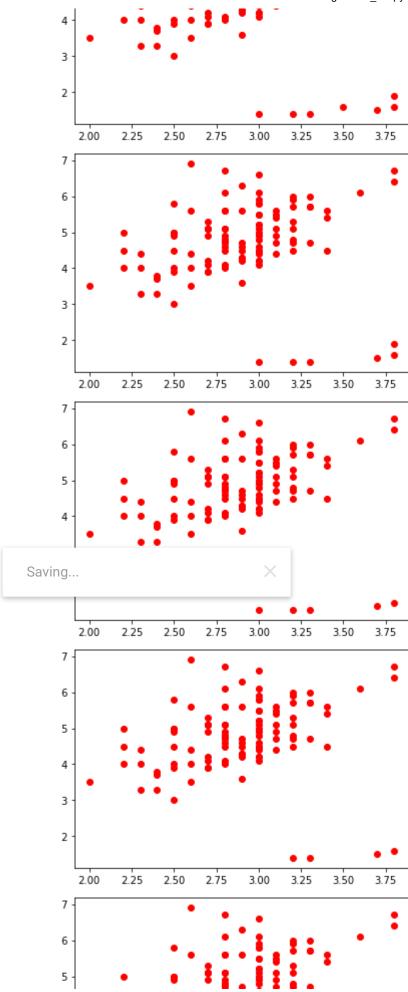


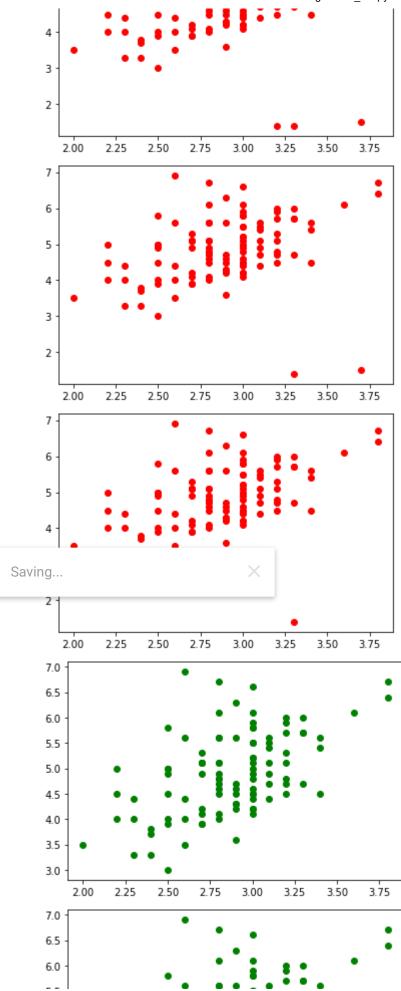


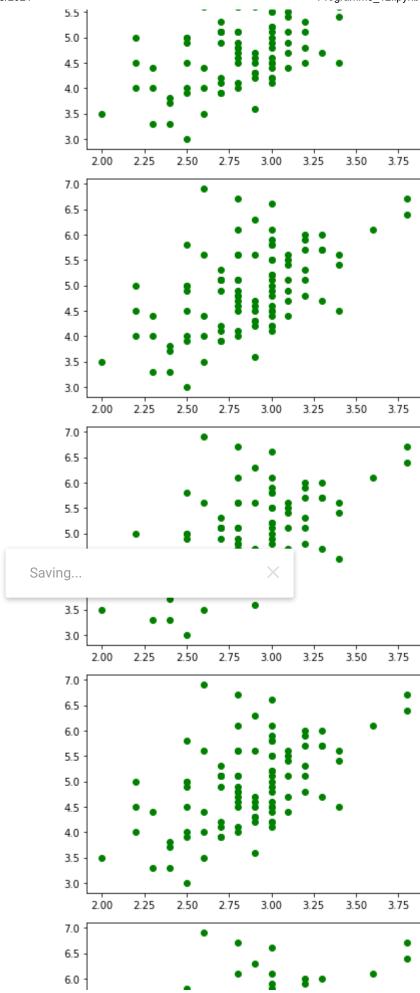


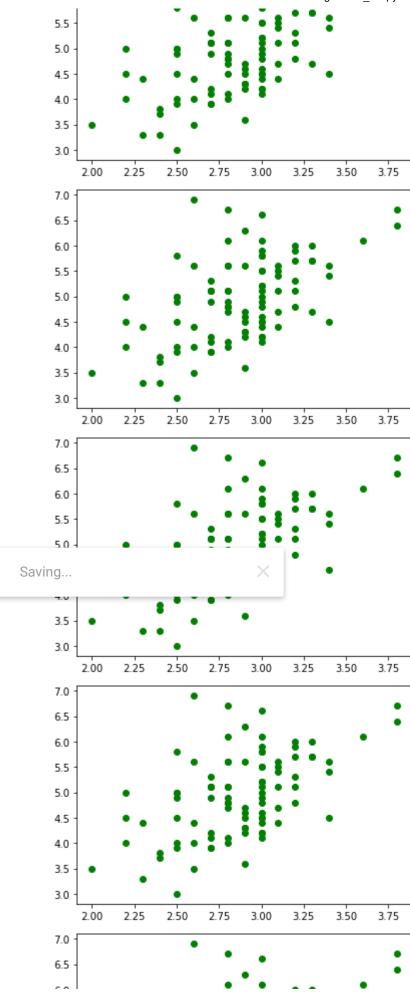


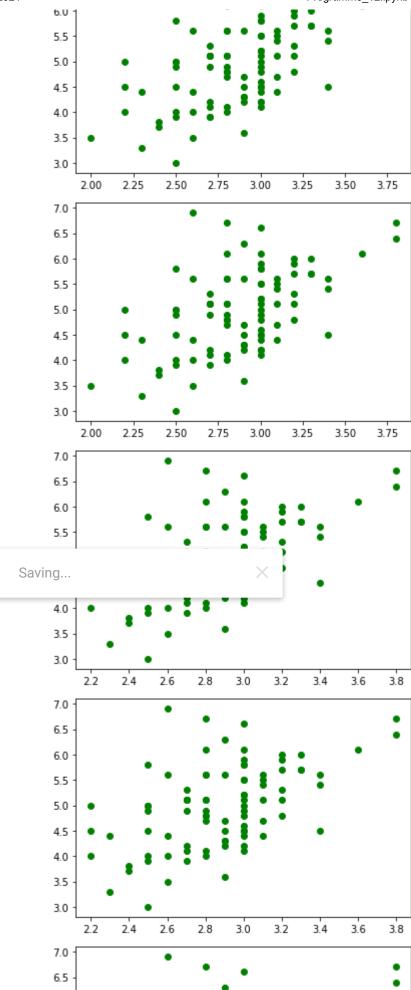


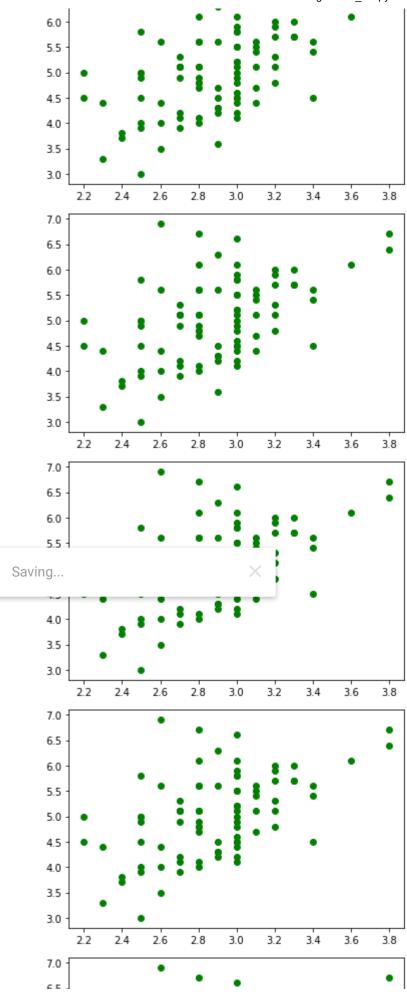


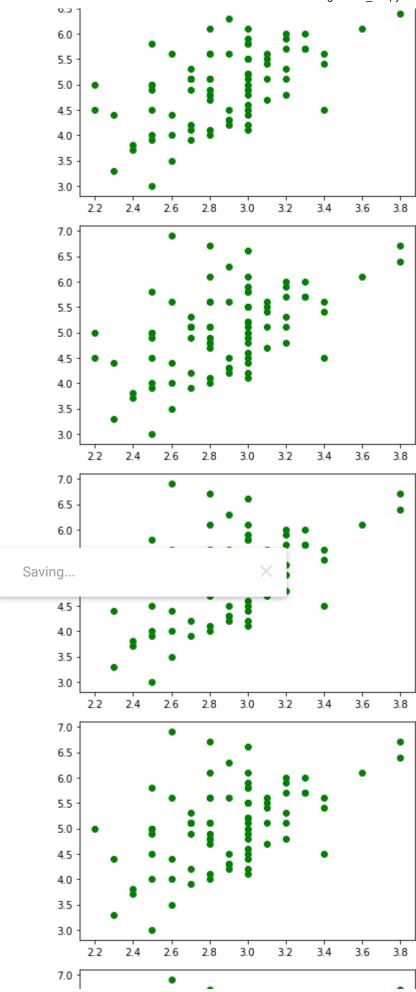


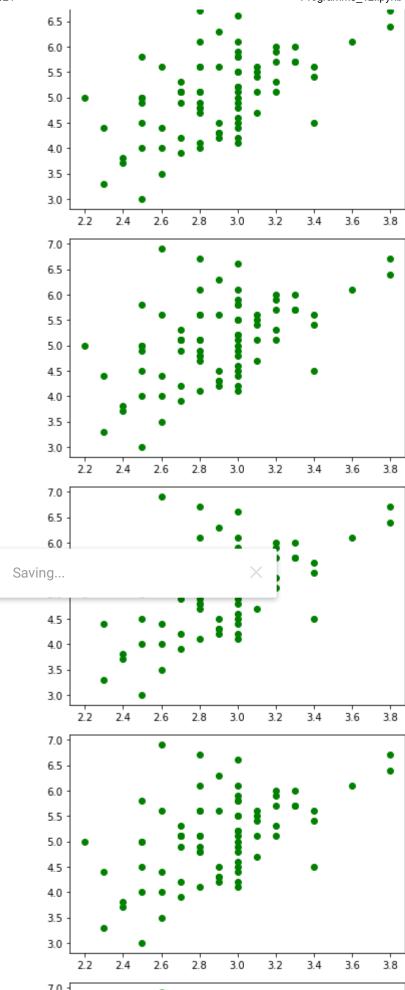


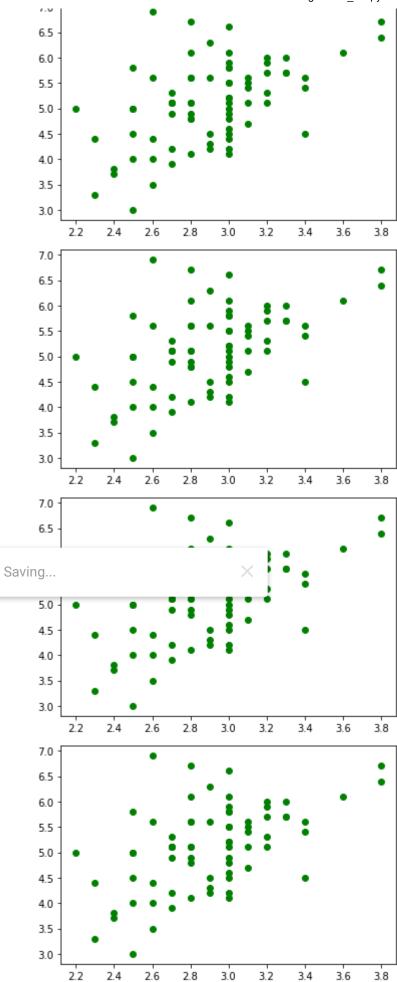


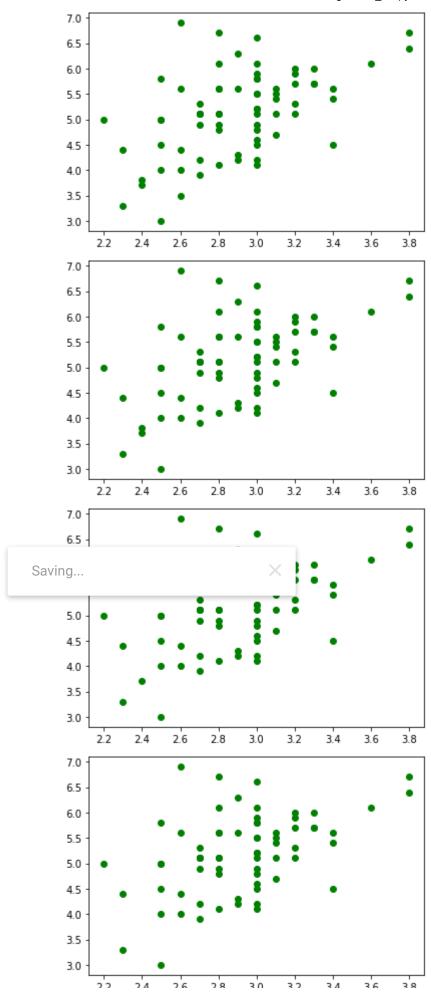


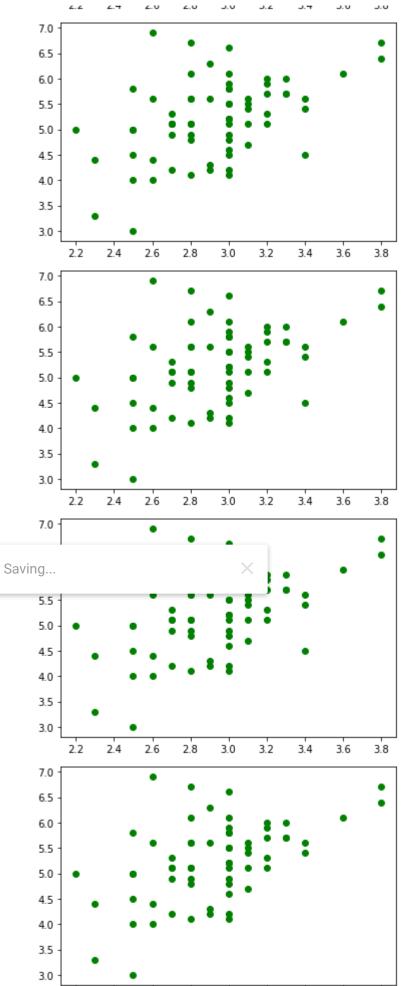


