



Performance measures

Confusion matrix

		True condition	
		Condition positive	Condition negative
Predicted condition	Predicted condition positive	True positive, Power	False positive, Type I error
	Predicted condition negative	False negative, Type II error	True negative

Source: https://en.wikipedia.org/wiki/Receiver_operating_characteristic

Measures of accuracy

- Terminology

- $TP \rightarrow$ true positives, $TN \rightarrow$ true negatives,
- $FP \rightarrow$ false positives, $FN \rightarrow$ false negatives
$$N = TP + TN + FP + FN$$
- TP – Correct identification of positive labels
- TN – Correct identification of negative labels
- FP – Incorrect identification of positive labels
- FN – Incorrect identification of negative labels

Measures of accuracy

- **Accuracy:** Overall effectiveness of a classifier
 - $A = \frac{TP+TN}{N}$
 - Maximum value that accuracy can take is 1
 - This happens when the classifier exactly classifies two groups (i.e., $FP = 0$ and $FN = 0$)
- **Remember**
 - Total number of true positive labels = $TP+FN$
- **Similarly**
 - Total number of true negative labels = $TN+FP$

Measures of accuracy

- Sensitivity: Effectiveness of a classifier to identify positive labels
 - $S_e = \frac{TP}{TP + FN}$
- Specificity: Effectiveness of a classifier to identify negative labels
 - $S_p = \frac{TN}{FP + TN}$
- Both S_e and S_p lie between 0 *and* 1, 1 is an ideal value for each of them
- Balanced accuracy
 - $BA = (sensitivity + specificity)/2$

Measures of accuracy

- Prevalence: How often does the yes condition actually occur in our sample

$$P = \frac{TP + FN}{N}$$

- Positive predictive value: Proportion of correct results in labels identified as positive

- $PPV = \frac{(sensitivity * prevalence)}{((sensitivity * prevalence) + ((1 - specificity) * (1 - prevalence)))}$

- Negative prediction value: Proportion of correct results in labels identified as negative

- $NPV = \frac{specificity * (1 - prevalence)}{(((1 - sensitivity) * prevalence) + ((specificity) * (1 - prevalence)))}$

Measures of accuracy

- Detection rate:
 - $DR = \frac{TP}{N}$
- Detection prevalence: prevalence of predicted events
 - $DP = \frac{TP+FP}{N}$
- The Kappa statistic (or value) is a metric that compares an **observed accuracy** with an **expected accuracy** (random chance)
- $$\text{Kappa} = \frac{\text{observed accuracy} - \text{expected accuracy}}{1 - \text{expected accuracy}}$$

