

Mašinsko učenje - Ocena modela - part II. Mere kvaliteta modela klasifikacije.

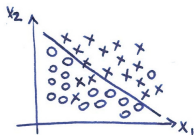
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- Formalizacija učenja.
- Polinomijalna regresija.
- Preobučavanje kod problema klasifikacije.
- Unakrsna validacija i ocena modela.

Overfitting and regularization

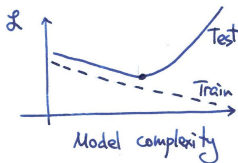
Overfitting, bias–variance tradeoff, regularization (ridge/lasso) — all these concepts still apply.



High bias

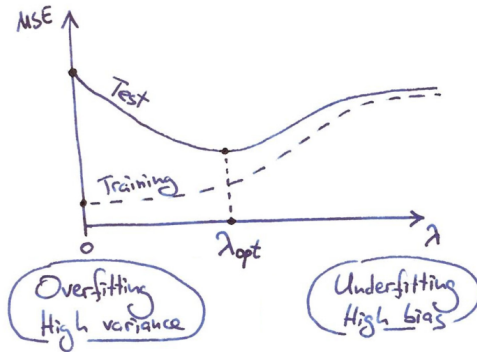


High variance



Izbor modela

- Svodi se na izbor za λ .



- Mere kvaliteta problema prema tipu problema:
 - Problemi regresije.
 - srednjekvadratna greška i njen koren,
 - srednja relativna greška,
 - koeficijent determinacije R^2 .
 - Klasifikacioni problemi.
 - tačnost klasifikacije (eng. accuracy),
 - preciznost i odziv (eng. precision and recall)
 - F_1 mera
 - Sensitivity and specificity.
 - AUC - površina ispod ROC krive.

Matrica konfurzije kao mera kvaliteta modela klasifikacije

- Matrica konfurzije (eng. confusion matrix).
- Element a_{ij} matrice konfurzije A je broj primera iz klase i koji su klasifikovani kao klasa j .

- Stvarno -	- Predviđeno -	
	pozitivno (1)	negativno (0)
pozitivno (1)	stvarno pozitivno	lažno negativno
negativno (0)	lažno pozitivno	stvarno negativno

- Prevod:
 - stvarno pozitivno (eng. true positive, TP)
 - stvarno negativno (eng. true negatives, TN)
 - lažno pozitivno (eng. false positive, FP)
 - lažno negativno (eng. false negatives, FN)

Sofisticirane mere kvaliteta modela klasifikacije

- Odziv (sensitivity, recall), koliko pozitivnih elemenata je korektno identifikovano:

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

- Specifičnost (specificity), koliko negativnih elemenata je korektno identifikovano:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

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

Primer - senzitivnost = 0.81:

Izvor slike: [<https://www.youtube.com/watch?v=vP06aMoz4v8>]

Sofisticirane mere kvaliteta modela klasifikacije

- Odziv (sensitivity, recall), koliko pozitivnih elemenata je korektno identificirano:

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

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$$\text{Specificity} = \frac{TN}{TN + FP}$$

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

Primer - senzitivnost = 0.85:

Izvor slike: [<https://www.youtube.com/watch?v=vP06aMoz4v8>]

- Tačnost klasifikacije (accuracy)

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

- Tačnost klasifikacije nije informativna u slučaju neizbalansiranih klasa.
- Primer: detekcija retkih bolesti.
- Preciznost (precision), udeo pozitivnih instanci u svim instancama proglašenim pozitivnim.

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

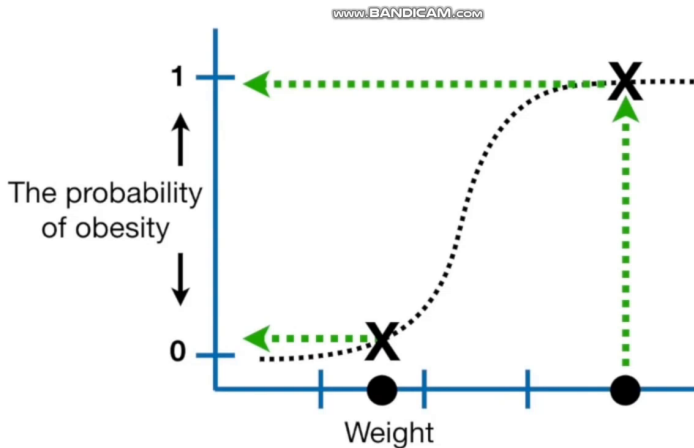
- Preciznost je maksimalna ukoliko $FP=0$.

