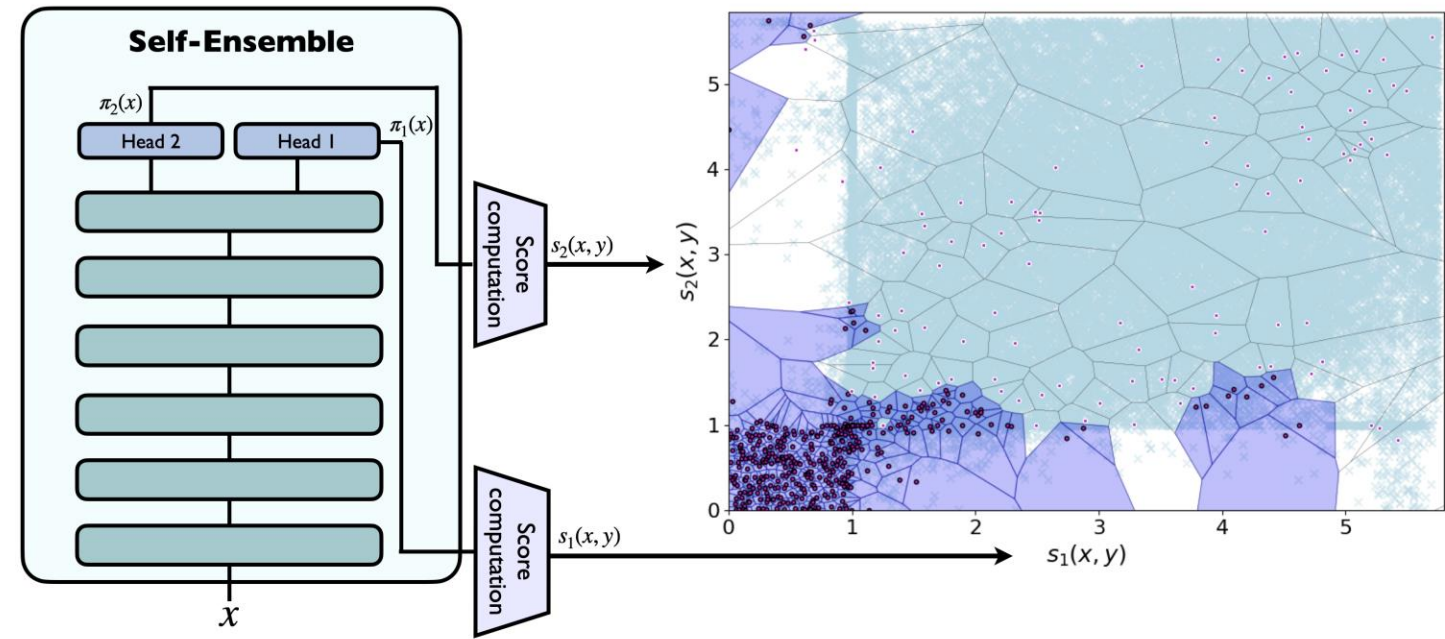


# Multi-Dimensional Conformal Prediction



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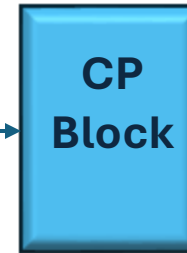
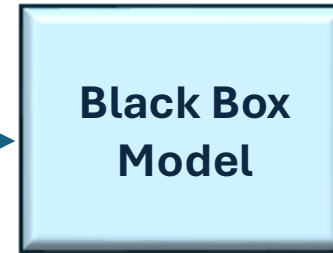
# Conformal Prediction

