

[https://www.w3schools.com/python/python\\_ml\\_decision\\_tree.a](https://www.w3schools.com/python/python_ml_decision_tree.a)

Machine Learning Lab3: Created by Jibrael Jos, PhD

Topic: Decision Tree Explorations

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Roll No: 23122023

Date: 21 March

Submission : 21 March 2024

Python Notebook as PDF (File Name MLSVMLab23.pdf)

and Observations in MLLab2\_23.xlsx

Where 21 can be replaced with your roll number

## Questions:

### 1. Run SVM2 for cancer.csv

```
In [ ]: #importing necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

# reading csv file.
x = pd.read_csv("cancer.csv")
a = np.array(x)

y = a[:,2]
x = np.column_stack((x.col1,x.col2))

print(x.shape)
print (x),(y)

(569, 2)
[[ 122.8  1001. ]
 [ 132.9  1326. ]
 [ 130.   1203. ]
 ...
 [ 108.3   858.1 ]
 [ 140.1  1265. ]
 [  47.92  181.  ]]
```

```
Out[ ]: (None,
array([[1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
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1., 1., 1., 0., 0., 0., 1., 1., 1., 1., 1., 1., 1., 1., 1., 1.,
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0.]])
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    0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
0.,
    0., 1., 1., 1., 1., 1., 1., 0.]])

```

```

In [ ]: # import support vector classifier
from sklearn.svm import SVC
clf = SVC(kernel='linear')

# fitting
clf.fit(x, y)

```

```

Out[ ]: SVC
SVC(kernel='linear')

```

```

In [ ]: #predicting
clf.predict([[120, 990]])

```

```

Out[ ]: array([1.])

```

## 2. Run Linear and Poly

```

In [ ]: import numpy as np

def make_meshgrid(x, y, h=0.2):#0.02
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_m
    return xx, yy

def plot_contours(ax, clf, xx, yy, **params):
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    out = ax.contourf(xx, yy, Z, **params)
    return out

```

```

In [ ]: X=x
model = SVC(kernel='poly',degree=5)
clf = model.fit(X, y)
print(clf)
fig, ax = plt.subplots()

title = ('Decision surface of poly SVC ')

X0, X1 = X[:, 0], X[:, 1]
print(X0,X1)

xx, yy = make_meshgrid(X0, X1)

plot_contours(ax, clf, xx, yy, cmap=plt.cm.summer, alpha=0.1)
ax.scatter(X0, X1, c=y, cmap=plt.cm.summer, s=30, edgecolors='k')
ax.set_ylabel('Col1')
ax.set_xlabel('Col2')

```

```
ax.set_xticks(())  
ax.set_yticks(())  
ax.set_title(title)  
ax.legend()  
plt.show()
```

SVC(degree=5, kernel='poly')

```

[122.8 132.9 130. 77.58 135.1 82.57 119.6 90.2 87.5 83.97
102.7 103.6 132.4 103.7 93.6 96.73 94.74 108.1 130. 87.46
85.63 60.34 102.5 137.2 110. 116. 97.41 122.1 102.4 115.
124.8 77.93 112.8 127.9 107. 110.1 93.63 82.61 95.54 88.4
86.18 71.9 128.3 87.32 85.42 123.7 51.71 85.98 78.04 86.91
74.72 87.21 75.71 120.3 97.26 73.34 125.5 95.55 82.61 54.34
64.55 54.66 96.42 59.2 82.69 97.4 60.11 71.8 58.79 81.37
123.6 58.79 114.2 90.43 79.19 104.1 87.91 120.2 143.7 83.19
73.81 86.49 171.5 129.1 76.95 121.1 94.25 122. 79.78 95.77
94.57 100.2 84.74 86.6 100.3 132.4 77.79 62.11 74.34 94.48
88.05 43.79 77.22 63.95 67.41 87.21 75.17 79.01 152.8 72.48
62.5 82.15 97.83 68.64 55.84 76.53 58.74 98.64 105.7 114.2
73.34 121.4 166.2 94.28 86.1 88.44 87.76 123.4 99.58 130.4
79.08 101.7 106.2 102. 120.2 81.72 74.72 73.06 96.85 73.
61.24 105.1 73.66 83.74 68.26 78.11 78.99 97.84 93.97 88.12
83.51 53.27 63.78 70.87 85.31 78.27 117.4 108.4 76.84 68.69
76.1 126.3 130.7 79.85 152.1 95.5 68.77 109.3 116.1 96.22
78.85 85.84 102.5 70.21 67.49 54.42 64.6 109.3 82.01 81.29
182.1 142.7 101.2 73.53 98.92 63.76 118.6 74.68 75.27 78.83
94.37 82.02 60.73 81.15 100.4 82.53 90.63 117.4 127.5 94.49
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134.7 75.51 188.5 114.5 92.87 90.96 77.32 65.05 129.7 128.
87.88 88.59 65.12 102.6 84.55 92.51 66.62 97.45 81.35 85.26
113.4 71.76 70.79 134.4 60.21 89.79 153.5 132.5 92.55 113.4
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96.03 97.03 83.14 75.54 81.78 88.06 69.14 75. 91.22 66.85
129.5 80.43 134.7 66.86 73.59 74.23 84.07 56.36 85.69 82.71
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66.52 131.1 82.82 135.9 78.01 81.25 90.03 76.09 106.9 107.5
105.8 84.52 71.94 71.38 77.88 111.8 84.08 122.9 64.41 155.1
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109. 97.65 141.3 134.8 87.84 106.3 70.15 85.89 88.27 73.3
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65.75 55.27 102.4 144.4 78.07 89.75 88.1 83.05 70.31 75.26
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102.1 81.47 133.8 123.7 94.89 91.12 82.67 89.78 88.68 89.59
71.73 112.4 88.37 66.82 117.5 77.61 117.3 95.88 94.25 138.1
76.83 127.7 76.77 93.86 80.62 86.34 74.87 84.1 82.61 61.68
111.2 186.9 92.25 73.88 84.28 86.87 85.98 61.06 119. 76.38
61.49 76.85 96.45 77.42 70.41 82.89 92.41 88.97 73.99 109.8
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68.51 71.49 81.35 59.01 82.5 65.67 64.73 59.26 96.39 74.52
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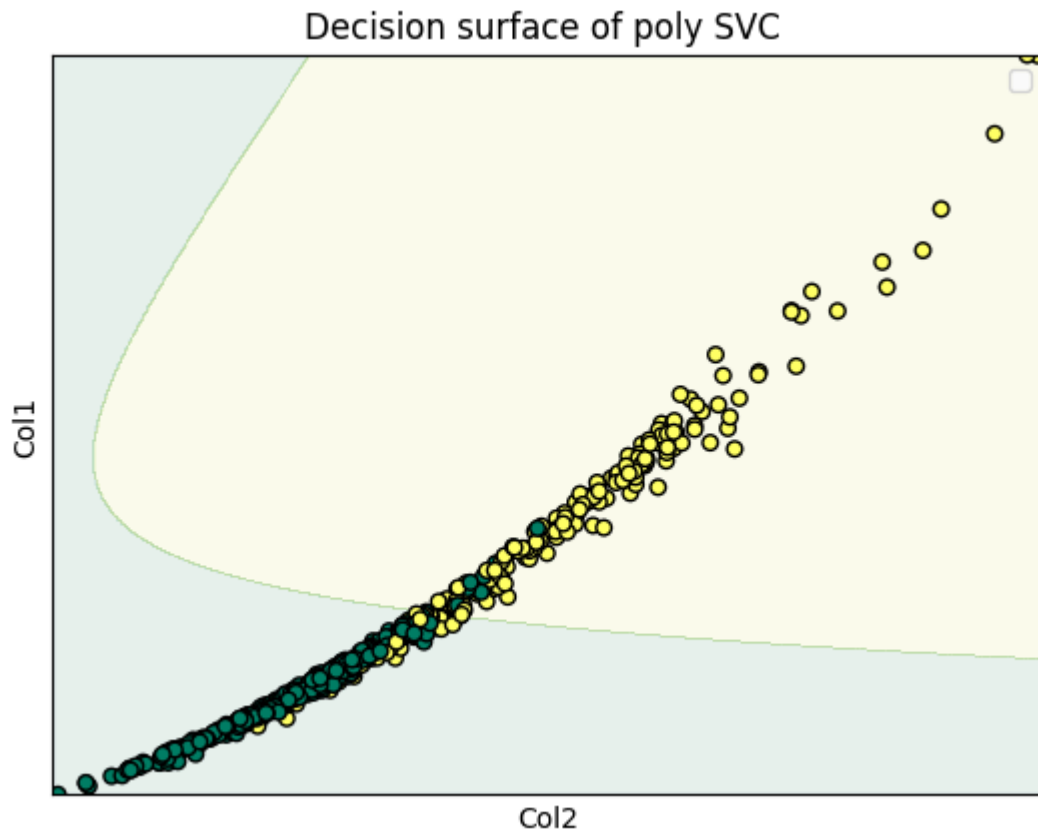
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662.7 728.2 551.7 555.1 705.6 1264. 451.1 294.5 412.6 642.5
582.7 143.5 458.7 298.3 336.1 530.2 412.5 466.7 1509. 396.5
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464.1 565.4 736.9 372.7 349.6 227.2 302.4 832.9 526.4 508.8
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609.9 507.4 288.1 477.4 671.4 516.4 588.9 1024. 1148. 642.7
461. 951.6 1685. 597.8 481.9 716.6 295.4 904.3 529.4 725.5
1290. 428. 2499. 948. 610.7 578.9 432.2 321.2 1230. 1223.
568.9 561.3 313.1 761.3 546.4 641.2 329.6 684.5 496.4 503.2
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600.4 386. 716.9 1347. 1479. 1261. 858.1 1265. 181. ]

