Creativity, Science and **Innovation**

Introduction to Federated Learning

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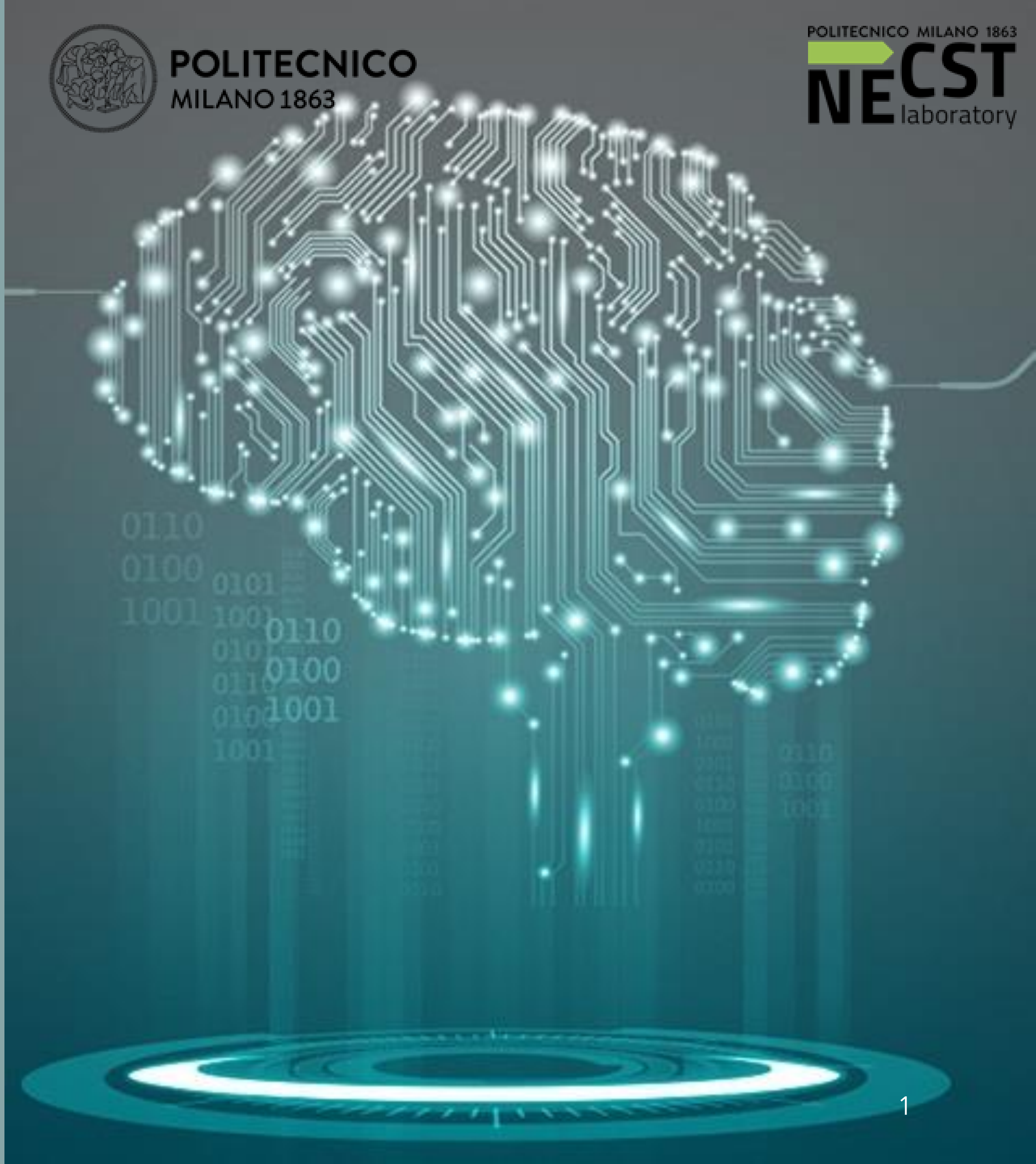

Machine Learning Pipeline

Steps to train a ML model:

1. **Collect a dataset** with the data of interest. Each user (client) collects their own data to build a unique big dataset for the task.

1

X	Y	Z	Label
[2,-1,4,...]	[12,5,8,...]	[9,5,8,...]	Walking (0)
[2,-2,4,...]	[11,2,9,...]	[4,1,5,...]	Running (1)
[1,3,-1,...]	[10,5,7,...]	[4,1,5,...]	Walking (0)
[2,-1,1,...]	[8,11,8,...]	[5,5,7,...]	Walking (0)
[1,5,3,...]	[9,5,8,...]	[8,2,8,...]	Going up (2)
[2,-1,4,...]	[5,5,7,...]	[2,3,4,...]	Walking (0)
[4,5,9,...]	[4,5,9,...]	[4,1,5,...]	Walking (0)

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2

ML model

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Machine Learning Pipeline

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2. **Train** an ML model on such data. The model will learn to predict the Label given the inputs
3. When you have the final model, you will be able to use it in **inference** mode on new data coming from the device

1

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[2,-1,4,...]	[12,5,8,...]	[9,5,8,...]	Walking (0)
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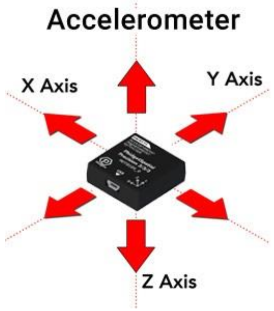
2

ML model



3

Prediction

Why Federated Learning?

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Due to new **regulations** (GDPR), to protect users' **privacy**, sensitive data cannot be shared

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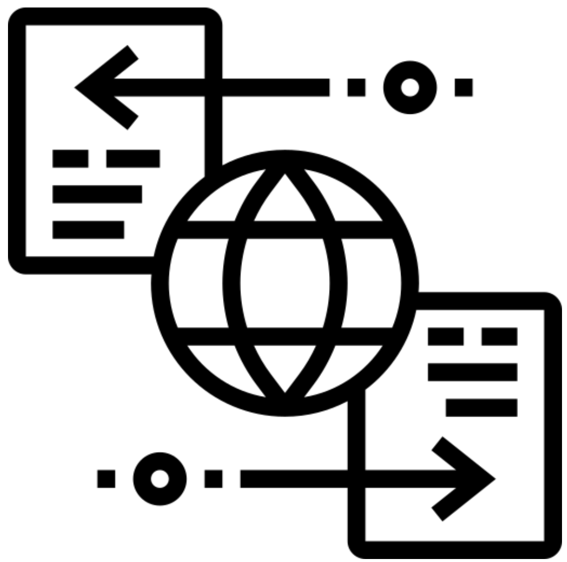
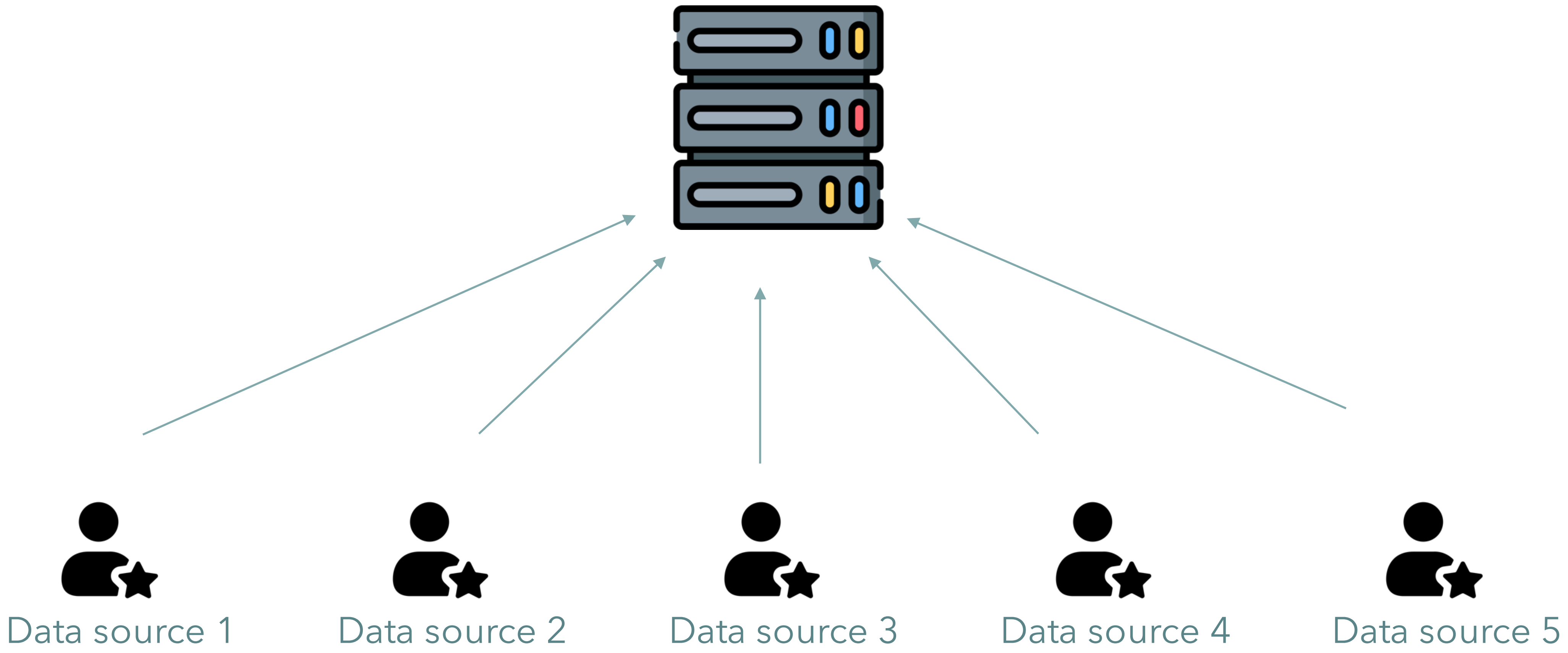
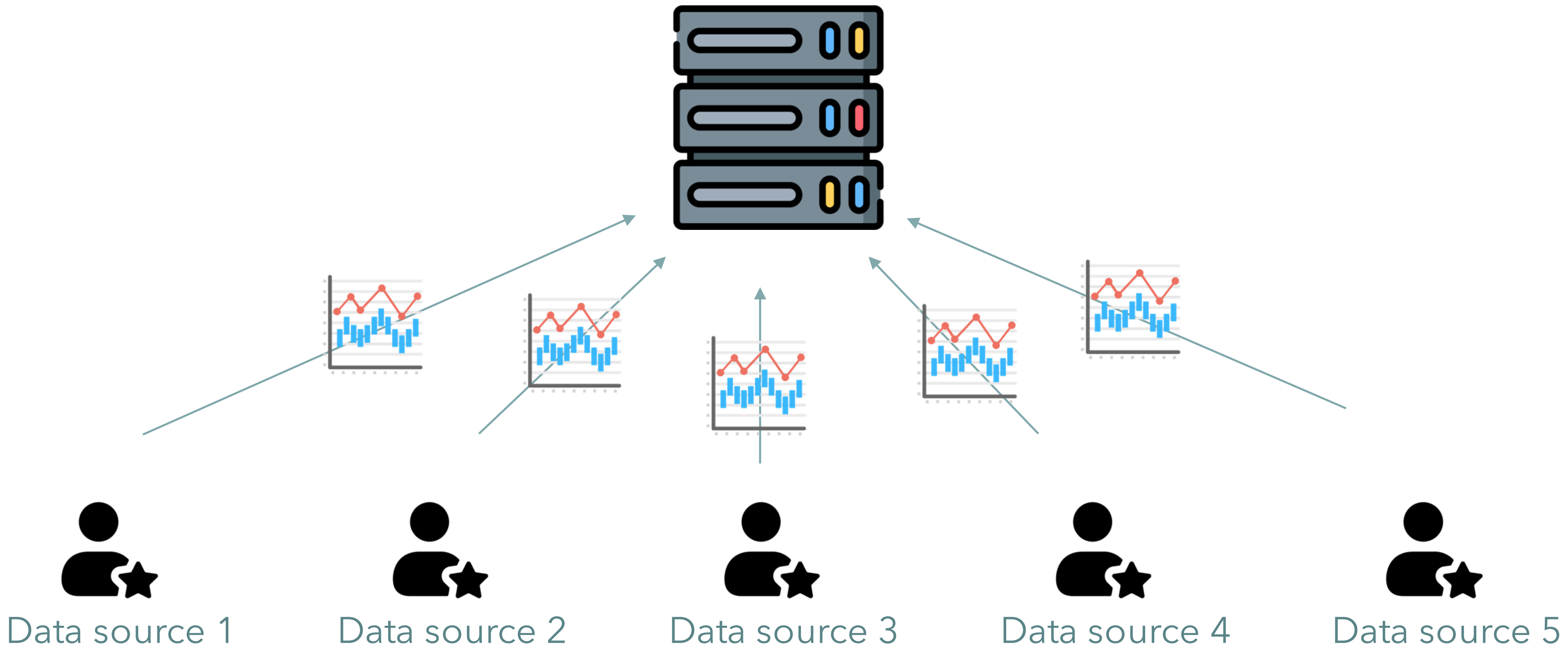


