

Foundations of Trustworthy AI

Jonathan Ullman
CS7180/7880 · Fall 2026

Class 4: Group conditional calibration
(+ wrap up from last week)

Sep 22, 2026

Calibrated Decision Loss

predictions $p_1, \dots, p_T \in [0, 1]$

outcomes $y_1, \dots, y_T \in \{0, 1\}$

for each $p \in [0, 1]$: $S_p = \{t: p_t = p\}$ $\bar{y}_p = \frac{1}{|S_p|} \sum_{t \in S_p} y_t$

$$ECE(\vec{p}, \vec{y}) = \frac{1}{T} \sum_p |S_p| |p - \bar{y}_p|$$

Expected calibration errors

for a decision task $G = (A, u)$ there is a best response fn

$$BR_G(p) = \arg \max_{a \in A} \mathbb{E}(u(a, y))$$

Calibrated Decision Loss

for a decision task $G = (A, u)$ there is a best response fn

↑ ↑
actions utility

$$BR_G(p) = \underset{a \in A}{\operatorname{argmax}} \mathbb{E}_{y \sim B_G(p)} (u(a, y))$$

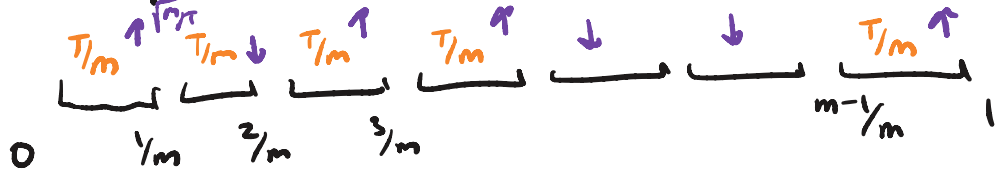
decision loss for $(\vec{p}, \vec{y})$ and task G

$$CDL_G(\vec{p}, \vec{y}) = \frac{1}{T} \sum_{t=1}^T \left[\underbrace{u(BR_G(\vec{y}_{p_t}), y_t)}_{\text{util. if you knew probabilities}} - \underbrace{u(BR_G(p_t), y_t)}_{\text{util. if you trust } p_t} \right]$$

$$CDL(\vec{p}, \vec{y}) = \max_{\text{tasks } G} CDL_G(\vec{p}, \vec{y})$$

Calibrated Decision Loss vs. ECE

Theorem [FV98]: There is an algorithm that makes sequential predictions such that $ECE(\vec{p}, \vec{y}) = O(1/T^{1/2})$



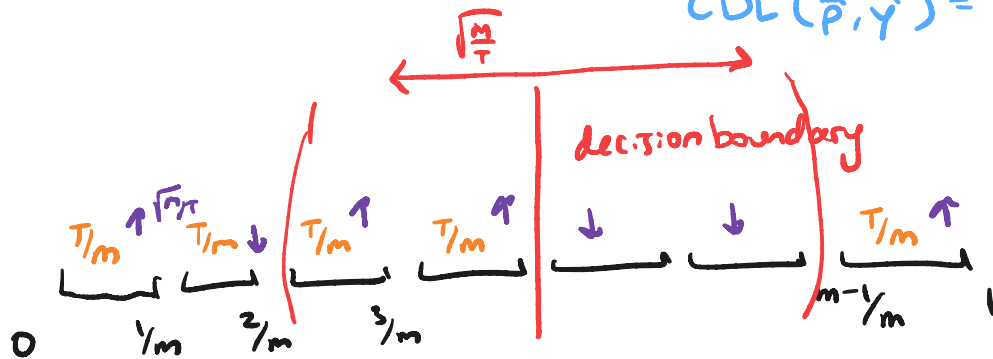
each day nature chooses a bucket p at random
then chooses $y_t \sim \text{Ber}(p)$

for each bucket $\bar{y}_p = p \pm \sqrt{\frac{1}{T/m}} = p \pm \sqrt{\frac{m}{T}}$

$$\begin{aligned} ECE(\vec{p}, \vec{y}) &= \frac{1}{T} \sum_{\text{buckets } p} |S_p| \cdot (\bar{y}_p - p) + \frac{1}{m} = \frac{1}{T} \cdot m \cdot \frac{T}{m} \cdot \sqrt{\frac{3}{T}} + \frac{1}{m} = \sqrt{\frac{3}{T}} + \frac{1}{m} \\ &= \sqrt{\frac{m}{T}} + \frac{1}{m} \quad \quad \quad \begin{matrix} m = T^{1/3} \\ = \frac{1}{T^{1/3}} \end{matrix} \end{aligned}$$

