Replace the code of Support Vector Machines method example of CSCE 5200 course Chapter 4. Use the original input data simulating frequencies of occurrence of terms in some source (replace data and extend its dimensionality in the Table 2.1 of Chapter 2). Execute the code in Python programming language (Java/C/C++/Matlab or other programming language can be also used if it is more convenient for you). Describe the problem statement, input data, method, code and results obtained. Upload the file consisting of the code and related report to the UNT Canvas environment.

In simple words, please code an approach different from the SVM code provided in canvas.

Background:

Support Vector Machine or SVM is a supervised machine learning algorithm used for both classification and regression.

The objective of SVM algorithm is to find a hyperplane in an N-dimensional space that distinctly classifies the data points.

An SVM is a kind of large-margin classifier.

It is a vector space based machine learning method where the goal is to find a decision boundary between two classes that is maximally far from any point in the training data (possibly discounting some points as outliers or noise).

Dimension of SVM

• The dimension of the hyperplane depends upon the number of features.

• If the number of input features is two, then the hyperplane is just a line.

• If the number of input features is three, then the hyperplane becomes a 2-D plane.

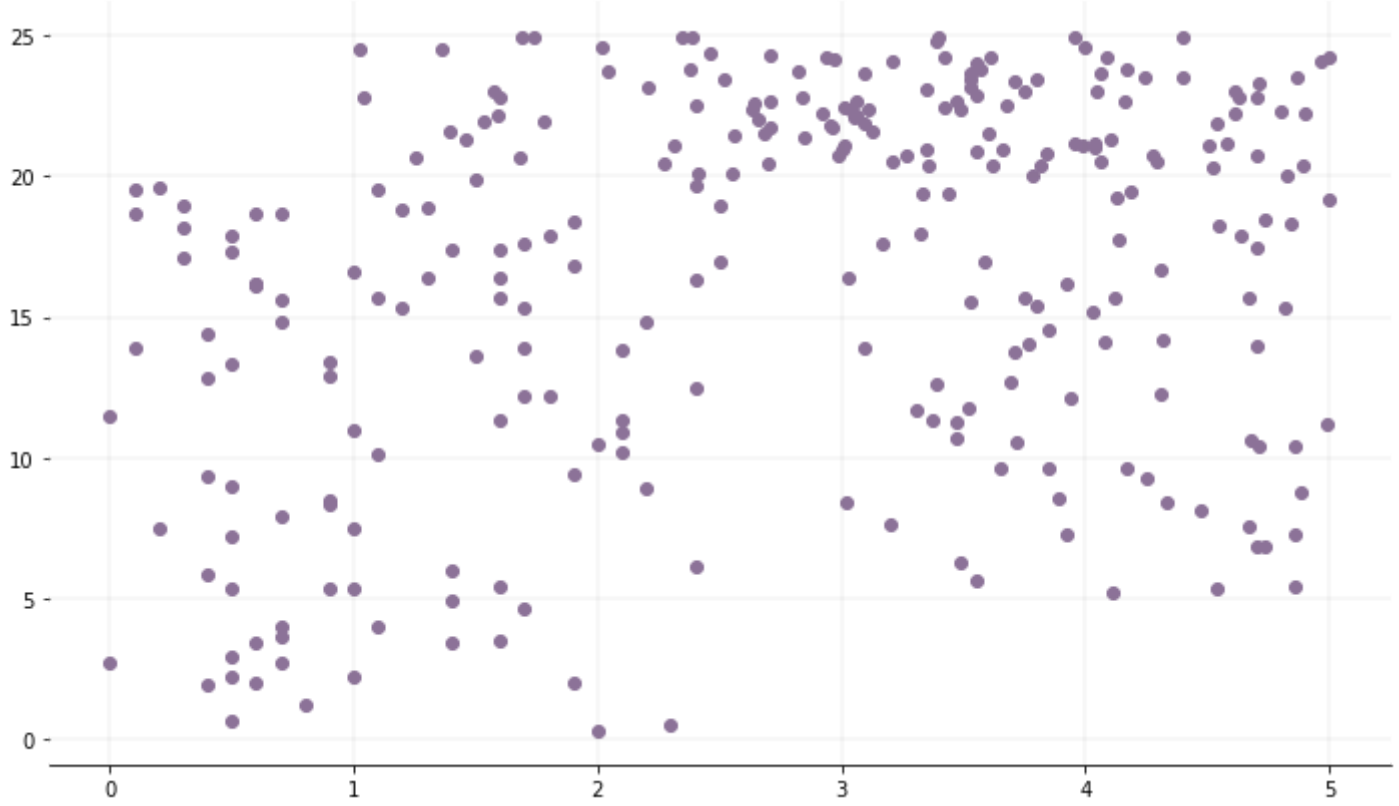
• It becomes difficult to imagine when the number of features exceeds three.

