Practical Machine Learning for Streaming Data

ACM SIGKDD Tutorial (hands-on) 2024

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https://adaptive-machine-learning.github.io/kdd2024_ml_for_streams/

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[3] TELECOM Paris, LCTI, France.

Classification algorithms

Hoeffding Tree*

* Also known as Very Fast Decision Tree (VFDT)

Goal: Grow a decision tree incrementally

This means that after every new training instance,
the tree may grow

Key question: When should a split happen?

Hypothesis: A small sample is often enough to choose a near optimal split decision

Hulten, G., Spencer, L., & Domingos, P. (2001). Mining time-changing data streams. In *ACM SIGKDD*.

Hoeffding Bound

It is a statistical inequality that provides a theoretical guarantee on the convergence of sample averages to the true mean with a high probability

In other words, the **Hoeffding Bound** helps in determining whether **the observed differences in the attributes' merit (purity) are statistically significant** or merely due to random variation

Wassily Hoeffding (1963) Probability Inequalities for Sums of Bounded Random Variables, Journal of the American Statistical Association, 58:301, 13-30, DOI: 10.1080/01621459.1963.10500830

Hoeffding Bound

When should we split a node?

Let X_1 and X_2 be the top 2 most informative attributes*

Is X_1 a stable option?

Hoeffding bound, split on X_1 if
$G(X_1) - G(X_2) > \epsilon$

Where $G(*)$ is a purity measure
(e.g. Gini index, Information gain)

* The top attributes to split, the ones that will cause the splits to be “purer”

Hoeffding Bound

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(e.g. Gini index, Information gain)

$$\epsilon = \sqrt{\frac{R^2 \ln 1/\delta}{2n}}$$

R = Range of observed random variable

δ = The desired probability of the estimate not being within ϵ of its expected value

n = Number of observed instances

* The top attributes to split, the ones that will cause the splits to be “purer”

Hoeffding Tree
wrap-up

- ϵ decreases with n (or the more instances observed)

- HT builds a tree that converges to the tree built by a batch learner given sufficiently large data

- A *grace period* can be used to avoid “splitting too fast”

- There are better options w.r.t. theoretical guarantees (See McDiarmid Trees*), but HTs still works well in practice

* Rutkowski, L., Pietruczuk, L., Duda, P., & Jaworski, M. (2012). Decision trees for mining data streams based on the McDiarmid's bound. *IEEE Transactions on Knowledge and Data Engineering*.

Other Streaming Decision Tree algorithms

- The **Extremely Fast Decision Tree (EFDT) [1]** algorithm improves upon the Hoeffding Tree by using a more relaxed criterion for splitting nodes, allowing it to grow the tree more quickly.
    - EFDT can revisit and revise earlier splits if better splits are found later, which can lead to subtree pruning and potentially sudden drops in accuracy.
- **PLASTIC [2]** avoids EFDT's subtree pruning by restructuring the tree rather than pruning it when revising splits.
    - This allows PLASTIC to maintain accuracy by rearranging the tree structure without discarding information

[1] Manapragada, Chaitanya, Geoffrey I. Webb, and Mahsa Salehi. Extremely fast decision tree. ACM SIGKDD International, 2018
[2] M. Heyden, H. M. Gomes, E. Fouché, B. Pfahringer, and K. Bohm. Leveraging Plasticity in Incremental Decision Trees. ECML-PKDD, [To Appear] 2024

Ensembles

Bagging

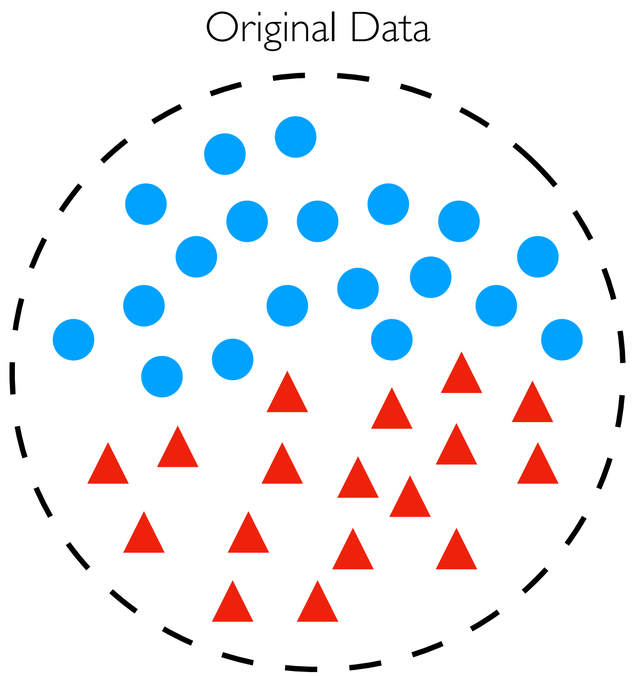
Bootstrap **Agg**regat**ing**

Bagging trains each model of the ensemble with a bootstrap sample from the original dataset.

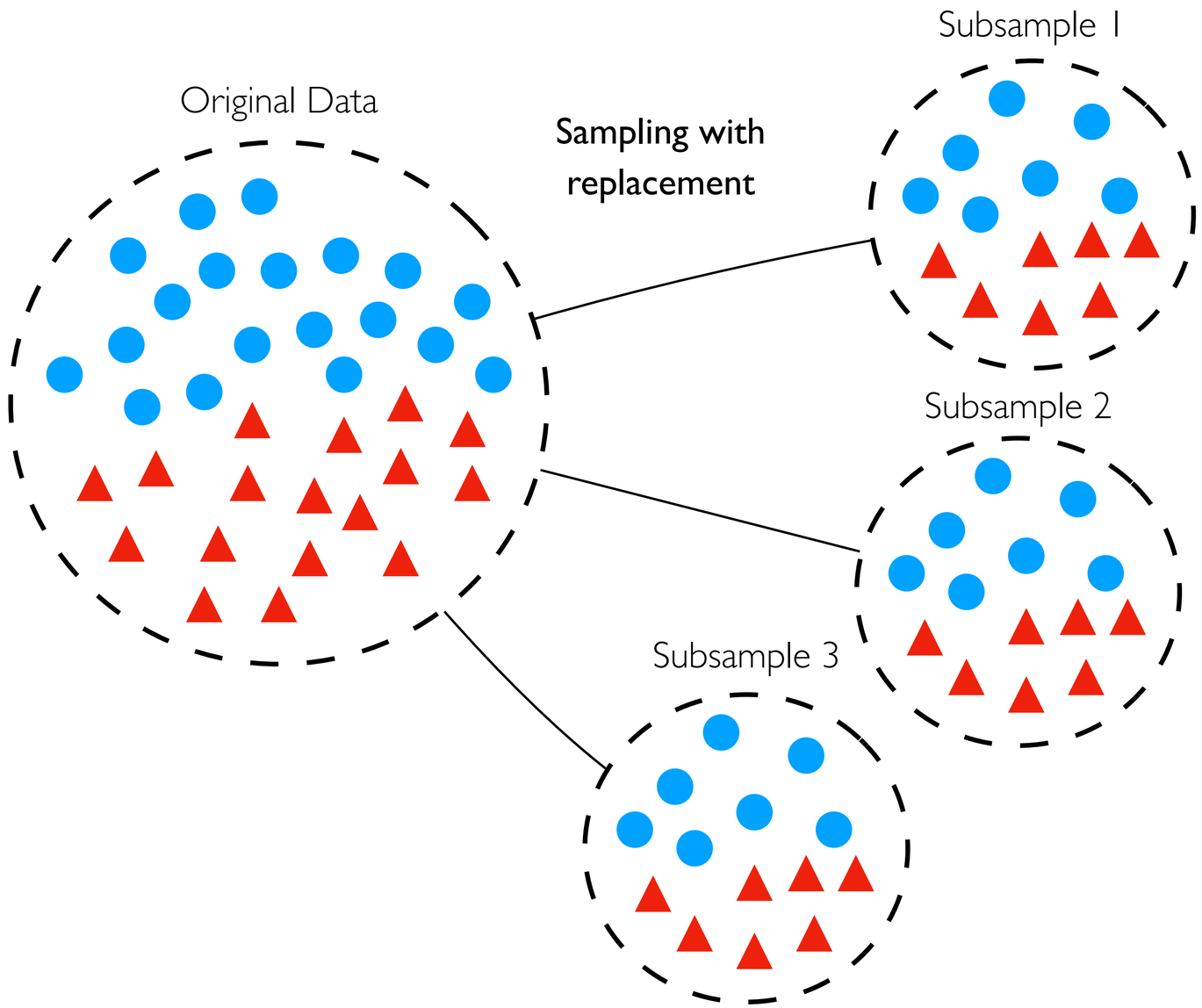
Every bootstrap contains each original sample **K** times, where **Pr(K=k)** follows a binomial distribution.