Standard  
Image  
classification



{Lion}

+ Conformal  
prediction



{Lion, Cat, Tiger}

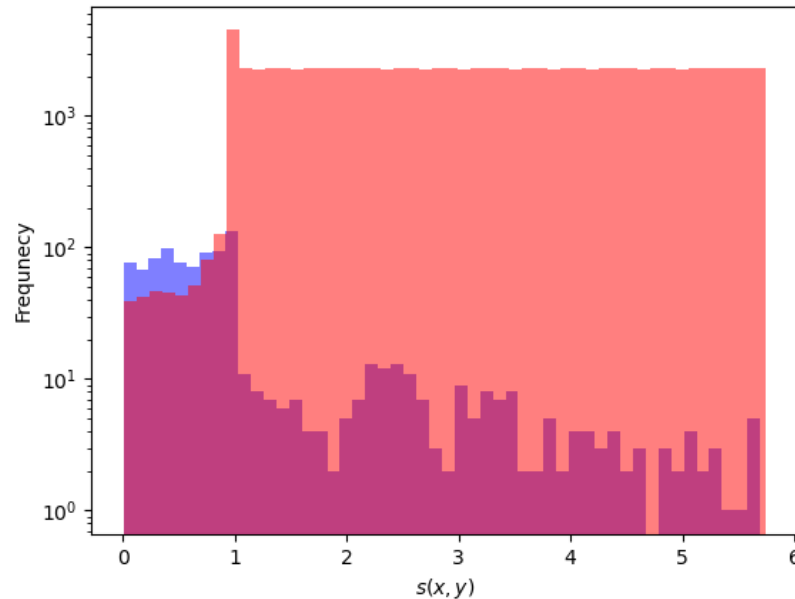
Contains true label with high-probability:

$$\mathbb{P}(Y \in \mathcal{C}(X)) \geq 1 - \alpha$$

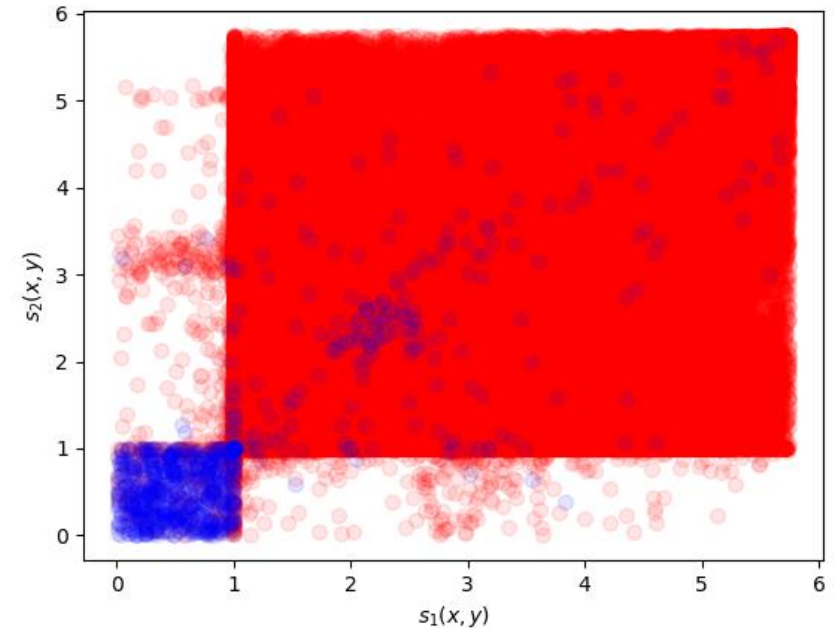
Important when deploying models in safety-critical applications (healthcare, autonomous-driving, finance..)