Communication overhead: when dealing with **heavy data**, such as images or volumes for medical data, data transfer is an issue

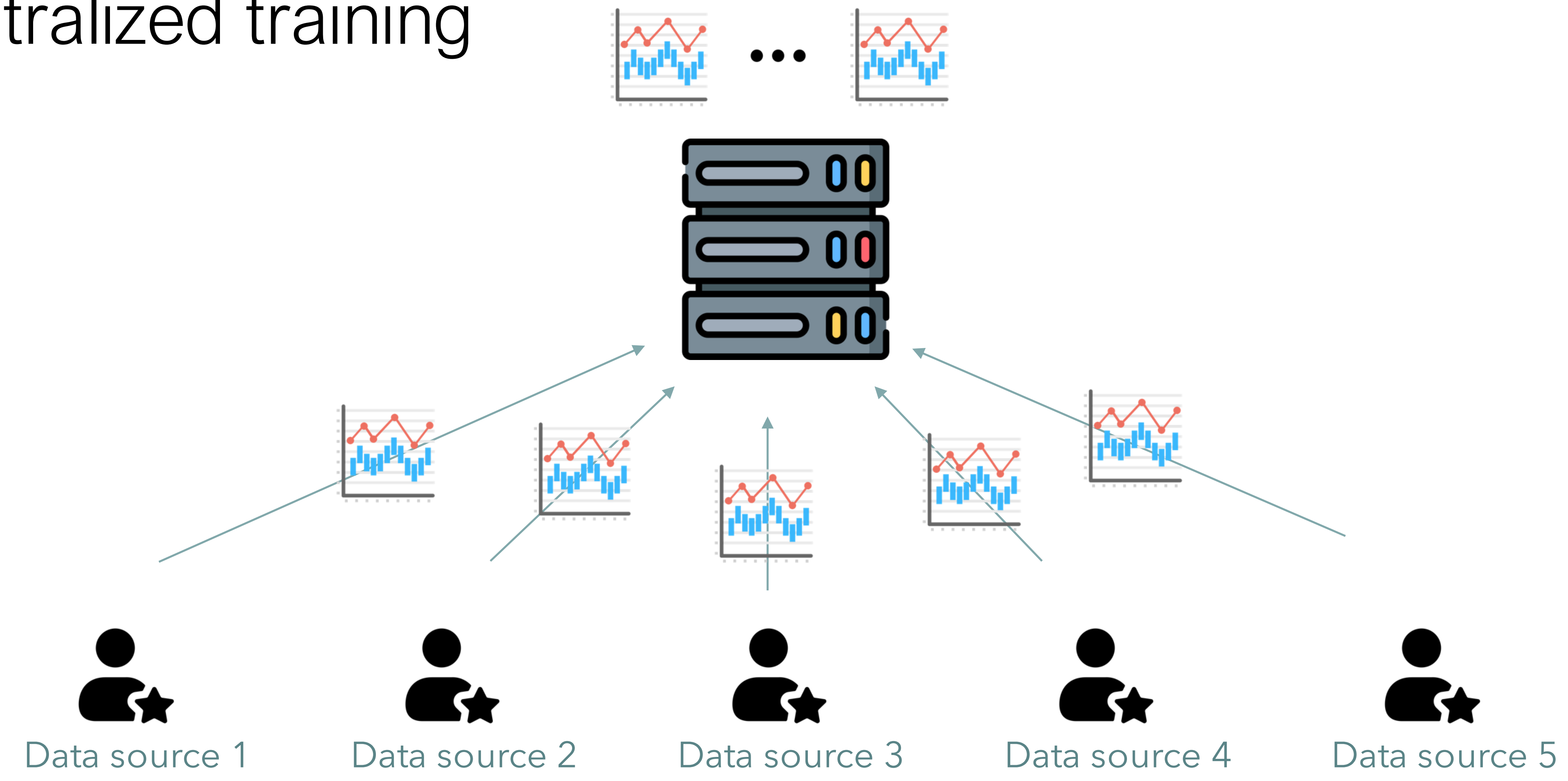
Centralized training



Centralized training



Centralized training



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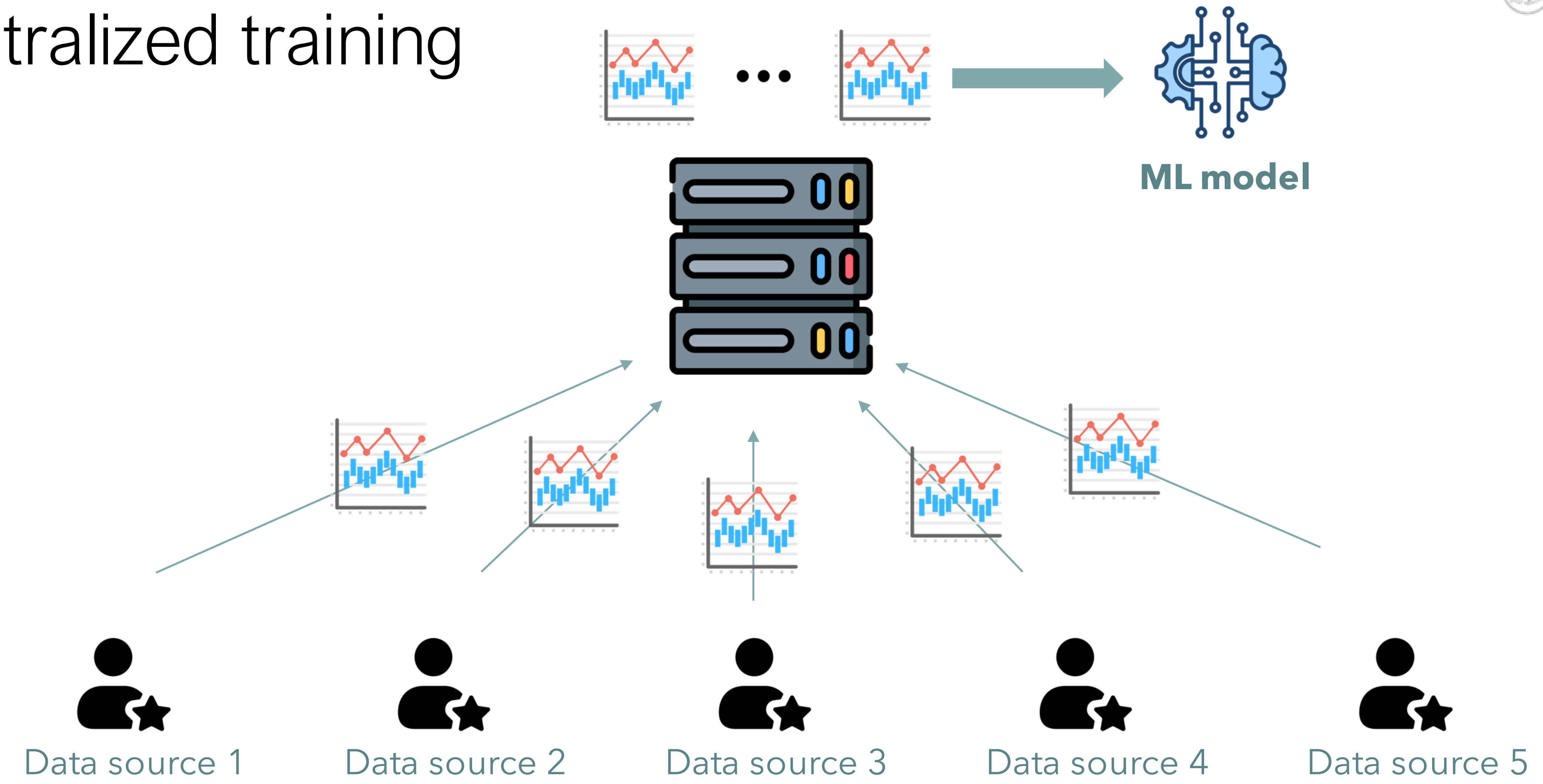
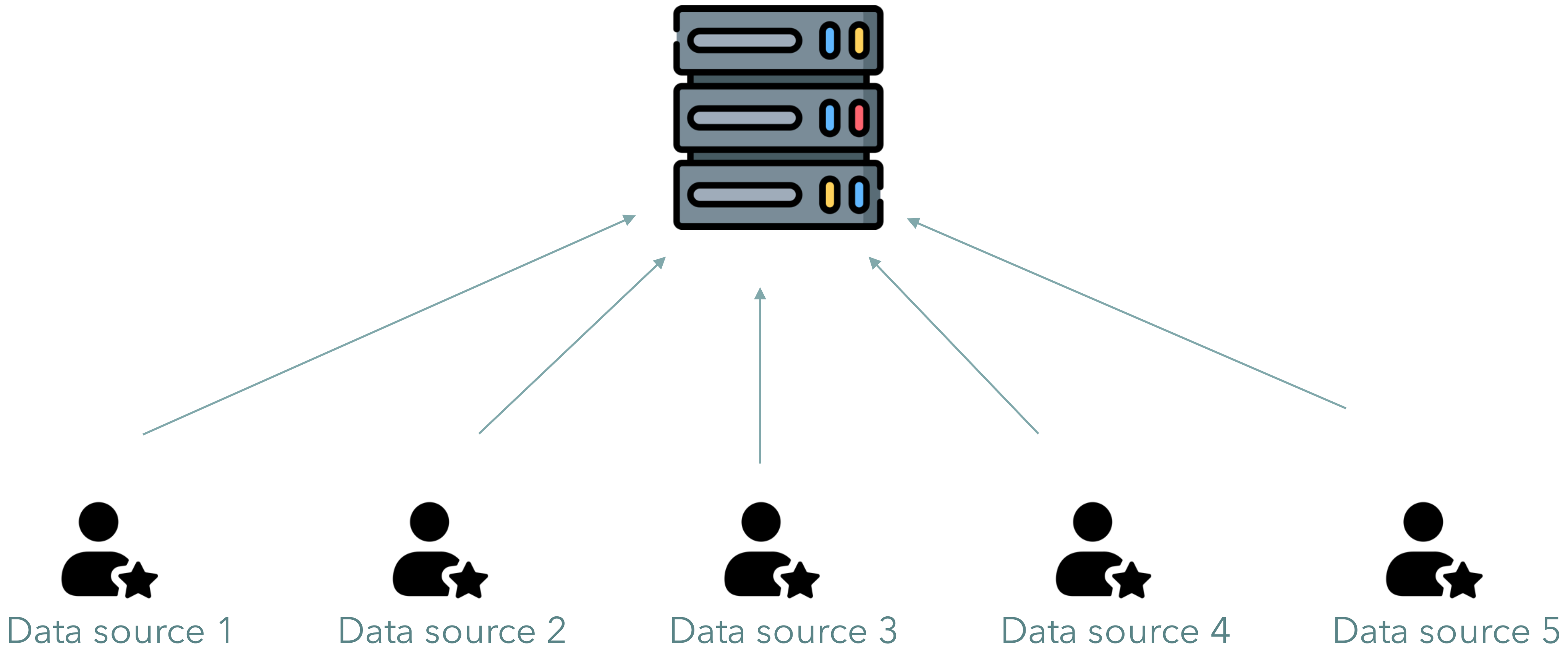