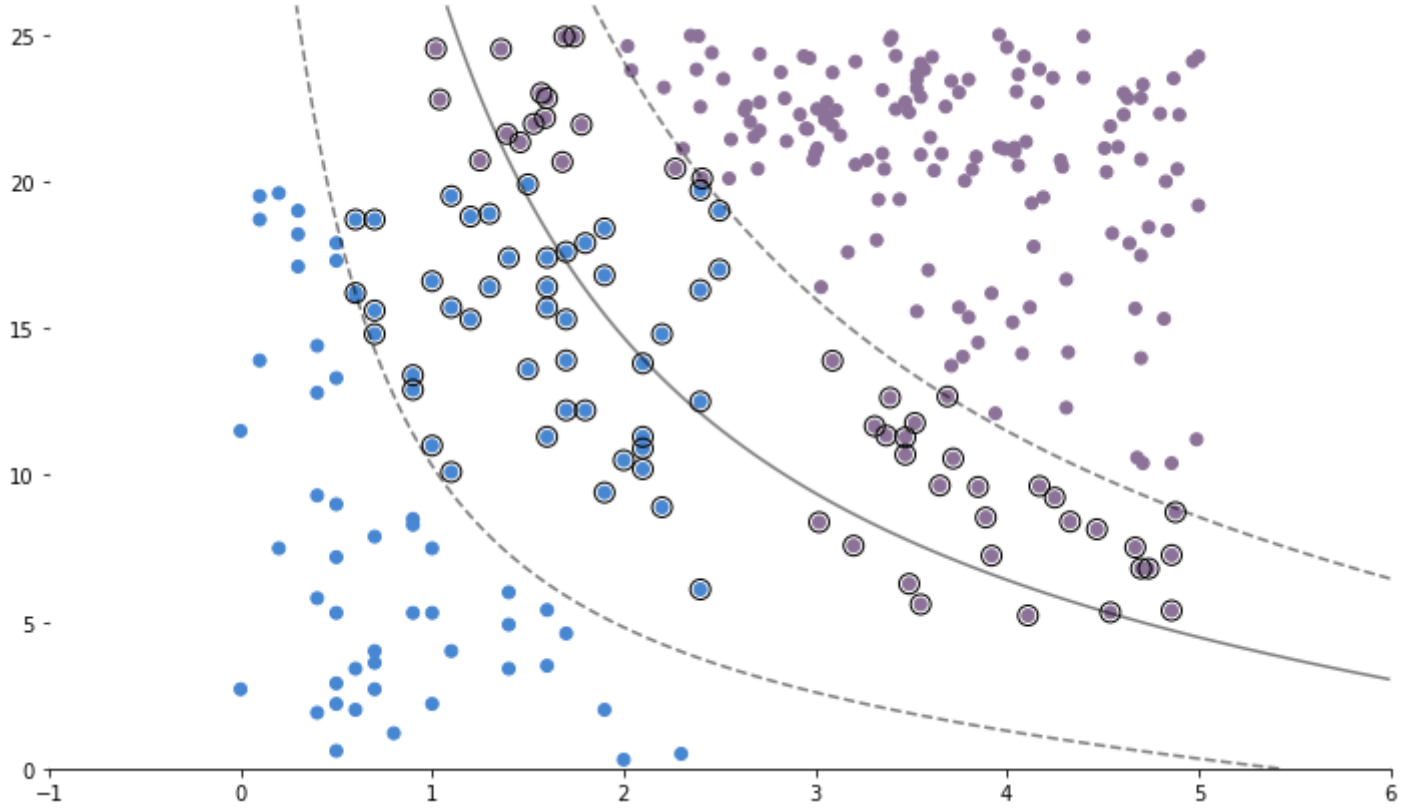
In [153]:
```
import random
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [154]:
```
def generate_random_dataset(size):
    x = []
    y = []
    target = []
    for i in range(size):
        x.append(np.round(random.uniform(0, 2.5), 1))
        y.append(np.round(random.uniform(0, 20), 1))
        target.append(0)

