

Conformal prediction and its extensions

1 CP: Conformal prediction

Methods for distribution-free prediction.

Assumption: exchangeability

- The **data** $Z_i = (X_i, Y_i)$ are assumed to be exchangeable (for example, i.i.d.).
 - Definition (Vovk, Gammernan, and Shafer 2005; Shafer and Vovk 2008). Suppose that for any collection of N values, the $N!$ different orderings are equally likely. Then we say that Z_1, \dots, Z_N are exchangeable. The exchangeability assumption is slightly weaker than the i.i.d. assumption.
- The **algorithm** which maps data to a fitted model $\hat{\mu} : \mathcal{X} \rightarrow \mathbb{R}$ is assumed to treat the data points symmetrically.
 - For example, OLS versus WLS.

1.1 Split conformal prediction

(inductive conformal prediction)

1. initial training data set: pre-trained model $\hat{\mu} : \mathcal{X} \rightarrow \mathbb{R}$.
2. holdout/calibration set: nonconformity scores $R_i = |Y_i - \hat{\mu}(X_i)|$, $i = 1, \dots, n$.
3. prediction set: $\widehat{C}_n(X_{n+1}) = \hat{\mu}(X_{n+1}) \pm Q_{1-\alpha} \left(\sum_{i=1}^n \frac{1}{n+1} \cdot \delta_{R_i} + \frac{1}{n+1} \cdot \delta_{+\infty} \right)$.
(the $\lceil (n+1)(1-\alpha) \rceil$ th smallest of R_1, \dots, R_n)

Drawback: the loss of accuracy due to sample splitting.

1.2 Full conformal prediction

(transductive conformal prediction)

1. training data & a hypothesized test point: $\hat{\mu}^y = \mathcal{A}((X_1, Y_1), \dots, (X_n, Y_n), (X_{n+1}, y))$ for each $y \in \mathbb{R}$.
2. residuals: $R_i^y = \begin{cases} |Y_i - \hat{\mu}^y(X_i)|, & i = 1, \dots, n \\ |y - \hat{\mu}^y(X_{n+1})|, & i = n + 1 \end{cases}$.
3. prediction set: $\widehat{C}_n(X_{n+1}) = \{y \in \mathbb{R} : R_{n+1}^y \leq Q_{1-\alpha}(\sum_{i=1}^{n+1} \frac{1}{n+1} \cdot \delta_{R_i^y})\}$.

Drawback: a steep computational cost.

THEOREM:

$\mathbb{P}\{Y_{n+1} \in \widehat{C}_n(X_{n+1})\} \geq 1 - \alpha$ holds true for both split conformal and full conformal.

1.3 Jackknife+

(close to cross-conformal prediction in Vovk (2013), offering a compromise between the computational and statistical costs)

1. training data with i th point removed: $\hat{\mu}_{-i} = \mathcal{A}((X_1, Y_1), \dots, (X_{i-1}, Y_{i-1}), (X_{i+1}, Y_{i+1}), \dots, (X_n, Y_n))$.
2. residuals: $R_i^{\text{LOO}} = |Y_i - \hat{\mu}_{-i}(X_i)|$.
3. prediction set:

$$\left[Q_\alpha \left(\sum_{i=1}^n \frac{1}{n+1} \cdot \delta_{\hat{\mu}_{-i}(X_{n+1}) - R_i^{\text{LOO}}} + \frac{1}{n+1} \cdot \delta_{-\infty} \right), Q_{1-\alpha} \left(\sum_{i=1}^n \frac{1}{n+1} \cdot \delta_{\hat{\mu}_{-i}(X_{n+1}) + R_i^{\text{LOO}}} + \frac{1}{n+1} \cdot \delta_{+\infty} \right) \right]$$

Drawback: while in practice it generally provides coverage close to the target level $1 - \alpha$, its theoretical guarantee only ensures $1 - 2\alpha$ probability of coverage in the worst case.

THEOREM:

$\mathbb{P}\{Y_{n+1} \in \widehat{C}_n(X_{n+1})\} \geq 1 - 2\alpha$ holds true for jackknife+.

2 Conformal time-series forecasting

Stankeviciute, M Alaa, and Schaar (2021): CF-RNNs

Multi-horizon time-series forecasting problem

Notation:

- the i th data point: $Z_i = (y_{1:t}^{(i)}, y_{t+1:t+H}^{(i)})$. Note that the label $y_{t+1:t+H}^{(i)}$ is now an H -dimensional value, in contrast with the scalar y value from before.

Assumption:

- exchangeable time-series observations

2.1 Methodology

(Split conformal prediction)

1. training set: train the underlying (auxiliary) model $\hat{\mu} : \mathbb{R}^t \rightarrow \mathbb{R}^H$, which produces multi-horizon forecasts **directly** (conditionally independent predictions).
2. calibration set: obtain the H -dimensional nonconformity scores

$$R_i = \left[|y_{t+1}^{(i)} - \hat{y}_{t+1}^{(i)}|, \dots, |y_{t+H}^{(i)} - \hat{y}_{t+H}^{(i)}| \right]^\top.$$

3. prediction set: $\Gamma_1^\alpha(y_{1:t}^{(n+1)}), \dots, \Gamma_H^\alpha(y_{1:t}^{(n+1)})$, where $\Gamma_h^\alpha(y_{1:t}^{(n+1)}) = [\hat{y}_{t+h}^{(n+1)} - \hat{\varepsilon}_h, \hat{y}_{t+h}^{(n+1)} + \hat{\varepsilon}_h]$, $\forall h \in \{1, \dots, H\}$ with the critical nonconformity scores $\hat{\varepsilon}_1, \dots, \hat{\varepsilon}_H$ become the $[(n+1)(1 - \alpha/H)]$ -th smallest residuals in the corresponding nonconformity score distributions. (Bonferroni correction)