Federated Learning training



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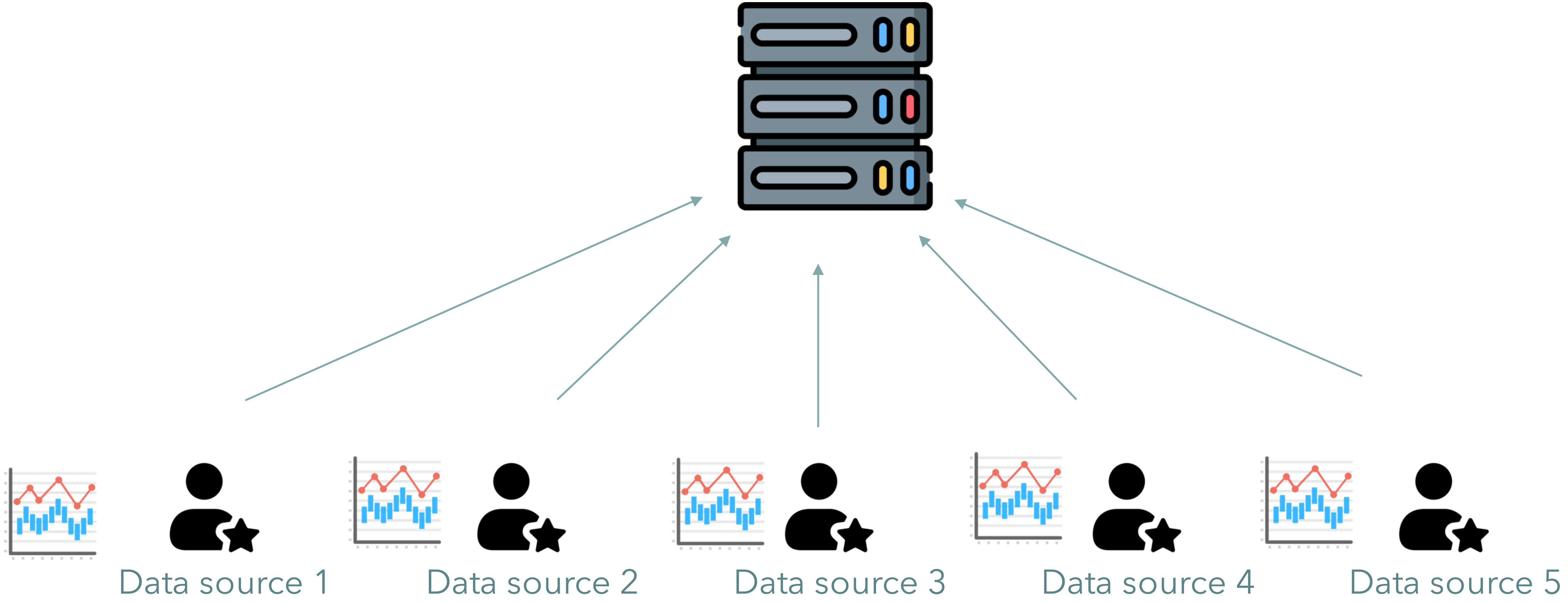
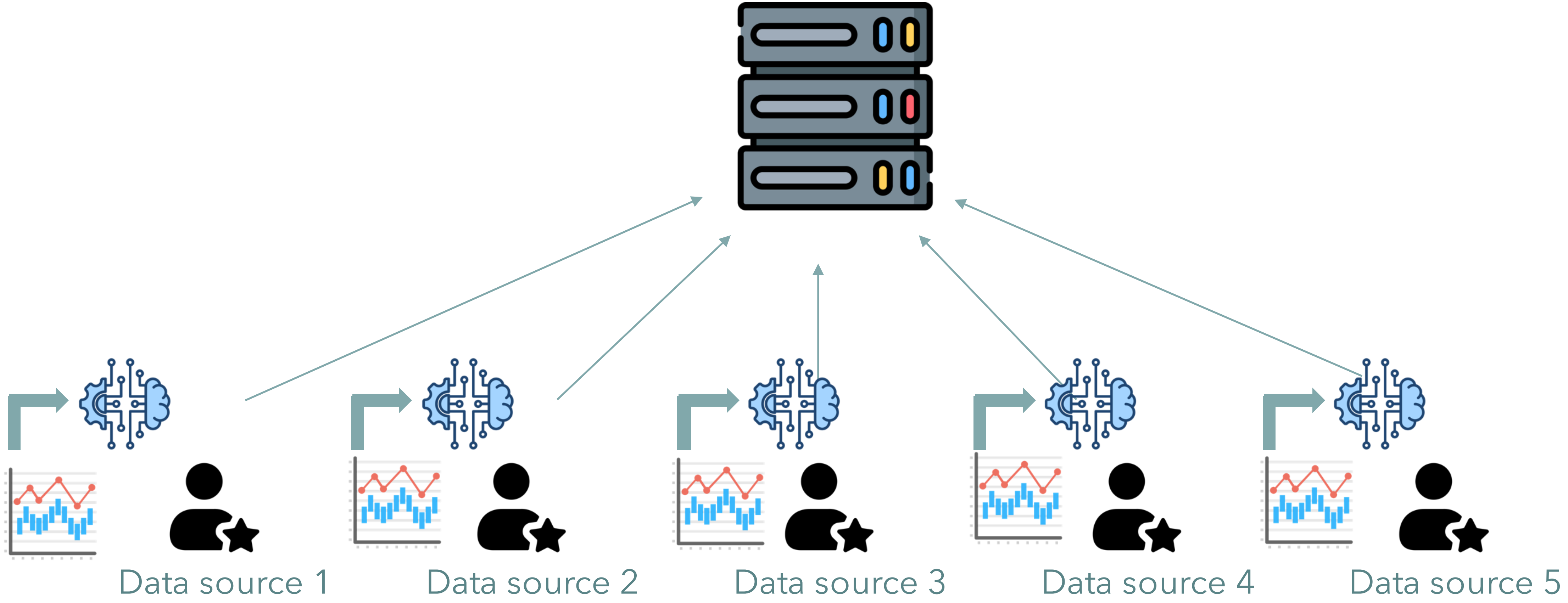
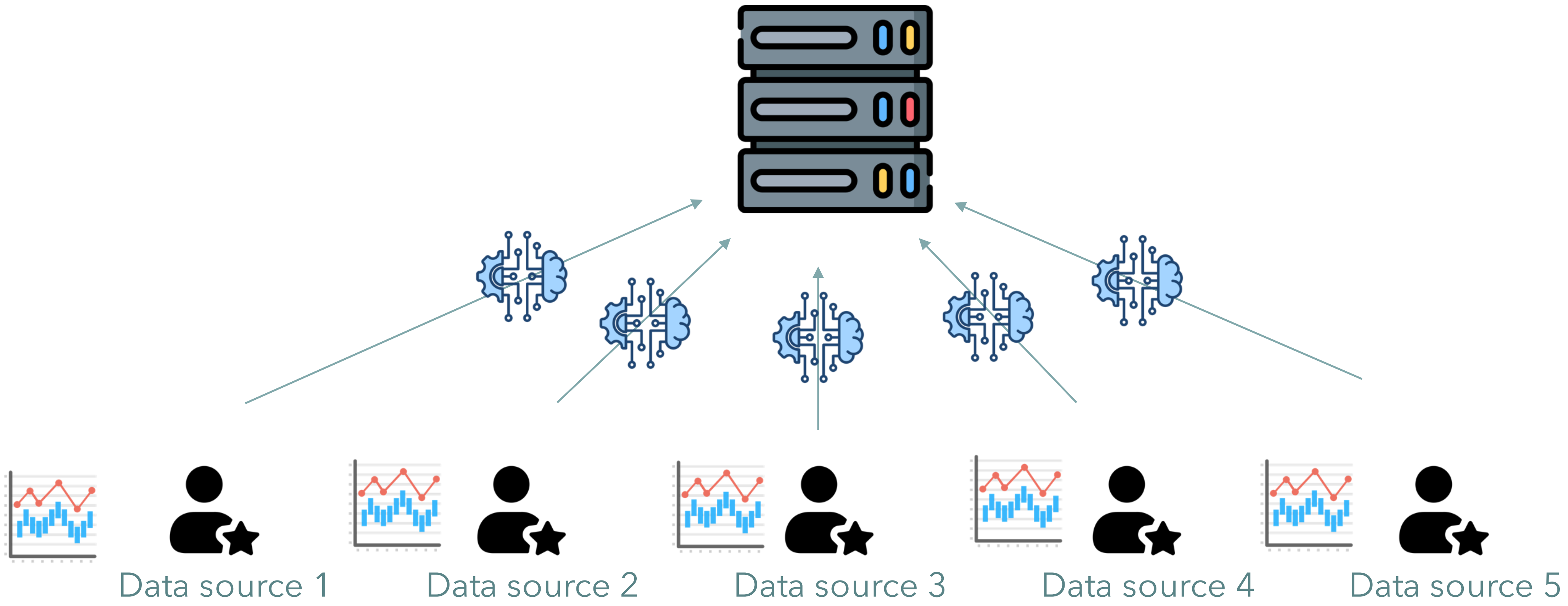