Measures of accuracy

- Observed accuracy

- $OA = \frac{a+d}{N}$

- Expected accuracy

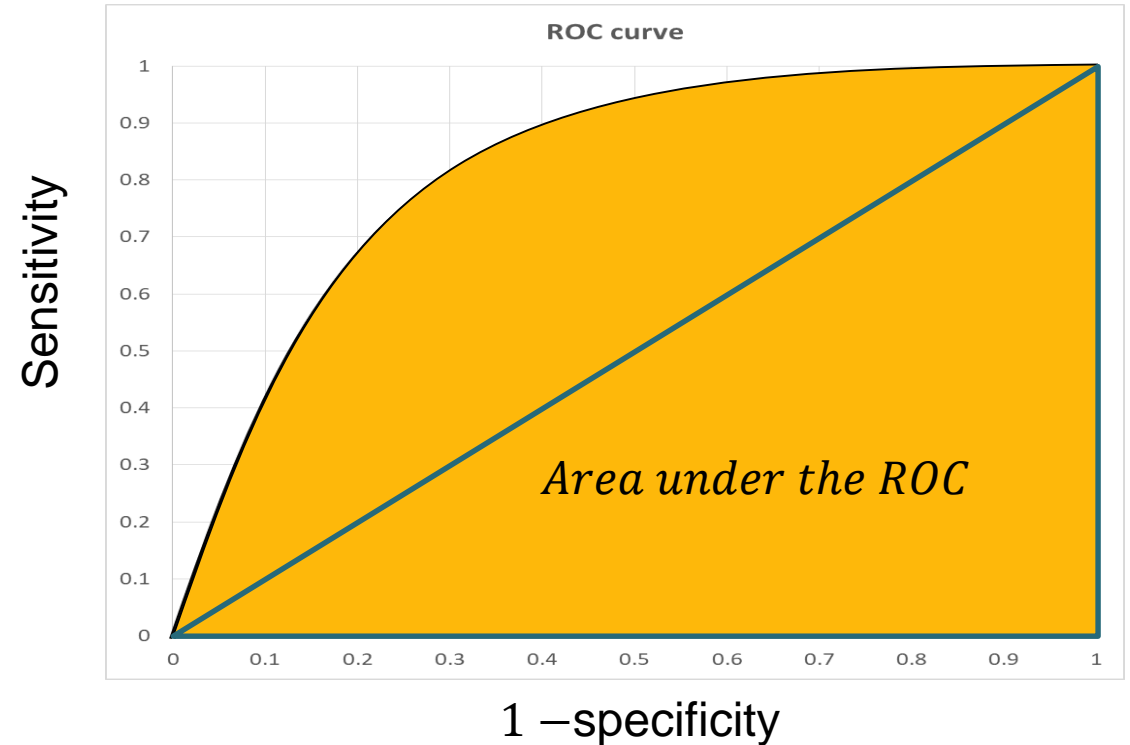
- $EA = \frac{(a+c)(a+b) + (b+d)(c+d)}{N}$

- Kappa =
$$\frac{\frac{(a+d)}{N} - \left(\frac{(a+c)(a+b) + (b+d)(c+d)}{N} \right)}{\left(1 - \left(\frac{(a+c)(a+b) + (b+d)(c+d)}{N} \right) \right)}$$

