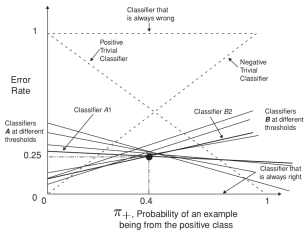


# Introduction to Machine Learning

## Evaluation: Cost Curves



### Learning goals

- Understand cost curves
- As alternative to ROC curves

# COST CURVES

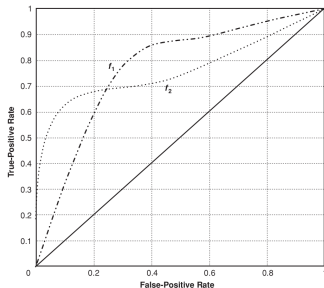
- Directly plot the misclassification costs / error
- Might be easier to interpret than ROC, especially in case of different misclassification costs or priors

## Example:

- $f_1$  and  $f_2$  with intersecting ROC curves
- $f_2$  dominates first, then  $f_1$

**BUT:** Unclear for which thresholds, costs or class distributions  $f_2$  better than  $f_1$

ROC curves for  $f_1$  and  $f_2$



Nathalie Japkowicz (2004): Evaluating Learning Algorithms : A Classification Perspective. (p. 125)

# COST CURVES

With law total probab, can write misclassif rate as function of  $\pi_+$ :

$$\begin{aligned}\rho_{MCE}(\pi_+) &= (1 - \pi_+) \cdot \mathbb{P}(\hat{y} = 1|y = 0) + \pi_+ \cdot \mathbb{P}(\hat{y} = 0|y = 1) \\ &= (1 - \pi_+) \cdot FPR + \pi_+ \cdot FNR \\ &= (FNR - FPR) \cdot \pi_+ + FPR\end{aligned}$$

Can do the same for costs:

$$Costs(\pi_+) = (1 - \pi_+) \cdot FPR \cdot cost_{FP} + \pi_+ \cdot FNR \cdot cost_{FN}$$

$$Costs_{norm}(\pi_+) = \frac{(1 - \pi_+) \cdot FPR \cdot cost_{FP} + \pi_+ \cdot FNR \cdot cost_{FN}}{(1 - \pi_+) \cdot cost_{FP} + \pi_+ \cdot cost_{FN}} \in [0, 1]$$

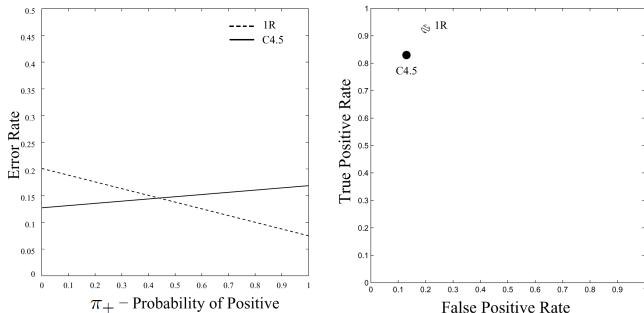
- Denominator =  $\max(Costs)$  = all obs misclassified (i.e.,  $FPR = FNR = 1$ ).
- If  $cost_{FN} = cost_{FP}$ , then  $Costs_{norm} = \rho_{MCE}$

		Confusion matrix	
		True class	
Pred. class	$\hat{y} = 1$	TP	FP
	$\hat{y} = 0$	FN	TN

		Cost matrix	
		True class	
Pred. class	$\hat{y} = 1$	0	$cost_{FP}$
	$\hat{y} = 0$	$cost_{FN}$	0

# COST CURVES

- Simplifying assumption: equal misclassification costs, i.e.,  $cost_{FN} = cost_{FP}$ .
- Normalized costs (or error rate in the case of  $cost_{FN} = cost_{FP}$ ) is plotted as a function of the proportion of positive instances,  $\pi_+ = \mathbb{P}(y = 1)$ .
- Cost curves are point–line duals of ROC curves, i.e., a single classifier is represented by a point in the ROC space and by a line in the cost space.



Chris Drummond and Robert C. Holte (2006): Cost curves: An improved method for visualizing classifier performance. Machine Learning, 65, 95-130 ([URL](#)).