Breiman, L. (1996). Bagging predictors. *Machine learning*, *24*(2), 123-140.

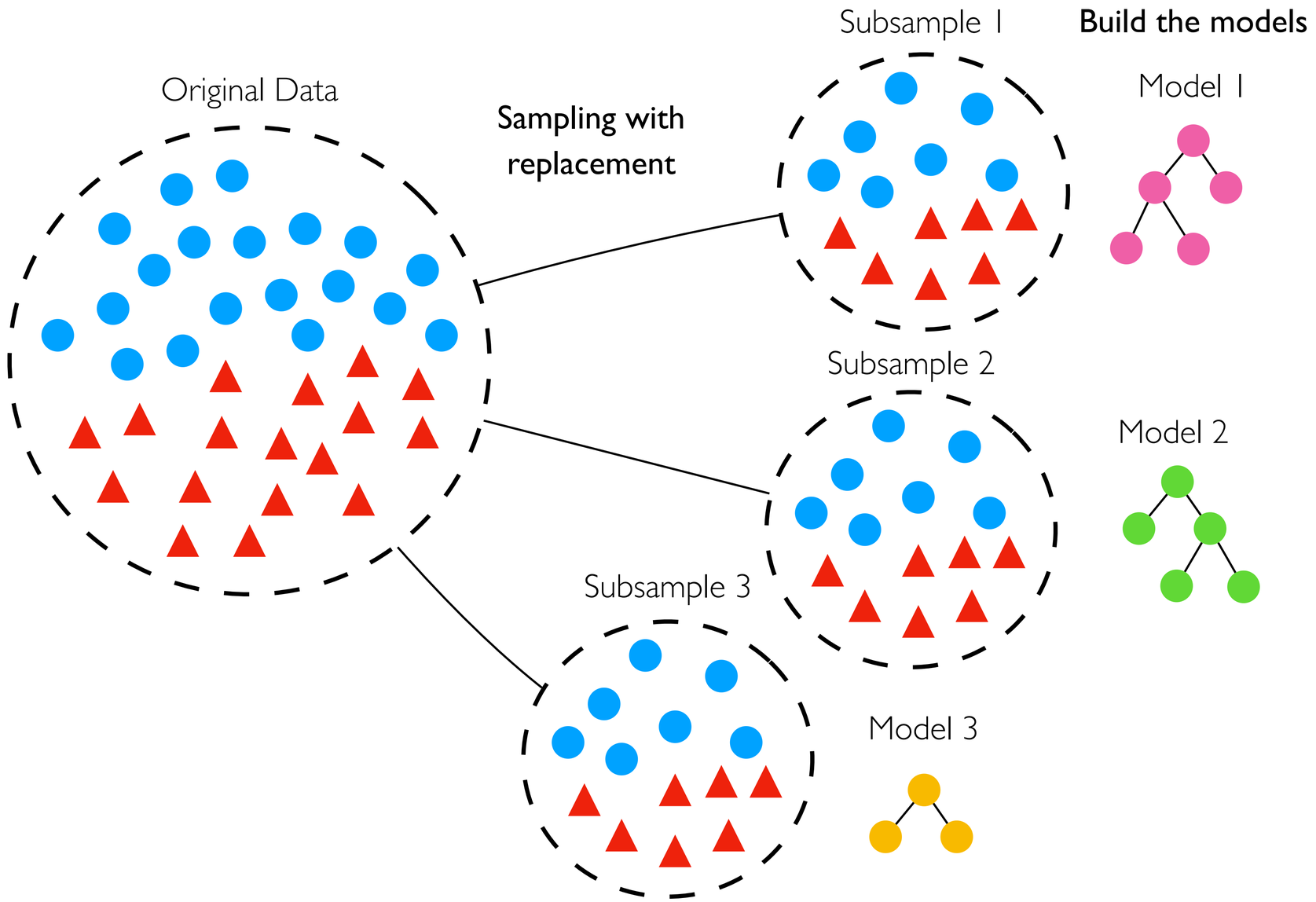
Bagging



Bagging


Original Data
Sampling with replacement
Subsample 1
Subsample 2
Subsample 3

Bagging


Original Data
Sampling with replacement
Subsample 1
Subsample 2
Subsample 3
Build the models
Model 1
Model 2
Model 3

Bagging

On average for each subsample:

~64% of the instances are from the original dataset

~37% are repeated instances

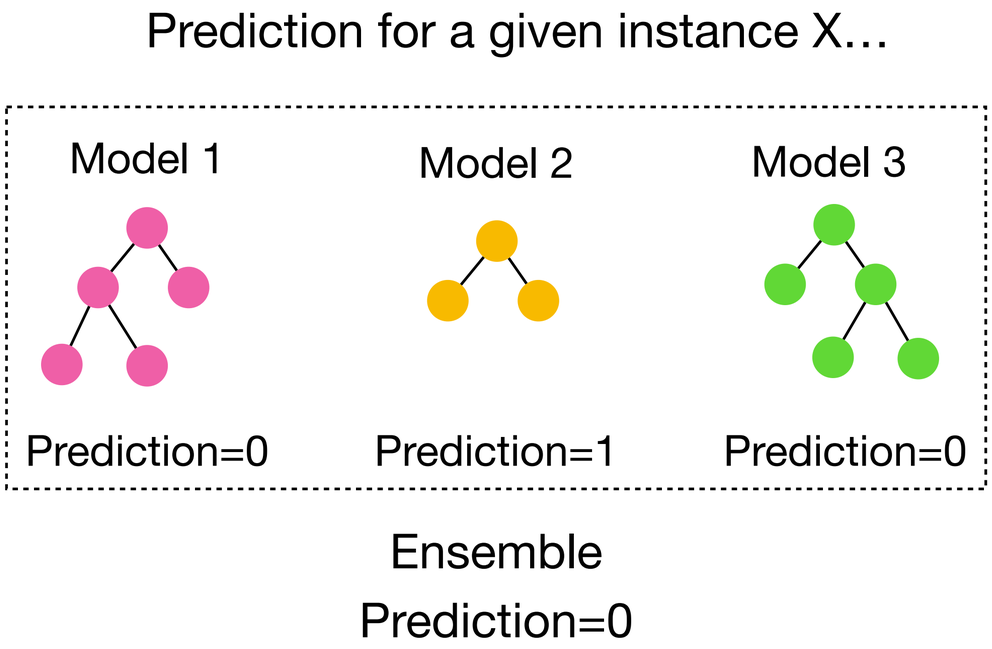
~37% of the original instances are not present*

* Out-Of-Bag (OOB)

Breiman, L. (1996). Bagging predictors. *Machine learning*, *24*(2), 123-140.

Bagging

The **predictions** of each learner are **aggregated** using majority vote to obtain the final prediction.



Online Bagging

- We cannot apply Bagging directly to data streams…
- Unfeasible to store all data before creating each bootstrap subsample

We need to build the subsamples online

N. Oza and S. Russel "Online bagging and boosting" Artificial Intelligence and Statistics, 2001

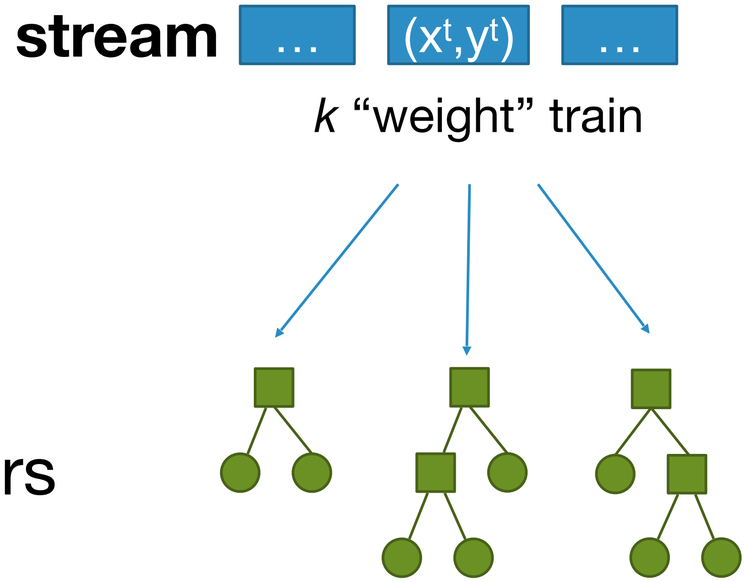
Online Bagging

- Given a dataset with **N** samples
- In Bagging, every bootstrap contains each original sample **K** times, where **Pr(K=k)** follows a binomial distribution
- Oza and Russel found out that for large **N**, the binomial distribution tends to a **Poisson(1)** distribution
- Online Bagging instead of sampling with replacement, gives each example a weight according to **Poisson(1)** distribution

N. Oza and S. Russel "Online bagging and boosting" Artificial Intelligence and Statistics, 2001

Online Bagging

$k \leftarrow Poisson$ (λ=1)
if $k > 0$ **then**
  $l \leftarrow FindLeaf(t, x)$
  $UpdateLeafCounts(l, x, k)$



Practical effect: train learners with different subsets of instances.

N. Oza and S. Russel "Online bagging and boosting" Artificial Intelligence and Statistics, 2001

Subsamples

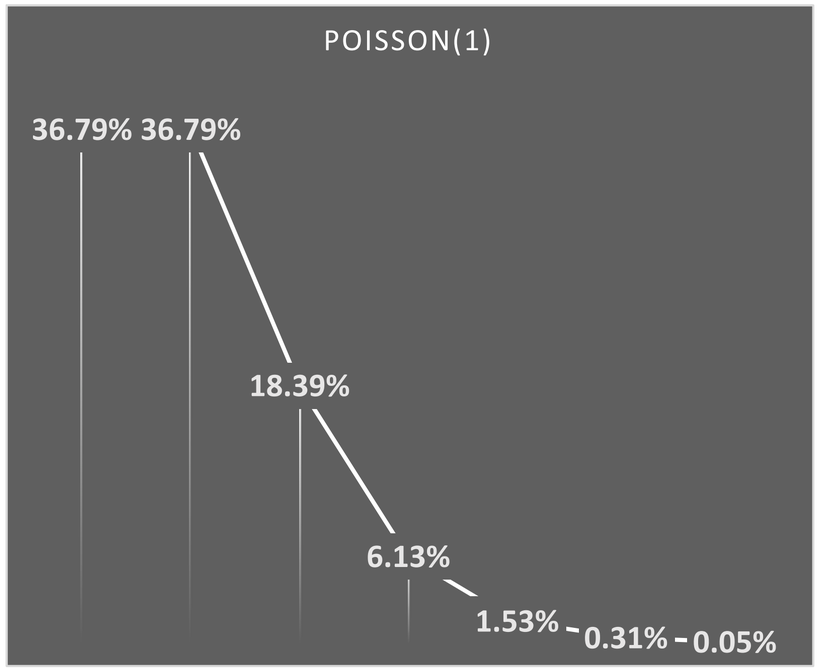
Batch bagging

~64% from the original dataset

~37% are repeated

~37% are not present

Online bagging



$k = 0 \quad 1 \quad 2 \quad 3 \quad 4 \quad 5 \quad 6 \quad \ldots$

Adaptive Random Forest (ARF)

Streaming version of the original Random Forest by Breiman

Uses a variation of the Hoeffding Tree

Main differences:

Bootstrap aggregation and the **base learner**

Overview:

1. Online bagging
2. Random subset of features
3. Drift detector for each tree

Breiman, L. (2001). Random forests. *Machine learning.*

Gomes, H. M., Bifet, A., Read, …, T. (2017). Adaptive random forests for evolving data stream classification. *Machine Learning.*

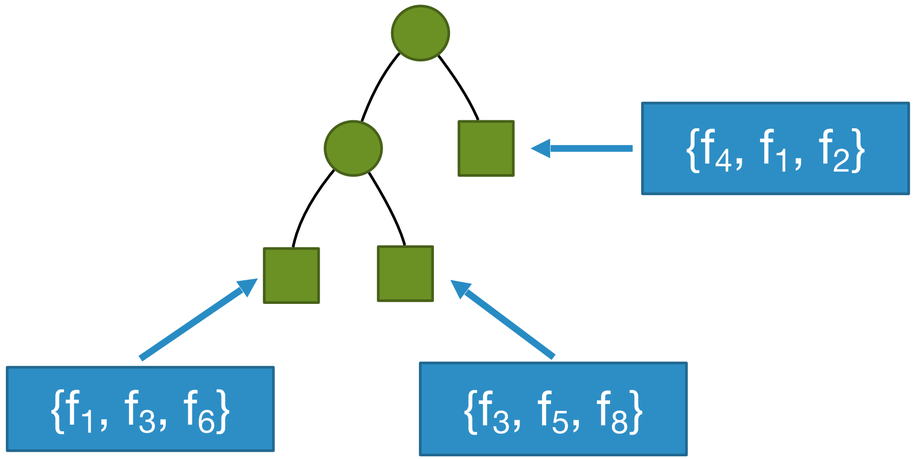
ARF: Drift Detection and Adaptation

- One **Warning** and one **Drift** detector per base model
- Relies on the **Adaptive WINdow** (ADWIN) algorithm for detection (other algorithms could be used)
- ***Background*** **learners** are started once a warning is detected, their subspace of features may not correspond to the subspace of features used by the *“foreground”* learner.
- Once a drift is detected, the ***background*** **learner replaces** the ***“foreground”*** **learner**.

