Q1 (a)

 We calculate the sum of squared errors for each Model using the formula

sum of squared errors =
$$\frac{1}{2} \sum_{i=1}^{n} (t_i - \mathbb{M}(\mathbf{d}_i))^2$$

The relevant aggregate figures are as follows:

Model 1 SSE: 16750

Model 2 SSE: 47369

Q1 (b)

The R² measure is calculated using the following formula

$$R^2 = 1 - \frac{sum\ of\ squared\ errors}{total\ sum\ of\ squares}$$

We already have the sum of squared errors from part (a).
However, we need to calculate the total sum of squares, which can be done using the formula

total sum of squares =
$$\frac{1}{2} \sum_{i=1}^{n} (t_i - \bar{t})^2$$

Q1 (b)

Using the formula, the total sum of squares for

Model 1 = 234064.4

Model 2 = 274579.6

Putting these values into the R² formula, we get

R² for Model 1 =
$$1 - \frac{16750}{234064.4} = 0.928$$

R² for Model 2 = $1 - \frac{47369}{274579.6} = 0.827$

Based on the above, Model 1 is better able to capture patterns than Model 2.

Q2

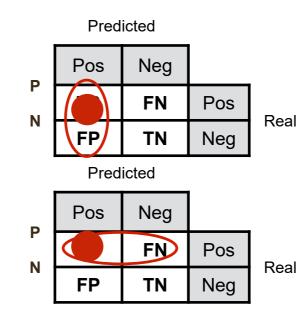
- The contingency table below shows the evaluation results for a binary classifier applied to a set of 768 test examples, which are annotated with the class labels (A, B). From this table calculate:
 - a) The precision score for both of the classes.
 - b) The recall score for both of the classes.
 - c) The F1-measure score for both of the classes.
 - d) The overall classification accuracy for all the data.

Predicte	ed Class		
Α	В		
407	93	Α	
108	160	В	Real Class

Q2(a,b)

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

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



Note: These measures are always relative to one class!

Predicted Class

А	В		_
407	93	Α	Real
108	160	В	Class

Class	Precision	Recall
A	407/(407+108) = 0.79	407/(407+93) = 0.814
В	160/(93+160) = 0.632	160/(108+160) = 0.597

Q2(c)

• F1-Measure: harmonic mean of precision and recall

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

Also relative to one class!

Class	Precision	Recall	F1
A	407/(407+108)	407/(407+93)	(2*0.79*0.814)/(0.79+0.814)
	= 0.79	= 0.814	= 0.802
В	160/(93+160)	160/(108+160)	(2*0.632*0.597)/(0.632+0.597)
	= 0.632	= 0.597	= 0.614

Q2(d)

Accuracy: Number of predictions correct / all predictions

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

Predicted Class

Α	В		
407	93	A	Real
108	160	В	Class

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

OVERALL ACCURACY:

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

= 73.8281%

Q3

 The table below shows the true classes for 12 example emails, which are labelled as "spam" or "non-spam". The table also reports the labels predicted by three different binary classifiers

Example	True Class Label	KNN	DecisionTree	LogisticRegression
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

Q3 (a,b)

Example	True Class Label	KNN	Decision Tree	Logistic Regression
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%

"Spam"	TP	5	3	6
	FP	1	3	1
Pro	ecision	5/6 = 0.833	3/6 = 0.5	6/7 = 0.857

Overall Accuracy:

Number of predictions correct / all predictions

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

Logistic Regression is most accurate

Logistic Regression has highest precision for spam