# Q1

- The confusion matrix below shows the evaluation results for a binary classifier applied to a set of 768 test examples, which are annotated with the class labels (Pass, Fail). Calculate:
  a) The precision score for both of the classes.
  b) The recall score for both of the classes.
  c) The F1-measure score for both of the classes.
  d) The overall classification accuracy and average class accuracy for all the data.

Predicted Class

| Pass | Fail | Real Class |
|---|---|---|
| **TP**<br>True Positive | **FN**<br>False Negative | Pass |
| **FP**<br>False Positive | **TN**<br>True Negative | Fail |

Predicted Class

| Pass | Fail | Real Class |
|---|---|---|
| 407 | 93 | Pass |
| 108 | 160 | Fail |

# Q1(a,b)

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN} = \text{Sensitivity}$$

Predicted

| | Pos | Neg | |
|---|---|---|---|
| **P** | **TP** | **FN** | Pos |
| **N** | **FP** | **TN** | Neg |

Real

Predicted

| | Pos | Neg | |
|---|---|---|---|
| **P** | **TP** | **FN** | Pos |
| **N** | **FP** | **TN** | Neg |

Real

Note: These measures are always relative to one class!

Predicted Class

| | Pass | Fail | |
|---|---|---|---|
| | 407 | 93 | Pass |
| | 108 | 160 | Fail |

Real Class

| Class | Precision | Recall |
|---|---|---|
| *Pass* | 407/(407+108) = 0.79 | 407/(407+93) = 0.814 |
| *Fail* | 160/(93+160) = 0.632 | 160/(108+160) = 0.597 |

# Q1(c)

c) Calculate the F1-measure score for both of the classes.

F1-Measure: harmonic mean of precision and recall

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Also relative to one class!

| Class | Precision | Recall | F1 |
|---|---|---|---|
| *Pass* | 407/(407+108)<br>= 0.79 | 407/(407+93)<br>= 0.814 | (2x0.79x0.814)/(0.79+0.814)<br>= 0.802 |
| *Fail* | 160/(93+160)<br>= 0.632 | 160/(108+160)<br>= 0.597 | (2x0.632x0.597)/(0.632+0.597)<br>= 0.614 |

# Q1(d)

d) Calculate the overall and average classification accuracy for all the data.

**Accuracy:** Number of predictions correct / all predictions

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN}$$

Accuracy score is relative to the overall dataset, often reported as a percentage.

| Real Class \ Predicted Class | Pass | Fail |
|---|---|---|
| Pass | 407 | 93 |
| Fail | 108 | 160 |

**OVERALL ACCURACY:**

(407+160)/(407+93+108+160)

= 73.8281%

**AVERAGE CLASS ACCURACY:**

= average Recall

(.894+.597)/2

= 70.55%

# Q2(a)

a) Calculate the **overall accuracy** for each of the 3 classifiers on this data. Based on your calculations, which classifier the most accurate?

| Example | True Class Label | KNN Prediction | J48 Prediction | SVM Prediction |
|---|---|---|---|---|
| 1 | spam | spam | spam | spam |
| 2 | non-spam | non-spam | spam | non-spam |
| 3 | spam | non-spam | non-spam | spam |
| 4 | non-spam | non-spam | non-spam | non-spam |
| 5 | spam | spam | spam | spam |
| 6 | non-spam | non-spam | non-spam | non-spam |
| 7 | non-spam | spam | spam | non-spam |
| 8 | non-spam | non-spam | spam | spam |
| 9 | spam | spam | non-spam | spam |
| 10 | spam | spam | non-spam | non-spam |
| 11 | spam | non-spam | non-spam | spam |
| 12 | spam | spam | spam | spam |

