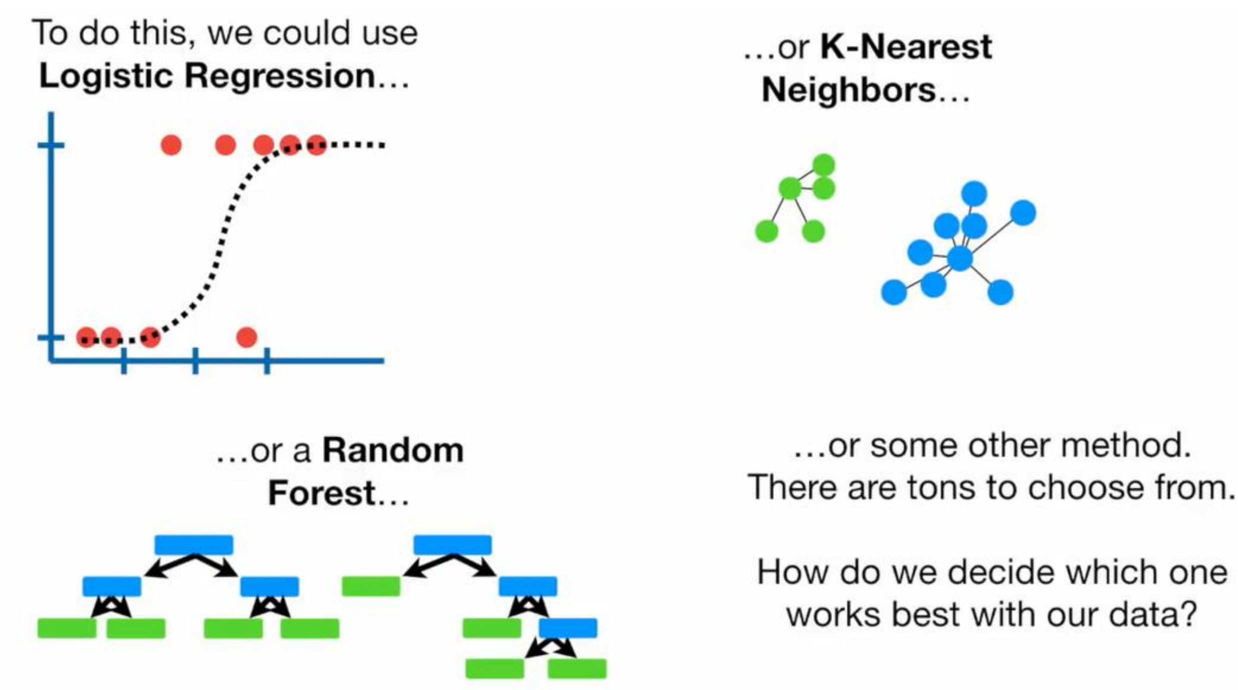
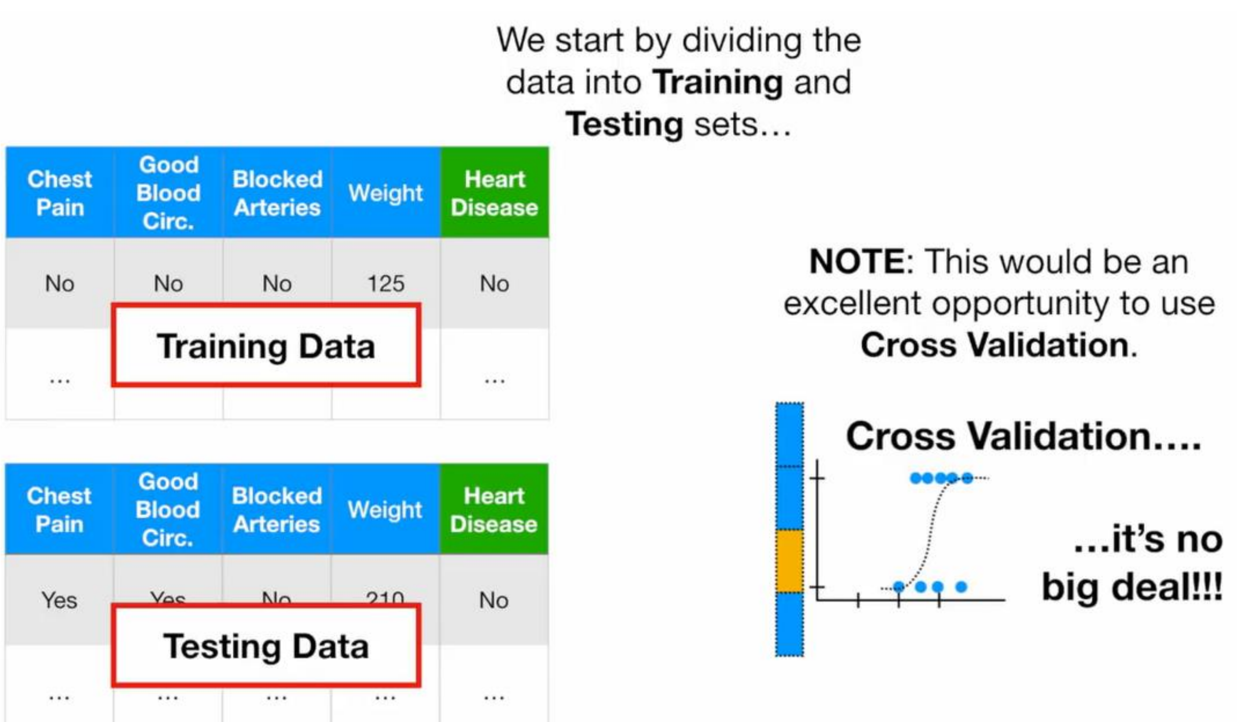
ANTICIPARE LA CRESCITA CON LE NUOVE COMPETENZE SUI BIG DATA – EDIZIONE 2