```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



```
In [ ]: X=x
model = SVC(kernel='linear')
clf = model.fit(X, y)
print(clf)
fig, ax = plt.subplots()

title = ('Decision surface of linear SVC ')

X0, X1 = X[:, 0], X[:, 1]
print(X0,X1)

xx, yy = make_meshgrid(X0, X1)

plot_contours(ax, clf, xx, yy, cmap=plt.cm.summer, alpha=0.1)
ax.scatter(X0, X1, c=y, cmap=plt.cm.summer, s=30, edgecolors='k')
ax.set_ylabel('Col1')
ax.set_xlabel('Col2')
ax.set_xticks(())
ax.set_yticks(())
ax.set_title(title)
ax.legend()
plt.show()
```

```

SVC(kernel='linear')
[122.8 132.9 130.    77.58 135.1  82.57 119.6  90.2  87.5  83.97
 102.7 103.6 132.4 103.7  93.6  96.73 94.74 108.1 130.   87.46
 85.63 60.34 102.5 137.2 110.   116.   97.41 122.1 102.4 115.
124.8  77.93 112.8 127.9 107.   110.1  93.63 82.61 95.54 88.4
 86.18 71.9 128.3  87.32 85.42 123.7  51.71 85.98 78.04 86.91
 74.72 87.21 75.71 120.3  97.26 73.34 125.5  95.55 82.61 54.34
 64.55 54.66 96.42  59.2  82.69 97.4  60.11 71.8  58.79 81.37
123.6  58.79 114.2  90.43 79.19 104.1  87.91 120.2 143.7 83.19
 73.81 86.49 171.5 129.1  76.95 121.1  94.25 122.   79.78 95.77
 94.57 100.2  84.74  86.6 100.3 132.4  77.79 62.11 74.34 94.48
 88.05 43.79 77.22 63.95 67.41 87.21 75.17 79.01 152.8 72.48
 62.5  82.15 97.83 68.64 55.84 76.53 58.74 98.64 105.7 114.2
 73.34 121.4 166.2  94.28 86.1  88.44 87.76 123.4  99.58 130.4
 79.08 101.7 106.2 102.   120.2 81.72 74.72 73.06 96.85 73.
 61.24 105.1  73.66 83.74 68.26 78.11 78.99 97.84 93.97 88.12
 83.51 53.27 63.78 70.87 85.31 78.27 117.4 108.4 76.84 68.69
 76.1 126.3 130.7  79.85 152.1  95.5  68.77 109.3 116.1 96.22
 78.85 85.84 102.5  70.21 67.49 54.42 64.6 109.3 82.01 81.29
182.1 142.7 101.2  73.53 98.92 63.76 118.6  74.68 75.27 78.83
 94.37 82.02 60.73 81.15 100.4  82.53 90.63 117.4 127.5 94.49
 78.54 115.1 158.9  91.56 81.09 98.78 62.92 109.7  87.02 98.17
134.7  75.51 188.5 114.5  92.87 90.96 77.32 65.05 129.7 128.
 87.88 88.59 65.12 102.6  84.55 92.51 66.62 97.45 81.35 85.26
113.4  71.76 70.79 134.4  60.21 89.79 153.5 132.5  92.55 113.4
 87.38 78.61 73.93 88.54 129.1  66.72 84.13 84.95 68.01 73.87
138.9  73.28 130.7 113.   126.5 91.43 133.6 103.2 110.2 103.7
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129.5  80.43 134.7  66.86 73.59 74.23 84.07 56.36 85.69 82.71
 74.33 92.68 82.29 73.73 54.09 79.19 77.25 118.7  60.07 78.6
 66.52 131.1  82.82 135.9  78.01 81.25 90.03 76.09 106.9 107.5
105.8  84.52 71.94 71.38 77.88 111.8  84.08 122.9 64.41 155.1
 94.15 61.64 71.49 129.9  75.03 66.2  76.66 94.87 73.02 77.23
 73.7 107.1 174.2  98.   71.24 81.92 85.09 88.52 56.74 59.82
 79.42 85.24 81.87 106.6  85.48 133.8 133.7  78.31 140.9 147.2
109.   97.65 141.3 134.8  87.84 106.3  70.15 85.89 88.27 73.3
 73.16 70.67 78.75 80.64 85.79 93.97 78.78 88.37 73.38 128.9
 65.75 55.27 102.4 144.4  78.07 89.75 88.1  83.05 70.31 75.26
124.4  76.14 84.18 83.18 78.29 70.39 104.3  82.63 117.8 78.41
 72.49 70.92 59.75 97.53 96.71 76.39 59.6 102.9 80.88 70.95
 74.2  98.22 75.46 89.46 61.93 63.19 67.49 68.79 70.47 80.98
102.1  81.47 133.8 123.7  94.89 91.12 82.67 89.78 88.68 89.59
 71.73 112.4  88.37 66.82 117.5 77.61 117.3  95.88 94.25 138.1
 76.83 127.7  76.77 93.86 80.62 86.34 74.87 84.1  82.61 61.68
111.2 186.9  92.25 73.88 84.28 86.87 85.98 61.06 119.   76.38
 61.49 76.85 96.45 77.42 70.41 82.89 92.41 88.97 73.99 109.8
 78.29 88.73 87.32 87.76 102.8 82.85 94.21 128.1  75.49 107.1
 78.18 114.6 118.4  78.83 84.06 96.12 82.69 80.45 121.3 137.8
 98.73 92.33 81.25 152.1  61.49 64.12 79.47 71.25 104.7 103.8
 76.31 94.66 88.64 94.29 97.26 72.76 120.8 130.5  84.45 82.51
 59.96 165.5  71.3  88.73 63.   54.53 87.44 78.94 90.31 77.83
 75.89 75.21 87.76 134.7  70.79 137.8  93.77 76.37 47.98 48.34
 74.65 95.81 94.7  84.88 89.77 87.19 65.31 65.85 61.05 68.89
 68.51 71.49 81.35 59.01 82.5  65.67 64.73 59.26 96.39 74.52
 91.38 70.67 103.4 143.  142.  131.2 108.3 140.1 47.92] [1001.  1
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```

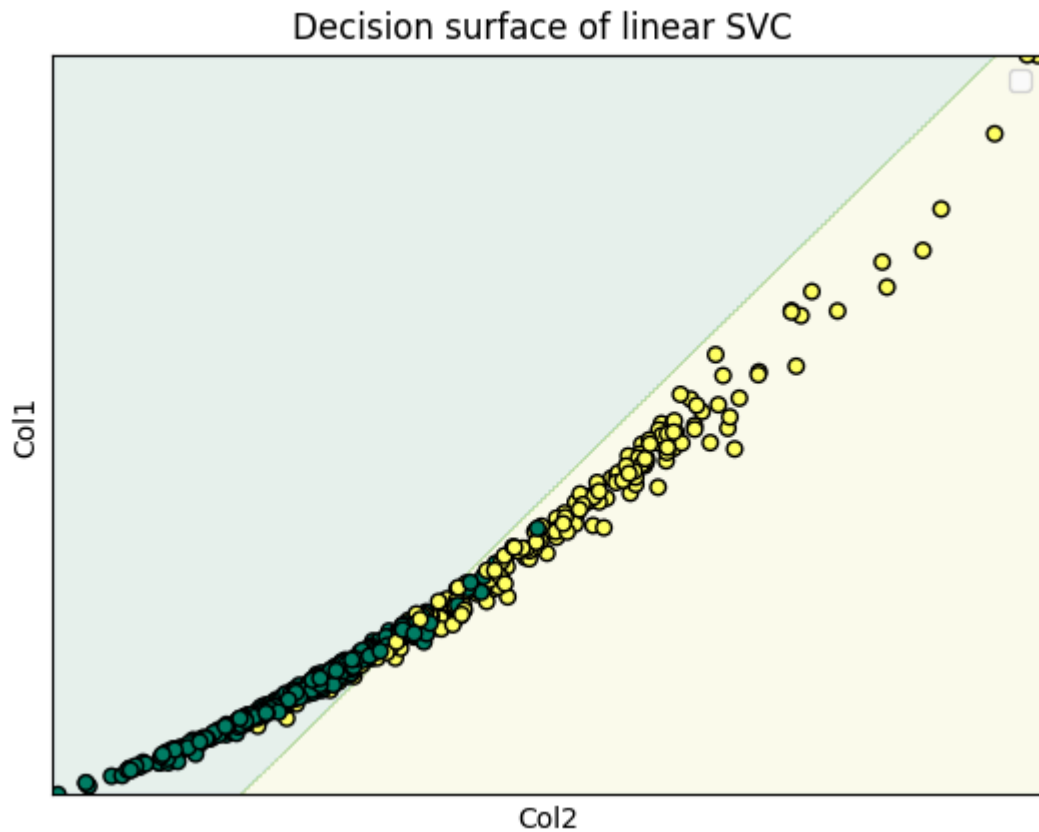


