

Lecture 13

Conformal prediction

Lecture Notes VI – Modern resampling methods. Conformal prediction

Marina Meila
`mmp@stat.washington.edu`

Department of Statistics
University of Washington

May 2025

Re-sampling

Bootstrap ✓

Jackknife ✓

- Loo → distribution of $y_i - \hat{y}_i$
leave-one-out
($\propto$ Loo CV) → averages "errors"
Validation likelihood (KDE)
...
⇒ score

Bag of little bootstraps ✓

Conformal prediction. Jackknife+ ←

Conformal prediction

now x

AFTER
TRAINING

- **Conformal prediction:** CI for a single prediction $\hat{y} = f(x)$

Given data set $\mathcal{D} = \{(x_i, y_i), i = 1 : N\}$

Training algorithm $\mathcal{A}$, so that $\mathcal{A}(\mathcal{D}) = \underline{f}$ the predictor

Want CI for $\hat{y} = f(x)$ where x is a new data point

so that the CI is NOT dependent on $\mathcal{A}$ being statistically correct (e.g. $\mathcal{A}$ overfits, ...)

- jackknife+ is a simple algorithm for CP
- More advanced algorithms exist. This is an active area of research in statistics.



!!!! Do NOT use CP to "crossvalidate" your algorithm!

Conformal prediction

- **Conformal prediction:** CI for a single prediction $\hat{y} = f(x)$

Given data set $\mathcal{D} = \{(x_i, y_i), i = 1 : N\}$

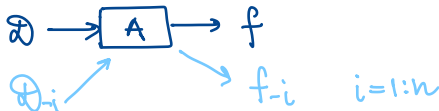
Training algorithm $\mathcal{A}$, so that $\mathcal{A}(\mathcal{D}) = f$ the predictor

Want CI for $\hat{y} = f(x)$ where x is a new data point

so that the CI is NOT dependent on $\mathcal{A}$ being statistically correct (e.g. $\mathcal{A}$ overfits, ...)

$1 - \alpha = \text{confidence level}$

- jackknife+ is a simple algorithm for CP
- More advanced algorithms exist. This is an active area of research in statistics.



!!!! Do NOT use CP to "crossvalidate" your algorithm!

$\mathcal{D}_{-i} = \mathcal{D} \setminus \{(x_i, y_i)\}$ Leave Out data point i

jackknife+

jackknife+ Algorithm

In data set $\mathcal{D} = \{(x_i, y_i), i = 1 : n\}$

Training algorithm $\mathcal{A}$, so that $\mathcal{A}(\mathcal{D}) = f$ the predictor

Confidence level $1 - \alpha$

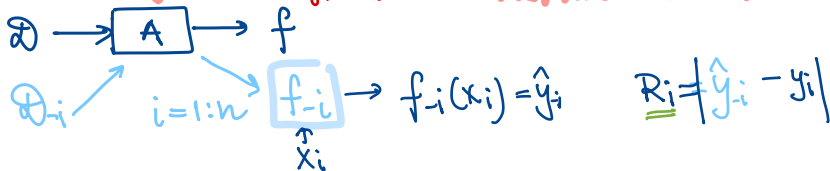
Want CI for $\hat{y} = f(x)$ where x is a new data point

1. Precompute $f_{-i} \leftarrow \mathcal{A}(\mathcal{D}_{-i})$ for $i = 1 : n$
2. Compute "leave one out" residuals $R_i = |y_i - f_{-i}(x_i)|$, for $i = 1 : n$
3. For every new x : compute $f(x)$, then get $1 - \alpha$ Prediction Interval $[a, b]$ for $f(x)$ by
 - 3.1 Compute lower bounds $a_i = f_{-i}(x) - R_i$, for $i = 1 : n$
 - 3.2 Sort $a_{1:n}$
 - 3.3 Set $a \leftarrow \lfloor \frac{\alpha}{2} n \rfloor$ quantile of $a_{1:n}$
 - 3.4 Compute upper bounds $b_i = f_{-i}(x) + R_i$, for $i = 1 : n$
 - 3.5 Sort $b_{1:n}$
 - 3.6 Set $b \leftarrow \lceil (1 - \frac{\alpha}{2}) n \rceil$ quantile of $b_{1:n}$
 - 3.7 Output $CI^\alpha = [a, b]$
4. Theorem $P[y(x) \in CI^\alpha] \geq 1 - \alpha$

jackknife+

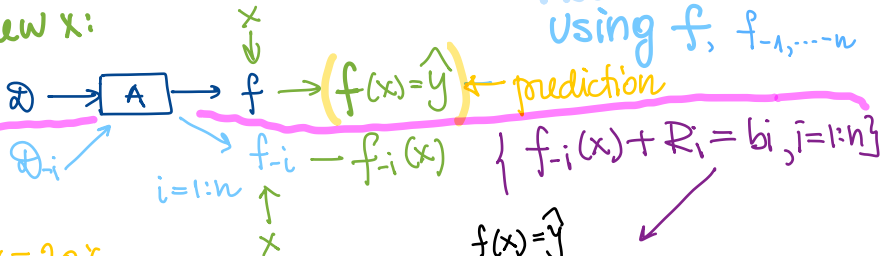
training, CV, ...

