Importing Libraries

```
import pandas as pd
from sklearn.datasets import load_breast_cancer,load_iris,load_wine
from sklearn.preprocessing import StandardScaler
```

Loading Datasets

```
bc_data = load_breast_cancer()
i_data = load_iris()
w_data = load_wine()
```

```
bcdf = pd.DataFrame(bc_data.data,columns=bc_data.feature_names)
bcdf["target"] = bc_data.target
idf = pd.DataFrame(i_data.data,columns=i_data.feature_names)
idf["target"] = i_data.target
wdf = pd.DataFrame(w_data.data,columns=w_data.feature_names)
wdf["target"] = w_data.target
```

Breast Cancer Data

```
bcdf
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	wor textu
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	...	17.
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	...	23.
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	...	25.
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	...	26.
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	...	16.
...	...	...	...	...	...	...	...	...	...	...	...	
564	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	...	26.
565	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	...	38.
566	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	...	34.
567	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	...	39.
568	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	...	30.

569 rows × 31 columns

```
print(bcdf.info())
bcdf.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 31 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   mean radius              569 non-null    float64
 1   mean texture             569 non-null    float64
 2   mean perimeter           569 non-null    float64
 3   mean area                569 non-null    float64
 4   mean smoothness          569 non-null    float64
 5   mean compactness         569 non-null    float64
 6   mean concavity           569 non-null    float64
 7   mean concave points      569 non-null    float64
 8   mean symmetry            569 non-null    float64
 9   mean fractal dimension   569 non-null    float64
 10  radius error             569 non-null    float64
 11  texture error            569 non-null    float64
 12  perimeter error          569 non-null    float64
 13  area error               569 non-null    float64
 14  smoothness error         569 non-null    float64
 15  compactness error        569 non-null    float64
 16  concavity error          569 non-null    float64
 17  concave points error     569 non-null    float64
 18  symmetry error           569 non-null    float64
 19  fractal dimension error  569 non-null    float64
 20  worst radius             569 non-null    float64
 21  worst texture            569 non-null    float64
 22  worst perimeter          569 non-null    float64
 23  worst area               569 non-null    float64
 24  worst smoothness         569 non-null    float64
 25  worst compactness        569 non-null    float64
 26  worst concavity          569 non-null    float64
 27  worst concave points     569 non-null    float64
 28  worst symmetry           569 non-null    float64
 29  worst fractal dimension  569 non-null    float64
 30  target                   569 non-null    int64
dtypes: float64(30), int64(1)
memory usage: 137.9 KB
None
```

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	m frac dimens
count	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.00
mean	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	0.062
std	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	0.007
min	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106000	0.049
25%	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	0.057
50%	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	0.061
75%	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	0.066
max	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	0.097

8 rows × 31 columns

Iris Dataset

```
idf
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
...	...	...	...	...	...
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

Next steps: Generate code with idf New interactive sheet

```
print(idf.info())
idf.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   sepal length (cm)  150 non-null    float64
 1   sepal width (cm)   150 non-null    float64
 2   petal length (cm)  150 non-null    float64
 3   petal width (cm)   150 non-null    float64
 4   target             150 non-null    int64  
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
None
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
count	150.000000	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333	1.000000
std	0.828066	0.435866	1.765298	0.762238	0.819232
min	4.300000	2.000000	1.000000	0.100000	0.000000
25%	5.100000	2.800000	1.600000	0.300000	0.000000
50%	5.800000	3.000000	4.350000	1.300000	1.000000
75%	6.400000	3.300000	5.100000	1.800000	2.000000
max	7.900000	4.400000	6.900000	2.500000	2.000000

Wine Dataset

```
wdf
```

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenols	proan
0	14.23	1.71	2.43	15.6	127.0	2.80	3.06	0.28	
1	13.20	1.78	2.14	11.2	100.0	2.65	2.76	0.26	
2	13.16	2.36	2.67	18.6	101.0	2.80	3.24	0.30	
3	14.37	1.95	2.50	16.8	113.0	3.85	3.49	0.24	
4	13.24	2.59	2.87	21.0	118.0	2.80	2.69	0.39	
...	...	...	...	...	...	...	...	...	
173	13.71	5.65	2.45	20.5	95.0	1.68	0.61	0.52	
174	13.40	3.91	2.48	23.0	102.0	1.80	0.75	0.43	
175	13.27	4.28	2.26	20.0	120.0	1.59	0.69	0.43	
176	13.17	2.59	2.37	20.0	120.0	1.65	0.68	0.53	
177	14.13	4.10	2.74	24.5	96.0	2.05	0.76	0.56	

178 rows × 14 columns

Next steps: Generate code with wdf New interactive sheet

```
print(wdf.info())
wdf.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 178 entries, 0 to 177
Data columns (total 14 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   alcohol                       178 non-null    float64
 1   malic_acid                    178 non-null    float64
 2   ash                           178 non-null    float64
 3   alcalinity_of_ash             178 non-null    float64
 4   magnesium                     178 non-null    float64
 5   total_phenols                 178 non-null    float64
 6   flavanoids                    178 non-null    float64
 7   nonflavanoid_phenols          178 non-null    float64
 8   proanthocyanins               178 non-null    float64
 9   color_intensity               178 non-null    float64
 10  hue                           178 non-null    float64
 11  od280/od315_of_diluted_wines  178 non-null    float64
 12  proline                       178 non-null    float64
 13  target                        178 non-null    int64  
dtypes: float64(13), int64(1)
memory usage: 19.6 KB
None
```

	alcohol	malic_acid	ash	alcalinity_of_ash	magnesium	total_phenols	flavanoids	nonflavanoid_phenc
count	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.000000	178.0000
mean	13.000618	2.336348	2.366517	19.494944	99.741573	2.295112	2.029270	0.3618
std	0.811827	1.117146	0.274344	3.339564	14.282484	0.625851	0.998859	0.1244
min	11.030000	0.740000	1.360000	10.600000	70.000000	0.980000	0.340000	0.1300
25%	12.362500	1.602500	2.210000	17.200000	88.000000	1.742500	1.205000	0.2700
50%	13.050000	1.865000	2.360000	19.500000	98.000000	2.355000	2.135000	0.3400
75%	13.677500	3.082500	2.557500	21.500000	107.000000	2.800000	2.875000	0.4375
max	14.830000	5.800000	3.230000	30.000000	162.000000	3.880000	5.080000	0.6600

Standarding Datasets

```
scaler = StandardScaler()
```

```
bcdf_stand = pd.DataFrame(scaler.fit_transform(bcdf),columns=bcdf.columns,index=bcdf.index)
bcdf_stand["target"] = bcdf["target"].values
```

```
idf_stand = pd.DataFrame(scaler.fit_transform(idf),columns=idf.columns,index=idf.index)
idf_stand["target"] = idf["target"].values
```

```
wdf_stand = pd.DataFrame(scaler.fit_transform(wdf),columns=wdf.columns,index=wdf.index)
wdf_stand["target"] = wdf["target"].values
```

Splitting data based on features and targets

```
bc_features = bcdf.iloc[:,:-1]
bc_target = bcdf.iloc[:,-1]
i_features = idf.iloc[:,:-1]
i_target = idf.iloc[:,-1]
w_features = wdf.iloc[:,:-1]
w_target = wdf.iloc[:,-1]
```

Importing libraries to train data

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,accuracy_score,confusion_matrix
from sklearn import svm
import seaborn as sns
import matplotlib.pyplot as plt
```

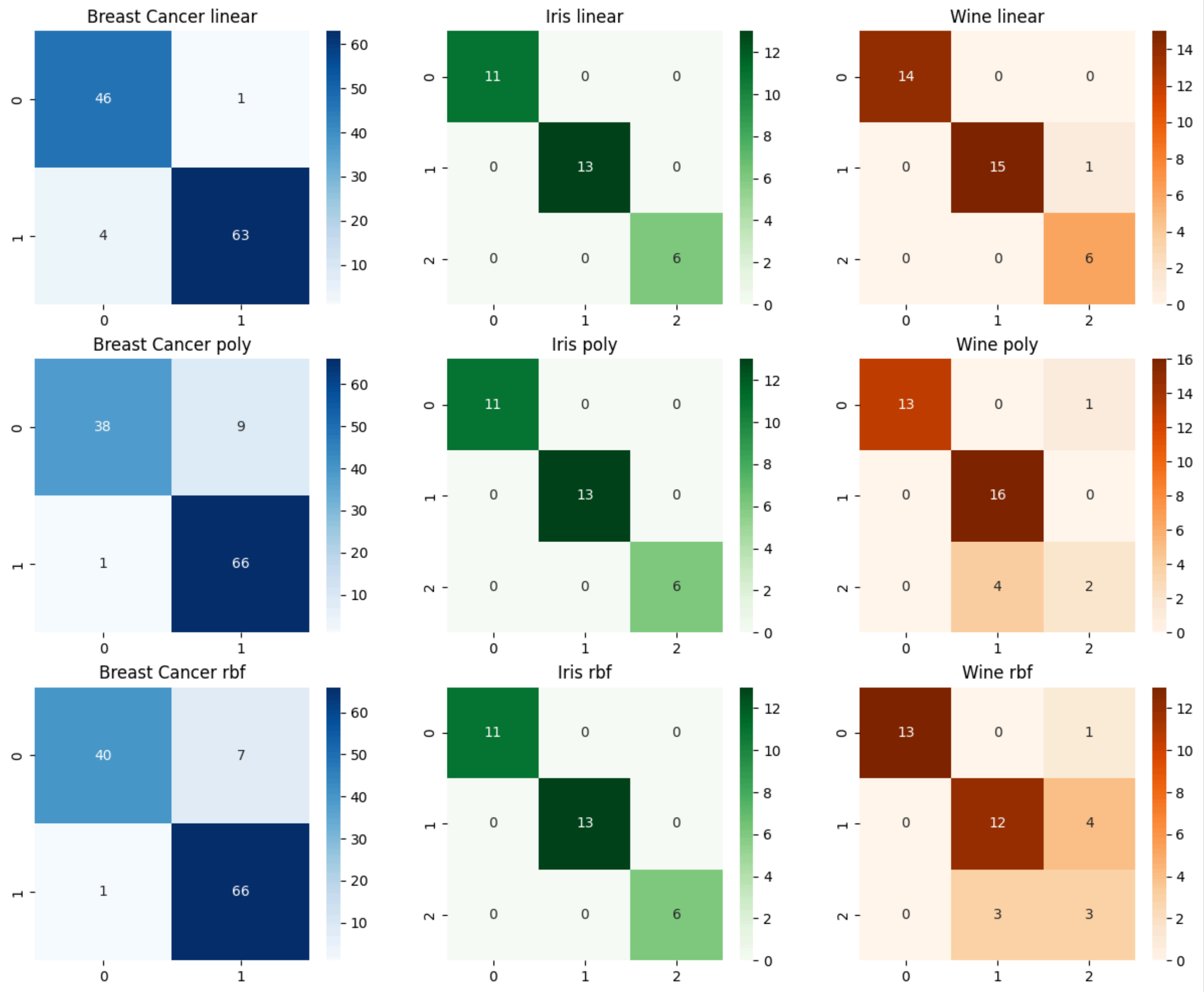
Splitting Dataset for taining and testing

```
bc_X_train,bc_X_test,bc_y_train,bc_y_test = train_test_split(bc_features,bc_target,test_size=0.2,random_state=0)
i_X_train,i_X_test,i_y_train,i_y_test = train_test_split(i_features,i_target,test_size=0.2,random_state=0)
w_X_train,w_X_test,w_y_train,w_y_test = train_test_split(w_features,w_target,test_size=0.2,random_state=0)
```

