

# Part III

# Model Calibration

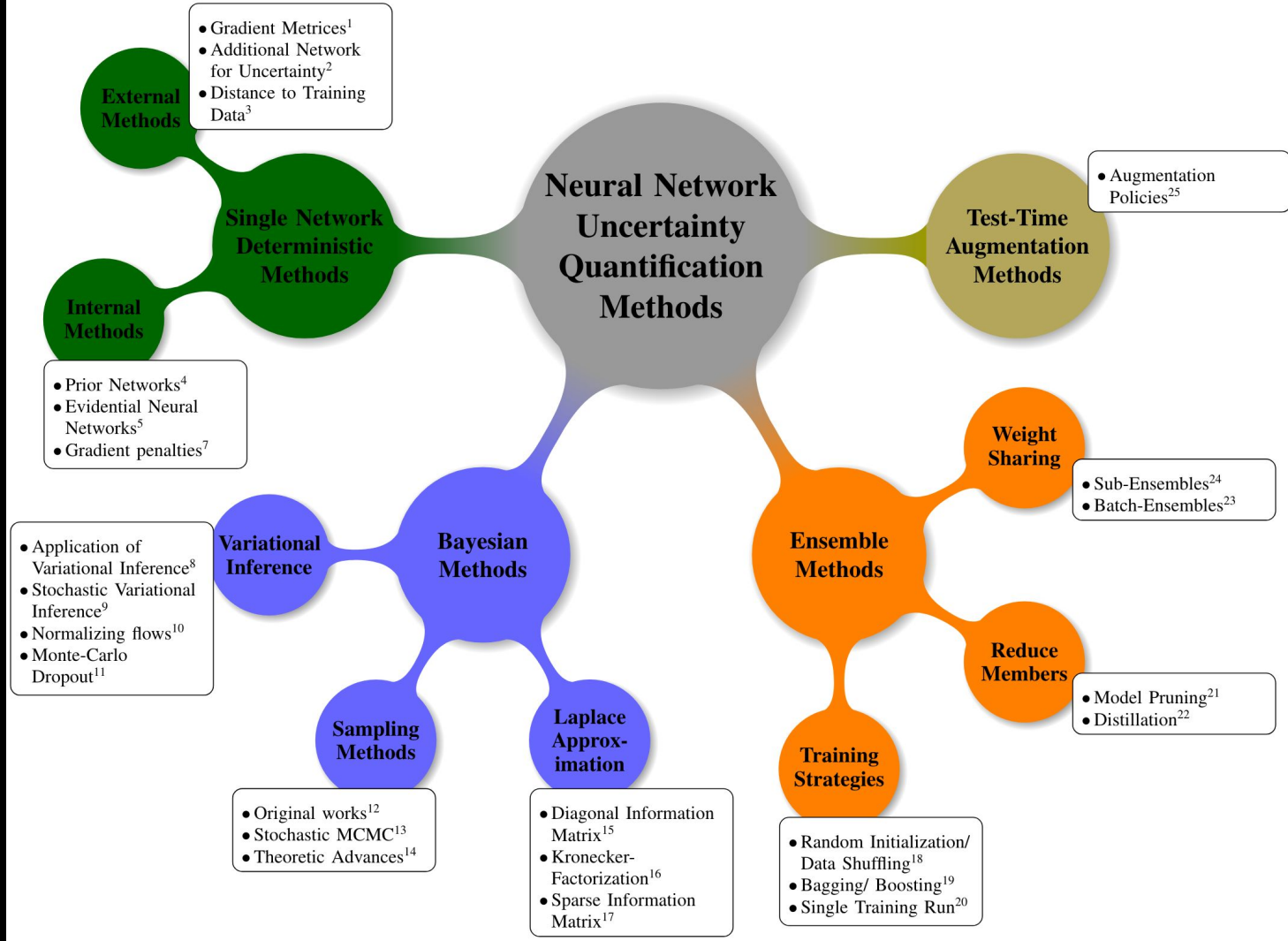
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**Meritxell Riera i Marin, Researcher**  
**Sycal Medical, Barcelona, Spain**  
**Universitat Pompeu Fabra, Barcelona, Spain**