Calibrated Decision Loss vs. ECE

Theorem [HW24]: There is an algorithm that makes sequential predictions such that ~~$ECE(\hat{p}, \tilde{y}) = O(1/T^{1/2})$~~
 $CDL(\hat{p}, \tilde{y}) = \tilde{O}(1/T^{1/2})$



for ECE, the error of every bucket is "relevant"

for CDL, most errors are "not relevant"

↳ only buckets in a small interval cause me to change decision

↳ can set $m \approx T^{1/2}$ and get $CDL(\hat{p}, \tilde{y}) \approx 1/T^{1/2}$

Group Conditional Bias

Example: predicting weather $y \in \{0, 1\}$

$x = (x_1, x_2)$ $x_1 \in \{\text{humid}, \text{dry}\}$
 $x_2 \in \{\text{cloudy}, \text{sunny}\}$

all four choices of x equally likely

true
probabilities

$P(y x)$	cloudy	sunny
humid	$3/4$	$1/2$
dry	$1/2$	$1/4$

For now only
consider offline predictions

For now, D is known

predictor f

$$f(x_1) = \begin{cases} 5/8 & \text{if } x_1 = \text{humid} \\ 3/8 & \text{if } x_1 = \text{dry} \end{cases}$$

f is perfectly calibrated

Average Bias Recap

Definition: For dist D and pred f the average bias is

$$\beta_D(f) = \mathbb{E}_D[f(x) - y]$$

↑
we will usually
drop D

Lemma: If $f_{\beta \rightarrow 0}(x) = f(x) - \beta_D(f)$

then $f_{\beta \rightarrow 0}$ is unbiased and also $\text{MSE}_D(f_{\beta \rightarrow 0}) = \text{MSE}_D(f) - \beta_D(f)^2$

Proof is an exercise

Group Conditional Bias

A group is a subset $G \subseteq \mathcal{X}$ represented by a function $g: \mathcal{X} \rightarrow \{0, 1\}$ ($g(x) = 1$ if $x \in G$, $g(x) = 0$ if $x \notin G$)

Example: $G = \{(x_1, x_2) : x_2 = \text{cloudy}\}$
 $g(x_1, x_2) = \begin{cases} 1 & \text{if } x_2 = \text{cloudy} \\ 0 & \text{if } x_2 = \text{sunny} \end{cases}$

Bias of f conditioned on G

$$\beta_D(f, g) = \mathbb{E}_D[f(x) - Y \mid g(x) = 1]$$

Group Conditional Bias

Example: predicting weather $y \in \{0, 1\}$

$x = (x_1, x_2)$ $x_1 \in \{\text{humid}, \text{dry}\}$
 $x_2 \in \{\text{cloudy}, \text{sunny}\}$

all four choices of x equally likely

true
probabilities

$P(y x)$	cloudy	sunny
humid	$3/4$	$1/2$
dry	$1/2$	$1/4$

f is unbiased on average

$$E[f(x) - y \mid \text{cloudy}]$$

$$= \underbrace{\frac{1}{2} \cdot \frac{5}{8} + \frac{1}{2} \cdot \frac{3}{8}}_{\text{true prob}} - \underbrace{\frac{1}{2} \cdot \frac{3}{4} + \frac{1}{2} \cdot \frac{1}{2}}_{\text{pred.}} = \frac{1}{2} - \frac{5}{8} = -\frac{1}{8}$$

For now only
consider offline predictions

For now, D is known

predictor f

$$f(x_1) = \begin{cases} 5/8 & \text{if } x_1 = \text{humid} \\ 3/8 & \text{if } x_1 = \text{dry} \end{cases}$$

f is perfectly calibrated

Group Conditional Bias

A group is a subset $G \subseteq \mathcal{X}$ represented by a function $g: \mathcal{X} \rightarrow \{0, 1\}$ ($g(x) = 1$ if $x \in G$, $g(x) = 0$ if $x \notin G$)

Bias of f conditioned on G $\beta_D(f, g) = \mathbb{E}[f(x) - Y \mid g(x) = 1]$

A class of groups $\mathcal{G} \subseteq 2^{\mathcal{X}}$ (a set of subsets of $\mathcal{X}$)

Define $\mu_D(g) = \mathbb{P}[g(x) = 1]$

Definition: Bias of f conditioned on groups $\mathcal{G}$ is

$$\alpha^2 = \max_{g \in \mathcal{G}} \beta_D^2(f, g) \cdot \mu_D(g)$$