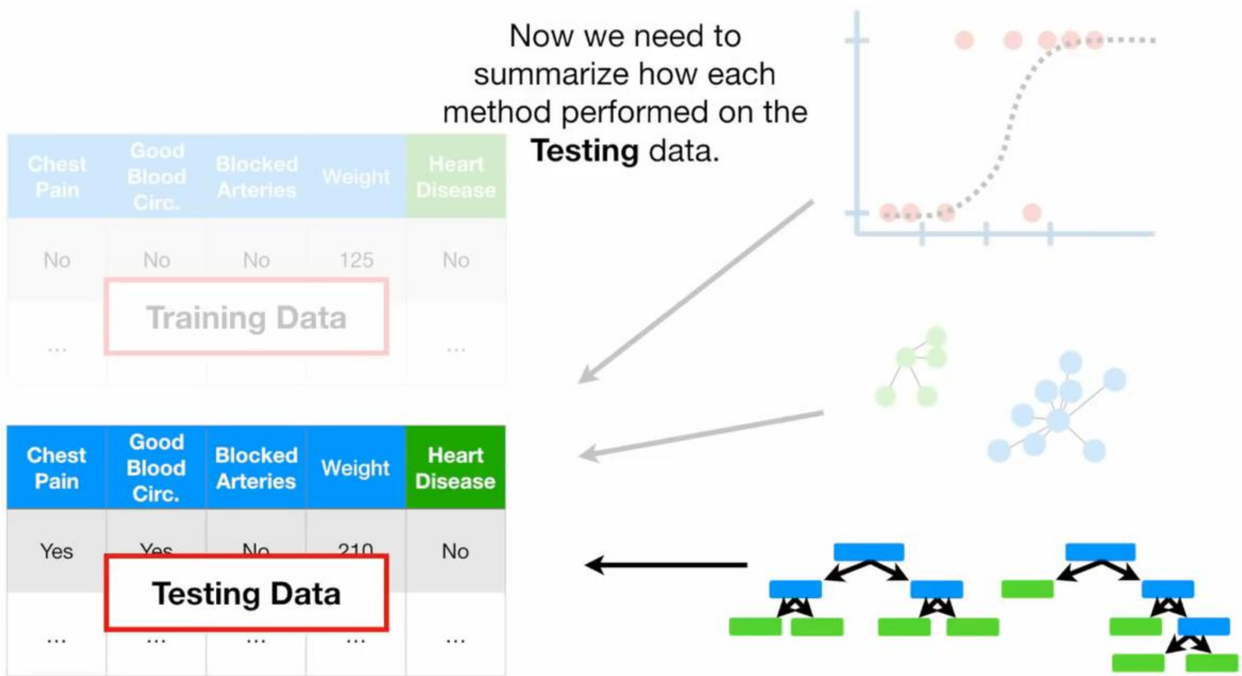
Operazione Rif. PA 2019-11596/RER "Anticipare la crescita con le nuove competenze sui Big Data - Edizione 2", approvata dalla Regione Emilia-Romagna con DGR n° 789 del 20 maggio 2019 e co-finanziata dal Fondo Sociale Europeo PO 2014-2020

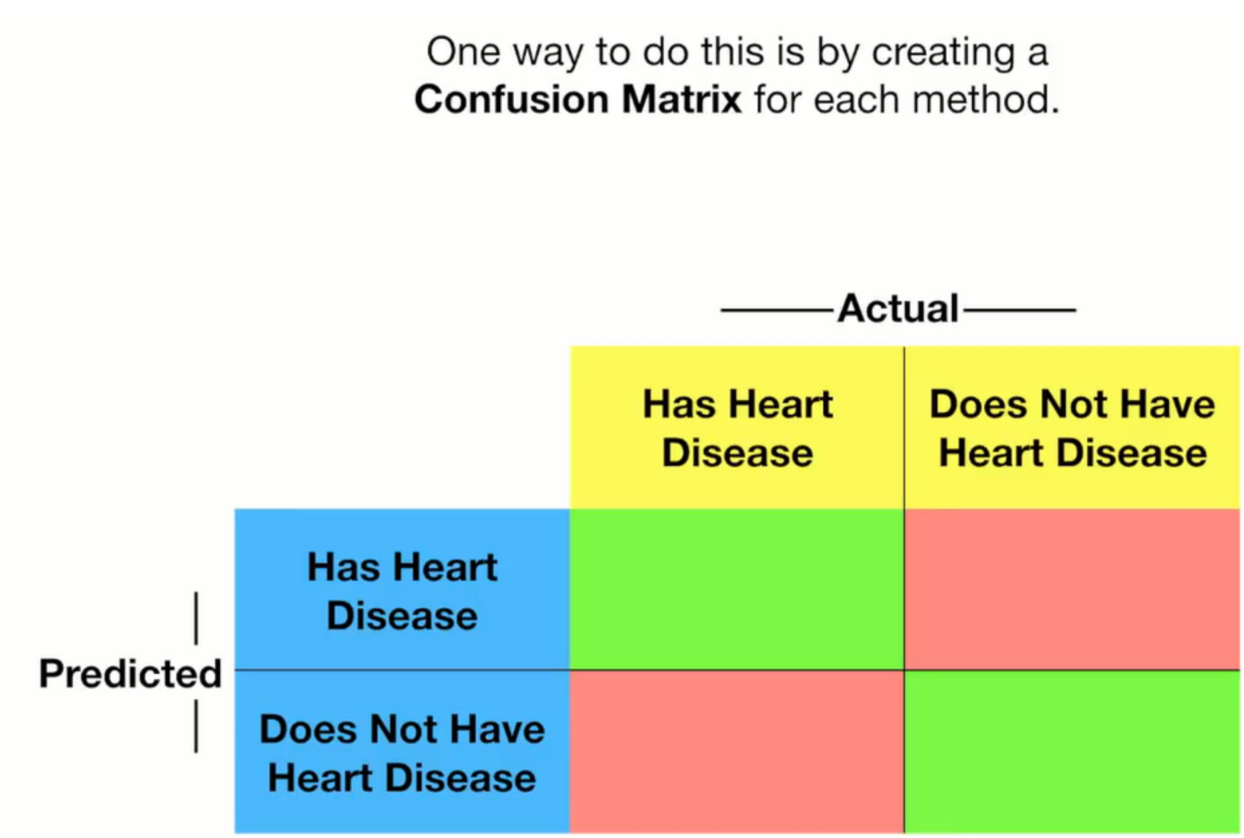
Prog. 4 Ed. 7 Titolo "Tecnologie & Software di Data Science