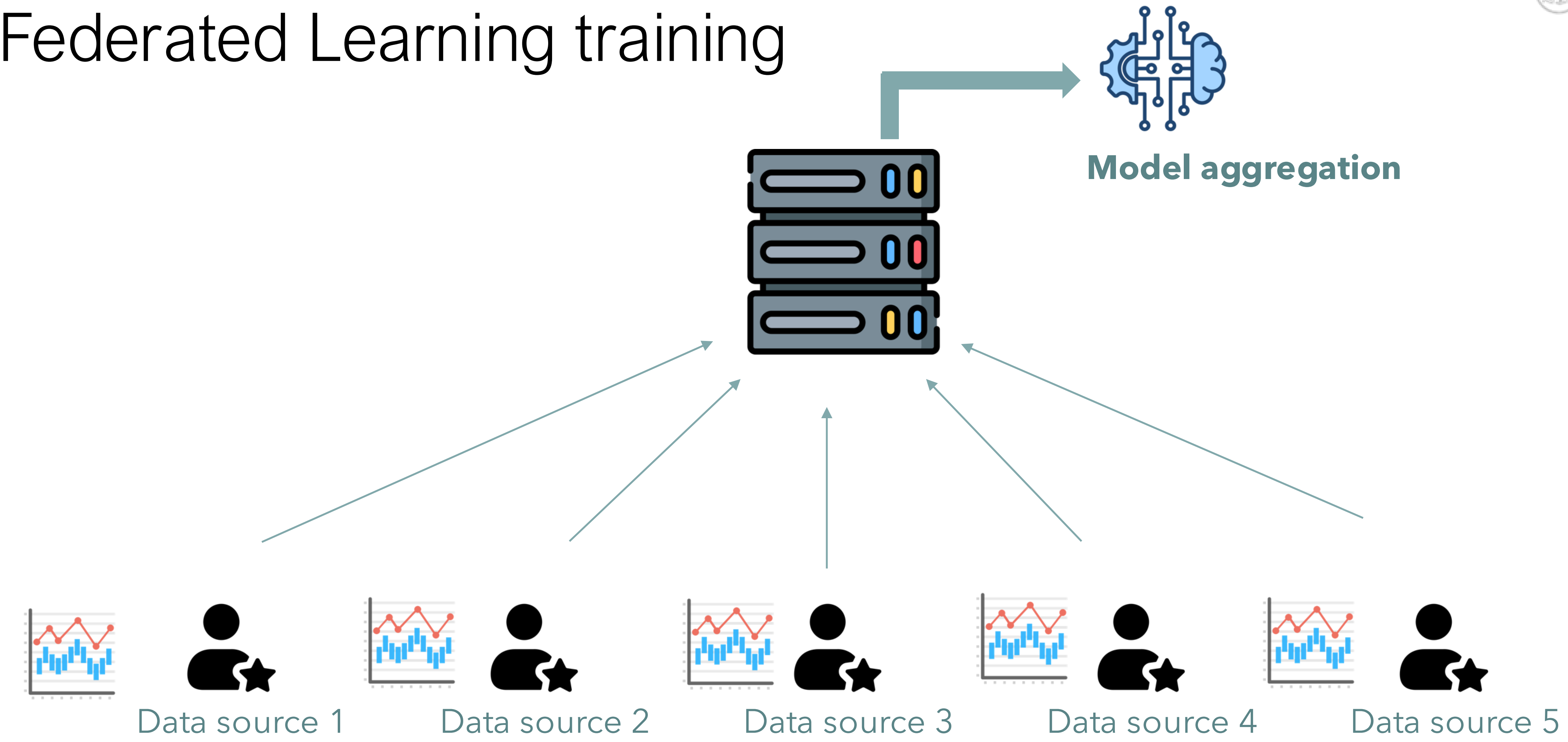
Federated Learning training



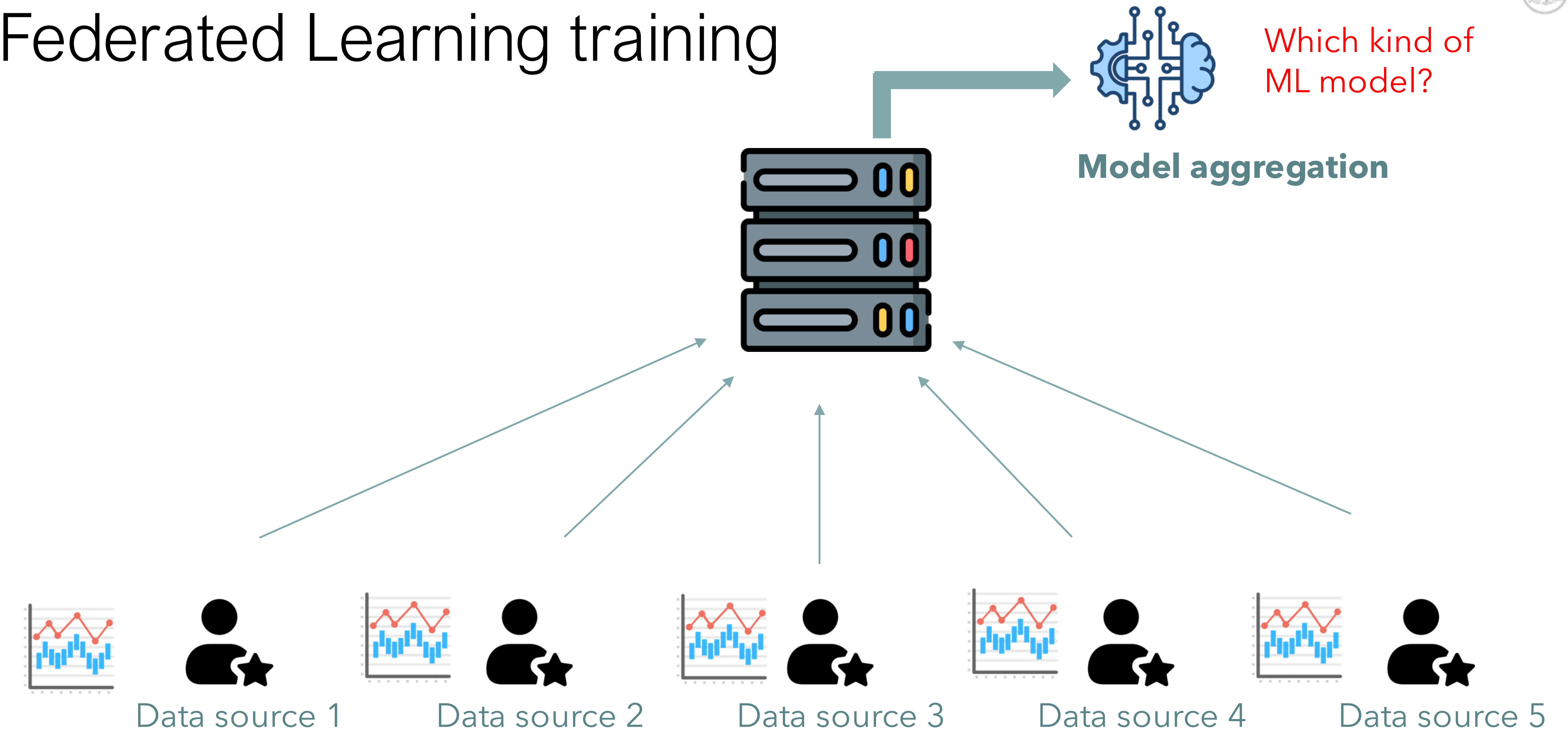
Federated Learning training



Federated Learning training



Federated Learning training



Which are the characteristics of the data over the different clients?

Federated Learning Setup

Model type

- Neural Networks
- Decision-Tree based Ensemble

Based on the model type, the way in which the federated training works is different

Data characteristics

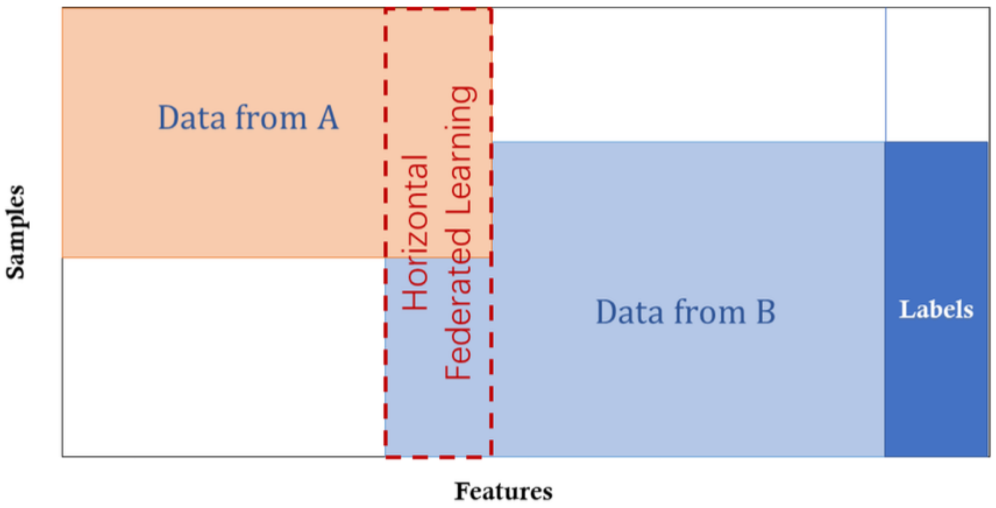
- Different data sources share the same features space: **Horizontal FL**
- Different data sources share the same sample space: **Vertical FL**

Federated Learning Setup

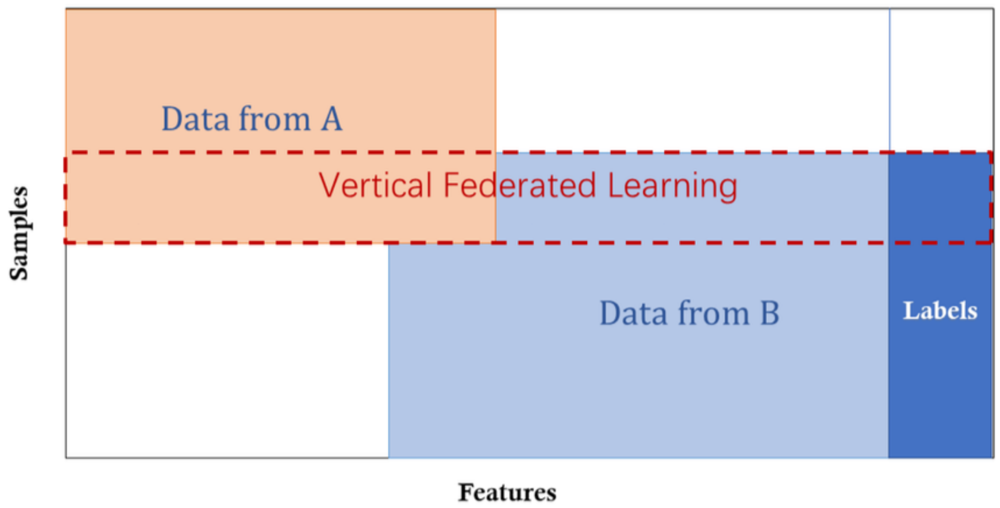
Data characteristics

Horizontal FL : Different data sources share the same features space

Vertical FL: Different data sources share the same sample space



(a) Horizontal Federated Learning



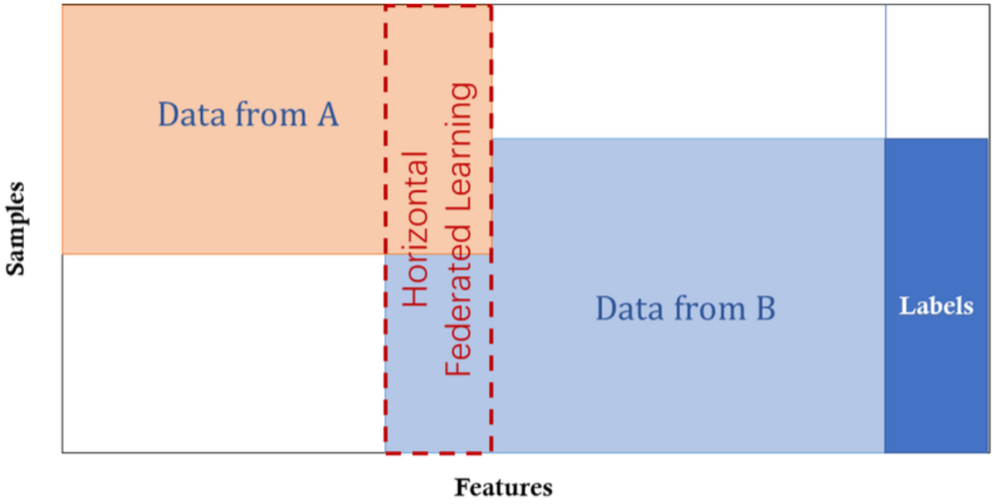
(b) Vertical Federated Learning

[1] Yang, Qiang, et al. "Federated machine learning: Concept and applications." *ACM Transactions on Intelligent Systems and Technology (TIST)* 10.2 (2019): 1-19.