        # class one
        x.append(np.round(random.uniform(1, 5), 2))
        y.append(np.round(random.uniform(20, 25), 2))
        target.append(1)

        x.append(np.round(random.uniform(3, 5), 2))
        y.append(np.round(random.uniform(5, 25), 2))
        target.append(1)

        df_x = pd.DataFrame(data=x)
        df_y = pd.DataFrame(data=y)
        df_target = pd.DataFrame(data=target)
        data_frame = pd.concat([df_x, df_y], ignore_index=True, axis=1)
        data_frame = pd.concat([data_frame, df_target], ignore_index=True, axis=1)
        data_frame.columns = ['x', 'y', 'target']
    return data_frame

# Generate  dataset
size = 100
dataset = generate_random_dataset(size)
features  = dataset[['x',  'y']]
label = dataset['target']

# Hold out 20% of the dataset for training
test_size  = int(np.round(size  * 0.2, 0))

# Split dataset into training and testing sets
x_train = features[:-test_size].values
y_train = label[:-test_size].values
x_test = features[-test_size:].values
y_test = label[-test_size:].values

# Plotting the training set
```

```
fig, ax = plt.subplots(figsize=(12, 7))

# removing to and right border
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['right'].set_visible(False)

# adding major gridlines
ax.grid(color='grey', linestyle='-', linewidth=0.25, alpha=0.5)
ax.scatter(features[:-test_size]['x'], features[:-test_size]['y'], color="#8C7298")

from sklearn import svm
model = svm.SVC(kernel='poly', degree=2)
model.fit(x_train, y_train)

plt.show()

fig, ax = plt.subplots(figsize=(12, 7))

# Removing to and right border
ax.spines['top'].set_visible(False)
ax.spines['left'].set_visible(False)
ax.spines['right'].set_visible(False)

# Create grid to evaluate model
XX = np.linspace(-1, max(features['x']) + 1, len(x_train))
yy = np.linspace(0, max(features['y']) + 1, len(y_train))
YY, XX = np.meshgrid(yy, XX)
xy = np.vstack([XX.ravel(), YY.ravel()]).T
train_size = len(features[:-test_size]['x'])

# Assigning different colors to the classes
colors = y_train
colors = np.where(colors == 1, '#8C7298', '#4786D1')

# Plot the dataset
ax.scatter(features[:-test_size]['x'], features[:-test_size]['y'], c=colors)

# Get the separating  hyperplane
Z = model.decision_function(xy).reshape(XX.shape)

# Draw the decision boundary and margins
ax.contour(XX, YY, Z, colors='k', levels=[-1,  0, 1], alpha=0.5, linestyles=['--',  '-', '--'])
```

```
# Highlight support vectors  with a circle around them
ax.scatter(model.support_vectors_[:,  0], model.support_vectors_[:,  1], s=100, linewidth=1, facecolors=
plt.show()

from sklearn.metrics  import accuracy_score
predictions_poly  = model.predict(x_test)
accuracy_poly = accuracy_score(y_test,  predictions_poly)
print("2nd degree  polynomial Kernel\nAccuracy  (normalized): " + str(accuracy_poly))
```






```
2nd degree  polynomial Kernel
Accuracy  (normalized): 0.9
```

Modifiying the approach using table 2.1 datasets

The LSVM algorithm will select a line that not only separates the two classes but stays as far away from the closest samples as possible. In fact, the “support vector” in “support vector machine” refers to two position vectors drawn from the origin to the points which dictate the decision boundary.

In [155]:
```
# LSVM - Linear Support Vector Machine
# import and read the dataset and specify the input and target

import pandas as pd
import numpy as np
dataset = pd.read_csv(r'/Users/roja/Downloads/frequency_table_data.csv')

dataset.shape

x = dataset['Frequency']
y = dataset['Rank']
```

In [156]:
```
# displaying the spreadsheet, dataset taken from table 2.1 from chapter 2

dataset
```

Out[156]:

	Token	Frequency	Rank
0	of	17523	11
1	a	14914	12
2	you	14088	13
3	my	12287	14
4	that	11192	15
5	in	11106	16
6	is	9344	17
7	not	8506	18
8	it	7799	19
9	me	7753	20
10	the	28317	7
11	and	26022	8
12	i	22639	9
13	to	19898	10

In [157]:
```
# features as input

x
```

Out[157]:
```
0     17523
1     14914
2     14088
3     12287
4     11192
5     11106
6      9344
7      8506
8      7799
9      7753
10    28317
11    26022
12    22639
13    19898
Name: Frequency, dtype: int64
```

In [158]:
```
# have the target

y
```

Out[158]:
```
0     11
1     12
2     13
3     14
4     15
5     16
6     17
7     18
8     19
9     20
10     7
11     8
12     9
13    10
Name: Rank, dtype: int64
```

In [159]:
```
# split the dataset into train and test using sklearn before building SVM algorithm model

from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.20)
```

In [160]:
```
# import classifier or SVC function from sklearn module, build a vector machine model

from sklearn.svm import SVC
svcclassifier = SVC(kernel='linear')
x_train = x_train.values.reshape(-1, 1)
x_test = x_test.values.reshape(-1, 1)
svcclassifier.fit(x_train, y_train)