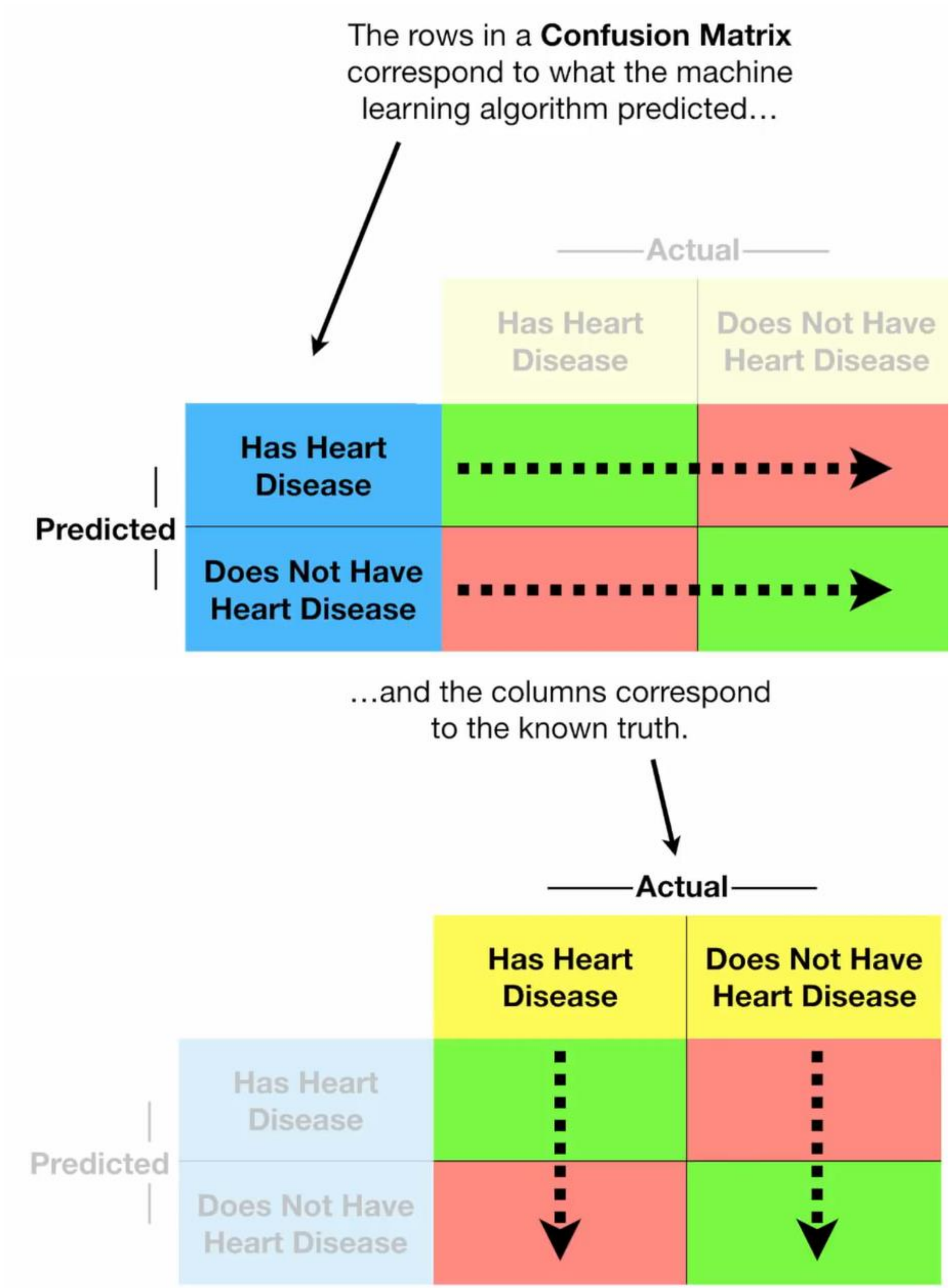
CONFUSION MATRIX



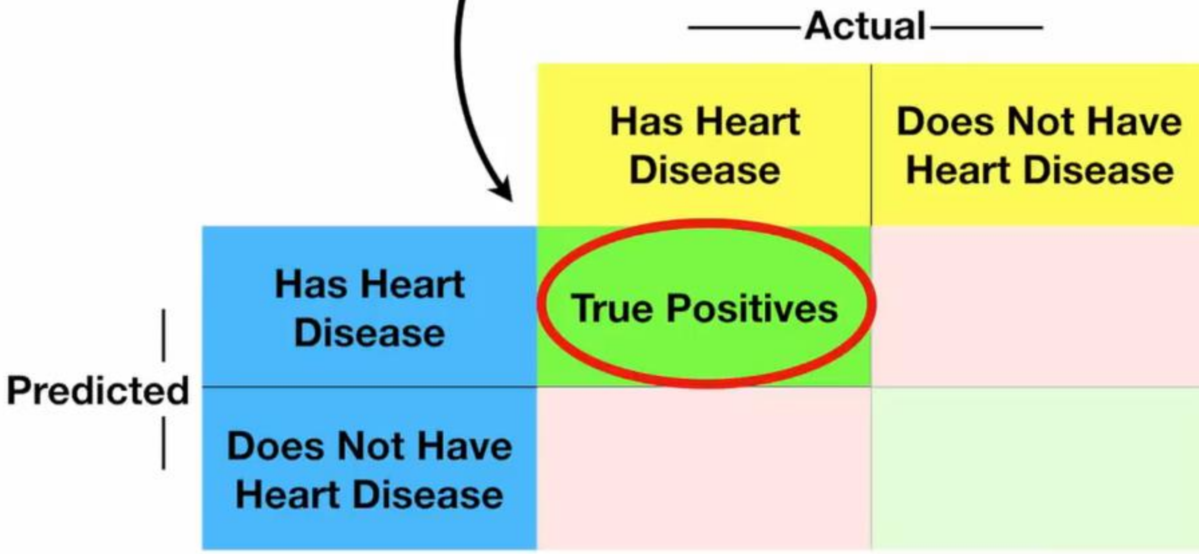



Now we need to summarize how each method performed on the **Testing** data.
Chest Pain
Good Blood Circ.
Blocked Arteries
Weight
Heart Disease
No
No
No
125
No
Training Data
...
...
Chest Pain
Good Blood Circ.
Blocked Arteries
Weight
Heart Disease
Yes
Yes
No
210
No
Testing Data
...
...
...
...
...

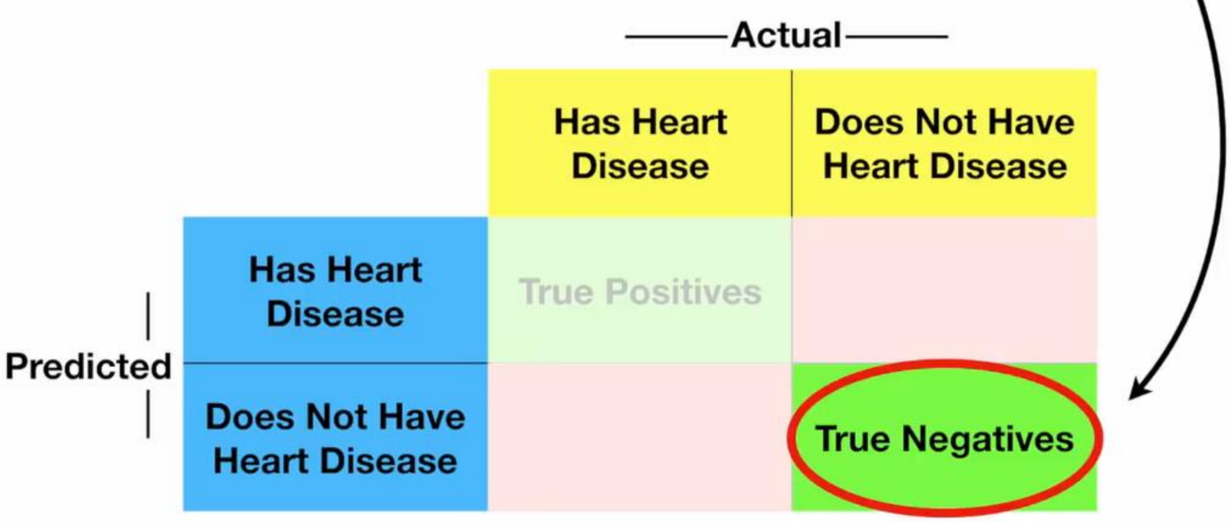

One way to do this is by creating a **Confusion Matrix** for each method.
Actual
Has Heart Disease
Does Not Have Heart Disease
Predicted
Has Heart Disease
Does Not Have Heart Disease


The rows in a **Confusion Matrix** correspond to what the machine learning algorithm predicted…
Actual
Has Heart Disease
Does Not Have Heart Disease
Predicted
Has Heart Disease
Does Not Have Heart Disease
…and the columns correspond to the known truth.
Actual
Has Heart Disease
Does Not Have Heart Disease
Predicted
Has Heart Disease
Does Not Have Heart Disease

…then the top left corner contains **True Positives**.



The **True Negatives** are in the bottom right-hand corner.



These are the patients that *did not have heart disease* that were correctly identified by the algorithm.

The bottom left-hand corner contains the **False Negatives**...