- F1 mera:

$$F_1 = 2 \frac{\textit{Precision} \cdot \textit{Sensitivity}}{\textit{Precision} + \textit{Sensitivity}}$$

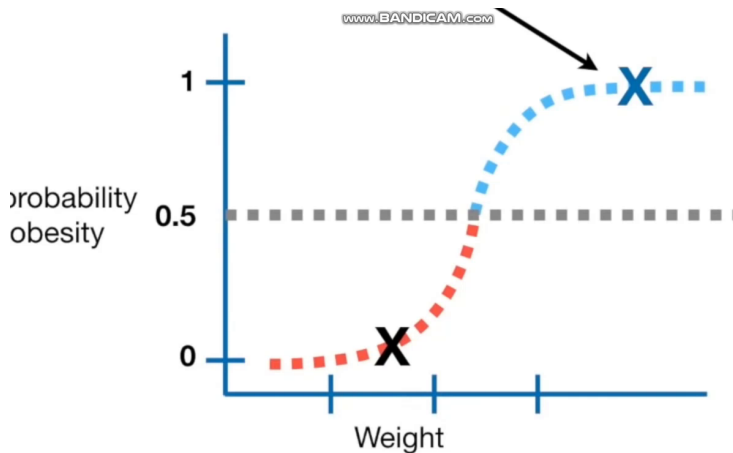
- Harmonijska srednja vrednost preciznosti i odziva.

AUC i ROC



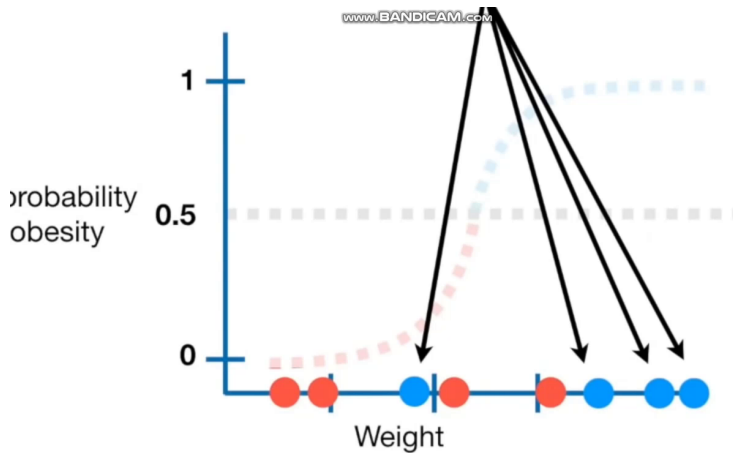
Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



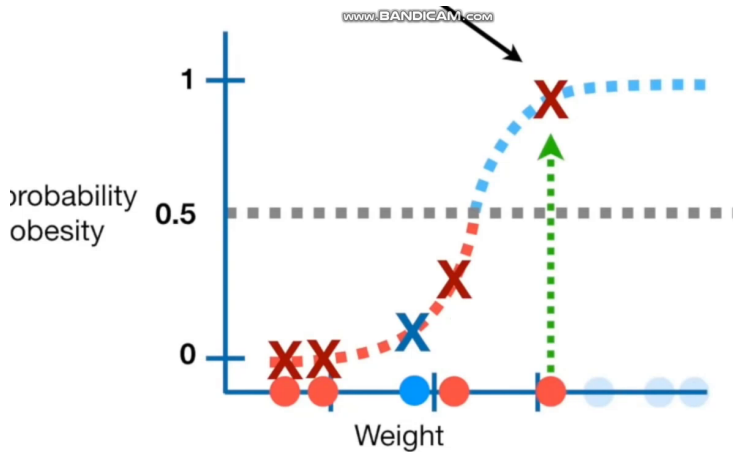
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AUC i ROC



