

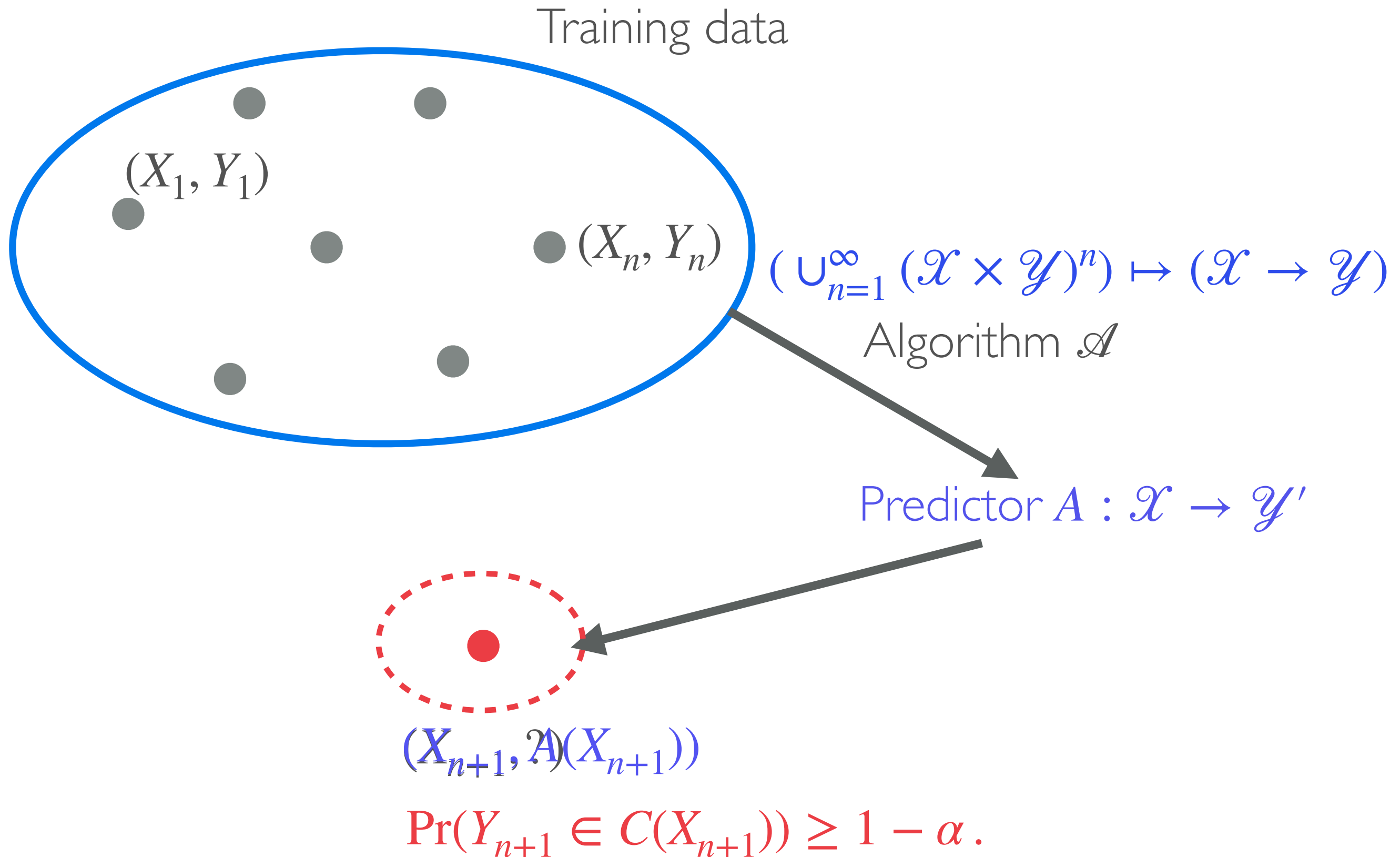
Assumption-free uncertainty quantification for black box models

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Outline

1. *What does “predictive inference” mean?*
2. Methods for assumption-free predictive inference
3. Empirical observations
4. Generalizations
5. Open problems + summary

Prediction vs “Predictive Inference”



Why “Predictive Inference”?

Why do we want $\Pr(Y_{n+1} \in C(X_{n+1})) \geq 1 - \alpha$?

eg: time taken to airport (Y) at some time of day (X)

A “mean” prediction of 80mins is not useful because 80 +/- 5 mins is very different from 80 +/- 40 mins.

To make real-world decisions based on predictions, we need to quantify uncertainty of those predictions.