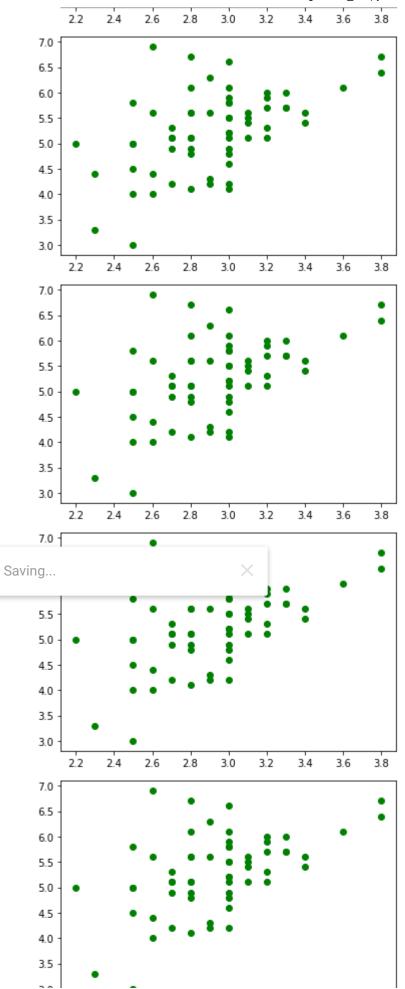


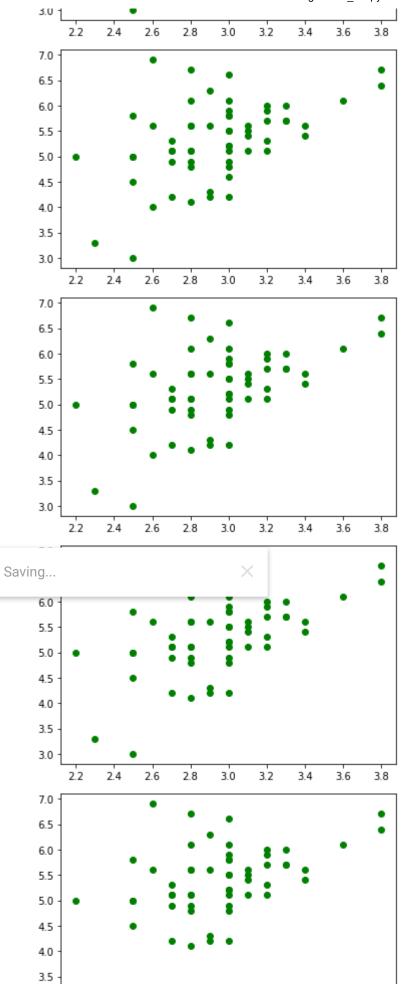


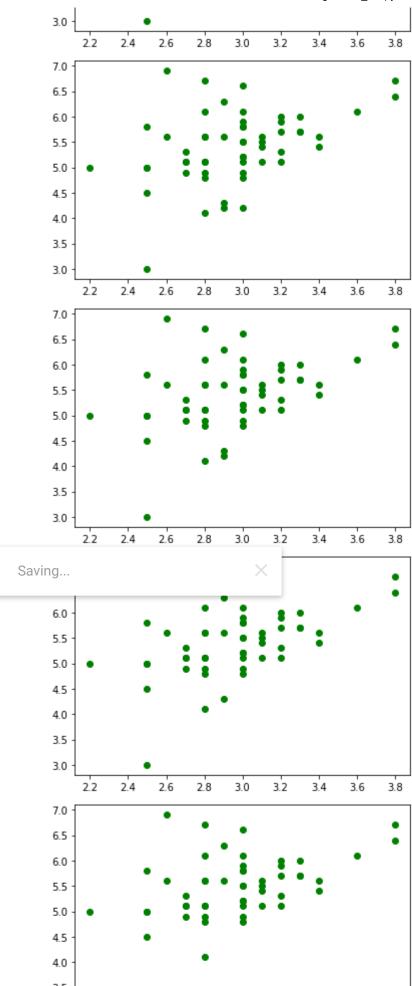


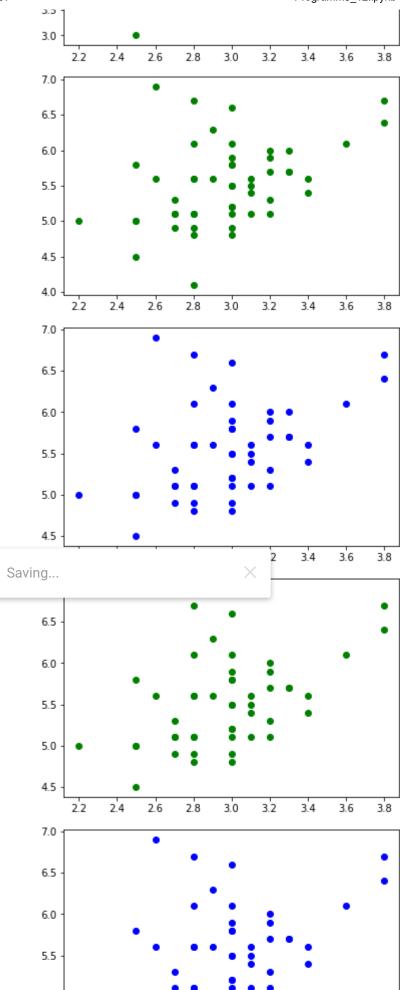


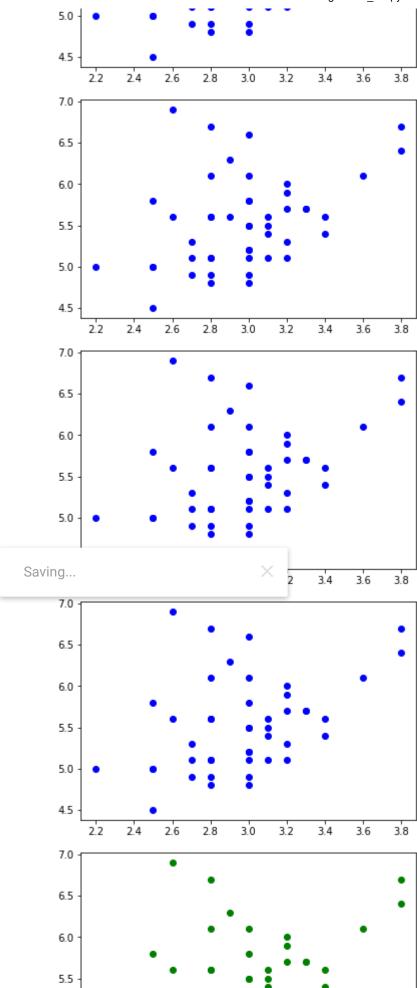


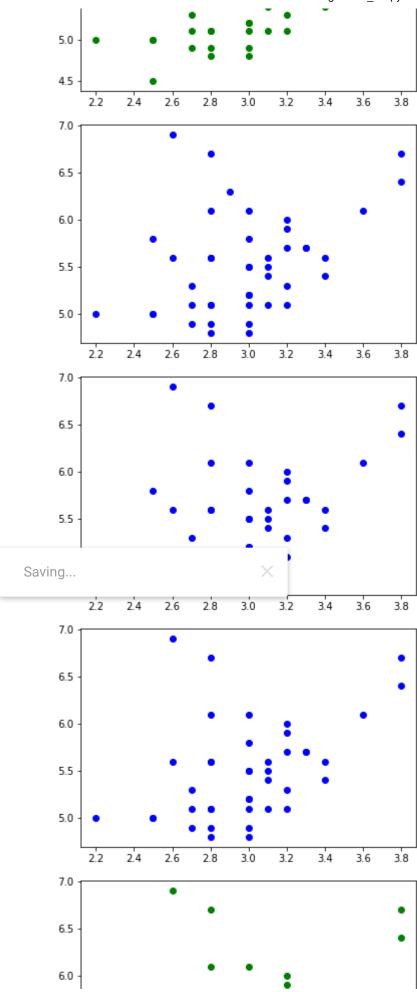


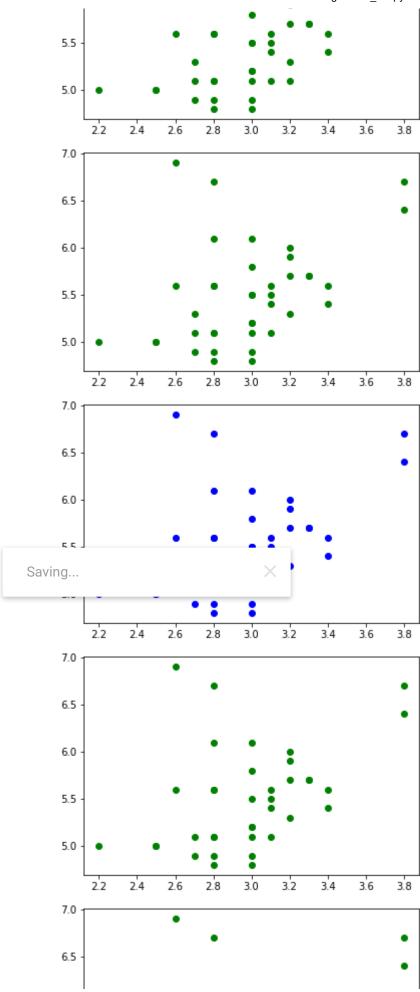


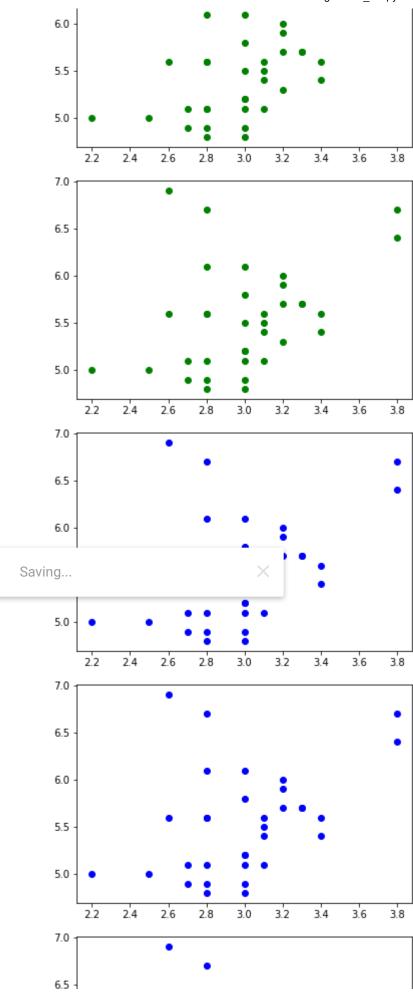


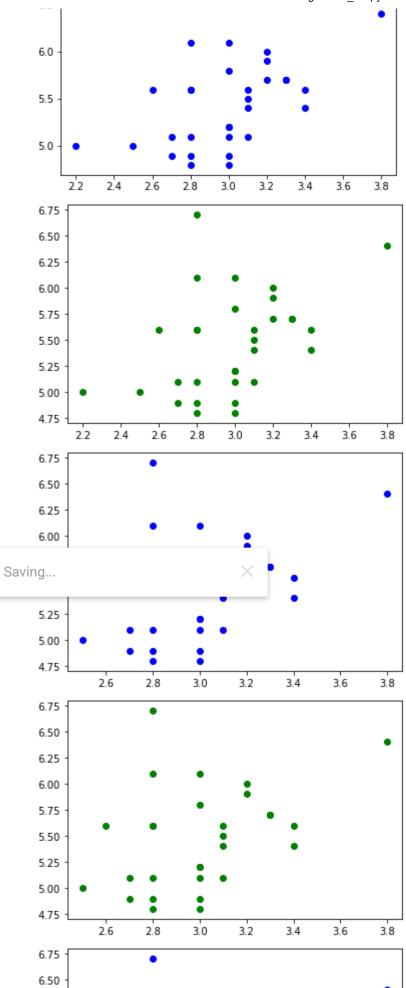


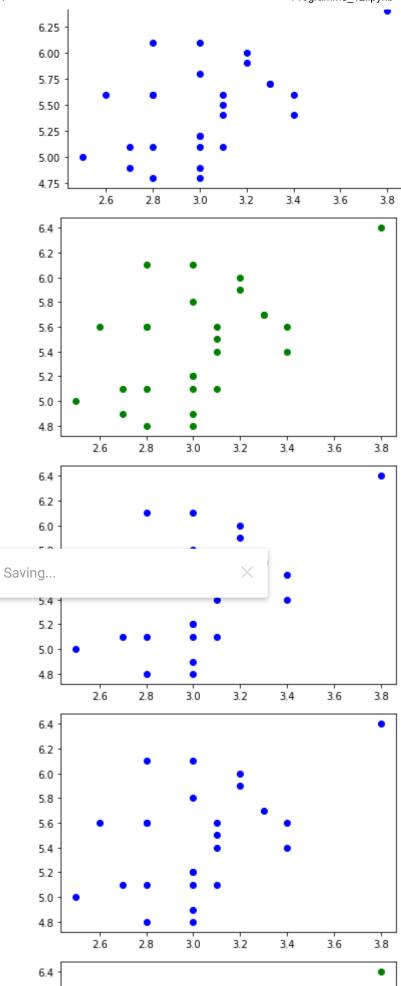


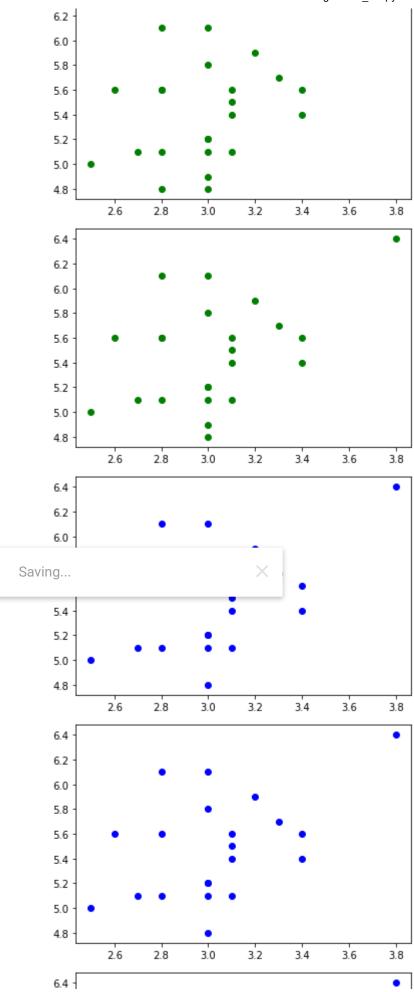


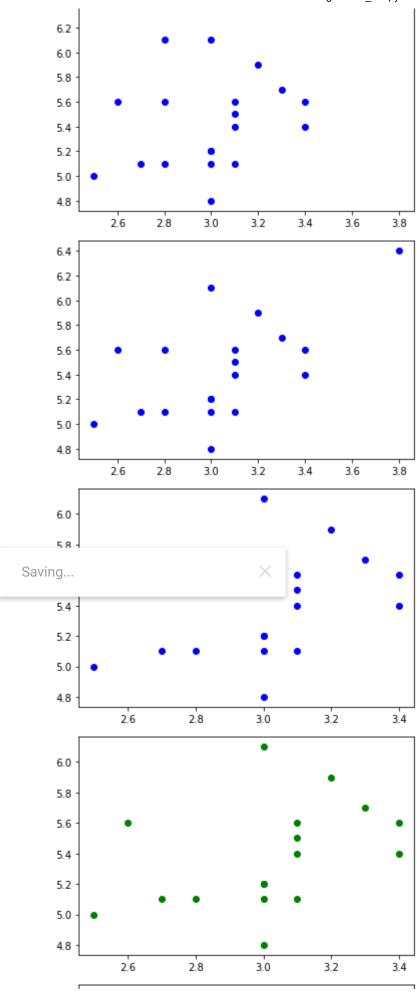