# predict the values using the SVM algorithm model

y_pred = svcclassifier.predict(x_test)

# evaluate the SVM model

from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[0 1 0 0 0 0]
 [0 0 0 0 0 0]
 [0 0 0 1 0 0]
 [0 0 0 0 0 0]
 [0 0 0 0 0 1]
 [0 0 0 0 0 0]]
              precision    recall  f1-score   support

          10       0.00      0.00      0.00       1.0
          11       0.00      0.00      0.00       0.0
          12       0.00      0.00      0.00       1.0
          13       0.00      0.00      0.00       0.0
          17       0.00      0.00      0.00       1.0
          18       0.00      0.00      0.00       0.0

    accuracy                           0.00       3.0
   macro avg       0.00      0.00      0.00       3.0
weighted avg       0.00      0.00      0.00       3.0


/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
```

```
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

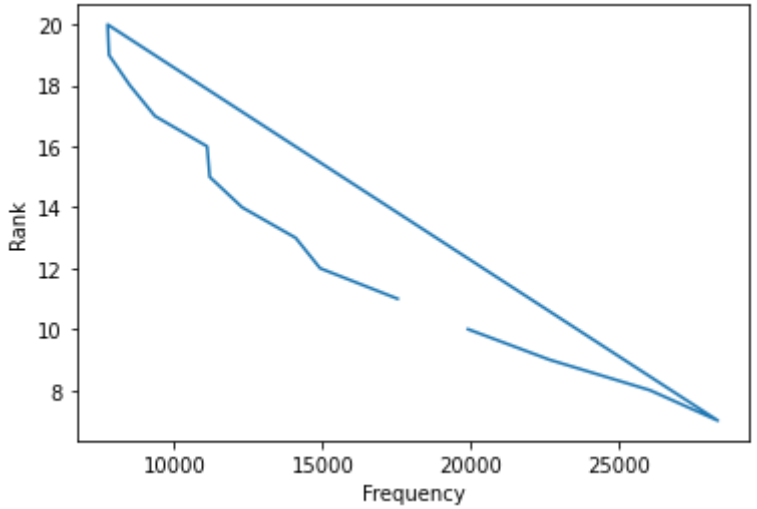
In [161]:
```
# Implementing Kernel SVM with Sklearn SVM module
# Polynomial SVM Kernel
# Importing SVC function and setting kernel as 'poly'

from sklearn.svm import SVC
svclassifier1 = SVC(kernel = 'poly', degree=2)
svclassifier1.fit(x_train, y_train)

# making predictions

y_pred1 = svclassifier1.predict(x_test)

# evaluating the model

from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, y_pred1))
print(classification_report(y_test, y_pred1))
```

```
[[0 1 0 0 0 0]
 [0 0 0 0 0 0]
 [0 0 0 1 0 0]
 [0 0 0 0 0 0]
 [0 0 0 0 0 1]
 [0 0 0 0 0 0]]
              precision    recall  f1-score   support

          10       0.00      0.00      0.00       1.0
          11       0.00      0.00      0.00       0.0
          12       0.00      0.00      0.00       1.0
          13       0.00      0.00      0.00       0.0
          17       0.00      0.00      0.00       1.0
          18       0.00      0.00      0.00       0.0

    accuracy                           0.00       3.0
   macro avg       0.00      0.00      0.00       3.0
weighted avg       0.00      0.00      0.00       3.0


/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
```