# Motivation



Single Dimension



Multi-Dimension



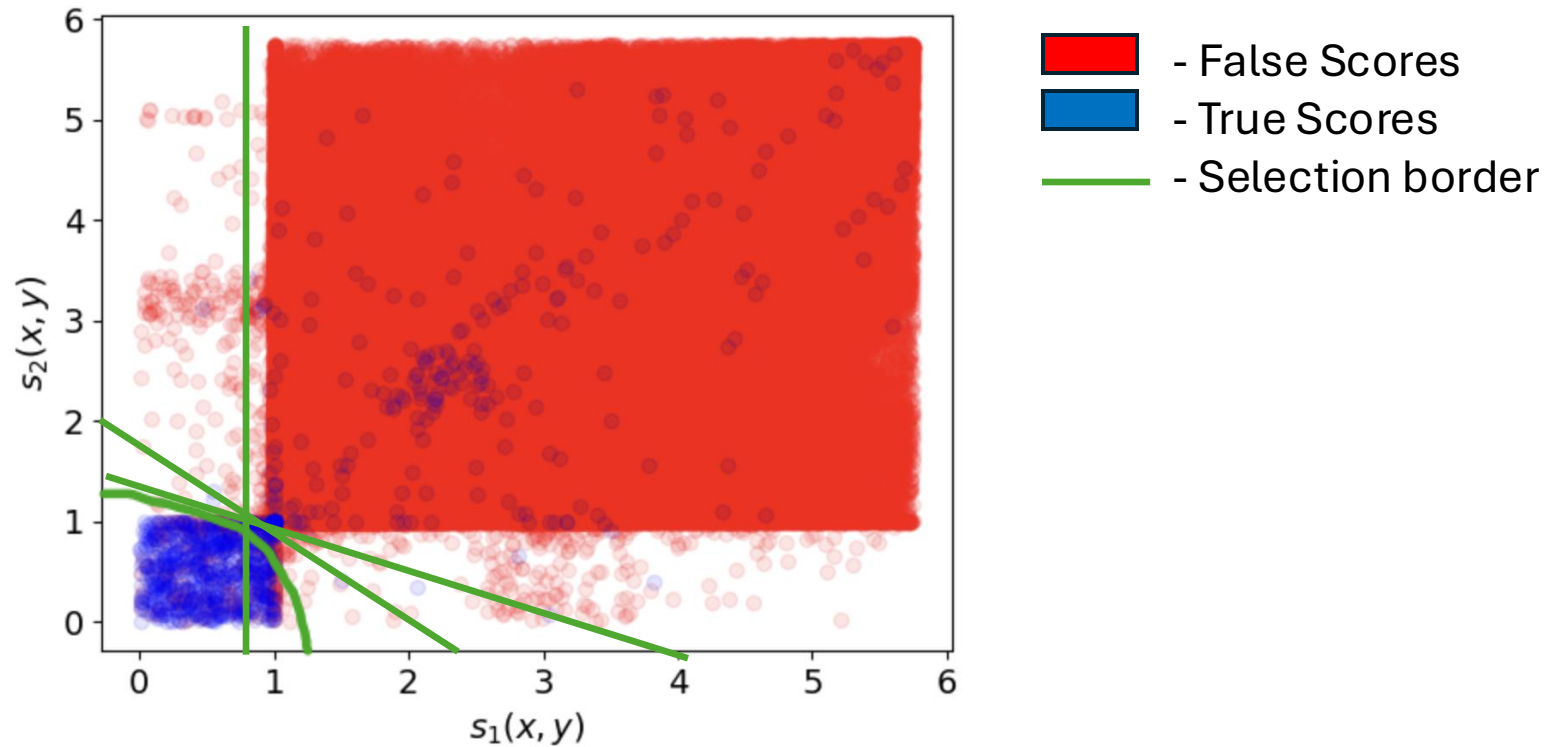
- **Conformal prediction effectiveness** depends on how uncertainty is quantified.
- **Traditional methods** use a **single-dimensional conformity score**.

 - False Scores  
 - True Scores

- ✗ A single score may **fail to capture uncertainty**.
- ✗ **Limited separation** between true and false predictions.

- ✓ Multiple scores present **complimentary viewpoints on uncertainty**.
- ✓ In higher dimensions we can obtain **better separation** between true and false predictions.

# Challenges in High Dimensions



- ? Numerous ways of splitting the space to obtain  $1 - \alpha$  coverage.
- ? Structured selection regions (e.g. weighted average) may be **suboptimal**
- ? **New optimization** is required for each  $\alpha$  level.