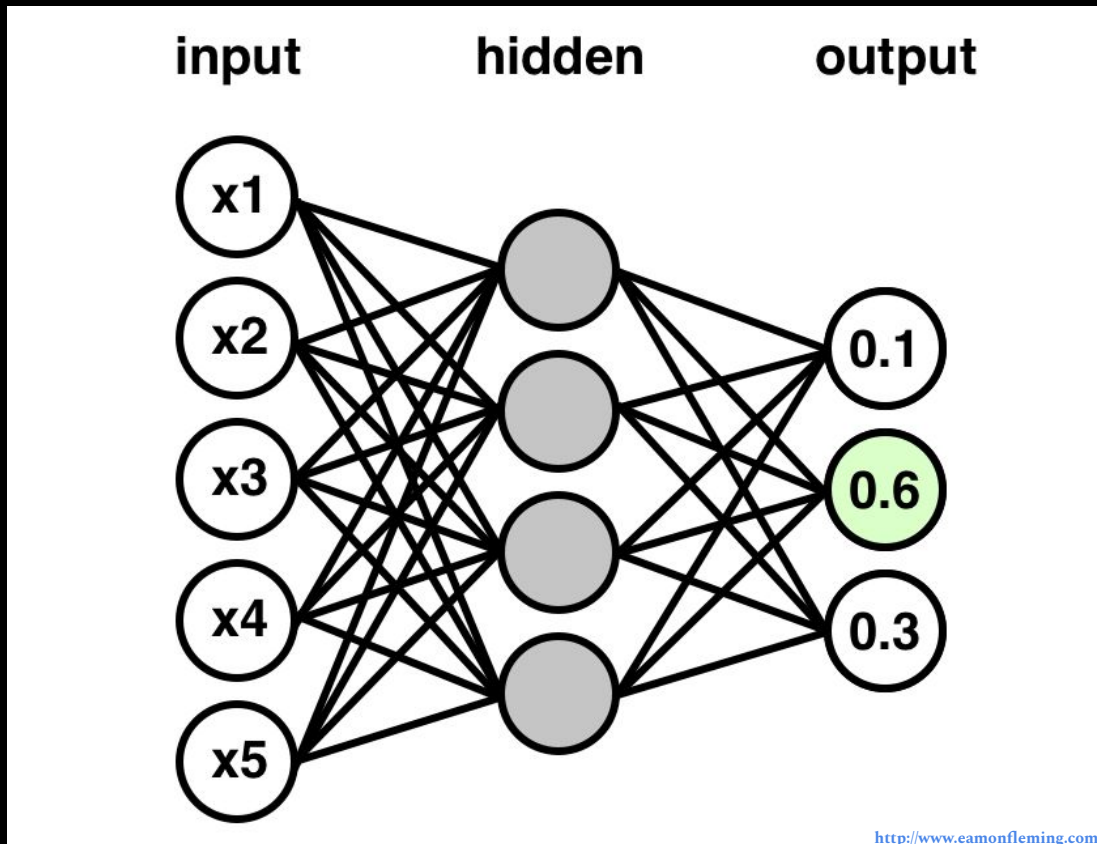


# Contents

1. Understanding Calibration
2. Measuring Calibration
3. Improving Calibration
4. Practical Hands-On Session



**But, don't we already have probabilities?  
(probability= confidence = uncertainty)?**





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NOW

HOURLY

10 DAY

MAPS

September 12 - September 21, 2023 ∨

Tue



24° | 18°

80% Chance  
of Storms

Wed



22° | 17°

30% Chance of Rain

Thu



25° | 18°

Partly Cloudy

Fri



30° | 20°

30% Chance of Rain

Sat



30° | 20°

50% Chance of Rain

Sun



25° | 17°

40% Chance of Rain



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Sun