Randomizing the feature set

Local randomization

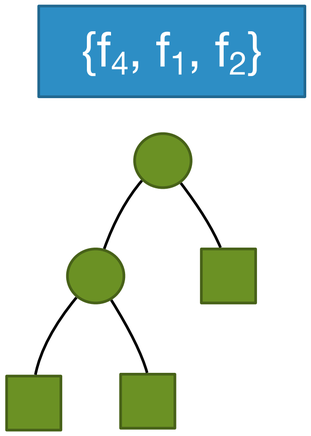
Random Forest



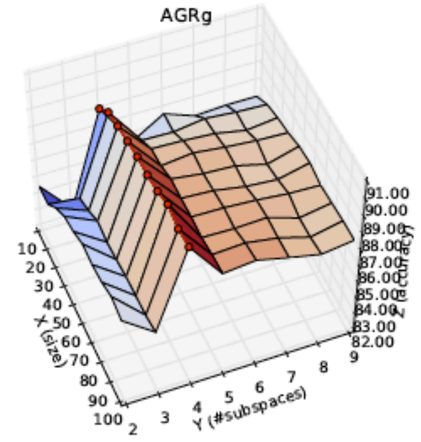
Global randomization

Random Subspaces

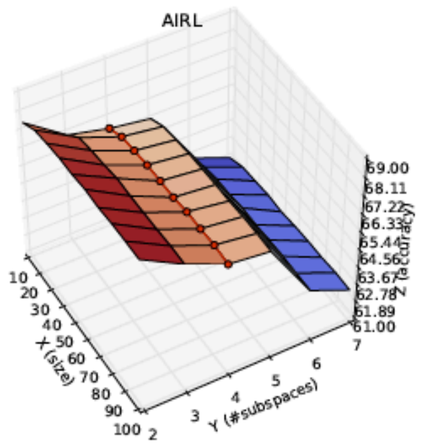
Random Patches



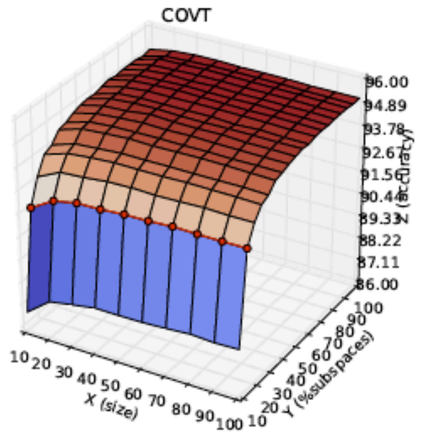
Impact of subspace size



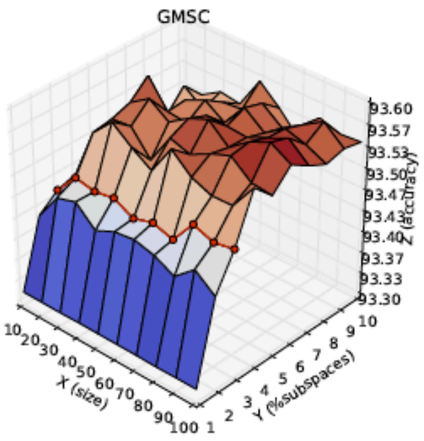
(a) AGR_g



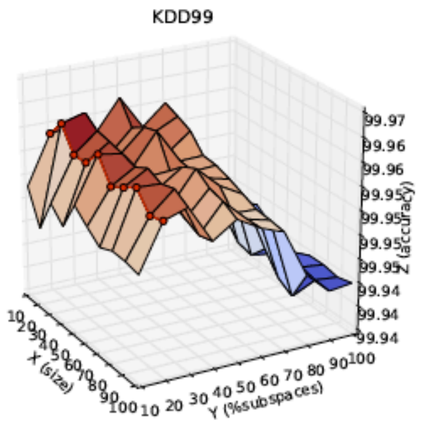
(b) AIRL



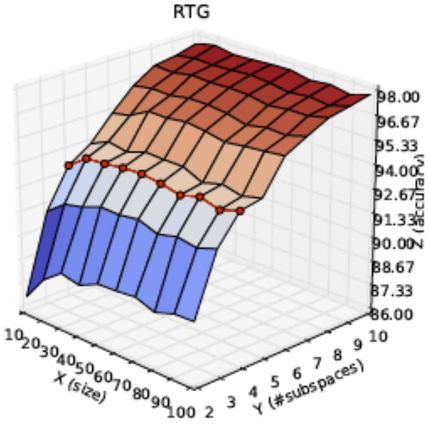
(c) COVT



(d) GMSC



(e) KDD99



(f) RTG

Boosting and Gradient Boosting

- XGBoost[1] and CatBoost[2] are popular **batch gradient boosting** methods

- One key challenge when adapting such algorithms other than a stream setting includes concept drift recovery

[1] T. Chen and C. Guestrin. Xgboost: A scalable tree boosting system. In Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discov and Data Mining, pages 785–794. ACM, 2016.
[2] Prokhorenkova, L., Gusev, G., Vorobev, A., Dorogush, A. V., & Gulin, A. (2018). CatBoost: unbiased boosting with categorical features. Advances in neural information processing systems, 31.

Boosting on Streams

- [2001] **OzaBoost** [1] uses weights from a Poisson(1) distribution to train multiple times using a given instance (similar to Online Bagging)
- [2012] **Online Smooth Boost** [2] is analogous to batch SmoothBoost, thus it uses a smooth distribution for weight assignment
- [2020] **Gradient boosted AXGB** [3] use Mini-batch trained XGBoost as its base learners and adjusts the booster when concept drifts are detected by ADWIN
- [2024] **Streaming Gradient Boosted Trees (SGBT)** [4] **performs better than** bagging-based stream learners

[1] N. Oza and S. Russel “Online bagging and boosting” Artificial Intelligence and Statistics, 2001
[2] Chen, Shang-Tse, Hsuan-Tien Lin, and Chi-Jen Lu. "An online boosting algorithm with theoretical justifications." International Conference on International Conference on Machine Learning. 2012.
[3] Montiel, J., Mitchell, R., Frank, E., Pfahringer, B., Abdessalem, T., Bifet, A.: Adaptive xgboost for evolving data streams. In: 2020 IJCNN
[4] Gunasekara, N., Pfahringer, B., Gomes, H., & Bifet, A. (2024). Gradient boosted trees for evolving data streams. Machine Learning, 113(5), 3325-3352.

Streaming Gradient Boosted Trees (SGBT)

- Uses ***weighted squared loss*** [1,2] with ***hessian(h_i)*** **as the weight** and ***gradient over hessian (g_i / h_i)*** as **the target** *considering previous boosting* step:

$$\sum_{i=1}^{n} \frac{1}{2} h_i (f_s(x_i) - g_i/h_i)^2 + \Omega(f_s) + constant$$

penalises the complexity of the tree

- The formulation of the loss function is similar to batch gradient boosting, but the key difference is that trees are updated incrementally
- There is a Tree Replacement (TR) mechanism which allows a tree to adapt to concept drift without the need for a complete reset

[1] Friedman, J., Hastie, T., Tibshirani, R.: Additive logistic regression: a statistical view of boosting (with discussion and a rejoinder by the authors). The annals of statistics 28(2), 337–407 (2000)
[2] Tianqi Chen and Carlos Guestrin. Xgboost: A scalable tree boosting system. In Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pages 785–794, 2016.
[4] Gunasekara, N., Pfahringer, B., Gomes, H., & Bifet, A. (2024). Gradient boosted trees for evolving data streams. Machine Learning, 113(5), 3325-3352.

Ensembles re-cap

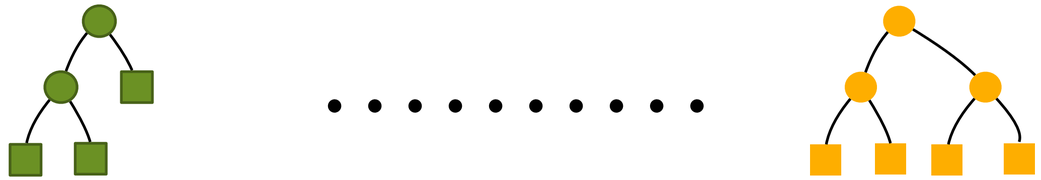
- Online Bagging-based methods are still very popular
  - One reason might be that the learners are independent from one another, which allows efficient parallel implementations [1, 2]
- Most methods incorporate **drift detectors** to adapt to changes
- **SGBT** is a promising option for streaming gradient boosting

[1] G. Cassales, H. M. Gomes, A. Bifet, B. Pfahringer and H. Senger, Improving the performance of bagging ensembles for data streams through mini-batching (2001), Information Sciences
[2] G. Cassales, H. M. Gomes, A. Bifet, B. Pfahringer and H. Senger, Balancing Performance and Energy Consumption of Bagging Ensembles for the Classification of Data Streams in Edge Computing (2022), IEEE Transactions on Network and Service Management, vol. 20, pp. 3038-3054, 2023

Regression algorithms

Adaptive Random Forest Regression (ARF-Reg)

- Similar to ARF for classification, i.e. same adaptation mechanisms
- Utilizes **regression trees (FIRTD)** [2]
- During **prediction**, uses the **mean** of each trees' **predictions**



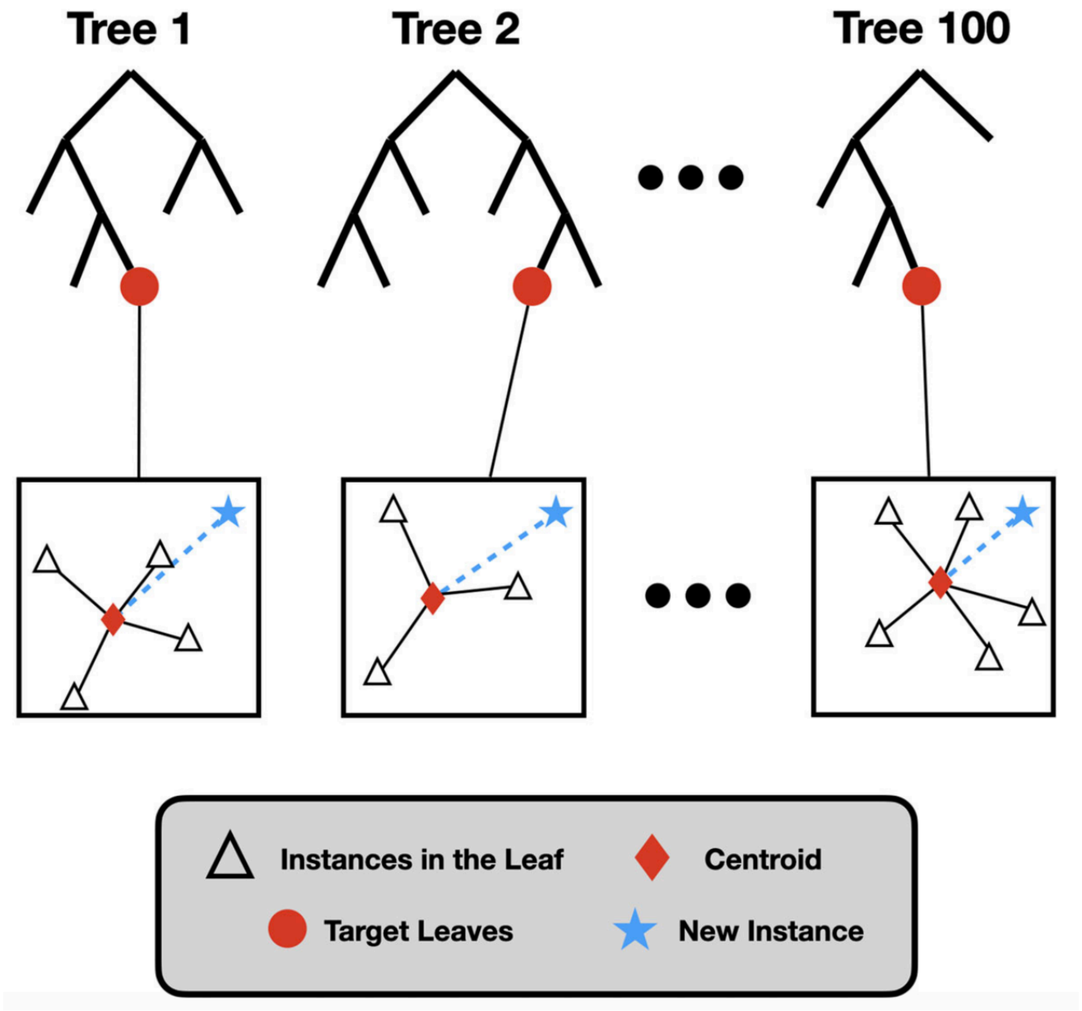
[1] Gomes H M, Barddal JP, Ferreira LEB, Bifet A (2018) Adaptive random forests for data stream regression. ESANN
[2] Ikonomovska, E., Gama, J., & Džeroski, S. (2011). Learning model trees from evolving data streams. Data mining and knowledge discovery, 23, 128-168.