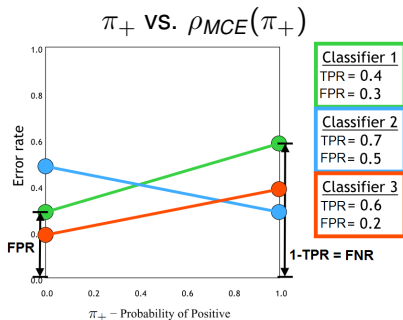
# COST CURVES - EXAMPLE

Cost curve of a classifier with slope ( $FNR - FPR$ ) and intercept  $FPR$ :

$$\rho_{MCE}(\pi_+) = (FNR - FPR) \cdot \pi_+ + FPR$$

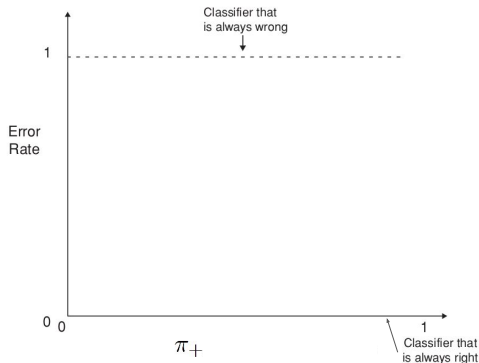
- Hard classifiers are points (TPR, FPR) in ROC space
- The cost curve of a classifier connects  $(\pi_+, \rho_{MCE})$ -points at  $(0, FPR)$  and  $(1, 1 - TPR)$
- Classifier 3 always dominates classifier 1
- Classifier 3 is better than classifier 2 when  $\pi_+ < 0.7$

Cost curves plot different values of



# COST CURVES - EXAMPLE

- Horizontal dashed line: worst classifier (100% error rate for all  $\pi_+$ ).  
 $\Rightarrow FNR = FPR = 1$
- x-axis: perfect classifier (0% error rate for all  $\pi_+$ ).  $\Rightarrow FNR = FPR = 0$

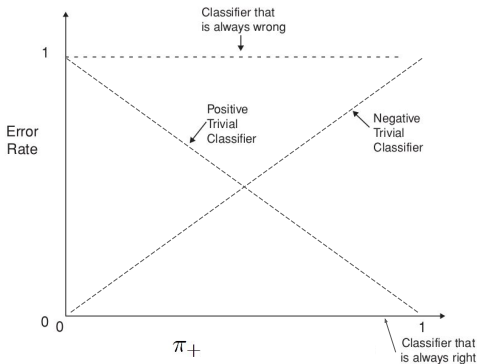


$$\rho_{MCE} = (FNR - FPR) \cdot \pi_+ + FPR$$

		Confusion matrix	
		True class	
Pred. class	$\hat{y} = 1$	TP	FP
	$\hat{y} = 0$	FN	TN

# COST CURVES - EXAMPLE

- Horizontal dashed line: worst classifier (100% error rate for all  $\pi_+$ ).  
 $\Rightarrow FNR = FPR = 1$
- x-axis: perfect classifier (0% error rate for all  $\pi_+$ ).  $\Rightarrow FNR = FPR = 0$
- Dashed diagonal lines: trivial classifiers, i.e., ascending diagonal always predicts negative instances ( $\Rightarrow FNR = 1$  and  $FPR = 0$ ) and vice versa.

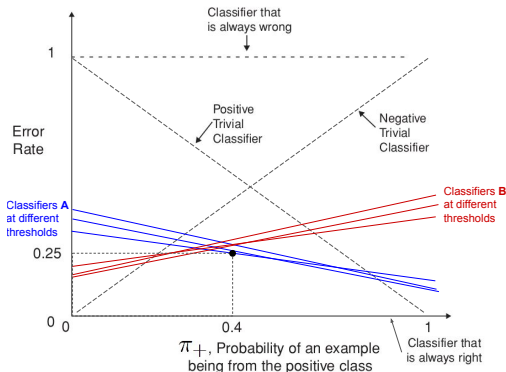


$$\rho_{MCE} = (FNR - FPR) \cdot \pi_+ + FPR$$

		Confusion matrix	
		True class	
Pred. class	$\hat{y} = 1$	$y = 1$	$y = 0$
	$\hat{y} = 0$	TP	FP
		FN	TN

# COST CURVES - EXAMPLE

- Horizontal dashed line: worst classifier (100% error rate for all  $\pi_+$ ).  
 $\Rightarrow FNR = FPR = 1$
- x-axis: perfect classifier (0% error rate for all  $\pi_+$ ).  $\Rightarrow FNR = FPR = 0$
- Dashed diagonal lines: trivial classifiers, i.e., ascending diagonal always predicts negative instances ( $\Rightarrow FNR = 1$  and  $FPR = 0$ ) and vice versa.
- Descending/ascending bold lines: two families of classifiers  $A$  and  $B$  (represented by points in their respective ROC curves).



$$\rho_{MCE} = (FNR - FPR) \cdot \pi_+ + FPR$$

		Confusion matrix	
		True class	
Pred. class	$\hat{y} = 1$	$y = 1$	$y = 0$
	$\hat{y} = 0$	TP	FP
		FN	TN



# ROC CURVES VS. COST CURVES

- ROC curves do not indicate in which situations classifier A is superior to another classifier B.
- Cost curves can do exactly that and therefore provide practically more relevant information than ROC curves.
- For simplification, we focused on cost curves based on the misclassification error by assuming  $cost_{FN} = cost_{FP}$ . However, cost curves can also be defined for different misclassification costs.