

AutoML in CapyMOA

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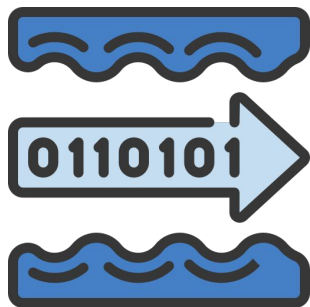
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01

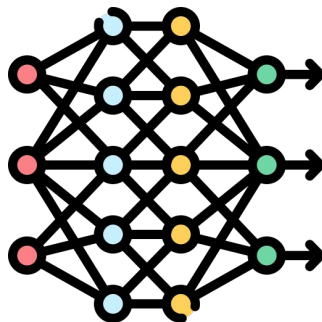
Introduction

Problem: AutoML in **Streaming Machine Learning**

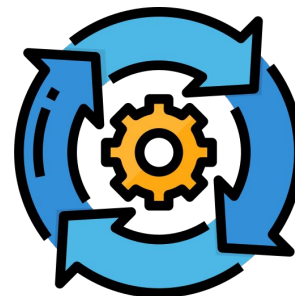
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**Streaming
Data**



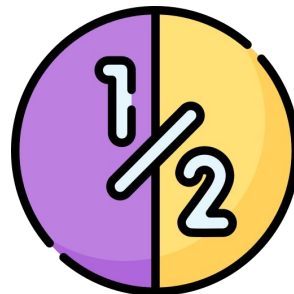
**Machine
Learning**



**Automatic
Model
Selection**



Bandit Classifier



Successive Halving Classifier

02

Successive Halving Classifier

Approach: Successive Halving Classifier



- Efficiently selects models by **avoiding full training** on all data.
- Models are evaluated at stages called "**rungs**".
- **Poor performers** are **discarded** early at each rung.
- **Promising models** receive **more resources** for further training.
- Designed to operate under a **fixed budget**.
- Aims to **maximize performance** with **minimal computation**.

Parameters of Successive Halving Classifier



- **Rungs:** A checkpoint where we evaluate and eliminate the worst performing models. It has a specific number of budget.
- **Budget:** The total amount of training data we're allowed to use across all models in all rungs.
- **Active Models:** The models that are still in the competition
- **Eta:** A number that tells us how many models to eliminate at each step (when $\text{eta}=2 \rightarrow$ Halving).

03

Bandit Classifier

Approach: Bandit Classifier



- Each model is linked to **an arm**.
- At each training step, the **policy** determines which arm/model to select.
- The reward is **based** on the **model's performance** on the given sample.