- Where a, b, c and d are TP, FP, FN and TN respectively

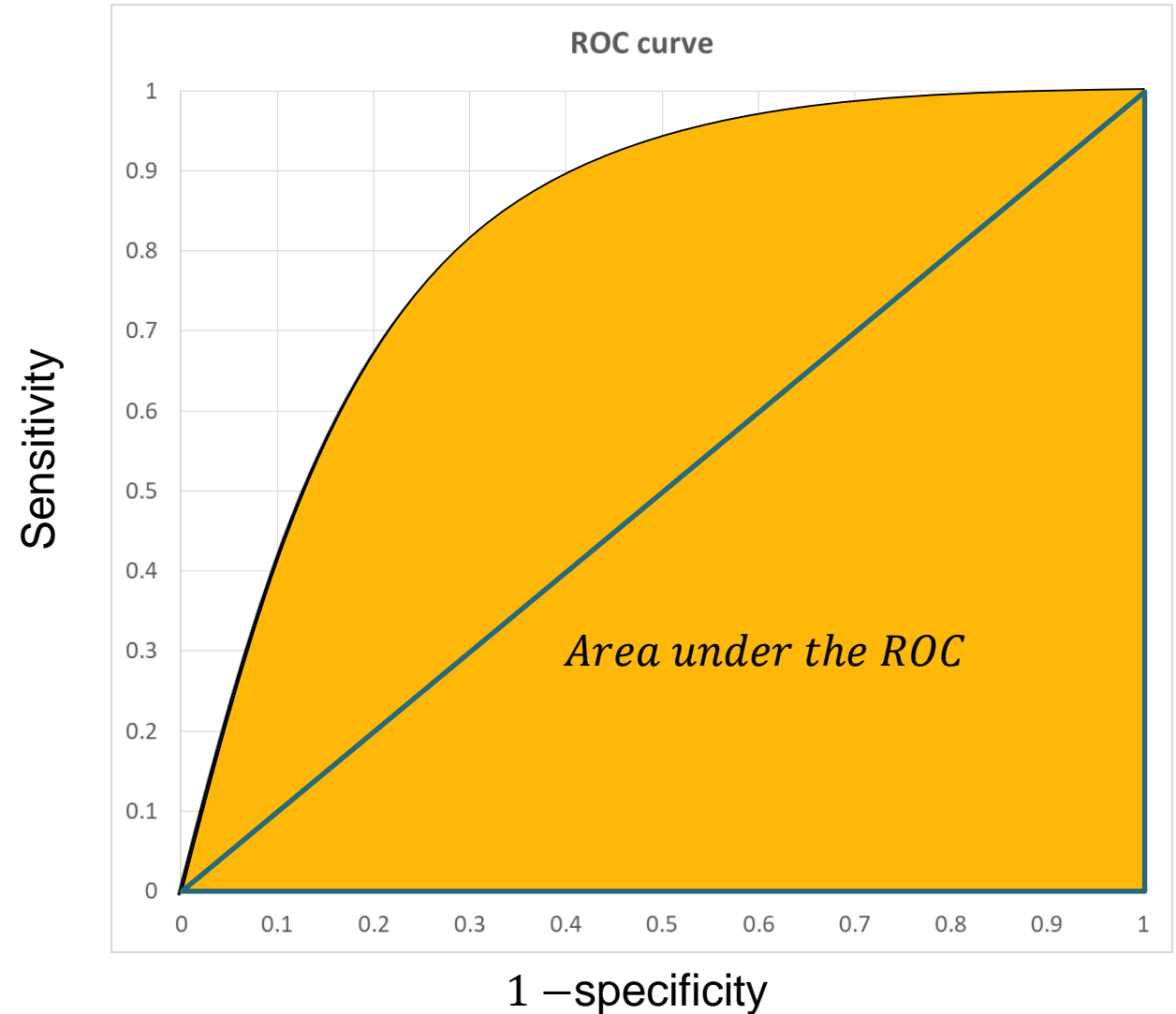
ROC

- ROC –An acronym for Receiver Operating Characteristics
- Originally developed and used in signal detection theory
- ROC graph:
 - Sensitivity as a function of specificity
 - sensitivity (Y-axis) and 1 –specificity (X-axis)