# Proposed Method: Multi Dimensional CP

## Partition

Partition the space into cells centered around each calibration score

## Scoring

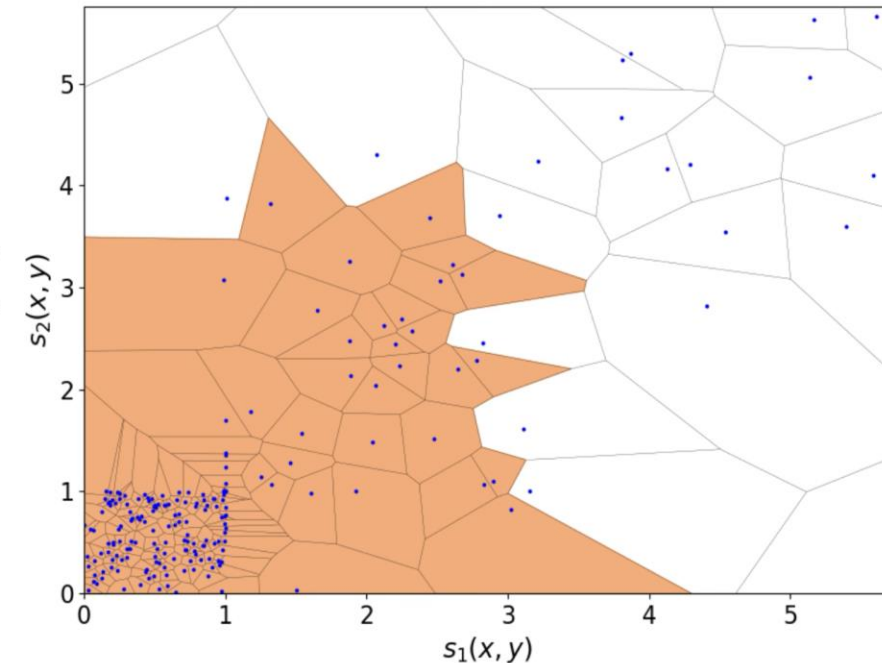
Compute cell scores:  $D_i = \frac{F_i + T_i}{T_i}$ ,  $F_i$  - false scores,  $T_i$  - true scores