		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	True Positives	
	Does Not Have Heart Disease	**False Negatives**	True Negatives

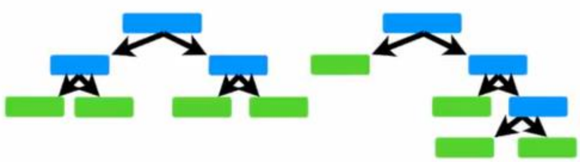
Lastly, the top right-hand corner contains the **False Positives**...

		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	True Positives	**False Positives**
	Does Not Have Heart Disease	False Negatives	True Negatives

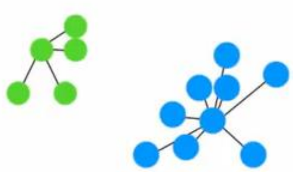
False Positives are patients that do not have heart disease, but the algorithm says they do.

...and the algorithm misclassified **22** patients that *did not* have heart disease by saying that they *did* (**False Positives**).

		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	142	**22**
	Does Not Have Heart Disease	**29**	110

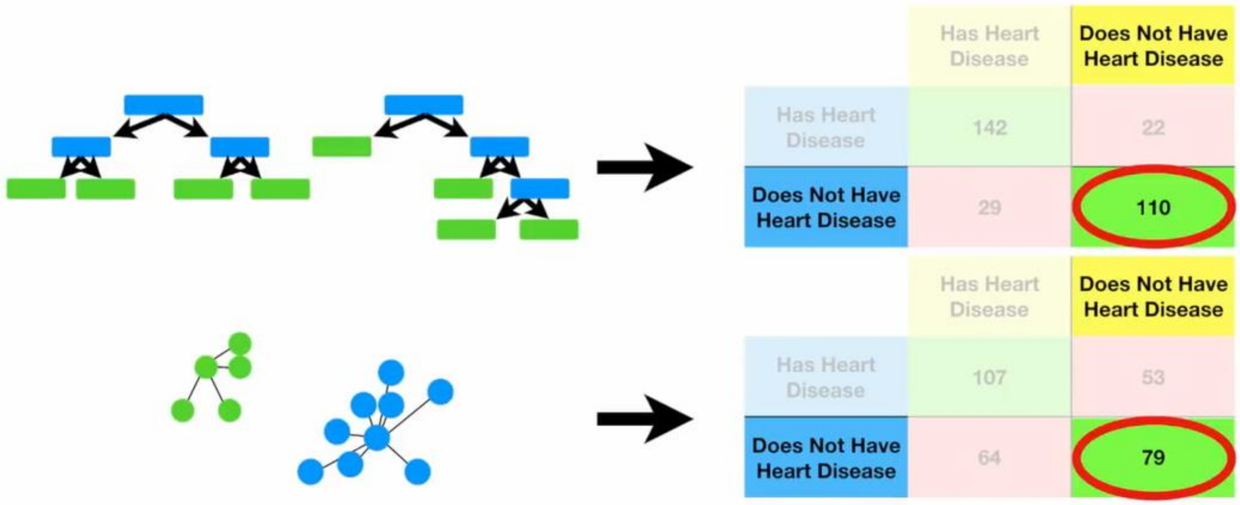


	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	142	22
Does Not Have Heart Disease	29	110

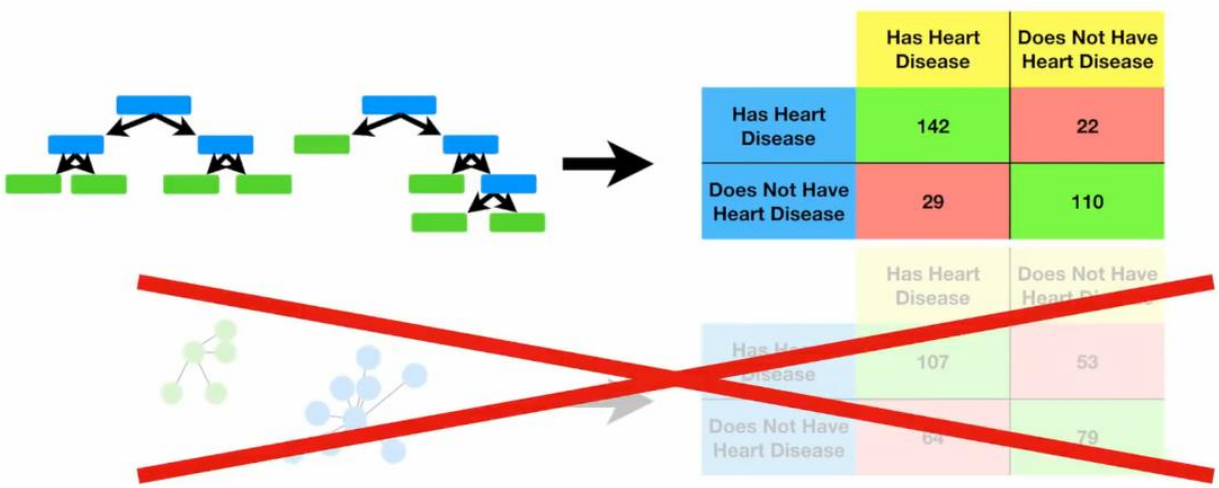


	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	107	53
Does Not Have Heart Disease	64	79

K-Nearest Neighbors was worse than the **Random Forest** at predicting patients *with* Heart Disease (**107** vs **142**)...