THEOREM:

- $\mathcal{D} = \left\{ (y_{1:t}^{(i)}, y_{t+1:t+H}^{(i)}) \right\}_{i=1}^n$: **exchangeable** time-series observations.
- $\hat{\mu}$: model predicting H -step forecasts using **the direct strategy**.

$$\mathbb{P}(\forall h \in \{1, \dots, H\} \cdot y_{t+h} \in [\hat{y}_{t+h} - \hat{\varepsilon}_h, \hat{y}_{t+h} + \hat{\varepsilon}_h]) \geq 1 - \alpha.$$

3 NexCP: Conformal prediction beyond exchangeability

Barber et al. (2023)

1. Nonexchangeable conformal with a **symmetric** algorithm (weights)
2. Nonexchangeable conformal with **nonsymmetric** algorithms (weights & swap)

3.1 Notation

- the i th data point $Z_i = (X_i, Y_i)$
- the full data sequence $Z = (Z_1, \dots, Z_{n+1})$
- the sequence after swap $Z^i = (Z_1, \dots, Z_{i-1}, Z_{n+1}, Z_{i+1}, Z_n, Z_i)$

3.2 Methodology

1. Choose **fixed (non-data-dependent)** weights $w_1, \dots, w_n \in [0, 1]$ with the intuition that a higher weight should be assigned to a data point that is “trusted” more.
2. Normalize weights $\tilde{w}_i = \frac{w_i}{w_1 + \dots + w_{n+1}}, i = 1, \dots, n$ and $\tilde{w}_{n+1} = \frac{1}{w_1 + \dots + w_{n+1}}$.
3. Generate “tagged” data points $(X_i, Y_i, t_i) \in \mathcal{X} \times \mathbb{R} \times \mathcal{T}$.
4. Swap data set, resulting in Z^K with $K \sim \sum_{i=1}^{n+1} \tilde{w}_i \cdot \delta_i$, i.e., two data points have swapped tags.
5. Apply algorithm \mathcal{A} to Z^K in place of Z .

3.3 Split conformal prediction

- prediction set: $\widehat{C}_n(X_{n+1}) = \hat{\mu}(X_{n+1}) \pm Q_{1-\alpha}(\sum_{i=1}^n \tilde{w}_i \cdot \delta_{R_i} + \tilde{w}_{n+1} \cdot \delta_{+\infty})$

3.4 Full conformal prediction

1. training data & a hypothesized test point: $\hat{\mu}^{y,k} = \mathcal{A}((X_{\pi_k(i)}, Y_{\pi_k(i)}^y, t_i) : i \in [n+1])$ for any $y \in \mathbb{R}$ and $k \in [n+1]$, where π_k is the permutation on $[n+1]$ swapping indices k and $n+1$, and $Y_i^y = \begin{cases} Y_i, & i = 1, \dots, n \\ y, & i = n+1 \end{cases}$.
2. residuals: $R_i^{y,k} = \begin{cases} |Y_i - \hat{\mu}^{y,k}(X_i)|, & i = 1, \dots, n \\ |y - \hat{\mu}^{y,k}(X_{n+1})|, & i = n+1 \end{cases}$.
3. prediction set: $\widehat{C}_n(X_{n+1}) = \{y : R_{n+1}^{y,K} \leq Q_{1-\alpha}(\sum_{i=1}^{n+1} \tilde{w}_i \cdot \delta_{R_i^{y,K}})\}$.

THEOREM:

- Lower bounds on coverage.

$$\mathbb{P}\{Y_{n+1} \in \widehat{C}_n(X_{n+1})\} \geq 1 - \alpha - \sum_{i=1}^n \tilde{w}_i \cdot d_{TV}(R(Z), R(Z^i))$$

- Upper bounds on coverage.

$$\mathbb{P}\{Y_{n+1} \in \widehat{C}_n(X_{n+1})\} < 1 - \alpha + \tilde{w}_{n+1} + \sum_{i=1}^n \tilde{w}_i \cdot d_{TV}(R(Z), R(Z^i)),$$

if $R_1^{Y_{n+1},K}, \dots, R_n^{Y_{n+1},K}, R_{n+1}^{Y_{n+1},K}$ are distinct with probability 1.

The results hold true for both nonexchangeable split conformal and full conformal.

So, if $\tilde{w}_{n+1} = \frac{1}{w_1 + \dots + w_{n+1}}$ is small (the effective sample size is large), then mild violations of exchangeability can only lead to mild undercoverage or to mild overcoverage.

3.5 Jackknife+

1. training data with i th point removed and data tag swapped:

$$\hat{\mu}_{-i}^k = \mathcal{A} \left((X_{\pi_k(j)}, Y_{\pi_k(j)}, t_j) : j \in [n+1], \pi_k(j) \notin \{i, n+1\} \right).$$

2. residuals: $R_i^{k, \text{LOO}} = |Y_i - \hat{\mu}_{-i}^k(X_i)|$.