Federated Learning Setup

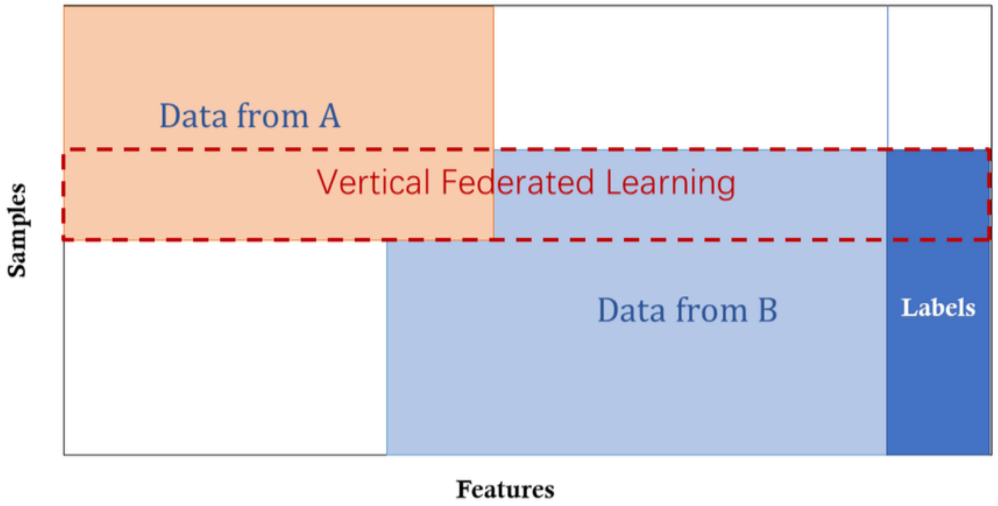
Data characteristics

Horizontal FL : Different data sources share the same features space



(a) Horizontal Federated Learning

Vertical FL: Different data sources share the same sample space



(b) Vertical Federated Learning

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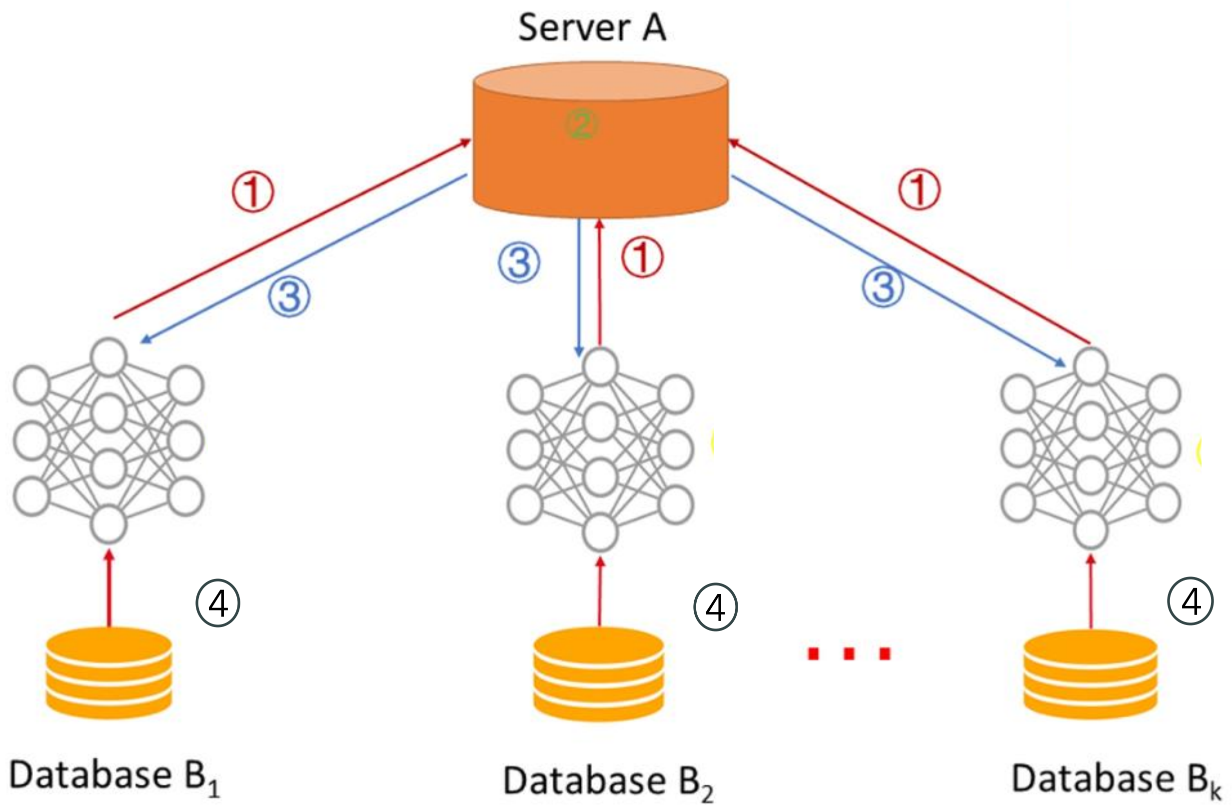
Horizontal Federated Learning – Neural Networks

1. Weights (or only gradients) are **encrypted** and **sent** from each client to the central server

2. The server **aggregates** the models with a pre-defined strategy (FedAvg)

3. The aggregated model is sent back to the clients

4. The clients can **evaluate** the aggregated model over their own data



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Horizontal Federated Learning – Performance

Typically, Federated models improve the performance of models trained only on local data, but they rarely reach the performance of a centralized training.

FL is a trade-off between **privacy** and **model performance**

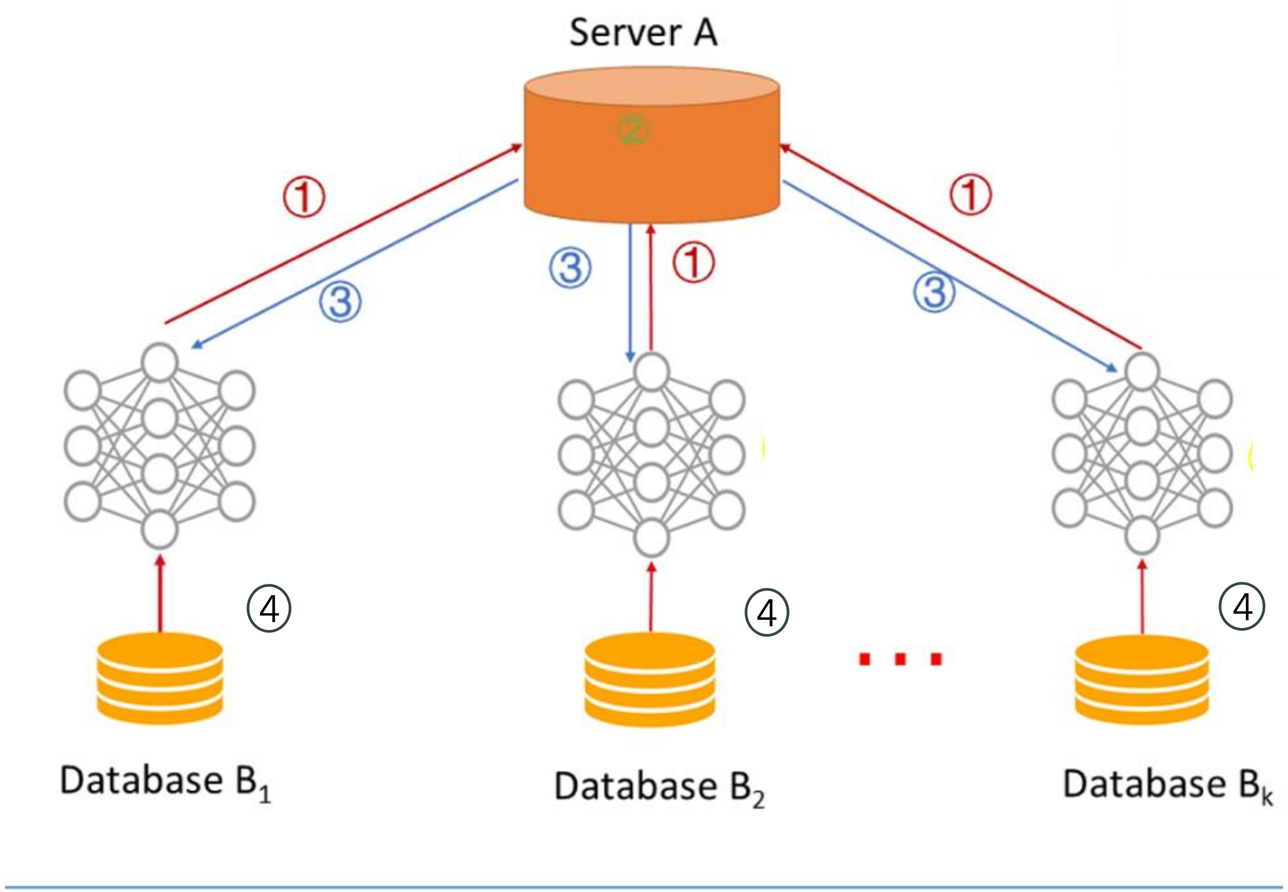
Perf.

Centralized model

Federated model

Local-only data model

Privacy



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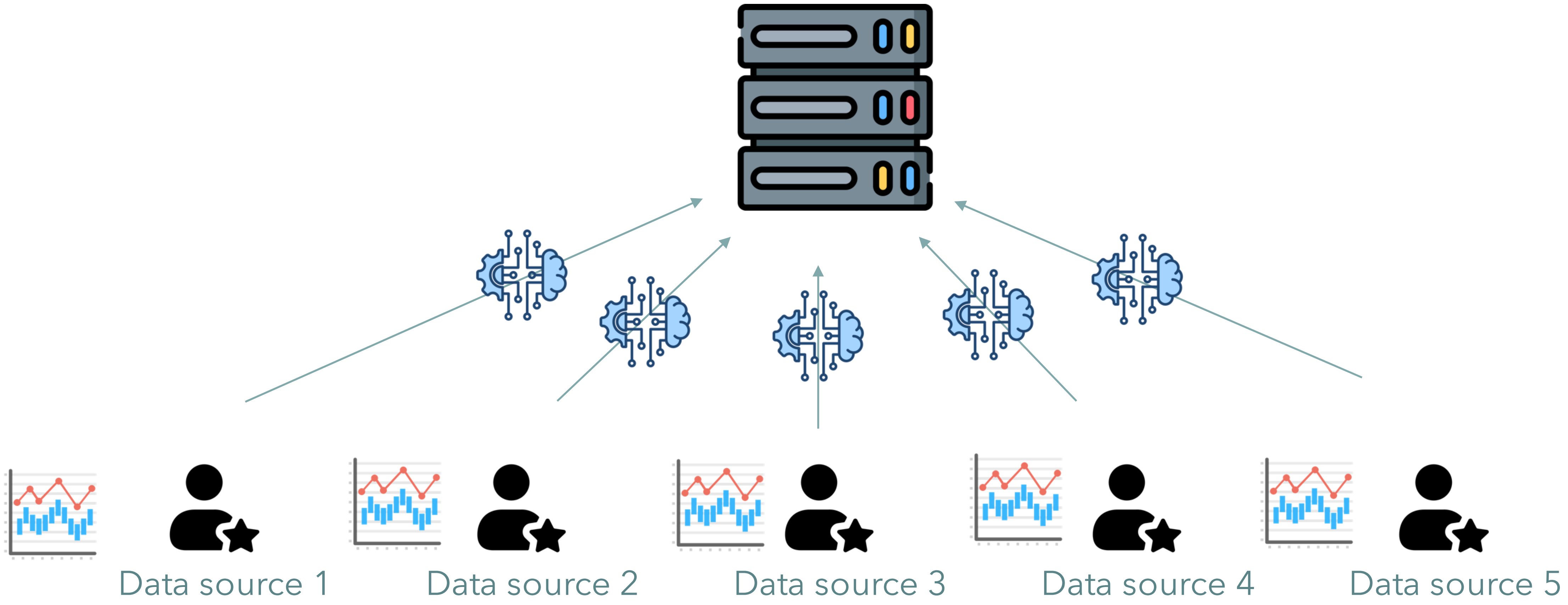
Horizontal Federated Learning – DT Ensembles



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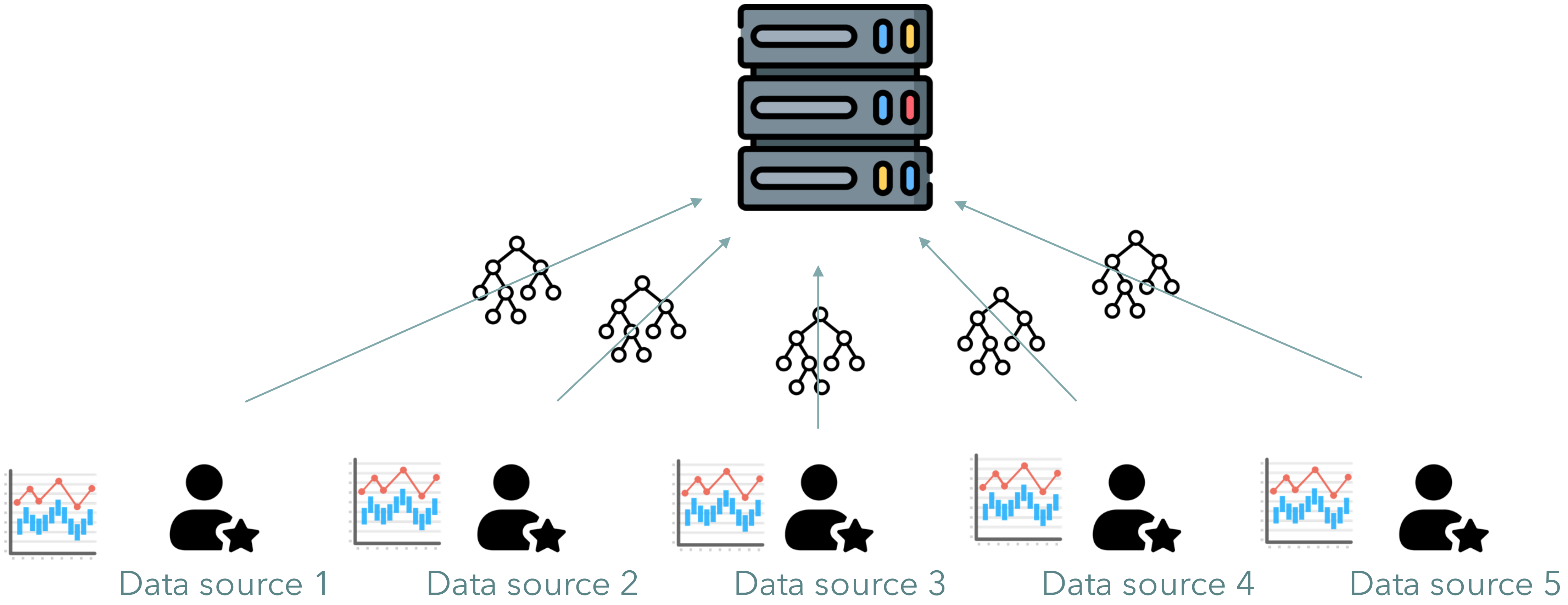