Epsilon Greedy Policy - Bandit Classifier

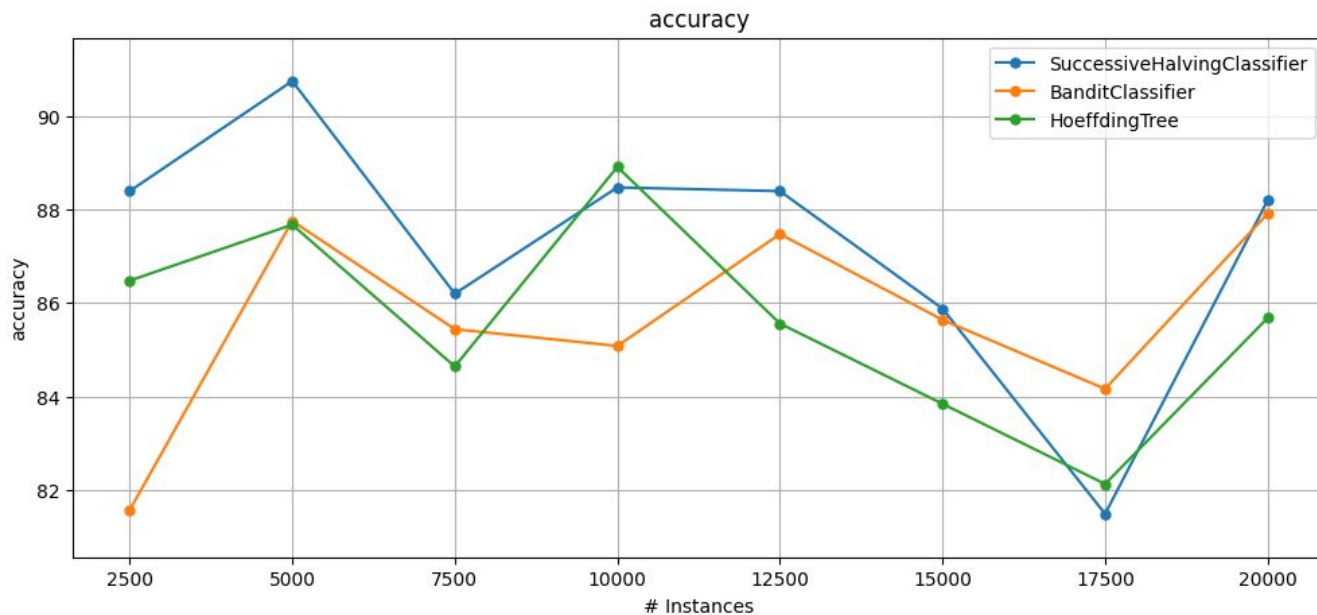


- **Best model** → probability **1 - epsilon**.
- **Other models** → probability **epsilon**.
- During the **burn-in period**, the policy always explores to gather initial information about **all models**.

04

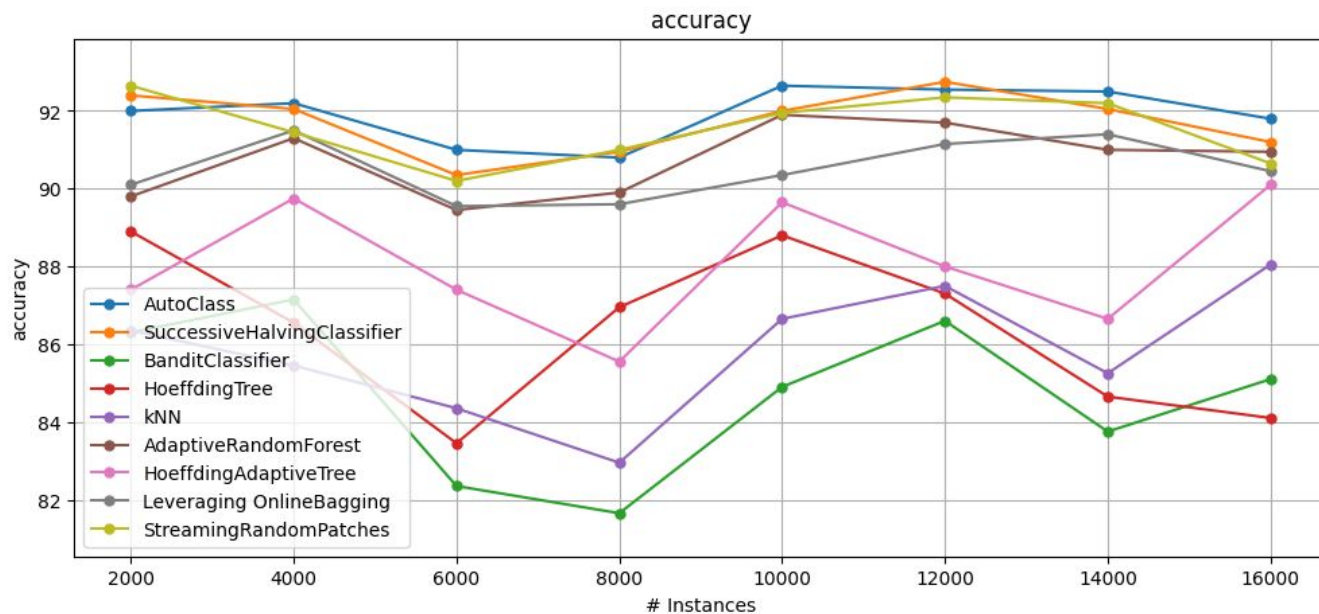
Comparison

Comparison of Models - Sanity Check



[SuccessiveHalving with 75 HT configs] Accuracy = 87.225, Time: 159.556s
[BanditClassifier with 75 HT configs] Accuracy = 85.800, Time: 100.866s
[Default HoeffdingTree] Accuracy = 85.615, Time: 0.139s

Comparison of Models – Electricity Stream

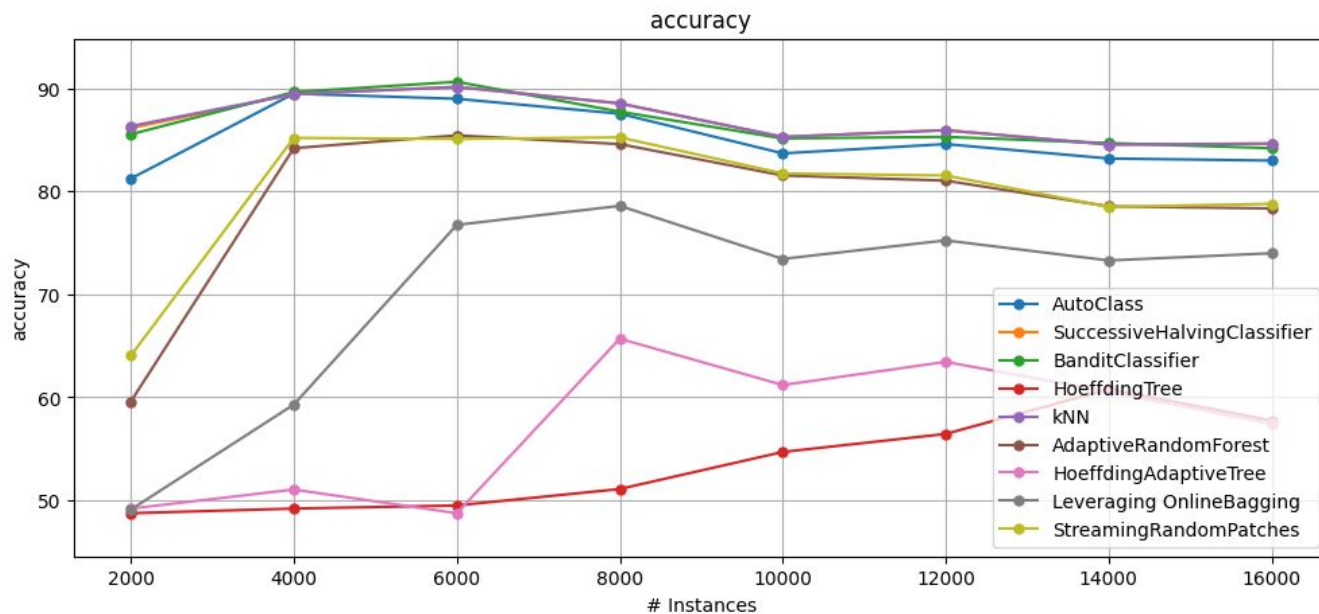


[AutoClass] Accuracy = 91.833, Time: 438.069s

[SuccessiveHalving] Accuracy = 91.600, Time: 264.252s

[BanditClassifier] Accuracy = 84.493, Time: 75.419s

Comparison of Models – RBFm Stream

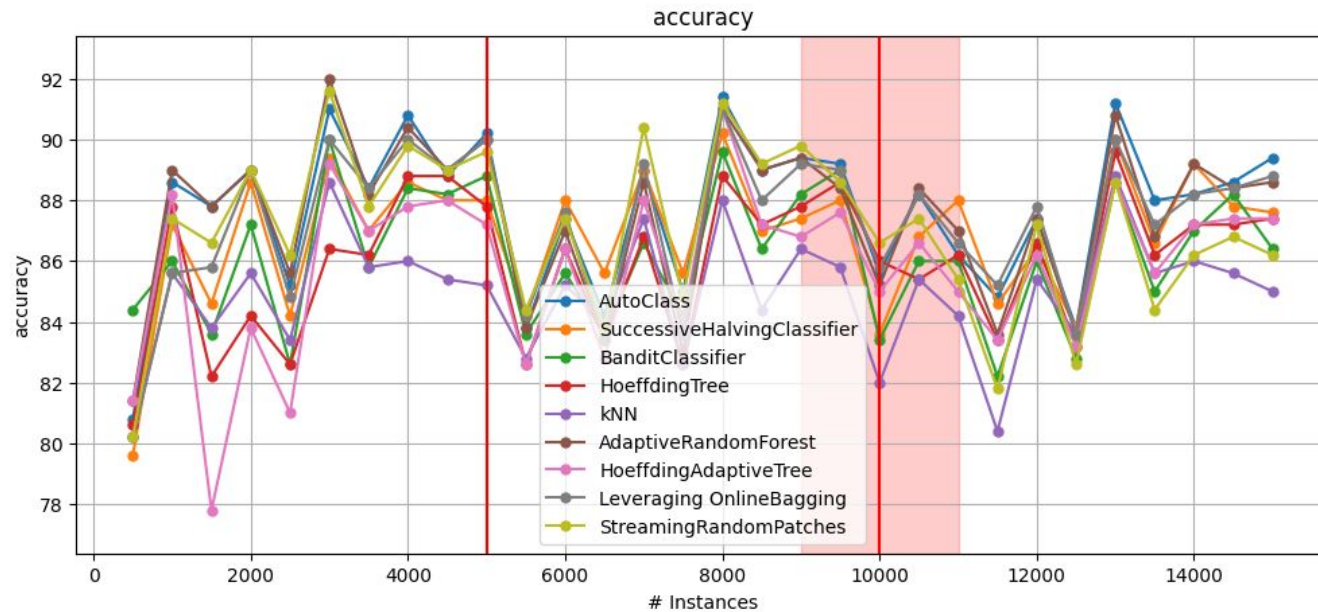


[AutoClass] Accuracy = 85.427, Time: 494.321s

[SuccessiveHalving] Accuracy = 87.013, Time: 250.490s

[BanditClassifier] Accuracy = 86.787, Time: 126.094s

Comparison of Models – SEA Stream with Drift

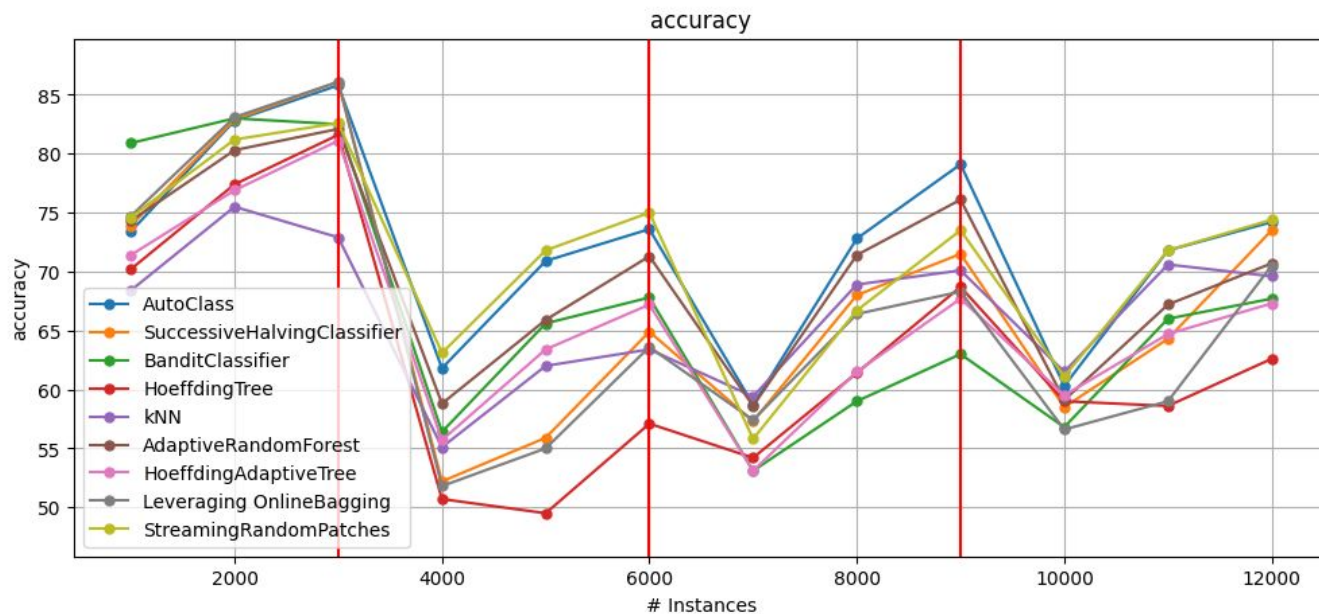


[AutoClass] Accuracy = 87.680, Time: 226.214s

[SuccessiveHalving] Accuracy = 86.820, Time: 178.488s

[BanditClassifier] Accuracy = 86.113, Time: 83.838s

Comparison of Models – Custom Stream with Concept Drift



[AutoClass] Accuracy = 72.100, Time: 776.176s

[SuccessiveHalving] Accuracy = 67.417, Time: 213.327s

[BanditClassifier] Accuracy = 66.817, Time: 105.817s

Comparison of Models

Stream	Model	Accuracy	Time (s)	Approximate Data Used (%)
Electricity	Bandit Classifier	84.49	75	5
	Successive Halving	91.6	264	10
	AutoClass	91.83	438	100
RBF	Bandit Classifier	86.78	126	5
	Successive Halving	87.01	250	10
	AutoClass	85.42	494	100
SEA - DataDrift	Bandit Classifier	86.11	83	5
	Successive Halving	86.82	178	20
	AutoClass	87.68	226	100
Custom Drift Stream	Bandit Classifier	66.81	105	5
	Successive Halving	67.41	213	20
	AutoClass	72.1	776	100

Time Calculation

- Bandit: $\text{burn_in} * n_models + (\text{max_instances} - \text{burn_in})$
- Successive: $\text{budget} = \text{max_instances} * K$
- AutoClass: $\text{max_instances} * n_models / 2$

Thank
you!