Self-Optimizing k-Nearest Leaves (SOKNL)

- **Extends** Adaptive Random Forest Regression
- Generates **a representative data point (centroid)** in each leaf by **compressing** information **from all instances in that leaf**
- During **prediction**, calculates **distances** between **input instance** and **centroids** for **relevant leaves**
- Uses **only k leaves** with **smallest distances** for **prediction**
- **Dynamically tuning k** values based on **historical information**

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "SOKNL: A novel way of integrating K-nearest neighbours with adaptive random forest regression for data streams" Data Mining and Knowledge Discovery (2022)

Self-Optimizing k-Nearest Leaves (SOKNL)



Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "SOKNL: A novel way of integrating K-nearest neighbours with adaptive random forest regression for data streams" Data Mining and Knowledge Discovery (2022)

Self-Optimizing k-Nearest Leaves (SOKNL)

at time t

K :	1	2	**3**	4	5
Error:	9.85	7.26	6.97	8.66	8.20

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "SOKNL: A novel way of integrating K-nearest neighbours with adaptive random forest regression for data streams" Data Mining and Knowledge Discovery (2022)

Self-Optimizing k-Nearest Leaves (SOKNL)

at time t + Δ

K :	1	2	3	4	**5**
Error:	9.94	8.65	8.24	7.95	7.61

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "SOKNL: A novel way of integrating K-nearest neighbours with adaptive random forest regression for data streams" Data Mining and Knowledge Discovery (2022)