3. prediction set:

$$\left[Q_\alpha \left(\sum_{i=1}^n \tilde{w}_i \cdot \delta_{\hat{\mu}_{-i}^K(X_{n+1}) - R_i^{K, \text{LOO}}} + \tilde{w}_{n+1} \cdot \delta_{-\infty} \right), Q_{1-\alpha} \left(\sum_{i=1}^n \tilde{w}_i \cdot \delta_{\hat{\mu}_{-i}^K(X_{n+1}) + R_i^{K, \text{LOO}}} + \tilde{w}_{n+1} \cdot \delta_{+\infty} \right) \right]$$

THEOREM:

$$\mathbb{P} \left\{ Y_{n+1} \in \widehat{C}_n(X_{n+1}) \right\} \geq 1 - 2\alpha - \sum_{i=1}^n \tilde{w}_i \cdot d_{\text{TV}}(R_{\text{jack}+}(Z), R_{\text{jack}+}(Z^i))$$

4 WCP: Conformal prediction under covariate shift

Tibshirani et al. (2019)

A weighted version of conformal prediction, using a quantile of a suitably weighted empirical distribution of nonconformity scores.

4.1 Setup/assumption - Covariate shift

Focus on settings in which the data $(X_i, Y_i), i = 1, \dots, n+1$ are no longer exchangeable. Specifically,

$$\begin{aligned} (X_i, Y_i) &\stackrel{\text{i.i.d.}}{\sim} P = P_X \times P_{Y|X}, \quad i = 1, \dots, n, \\ (X_{n+1}, Y_{n+1}) &\sim \widetilde{P} = \widetilde{P}_X \times P_{Y|X}, \text{ independently.} \end{aligned} \tag{1}$$

the test and training covariate distributions differ, but the likelihood ratio between the two distributions, $d\widetilde{P}_X/dP_X$, must be known exactly or well approximated for correct coverage.

4.2 Methodology

Prediction set:

- CP: $\widehat{C}_n(X_{n+1}) = \widehat{\mu}(X_{n+1}) \pm Q_{1-\alpha} \left(\sum_{i=1}^n \frac{1}{n+1} \cdot \delta_{R_i} + \frac{1}{n+1} \cdot \delta_{+\infty} \right)$.
- NexCP: $\widehat{C}_n(X_{n+1}) = \widehat{\mu}(X_{n+1}) \pm Q_{1-\alpha} \left(\sum_{i=1}^n \tilde{w}_i \cdot \delta_{R_i} + \tilde{w}_{n+1} \cdot \delta_{+\infty} \right)$.
 - weights w are fixed
 - $\tilde{w}_i = \frac{w_i}{w_1 + \dots + w_n + 1}, i = 1, \dots, n$ and $\tilde{w}_{n+1} = \frac{1}{w_1 + \dots + w_n + 1}$
- WCP: $\widehat{C}_n(X_{n+1}) = \widehat{\mu}(X_{n+1}) \pm Q_{1-\alpha} \left(\sum_{i=1}^n p_i^w(x) \delta_{R_i} + p_{n+1}^w(x) \delta_{+\infty} \right)$.
 - $w = d\tilde{P}_X/dP_X$ or $w \propto d\tilde{P}_X/dP_X$
 - $p_i^w(x) = \frac{w(X_i)}{\sum_{j=1}^n w(X_j) + w(x)}, i = 1, \dots, n$, and $p_{n+1}^w(x) = \frac{w(x)}{\sum_{j=1}^n w(X_j) + w(x)}$

The **weight function** \hat{w} can be estimated using logistic regression, random forests, etc.

THEOREM:

Assume data from the model Equation 1. Assume \tilde{P}_X is absolutely continuous with respect to P_X , and denote $w = d\tilde{P}_X/dP_X$. For any score function S , and any $\alpha \in (0, 1)$, define for $x \in \mathbb{R}^d$. Then

$$\mathbb{P} \{ Y_{n+1} \in \widehat{C}_n(X_{n+1}) \} \geq 1 - \alpha.$$

4.3 Comparison to NexCP

1. Assumption
 - WCP: covariate shift
 - NexCP: do not make any assumption on the joint distribution of the $n + 1$ points
2. Weights
 - WCP: a function of the data point (X_i, Y_i) to compensate for the **known** distribution shift.
 - NexCP: required to be fixed, can compensate for **unknown** violations of the exchangeability assumption, as long as the violations are **small** (to ensure a low coverage gap).
3. Nonsymmetric algorithm
 - WCP: No.
 - NexCP: Yes.
4. For exchangeable data

- WCP: does not have any coverage guarantee.
- NexCP: retains exact coverage.

5 ACP: Adaptive conformal inference under distribution shift

Gibbs and Candes (2021)

- No assumptions on the data-generating distribution.
- Modelling the distribution shift as a learning problem in a single parameter whose optimal value is varying over time and must be continuously re-estimated.
- Adjust significance level α based on rolling coverage of Y_t .

5.1 Methodology

Work with score function $S(\cdot)$ and quantile function $\hat{Q}(\cdot)$.

Some facts:

- If the distribution of the data is shifting over time, both functions should be regularly re-estimated to align with the most recent observations.
- The realized miscoverage rate $M_t(\alpha)$ also varies over time and may not be equal or close to α .

Assumptions:

Assume that there may be an alternative value $\alpha^* \in [0, 1]$ such that $M_t(\alpha^*) \cong \alpha$.

Assume that with probability one, $\hat{Q}_t(\cdot)$ is continuous, non-decreasing and such that $\hat{Q}_t(0) = -\infty$ and $\hat{Q}_t(1) = \infty$.

Adaptive conformal inference:

- Under assumptions, $M_t(\cdot)$ will be non-decreasing on $[0, 1]$ with $M_t(0) = 0$ and $M_t(1) = 1$.
- Define $\alpha_t^* := \sup \{\beta \in [0, 1] : M_t(\beta) \leq \alpha\}$, then $M_t(\alpha_t^*) = \alpha$.
- Use a simple **update process** to perform the calibration.
 - Intuition: after examining the empirical miscoverage frequency of the previous prediction sets, decreasing (increasing) estimate of α_t^* if the prediction sets were historically under-covering (over-covering) Y_t .

- Let $\alpha_1 = \alpha$, consider the **update**

$$\alpha_{t+1} := \alpha_t + \gamma (\alpha - \text{err}_t)$$

OR

$$\alpha_{t+1} = \alpha_t + \gamma \left(\alpha - \sum_{s=1}^t w_s \text{err}_s \right),$$

where $\gamma > 0$ is a fixed step size parameter whose choice gives a tradeoff between adaptability and stability.

So the distribution is allowed to shift continuously over time.

THEOREM:

With probability one we have that for all $T \in \mathbb{N}$,

$$\left| \frac{1}{T} \sum_{t=1}^T \text{err}_t - \alpha \right| \leq \frac{\max\{\alpha_1, 1 - \alpha_1\} + \gamma}{T\gamma}.$$

In particular, $\lim_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T \text{err}_t \stackrel{\text{a.s.}}{=} \alpha$.

6 PID: Conformal PID control for time series prediction

Angelopoulos, Candes, and Tibshirani (2023)

- PID: proportional-integral-derivative (control theory).
- reactive + forward-looking.

6.1 Methodology

The proposed conformal PID controller is given by

$$q_{t+1} = \underbrace{\eta(\text{err}_t - \alpha)}_{\text{P}} + r_t \underbrace{\left(\sum_{i=1}^t (\text{err}_i - \alpha) \right)}_{\text{I}} + \underbrace{g'_t}_{\text{D}}.$$

The goal is to achieve **long-run coverage** in time, i.e., $\frac{1}{T} \sum_{t=1}^T \text{err}_t = \alpha + o(1)$, where $o(1)$ denotes a quantity that tends to zero as $T \rightarrow \infty$.

- P: Quantile tracking. ACI can be regarded as a special case but it can sometimes output infinite or null prediction sets, while quantile tracking on the scale of the original score sequence does not have this behavior.
- I: Error integration. r_t should be a saturation function to achieve long-run coverage.
- D: Scorecasting (forward-looking). It trains a second model to predict the quantile of the next score.

Reparametrize the PID formula to produce a sequence of quantile estimates q_t , $t \in N$ used in the prediction sets:

let \hat{q}_{t+1} be any function of the past: x_i, y_i, q_i , for $i \leq t$, then update

$$q_{t+1} = \underbrace{\hat{q}_{t+1}}_{\text{scorecaster}} + r_t \underbrace{\left(\sum_{i=1}^t (\text{err}_i - \alpha) \right)}_{\text{integrator}},$$

which is generally useful and is the main focus of the paper.

The applications only consider one-step-ahead forecast.

7 Others

7.1 EnbPI: predictive inference method around ensemble estimators

Xu and Xie (2021)

- For Dynamic time series
- Ensemble point forecasts + update residuals

7.2 SPCI: Sequential Predictive Conformal Inference

Xu and Xie (2023)

- Adaptively re-estimate the conditional quantile of non-conformity scores, upon leveraging the temporal dependency among residuals. Random Forest for quantile regression is used.

7.3 Kath & Ziel (2021, IJF)

Kath and Ziel (2021)

Method 1.

The steps are:

1. Re-arrange time series data as form $Z = \{(x_1, y_1), \dots, (x_L, y_L)\}$.
2. Randomly split observations into subsets π (training set) and $1 - \pi$ (calibration set).
3. Train a random forecast model using the training set and generate out-of-sample forecasts.
4. Calculate non-conformity score.
5. Obtain final prediction interval estimation.

Method 2.

The differences compared to Method 1 are:

1. Here an adjusted normalized non-conformity score $\lambda_{i,h} = \frac{|y_{i,h} - \hat{y}_{i,h}|}{|\hat{\varepsilon}_{i,h}|}$ is used.
2. A second explicit error estimation model is trained to estimate the error associated with the prediction $\hat{y}_{t,h}$, i.e., $\varepsilon_{t,h}$.
3. The new interval forecast is now given by $y_{\alpha,T+1,h} = \hat{y}_{T+1,h} \pm \lambda_{L+1,h}^\alpha |\hat{\varepsilon}_{L+1,h}|$.

The applications only consider one-step-ahead forecast.

7.4 TimeGPT

Garza and Mergenthaler-Canseco (2023)

For uncertainty quantification, they perform rolling forecasts on the latest available data to estimate the model's errors in forecasting the particular target time series.

The h -step-ahead forecast is generated based on h -step-ahead non-conformity errors on the calibration set separately.

7.5 LCP: Localized conformal prediction

Guan (2022)

The **weight** on data point i is determined as a **function of the distance** $\|X_i - X_{n+1}\|_2$, to enable predictive coverage that holds **locally** (in neighborhoods of X space, that is, an approximation of prediction that holds conditional on the value of X_{n+1}).

8 Simulation

8.1 Setup

Simulate a time series y with length $T = 5000$ from an AR(2) model with $\phi_1 = 0.8$, $\phi_2 = -0.5$, and $\sigma^2 = 1$.

Only consider one-step-ahead forecasting, i.e., $h = 1$.