Fitting and measuring models

```
kernels = ["linear","poly","rbf"]

bc_report = {
    "linear":None,
    "poly":None,
    "rbf":None,
    "accuracy":0
}

i_report = {
    "linear":None,
    "poly":None,
    "rbf":None,
    "accuracy":0
}

w_report = {
    "linear":None,
    "poly":None,
    "rbf":None,
    "accuracy":0
}

i = 1;
plt.figure(figsize=(15,12))
for kernel in kernels:
  bc_model = svm.SVC(kernel=kernel,gamma="scale")
  bc_model.fit(bc_X_train,bc_y_train)
  bc_report[kernel] = classification_report(bc_y_test,bc_model.predict(bc_X_test),output_dict=True,target_names =
  bc_pred = bc_model.predict(bc_X_test)
  bc_report["accuracy"] += accuracy_score(bc_y_test,bc_pred)
  plt.subplot(3,3,i)
  i+=1
  sns.heatmap(confusion_matrix(bc_y_test,bc_pred),annot=True,cmap=plt.cm.Blues)
  plt.title(f"Breast Cancer {kernel}")

  i_model = svm.SVC(kernel=kernel,gamma="scale")
  i_model.fit(i_X_train,i_y_train)
  i_report[kernel] = classification_report(i_y_test,i_model.predict(i_X_test),output_dict=True,target_names = i_d
  i_pred = i_model.predict(i_X_test)
  i_report["accuracy"] += accuracy_score(i_y_test,i_pred)
  plt.subplot(3,3,i)
  i+=1
  sns.heatmap(confusion_matrix(i_y_test,i_pred),annot=True,cmap=plt.cm.Greens)
  plt.title(f"Iris {kernel}")

  w_model = svm.SVC(kernel=kernel,gamma="scale")
```

```
    w_model = svm.SVC(kernel=kernel,gamma='scale')
    w_model.fit(w_X_train,w_y_train)
    w_report[kernel] = classification_report(w_y_test,w_model.predict(w_X_test),output_dict=True,target_names = w_d
    w_pred = w_model.predict(w_X_test)
    w_report["accuracy"] += accuracy_score(w_y_test,w_pred)
    plt.subplot(3,3,i)
    i+=1
    sns.heatmap(confusion_matrix(w_y_test,w_pred),annot=True,cmap=plt.cm.Oranges)
    plt.title(f"Wine {kernel}")
  plt.show()
```



Breast Cancer Model Report

```
print(f"Accuracy : {(bc_report["accuracy"]/3)*100:.2f}%")
```

```
Accuracy : 93.27%
```

Linear Kernel

```
pd.DataFrame(bc_report["linear"])
```

	malignant	benign	accuracy	macro avg	weighted avg
precision	0.920000	0.984375	0.95614	0.952187	0.957834
recall	0.978723	0.940299	0.95614	0.959511	0.956140
f1-score	0.948454	0.961832	0.95614	0.955143	0.956316
support	47.000000	67.000000	0.95614	114.000000	114.000000

Polynomial Kernel

```
pd.DataFrame(bc_report["poly"])
```

	malignant	benign	accuracy	macro avg	weighted avg
precision	0.974359	0.880000	0.912281	0.927179	0.918902
recall	0.808511	0.985075	0.912281	0.896793	0.912281
f1-score	0.883721	0.929577	0.912281	0.906649	0.910672
support	47.000000	67.000000	0.912281	114.000000	114.000000

RBF Kernel

```
pd.DataFrame(bc_report["rbf"])
```

	malignant	benign	accuracy	macro avg	weighted avg
precision	0.975610	0.904110	0.929825	0.939860	0.933588
recall	0.851064	0.985075	0.929825	0.918069	0.929825
f1-score	0.909091	0.942857	0.929825	0.925974	0.928936
support	47.000000	67.000000	0.929825	114.000000	114.000000

Iris Model Report

```
print(f"Accuracy : {(i_report["accuracy"]/3)*100:.2f}%")
```

```
Accuracy : 100.00%
```

Linear Kernel

```
pd.DataFrame(i_report["linear"])
```

	setosa	versicolor	virginica	accuracy	macro avg	weighted avg
precision	1.0	1.0	1.0	1.0	1.0	1.0
recall	1.0	1.0	1.0	1.0	1.0	1.0
f1-score	1.0	1.0	1.0	1.0	1.0	1.0
support	11.0	13.0	6.0	1.0	30.0	30.0

Polynomial Kernel

```
pd.DataFrame(i_report["poly"])
```

	setosa	versicolor	virginica	accuracy	macro avg	weighted avg
precision	1.0	1.0	1.0	1.0	1.0	1.0
recall	1.0	1.0	1.0	1.0	1.0	1.0
f1-score	1.0	1.0	1.0	1.0	1.0	1.0
support	11.0	13.0	6.0	1.0	30.0	30.0

RBF Kernel

```
pd.DataFrame(i_report["rbf"])
```

	setosa	versicolor	virginica	accuracy	macro avg	weighted avg
precision	1.0	1.0	1.0	1.0	1.0	1.0
recall	1.0	1.0	1.0	1.0	1.0	1.0
f1-score	1.0	1.0	1.0	1.0	1.0	1.0
support	11.0	13.0	6.0	1.0	30.0	30.0