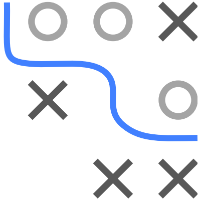
COST-SENSITIVE LEARNING: IN A NUTSHELL

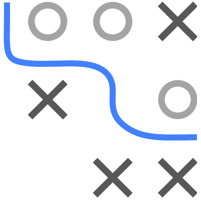


- Cost-sensitive learning:
  - Classical learning: data sets are balanced, and all errors have equal costs
  - We now assume given, unequal cost
  - And try to minimize them in expectation
- Applications:
  - Medicine — Misdiagnosing as healthy vs. having a disease
  - (Extreme) Weather prediction — Incorrectly predicting that no hurricane occurs
  - Credit granting — Lending to a risky client vs. not lending to a trustworthy client.

		Truth	
		Default	Pays Back
Pred.	Default	0	10
	Pays Back	1000	0

- In these examples, **the costs of a false negative is much higher than the costs of a false positive**.
- In some applications, the costs are **unknown** $\rightsquigarrow$ need to be specified by experts, or be learnt.

COST MATRIX

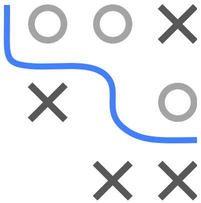


- Input: cost matrix **C**

		True Class y			
		1	2	...	g
Classification	1	$C(1,1)$	$C(1,2)$	...	$C(1,g)$
	2	$C(2,1)$	$C(2,2)$	...	$C(2,g)$
$\hat{y}$					
	$\vdots$	$\vdots$	$\vdots$	...	$\vdots$
	g	$C(g,1)$	$C(g,2)$	...	$C(g,g)$

- $C(j,k)$ is the cost of classifying class k as j,
- 0-1-loss would simply be: $C(j,k) = \mathbb{1}_{[j \neq k]}$
- **C** designed by experts with domain knowledge
  1. Too low costs: not enough change in model, still costly errors
  2. Too high costs: might never predict costly classes

COST MATRIX FOR IMBALANCED LEARNING



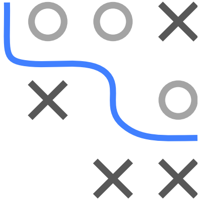
- Common heuristic for imbalanced data sets:
  - $C(j,k) = \frac{n_j}{n_k}$ with $n_k \ll n_j$,
    misclassifying a minority class k as a majority class j
  - $C(j,k) = 1$ with $n_j \ll n_k$,
    misclassifying a majority class k as a minority class j
  - 0 for a correct classification

- Imbalanced binary classification:

	True class	
	$y = 1$	$y = -1$
Pred. $\hat{y}$ = 1	0	1
class $\hat{y}$ = -1	$\frac{n_-}{n_+}$	0

- So: much higher costs for FNs

MINIMUM EXPECTED COST PRINCIPLE



- Suppose we have:
  - a cost matrix **C**
  - knowledge of the true posterior $p(\cdot \mid \mathbf{x})$
- Predict class j with smallest expected costs when marginalizing over true classes:

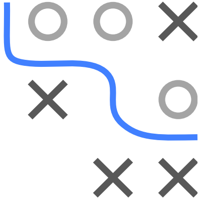
$$\mathbb{E}_{K \sim p(\cdot \mid \mathbf{x})}(C(j, K)) = \sum_{k=1}^{g} p(k \mid \mathbf{x}) C(j, k)$$

- If we trust we trust a probabilistic classifier, we can convert its scores to labels:

$$h(\mathbf{x}) := \arg\min_{j=1,\ldots,g} \sum_{k=1}^{g} \pi_k(\mathbf{x}) C(j, k).$$

- Can be better to take a less probable class (Elkan et. al. 2001)

OPTIMAL THRESHOLD FOR BINARY CASE



- Optimal decisions do not change if
  - **C** is multiplied by positive constant
  - **C** is added with constant shift
- Scale and shift **C** to get simpler **C**$'$:

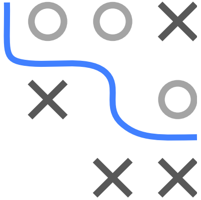
		True class	
		$y = 1$	$y = -1$
Pred.	$\hat{y}$ = 1	$C'(1, 1)$	1
class	$\hat{y}$ = -1	$C'(-1, 1)$	0

where

- $C'(-1, 1) = \frac{C(-1,1) - C(-1,-1)}{C(1,-1) - C(-1,-1)}$
- $C'(1, 1) = \frac{C(1,1) - C(-1,-1)}{C(1,-1) - C(-1,-1)}$
- We predict **x** as class 1 if

$$\mathbb{E}_{K \sim p(\cdot \mid \mathbf{x})}(C'(1, K)) \leq \mathbb{E}_{K \sim p(\cdot \mid \mathbf{x})}(C'(-1, K))$$

OPTIMAL THRESHOLD FOR BINARY CASE / 2



- Let's unroll the expected value and use $\mathbf{C}'$:

$$p(-1 \mid \mathbf{x})C'(1,-1) + p(1 \mid \mathbf{x})C'(1,1) \leq p(-1 \mid \mathbf{x})C'(-1,-1) + p(1 \mid \mathbf{x})C'(-1,1)$$
$$\Rightarrow [1 - p(1 \mid \mathbf{x})] \cdot 1 + p(1 \mid \mathbf{x})C'(1,1) \leq p(1 \mid \mathbf{x})C'(-1,1)$$
$$\Rightarrow p(1 \mid \mathbf{x}) \geq \frac{1}{C'(-1,1) - C'(1,1) + 1}$$
$$\Rightarrow p(1 \mid \mathbf{x}) \geq \frac{C(1,-1) - C(-1,-1)}{C(-1,1) - C(1,1) + C(1,-1) - C(-1,-1)} = c^*$$

- If even $C(1,1) = C(-1,-1) = 0$, we get:

$$p(1 \mid \mathbf{x}) \geq \frac{C(1,-1)}{C(-1,1) + C(1,-1)} = c^*$$

- Optimal threshold c^* for probabilistic classifier

$$h(\mathbf{x}) := 2 \cdot \mathbb{1}_{[\pi(\mathbf{x}) \geq c^*]} - 1$$