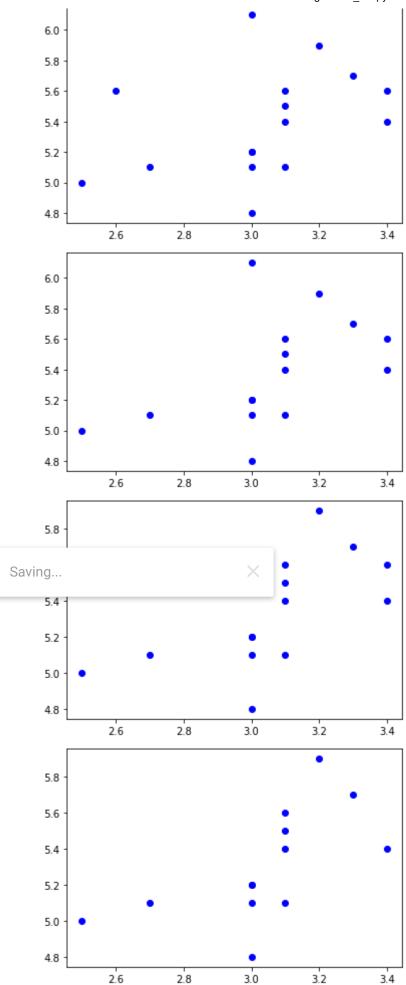


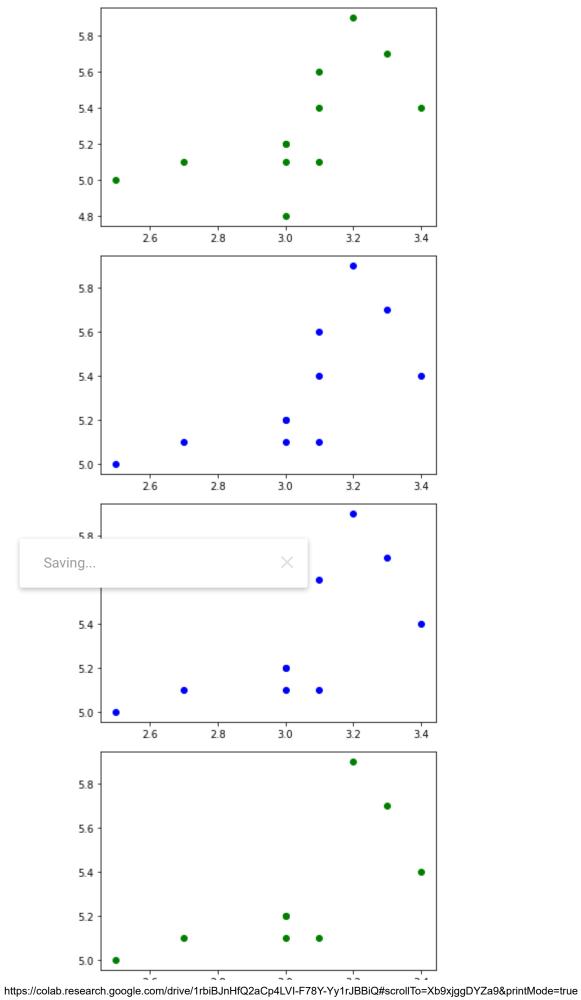


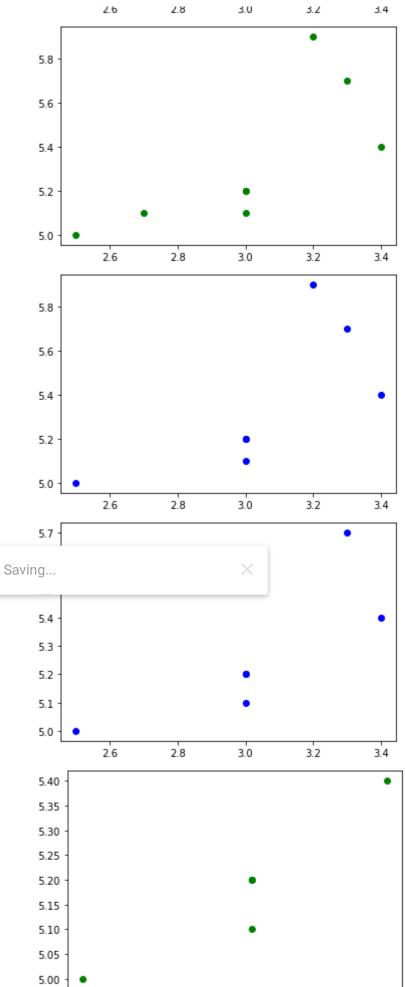


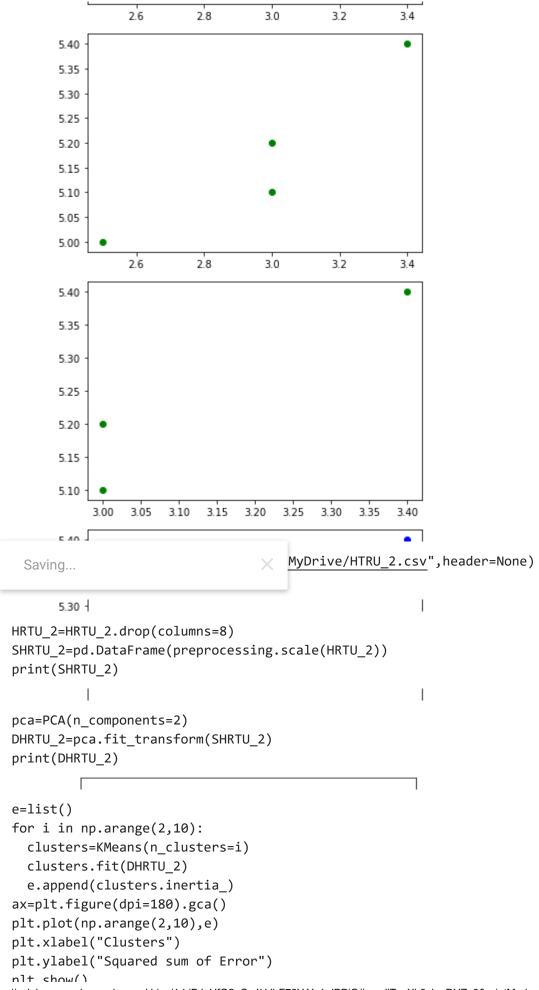












```
285 290 295 300 305 310 315

clusters= KMeans(n_clusters=3)
clusters.fit(DHRTU_2)
labels=clusters.labels_
ax=plt.figure(dpi=180).gca()
plt.scatter(DHRTU_2[:,0],DHRTU_2[:,1],c=labels,edgecolors='k',)
```

Silhouette Method

```
from sklearn.metrics import silhouette_score
from sklearn import cluster, datasets, mixture