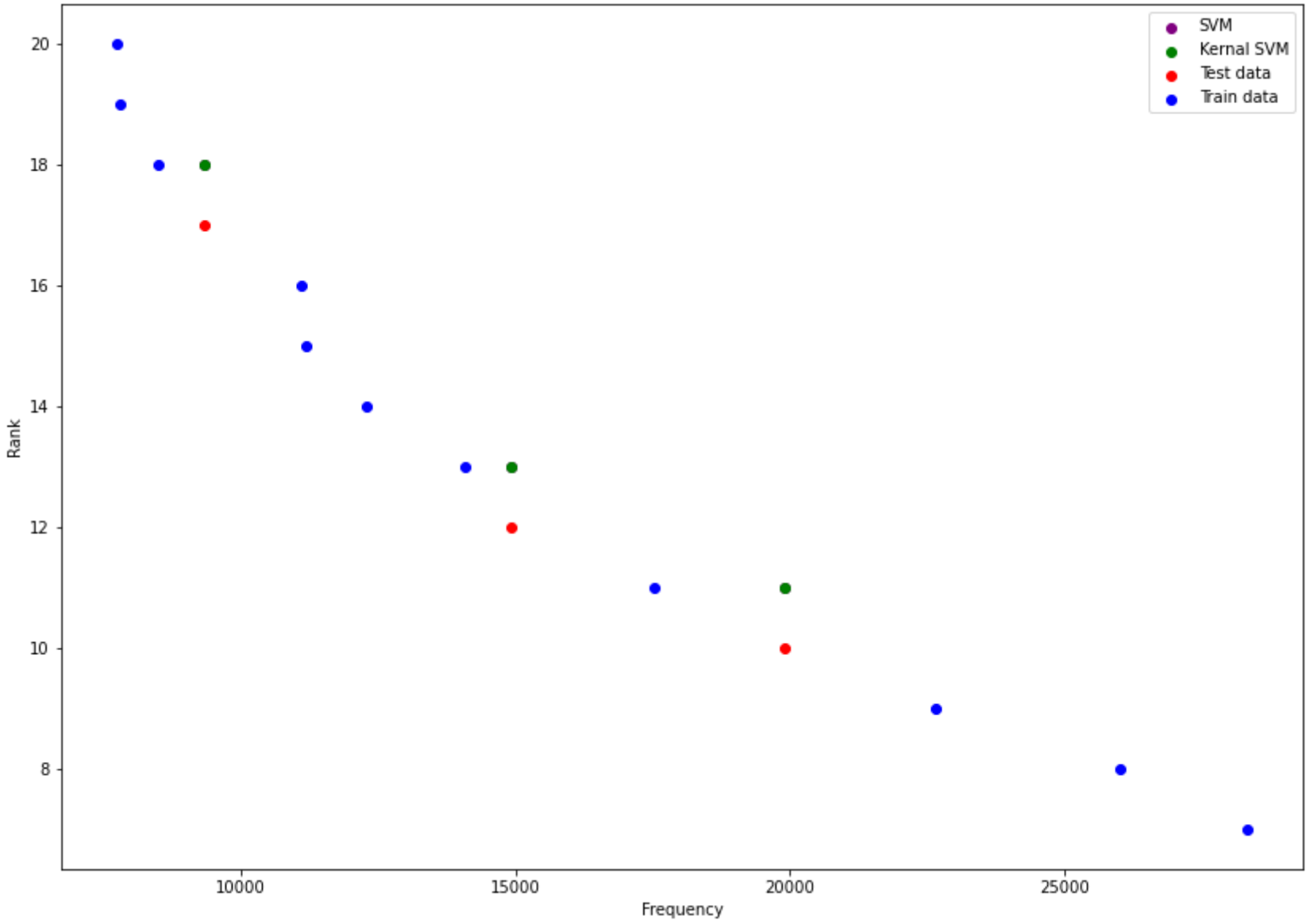
```
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicte
d samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/Users/roja/opt/anaconda3/lib/python3.9/site-packages/sklearn/metrics/_classification.py:1248: Undefin
edMetricWarning: Recall and F-score are ill-defined and being set to 0.0 in labels with no true sample
s. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Conclusion: Therefore, we learnt how to build support vector machine models with the help of the support vector classifier function. Also, we talked about kernel SVM implementation in Python and Sklearn, which is a very useful method while dealing with non-linearly separable datasets.

In [162]:
```
from matplotlib import pyplot as plt
from sklearn import svm

model = svm.SVC(kernel='poly', degree=8)
model.fit(x_train, y_train)

plt.plot(x, y)
plt.xlabel("Frequency")
plt.ylabel("Rank")
plt.show()

fig, ax = plt.subplots(figsize=(14, 10))

ax.set_xlabel('Frequency')
ax.set_ylabel('Rank')
# Plot the dataset
ax.scatter(x_test, y_pred, c = 'purple', cmap = 'winter', label="SVM")
ax.scatter(x_test, y_pred1, c = 'green', cmap = 'winter', label="Kernal SVM")

ax.scatter(x_test, y_test, c = 'red', cmap = 'winter', label="Test data")
ax.scatter(x_train, y_train, c = 'blue', cmap = 'winter', label="Train data")

ax.legend()
```



Out[162]: <matplotlib.legend.Legend at 0x7fa4a5016490>


SVM
Kernal SVM
Test data
Train data
Rank
Frequency
20
18
16
14
12
10
8
10000
15000
20000
25000

In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [ ]: