Machine Learning for Streaming Data

IJCAI Tutorial 2024

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https://nuwangunasekara.github.io/ijcai2024/

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Prediction Intervals

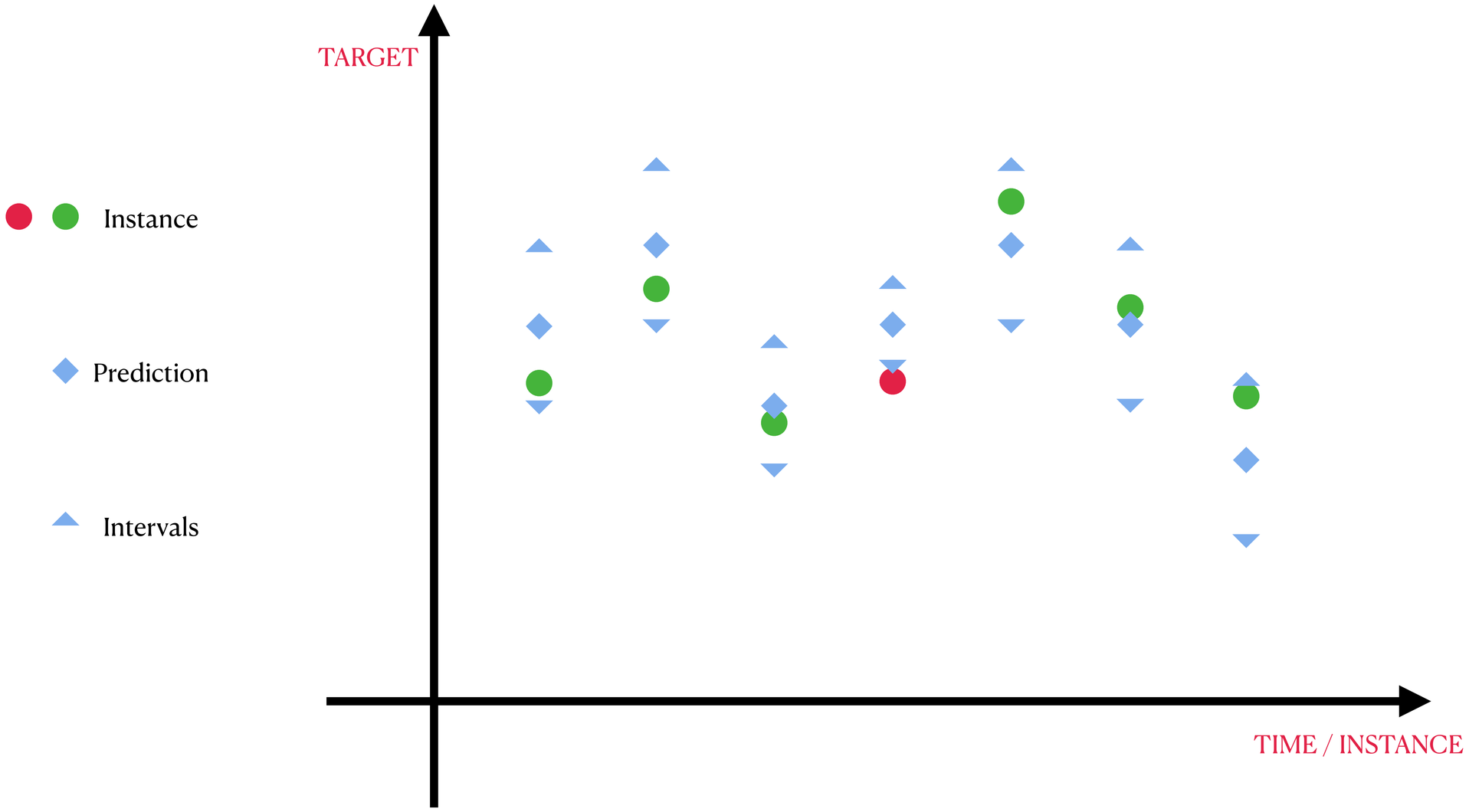
Prediction Intervals

Prediction Intervals (PIs) are very useful improve our confidence in predictions yield in regression tasks