Prediction Intervals

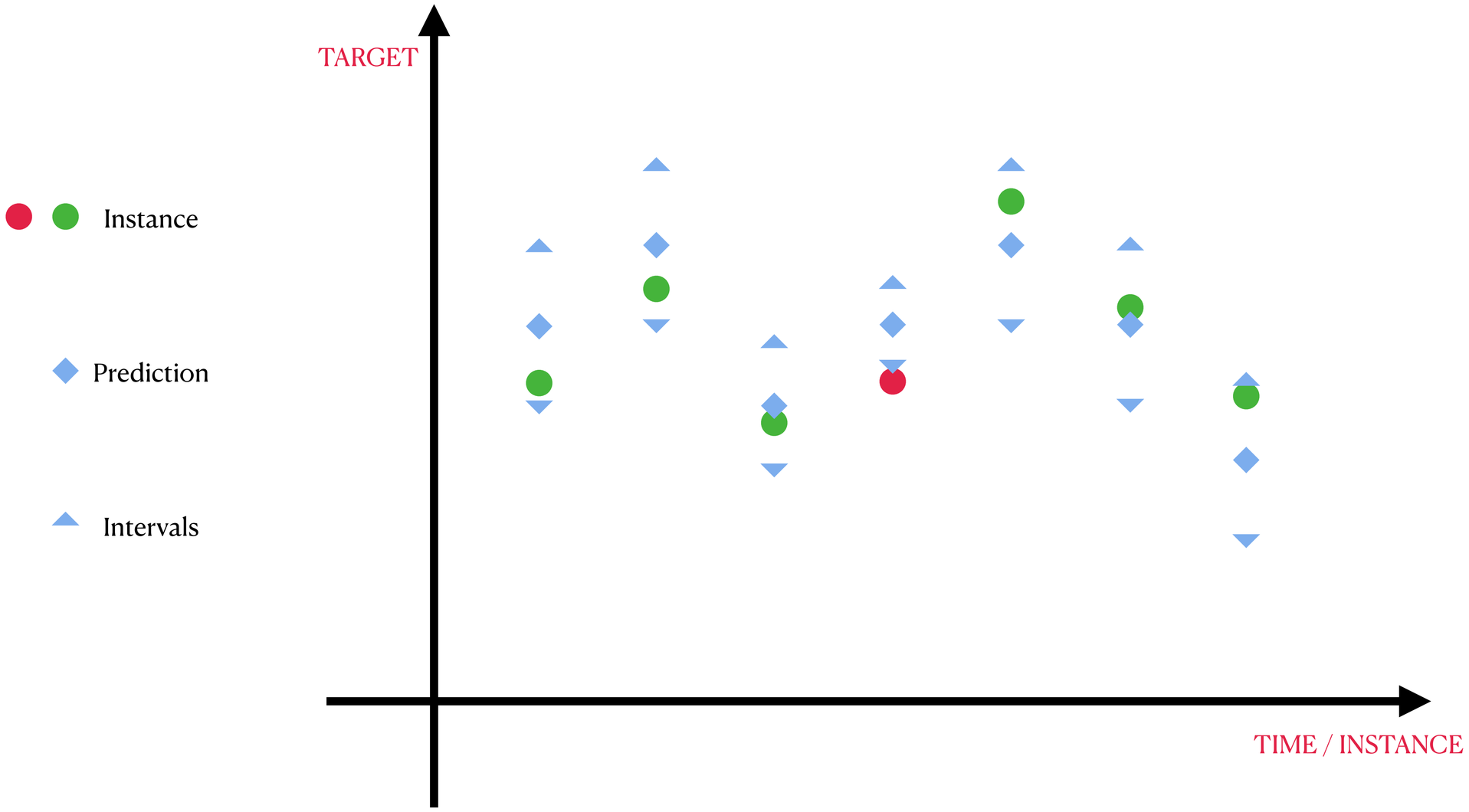
Prediction Intervals

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

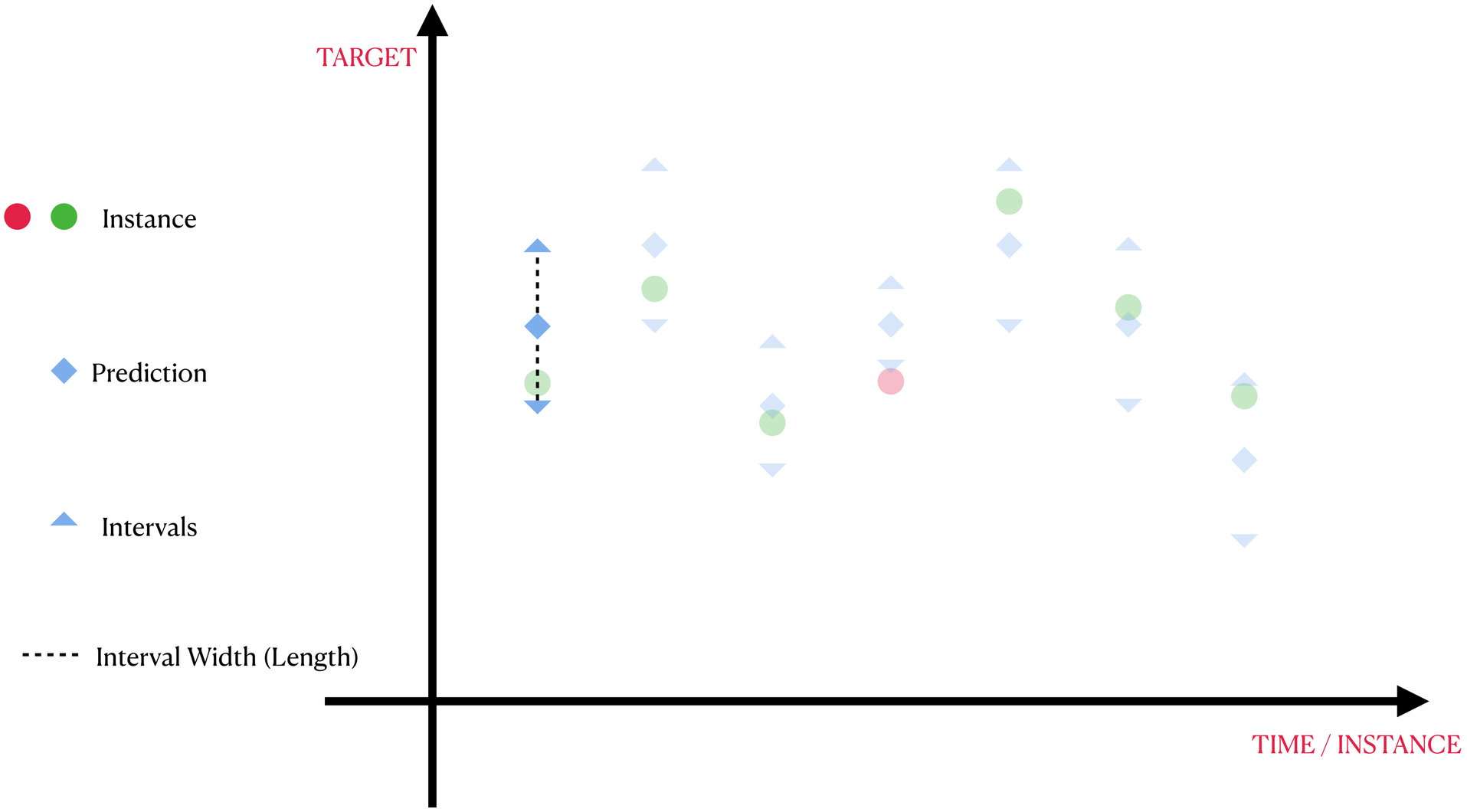
Challenge

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

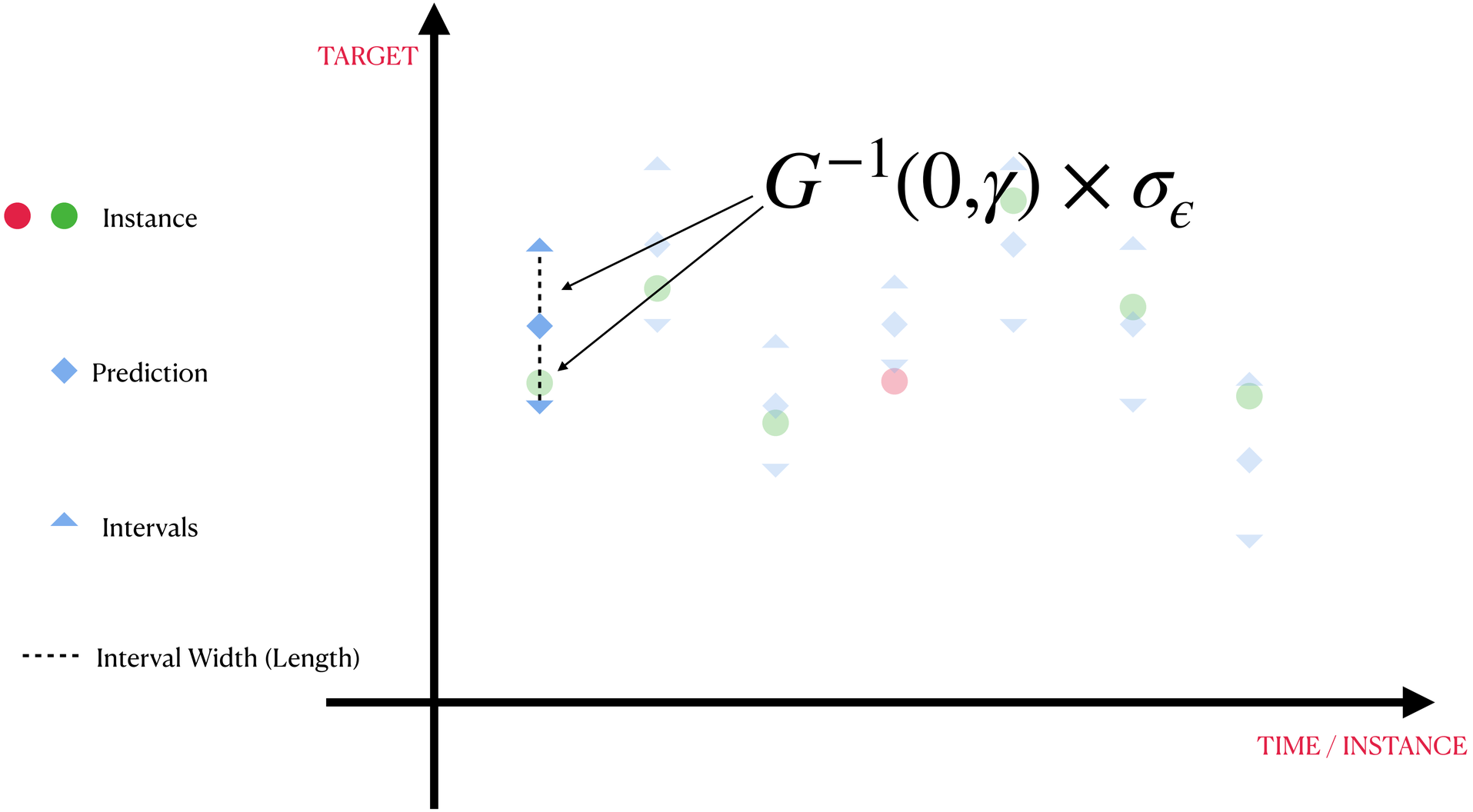
Prediction Interval



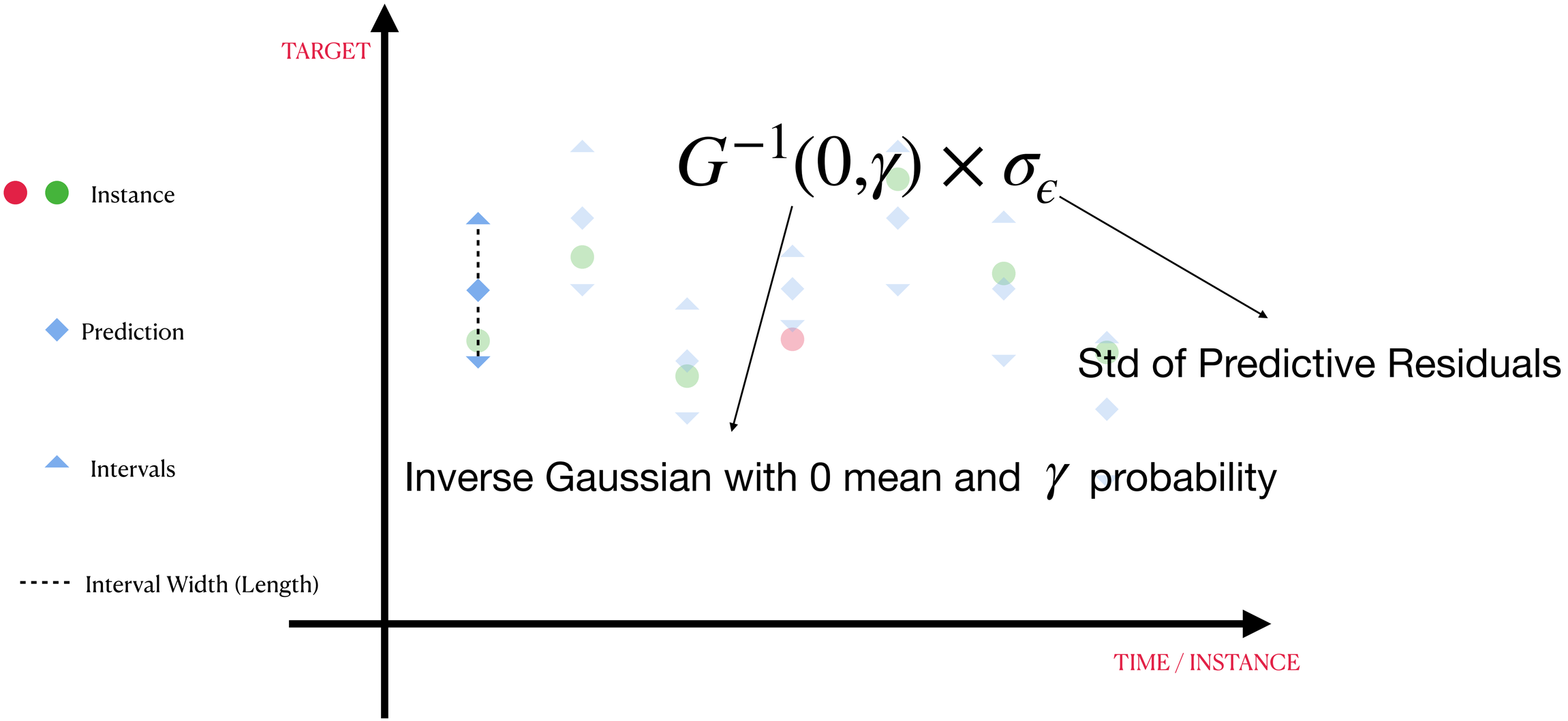
Prediction Interval



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)

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

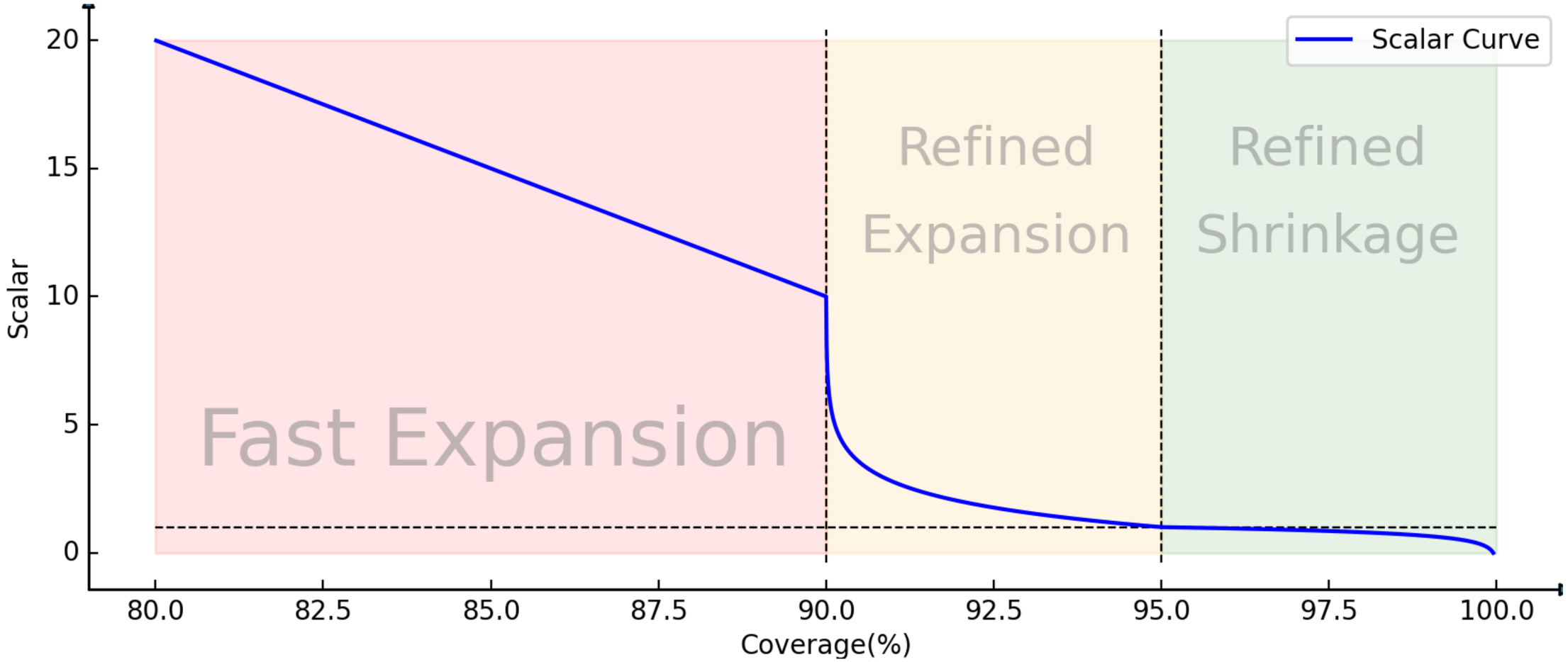