25° | 17°

40% Chance of Rain

Mon



25° | 17°

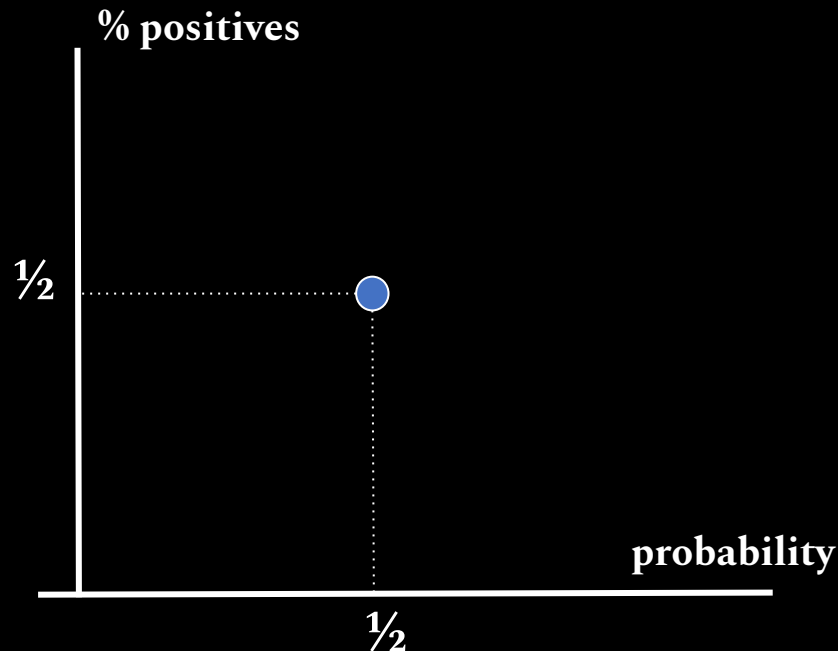
Unknown

# 1. Understanding Calibration

<b>p</b>	<b>y</b>	<b>p</b>	<b>y</b>
$\frac{1}{2}$	<b>0</b>	$\frac{3}{4}$	<b>0</b>
$\frac{1}{2}$	<b>0</b>	$\frac{3}{4}$	<b>1</b>
$\frac{1}{2}$	<b>0</b>	$\frac{3}{4}$	<b>1</b>
$\frac{1}{2}$	<b>1</b>	$\frac{3}{4}$	<b>1</b>
$\frac{1}{2}$	<b>1</b>	<b>1</b>	<b>1</b>
$\frac{1}{2}$	<b>1</b>	<b>1</b>	<b>1</b>

# 1. Understanding Calibration

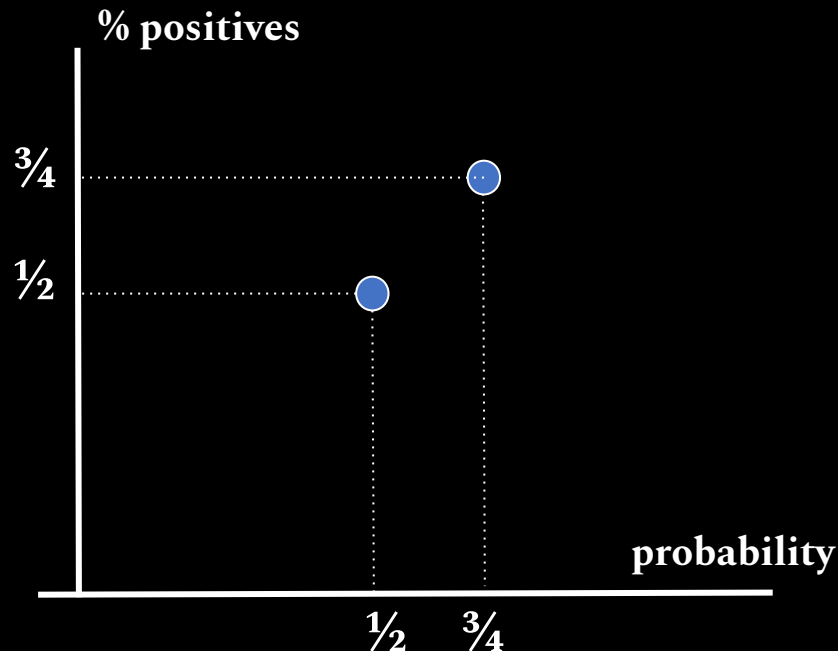
p	y	p	y
$\frac{1}{2}$	0	$\frac{3}{4}$	0
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	1	$\frac{3}{4}$	1
$\frac{1}{2}$	1	1	1
$\frac{1}{2}$	1	1	1