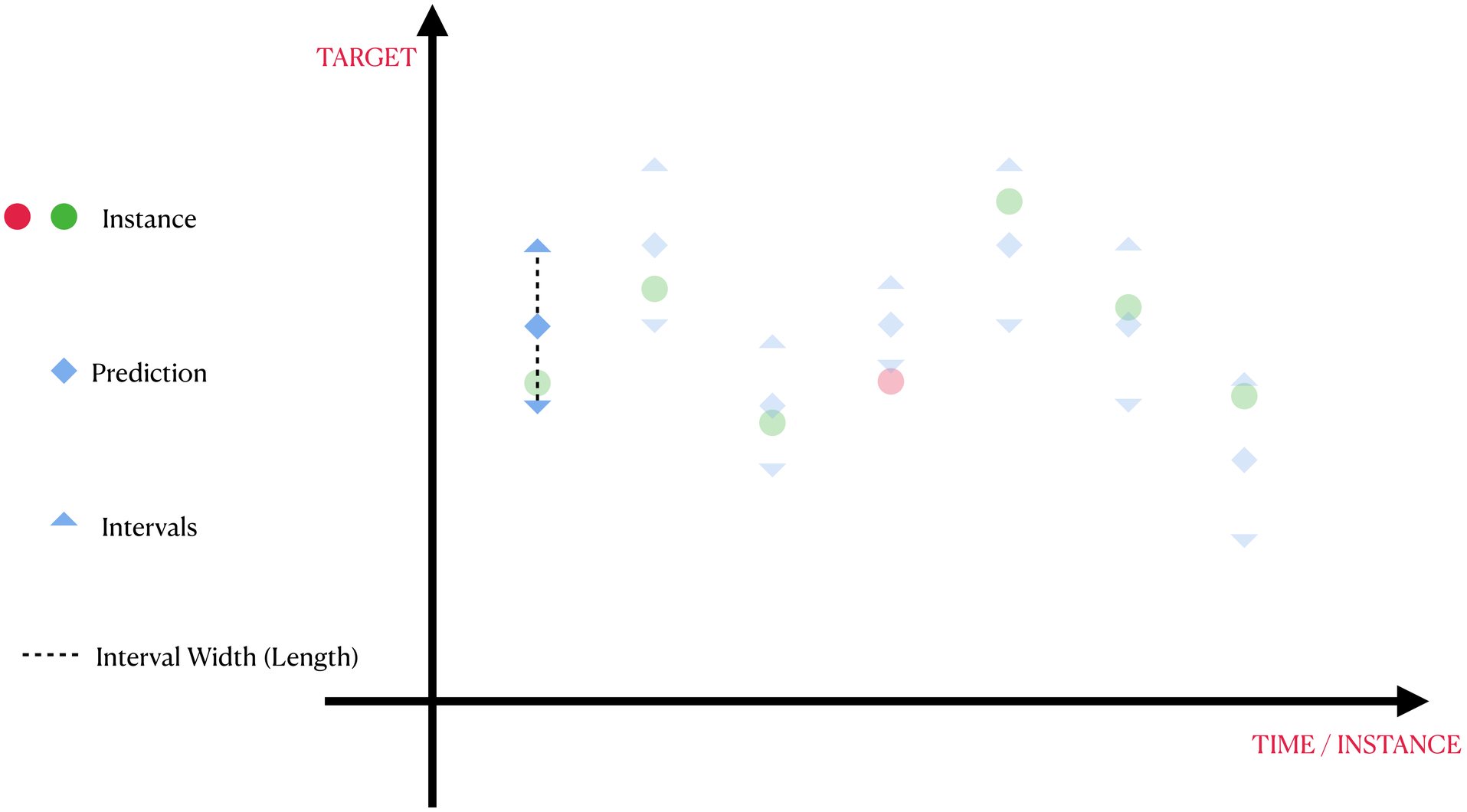
Challenge

Traditional PI methods were not designed to adapt to evolving streams (i.e. those with concept drift)

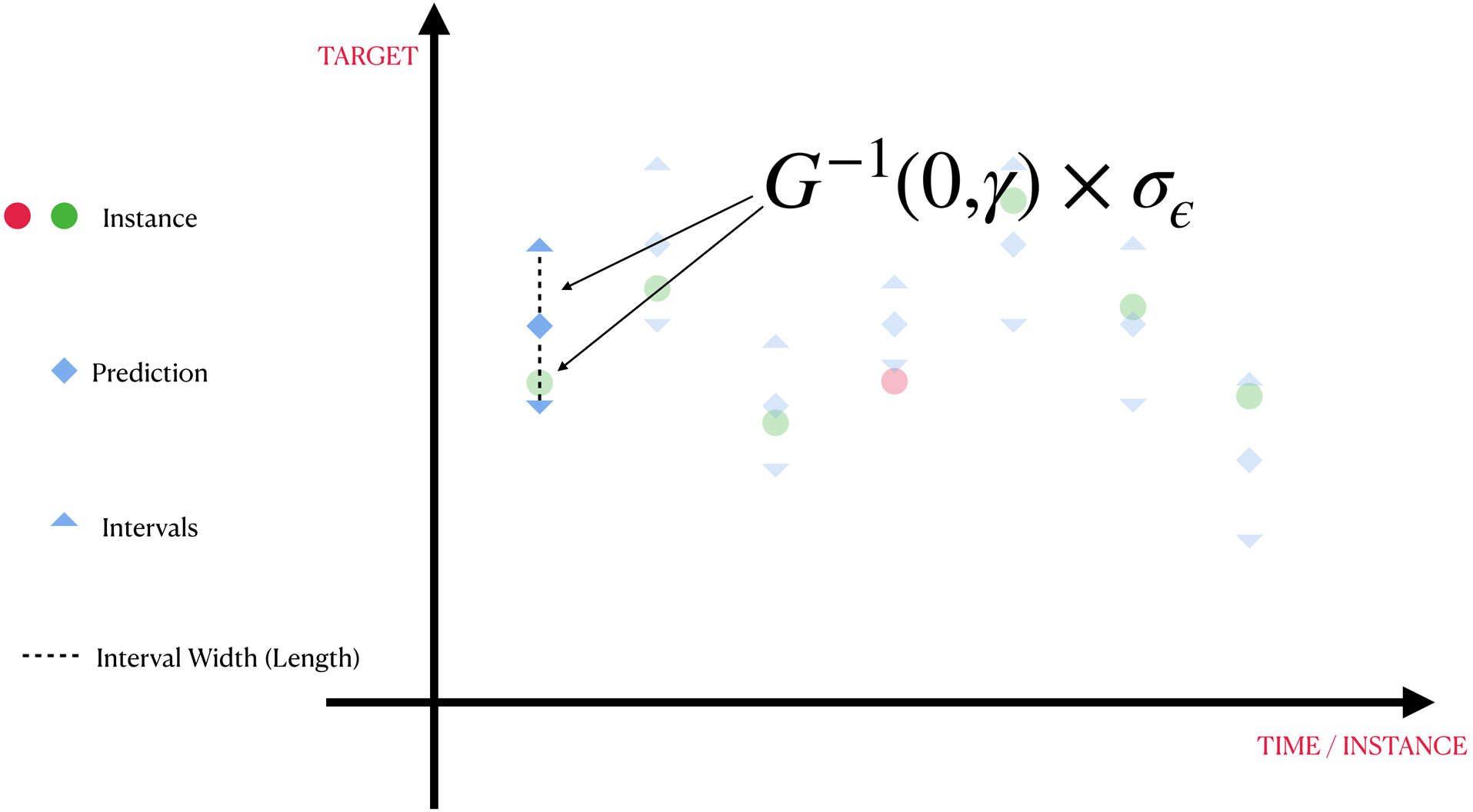
Prediction Interval



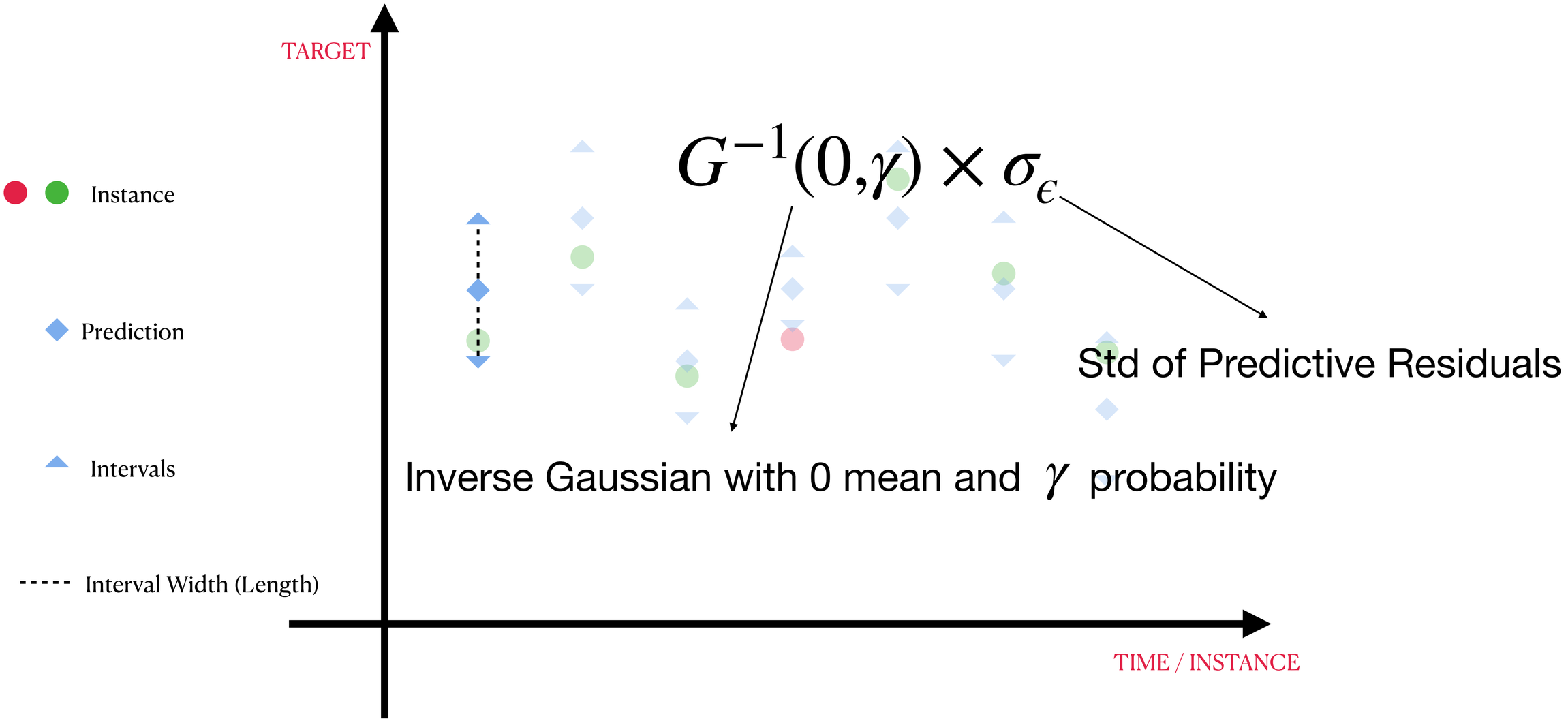
Prediction Interval



Mean and Variance Estimation (MVE)



Mean and Variance Estimation (MVE)



Mean and Variance Estimation (MVE)

$$\Pr\left(y \in \left[\hat{y} - G^{-1}(0,\gamma) \times \sigma_\epsilon, \hat{y} + G^{-1}(0,\gamma) \times \sigma_\epsilon\right]\right) \approx \gamma$$

$$\text{PI}_{\text{MVE}} \in \left(\hat{y} - G^{-1}(0,\gamma) \times \sigma_\epsilon \, , \hat{y} + G^{-1}(0,\gamma) \times \sigma_\epsilon \right)$$

γ : Confidence Level / Significance Level

Adaptive Prediction Interval (AdaPI)

$$\Pr\Big(y \in \big[\hat{y} - \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon, \hat{y} + \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon\big] \Big) \approx \gamma$$

$$\mathrm{PI}_{\mathrm{AdaPI}} \in \big(\hat{y} - \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon \ , \hat{y} + \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon \ \big)$$

γ : Confidence Level / Significance Level

$\mathcal{S}$: Scalar

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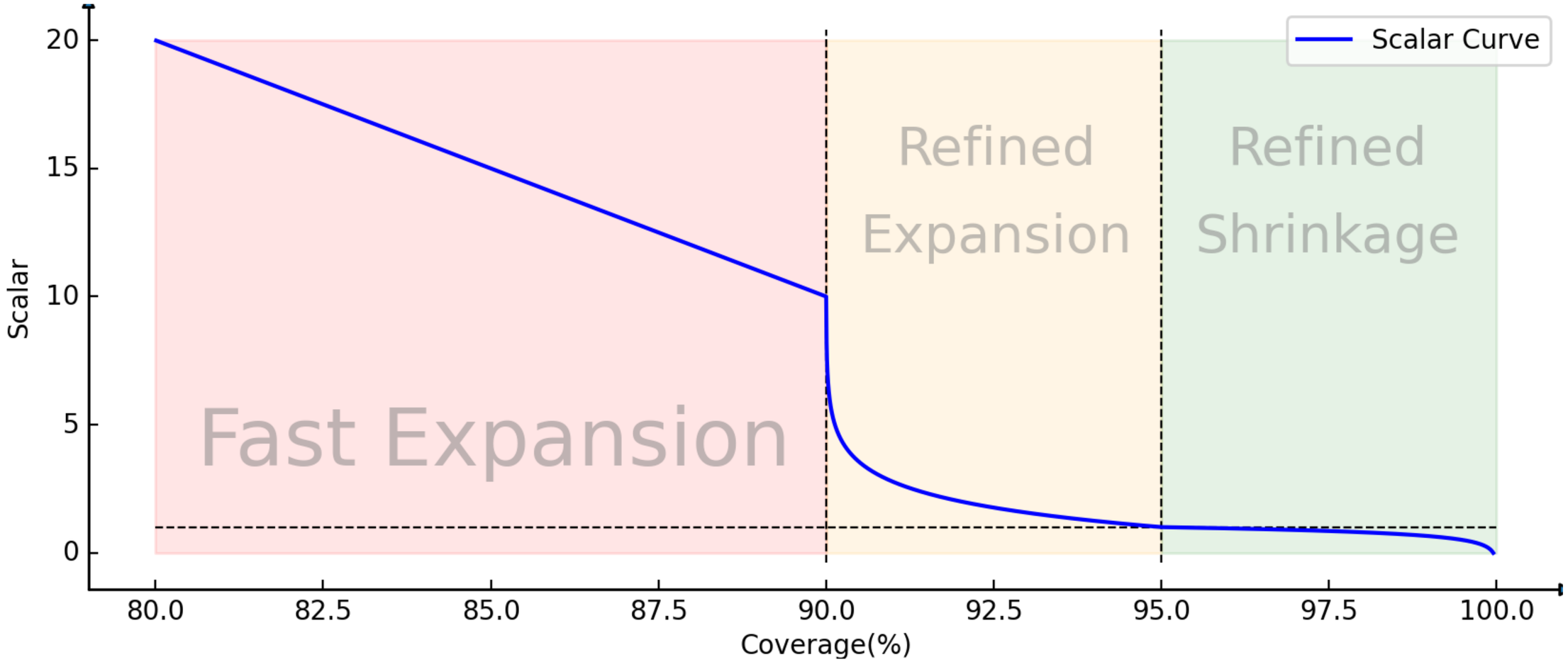
Scalar for AdaPI



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Evaluation Metrics for PI

$$\text{Coverage} = \frac{1}{N}\sum_{i=1}^{N} I_i$$

$$NMPIW = \frac{\frac{1}{N}\sum_{i=1}^{N}(P_{u_i} - P_{l_i})}{R}$$

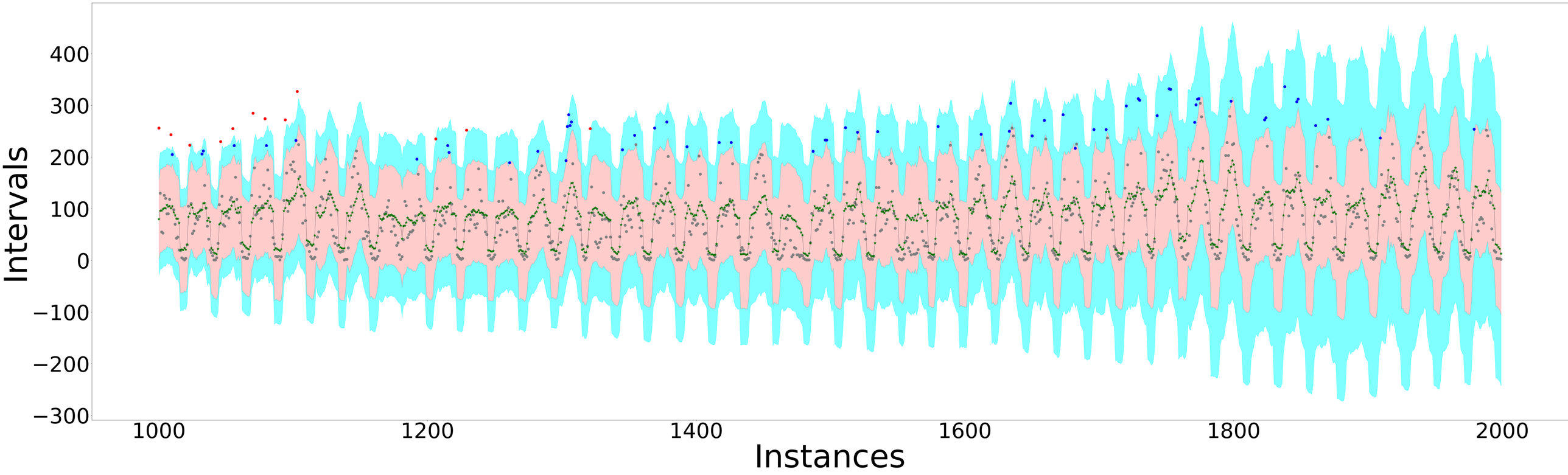
NMPIW : Normalized Mean Prediction Interval Width

R : Range of Target Values

P_u, P_l : Upper and Lower Bounds of Prediction Intervals

Expansion Case

Datasets: Bike



Blue area: AdaPI Red area: MVE

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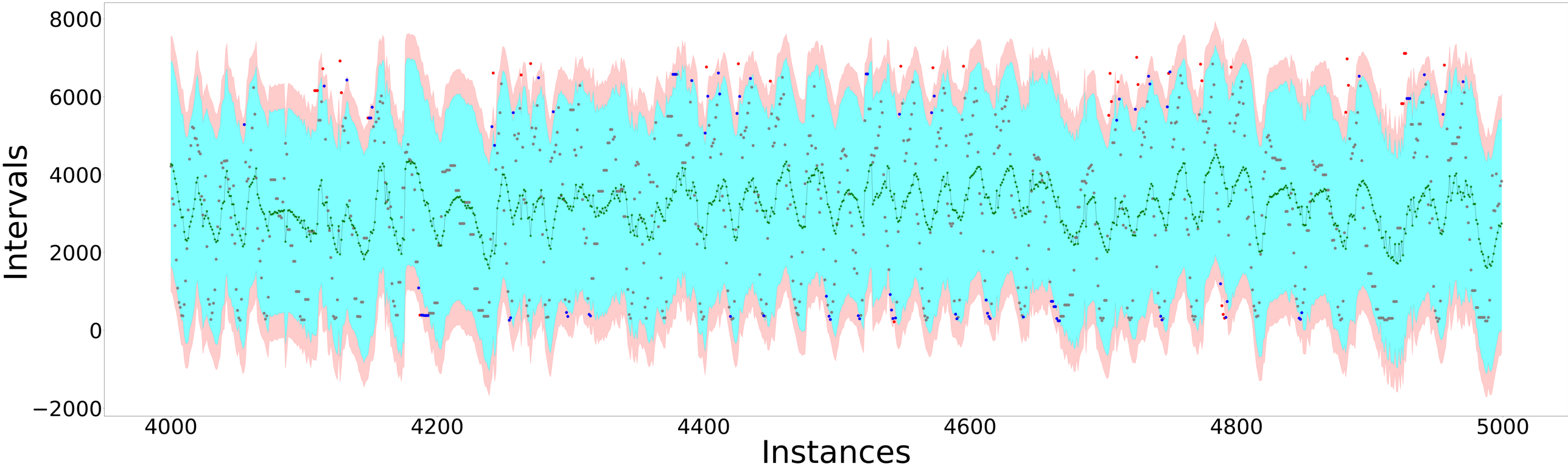
Shrinkage Case

Datasets: MetroTraffic



Blue area: AdaPI Red area: MVE

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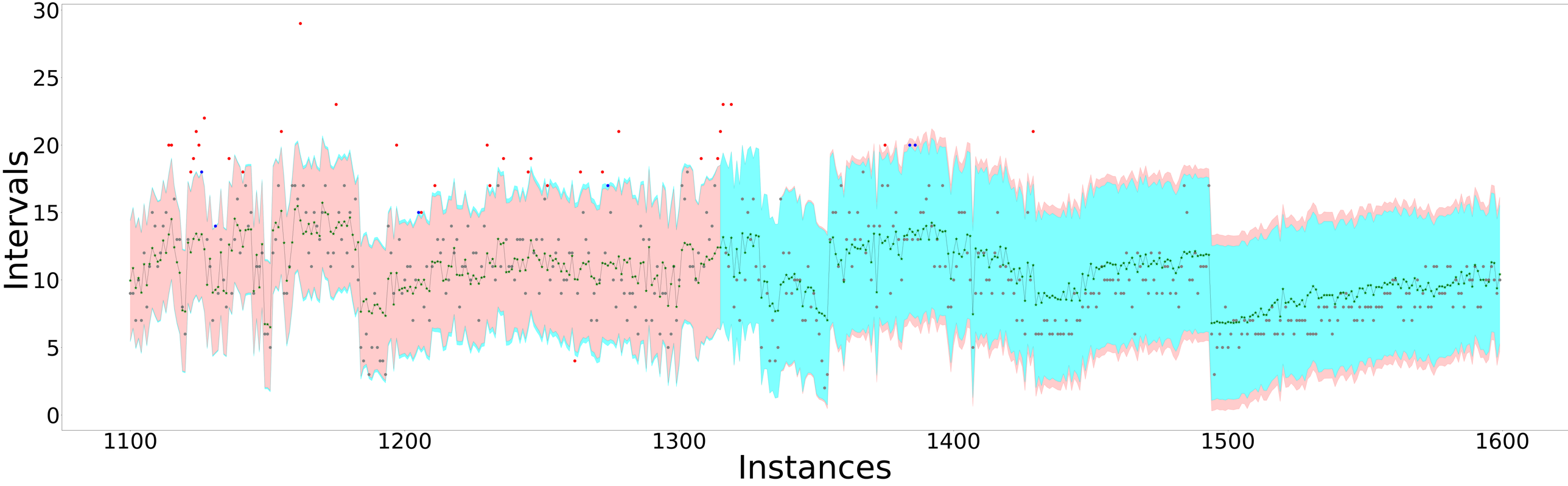
Switching Case

Datasets: Abalone



Blue area: AdaPI Red area: MVE

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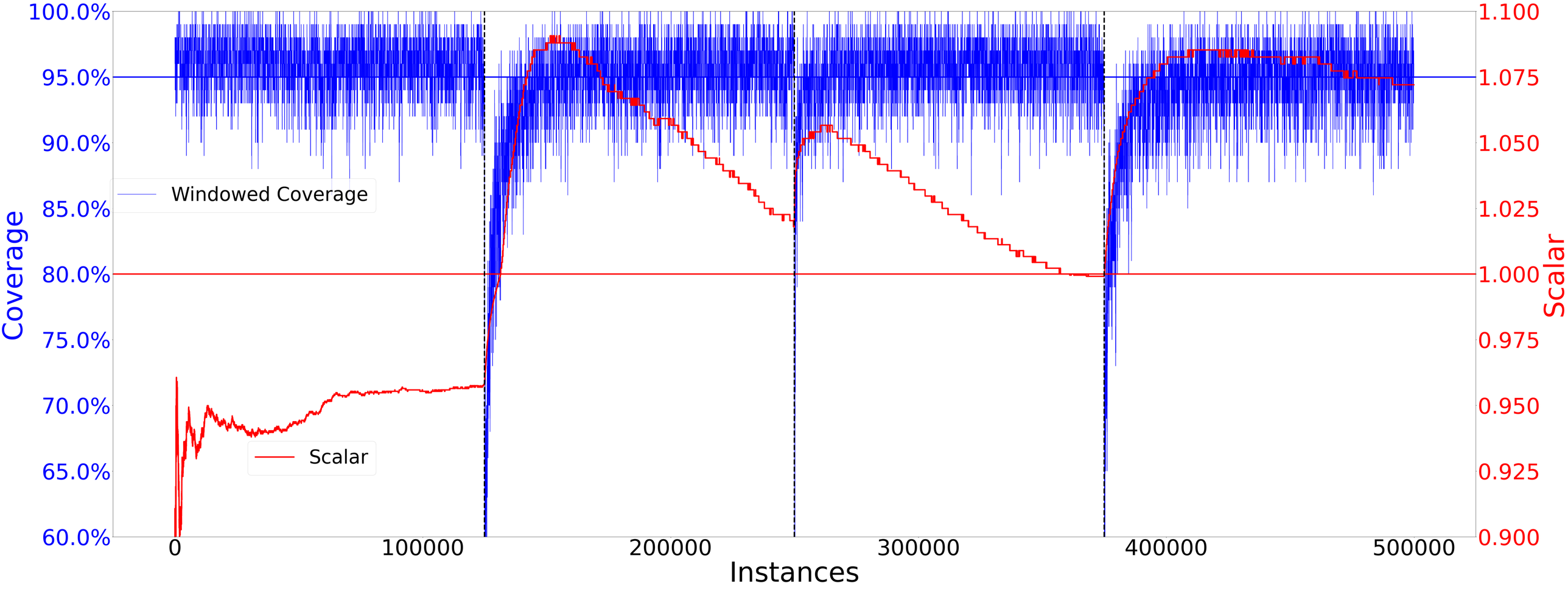
Dealing with Drifts

Datasets: HyperA



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Prediction Intervals Summary

Prediction Interval (PI) is essential for uncertainty quantification in regression tasks.

Challenges

Traditional PI methods are not suitable for dynamic data streams.

Solution

Mean and Variance Estimation (MVE); ADAPI*

Evaluation

Coverage

Normalised Mean Prediction Interval Width (NMPIW)

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Practical examples

IJCAI_2024_prediction_intervals.ipynb