Prediction interval vs Confidence interval

Predictor (prediction algorithm)

$$(\cup_{n=1}^{\infty} (\mathcal{X} \times \mathcal{Y})^n) \mapsto (\mathcal{X} \rightarrow \mathcal{Y}')$$

Prediction interval (or set)

$$\Pr(Y_{n+1} \in C(X_{n+1})) \geq 1 - \alpha. \quad \text{vol}(C_n) \geq q_{1-\alpha}(P_{Y|X=X_{n+1}}).$$

Estimator (estimation algorithm)

$$(\cup_{n=1}^{\infty} (\mathcal{X} \times \mathcal{Y})^n) \mapsto \Theta$$

Confidence interval (or set)

$$\Pr(\theta \in C_n) \geq 1 - \alpha. \quad \text{Often, vol}(C_n) \rightarrow 0 \text{ as } n \rightarrow \infty.$$

Need to assume a model relating Y to X .

θ is a subset of model parameters.

eg: assume $Y = X\theta + \text{noise}$.

“Assumption-free” Predictive Inference

Given data $D_n \equiv (X_1, Y_1), \dots, (X_n, Y_n) \sim P_X \times P_{Y|X} \equiv P_{XY}$,

any algorithm $\mathcal{A} : (\cup_{n=1}^{\infty} (\mathcal{X} \times \mathcal{Y})^n) \mapsto (\mathcal{X} \rightarrow \mathcal{Y}')$,

and $X_{n+1} \sim P_X$, produce a set $C(X_{n+1}) \equiv C_{\mathcal{A}, D_n}(X_{n+1})$ s.t.

for all P_{XY} , algorithms \mathcal{A} , $\Pr(Y_{n+1} \in C(X_{n+1})) \geq 1 - \alpha$.



Remarks

- (a) *don't need iid data, just exchangeable*
- (b) *algorithm optional, assumed permutation-invariant*
- (c) *trivial without size/efficiency requirement*
- (d) *probability is over all training, test data, algorithm*
- (e) *not conditional on X_{n+1}*

Conditional coverage is impossible without assumptions

We will achieve $\Pr(Y_{n+1} \in C(X_{n+1})) \geq 1 - \alpha$.

Not $\forall x, \Pr(Y_{n+1} \in C(X_{n+1}) \mid X_{n+1} = x) \geq 1 - \alpha$.

In fact, one can prove that assumption-free conditional inference is impossible.
(the expected volume of the set must be infinite)

Balasubramanian, Ho and Vovk '14

Lei, Wasserman, Rinaldo, Tibshirani '18

BaCaRaTi'19

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1. What does “predictive inference” mean?

2. *Methods for assumption-free predictive inference*

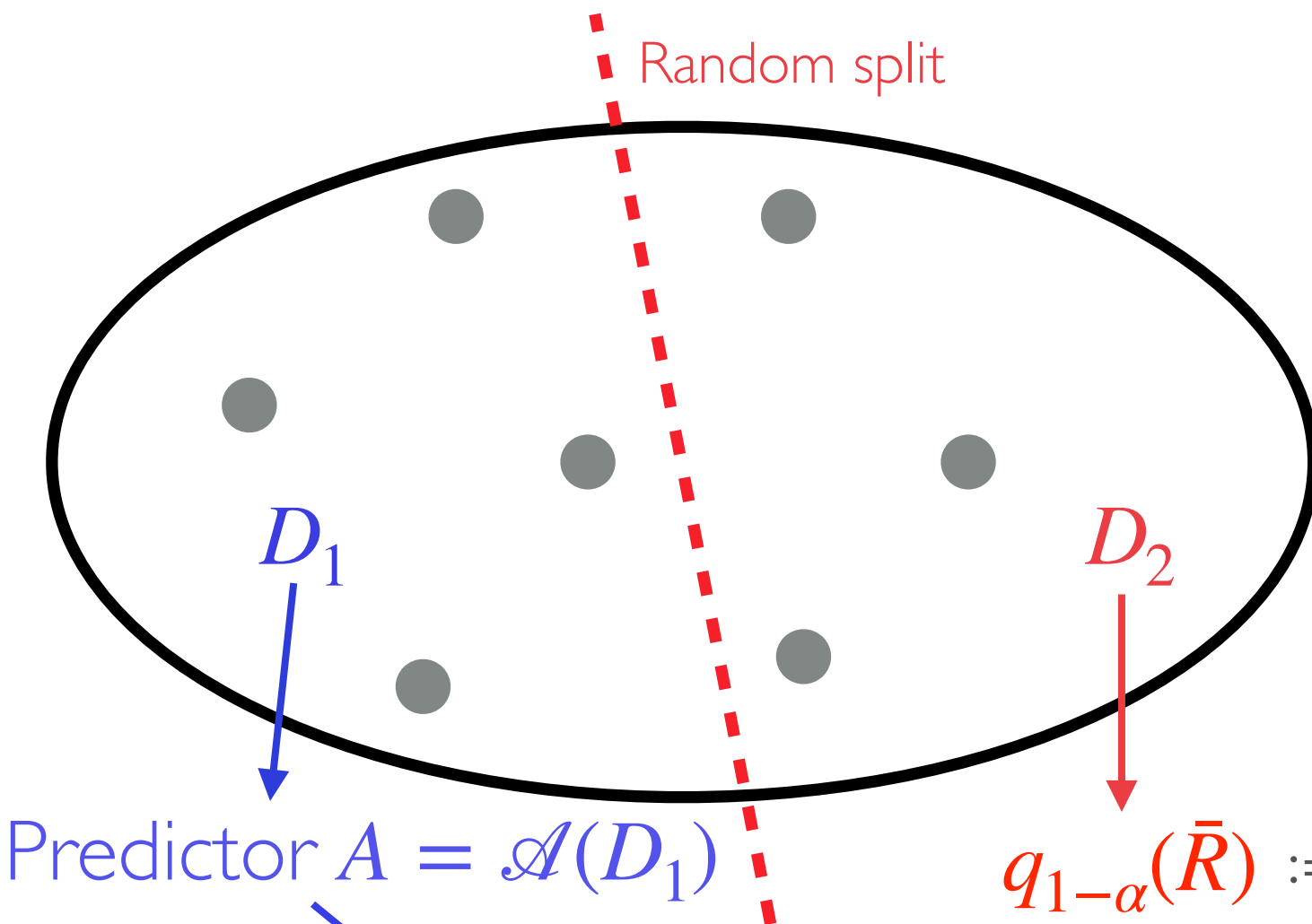
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Split/“Inductive” Conformal Prediction