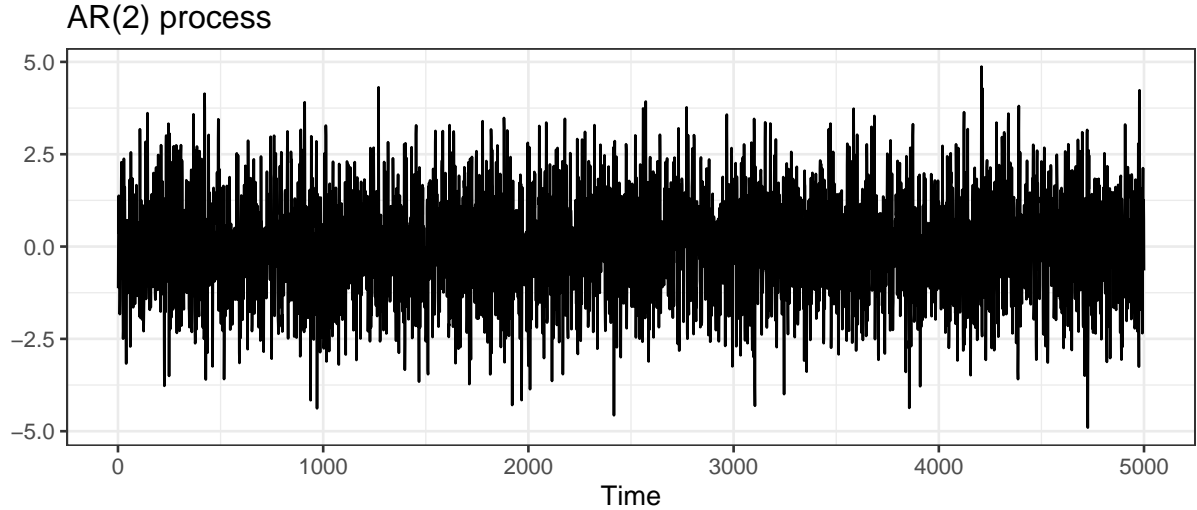


Figure 1: Simulated time series from an AR(2) model.

8.2 Split conformal prediction with fixed training set

8.2.1 Details

Let n be the number of data used to fit an AR(2) model, and m be the number of data in the calibration set.

- Step 1. Rearrange the time series as $Z_i = (X_i, Y_i)$, where $X_i = y_{i:(i+1)}$ and $Y_i = y_{i+2}$, $i = 1, 2, \dots, T - 2$.
- Step 2. Train an AR(2) model $\hat{\mu}$ based on training set with length n , $Z_{tr} = (Z_1, Z_2, \dots, Z_n)$.
- Step 3. Calculate nonconformity scores (absolute residuals) based on calibration set with length m , i.e., $R_i = |Y_i - \hat{\mu}(X_i)|$, $i = n + 1, n + 2, \dots, n + m$.
- Step 4. Generate PI on test set. $\hat{C}_m(X_i) = \hat{\mu}(X_i) \pm Q_{1-\alpha} \left(\sum_{j=n+1}^{n+m} w_j \cdot \delta_{R_j} + w_i \cdot \delta_{+\infty} \right)$ for $i = n + m + 1, \dots, T - 2$.

8.2.2 Results

Let $n = m = 500$ and fit the AR(2) model using the `lm` function.

Consider methods: CP, WCP.LR, WCP.RF, NexCP with $\alpha = 0.1$.

Issues:

- PIs have constant width over the test set. We can generate PIs with varying local width by using a function to perform training on the absolute residuals i.e., to produce an estimator of $E(R|X)$.
- When generating weights via GLM or RF in WCP method, we need to use all data from the test set, which is not reasonable.
- Regression-based model.

8.3 Split conformal prediction with rolling training set

8.3.1 Details

Let n be the number of observations used to fit an AR(2) model, and m be the number of observations in the calibration set.

For $i = n + 1, n + 2, \dots, T$:

- Step 1. Fit an AR(2) model $\hat{\mu}_{i-1}$ based on observations $y_{(i-n):(i-1)}$, generate one-step-ahead forecast \hat{y}_i .
- When $i > n + m$:
 - Step 2. Calculate weights for the updated calibration set with length m and the updated test set with length 1 using different methods. Here WCP can not be applied because we only have a test set with length equal to one.

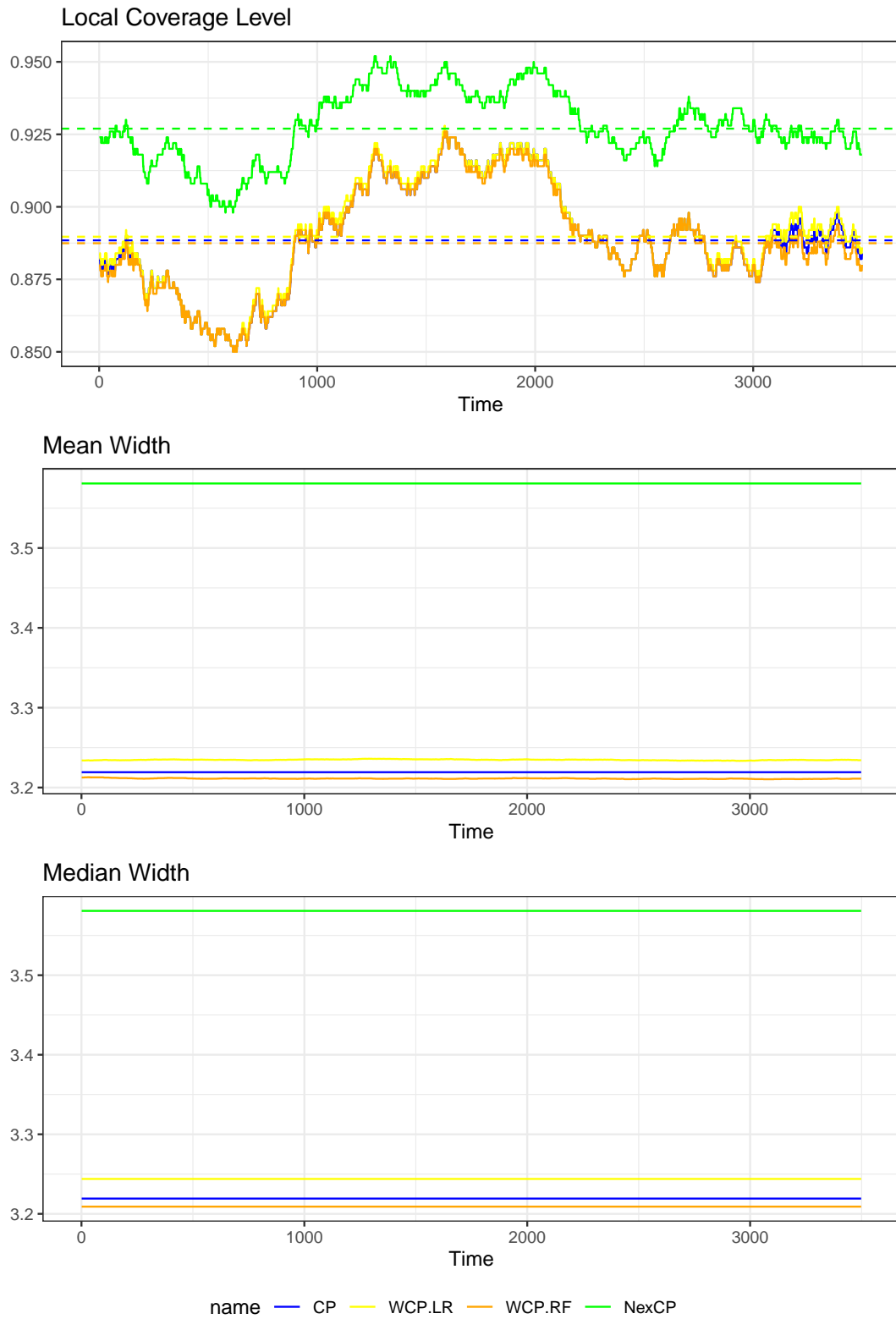


Figure 2: Local coverage frequencies and width for split conformal prediction methods with fixed training set ($k=500$).

- Step 3. Generate PI on test set. $\hat{y}_i \pm Q_{1-\alpha} \left(\sum_{j=i-m}^{i-1} w_j \cdot \delta_{R_j} + w_i \cdot \delta_{+\infty} \right)$.
- Setp 4 for ACP. Update α based on the recent empirical miscoverage frequency.
- Step 5. Calculate nonconformity scores (absolute residuals) $R_i = |y_i - \hat{y}_i|$.

8.3.2 Results

Let $n = m = 500$ and fit AR(2) models using the `Arima` function with setting `order = c(2,0,0)`, `include.mean = TRUE`, `method = "CSS"` to make it comparable with the previous result.

Consider methods: AR, CP, NexCP, ACP, PID with $\alpha = 0.1$.

For the PID method:

- The AR(2) models are trained using `nfit` observations through a rolling window strategy, as with the other methods.
- Theta method is used as the scorecaster to forecast the conformity scores. An expanding window strategy is used if `ncast = NULL`; a rolling window strategy is used if `ncast != NULL` (here we use rolling windows with `ncast = ncal` for comparison with other methods).
- The first `nburnin` outputs are removed to have output of equal length. (`nburnin` is equal to `ncal` in other methods.)
- Some parameters.
 - Constants `Csat` and `KI` for the integrator $r_t(x) = K_I \tan(x \log(t) / (tC_{\text{sat}}))$ are determined by some heuristics. See appendix B for more details. Here, $T = 5000$, $\delta = 0.01$, and $K_I = 2$.
 - The learning rate for the quantile tracking (P): $\eta = 0.1\hat{B}_t$.

Features:

- The fitted model is updating over time.
- PIs have changing width over the test set.
- Other non-regression-based models can be considered.
- Time-consuming because of the rolling window approach (but is still very quick for this simulation).

