Streaming Machine Learning (SML)

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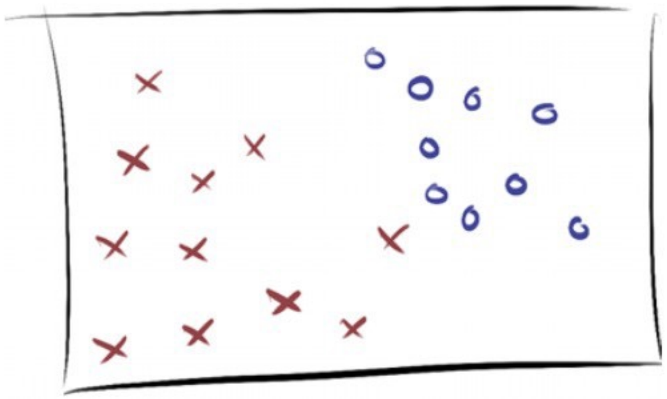
Part IV

Ensemble Classification

Credits

- Albert Bifet DATA STREAM MINING 2020-2021 course at Telecom Paris
- Alessio Bernardo & Emanuele Della Valle

SML Ensemble Classification models



Ensemble Classifiers

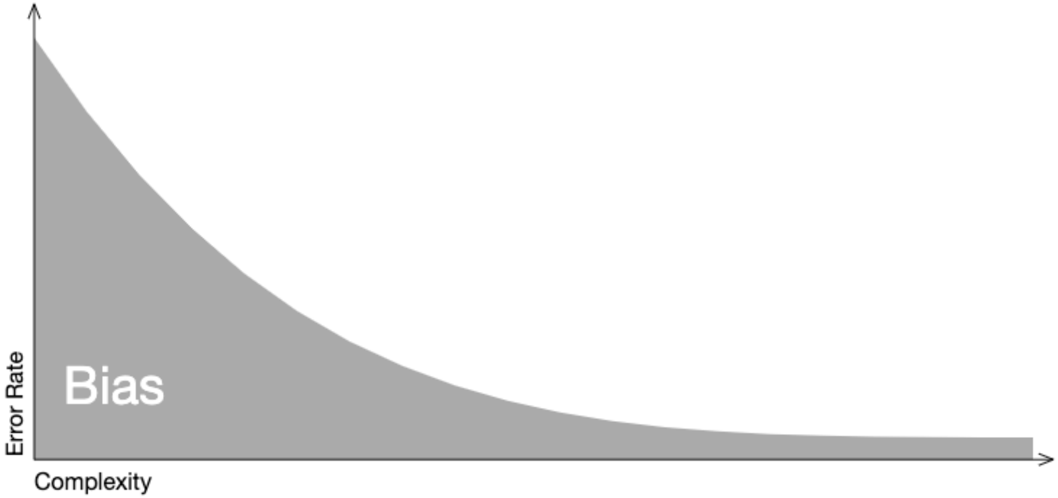
*"An **ensemble** can be described as a **composition** of **multiple weak** learners to form one with (expected) **higher** predictive **performance** (strong learner), such that a weak learner is loosely defined as a learner that performs slightly better than random guessing"*

Freund and Schapire, 1997

Bias-Variance trade-off

Bias

When a model is less complex, it ignores relevant information, and error due to bias is high. As the model becomes more complex, error due to bias decreases.