Training data



Hold-out scores $R_i \equiv R_A(X_i, Y_i)$

eg: residual $R_i := |Y_i - A(X_i)|$

Let $\bar{R} = \{R_i\}_{i \in D_2}$

$$R_{n+1} = |Y_{n+1} - A(X_{n+1})|$$

$R_1, \dots, R_{n_2}, R_{n+1}$ exchangeable

$\implies \text{rank}(R_{n+1})$ is uniform ★

$q_{1-\alpha}(\bar{R}) := [(1 - \alpha)(n_2 + 1)]$ ranked element of \bar{R}

w.h.p. $R_{n+1} \equiv |Y_{n+1} - A(X_{n+1})| \leq q_{1-\alpha}(\bar{R})$

\implies w.h.p. $Y_{n+1} \in \{y : |y - A(X_{n+1})| \leq q_{1-\alpha}(\bar{R})\}$

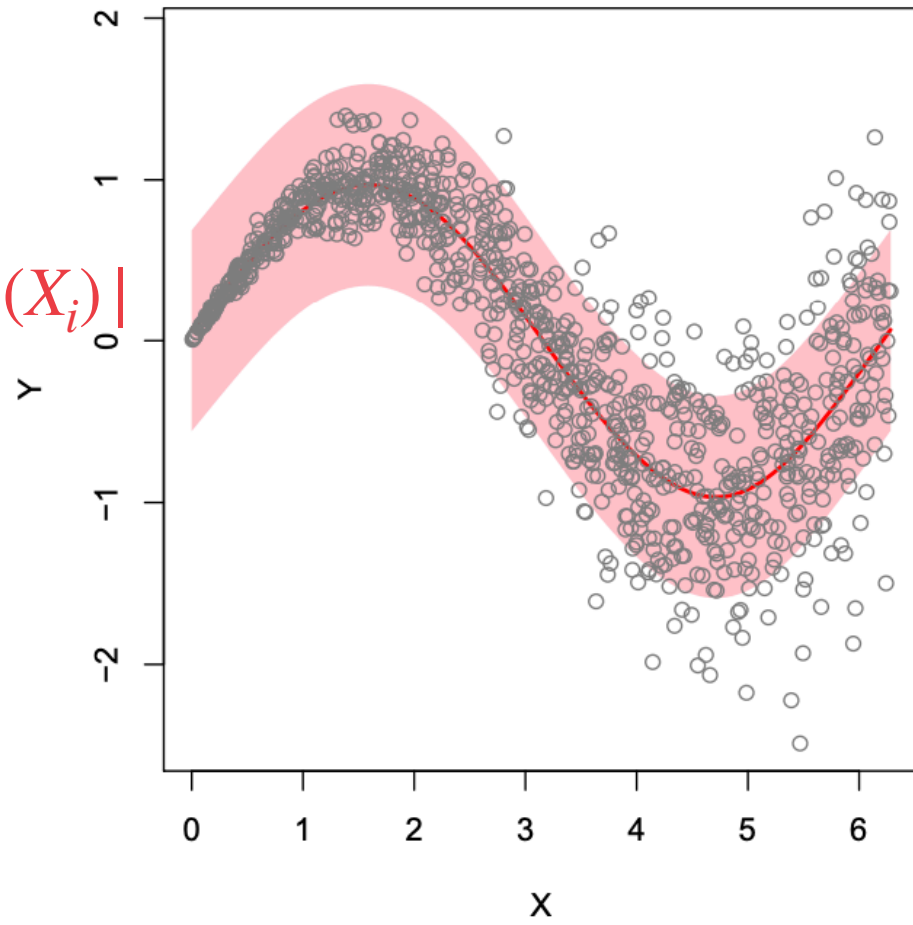
$$C(X_{n+1}) := [A(X_{n+1}) \pm q_{1-\alpha}(\bar{R})] \equiv \{y : |y - A(X_{n+1})| \leq q_{1-\alpha}(\bar{R})\}$$