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AUC i ROC

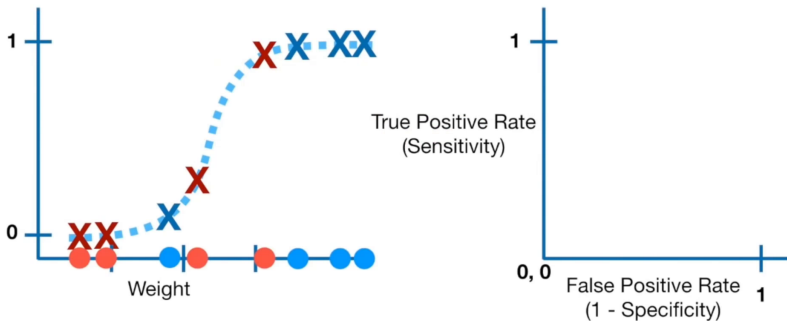


Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

www.BANDICAM.com

To get a better sense of how the **ROC** works, let's draw one from start to finish using our example data.

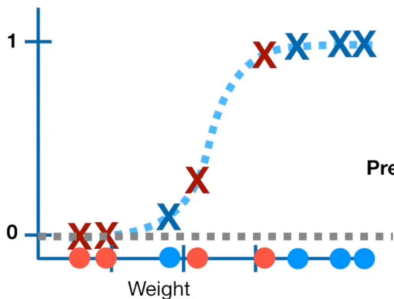


Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

www.BANDICAM.com

...and that gives us this **Confusion Matrix**.



		Actual	
		Is Obese	Is Not Obese
Predicted	Is Obese	4	4
	Is Not Obese	0	0

Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]



AUC i ROC

www.BANDICAM.com

$$\text{True Positive Rate} = \text{Sensitivity} = \frac{4}{4 + 0} = 1$$

$$\text{False Positive Rate} = 1 - \text{Specificity} = \frac{4}{4 + 0} = 1$$

This means that every single sample that was **not obese** was *incorrectly* classified as **obese**.

Predicted

	Actual	
	Is Obese	Is Not Obese
Is Obese	4	4
Is Not Obese	0	0



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

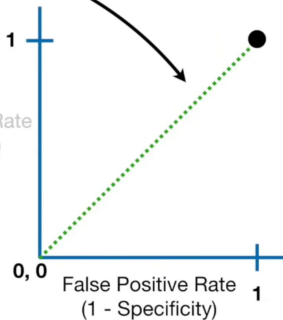
AUC i ROC

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This **green diagonal line** shows where the **True Positive Rate = False Positive Rate**

Any point on this **line** means that the **proportion of correctly classified obese** samples is the same as the **proportion of incorrectly classified samples that are not obese.**

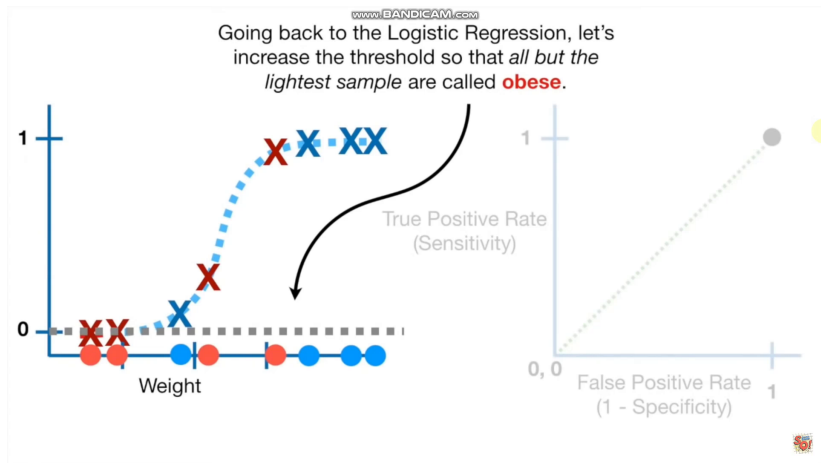
True Positive Rate
(Sensitivity)



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]



AUC i ROC



AUC i ROC

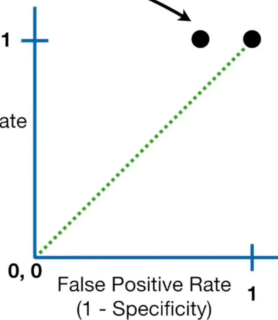
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$$\text{True Positive Rate} = \text{Sensitivity} = \frac{4}{4 + 0} = 1$$

$$\text{False Positive Rate} = 1 - \text{Specificity} = \frac{3}{3 + 1} = 0.75$$

...and plot a point at 0.75, 1.

True Positive Rate
(Sensitivity)

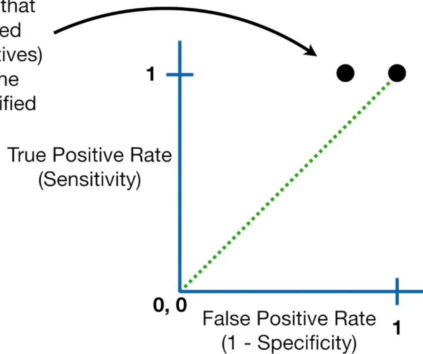


Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

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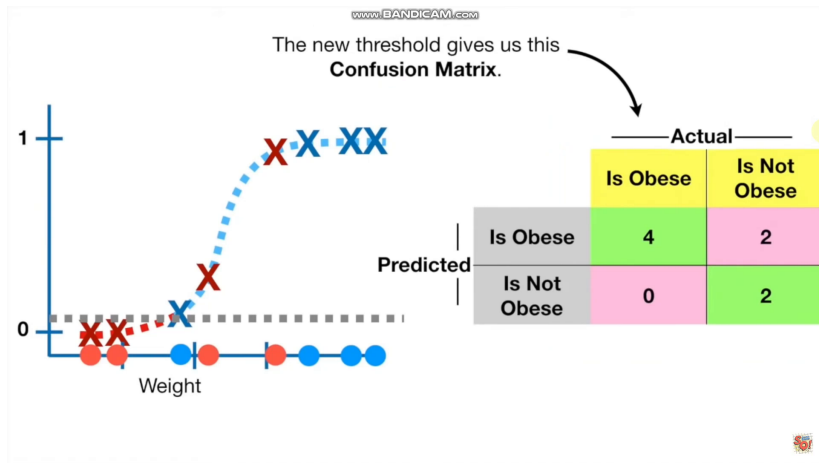
Since the new point (**0.75, 1**) is to the left of the **dotted green line**, we know that the proportion of correctly classified samples that were **obese** (true positives) is *greater* than the proportion of the samples that were incorrectly classified as **obese** (false positives).



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]



AUC i ROC



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

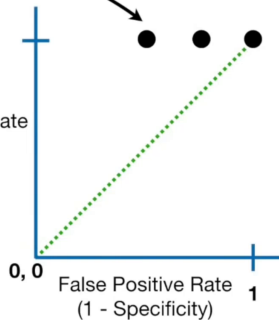
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$$\text{True Positive Rate} = \text{Sensitivity} = \frac{4}{4 + 0} = 1$$

$$\text{False Positive Rate} = 1 - \text{Specificity} = \frac{2}{2 + 2} = 0.5$$

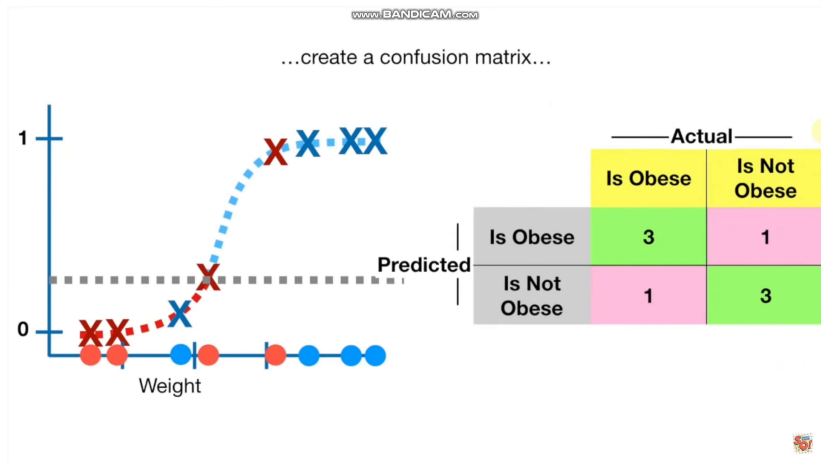
...and plot a point at 0.5, 1.

True Positive Rate
(Sensitivity)



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

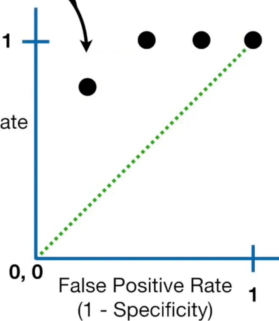
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$$\text{True Positive Rate} = \text{Sensitivity} = \frac{3}{3+1} = 0.75$$

$$\text{False Positive Rate} = 1 - \text{Specificity} = \frac{1}{1+3} = 0.25$$

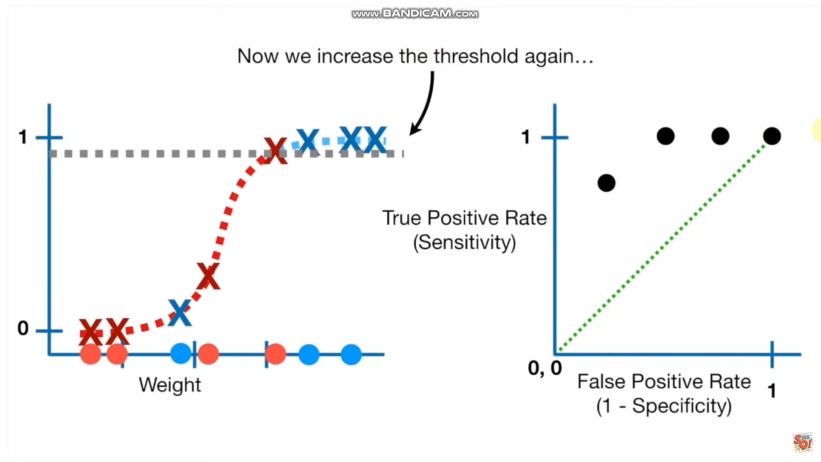
...and plot the point.

True Positive Rate
(Sensitivity)



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



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AUC i ROC

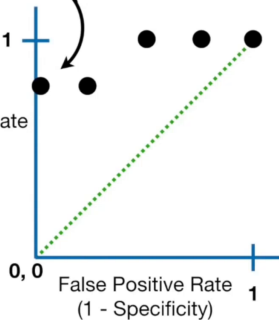
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$$\text{True Positive Rate} = \text{Sensitivity} = \frac{3}{3 + 1} = 0.75$$

$$\text{False Positive Rate} = 1 - \text{Specificity} = \frac{0}{0 + 4} = 0$$

...and plot the point.

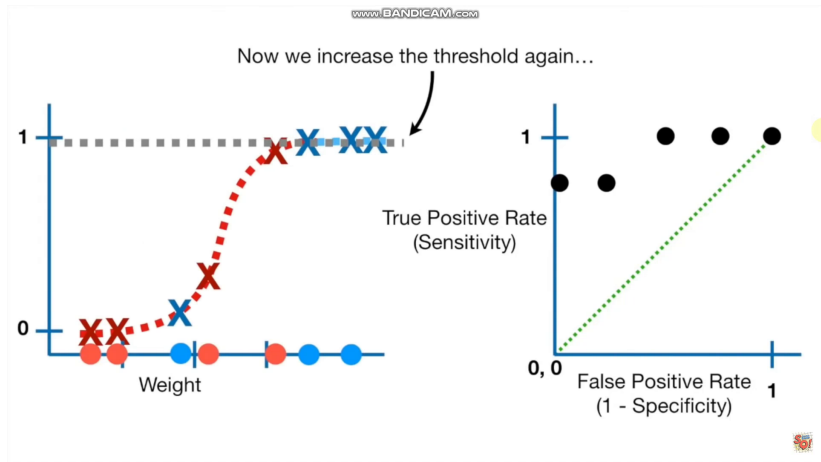
True Positive Rate
(Sensitivity)



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

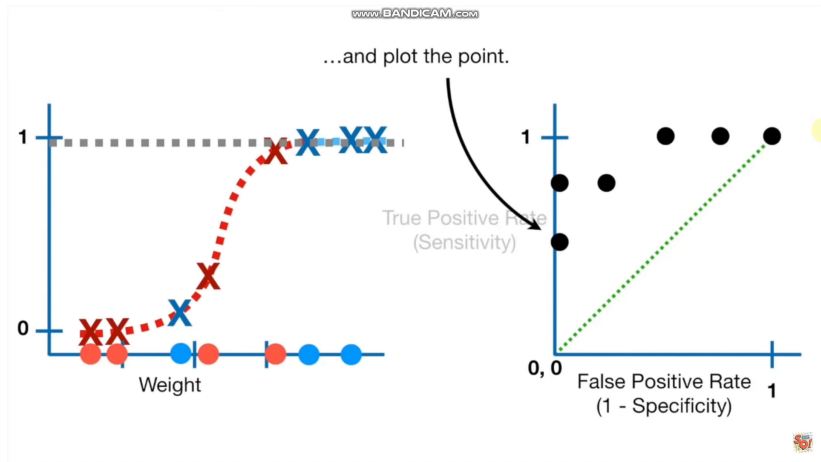


AUC i ROC



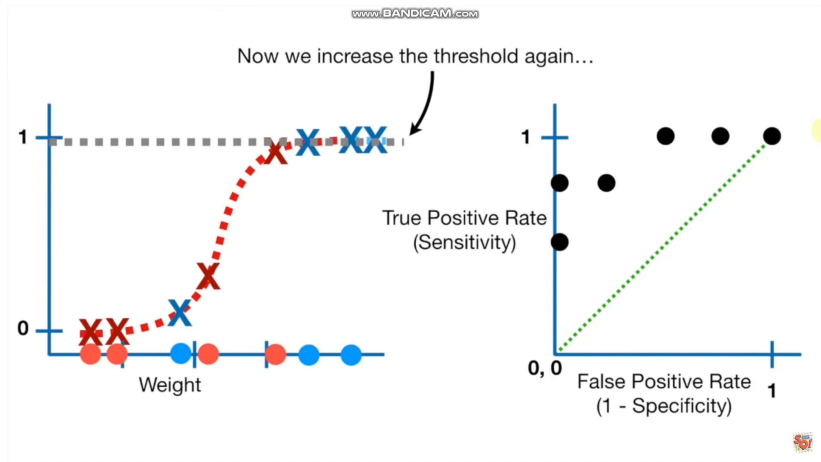
Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



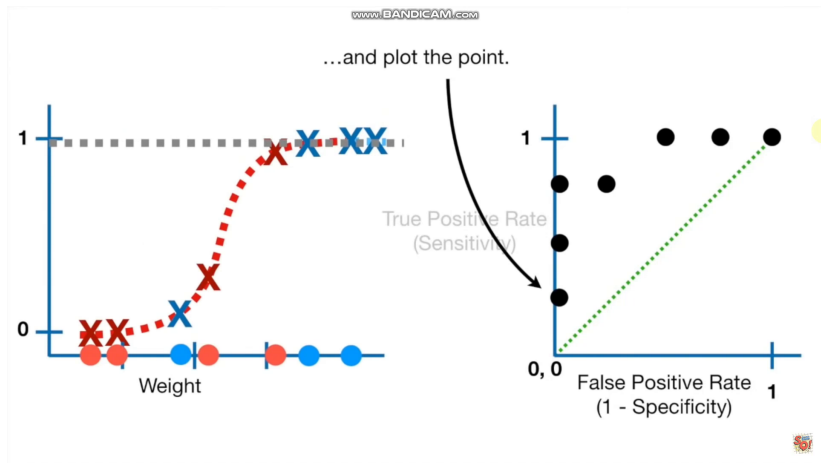
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AUC i ROC



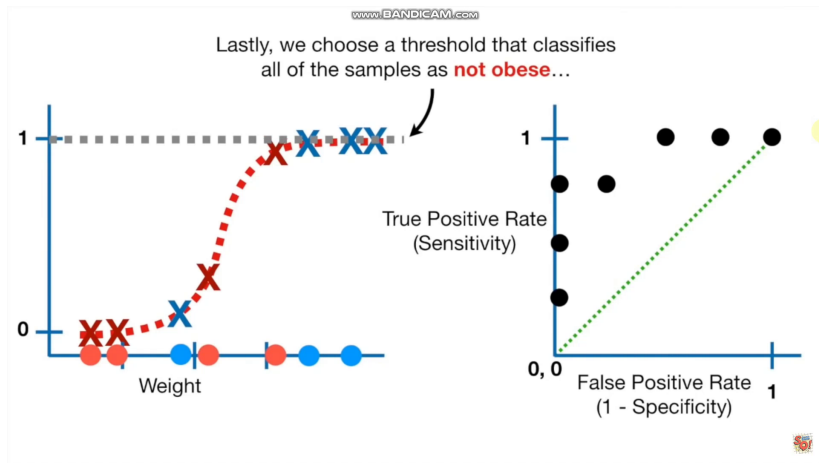
Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



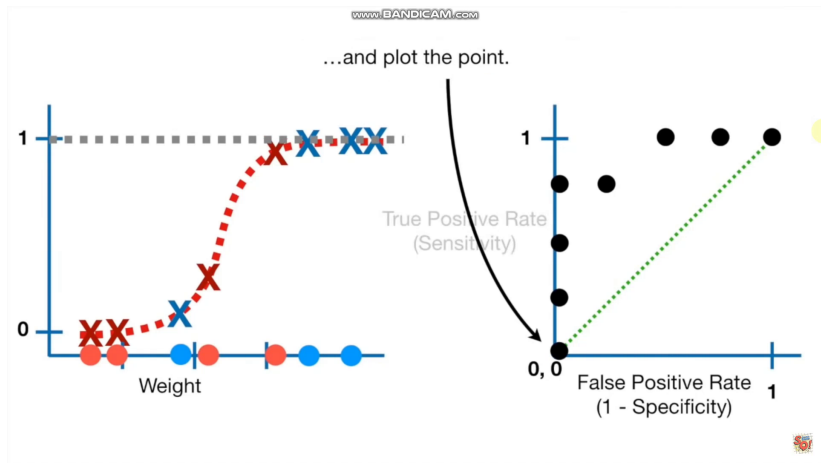
Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC



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AUC i ROC

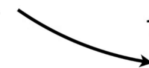


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AUC i ROC

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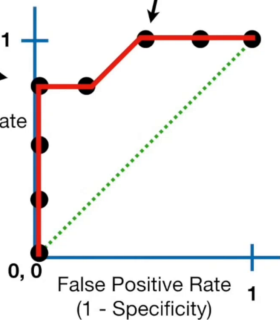
And depending on how many **False Positives** I'm willing to accept, the optimal threshold is either this one...



...or this one.



True Positive Rate
(Sensitivity)

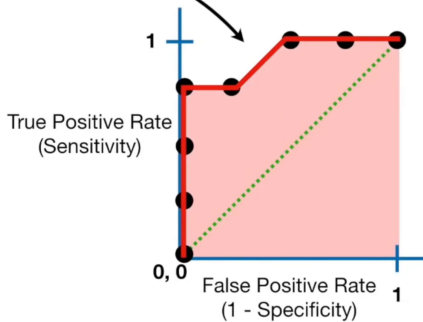


Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

AUC i ROC

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The **AUC** (Area Under the Curve) is **0.9**

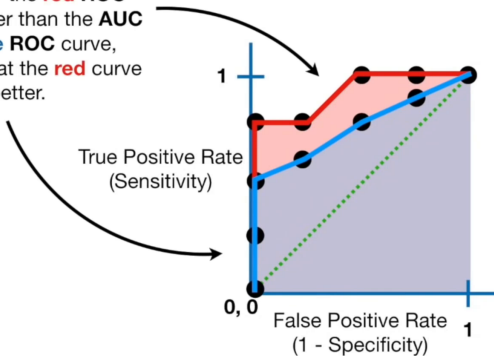


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AUC i ROC

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The **AUC** for the **red ROC** curve is greater than the **AUC** for the **blue ROC** curve, suggesting that the **red** curve is better.



Izvor slike: [<https://www.youtube.com/watch?v=4jRBRDbJemM>]

- 
- Preciznost umesto *false positive rate* ukoliko su podaci neblansirani.
 - Ovo je prikladno kod klasifikacije rethih oboljenja.



Hvala na pažnji.
Molim vas pitajte sve šta
vas interesuje.