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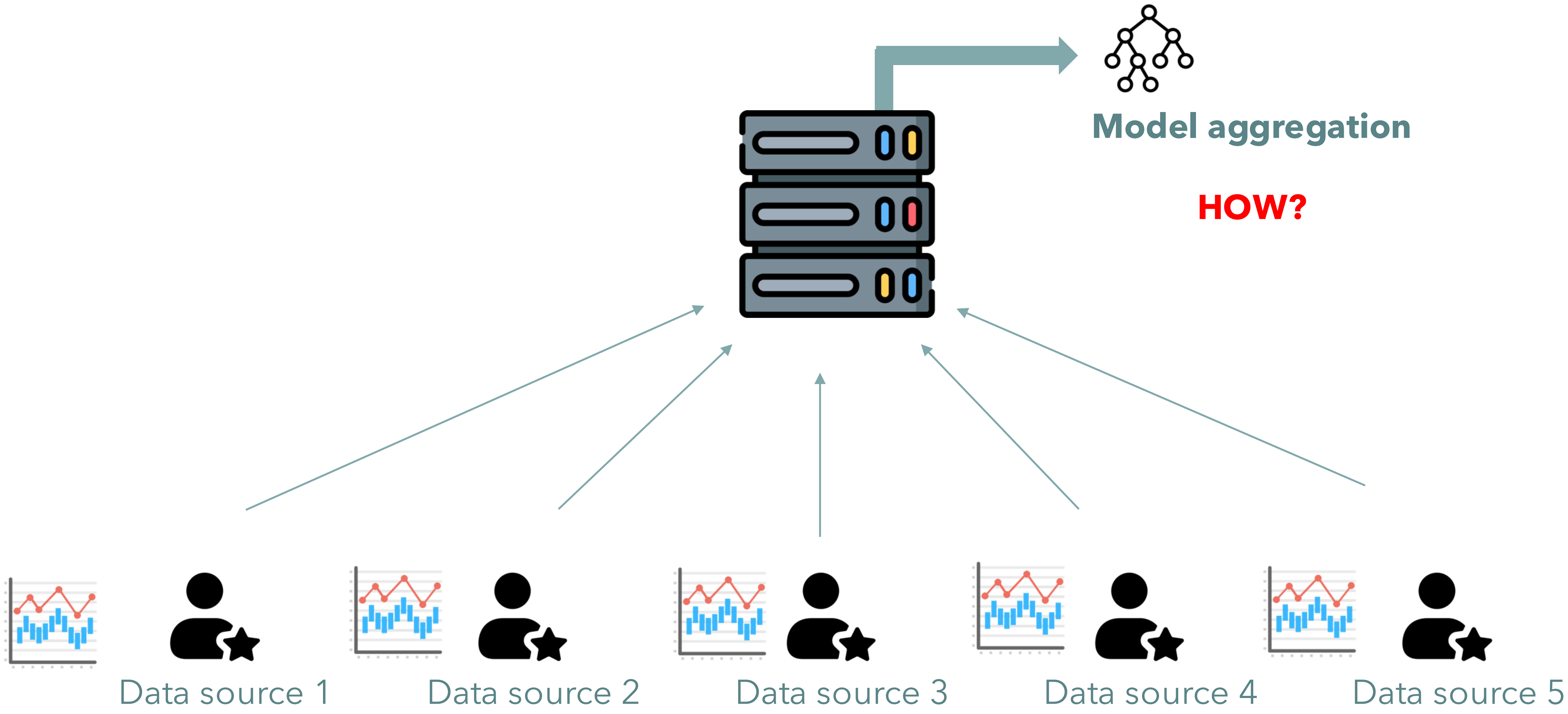

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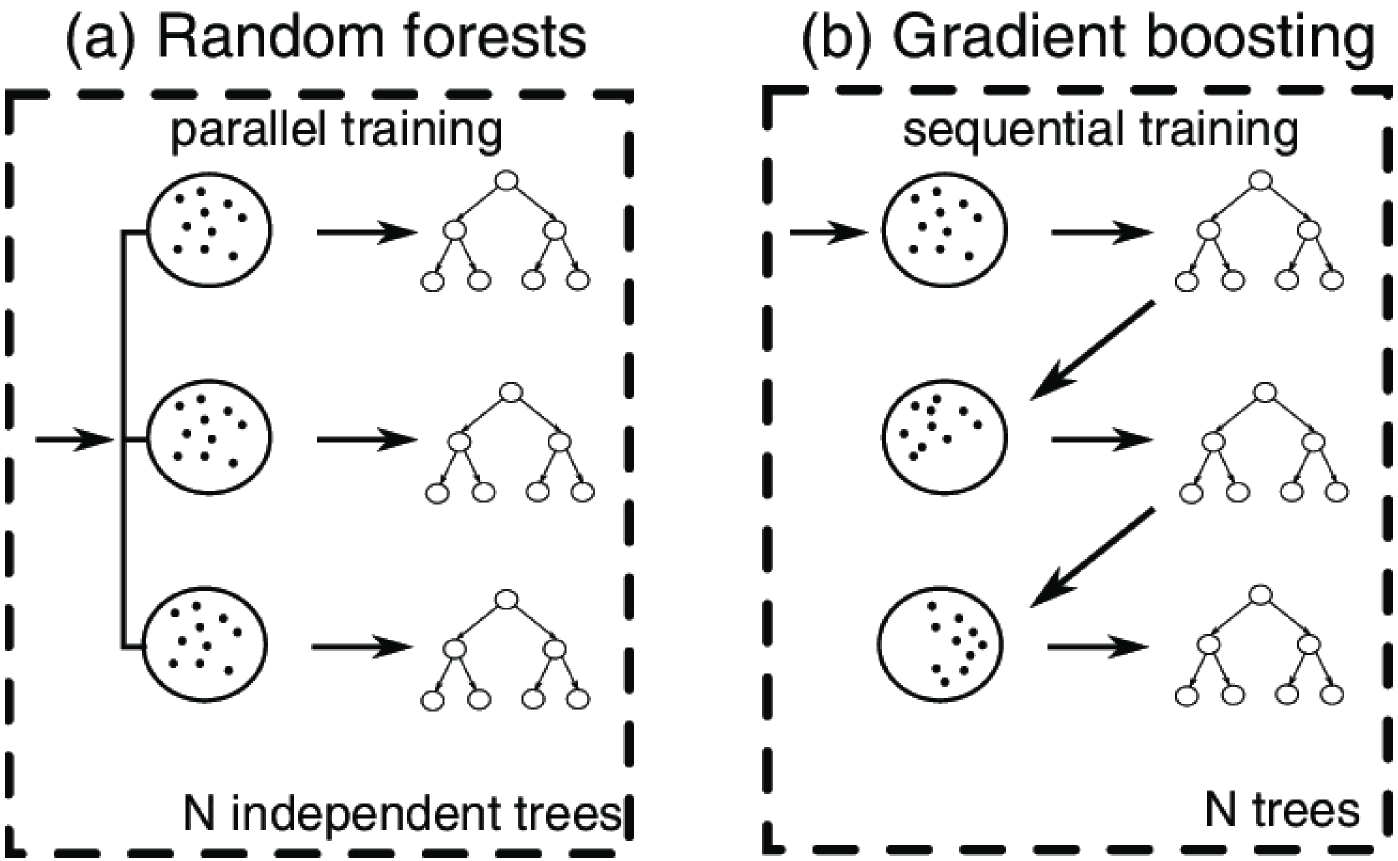
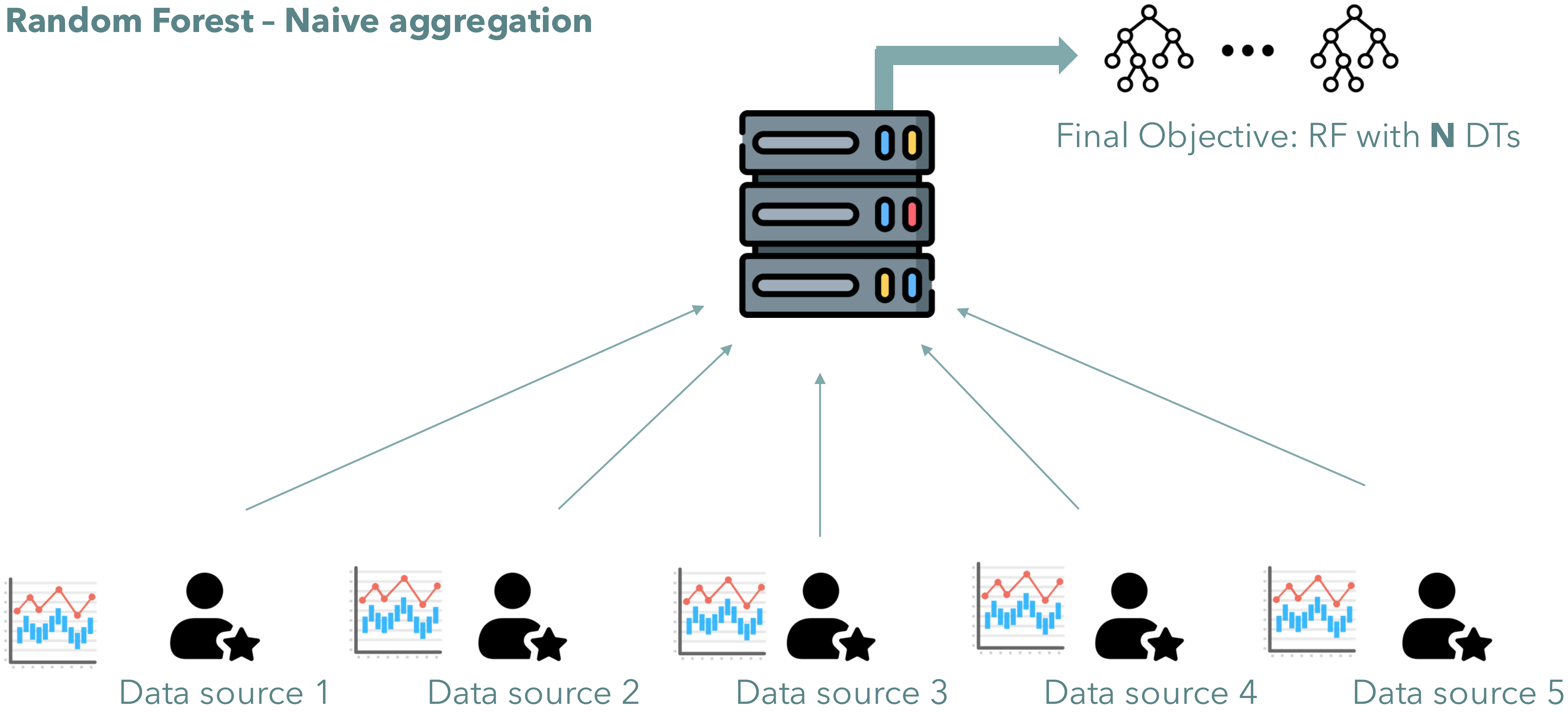


[2] Kowalek, P., Loch-Olszewska, H., & Szwabiński, J. (2019). Classification of diffusion modes in single-particle tracking data: Feature-based versus deep-learning approach. *Physical Review E*, *100*(3), 032410.