```

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427.9 571.8 437.6 1033. 712.8 409. 1152. 656.9 527.2 224.5
311.9 221.8 645.7 260.9 499. 668.3 269.4 394.1 250.5 502.5
1130. 244. 929.4 584.1 470.9 817.7 559.2 1006. 1245. 506.3
401.5 520. 1878. 1132. 443.3 1075. 648.2 1076. 466.1 651.9
662.7 728.2 551.7 555.1 705.6 1264. 451.1 294.5 412.6 642.5
582.7 143.5 458.7 298.3 336.1 530.2 412.5 466.7 1509. 396.5
290.2 480.4 629.9 334.2 230.9 438.6 245.2 682.5 782.6 982.
403.3 1077. 1761. 640.7 553.5 588.7 572.6 1138. 674.5 1192.
455.8 748.9 809.8 761.7 1075. 506.3 423.6 399.8 678.1 384.8
288.5 813. 398. 512.2 355.3 432.8 432. 689.5 640.1 585.
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2250. 1311. 766.6 402. 710.6 317.5 1041. 420.3 428.9 463.7
609.9 507.4 288.1 477.4 671.4 516.4 588.9 1024. 1148. 642.7
461. 951.6 1685. 597.8 481.9 716.6 295.4 904.3 529.4 725.5
1290. 428. 2499. 948. 610.7 578.9 432.2 321.2 1230. 1223.
568.9 561.3 313.1 761.3 546.4 641.2 329.6 684.5 496.4 503.2
895. 395.7 386.8 1319. 279.6 603.4 1670. 1306. 623.9 920.6
575.3 476.5 389.4 590. 1155. 337.7 541.6 512.2 347. 406.3
1364. 407.4 1206. 928.2 1169. 602.4 1207. 713.3 773.5 744.9
1288. 933.1 947.8 758.6 928.3 1419. 346.4 561. 512.2 344.9
632.6 388. 1491. 289.9 998.9 435.6 396.6 1102. 572.3 587.4
1138. 427.3 1145. 805.1 516.6 489. 441. 515.9 394.1 396.
651. 687.3 513.7 432.7 492.1 582.7 363.7 431.1 633.1 334.2
1217. 471.3 1247. 334.3 403.1 417.2 537.3 246.3 566.2 530.6
418.7 664.9 504.1 409.1 221.2 481.6 461.4 1027. 244.5 477.3
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793.2 514. 387.3 390. 464.4 918.6 514.3 1092. 310.8 1747.
641.2 280.5 373.9 1194. 420.3 321.6 445.3 668.7 402.7 426.7
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321.6 234.3 744.7 1407. 446.2 609.1 558.1 508.3 378.2 431.9
994. 442.7 525.2 507.6 469.1 370. 800. 514.5 991.7 466.1
399.8 373.2 268.8 693.7 719.5 433.8 271.2 803.1 495. 380.3
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371.5 928.8 585.9 340.9 990. 441.3 981.6 674.8 659.7 1384.
432. 1191. 442.5 644.2 492.9 557.2 415.1 537.9 520.2 290.9
930.9 2501. 646.1 412.7 537.3 542.9 536.9 286.3 980.5 408.8
289.1 449.9 686.9 465.4 358.9 506.9 618.4 599.4 404.9 815.8
455.3 602.9 546.3 571.1 747.2 476.7 666. 1167. 420.5 857.6
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402.9 656.4 668.6 538.4 584.8 573.2 324.9 320.8 285.7 361.6
360.5 378.4 507.9 264. 514.3 321.4 311.7 271.3 657.1 403.5
600.4 386. 716.9 1347. 1479. 1261. 858.1 1265. 181. ]

```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



```
In [ ]: X=x
model = SVC(kernel='poly',gamma='scale')
clf = model.fit(X, y)
print(clf)
fig, ax = plt.subplots()

title = ('Decision surface of linear SVC ')

X0, X1 = X[:, 0], X[:, 1]
print(X0,X1)
xx, yy = make_meshgrid(X0, X1)

plot_contours(ax, clf, xx, yy, cmap=plt.cm.summer, alpha=0.1)
ax.scatter(X0, X1, c=y, cmap=plt.cm.summer, s=30, edgecolors='k')
ax.set_ylabel('Col1')
ax.set_xlabel('Col2')
ax.set_xticks(())
ax.set_yticks(())
ax.set_title(title)
ax.legend()
plt.show()
```

```

SVC(kernel='poly')
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85.63 60.34 102.5 137.2 110. 116. 97.41 122.1 102.4 115.
124.8 77.93 112.8 127.9 107. 110.1 93.63 82.61 95.54 88.4
86.18 71.9 128.3 87.32 85.42 123.7 51.71 85.98 78.04 86.91
74.72 87.21 75.71 120.3 97.26 73.34 125.5 95.55 82.61 54.34
64.55 54.66 96.42 59.2 82.69 97.4 60.11 71.8 58.79 81.37
123.6 58.79 114.2 90.43 79.19 104.1 87.91 120.2 143.7 83.19
73.81 86.49 171.5 129.1 76.95 121.1 94.25 122. 79.78 95.77
94.57 100.2 84.74 86.6 100.3 132.4 77.79 62.11 74.34 94.48
88.05 43.79 77.22 63.95 67.41 87.21 75.17 79.01 152.8 72.48
62.5 82.15 97.83 68.64 55.84 76.53 58.74 98.64 105.7 114.2
73.34 121.4 166.2 94.28 86.1 88.44 87.76 123.4 99.58 130.4
79.08 101.7 106.2 102. 120.2 81.72 74.72 73.06 96.85 73.
61.24 105.1 73.66 83.74 68.26 78.11 78.99 97.84 93.97 88.12
83.51 53.27 63.78 70.87 85.31 78.27 117.4 108.4 76.84 68.69
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78.85 85.84 102.5 70.21 67.49 54.42 64.6 109.3 82.01 81.29
182.1 142.7 101.2 73.53 98.92 63.76 118.6 74.68 75.27 78.83
94.37 82.02 60.73 81.15 100.4 82.53 90.63 117.4 127.5 94.49
78.54 115.1 158.9 91.56 81.09 98.78 62.92 109.7 87.02 98.17
134.7 75.51 188.5 114.5 92.87 90.96 77.32 65.05 129.7 128.
87.88 88.59 65.12 102.6 84.55 92.51 66.62 97.45 81.35 85.26
113.4 71.76 70.79 134.4 60.21 89.79 153.5 132.5 92.55 113.4
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132.9 111. 114.4 100. 111.6 135.7 69.28 87.16 82.38 69.5
90.3 72.23 147.3 61.5 115.2 76.2 71.79 120.9 86.24 88.99
126.2 74.24 127.2 108.8 84.08 79.83 77.87 81.89 73.72 72.17
96.03 97.03 83.14 75.54 81.78 88.06 69.14 75. 91.22 66.85
129.5 80.43 134.7 66.86 73.59 74.23 84.07 56.36 85.69 82.71
74.33 92.68 82.29 73.73 54.09 79.19 77.25 118.7 60.07 78.6
66.52 131.1 82.82 135.9 78.01 81.25 90.03 76.09 106.9 107.5
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75.89 75.21 87.76 134.7 70.79 137.8 93.77 76.37 47.98 48.34
74.65 95.81 94.7 84.88 89.77 87.19 65.31 65.85 61.05 68.89
68.51 71.49 81.35 59.01 82.5 65.67 64.73 59.26 96.39 74.52
91.38 70.67 103.4 143. 142. 131.2 108.3 140.1 47.92] [1001. 1
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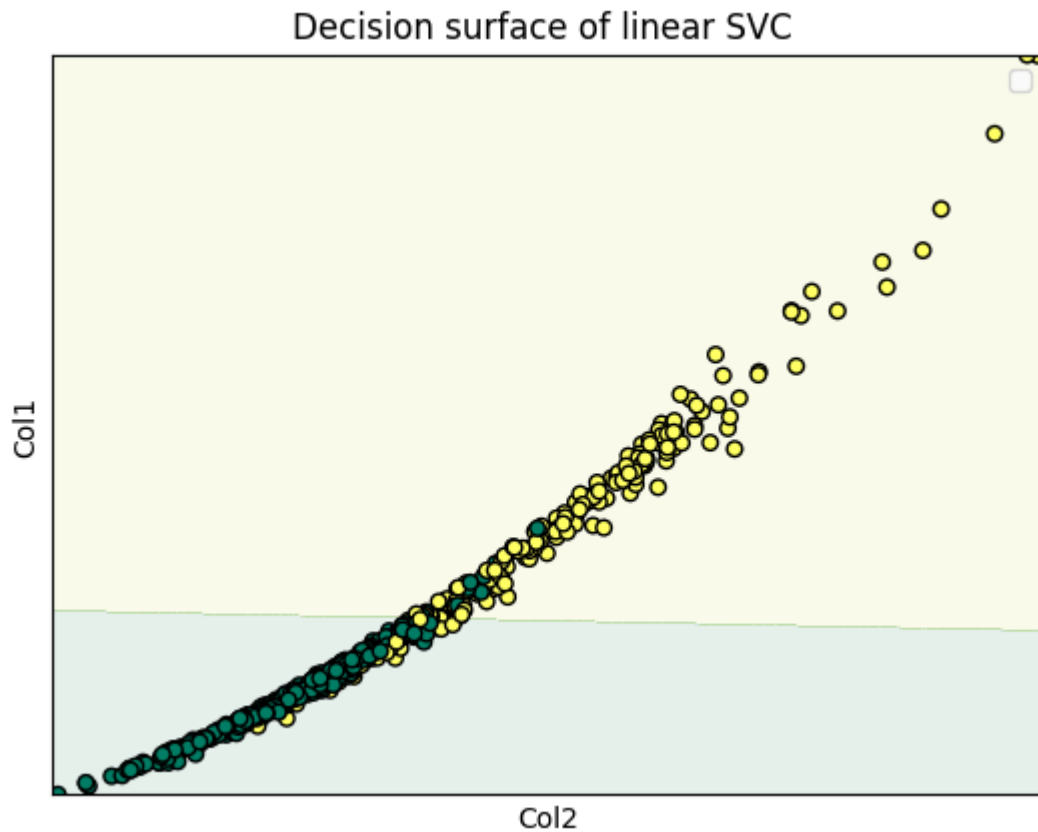
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563. 371.1 1104. 545.2 531.5 1076. 201.9 534.6 449.3 561.
427.9 571.8 437.6 1033. 712.8 409. 1152. 656.9 527.2 224.5
311.9 221.8 645.7 260.9 499. 668.3 269.4 394.1 250.5 502.5
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582.7 143.5 458.7 298.3 336.1 530.2 412.5 466.7 1509. 396.5
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419.8 1157. 1214. 464.5 1686. 690.2 357.6 886.3 984.6 685.9
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2250. 1311. 766.6 402. 710.6 317.5 1041. 420.3 428.9 463.7
609.9 507.4 288.1 477.4 671.4 516.4 588.9 1024. 1148. 642.7
461. 951.6 1685. 597.8 481.9 716.6 295.4 904.3 529.4 725.5
1290. 428. 2499. 948. 610.7 578.9 432.2 321.2 1230. 1223.
568.9 561.3 313.1 761.3 546.4 641.2 329.6 684.5 496.4 503.2
895. 395.7 386.8 1319. 279.6 603.4 1670. 1306. 623.9 920.6
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1364. 407.4 1206. 928.2 1169. 602.4 1207. 713.3 773.5 744.9
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632.6 388. 1491. 289.9 998.9 435.6 396.6 1102. 572.3 587.4
1138. 427.3 1145. 805.1 516.6 489. 441. 515.9 394.1 396.
651. 687.3 513.7 432.7 492.1 582.7 363.7 431.1 633.1 334.2
1217. 471.3 1247. 334.3 403.1 417.2 537.3 246.3 566.2 530.6
418.7 664.9 504.1 409.1 221.2 481.6 461.4 1027. 244.5 477.3
324.2 1274. 504.8 1264. 457.9 489.9 616.5 446. 813.7 826.8
793.2 514. 387.3 390. 464.4 918.6 514.3 1092. 310.8 1747.
641.2 280.5 373.9 1194. 420.3 321.6 445.3 668.7 402.7 426.7
421. 758.6 2010. 716.6 384.6 485.8 512. 593.7 241. 278.6
491.9 546.1 496.6 838.1 552.4 1293. 1234. 458.4 1546. 1482.
840.4 711.8 1386. 1335. 579.1 788.5 338.3 562.1 580.6 361.6
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321.6 234.3 744.7 1407. 446.2 609.1 558.1 508.3 378.2 431.9
994. 442.7 525.2 507.6 469.1 370. 800. 514.5 991.7 466.1
399.8 373.2 268.8 693.7 719.5 433.8 271.2 803.1 495. 380.3
409.7 656.1 408.2 575.3 289.7 307.3 333.6 359.9 381.1 501.3
685. 467.8 1250. 1110. 673.7 599.5 509.2 611.2 592.6 606.5
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466.5 992.1 1007. 477.3 538.7 680.9 485.6 480.1 1068. 1320.
689.4 595.9 476.3 1682. 248.7 272.5 453.1 366.5 819.8 731.3
426. 680.7 556.7 658.8 701.9 391.2 1052. 1214. 493.1 493.8
257.8 1841. 388.1 571. 293.2 221.3 551.1 468.5 594.2 445.2
422.9 416.2 575.5 1299. 365.6 1308. 629.8 406.4 178.8 170.4
402.9 656.4 668.6 538.4 584.8 573.2 324.9 320.8 285.7 361.6
360.5 378.4 507.9 264. 514.3 321.4 311.7 271.3 657.1 403.5
600.4 386. 716.9 1347. 1479. 1261. 858.1 1265. 181. ]

```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



```
In [ ]: X=x
model = SVC(kernel='poly',tol=1,shrinking=True,probability=True)
clf = model.fit(X, y)
print(clf)
fig, ax = plt.subplots()

title = ('Decision surface of linear SVC ')

X0, X1 = X[:, 0], X[:, 1]
print(X0,X1)
xx, yy = make_meshgrid(X0, X1)

plot_contours(ax, clf, xx, yy, cmap=plt.cm.summer, alpha=0.1)
ax.scatter(X0, X1, c=y, cmap=plt.cm.summer, s=30, edgecolors='k')
ax.set_ylabel('Col1')
ax.set_xlabel('Col2')
ax.set_xticks(())
ax.set_yticks(())
ax.set_title(title)
ax.legend()
plt.show()
```

```

SVC(kernel='poly', probability=True, tol=1)
[122.8 132.9 130.    77.58 135.1  82.57 119.6  90.2  87.5  83.97
 102.7 103.6 132.4 103.7  93.6  96.73 94.74 108.1 130.    87.46
 85.63 60.34 102.5 137.2 110.    116.    97.41 122.1 102.4 115.
 124.8 77.93 112.8 127.9 107.    110.1  93.63 82.61 95.54 88.4
 86.18 71.9 128.3  87.32 85.42 123.7  51.71 85.98 78.04 86.91
 74.72 87.21 75.71 120.3  97.26 73.34 125.5  95.55 82.61 54.34
 64.55 54.66 96.42  59.2  82.69 97.4  60.11 71.8  58.79 81.37
 123.6 58.79 114.2  90.43 79.19 104.1  87.91 120.2 143.7 83.19
 73.81 86.49 171.5 129.1  76.95 121.1  94.25 122.    79.78 95.77
 94.57 100.2  84.74  86.6 100.3 132.4  77.79 62.11 74.34 94.48
 88.05 43.79 77.22 63.95 67.41 87.21 75.17 79.01 152.8 72.48
 62.5  82.15 97.83 68.64 55.84 76.53 58.74 98.64 105.7 114.2
 73.34 121.4 166.2  94.28 86.1  88.44 87.76 123.4  99.58 130.4
 79.08 101.7 106.2 102.    120.2 81.72 74.72 73.06 96.85 73.
 61.24 105.1  73.66 83.74 68.26 78.11 78.99 97.84 93.97 88.12
 83.51 53.27 63.78 70.87 85.31 78.27 117.4 108.4 76.84 68.69
 76.1 126.3 130.7  79.85 152.1  95.5  68.77 109.3 116.1 96.22
 78.85 85.84 102.5  70.21 67.49 54.42 64.6 109.3 82.01 81.29
 182.1 142.7 101.2  73.53 98.92 63.76 118.6  74.68 75.27 78.83
 94.37 82.02 60.73 81.15 100.4  82.53 90.63 117.4 127.5 94.49
 78.54 115.1 158.9  91.56 81.09 98.78 62.92 109.7  87.02 98.17
 134.7 75.51 188.5 114.5  92.87 90.96 77.32 65.05 129.7 128.
 87.88 88.59 65.12 102.6  84.55 92.51 66.62 97.45 81.35 85.26
 113.4 71.76 70.79 134.4  60.21 89.79 153.5 132.5  92.55 113.4
 87.38 78.61 73.93 88.54 129.1  66.72 84.13 84.95 68.01 73.87
 138.9 73.28 130.7 113.    126.5 91.43 133.6 103.2 110.2 103.7
 132.9 111.    114.4 100.    111.6 135.7  69.28 87.16 82.38 69.5
 90.3  72.23 147.3  61.5 115.2  76.2  71.79 120.9 86.24 88.99
 126.2 74.24 127.2 108.8  84.08 79.83 77.87 81.89 73.72 72.17
 96.03 97.03 83.14 75.54 81.78 88.06 69.14 75.    91.22 66.85
 129.5 80.43 134.7  66.86 73.59 74.23 84.07 56.36 85.69 82.71
 74.33 92.68 82.29 73.73 54.09 79.19 77.25 118.7  60.07 78.6
 66.52 131.1  82.82 135.9  78.01 81.25 90.03 76.09 106.9 107.5
 105.8 84.52 71.94 71.38 77.88 111.8  84.08 122.9 64.41 155.1
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 73.7 107.1 174.2  98.    71.24 81.92 85.09 88.52 56.74 59.82
 79.42 85.24 81.87 106.6  85.48 133.8 133.7  78.31 140.9 147.2
 109.    97.65 141.3 134.8  87.84 106.3  70.15 85.89 88.27 73.3
 73.16 70.67 78.75 80.64 85.79 93.97 78.78 88.37 73.38 128.9
 65.75 55.27 102.4 144.4  78.07 89.75 88.1  83.05 70.31 75.26
 124.4 76.14 84.18 83.18 78.29 70.39 104.3  82.63 117.8 78.41
 72.49 70.92 59.75 97.53 96.71 76.39 59.6 102.9 80.88 70.95
 74.2  98.22 75.46 89.46 61.93 63.19 67.49 68.79 70.47 80.98
 102.1 81.47 133.8 123.7  94.89 91.12 82.67 89.78 88.68 89.59
 71.73 112.4  88.37 66.82 117.5  77.61 117.3  95.88 94.25 138.1
 76.83 127.7  76.77 93.86 80.62 86.34 74.87 84.1  82.61 61.68
 111.2 186.9  92.25 73.88 84.28 86.87 85.98 61.06 119.    76.38
 61.49 76.85 96.45 77.42 70.41 82.89 92.41 88.97 73.99 109.8
 78.29 88.73 87.32 87.76 102.8  82.85 94.21 128.1  75.49 107.1
 78.18 114.6 118.4  78.83 84.06 96.12 82.69 80.45 121.3 137.8
 98.73 92.33 81.25 152.1  61.49 64.12 79.47 71.25 104.7 103.8
 76.31 94.66 88.64 94.29 97.26 72.76 120.8 130.5  84.45 82.51
 59.96 165.5  71.3  88.73 63.    54.53 87.44 78.94 90.31 77.83
 75.89 75.21 87.76 134.7  70.79 137.8  93.77 76.37 47.98 48.34
 74.65 95.81 94.7  84.88 89.77 87.19 65.31 65.85 61.05 68.89
 68.51 71.49 81.35 59.01 82.5  65.67 64.73 59.26 96.39 74.52
 91.38 70.67 103.4 143.    142.    131.2 108.3 140.1 47.92] [1001.  1
 326. 1203. 386.1 1297. 477.1 1040. 577.9 519.8 475.9
 797.8 781. 1123. 782.7 578.3 658.8 684.5 798.8 1260. 566.3

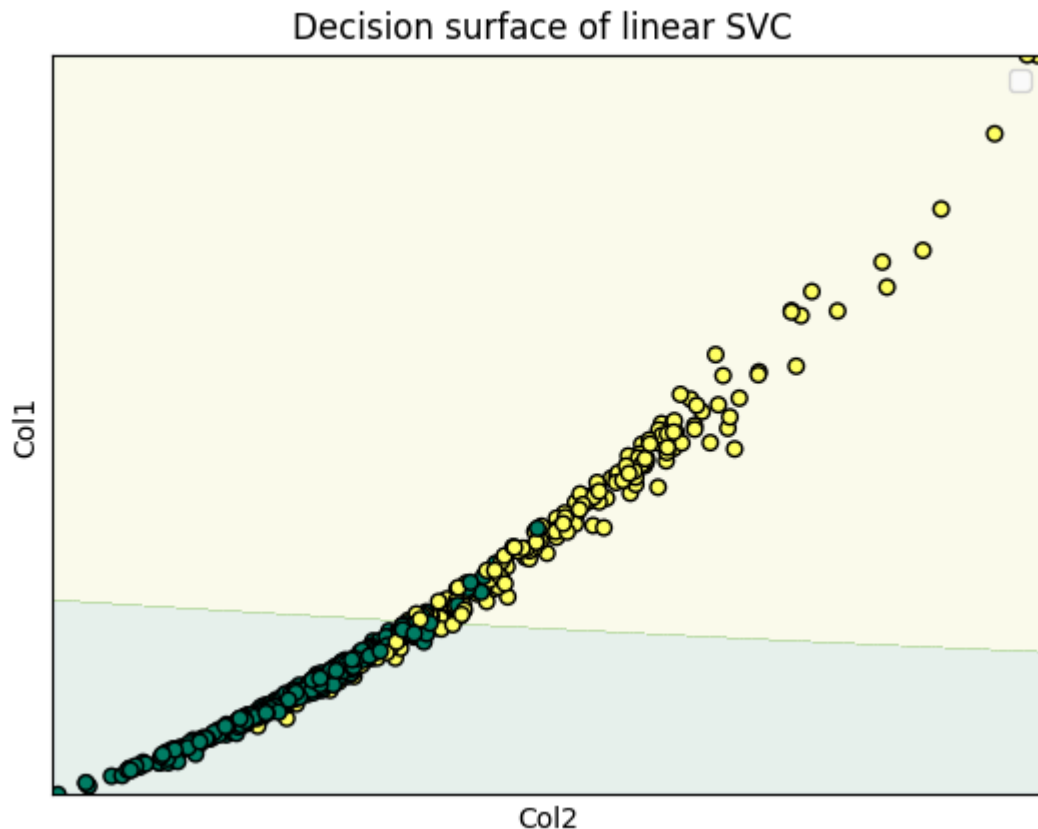
```

```

520. 273.9 704.4 1404. 904.6 912.7 644.8 1094. 732.4 955.1
1088. 440.6 899.3 1162. 807.2 869.5 633. 523.8 698.8 559.2
563. 371.1 1104. 545.2 531.5 1076. 201.9 534.6 449.3 561.
427.9 571.8 437.6 1033. 712.8 409. 1152. 656.9 527.2 224.5
311.9 221.8 645.7 260.9 499. 668.3 269.4 394.1 250.5 502.5
1130. 244. 929.4 584.1 470.9 817.7 559.2 1006. 1245. 506.3
401.5 520. 1878. 1132. 443.3 1075. 648.2 1076. 466.1 651.9
662.7 728.2 551.7 555.1 705.6 1264. 451.1 294.5 412.6 642.5
582.7 143.5 458.7 298.3 336.1 530.2 412.5 466.7 1509. 396.5
290.2 480.4 629.9 334.2 230.9 438.6 245.2 682.5 782.6 982.
403.3 1077. 1761. 640.7 553.5 588.7 572.6 1138. 674.5 1192.
455.8 748.9 809.8 761.7 1075. 506.3 423.6 399.8 678.1 384.8
288.5 813. 398. 512.2 355.3 432.8 432. 689.5 640.1 585.
519.4 203.9 300.2 381.9 538.9 460.3 963.7 880.2 448.6 366.8
419.8 1157. 1214. 464.5 1686. 690.2 357.6 886.3 984.6 685.9
464.1 565.4 736.9 372.7 349.6 227.2 302.4 832.9 526.4 508.8
2250. 1311. 766.6 402. 710.6 317.5 1041. 420.3 428.9 463.7
609.9 507.4 288.1 477.4 671.4 516.4 588.9 1024. 1148. 642.7
461. 951.6 1685. 597.8 481.9 716.6 295.4 904.3 529.4 725.5
1290. 428. 2499. 948. 610.7 578.9 432.2 321.2 1230. 1223.
568.9 561.3 313.1 761.3 546.4 641.2 329.6 684.5 496.4 503.2
895. 395.7 386.8 1319. 279.6 603.4 1670. 1306. 623.9 920.6
575.3 476.5 389.4 590. 1155. 337.7 541.6 512.2 347. 406.3
1364. 407.4 1206. 928.2 1169. 602.4 1207. 713.3 773.5 744.9
1288. 933.1 947.8 758.6 928.3 1419. 346.4 561. 512.2 344.9
632.6 388. 1491. 289.9 998.9 435.6 396.6 1102. 572.3 587.4
1138. 427.3 1145. 805.1 516.6 489. 441. 515.9 394.1 396.
651. 687.3 513.7 432.7 492.1 582.7 363.7 431.1 633.1 334.2
1217. 471.3 1247. 334.3 403.1 417.2 537.3 246.3 566.2 530.6
418.7 664.9 504.1 409.1 221.2 481.6 461.4 1027. 244.5 477.3
324.2 1274. 504.8 1264. 457.9 489.9 616.5 446. 813.7 826.8
793.2 514. 387.3 390. 464.4 918.6 514.3 1092. 310.8 1747.
641.2 280.5 373.9 1194. 420.3 321.6 445.3 668.7 402.7 426.7
421. 758.6 2010. 716.6 384.6 485.8 512. 593.7 241. 278.6
491.9 546.1 496.6 838.1 552.4 1293. 1234. 458.4 1546. 1482.
840.4 711.8 1386. 1335. 579.1 788.5 338.3 562.1 580.6 361.6
386.3 372.7 447.8 462.9 541.8 664.7 462. 596.6 392. 1174.
321.6 234.3 744.7 1407. 446.2 609.1 558.1 508.3 378.2 431.9
994. 442.7 525.2 507.6 469.1 370. 800. 514.5 991.7 466.1
399.8 373.2 268.8 693.7 719.5 433.8 271.2 803.1 495. 380.3
409.7 656.1 408.2 575.3 289.7 307.3 333.6 359.9 381.1 501.3
685. 467.8 1250. 1110. 673.7 599.5 509.2 611.2 592.6 606.5
371.5 928.8 585.9 340.9 990. 441.3 981.6 674.8 659.7 1384.
432. 1191. 442.5 644.2 492.9 557.2 415.1 537.9 520.2 290.9
930.9 2501. 646.1 412.7 537.3 542.9 536.9 286.3 980.5 408.8
289.1 449.9 686.9 465.4 358.9 506.9 618.4 599.4 404.9 815.8
455.3 602.9 546.3 571.1 747.2 476.7 666. 1167. 420.5 857.6
466.5 992.1 1007. 477.3 538.7 680.9 485.6 480.1 1068. 1320.
689.4 595.9 476.3 1682. 248.7 272.5 453.1 366.5 819.8 731.3
426. 680.7 556.7 658.8 701.9 391.2 1052. 1214. 493.1 493.8
257.8 1841. 388.1 571. 293.2 221.3 551.1 468.5 594.2 445.2
422.9 416.2 575.5 1299. 365.6 1308. 629.8 406.4 178.8 170.4
402.9 656.4 668.6 538.4 584.8 573.2 324.9 320.8 285.7 361.6
360.5 378.4 507.9 264. 514.3 321.4 311.7 271.3 657.1 403.5
600.4 386. 716.9 1347. 1479. 1261. 858.1 1265. 181. ]

```

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.



### 3. Check accuracy in terms of percentage

if possible try train test split to get training accuracy and testing accuracy

```
In [ ]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
df = pd.read_csv('cancer.csv')
x = df.drop('diagnosis', axis=1)
y = df['diagnosis']
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2,
clf = SVC(kernel='linear')
clf.fit(X_train, y_train)

y_train_pred = clf.predict(X_train)
y_test_pred = clf.predict(X_test)

train_accuracy = accuracy_score(y_train, y_train_pred) * 100
test_accuracy = accuracy_score(y_test, y_test_pred) * 100

print("Accuracy for training data : ", train_accuracy)
print("Accuracy for testing data : ", test_accuracy)
```

Accuracy for training data : 89.23076923076924

Accuracy for testing data : 88.59649122807018

### 5. Check SVM with Data we used in Decision Tree



```
In [ ]: import matplotlib.pyplot as plt

df = pd.read_csv("dataTree1.csv")

d = {'UK': 0, 'USA': 1, 'N': 2}
df['Nationality'] = df['Nationality'].map(d)
d = {'YES': 1, 'NO': 0}
df['Go'] = df['Go'].map(d)

features = ['Age', 'Experience', 'Rank', 'Nationality']

features = ['Experience', 'Rank']
print(features)
X1a = df[features]
y = df['Go']

model = SVC()
clf = model.fit(X1a, y)

features = ['Experience', 'Rank']
print(features)
X = df[features]

['Experience', 'Rank']
['Experience', 'Rank']
```

## 5. Check SVM with Data we used in Decision Tree

```
In [ ]: import pandas as pd
import numpy as np
df = pd.read_csv('dataTree1.csv')
go = {'NO': 0, 'YES': 1}
df['Go'] = df['Go'].map(go)
nationality = {'UK': 0, 'USA': 1, 'N': 2}
df['Nationality'] = df['Nationality'].map(nationality)
month = {'Jan': 0, 'April': 1, 'May': 2, 'June': 3, 'July': 4, 'Sep': 5}
df['Month'] = df['Month'].map(month)
arr = np.array(df)
y = arr[:, 4]
x = np.column_stack((df.Age, df.Experience, df.Rank, df.Nationality))
```

```
In [ ]: import numpy as np

def make_meshgrid(x, y, h=.02):
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    return xx, yy

def plot_contours(ax, clf, xx, yy, **params):
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    out = ax.contourf(xx, yy, Z, **params)
    return out

model = SVC(kernel='linear')
clf = model.fit(X1a, y)
print(clf)
fig, ax = plt.subplots()
```

```

title = ('Decision surface of linear SVC ')

X0, X1 = X.iloc[:, 0], X.iloc[:, 1]
xx, yy = make_meshgrid(X0, X1)

plot_contours(ax, clf, xx, yy, cmap=plt.cm.summer, alpha=0.1)
ax.scatter(X0, X1, c=y, cmap=plt.cm.summer, s=30, edgecolors='k')
ax.set_ylabel('Rank')
ax.set_xlabel('Experience')
ax.set_xticks(())
ax.set_yticks(())
ax.set_title(title)
ax.legend()
plt.show()

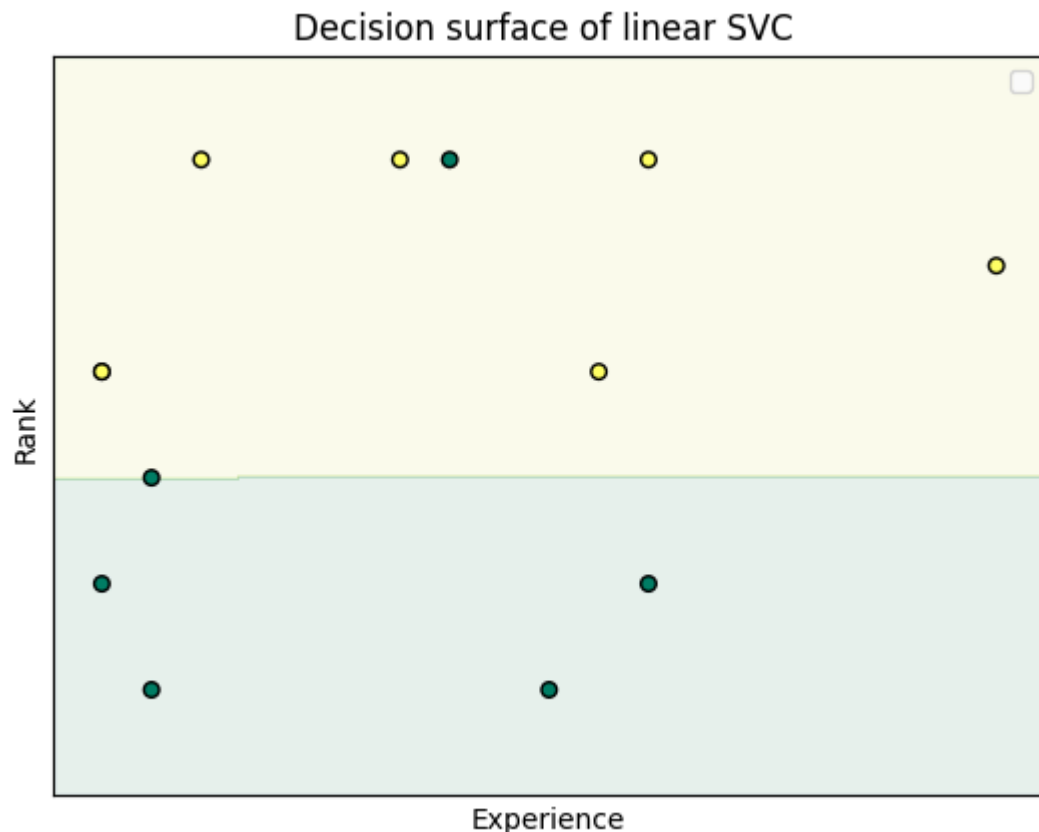
```

/Library/Frameworks/Python.framework/Versions/3.11/lib/python3.11/site-packages/sklearn/base.py:465: UserWarning: X does not have valid feature names, but SVC was fitted with feature names

warnings.warn(

No artists with labels found to put in legend. Note that artists whose label start with an underscore are ignored when legend() is called with no argument.

SVC(kernel='linear')



6. Run the Decision Tree for Cancer ALL data with 30 columns for X and Diagnosis column for y.(Please remove ID column)

```

In [ ]: df = pd.read_excel("cancerAll.xlsx")
df = df.drop("ID",axis=1)
x=['radius', 'texture', 'perimeter', 'area', 's', 'c',
   'concavity', 'cp', 'sym', 'fd', 'radius.1', 'texture.1', 'perimete
   'area.1', 's.1', 'c.1', 'concavity.1', 'cp.1', 'sym.1', 'fd.1',
   'radius.2', 'texture.2', 'perimeter.2', 'area.2', 's.2', 'c.2',
   'concavity.2', 'cp.2', 'sym.2', 'fd.2']

```

```
X = df[x]
Y = df["diagnosis"]

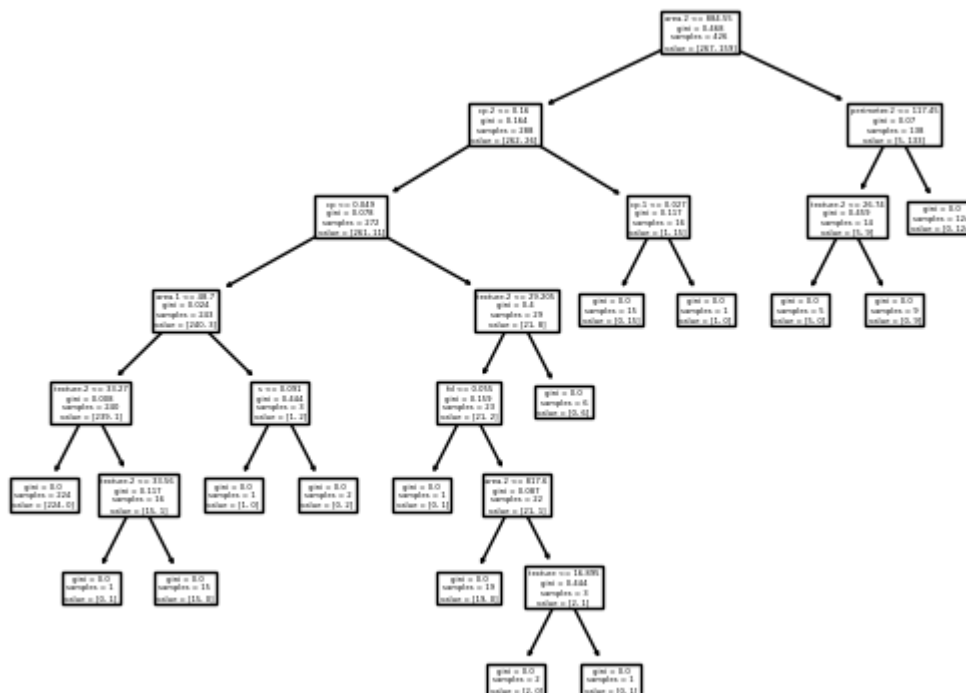
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from sklearn.tree import export_graphviz
from graphviz import Source
x_train,x_test,y_train,y_test = train_test_split(X,Y,random_state=3)
model = DecisionTreeClassifier(criterion="gini",splitter="best")
model = model.fit(x_train,y_train)
y_pred = model.predict(x_test)
accuracy = accuracy_score(y_test,y_pred)*100
print(accuracy)
tree.plot_tree(model, feature_names=x)
```

93.7062937062937