## Ranking

Rank the cells  $D_{(1)} \leq D_{(2)} \leq \dots \leq D_{(k)}$

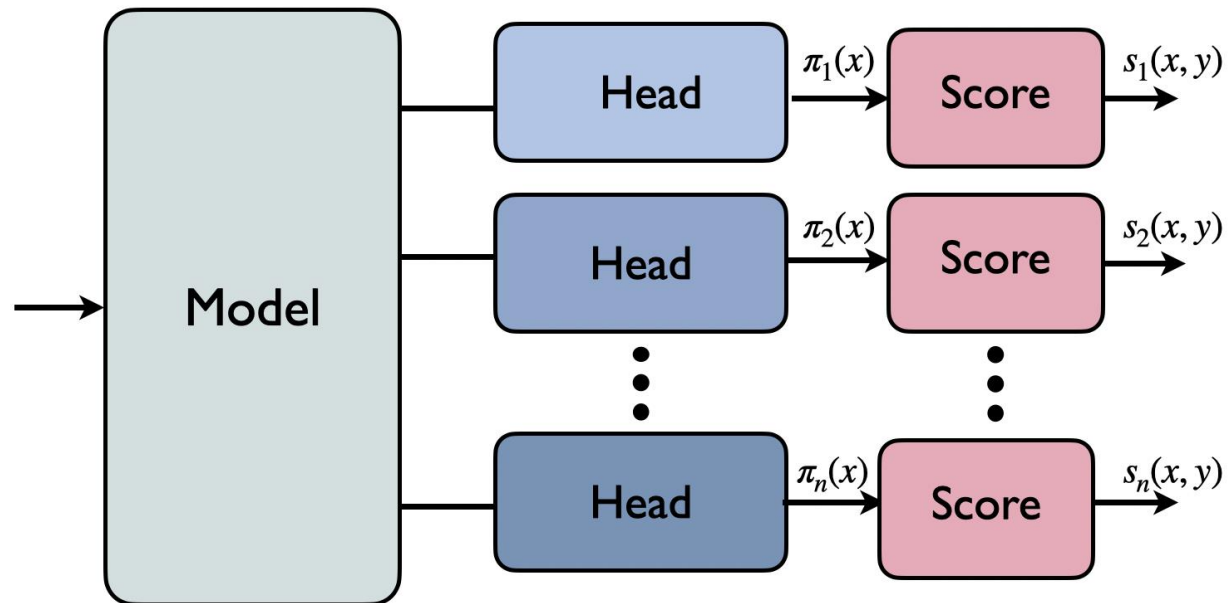
## Selection

Select the region  $\mathcal{C}_{\text{in}}^{\eta^*} = \bigcup_{i=1}^{\eta^*} \mathcal{C}_{(i)}$ , ensuring  $(1 - \alpha)$  coverage.



# Constructing a Multi Dimensional Score

- We propose a new method for obtaining **diverse scores** with **low cost**.
- We attach **multiple classification heads**  $\{\pi_i(x)\}_{i=1}^n$ .
- We add a **regularization term** to increase diversity among heads:  $\frac{\beta}{n(n-1)} \sum_{i=1}^n \sum_{i \neq j} \text{sim}(\pi_i(x), \pi_j(x))$



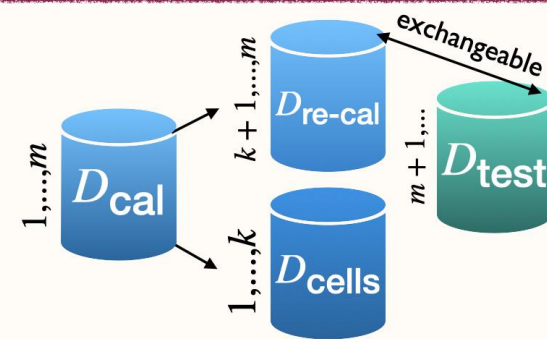
# Theoretical analysis

Coverage Guarantees

Let  $\mathcal{D}_{\text{cells}}$  and  $\mathcal{D}_{\text{re-cal}}$  be two **disjoint subsets**,  
and  $\{(X_i, Y_i)\}_{i=k+1}^{m+1}$  is **exchangeable**.

For any multi-dimensional score  $s : \mathcal{X} \times \mathcal{Y} \rightarrow \mathcal{S} \subseteq \mathbb{R}^n$  and  $\alpha \in (0,1)$ ,  
the prediction set  $\Gamma_{\eta^*}(X_{m+1}) = \left\{ y \in \mathcal{Y} \mid s(X_{m+1}, y) \in \mathcal{C}_{\text{in}}^{\eta^*} \right\}$  satisfies:

$$\mathbb{P} \left( Y_{m+1} \in \Gamma_{\eta^*}(X_{m+1}) \right) \geq 1 - \alpha$$



Efficiency

It can be shown that our selection procedure is equivalent to solving:

$$\operatorname{argmin}_{I \subseteq 2^k} \mathbb{E} [\text{size}(\Gamma^I(X))] \quad \text{Set-size minimization}$$

$$\text{s.t. } \mathbb{E} [\mathbf{1}\{Y \in \Gamma^I(X)\}] \geq 1 - \alpha \quad \text{Coverage constraint}$$

where  $\Gamma^I(x) = \{y \in \mathcal{Y} \mid s(x, y) \in \cup_{i \in I} \mathcal{C}_i\}$  is a **union of cells**.