TRAIN + TEST



new x:

PREDICTING
Using $f, f_{-1}, \dots, f_{-n}$

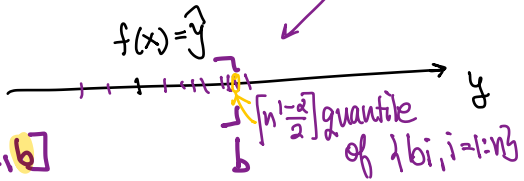


$\alpha = 20\%$

$1 - \frac{\alpha}{2} = 90\%$

$\lceil n^{\frac{1-\alpha}{2}} \rceil$

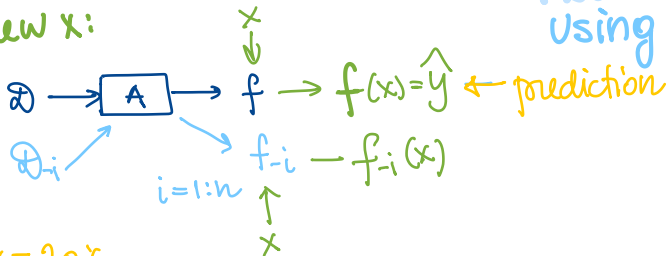
$c_{\alpha} = [a, b]$



jackknife+

$$CI_\alpha = [\underline{a}, b]$$

new x:



PREDICTING
Using f

"ceiling"

$$\lceil z \rceil = \min$$

$$\{m \in \mathbb{Z}, m \geq z\}$$

floor

$$\lfloor z \rfloor = \max$$

$$\{m \in \mathbb{Z}, m \leq z\}$$

$$\alpha = 20\%$$

$$\frac{\alpha}{2} = 10\%$$

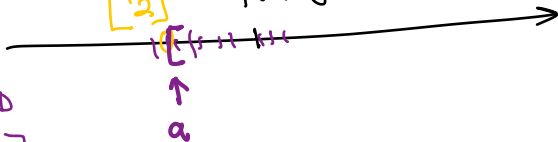
$$f_{-i}(x) - \bar{f}_i = a_i$$

$$\{a_i, i = 1:n\}$$

$$q = \lfloor n \frac{\alpha}{2} \rfloor \text{ quantile}$$

$$\lfloor n \frac{\alpha}{2} \rfloor$$

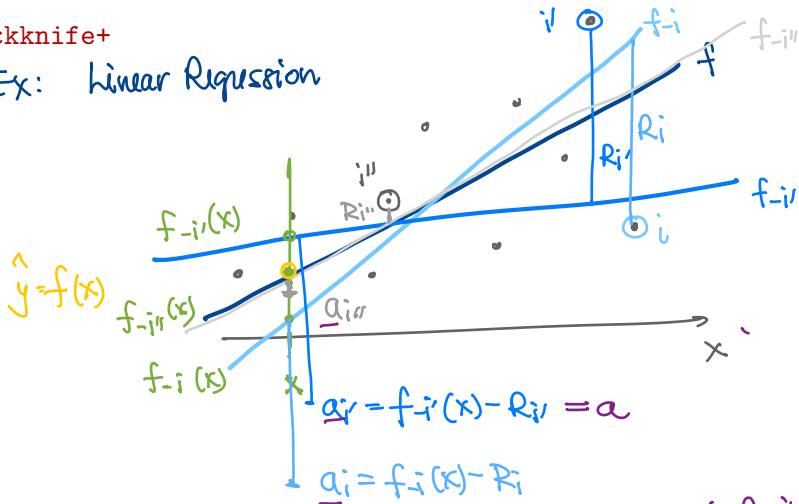
$$f(x) = \hat{y}$$



Rem: $f(x)$ NOT USED
to obtain $[a, b]$

jackknife+

Ex: Linear Regression



← pick 10% quantile
 $\{a_1, \dots, a_n\} \Rightarrow a$

$\alpha = 20\%$
 $n \frac{\alpha}{2} = 1$

jackknife+

Ex: Linear Regression

$b = \lceil n^{\frac{1-\alpha}{2}} \rceil$ quantile
of $\{b_i, i=1:n\}$