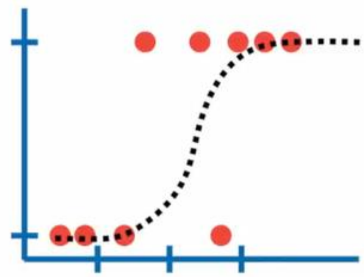
…and worse at predicting patients
without Heart Disease (**79** vs **110**)…



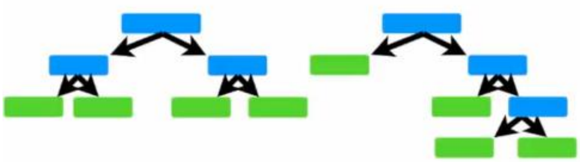
…so if we had to choose between
using the **Random Forest** and
K-Nearest Neighbors, we would
choose the **Random Forest**.

	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	142	22
Does Not Have Heart Disease	29	110

Lastly, we can apply **Logistic Regression** to the **Testing Dataset** and create a **Confusion Matrix**.

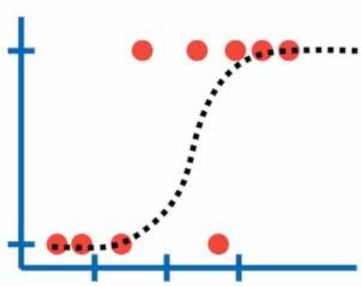


	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	139	20
Does Not Have Heart Disease	32	112



	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	142	22
Does Not Have Heart Disease	29	110

These two **Confusion Matrices** are very similar and make it hard to choose which machine learning method is a better fit for this data.



	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	139	20
Does Not Have Heart Disease	32	112

Sensitivity, **Specificity**, **ROC** and **AUC**

		Actual		
		Troll 2	Gore Police	Cool as Ice
Predicted	Troll 2	12	102	93
	Gore Police	112	23	77
	Cool as Ice	83	92	17

...and if we had 40 things to choose from, we get a confusion matrix with 40 rows and 40 columns.

In summary, a **Confusion Matrix** tells you what your machine learning algorithm did right…

…and what it did wrong.

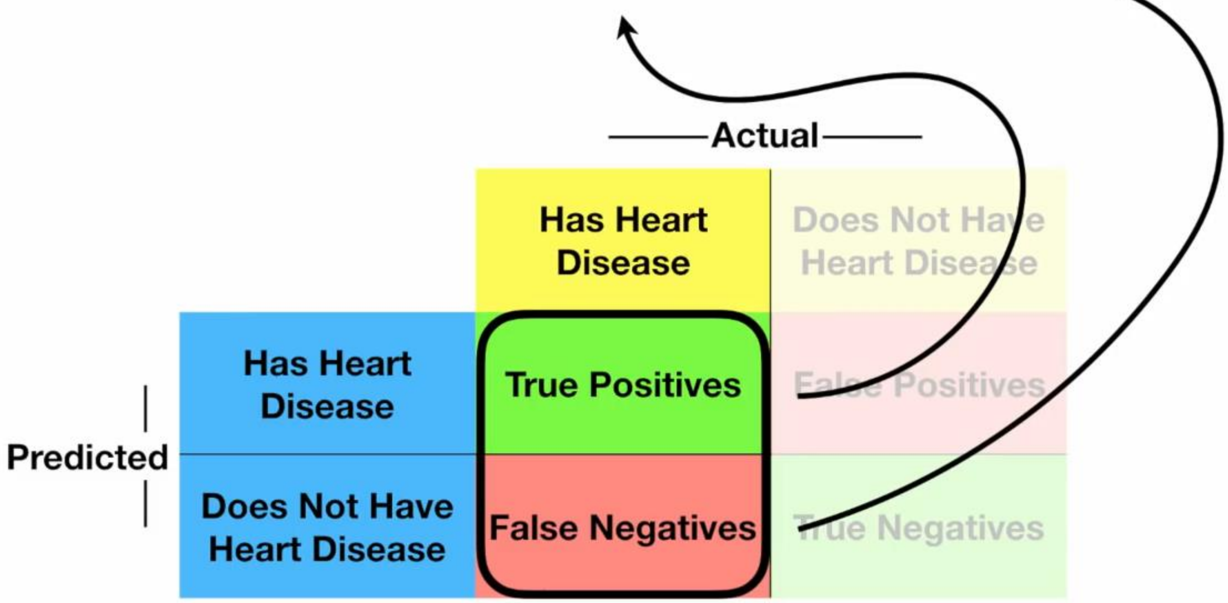
		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	**True Positives**	**False Positives**
	Does Not Have Heart Disease	**False Negatives**	**True Negatives**

Once we've filled out the **Confusion Matrix**, we can calculate two useful metrics: **Sensitivity** and **Specificity**.

		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	**True Positives**	**False Positives**
	Does Not Have Heart Disease	**False Negatives**	**True Negatives**