# Q2(a)

| Example | True Class Label | KNN Prediction | J48 Prediction | SVM Prediction |
|---|---|---|---|---|
| 1 | spam | spam | spam | spam |
| 2 | non-spam | non-spam | spam | non-spam |
| 3 | spam | non-spam | non-spam | spam |
| 4 | non-spam | non-spam | non-spam | non-spam |
| 5 | spam | spam | spam | spam |
| 6 | non-spam | non-spam | non-spam | non-spam |
| 7 | non-spam | spam | spam | non-spam |
| 8 | non-spam | non-spam | spam | spam |
| 9 | spam | spam | non-spam | spam |
| 10 | spam | spam | non-spam | non-spam |
| 11 | spam | non-spam | non-spam | spam |
| 12 | spam | spam | spam | spam |

| | | | |
|---|---|---|---|
| **#Correct** | 9/12 | 5/12 | 10/12 |
| **Accuracy** | 75% | 41.7% | 83.3% |

Overall Accuracy:
Number of predictions correct / all predictions

→ **SVM is most accurate**

# Q2(b)

| Example | True Class Label | KNN Prediction | J48 Prediction | SVM Prediction |
|---|---|---|---|---|
| 1 | spam | spam | spam | spam |
| 2 | non-spam | non-spam | spam | non-spam |
| 3 | spam | non-spam | non-spam | spam |
| 4 | non-spam | non-spam | non-spam | non-spam |
| 5 | spam | spam | spam | spam |
| 6 | non-spam | non-spam | non-spam | non-spam |
| 7 | non-spam | spam | spam | non-spam |
| 8 | non-spam | non-spam | spam | spam |
| 9 | spam | spam | non-spam | spam |
| 10 | spam | spam | non-spam | non-spam |
| 11 | spam | non-spam | non-spam | spam |
| 12 | spam | spam | spam | spam |

| | | | | |
|---|---|---|---|---|
| **"Spam"** | **TP** | 5 | 3 | 6 |
| | **FP** | 1 | 3 | 1 |
| | **Precision** | 5/6 = 0.833 | 3/6 = 0.5 | 6/7 = 0.857 |

Precision for spam:
Number of correct spam predictions / all predictions of spam

**→SVM has highest precision for spam**

# Q2(c)

- Which classifier would you recommend for this dataset and why?
- FPs are undesirable for spam classification so need to select a classifier with low FP Rate and high —> SVM

# Q3(a)

- 10-fold cross validation experiment. Dataset of 5000 images, so 500 images in each test set.

a) What is the overall accuracy of the classifier based on the cross-validation results?

| Fold | Class: Cats | | Class: Dogs | | Class: People | |
|---|---|---|---|---|---|---|
| | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect |
| 1 | 82 | 68 | 82 | 68 | 164 | 36 |
| 2 | 81 | 69 | 102 | 48 | 176 | 24 |
| 3 | 99 | 51 | 97 | 53 | 160 | 40 |
| 4 | 81 | 69 | 102 | 48 | 148 | 52 |
| 5 | 94 | 56 | 99 | 51 | 148 | 52 |
| 6 | 97 | 53 | 91 | 59 | 162 | 38 |
| 7 | 81 | 69 | 94 | 56 | 148 | 52 |
| 8 | 76 | 74 | 79 | 71 | 181 | 19 |
| 9 | 76 | 74 | 97 | 53 | 160 | 40 |
| 10 | 96 | 54 | 79 | 71 | 179 | 21 |

# Q3(a)

## Calculate accuracy for each fold

| Fold | Class: Cats | | Class: Dogs | | Class: People | | |
|---|---|---|---|---|---|---|---|
| | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect | **Accuracy** |
| 1 | 82 | 68 | 82 | 68 | 164 | 36 | 65.6% |
| 2 | 81 | 69 | 102 | 48 | 176 | 24 | 71.8% |
| 3 | 99 | 51 | 97 | 53 | 160 | 40 | 71.2% |
| 4 | 81 | 69 | 102 | 48 | 148 | 52 | 66.2% |
| 5 | 94 | 56 | 99 | 51 | 148 | 52 | 68.2% |
| 6 | 97 | 53 | 91 | 59 | 162 | 38 | 70.0% |
| 7 | 81 | 69 | 94 | 56 | 148 | 52 | 64.6% |
| 8 | 76 | 74 | 79 | 71 | 181 | 19 | 67.2% |
| 9 | 76 | 74 | 97 | 53 | 160 | 40 | 66.6% |
| 10 | 96 | 54 | 79 | 71 | 179 | 21 | 70.8% |
| | | | | | | | |