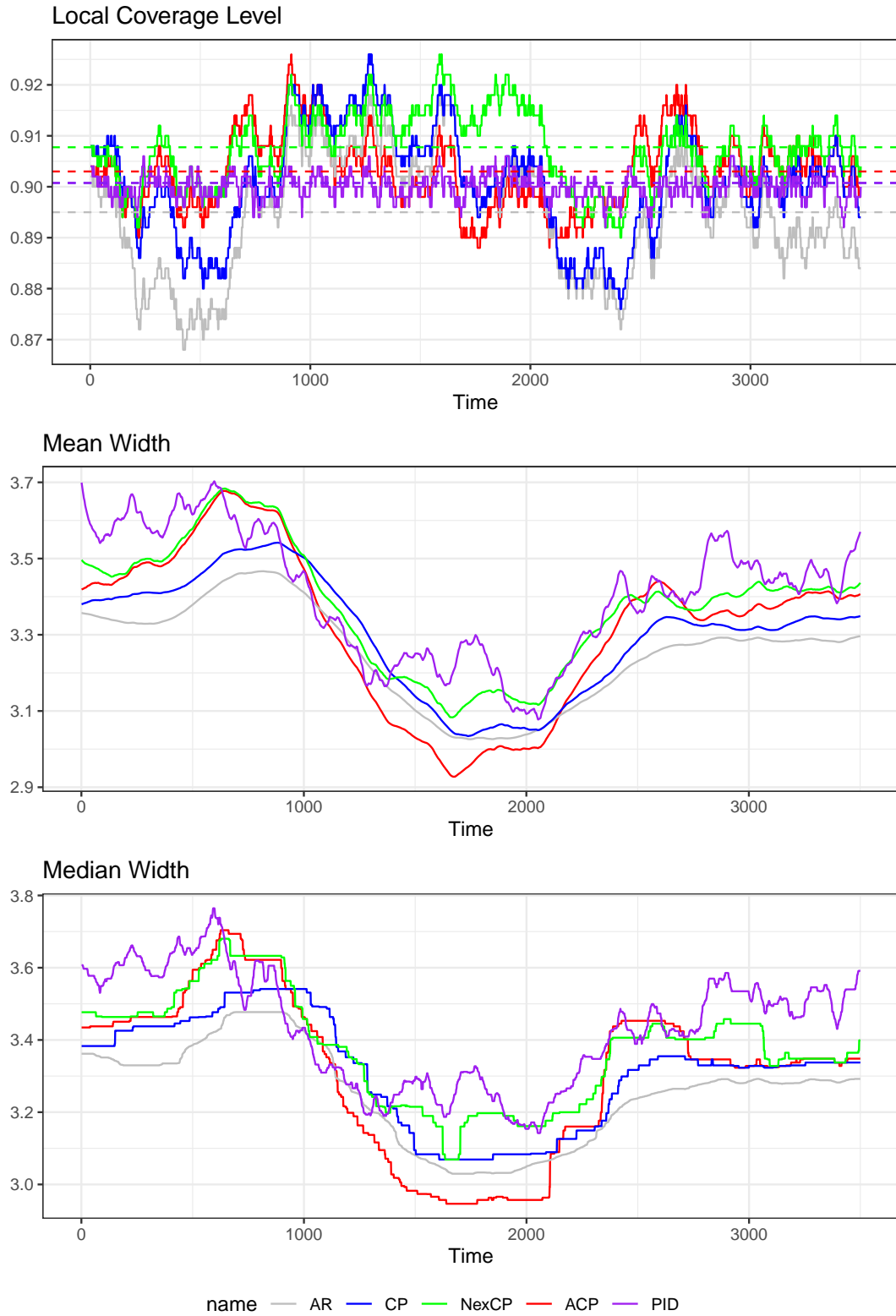


Figure 3: Local coverage frequencies and width for split conformal prediction methods with rolling training set and calibration set ($k=500$).

8.3.3 Analysis on PID

The effect of integration (C_{sat} and K_I)

C_{sat} controls the guaranteed coverage.

K_I controls the change scale of the integrator.

1. Wrong setting: $C_{\text{sat}} = 1$, $K_I = 200$
2. Heuristics setting: $C_{\text{sat}} = 0.5618745$, $K_I = 2$ used in the Results section.

The effect of scorecasting (more variance introduced if there is no pattern in the score sequence)

9 To do list

- ☐ Generalize the existing methods and get a general function for implementation.
 - ☐ Symmetric/asymmetric scores.
 - ☐ Expanding/rolling window strategy.
 - ☐ Include weights in PID.
 - ☐ Handle seasonal time series and specify methods used for forecasting and scorecasting.
- ☐ Multi-step ahead forecasting.
 - ☐ Correlation between multi step ahead residuals.
 - ☐ Similar strategy as PID.
- ☐ More simulations and real-world data.
- ☐ Theoretical proof.
- ☐ Other data-dependent weight.
- ☐ Hierarchical time series?

10 References

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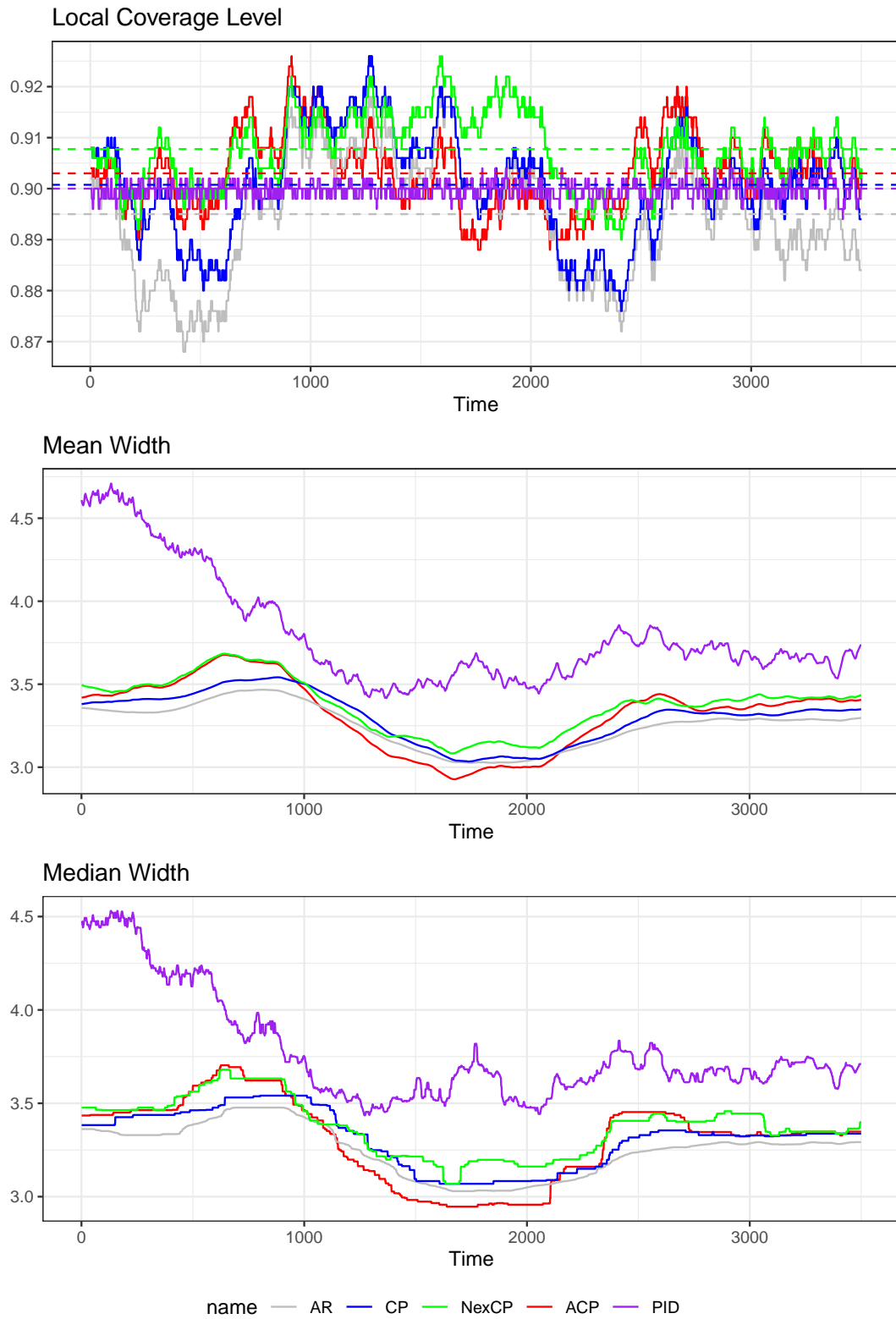