$$\Pr(Y_{n+1} \in C(X_{n+1})) \geq 1 - \alpha.$$

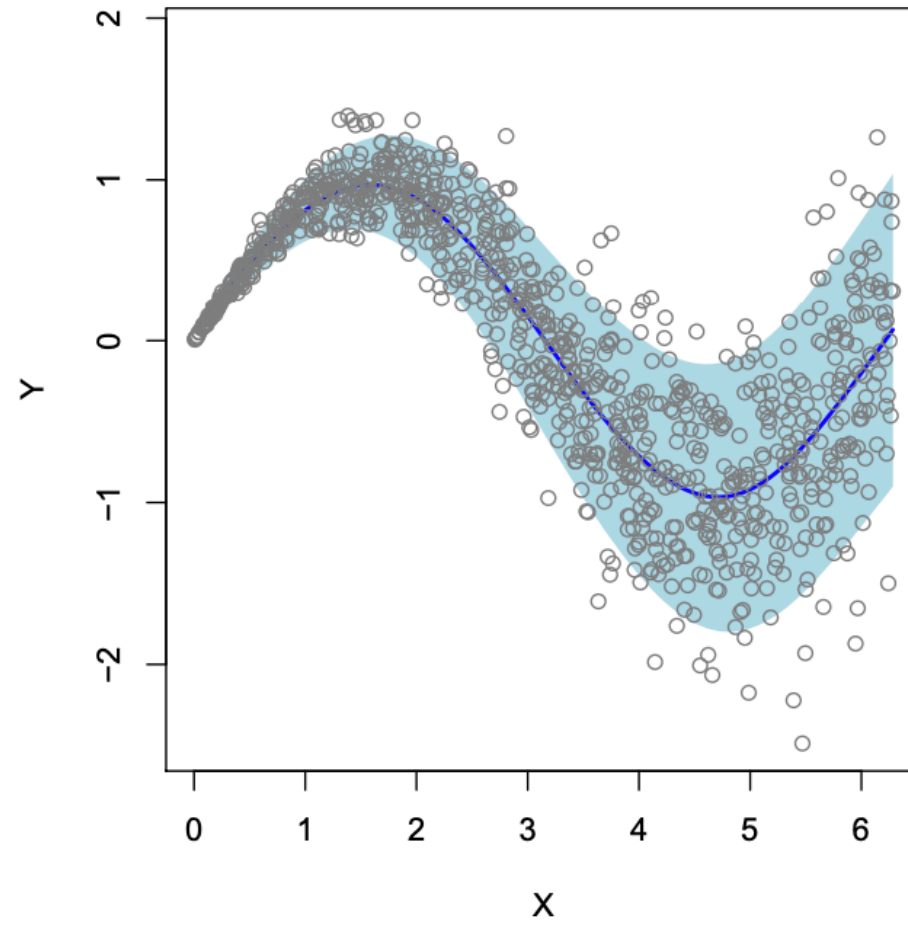
$$\leq^* 1 - \alpha + \frac{1}{n_2 + 1}.$$

Papadopoulos, Proedrou, Vovk, Gammerman '02
Lei, Wasserman, Rinaldo, Tibshirani '18

Split Conformal Prediction Intervals
Coverage: 0.897, Average Length: 1.247



Locally-Weighted Split Conformal
Coverage: 0.899, Average Length: 1.105



$$R_i := |Y_i - A(X_i)|$$

$$R_i := \frac{|Y_i - A(X_i)|}{\sigma(X_i)}$$

Classifier $A : \mathcal{X} \rightarrow \Delta(\mathcal{Y})$ or $\mathbb{R}^{\mathcal{Y}}$

$$R_i := \sum_{k=1}^K [A(X_i)]_k \mathbf{1}_{[A(X_i)]_k > [A(X_i)]_{Y_i}}$$

or $R_i := \text{rank}(Y_i) \text{ in } A(X_i)$