Horizontal Federated Learning – DT Ensembles

Random Forest - Naive aggregation



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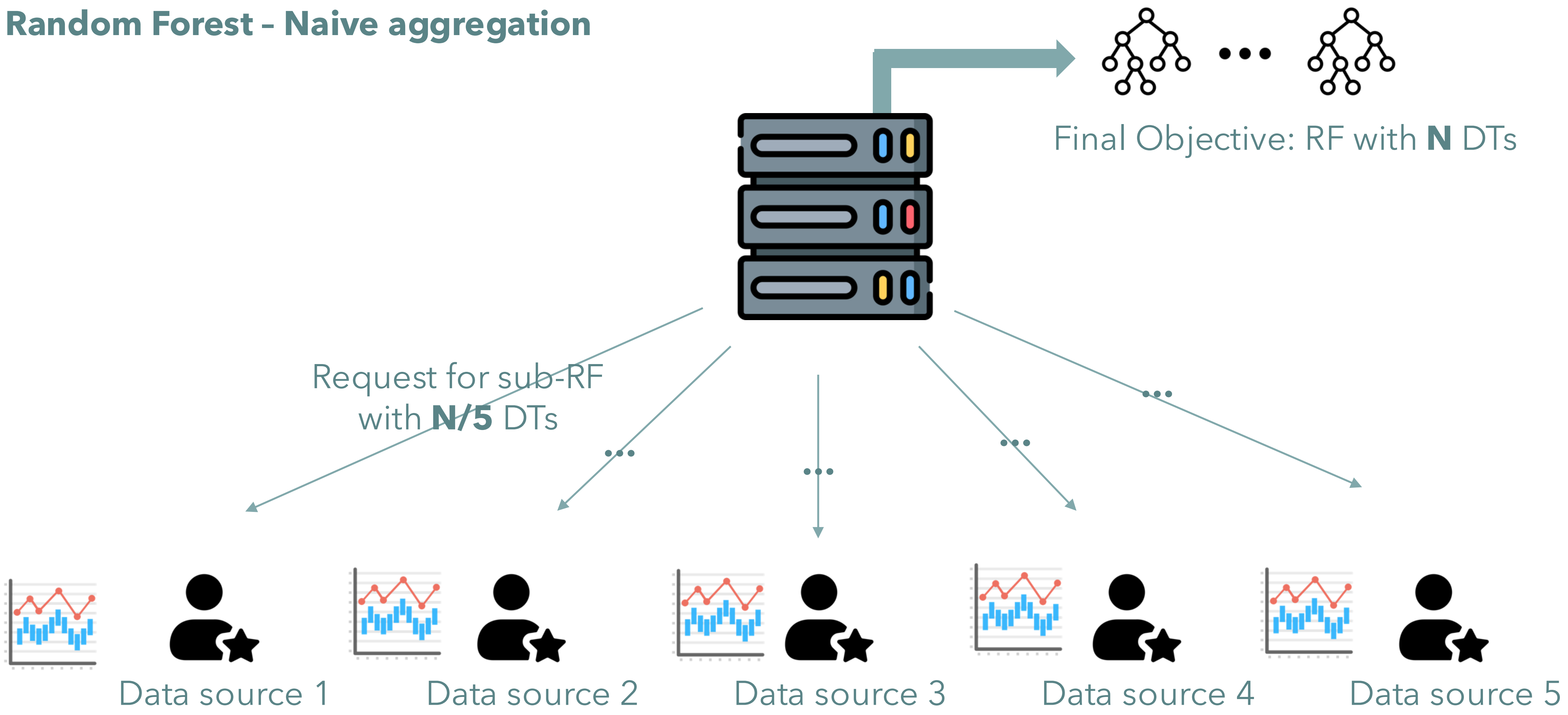

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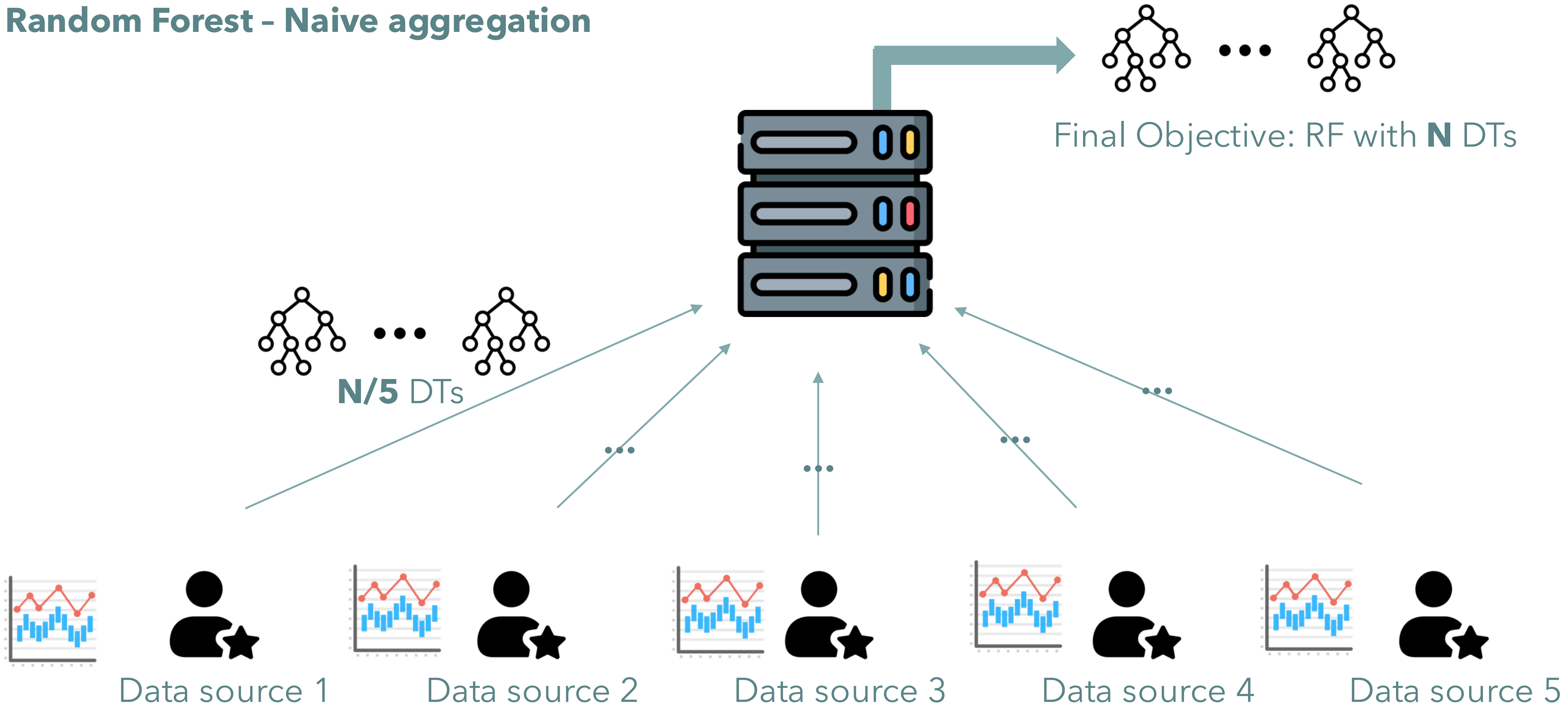

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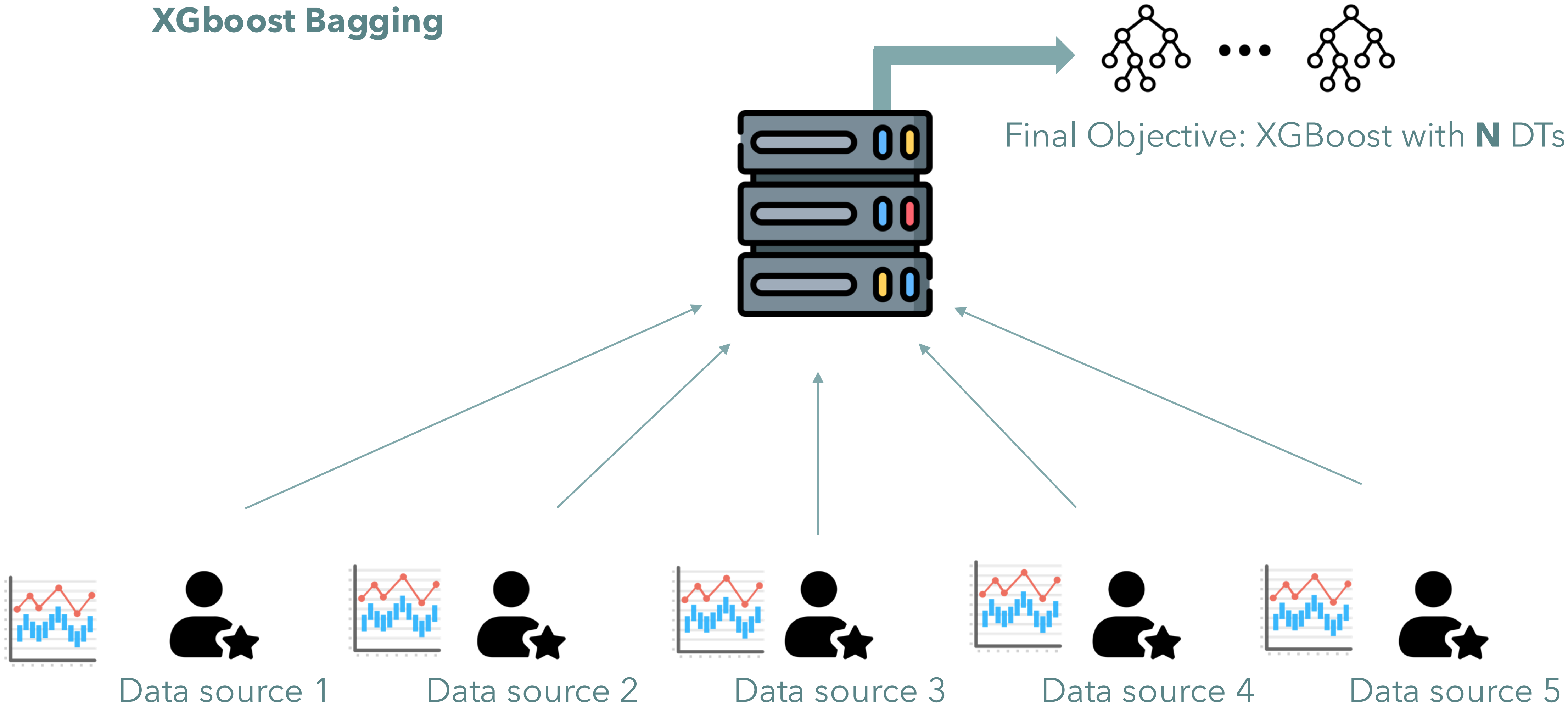
XGboost Bagging



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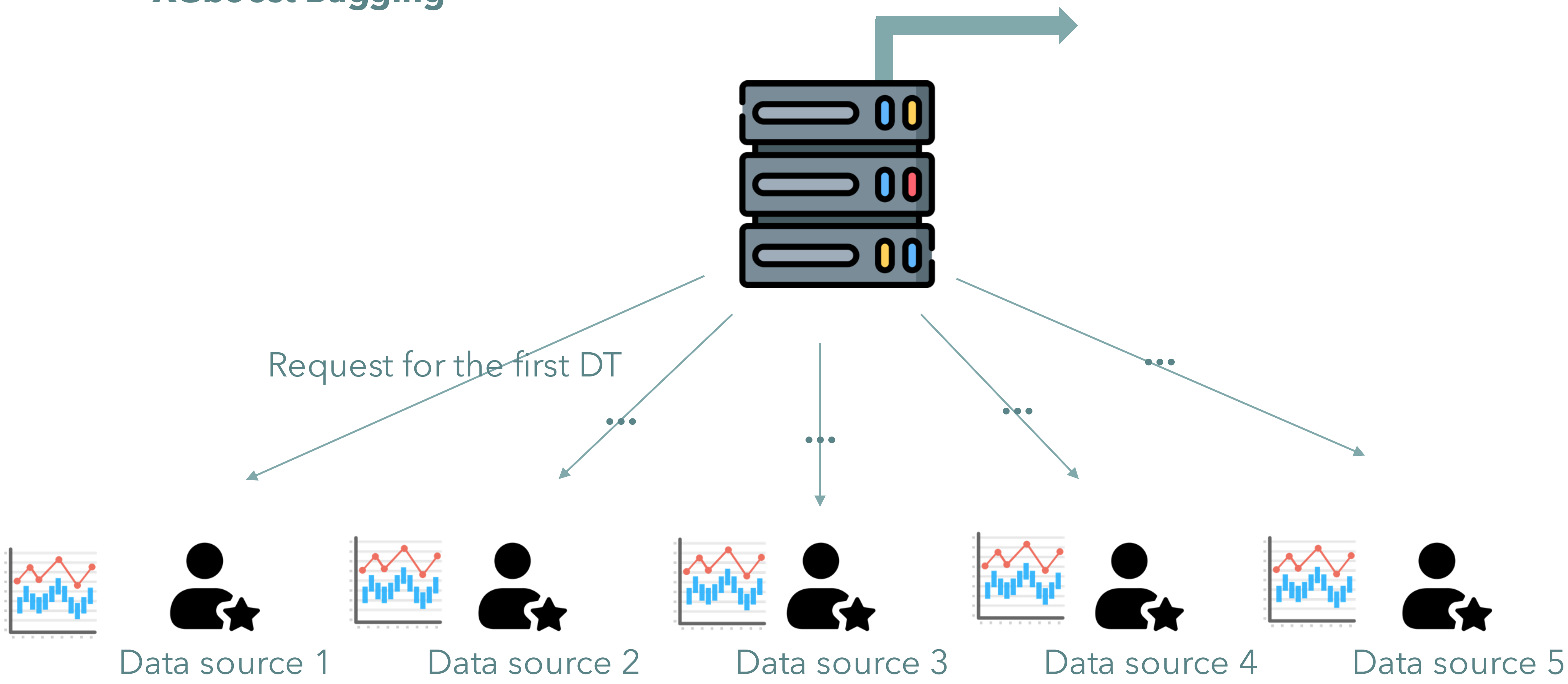