$$\mathrm{PI}_{\mathrm{AdaPI}} \in \big(\hat{y} - \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon \ , \hat{y} + \mathcal{S} \times G^{-1}(0,\gamma) \times \sigma_\epsilon \ \big)$$

γ : Confidence Level / Significance Level

$\mathcal{S}$: Scalar

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Scalar for AdaPI



Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Evaluation Metrics for PI

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

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

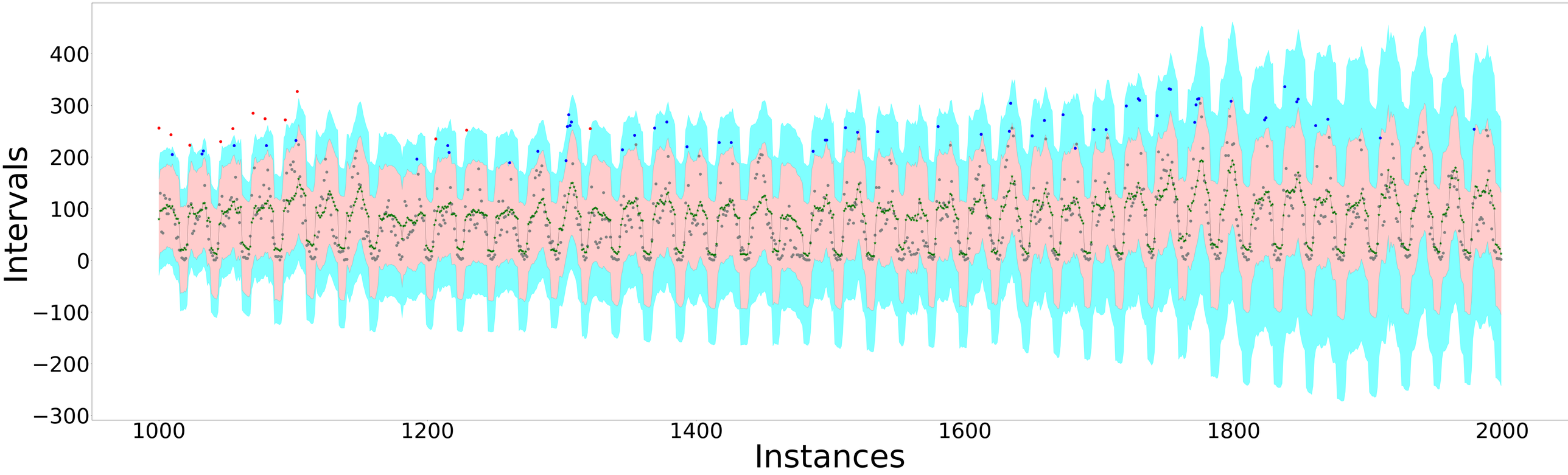
NMPIW : Normalized Mean Prediction Interval Width

R : Range of Target Values

P_u, P_l : Upper and Lower Bounds of Prediction Intervals

Expansion Case

Datasets: Bike

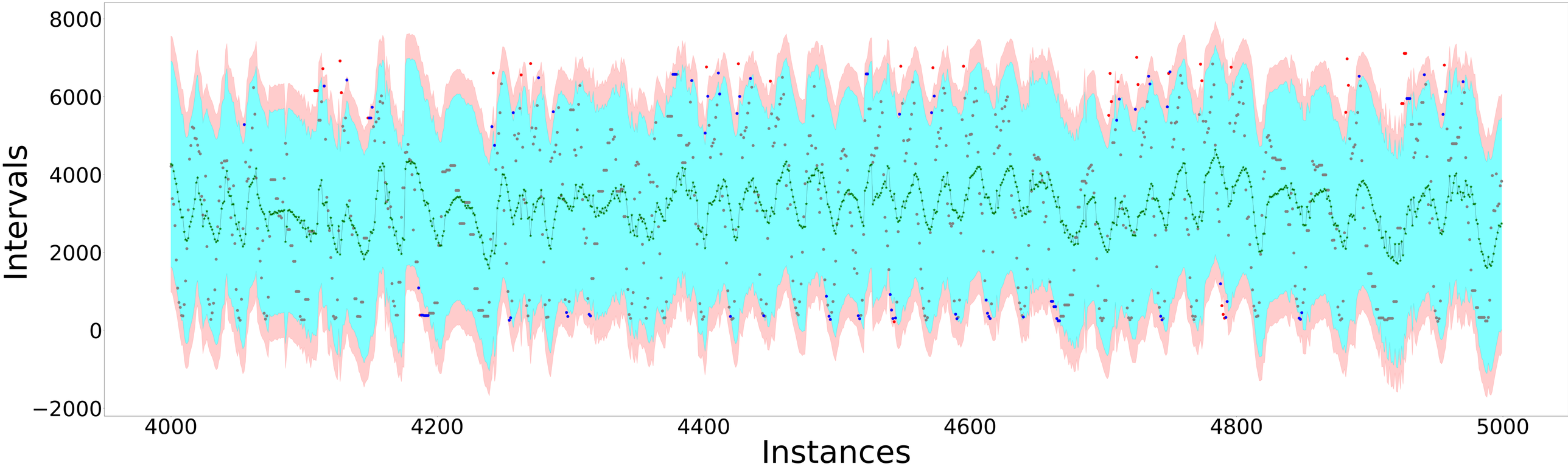


Blue area: AdaPI Red area: MVE

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Shrinkage Case

Datasets: MetroTraffic

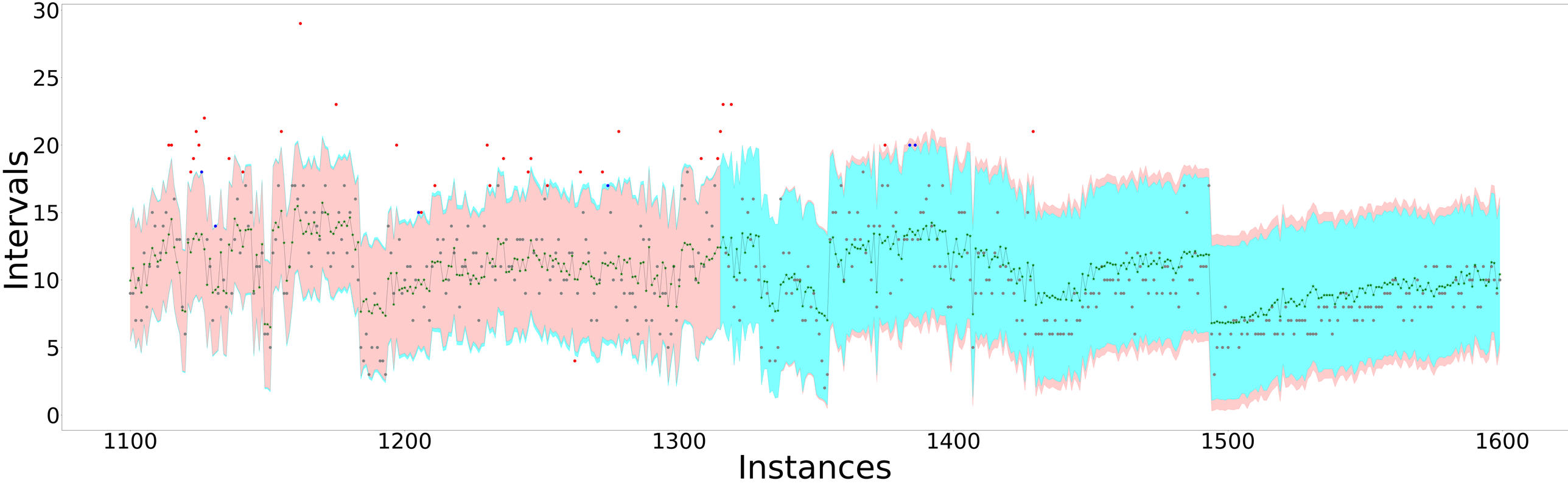


Blue area: AdaPI Red area: MVE

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Switching Case

Datasets: Abalone

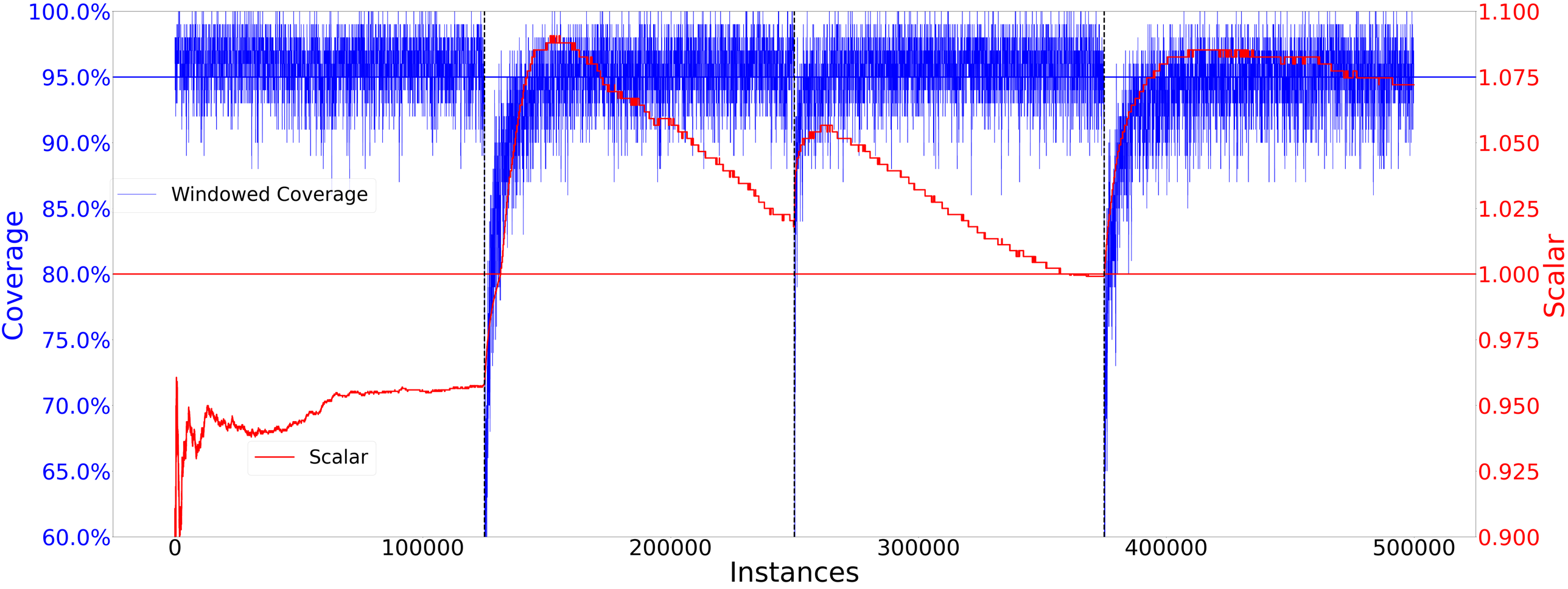


Blue area: AdaPI Red area: MVE

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Dealing with Drifts

Datasets: HyperA



Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Prediction Intervals Re-cap

Prediction Intervals (PIs) are quite useful to analyse the output of regression models

Challenges

Traditional PI methods are not suitable for dynamic data streams.

One possible solution: Mean and Variance Estimation (MVE); ADAPI*

Evaluation

- Coverage
- Normalised Mean Prediction Interval Width (NMPIW)

Yibin Sun, B Pfahringer, H M Gomes, and A Bifet. "Adaptive Prediction Interval for Data Stream Regression." PAKDD (2024)

Hands-on example

KDD_2024_supervised.ipynb