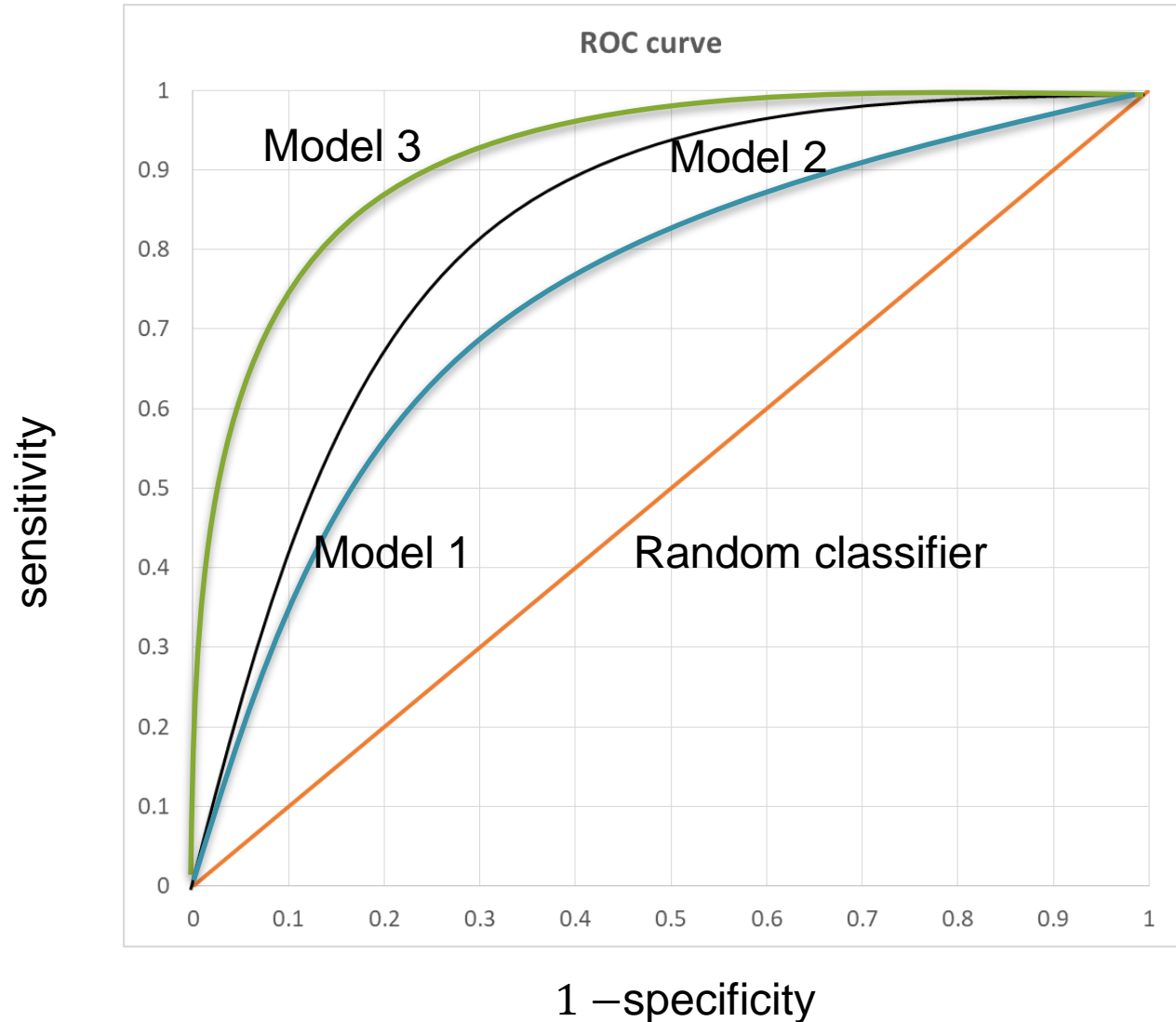
ROC

- ROC can be used to
 - See the classifier performance at different threshold levels (from 0 to 1)
 - AUC- Area under the ROC
 - An area of 1 represents a perfect test; an area of 0.5 represents a worthless model.
 - .90 – 1 = excellent
 - .80 – .90 = good
 - .70 – .80 = fair
 - .60 – .70 = poor
 - $AUC < 0.5$, check whether your labels are marked in opposite



ROC

- ROC can be used to
 - Compare different classifiers at one threshold or overall threshold levels
 - Performance
 - $\text{Model 3} > \text{Model 2} > \text{Model 1}$



```
operation == "MIRROR_X":  
    mirror_mod.use_x = True  
    mirror_mod.use_y = False  
    mirror_mod.use_z = False  
operation == "MIRROR_Y":  
    mirror_mod.use_x = False  
    mirror_mod.use_y = True  
    mirror_mod.use_z = False  
operation == "MIRROR_Z":  
    mirror_mod.use_x = False  
    mirror_mod.use_y = False  
    mirror_mod.use_z = True
```

```
#selection at the end -add  
mirror_ob.select= 1  
modifier_ob.select=1  
context.scene.objects.active  
= ("Selected" + str(modifier_ob.name))  
mirror_ob.select = 0  
= bpy.context.selected_objects  
data.objects[one.name].select  
print("please select exactly one mirror")
```

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```
def mirror(modifier):  
    #add mirror to the selected  
    #object -mirror_x  
    mirror_ob = bpy.context.selected_objects[0]  
    mirror_mod = modifier
```

THANK YOU