# Results

## Coverage & Set-size

### Baselines

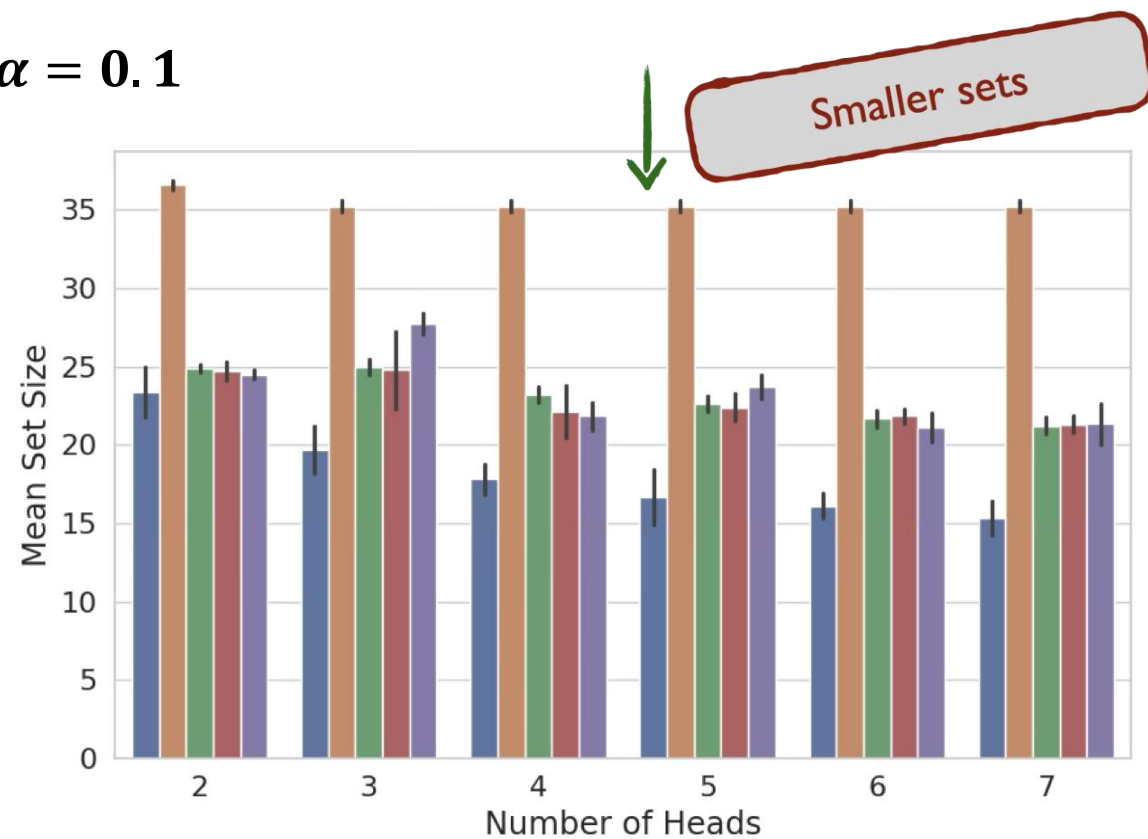
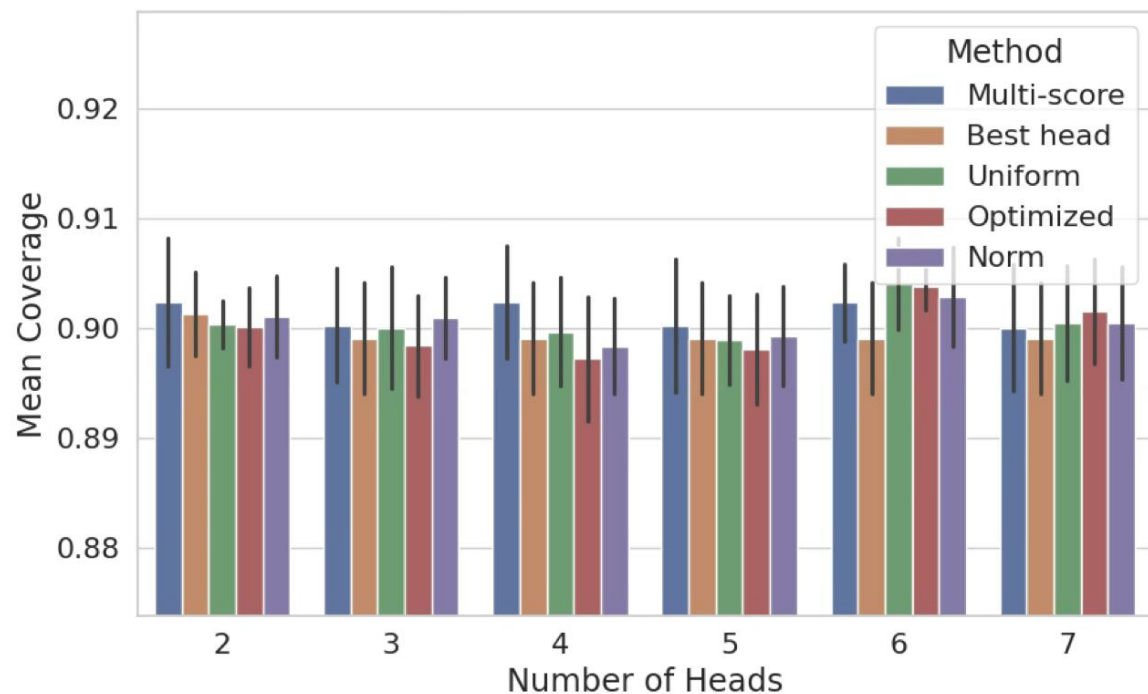
**Best Head** - single best head