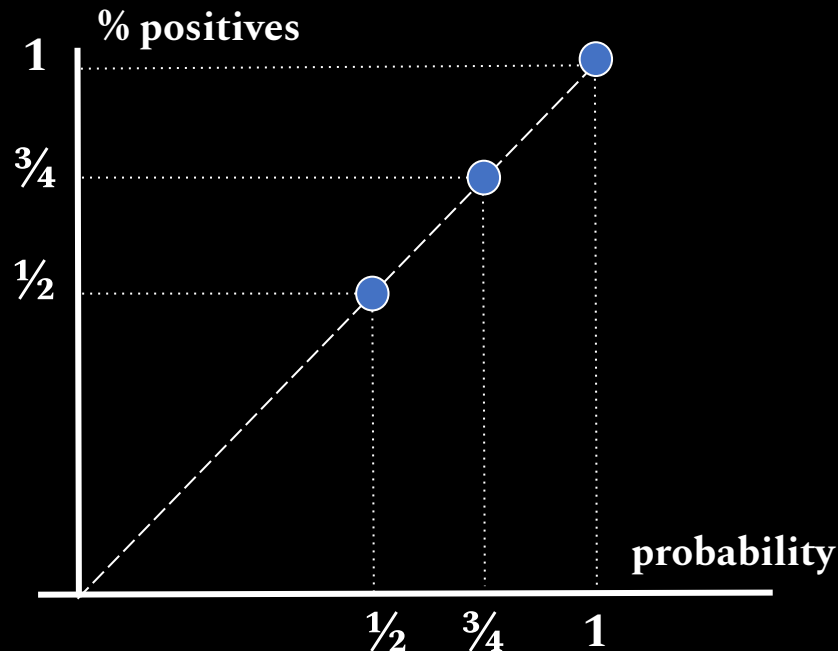
# 1. Understanding Calibration

p	y	p	y
$\frac{1}{2}$	0	$\frac{3}{4}$	0
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	1	$\frac{3}{4}$	1
$\frac{1}{2}$	1	1	1
$\frac{1}{2}$	1	1	1



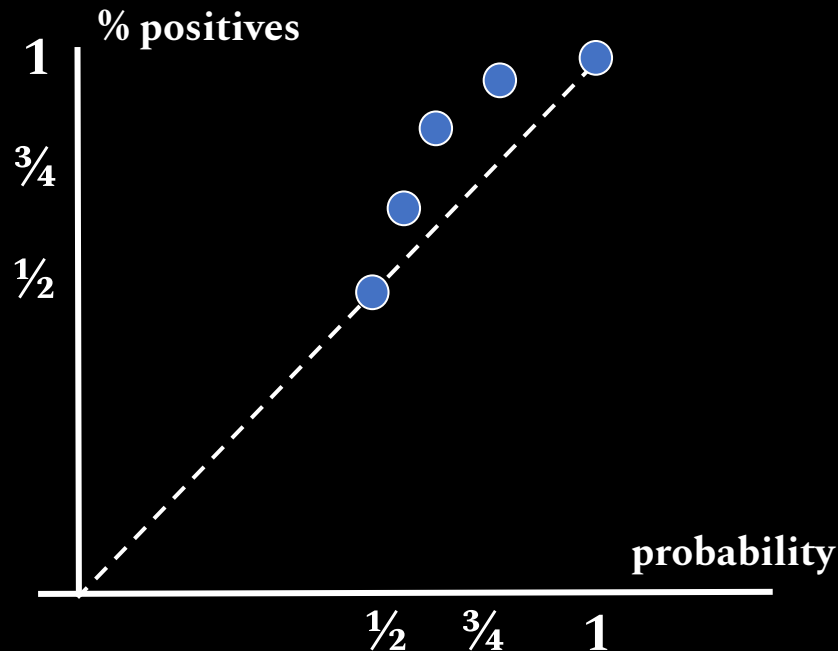
# 1. Understanding Calibration

p	y	p	y
$\frac{1}{2}$	0	$\frac{3}{4}$	0
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	0	$\frac{3}{4}$	1
$\frac{1}{2}$	1	$\frac{3}{4}$	1
$\frac{1}{2}$	1	1	1
$\frac{1}{2}$	1	1	1