Fold 1: (82+82+164)/(82+68+82+68+164+36) = 65.6% accuracy for fold …

# Q3(a)

Overall accuracy is average of fold accuracy

| Fold | Class: Cats | | Class: Dogs | | Class: People | | |
|---|---|---|---|---|---|---|---|
| | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect | **Accuracy** |
| 1 | 82 | 68 | 82 | 68 | 164 | 36 | 65.6% |
| 2 | 81 | 69 | 102 | 48 | 176 | 24 | 71.8% |
| 3 | 99 | 51 | 97 | 53 | 160 | 40 | 71.2% |
| 4 | 81 | 69 | 102 | 48 | 148 | 52 | 66.2% |
| 5 | 94 | 56 | 99 | 51 | 148 | 52 | 68.2% |
| 6 | 97 | 53 | 91 | 59 | 162 | 38 | 70.0% |
| 7 | 81 | 69 | 94 | 56 | 148 | 52 | 64.6% |
| 8 | 76 | 74 | 79 | 71 | 181 | 19 | 67.2% |
| 9 | 76 | 74 | 97 | 53 | 160 | 40 | 66.6% |
| 10 | 96 | 54 | 79 | 71 | 179 | 21 | 70.8% |
| **Mean** | | | | | | | **68.2%** |

Fold 1: (82+82+164)/(82+68+82+68+164+36) = 65.6% accuracy for fold …

Overall: (65.6% + 71.8% + 71.2% + 66.2% + 68.2% + 70.0% + 64.6% + 67.2% + 66.6% + 70.8%)/10 = 68.2%

# Q3(b)

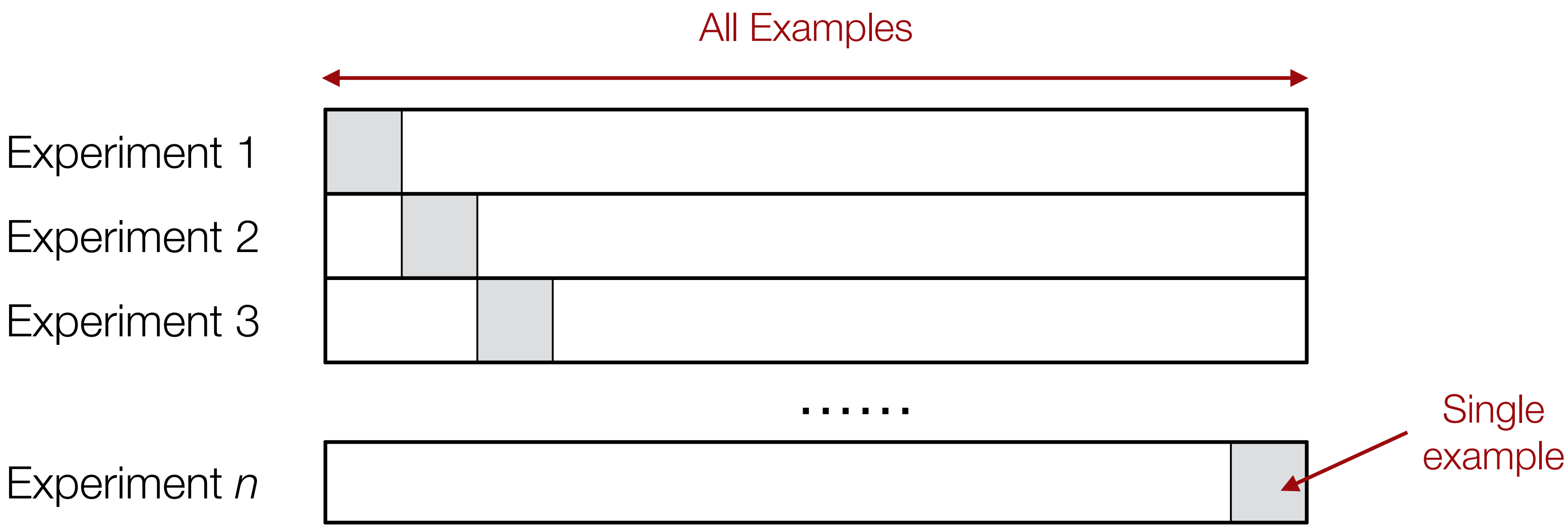
b) What conclusion might be draw about the different classes in the data, based on the results above?