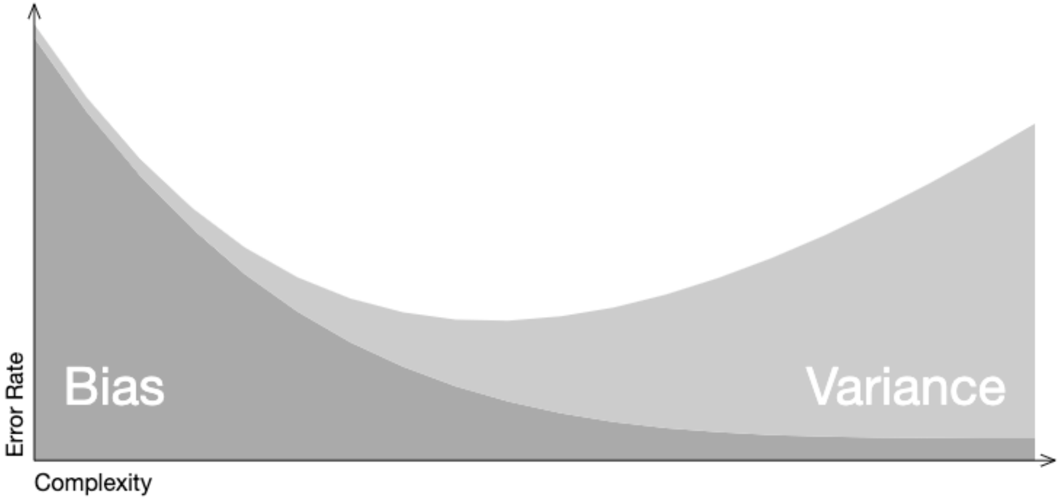


http://www.r2d3.us/visual-intro-to-machine-learning-part-2/

Bias-Variance trade-off

Variance

On the other hand, when a model is less complex, error due to variance il low. Error due to variance increases as complexity increases.

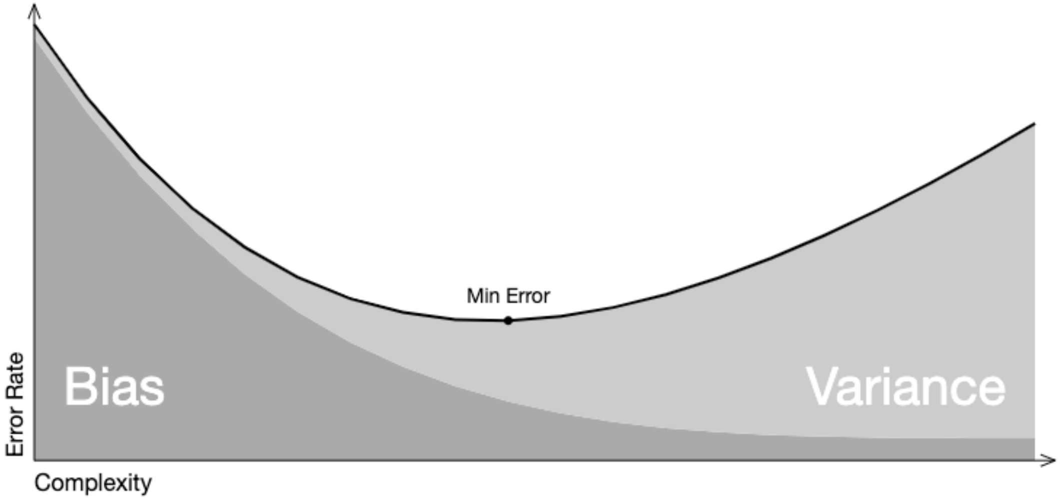


http://www.r2d3.us/visual-intro-to-machine-learning-part-2/

Bias-Variance trade-off

Trade-off

Overall model error is a function error due to **bias** and **variance.** The ideal model minimized error from each.



http://www.r2d3.us/visual-intro-to-machine-learning-part-2/

Ensemble Classifiers in ML

Bagging

- Fits ***M*** **independent** models and “average” their predictions in order to obtain a model with a **lower variance**…
- But we have only **one** dataset, how can we build **independent** models?

Bootstrapping

- Create ***M*** bootstrap samples (one for each model) from the original dataset of size ***N***, created by drawing random samples with replacement. Each bootstrap contains each original sample ***K*** times, where ***Pr(K=k)*** follows a binomial distribution.
- ***0.632*** of the data points in the original sample show up in the bootstrap sample (the other ***0.368*** won't be present in it)

L. Breiman. **Bagging predictors.** Machine Learning, 1996

Ensemble Classifiers in ML

Bagging → Random Forests

- The **random forest** approach is a **bagging** method where ***M*** trees, fitted on **bootstrap samples**, are combined to produce an output with lower variance.
- To make the ***M*** trees a bit less **correlated** with each others: random forest also samples over features and keep only a random subset of them to build the tree.

L. Breiman. **Random Forests.** Machine Learning, 2001

Ensemble Classifiers in ML

Boosting

- **Sequential** method that combines weak models **no longer** fitted **independently** from each others.
- It fits models **iteratively** such that the training of model at a given **step depends** on the models fitted at the **previous steps:** it gives **more importance** to observations in the dataset that were **badly handled** by the **previous** models in the sequence.
- It produces an ensemble model that is in general **less biased** than the weak learners that compose it.

Y. Freund & R. Schapire. **Experiments with a new boosting algorithm.** ICML, 1996

Ensemble Classifiers in ML

Boosting → Adaptive Boosting (AdaBoost)

It puts **more weight** on **difficult** to classify instances and **less** on those already **handled** well:

- First, it **updates** the observations **weights** in the dataset and train a **new weak learner** with a special **focus** given to the **observations misclassified** by the current ensemble model.
- Second, it **adds** the **weak learner** to the weighted sum according to an **update coefficient** that expresses the performances of this weak model: the **better** a weak learner performs, the **more** it contributes to the strong learner.

Y. Freund & R. Schapire. **Experiments with a new boosting algorithm.** ICML, 1996

Ensemble Classifiers in ML

Boosting → Gradient Boosting

Instead of fitting a weak learner on the data at each iteration, it actually **fits** a new weak learner to the **residual errors** made by the previous one:

- For every instance in the training set, it calculates the **residuals** for that instance, or, in other words, the **observed value minus the predicted value**.
- Once it has done this, it **adds** a **weak learner** that tries to **predict** the **residuals** that was previously calculated.

J. H. Friedman. **Stochastic gradient boosting.** Computational statistics & data analysis, 2022

Ensemble Classifiers in ML

Stacking

- It considers heterogeneous weak learners (different learning algorithms are combined).
- It learns to combine the base models using a meta-model.
- It produces an ensemble model that is in general **less biased** than the weak learners that compose it.

K. M. Ting & I. H. Witten. **Stacking bagged and dagged models.** 1997

Ensemble Classifiers in SML

- **Diversity:** induce diversity among learners
- **Combination:** combine the predictions
- **Adaptation:** adapt to evolving data

Pro

- High Predictive performance
- Flexibility

Cons

- Computational resources

Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Induce Diversity

Horizontal Partitioning

- **Bagging:** build a set of ***M*** base models, with a bootstrap sample from the original dataset of size ***N***, created by drawing random samples with replacement. Each bootstrap contains each original sample ***K*** times, where ***Pr(K=k)*** follows a binomial distribution.

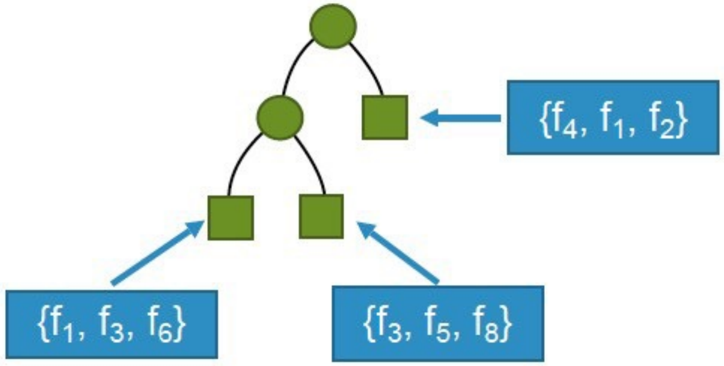
Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Induce Diversity

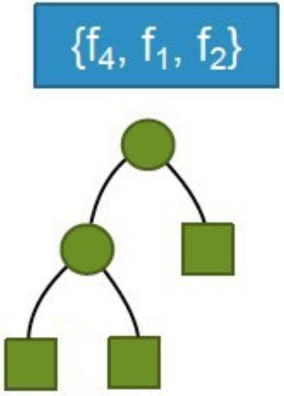
Vertical Partitioning

- **Random Subspaces:** train learners on different subsets of features

Local Randomization



Global Randomization



Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Induce Diversity

Others

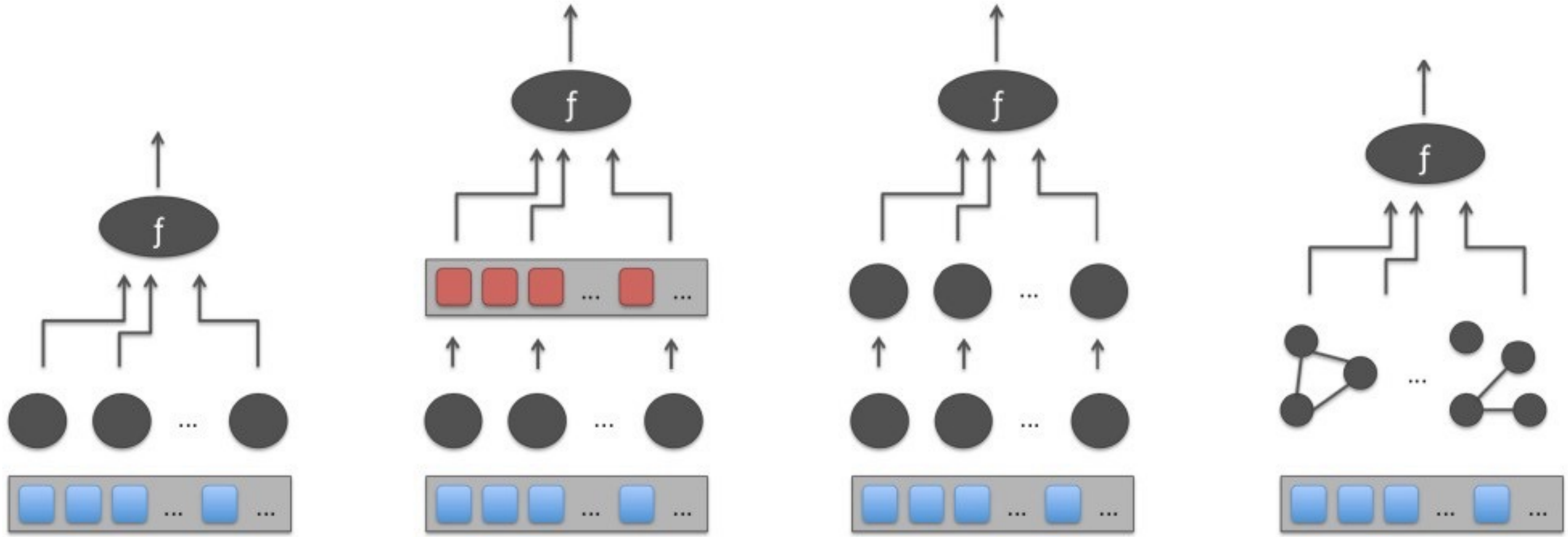
- **Base Learner Manipulation:** varying parameters of the same base learner
- **Heterogeneous Base Learners:** use heterogeneous base learners and obtain ensemble members with different biases

Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Combination

Base learners Instances

Architecture



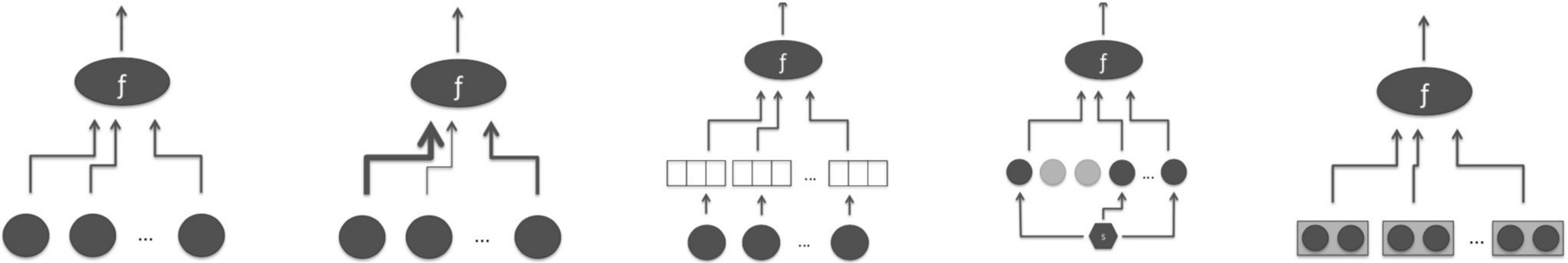
Flat **Meta-Learner** **Hierarchical** **Network**

Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Combination

Voting

Base learners Instances



Majority **Weighted Majority** **Rank** **Abstaining** **Relational**

Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Adaptation

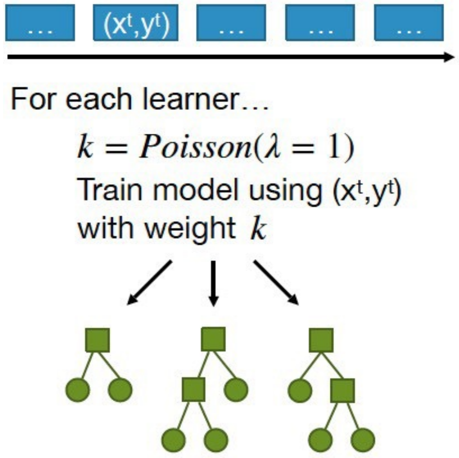
Cardinality

- **Fixed:** fixed numbers of base learners
- **Dynamic:** add classifiers on the fly

Gomes, H. M., Barddal, J. P., Enembreck, F., & Bifet, A. (2017). **A survey on ensemble learning for data stream classification.** ACM, 50(2), 1-36.

Online Bagging

- Since data streams are supposed to be unbounded (large ***N***), the binomial distribution tends to a **Poisson(1)** distribution.

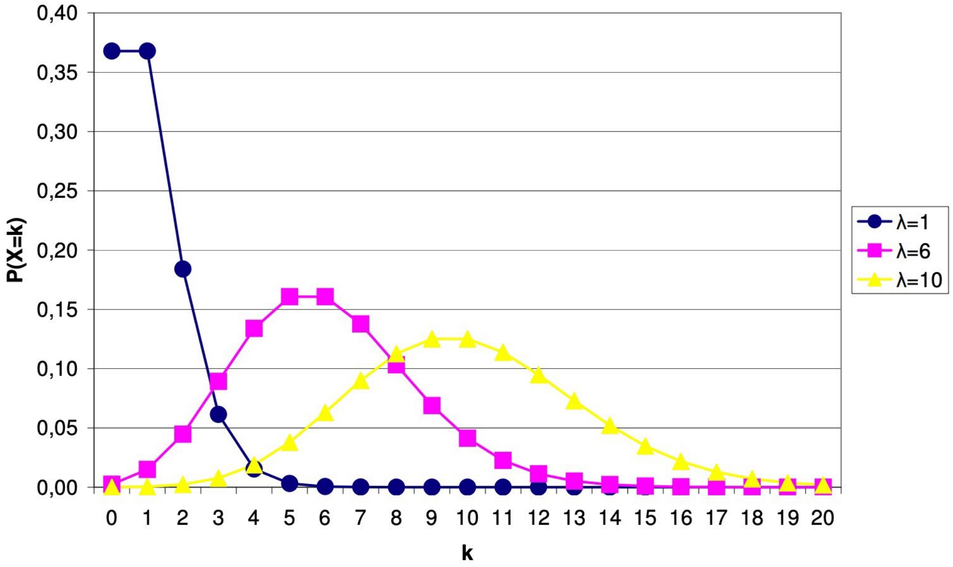


Train learners on different subsets of instances

Oza and Russel, **"Online bagging and boosting,"** in Artificial Intelligence and Statistics 2001.

Leveraging Bagging

- Add an **ADWIN** drift detector per base learner
- Use more weight during training - **Poisson(6)**



Bifet, G. Holmes, and B. Pfahringer, **“Leveraging bagging for evolving data streams,”** in PKDD, 2010

Adaptive Random Forest (ARF)

- **Base Learners**: Hoeffding Trees
- **Diversity:** Leveraging Bagging + **Local** Random Subspaces
- **Combination:**
  - Flat architecture
  - Weighted majority voting
- **Adaptation:** Adaptive window + warning period (train background learners)

H. M. Gomes et al, **"Adaptive random forests for evolving data stream classification,"** Machine Learning, 2017.

Streaming Random Patches (SRP)

- **Base Learners**: User choice
- **Diversity:** Leveraging Bagging + **Global** Random Subspaces
- **Combination:**
  - Flat architecture
  - Weighted majority voting
- **Adaptation:** Adaptive window + warning period

Gomes, Read and Bifet, **"Streaming Random Patches for Evolving Data Stream Classification"**, ICDM, 2019

QUIZ

1. What is the difference between Online Bagging and Leveraging Bagging?
    a. They give the same weights to the instances
    b. The former gives higher weights to the instances, inducing more diversity
    c. The latter gives higher weights to the instances, inducing more diversity
2. What are the **2** most important differences between ARF and SRP?
    a. ARF uses only HT as base learners and leveraging bagging, SRP uses HT as base learners and online bagging
    b. ARF uses ADWIN and local random subspaces, SRP does not use any CD detector and uses global random subspaces
    c. ARF uses only HT as base learners and local random subspaces, SRP can use everything as base learners and global random subspaces

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EXERCISE 4: Stream Ensemble Classification
LAB 4: Final Challenge