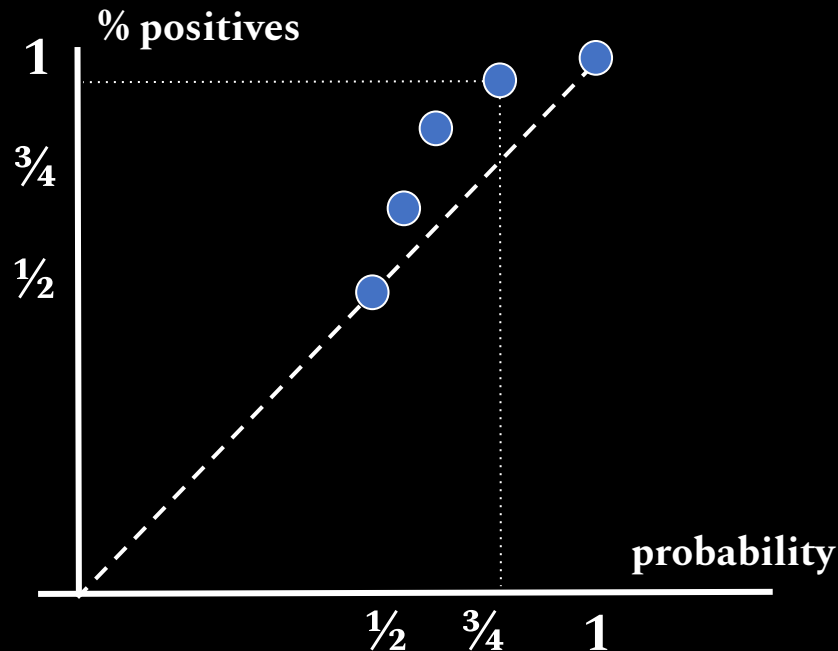
# 1. Understanding Calibration

**QUESTION:**  
Are these predictions  
under-confident  
or  
over-confident?



# 1. Understanding Calibration

**QUESTION:**  
Are these predictions  
under-confident  
or  
over-confident?



## 2. Measuring Calibration

- **Reliability Plots**

Not enough items with a given confidence to estimate population statistics decently:

model predicts with  $p=0.2 \rightarrow$  “20%” positives

What if you only have 2 items predicted with  $p=0.2$ ?

We can group predictions in bins, and **plot them against  $y=x$** .

- **Expected Calibration Error**

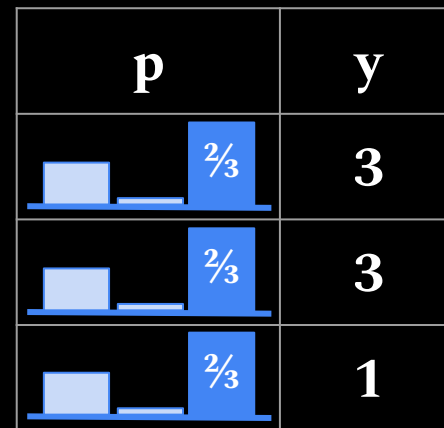
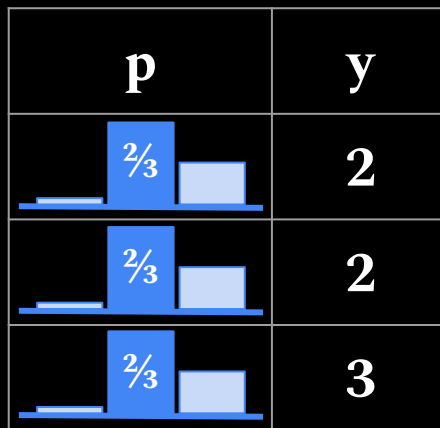
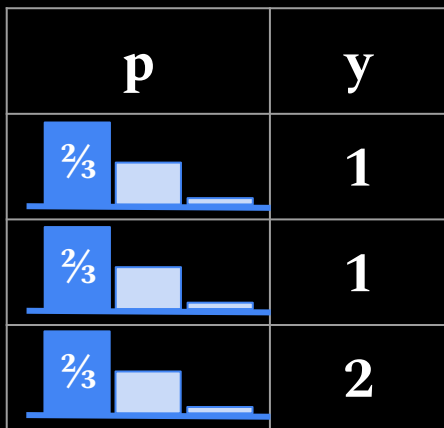
The average of gaps across bins, weighted by bin population:

$$\text{ECE} = \frac{1}{M} \sum_{i=1}^M \frac{1}{|B_i|} |\text{prob}(B_i) - \text{pos}(B_i)|$$

## 2. Measuring Calibration

- Generalizing from Binary to Multi-Class classifiers

**Full-calibration:** consider the whole probability vector.

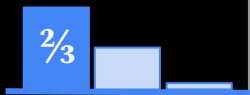
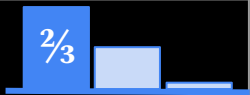
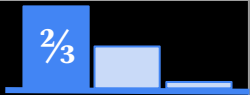



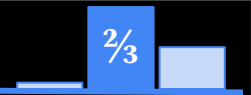

## 2. Measuring Calibration




- Generalizing from Binary to Multi-Class classifiers

**Full-calibration:** consider the whole probability vector.

**Confidence calibration:** only consider highest probability.

p	y
	1
	1
	2

p	y
	2
	2
	3

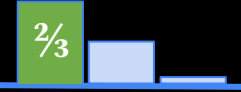
p	y
	3
	3
	1


## 2. Measuring Calibration

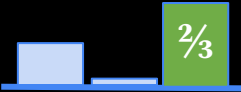
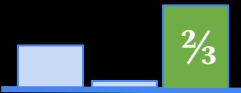

- Generalizing from Binary to Multi-Class classifiers

**Full-calibration:** consider the whole probability vector.

**Confidence calibration:** only consider highest probability.

p	$(\hat{y}, c)$	y
	$(1, 2/3)$	1
	$(1, 2/3)$	1
	$(1, 2/3)$	2

p	$(\hat{y}, c)$	y
	$(2, 2/3)$	2
	$(2, 2/3)$	2
	$(2, 2/3)$	3

p	$(\hat{y}, c)$	y
	$(3, 2/3)$	3
	$(3, 2/3)$	3
	$(3, 2/3)$	1

\*Also **Class-wise calibration:** consider marginal probabilities, 1vsRest.



## 2. Measuring Calibration

- Expected Full Calibration Error

$$\text{full-ECE} = \frac{1}{M} \sum_{i=1}^M \frac{1}{|\mathbb{B}_i|} \| \text{prob}(\mathbb{B}_i) - \text{true}(\mathbb{B}_i) \|$$

- Expected Confidence-Calibration Error

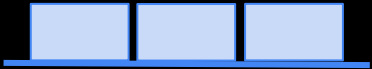
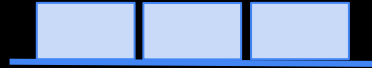

$$\text{conf-ECE} = \frac{1}{M} \sum_{i=1}^M \frac{1}{|B_i|} |\text{conf}(B_i) - \text{acc}(B_i)|$$

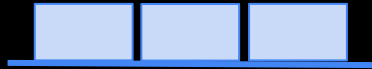
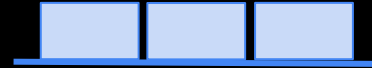

- Expected Class-Wise Calibration Error

$$\text{cw-ECE} = \frac{1}{K} \sum_{k=1}^K \text{bin-ECE}_k \quad [\text{one-vs-rest}]$$

## 2. Measuring Calibration

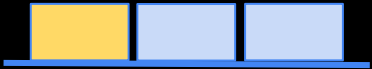


- Alternative Calibration Measures: Proper Scoring Rules

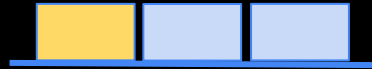


p	$\hat{y}$	y
		1
		1
		2

p	$\hat{y}$	y
		2
		3
		3

## 2. Measuring Calibration

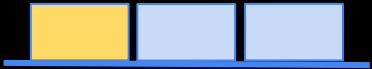

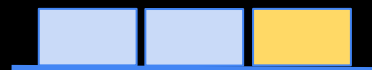
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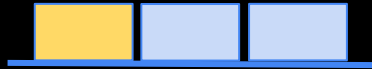

