



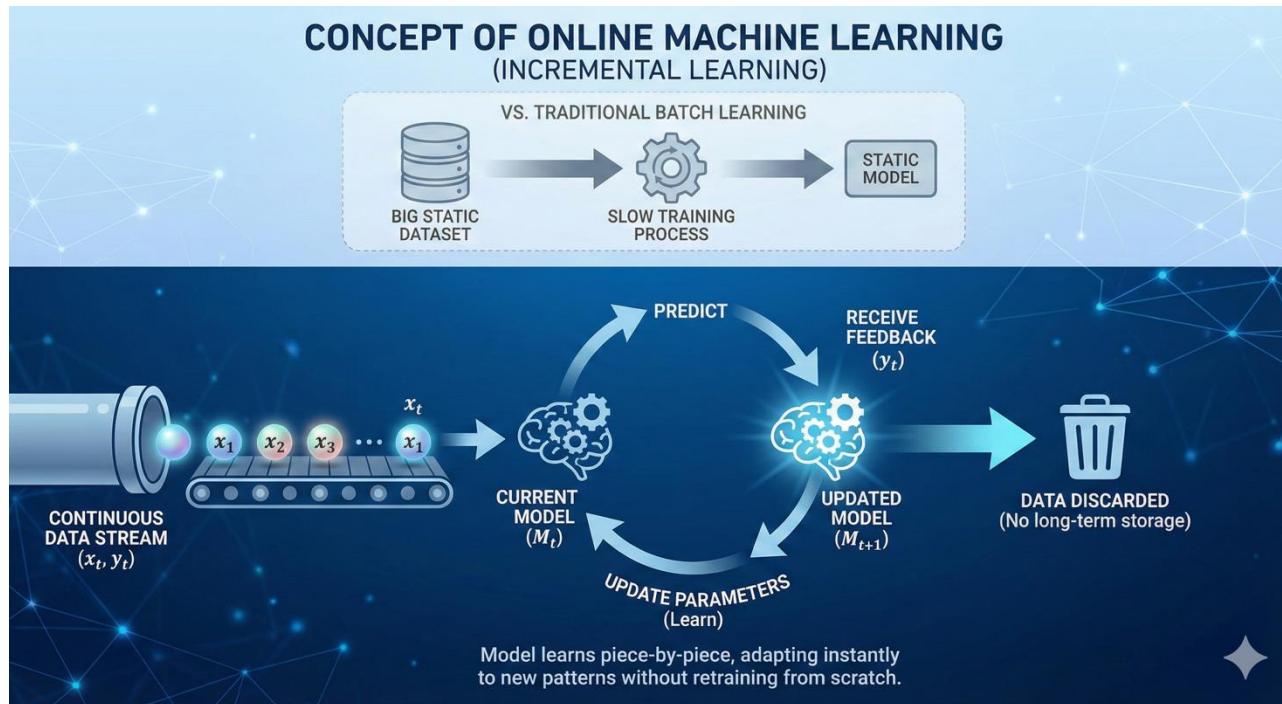
Introduction to Online Machine Learning

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Batch vs. Online

- **Traditional ML (Batch Learning):**
 - **Static:** Model is trained once on a fixed dataset (e.g., CSV file).
 - **Offline:** Training can take hours/days; model is deployed as a read-only artifact.
 - **Equation:** $\text{Model} = \text{Train}(X_{\text{all}}, y_{\text{all}})$
 - **Limitation:** If data changes, you must retrain from scratch.
- **Online ML (Incremental Learning):**
 - **Dynamic:** Model updates continuously as new data arrives.
 - **Real-Time:** Training happens in milliseconds per sample.
 - **Equation:** $\text{Model}_t = \text{Update}(\text{Model}_{t-1}, x_{\text{new}}, y_{\text{new}})$
 - **Advantage:** Adapts immediately to new trends; requires less memory (doesn't store history).



Why Online ML?

Embedded ML



- **Big Data Volume:** Dataset is too large to fit in RAM (e.g., years of server logs).
- **Dynamic Environments:** User/Sensor behavior changes.
- **Edge Computing (IoT):** Devices like Raspberry Pi have limited memory; cannot store huge datasets for batch training.
- **Cold Start:** Start learning immediately without waiting to accumulate a "training set."



Key Terminology

- **Instance/Observation:** A single data point (x, y) arriving at time t .
- **Concept Drift:** When the statistical properties of the target variable change over time (e.g., "Normal" temperature changes from Winter to Summer).
- **Forgetting Factor / Window:** Mechanism to discard old, irrelevant data (fading memory).
- **Interleaved Test-Then-Train:** The standard evaluation method—predict first, then use the true label to update the model, then measure error.
- **Regret:** The difference in performance between the online model and the best possible static model trained on all data in hindsight.

Methodologies & Evaluation

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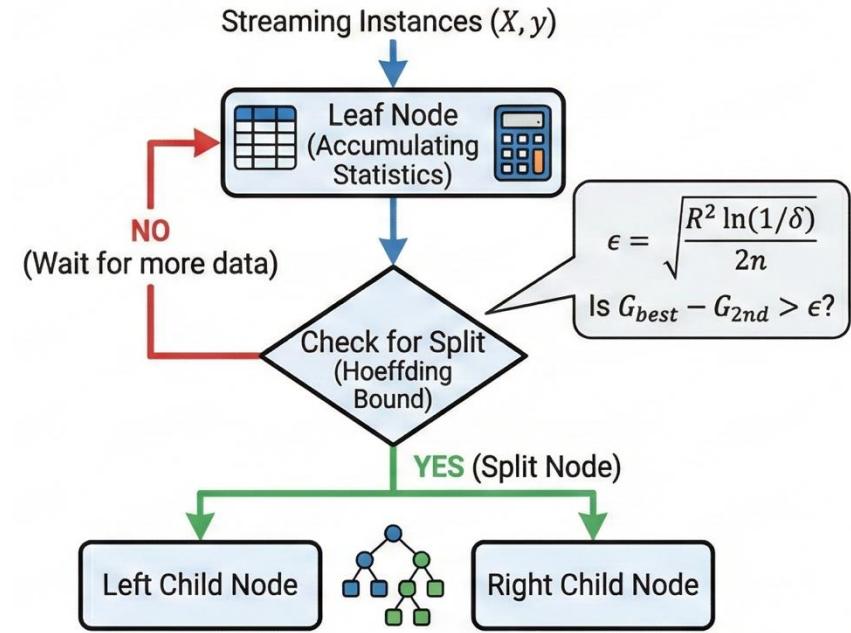
- **Prequential Evaluation (Predictive Sequential):**
 - Instead of "Train/Test Split", every sample serves as a test sample *before* it becomes a training sample.
 - Accuracy is a running average over time.
- **Windowing Strategies:**
 - **Landmark Window:** All data since the beginning (rarely used, too heavy).
 - **Sliding Window:** Only the last 'N' samples matter (FIFO).
 - **Damped Window:** Recent samples have higher weight; older samples decay exponentially.

Algorithms – Linear & Tree-Based



- **Stochastic Gradient Descent (SGD):** The backbone of online learning.
Updates weights slightly for every error.
 - Used for: Regression, SVM, Basic Neural Networks.
- **Hoeffding Trees (Very Fast Decision Trees - VFDT):**
 - Wait for enough statistical evidence (using Hoeffding Bound) to split a node.
 - Hoeffding Bound calculates the number of samples (n) needed to guarantee that the observed best split is truly the best.
 - *Result:* A decision tree that is nearly identical to a batch tree but built incrementally.
 - *Used for:* Classification in changing streams.

HOEFFDING TREE SPLIT DECISION PROCESS



Hoeffding Bound guarantees split quality with high confidence.

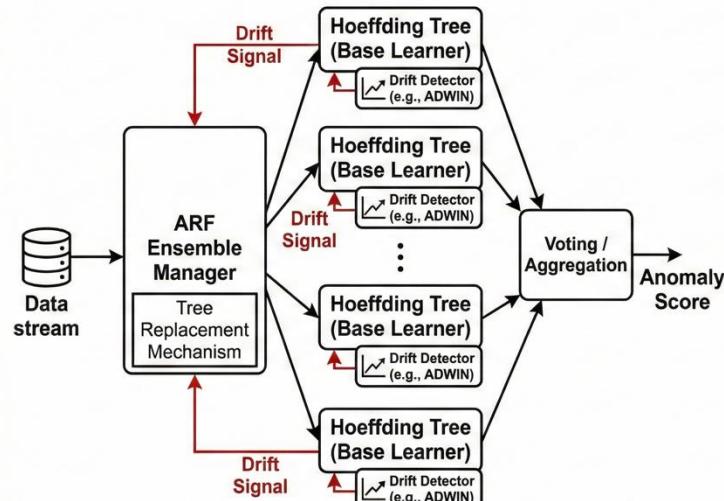
Ensemble & Anomaly Detection

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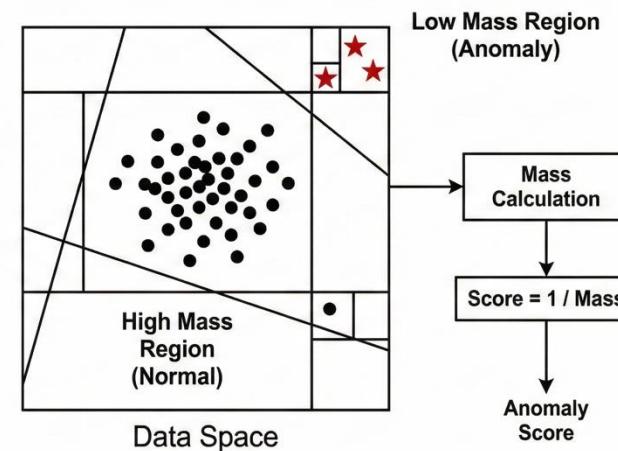
- **Adaptive Random Forest (ARF):**
 - A forest of Hoeffding Trees.
 - Includes drift detection per tree; replaces trees that perform poorly due to drift.
- **Half-Space Trees (HST):**
 - Used for **Anomaly Detection**.
 - Randomly partitions space; anomalies fall into sparse regions (low mass).
 - Fast, efficient, no labels required (Unsupervised).

Adaptive Random Forest (ARF) for Anomaly Detection



Ensemble of online trees that adapts to concept drift by replacing individual learners.

Half-Space Trees (HST) for Anomaly Detection



Randomly partitions space; anomalies fall into sparse regions with low data mass.

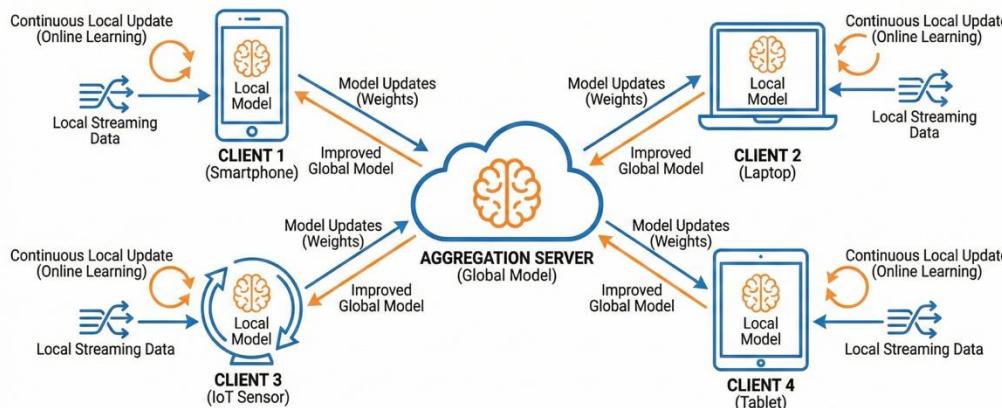
Federated Online Learning

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- Combines two advanced concepts: **Federated Learning** + **Online Learning**.
- Example
 - Your Raspberry Pi receives a stream of sensor data.
 - It updates its local model immediately (Online Learning) to adapt to current conditions.
 - Periodically, it sends just the *updates* (weight changes) to a central server.
 - The server aggregates these updates from 1,000 devices and sends back a better global model.
 - The Pi continues learning online, now starting from this smarter global baseline.
- Highlights
 - Devices (Edge) learn online locally.
 - Only model updates (weights) are sent to the cloud, not data.
 - Preserves privacy while learning from millions of streams.

CONCEPT OF FEDERATED ONLINE LEARNING



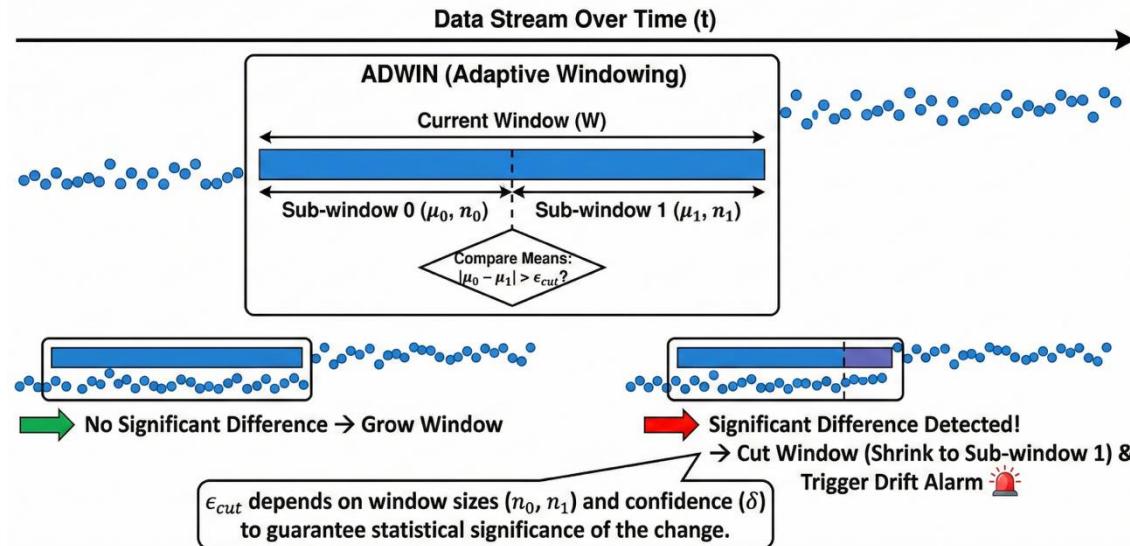
Edge devices continuously learn from local streams and periodically exchange model updates with a central server to improve a shared global model, ensuring privacy.



Concept Drift

- **Definition:** The relationship between input data and output label changes.
- **Types:**
 - **Sudden Drift:** Immediate change (e.g., accidents changed traffic patterns).
 - **Gradual Drift:** Slow evolution (e.g., mechanical wear on a sensor).
 - **Recurring Drift:** Seasonal patterns (e.g., seasonal temperature).
- **Impact:** A static model's accuracy plummets.
- **Solution:** Drift Detectors (ADWIN, DDM) trigger model resets or adaptive window sizing.

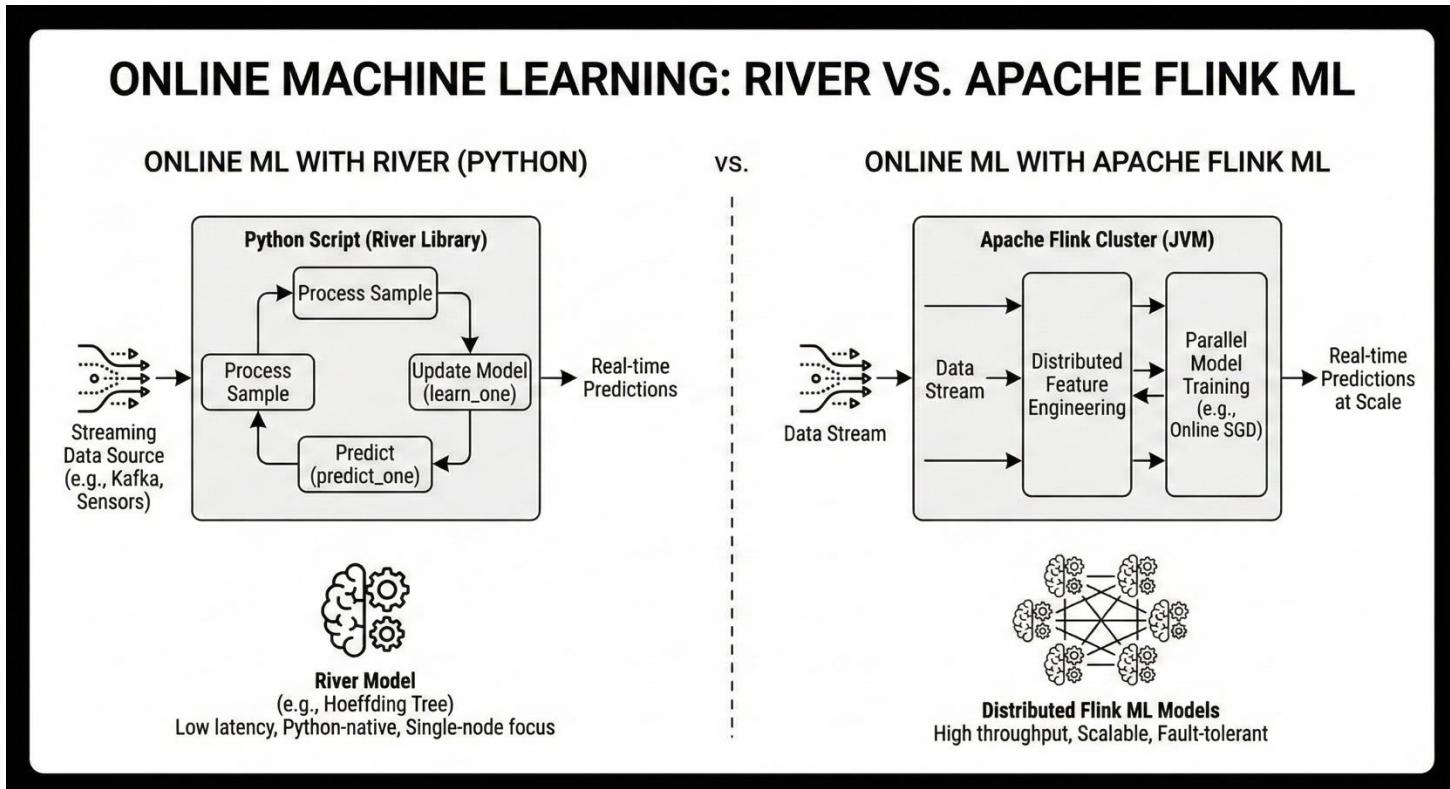
CONCEPT OF DRIFT DETECTORS (ADWIN)





Tools & Ecosystem

- **River (Python):** (Previously Creme/Scikit-Multiflow). The standard for Python. Scikit-learn like API (`learn_one`, `predict_one`).
- **Apache Flink ML:** For distributed streaming ML at enterprise scale.



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Embedded ML