| Fold | Class: Cats | | Class: Dogs | | Class: People | | |
|---|---|---|---|---|---|---|---|
| | Correct | Incorrect | Correct | Incorrect | Correct | Incorrect | **Accuracy** |
| 1 | 82 | 68 | 82 | 68 | 164 | 36 | 65.6% |
| 2 | 81 | 69 | 102 | 48 | 176 | 24 | 71.8% |
| 3 | 99 | 51 | 97 | 53 | 160 | 40 | 71.2% |
| 4 | 81 | 69 | 102 | 48 | 148 | 52 | 66.2% |
| 5 | 94 | 56 | 99 | 51 | 148 | 52 | 68.2% |
| 6 | 97 | 53 | 91 | 59 | 162 | 38 | 70.0% |
| 7 | 81 | 69 | 94 | 56 | 148 | 52 | 64.6% |
| 8 | 76 | 74 | 79 | 71 | 181 | 19 | 67.2% |
| 9 | 76 | 74 | 97 | 53 | 160 | 40 | 66.6% |
| 10 | 96 | 54 | 79 | 71 | 179 | 21 | 70.8% |
| **Mean** | 86.3 | 63.7 | 92.2 | 57.8 | 162.6 | 37.4 | **68.2%** |
| **Class Acc.** | **57.5%** | | **61.5%** | | **81.3%** | | |

➡ High accuracy for class "People", low accuracy for "Cats" and "Dogs". Suggests system is poor at distinguishing between these classes.

# Q3(c)

c) Would "leave-one-out cross validation" be an appropriate evaluation strategy on this dataset?




If each fold has 500 examples, then overall dataset has *n=5000* examples.

So leave-one-out would require running 5000 experiments where 1 example is left out each time.

Could be computationally impractical to do this, so *k*-fold cross validation would be more suitable.

# Q4

The notebook **`05 ROC Exercise`** contains code for loading the diabetes dataset (**`diabetes.csv`**).

a) Using the code in **`08 ROC`** as a template produce ROC curves for kNN, SVM and Naive Bayes classifiers on the diabetes data.

b) Repeat this exercise using synthetic data generated using the code below. What insights do these ROC curves provide?

```
from sklearn.datasets import make_classification
X, y = make_classification(n_samples=1000, n_features=4, n_classes=2
                                    class_sep=0.75, random_state=1)
```