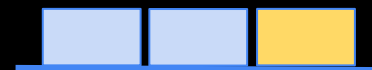
p	$\hat{y}$	y
		1
		1
		2

p	$\hat{y}$	y
		2
		3
		3

## 2. Measuring Calibration

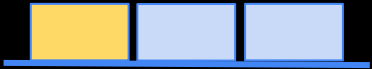


- Alternative Calibration Measures: Proper Scoring Rules

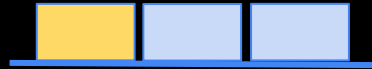


p	$\hat{y}$	y
	1	1
	2	1
	3	2

p	$\hat{y}$	y
	1	2
	2	3
	3	3

## 2. Measuring Calibration

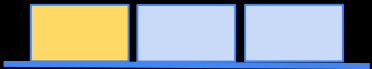

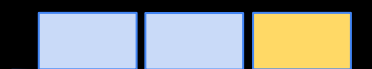
- Alternative Calibration Measures: Proper Scoring Rules

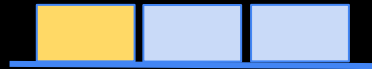


p	$\hat{y}$	y
	1	1
	2	1
	3	2

p	$\hat{y}$	y
	1	2
	2	3
	3	3

## 2. Measuring Calibration

- Alternative Calibration Measures: Proper Scoring Rules

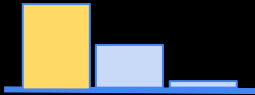


p	$\hat{y}$	y
	1	1
	2	1
	3	2

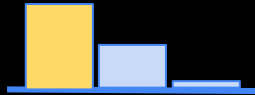
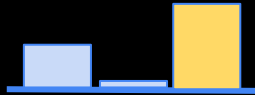
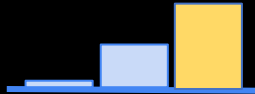
p	$\hat{y}$	y
	1	2
	2	3
	3	3

This classifier predicts a random class with full uncertainty. It always has a confidence of  $\sim 1/3$ , and it has an accuracy of  $1/3$ . Therefore it is perfectly confidence-calibrated, but useless.

## 2. Measuring Calibration

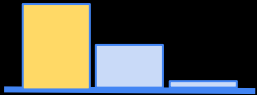
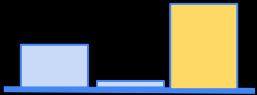

- Alternative Calibration Measures: **Proper Scoring Rules**

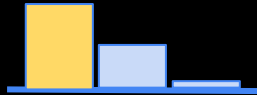
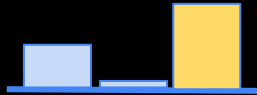
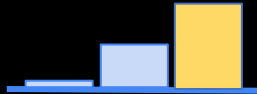
p	$\hat{y}$	y
		1
		1
		2

p	$\hat{y}$	y
		2
		3
		3

## 2. Measuring Calibration

- Alternative Calibration Measures: Proper Scoring Rules

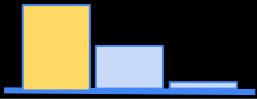
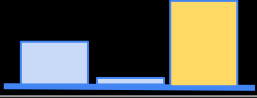

p	$\hat{y}$	y
	1	1
	3	1
	2	2

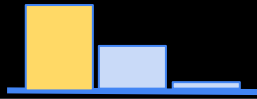
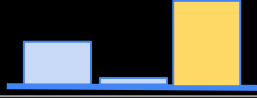
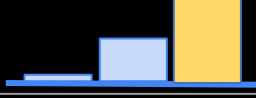
p	$\hat{y}$	y
	1	2
	3	3
	3	3



