

# MVP: Practical Adversarial Multivalid Conformal Prediction

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# Prediction Sets and Conformal Prediction

- ◇ Traditionally: given features  $x \in \mathcal{X}$ , produce accurate point estimate for label  $y_x \in \mathcal{Y}$
- ◇ A different perspective: create a *prediction set*  $T(x) \subseteq \mathcal{Y}$  that contains  $y_x$  with probability 0.9:

$$\Pr_{(x, y_x)} [y_x \in T(x)] = 0.9 \text{ (“valid 0.9 marginal coverage”)}$$

- ◇ **Conformal prediction:** A widely adopted paradigm for building prediction sets:
  1. Pre-train a *conformal score function*  $s(x, y) \in \mathbb{R}$ : higher values  $\Rightarrow$  more disagreement between  $x, y$
  2. Given  $x$ , compute a *threshold*  $q$  and output prediction set  $T(x) = \{y: s(x, y) \leq q\}$
- ◇ Conformal guarantees: exchangeable dataset  $\Rightarrow$  valid 0.9 coverage on test data, no matter the score

# Our contribution: MVP (MultiValid Prediction)

## Vanilla Conformal Prediction

- ◆ Offline (batch) setting: a separate training/calibration set and a test set
- ◆ Requires I.I.D. or exchangeable data
- ◆ Marginal coverage guarantees

## Our Method: MVP

- ◆ Online setting: data revealed sequentially, used both for training and testing
- ◆ Works even for adversarial data
- ◆ **MultiValid coverage:** Stronger than marginal:
  - ◆ Valid coverage on arbitrary feature space regions
  - ◆ Threshold Calibration (validity conditional on the predicted threshold)

# MultiValidity $\Rightarrow$ Group Conditional Coverage

- ◇ Given a group collection  $\mathcal{G} = \{G_1, G_2, \dots, G_n\}$  where each  $G_i \subseteq \mathcal{X}$  (groups can overlap)
  - ◇ If  $x \in \mathcal{X}$  are individuals and  $y \in Y$  their credit scores, groups  $G_i$  could be demographic groups
  - ◇ If  $x \in \mathcal{X}$  encode market data and  $y \in Y$  represent stock volatility, groups  $G_i$  could be market events
- ◇ MultiValid coverage  $\Rightarrow$  valid 0.9 coverage conditional on  $x \in G_i$  for all  $i$
- ◇ Ensures that no group receives unfairly bad coverage

# MVP: MultiValid Prediction

Adversarial data points  $(x_1, y_1), \dots, (x_T, y_T)$  revealed sequentially

In round  $t$ : Get score  $s_t: \mathcal{X} \times \mathcal{Y} \rightarrow [0, 1]$ , feature  $x_t \rightarrow$  Form prediction set  $\mathbf{T}_t \rightarrow$  See label  $y_t$

How to pick threshold  $q_t \in \{0, \frac{1}{m}, \frac{2}{m}, \dots, \frac{m-1}{m}, 1\}$  at every round  $t = 1 \dots T$ :

1. For each threshold value  $\frac{i}{m}$ , softmax its past miscoverage rates over all groups  $G \in \mathcal{G}$
2. This softmax tells for each candidate threshold  $\frac{i}{m}$  if it tends to over- or undercover
3. Find  $i \in [m]$  such that  $\frac{i-1}{m}$  undercovers but  $\frac{i}{m}$  overcovers. Randomize over these two!