**Uniform** - uniform avg.

**Optimized** - optimized weighted avg.

**Norm** - circle-shaped region

CIFAR-100,  $\alpha = 0.1$

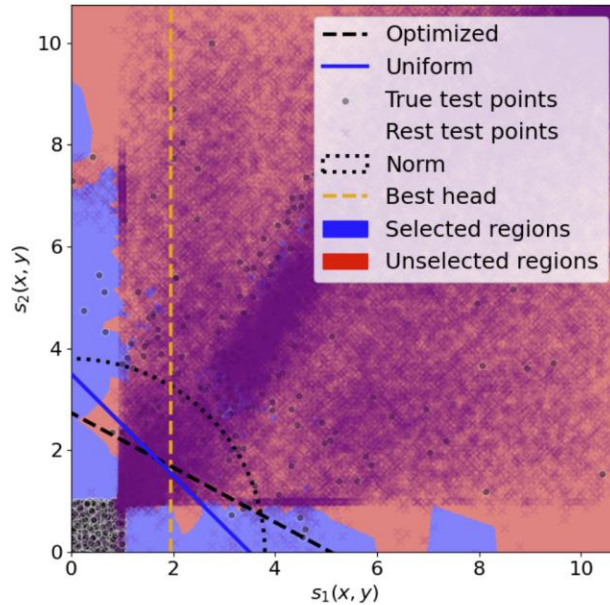


# Results

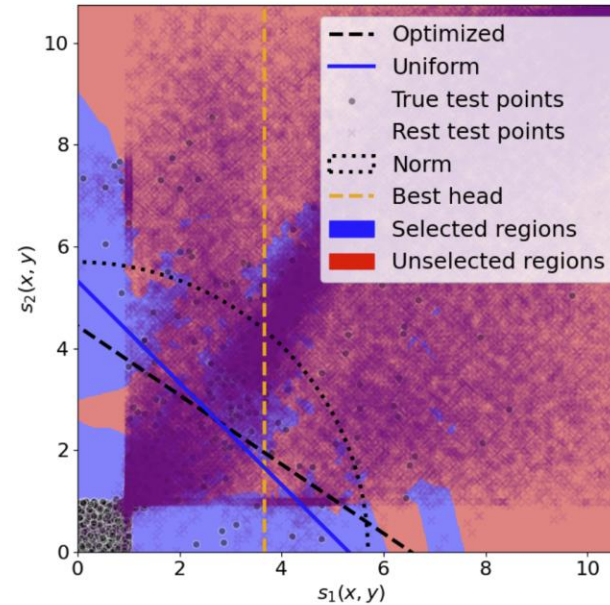
## selected region

### Showing:

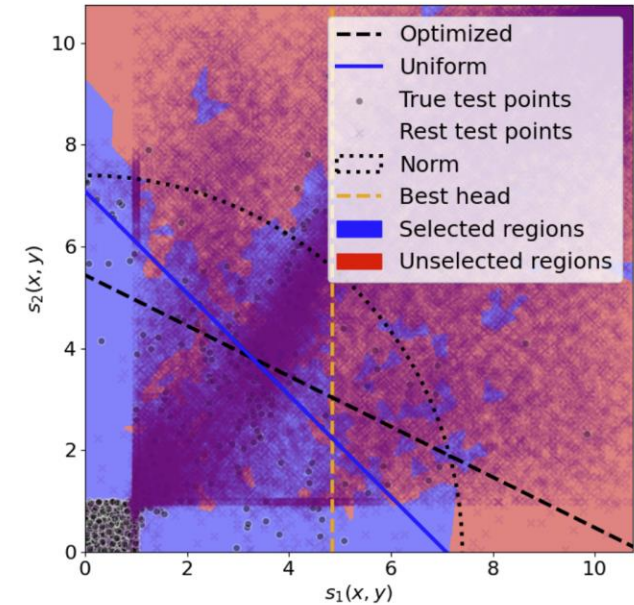
- The region selected by our method in **blue**.
- The decision boundaries for the baselines.
- True test points: **Green circles**
- Incorrect labels: **Purple x-marks**.



(a)  $\alpha = 0.2$



(b)  $\alpha = 0.1$

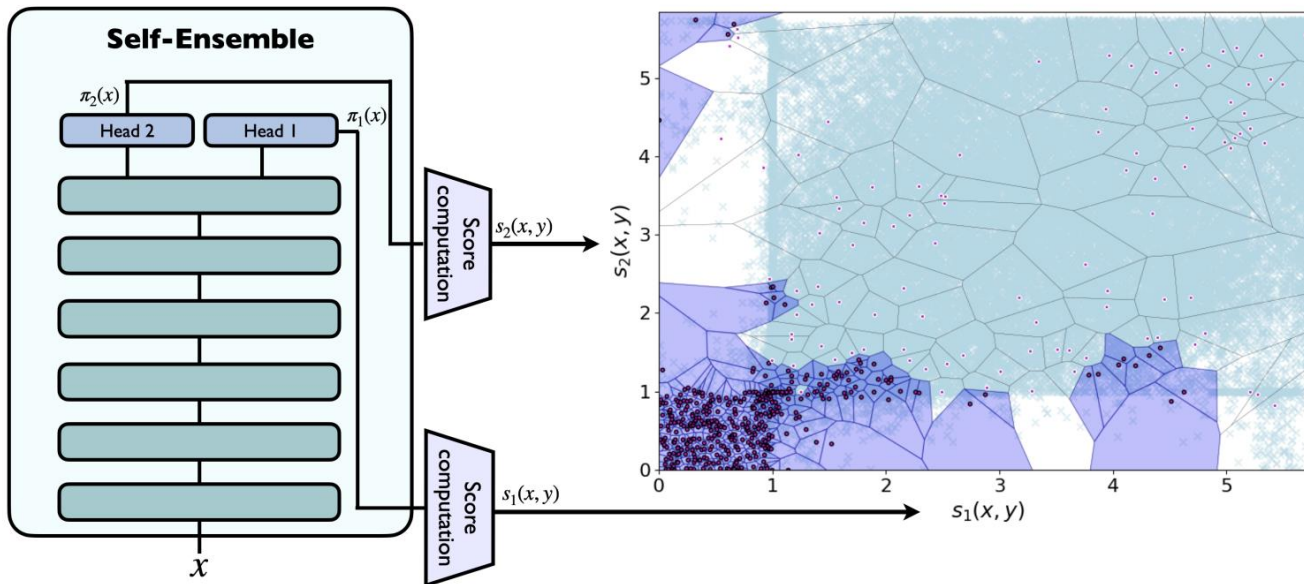


(c)  $\alpha = 0.05$

Our method effectively **focuses on regions with fewer false labels**, while the baselines are constrained by their fixed structure, including areas with a high density of false labels.

# Summary

- Introduce an extension of conformal prediction to higher dimensions
- Provides smaller and more informative prediction sets
- Requires no additional optimization
- Offers flexible, finite-sample coverage guarantees



Visit our Github page & Colab demo -  
<https://github.com/yamtawa/Multi-CP>

Or check out the paper for more details -  
[MULTI-DIMENSIONAL CONFORMAL PREDICTION](#)