## 2. Measuring Calibration

- Alternative Calibration Measures: Proper Scoring Rules

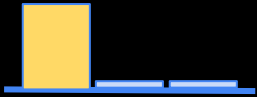
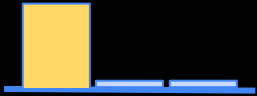

p	$\hat{y}$	y
	1	1
	3	1
	2	2


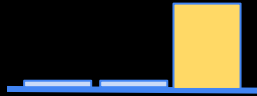
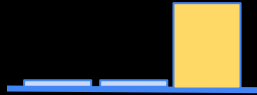
p	$\hat{y}$	y
	1	2
	3	3
	3	3

This classifier always predicts with  $\frac{2}{3}$  confidence. Also, it has an accuracy of  $\frac{2}{3}$ . It is **perfectly confidence-calibrated**, but it has more **discrimination ability** than random guessing.

## 2. Measuring Calibration

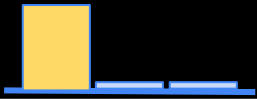
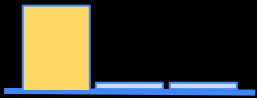

- Alternative Calibration Measures: **Proper Scoring Rules**


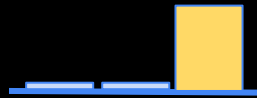
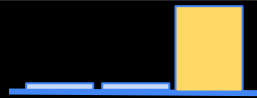
p	$\hat{y}$	y
	1	1
	1	1
	2	2

p	$\hat{y}$	y
	2	2
	3	3
	3	3

## 2. Measuring Calibration

- Alternative Calibration Measures: Proper Scoring Rules

p	$\hat{y}$	y
	1	1
	1	1
	2	2

p	$\hat{y}$	y
	2	2
	3	3
	3	3

This is a god-like classifier. It is always 100% confident, and always right. It is full-calibrated and perfectly discriminative.

PSRs are a tool for measuring calibration & discrimination jointly.

## 2. Measuring Calibration

- Proper Scoring Rules

Measure discrimination+calibration at individual item level

Most popular: Brier Score, Logarithmic Score (aka Cross-Entropy)

$$\text{Brier}(\mathbf{p}, \mathbf{y}) = \|\mathbf{p} - \mathbf{y}\|_2^2$$

$$\text{CE}(\mathbf{p}, \mathbf{y}) = -\log(p_y)$$

**Example:**  $y = 3$ ,  $\mathbf{y} = (0, 0, 1)$ ,  $\mathbf{p}_{\text{bad}} = \left(\frac{1}{3}, \frac{1}{3}, \frac{1}{3}\right)$ ,  $\mathbf{p}_{\text{better}} = \left(0, \frac{1}{3}, \frac{2}{3}\right)$

$$\text{Brier}(\mathbf{p}_{\text{bad}}, \mathbf{y}) = 2/3 \quad \text{Brier}(\mathbf{p}_{\text{better}}, \mathbf{y}) = 2/9 \quad \text{Brier}(\mathbf{y}, \mathbf{y}) = 0$$

$$\text{CE}(\mathbf{p}_{\text{bad}}, \mathbf{y}) \approx 0.477 \quad \text{CE}(\mathbf{p}_{\text{better}}, \mathbf{y}) \approx 0.176 \quad \text{CE}(\mathbf{y}, \mathbf{y}) = 0$$

Note that a fully uncertain prediction  $\mathbf{p}_{\text{bad}}$  does not score well.

# 3. Improving Calibration

- **Model Ensembling**

Ensembling several diverse models can reduce over-confidence.

- **Training Time Calibration**

Over-parametrized NNs can keep on learning the training set until they are fully confident, minimizing NLL indefinitely.

We can **regularize** to **disencourage confidence** : Label Smoothing, MixUp, Focal Loss... Careful of **underfitting**! Report also PSRs.

- **Post-Training Calibration**

**Temperature Scaling**: Uses a validation set to learn a scalar  $T$  dividing logits before applying softmax and tempers their value:

$$p_j = \frac{e^{z_j}}{\sum_{k=1}^N e^{z_k}} \longmapsto p_j = \frac{e^{(z_j/T)}}{\sum_{k=1}^N e^{(z_k/T)}}$$

# 4. Hands-On