Figure 4: (Wrong setting.) Local coverage frequencies and width for split conformal prediction methods with rolling training set and calibration set ($k=500$).

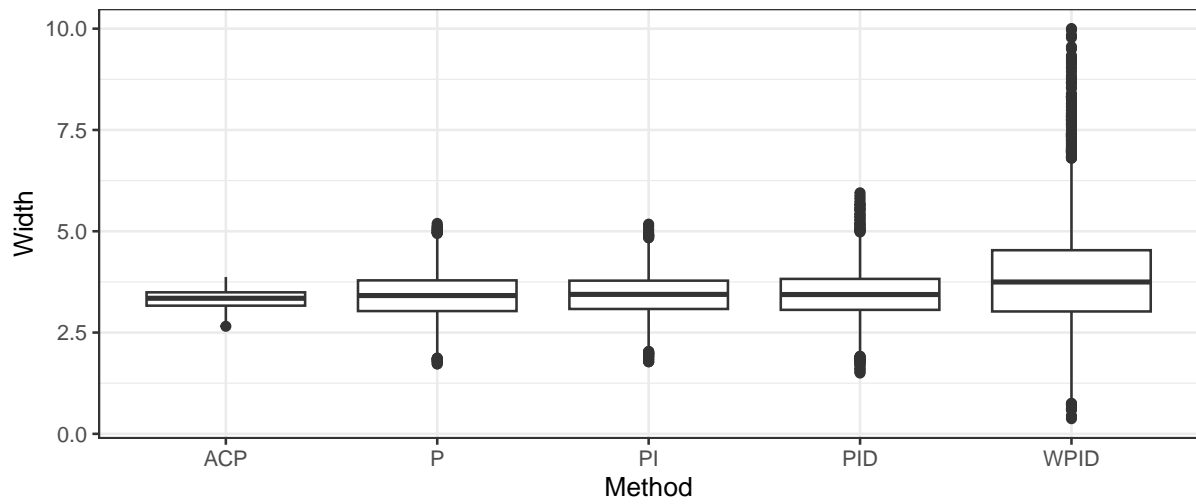


Figure 5: Boxplots for the width of various methods. For ACP, the learning rate is set to 0.005. For P, PI, and PID, the learning rate is set to 0.1B.

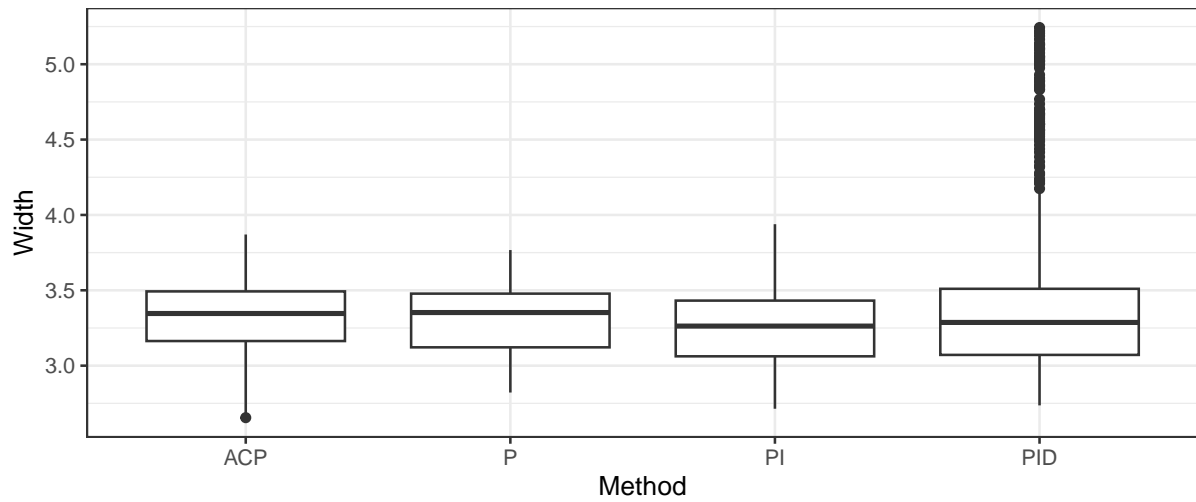


Figure 6: Boxplots for the width of various methods. For ACP, the learning rate is still set to 0.005. But, for P, PI, and PID, the learning rate is set to 0.01B.

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