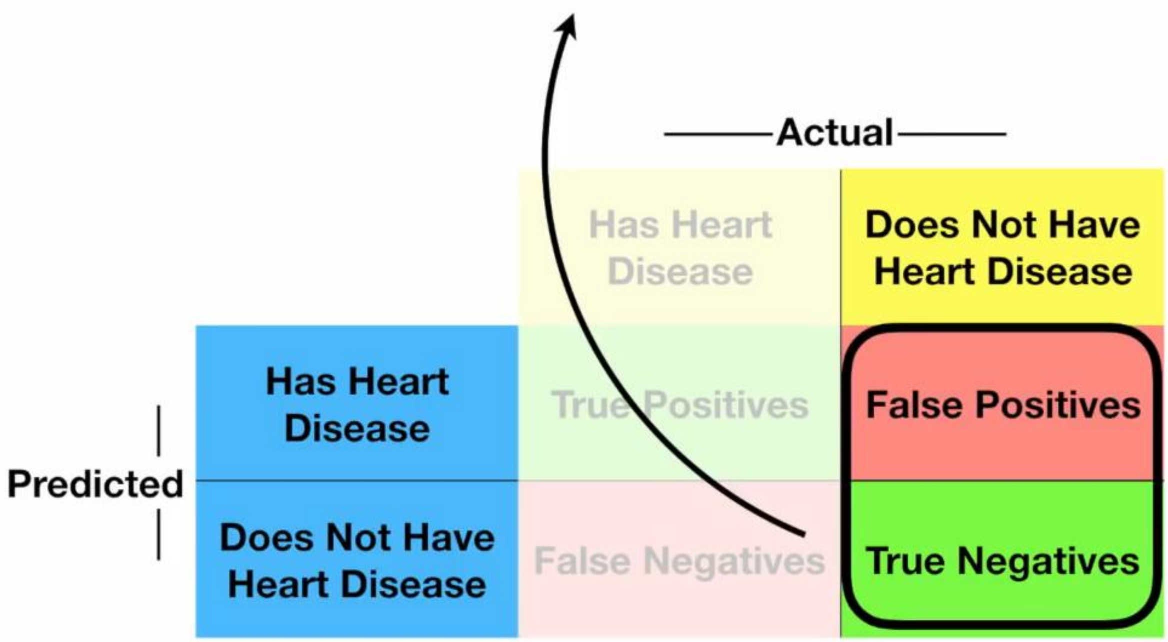
In this case, **Sensitivity** tells us what percentage of patients *with* heart disease were correctly identified.

$$\textbf{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

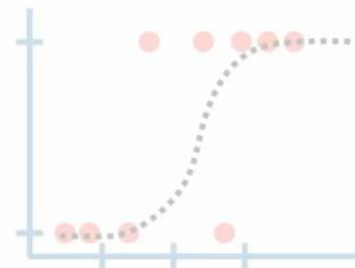


Specificity tells us what percentage of patients *without* heart disease were correctly identified.

$$\textbf{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Positives}}$$



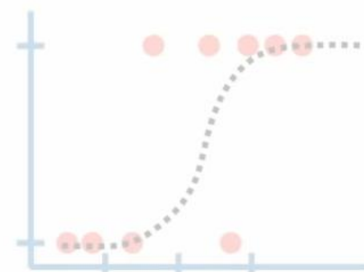
$$\textbf{Sensitivity} = \frac{139}{139 + 32} = 0.81$$



Sensitivity tells us that **81**% of the people *with* Heart Disease were correctly identified by the **Logistic Regression** model.

	Has Heart Disease	Does Not Have Heart Disease
Has Heart Disease	**139**	20
Does Not Have Heart Disease	**32**	112

$$\textbf{Specificity} = \frac{112}{112 + 20} = 0.85$$



Specificity tells us that **85**% of the people *without* Heart Disease were correctly identified by the **Logistic Regression** model.

	Has Heart Disease	**Does Not Have Heart Disease**
Has Heart Disease	139	**20**
Does Not Have Heart Disease	32	**112**

$$\textbf{Sensitivity} = \frac{142}{142 + 29} = 0.83$$

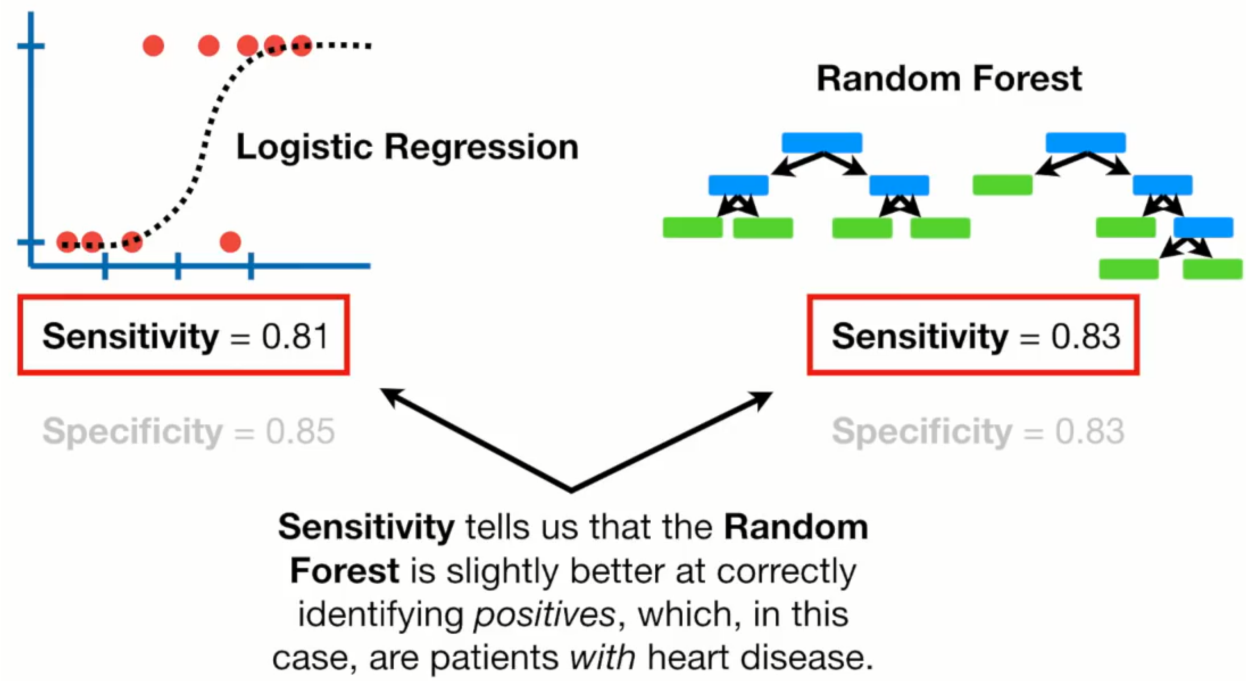
$$\textbf{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives + False Positives}}$$

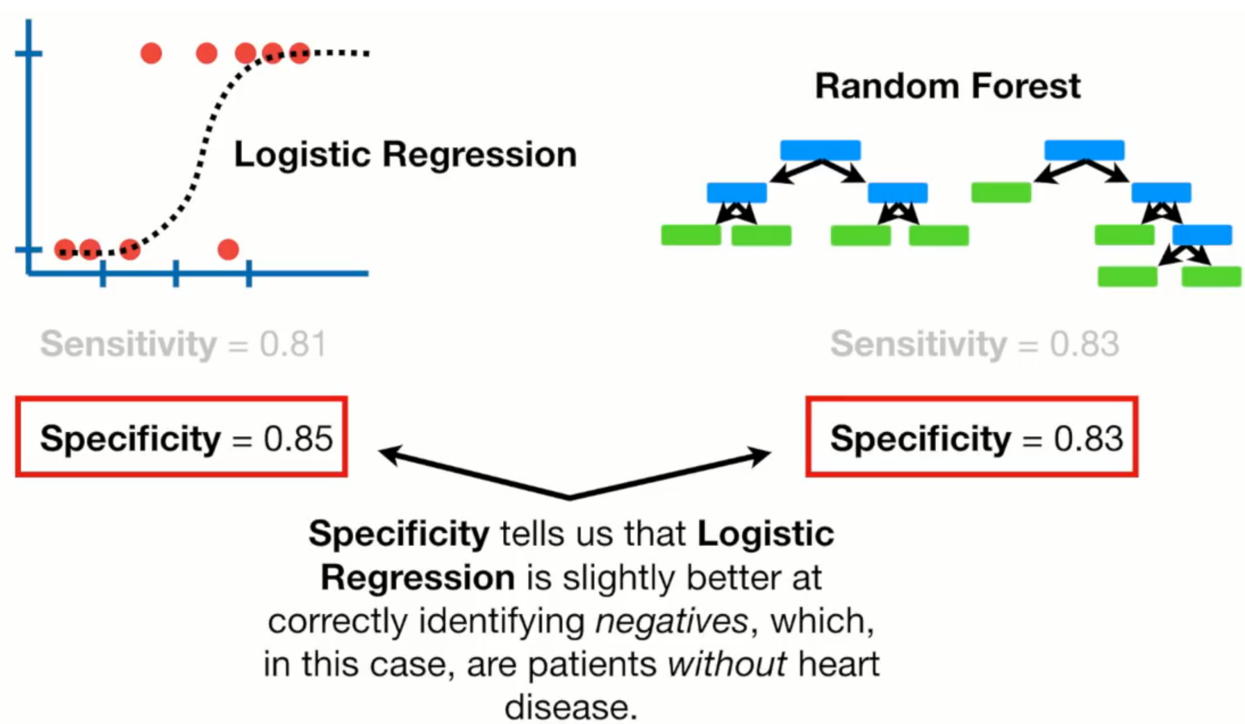
		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	**142**	**22**
	Does Not Have Heart Disease	**29**	**110**

$$\textbf{Sensitivity} = \frac{142}{142 + 29} = 0.83$$

$$\textbf{Specificity} = \frac{110}{110 + 22} = 0.83$$

		Actual	
		Has Heart Disease	**Does Not Have Heart Disease**
Predicted	**Has Heart Disease**	**142**	**22**
	Does Not Have Heart Disease	**29**	**110**

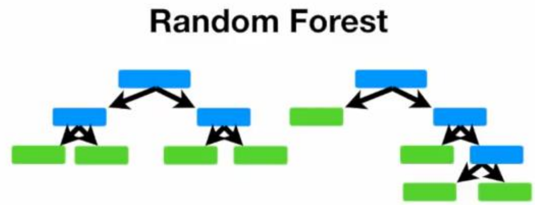

Random Forest
Logistic Regression
Sensitivity = 0.81
Specificity = 0.85
Sensitivity = 0.83
Specificity = 0.83
Sensitivity tells us that the **Random Forest** is slightly better at correctly identifying *positives*, which, in this case, are patients *with* heart disease.


Random Forest
Logistic Regression
Sensitivity = 0.81
Specificity = 0.85
Sensitivity = 0.83
Specificity = 0.83
Specificity tells us that **Logistic Regression** is slightly better at correctly identifying *negatives*, which, in this case, are patients *without* heart disease.

<table>
<tr>
<td>


Sensitivity = 0.81

Specificity = 0.85

We would choose the **Logistic Regression** model if correctly identifying patients **without** heart disease was more important than correctly identifying patients **with** heart disease.
</td>
<td>


Sensitivity = 0.83

Specificity = 0.83

Alternatively, we would choose the **Random Forest** model if correctly identifying patients **with** heart disease was more important than correctly identifying patients **without** heart disease.
</td>
</tr>
</table>

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

$$accuracy = \frac{TP + TN}{TP + FN + TN + FP}$$

$$specificity = \frac{TN}{TN + FP}$$