from sklearn.neighbors import kneighbors_graph
from sklearn.preprocessing import StandardScaler
from itertools import cycle, islice

score=[]
for i in np.arange(2,10):
    clusters=KMeans(n_clusters=i)
    clusters.fit(DHRTU_2)
    score.append(silhouette_score(DHRTU_2,clusters.labels_)))

ax=plt.figure(dpi=180).gca()
plt.plot(np.arange(2,10),score)
plt.xlabel("Clusters")

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```

```
0.70
          0.65
          0.60
      Silhouette score
          0.55
          0.50
np.random.seed(0)
n_samples =1500
noisy circles =datasets.make circles(n samples=n samples, factor=0.5, noise=0.05)
print(noisy circles)
noisy moons=datasets.make moons(n samples=n samples, noise=0.05)
print(noisy moons)
blobs = datasets.make_blobs(n_samples=n_samples, random_state=8)
print(blobs)
no structures =np.random.rand(n samples,2),None
print(no structures)
     (array([[-0.67799938, -0.69875698],
            [ 0.93143746, 0.19139133],
                                     5],
 Saving...
            [0.01719727, -0.94513802],
            [ 0.91377877, -0.59884164]]), array([0, 0, 1, ..., 1, 0, 0]))
     (array([[ 0.49627131, -0.34275349],
            [-0.16629956, 0.92234209],
            [ 0.71895601, 0.66529038],
            [ 1.90950927, 0.02989686],
            [ 0.54623069, -0.36003133],
            [ 0.04090016, 0.37069297]]), array([1, 0, 0, ..., 1, 1, 1]))
     (array([ 5.86749807, 8.17715188],
            [ 5.61369982, 9.93295527],
            [ 7.22508428, 10.44886194],
            [ 7.73674097, 10.82855388],
            [-4.61701094, -9.64855983],
            [-3.48640175, -9.25766922]]), array([0, 0, 0, ..., 0, 2, 2]))
     (array([[0.59945663, 0.24694133],
            [0.5173267, 0.57255303],
            [0.55229185, 0.40567924],
            [0.8384347 , 0.52906874],
```

```
[0.84228843, 0.11517496],
            [0 01063613 0 23503146]]) Nono)
datasets=[noisy_circles,noisy_moons,blobs,no_structures]
for i,j in datasets:
 X=StandardScaler().fit_transform(i)
 for num in range(2,5):
   kmeans = KMeans(n_clusters=n)
   kmeans1=kmeans.fit(X)
   centroid=kmeans1.cluster_centers_
   l=kmeans1.labels_
   plt.scatter(X[:,0],X[:,1],c=l,cmap='gist_rainbow')
   plt.scatter(centroid[:,0],centroid[:,1],marker='X',color='blue',label='centroid')
   plt.xlabel('X')
   plt.ylabel('Y')
   plt.legend()
   plt.show()
```

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