# Empirical Performance

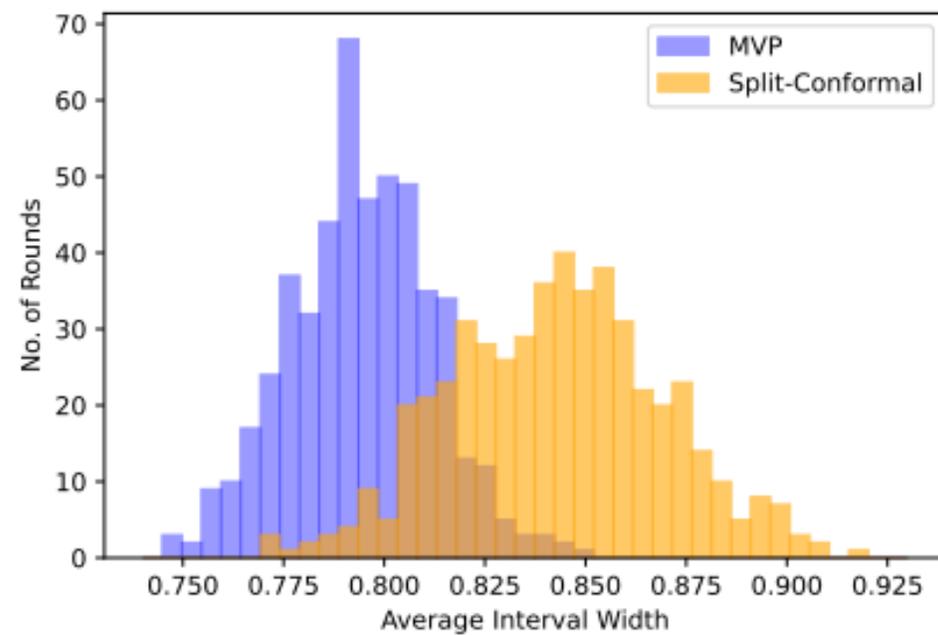
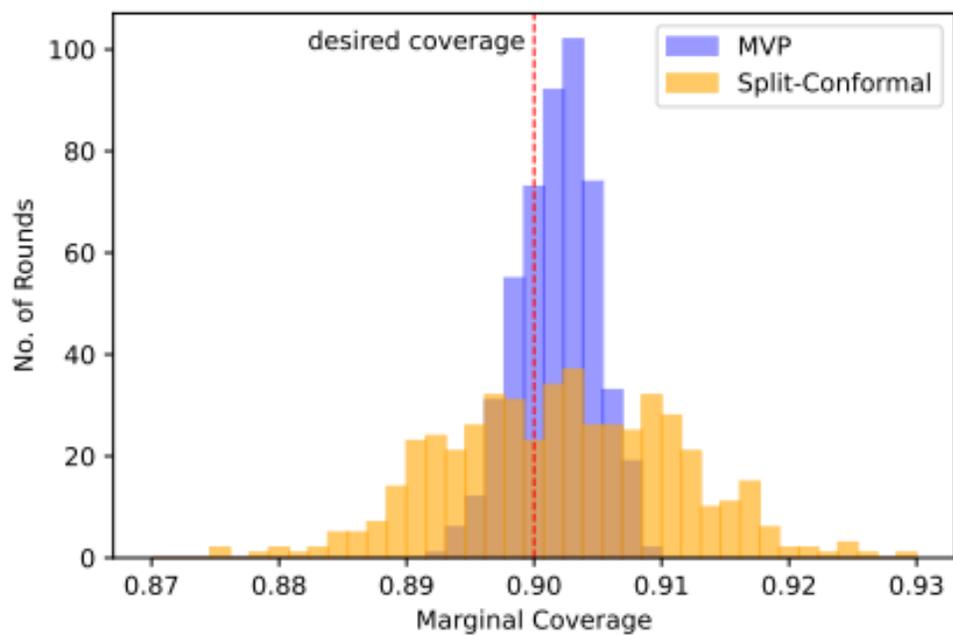
Strong coverage guarantees  
on various kinds of data:

- IID/Exchangeable data
- Covariate shift
- Time series
- Adversarial data

Matches/exceeds performance of  
existing methods “on their turf”:

- Split conformal prediction [Lei et al.]
- Conformal prediction under covariate shift [Tibshirani et al.]
- Conservative nonoverlapping group-conditional coverage [Foygel Barber et al.]
- ACI [Gibbs and Candès]

# Empirical Performance



# Thanks!

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