```

Out[ ]: [Text(0.7083333333333334, 0.9375, 'area.2 <= 884.55\ngini = 0.468\nsamples = 426\nvalue = [267, 159]'),
Text(0.5119047619047619, 0.8125, 'cp.2 <= 0.16\ngini = 0.164\nsamples = 288\nvalue = [262, 26]'),
Text(0.35714285714285715, 0.6875, 'cp <= 0.049\ngini = 0.078\nsamples = 272\nvalue = [261, 11]'),
Text(0.19047619047619047, 0.5625, 'area.1 <= 48.7\ngini = 0.024\nsamples = 243\nvalue = [240, 3]'),
Text(0.09523809523809523, 0.4375, 'texture.2 <= 33.27\ngini = 0.008\nsamples = 240\nvalue = [239, 1]'),
Text(0.047619047619047616, 0.3125, 'gini = 0.0\nsamples = 224\nvalue = [224, 0]'),
Text(0.14285714285714285, 0.3125, 'texture.2 <= 33.56\ngini = 0.117\nsamples = 16\nvalue = [15, 1]'),
Text(0.09523809523809523, 0.1875, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.19047619047619047, 0.1875, 'gini = 0.0\nsamples = 15\nvalue = [15, 0]'),
Text(0.2857142857142857, 0.4375, 's <= 0.091\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
Text(0.23809523809523808, 0.3125, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(0.3333333333333333, 0.3125, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(0.5238095238095238, 0.5625, 'texture.2 <= 29.205\ngini = 0.4\nsamples = 29\nvalue = [21, 8]'),
Text(0.47619047619047616, 0.4375, 'fd <= 0.055\ngini = 0.159\nsamples = 23\nvalue = [21, 2]'),
Text(0.42857142857142855, 0.3125, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.5238095238095238, 0.3125, 'area.2 <= 817.6\ngini = 0.087\nsamples = 22\nvalue = [21, 1]'),
Text(0.47619047619047616, 0.1875, 'gini = 0.0\nsamples = 19\nvalue = [19, 0]'),
Text(0.5714285714285714, 0.1875, 'texture <= 16.895\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(0.5238095238095238, 0.0625, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(0.6190476190476191, 0.0625, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.5714285714285714, 0.4375, 'gini = 0.0\nsamples = 6\nvalue = [0, 6]'),
Text(0.6666666666666666, 0.6875, 'cp.1 <= 0.027\ngini = 0.117\nsamples = 16\nvalue = [1, 15]'),
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Text(0.7142857142857143, 0.5625, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(0.9047619047619048, 0.8125, 'perimeter.2 <= 117.45\ngini = 0.07\nsamples = 138\nvalue = [5, 133]'),
Text(0.8571428571428571, 0.6875, 'texture.2 <= 26.74\ngini = 0.459\nsamples = 14\nvalue = [5, 9]'),
Text(0.8095238095238095, 0.5625, 'gini = 0.0\nsamples = 5\nvalue = [5, 0]'),
Text(0.9047619047619048, 0.5625, 'gini = 0.0\nsamples = 9\nvalue = [0, 9]'),
Text(0.9523809523809523, 0.6875, 'gini = 0.0\nsamples = 124\nvalue = [0, 124]')]

```

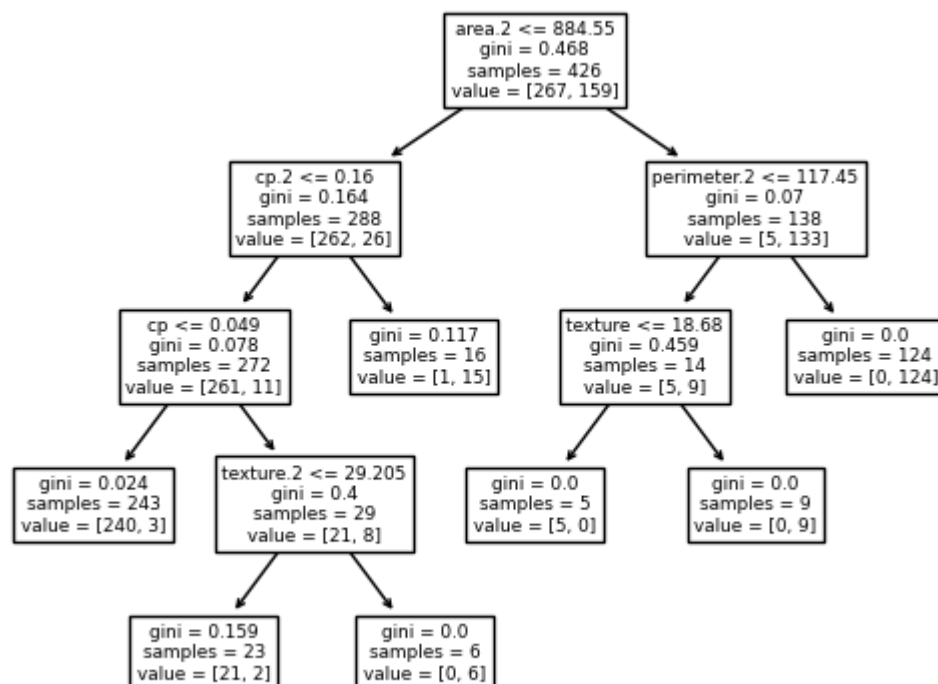


94.4055944055944

```

Out[ ]: [Text(0.5555555555555556, 0.9, 'area.2 <= 884.55\ngini = 0.468\nsamples
= 426\nvalue = [267, 159]'),
Text(0.3333333333333333, 0.7, 'cp.2 <= 0.16\ngini = 0.164\nsamples = 28
8\nvalue = [262, 26]'),
Text(0.2222222222222222, 0.5, 'cp <= 0.049\ngini = 0.078\nsamples = 272
\nvalue = [261, 11]'),
Text(0.1111111111111111, 0.3, 'gini = 0.024\nsamples = 243\nvalue = [24
0, 3]'),
Text(0.3333333333333333, 0.3, 'texture.2 <= 29.205\ngini = 0.4\nsamples
= 29\nvalue = [21, 8]'),
Text(0.2222222222222222, 0.1, 'gini = 0.159\nsamples = 23\nvalue = [21,
2]'),
Text(0.4444444444444444, 0.1, 'gini = 0.0\nsamples = 6\nvalue = [0,
6]'),
Text(0.4444444444444444, 0.5, 'gini = 0.117\nsamples = 16\nvalue = [1,
15]'),
Text(0.7777777777777778, 0.7, 'perimeter.2 <= 117.45\ngini = 0.07\nnsamp
les = 138\nvalue = [5, 133]'),
Text(0.6666666666666666, 0.5, 'texture <= 18.68\ngini = 0.459\nsamples
= 14\nvalue = [5, 9]'),
Text(0.5555555555555556, 0.3, 'gini = 0.0\nsamples = 5\nvalue = [5,
0]'),
Text(0.7777777777777778, 0.3, 'gini = 0.0\nsamples = 9\nvalue = [0,
9]'),
Text(0.8888888888888888, 0.5, 'gini = 0.0\nsamples = 124\nvalue = [0, 1
24]')]

```



```

In [ ]: from sklearn.svm import SVC
x = ['area.2', 'cp.2', 'cp', 'texture.2', 'perimeter.2', 'texture']
X = df[x]
model = SVC(kernel='linear')
clf = model.fit(X, Y)
print(clf)
y_pred = clf.predict(X)
accuracy = accuracy_score(Y, y_pred)*100
print("Accuracy of the model: ", accuracy)

```

```
SVC(kernel='linear')  
Accuraccy of the model: 94.5518453427065
```

In [ ]: