



Evaluation Metrics

Lesson 1











How good is a model?

$$\frac{\text{Accuracy}}{\text{Total number of examples}} = \frac{\text{Examples correctly classified}}{\text{Total number of examples}}$$









Ground Truth Model 1 1.00 ☑ Share Normal Normal Normal Normal Normal Disease Normal Disease Normal Normal 1:46 / 2:35

1.00

Ground Truth

Model 2

Model 1

Normal

Normal

Normal

Normal

Normal

Disease

Normal

Disease

Normal

Normal

0	-	
	+	

.

-

-

+

-

+

+

-

Model 1	
-	
-	
-	
-	
-	
-	
-	

-

-

-

Accuracy = P(correct)

Accuracy = $P(correct \cap disease) + P(correct \cap normal)$

Using $P(A \cap B) = P(A \mid B) P(B)$

Accuracy = P(correct | disease)P(disease) + P(correct | normal)P(normal)

Accuracy = P(+ | disease)P(disease) + P(- | normal)P(normal)





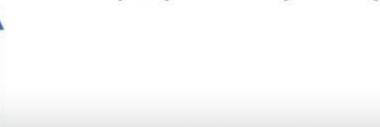


Accuracy =
$$P(correct \cap disease) + P(correct \cap normal)$$

Using
$$P(A \cap B) = P(A \mid B) P(B)$$

Accuracy =
$$P(correct | disease)P(disease) + P(correct | normal)P(normal)$$

Accuracy =
$$P(+ | disease)P(disease) + P(- | normal)P(normal)$$



Sensitivity (true positive rate) Specificity (true negative rate)







P(+ | disease)

If a patient has the disease, what is the probability that the model predicts positive?

Sensitivity

P(- | normal)

If a patient is normal, what is the probability that the model predicts negative?

Specificity





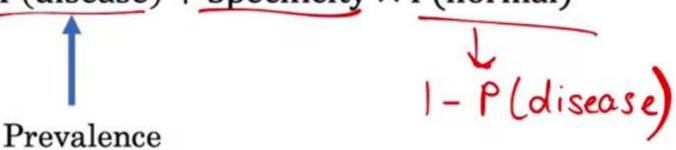






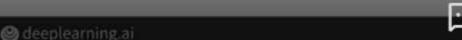
Accuracy = P(correct)

 $Accuracy = Sensitivity \times P(disease) + Specificity \times P(normal)$



Accuracy = Sensitivity \times prevalence + Specificity \times (1 – prevalence)





Accuracy = Sensitivity \times prevalence + Specificity \times (1 - prevalence)









1.00

Ground Truth Normal

Normal

Disease

Normal

Normal

Disease

Normal

Disease

Normal

Normal

#(disease)

#(normal)

Sensitivity P(+ | disease)

Specificity

P(-|normal)

#(- and normal) = 6 = 0.86

#(+ and disease) = 2 = 0.67



Model



☑ Share





Ground Truth

Model

			- 1
N	or	m	ดไ
T.4	UI.	111	a_1

Normal

Disease

Normal

Normal

Disease

Normal

Disease

Normal

Normal

Sensitivity =
$$0.67$$

Specificity =
$$0.86$$

Prevalence

P(disease)

$$\frac{\text{#(disease)}}{\text{#(total)}} = \frac{3}{10} = 0.3$$

Accuracy

Sensitivity \times prevalence +Specificity \times (1 – prevalence)

$$= 0.67 \times 0.3 + 0.86 \times 0.7 = 0.8$$

P(+ | disease)

If a patient has the disease, what is the probability that the model predicts positive?



If a model prediction is positive, what is the probability that a patient has the disease?

$$P(\text{disease} \mid +)$$

PPV

Specificity

 $P(- \mid \text{normal})$

If a patient is normal, what is the probability that the model predicts negative?



If a model prediction is negative, what is the probability that a patient is normal?

$$P(\text{normal} \mid \underline{\hspace{0.1cm}})$$

NPV

Ground Truth

Model

☑ Share

PPV Disease

$$P(\text{disease} \mid +)$$

$$\frac{\#(+ \text{ and disease})}{\#(+)} = \frac{2}{4} = 0.5$$

Normal

Normal

Disease

Normal

Disease

Normal

Mouman TANTINGT **NPV**

$$P(\text{normal} \mid -)$$

$$\frac{\#(-\text{ and normal})}{\#(-)} = \frac{5}{6} = \frac{0.83}{6}$$







$$P(\text{disease} \mid +)$$

 $P(\text{normal} \mid -)$

PPV

NPV

$$P(+ | \text{disease})$$
 $P(- | \text{normal})$

Sensitivity

Specificity



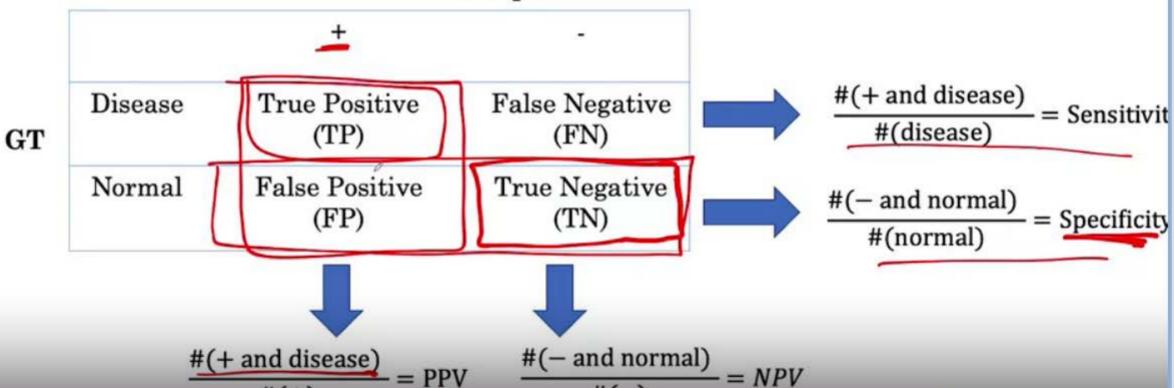




1.00

Ground Truth	1				Model
Normal					-
Disease					+
Normal		Mode	Outp	ut	+
Normal			+	-	-
Normal	G T	Disease	20	1	-
Disease		Normal	2	5	-
Normal		Ttormar			-
Disease					+
Normal					+
Normal					-

Model Output



#(-)







#(1)

GT

Model Output

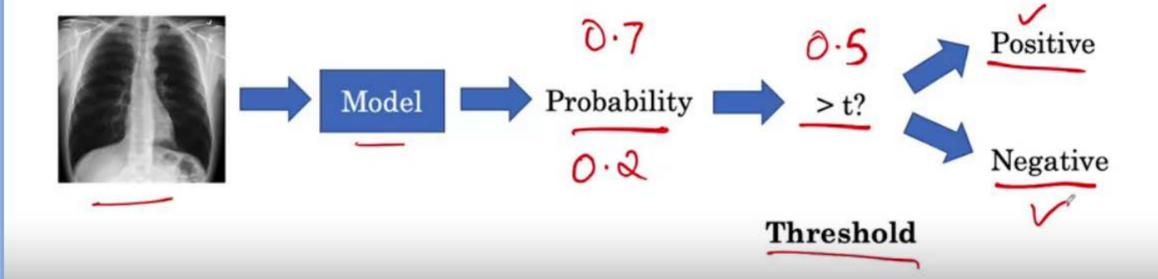
Disease True Positive (FN)

Normal False Positive (FP)

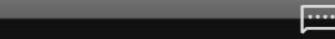
True Negative (TN)

True Negative (TN) $\frac{TP}{TP+FN} = \text{Sensitivity}$ $\frac{TN}{FP+TN} = \text{Specificity}$

$$\frac{TP}{TP + FP} = \underline{PPV} \quad \frac{TN}{TN + FN} = \underline{NPV}$$



@ deeplearning.ai



$$P(+ | \text{disease}) \quad P(- | \text{normal})$$

$$P(- \mid \text{normal})$$

Specificity

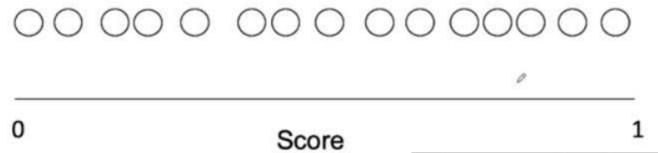








X-Ray	Output Probability (Score)
1	0.30
2	0.42
3	0.78
15	0.98

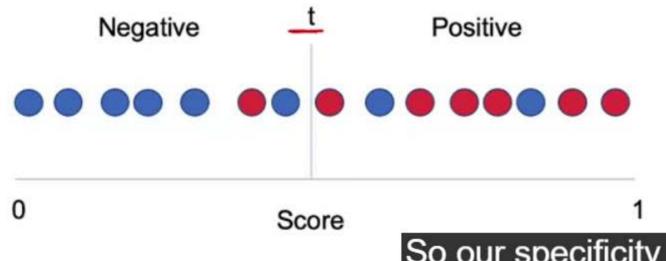


We can plot these

$$P(+ | \text{disease}) \quad P(- | \text{normal})$$

$$P(- \mid \text{normal})$$

$$\frac{6}{7} = 0.85$$



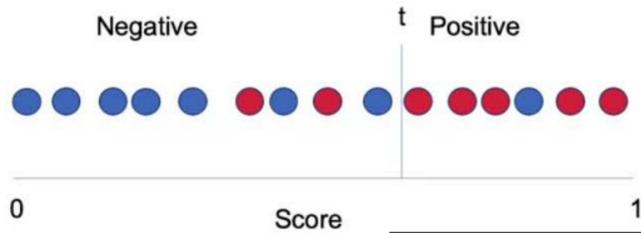
So our specificity is six over eight or 0.75.

$$P(+ | \text{disease}) \quad P(- | \text{normal})$$

Specificity

$$\frac{5}{7} = 0.71$$

$$\frac{7}{8} = 0.88$$



because we are now correctly classifying

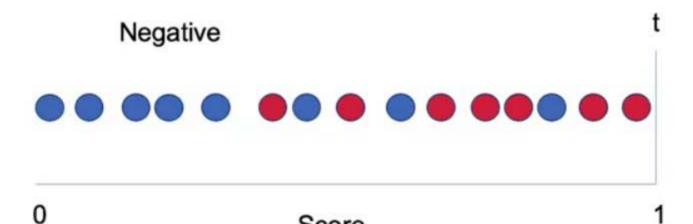
$$P(+ | \text{disease}) \quad P(- | \text{normal})$$

$$P(- | \text{normal})$$

$$\frac{0}{7} = 0$$

Specificity

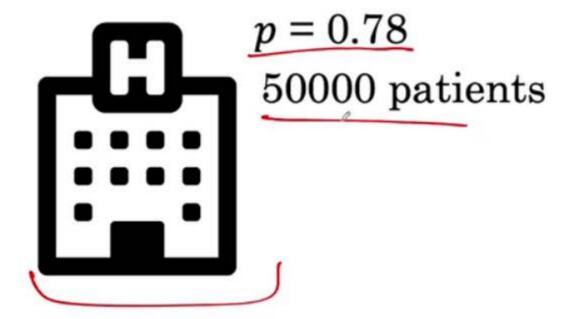
$$\frac{8}{8} = 1$$



Score

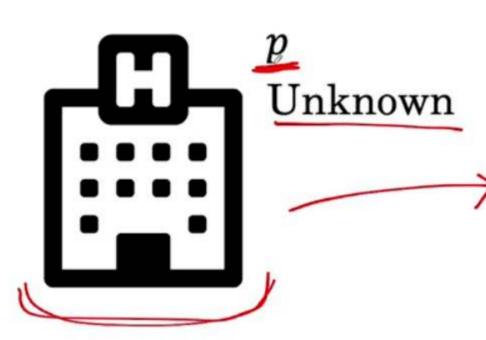
since all the examples are classified as negative.

1.00



This is called the population accuracy, here with small p.





$$\hat{p} = 0.80$$
, n = 100

Known

Can we say anything about the range in





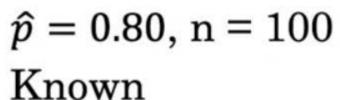








pUnknown





With 95% confidence, p is in the interval [0.72, 0.88]

but it's important to understand













0.80 (95% CI 0.72, 0.88)

Interpretation of 95% confidence interval

With 95% confidence, p is in the interval [0.72, 0.88]

Mis-interpretation

There is a 95% probability that p lies within the interval [0.72, 0.88]

Mis-interpretation

95% of the sample accuracies lie within the interval [0.72, 0.88]

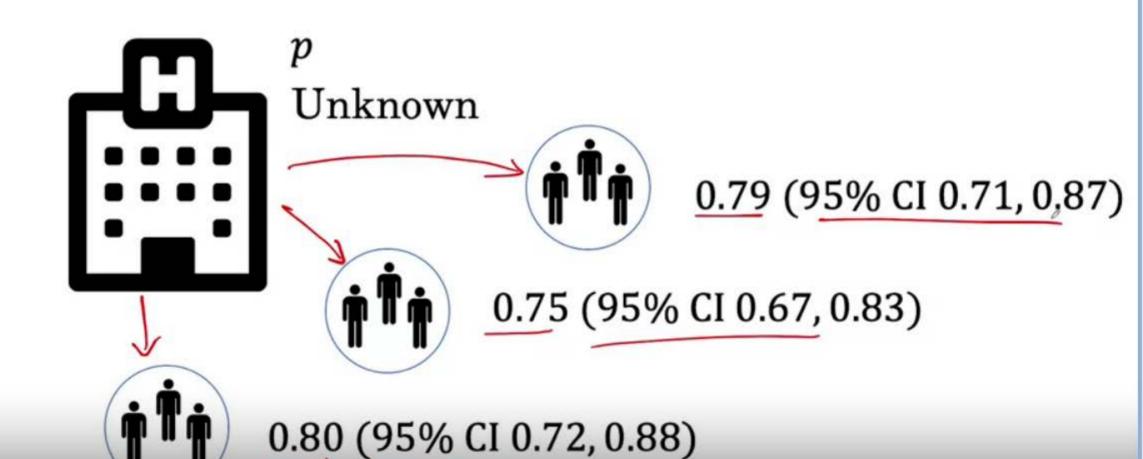












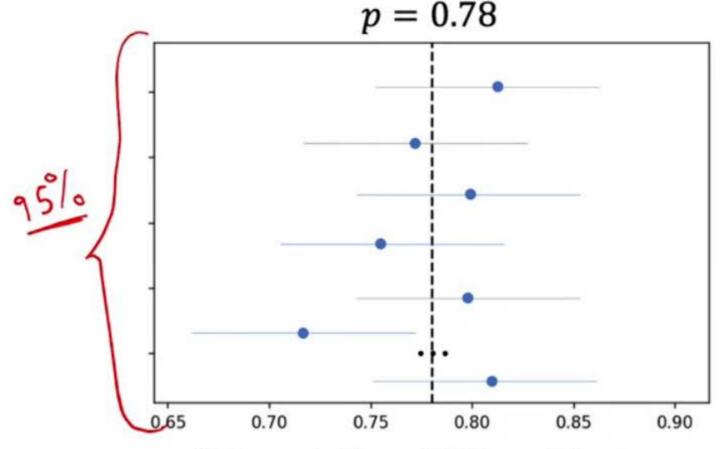












Interpretation of 95% confidence

In repeated sampling, this method produces intervals that include the population accuracy in about 95% of samples

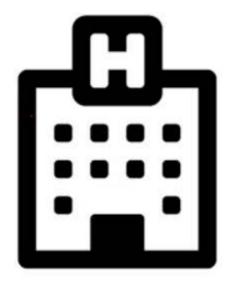


Play

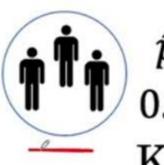






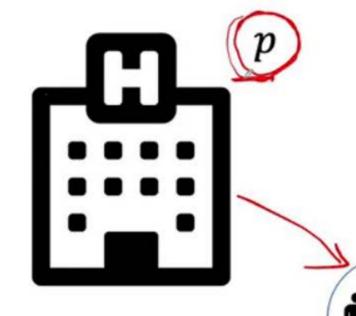


pUnknown



p̂ = 0.80, n = 1000.80 (95% CI 0.72, 0.88)Known







$$\hat{p} = 0.80, \, \mathbf{n} = \mathbf{100}$$
0.80 (95% CI **0**. **72**, **0**. **88**)

$$\hat{p} = 0.80, \mathbf{n} = 500$$

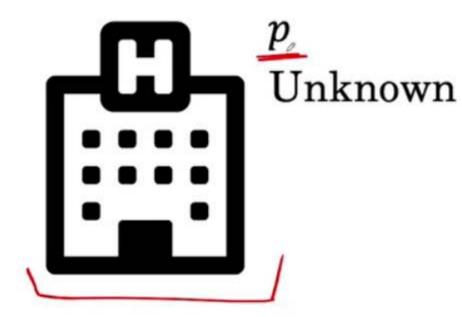
0.80 (95% CI **0.76, 0.84**)











0.80 (95% CI 0.72, 0.88) Known