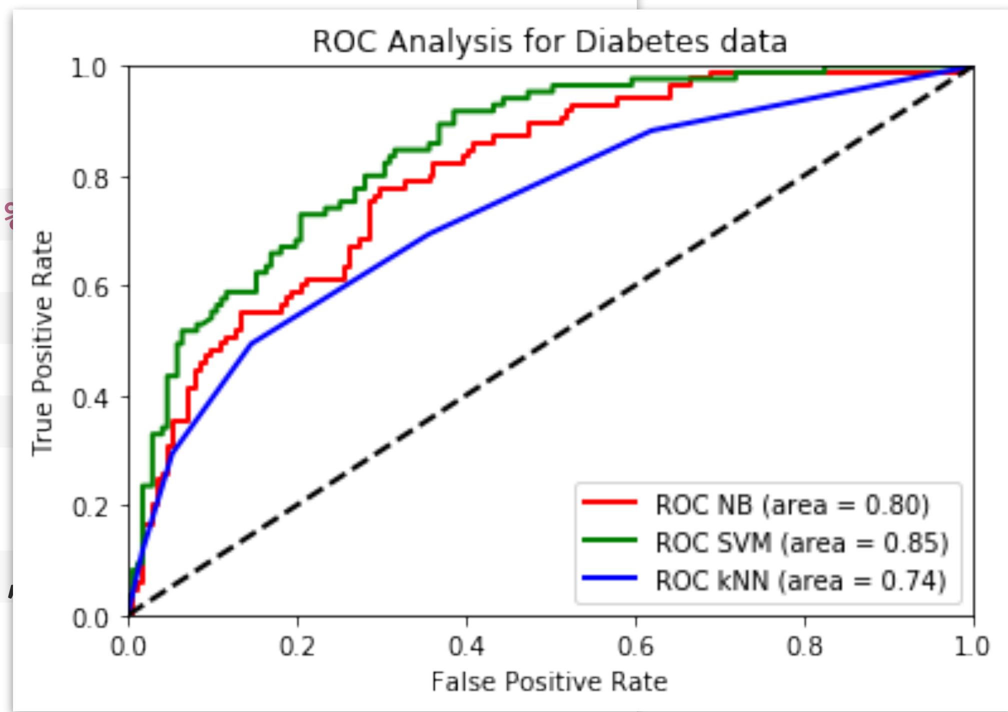
# Q4(a)

```
gnb = GaussianNB()
y_score = gnb.fit(X_train, y_train).predict_proba(X_test)
fprG, tprG, t = roc_curve(y_test, y_score[:,1])
roc_aucG = auc(fprG, tprG)

kNN = KNeighborsClassifier(n_neighbors = 5)
y_score = kNN.fit(X_train, y_train).predict_proba(X_test)
fprN, tprN, t = roc_curve(y_test, y_score[:,1])
roc_aucN = auc(fprN, tprN)

di_svm = SVC(kernel = 'linear',C=1, probability=True)
y_score = di_SVM.fit(X_train, y_train).predict_proba(X_test)
fprS, tprS, t = roc_curve(y_test, y_score[:,1])
roc_aucS = auc(fprS, tprS)

y_score[:5]
Out[54]:
array([[0.06800138, 0.93199862],
       [0.82309978, 0.17690022],
       [0.89492645, 0.10507355],
       [0.37098204, 0.62901796],
       [0.86324697, 0.13675303]])
```

# Q4(a)

- Plotting code similar to that in notebook **`05 ROC`**

```
import matplotlib.pyplot as plt
%matplotlib inline
plt.figure()
lw = 2
plt.plot(fprG, tprG, color='red',
         lw=lw, label='ROC NB (area = %
plt.plot(fprS, tprS, color='green',
         lw=lw, label='ROC SVM (area =
plt.plot(fprN, tprN, color='blue',
         lw=lw, label='ROC kNN (area =


plt.plot([0, 1], [0, 1], color='black',
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.0])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Analysis for Diabetes data')
plt.legend(loc="lower right")
plt.show()
```



# Q4(b)

- Repeat with synthetic data

```python
from sklearn.datasets import make_classification
X, y = make_classification(n_samples=1000, n_features=4, n_classes=2,
                           class_sep = 0.75, random_state=1)

X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0,test_size=1/3)

gnb = GaussianNB()
y_score = gnb.fit(X_train, y_train).predict_proba(X_test)
fprG, tprG, t = roc_curve(y_test, y_score[:,1])
roc_aucG = auc(fprG, tprG)

kNN = KNeighborsClassifier(n_neighbors = 5)
y_score = kNN.fit(X_train, y_train).predict_pr
fprN, tprN, t = roc_curve(y_test, y_score[:,1]
roc_aucN = auc(fprN, tprN)

di_svm = SVC(kernel = 'linear',C=1, probabilit
y_score = di_SVM.fit(X_train, y_train).predict
fprS, tprS, t = roc_curve(y_test, y_score[:,1]
roc_aucS = auc(fprS, tprS)
```