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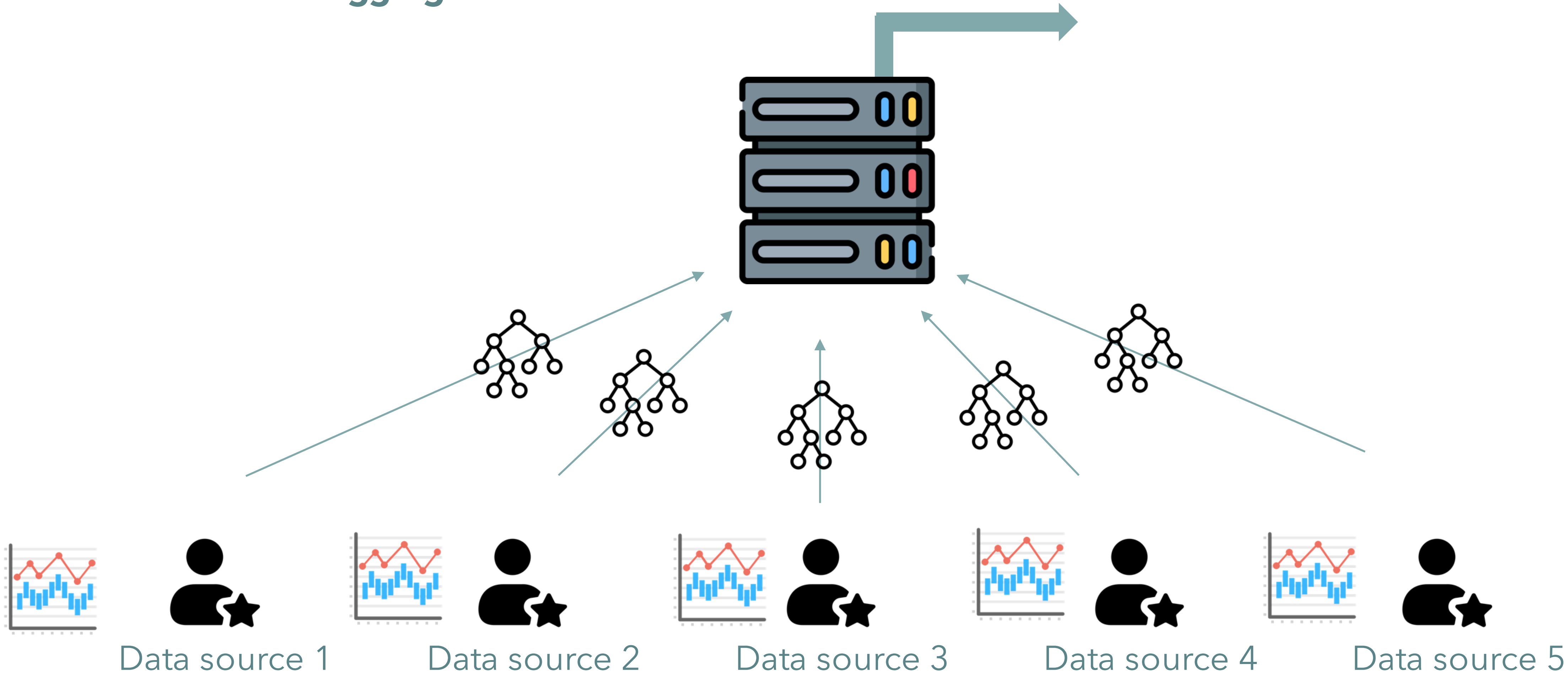

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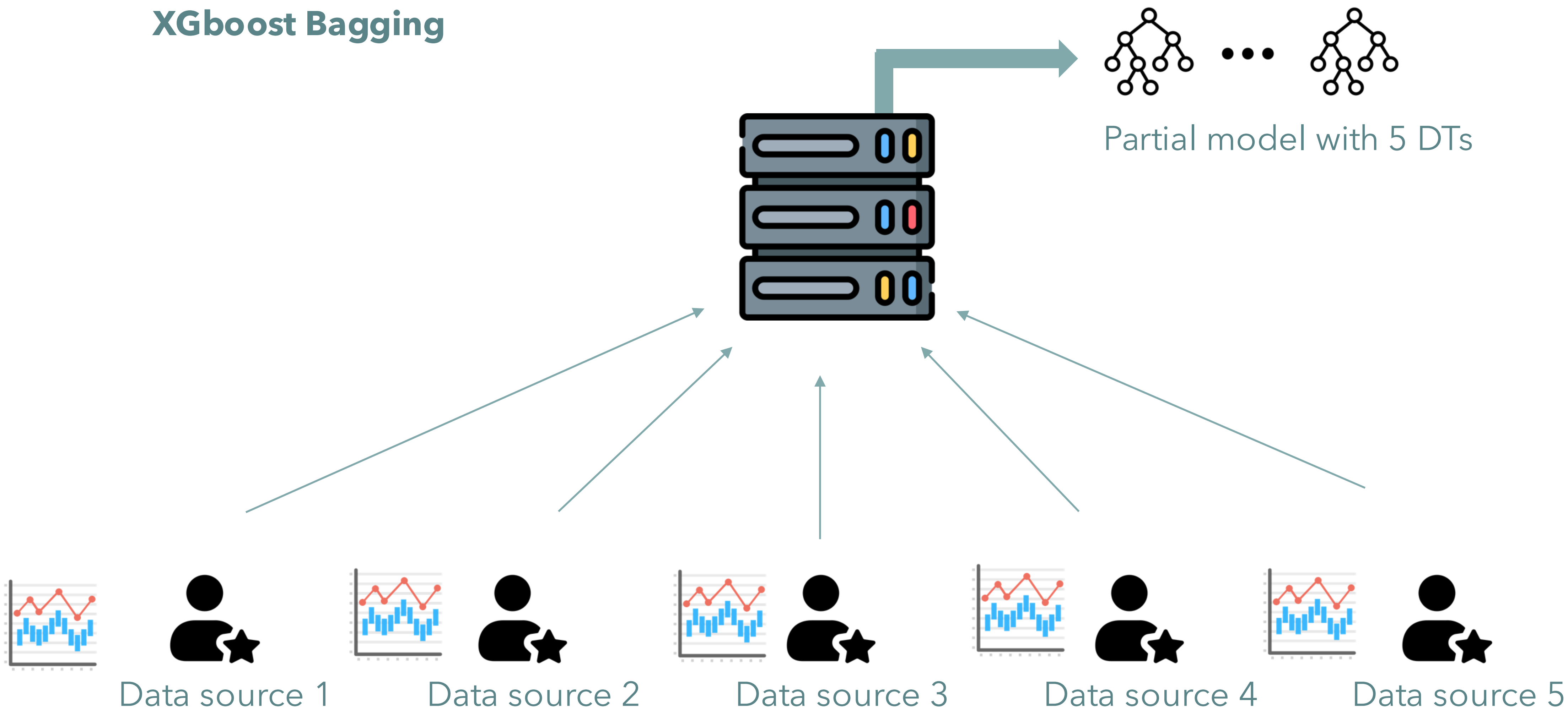

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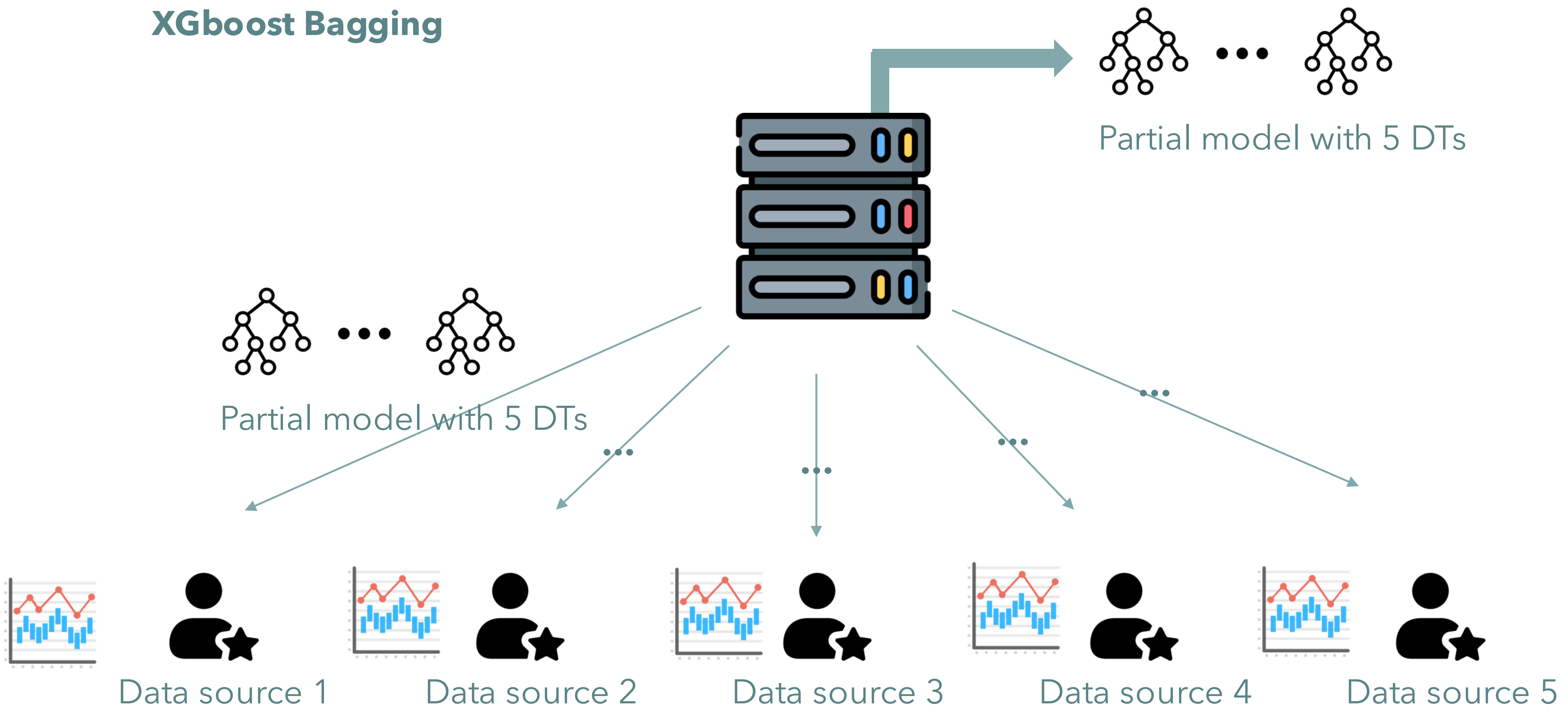

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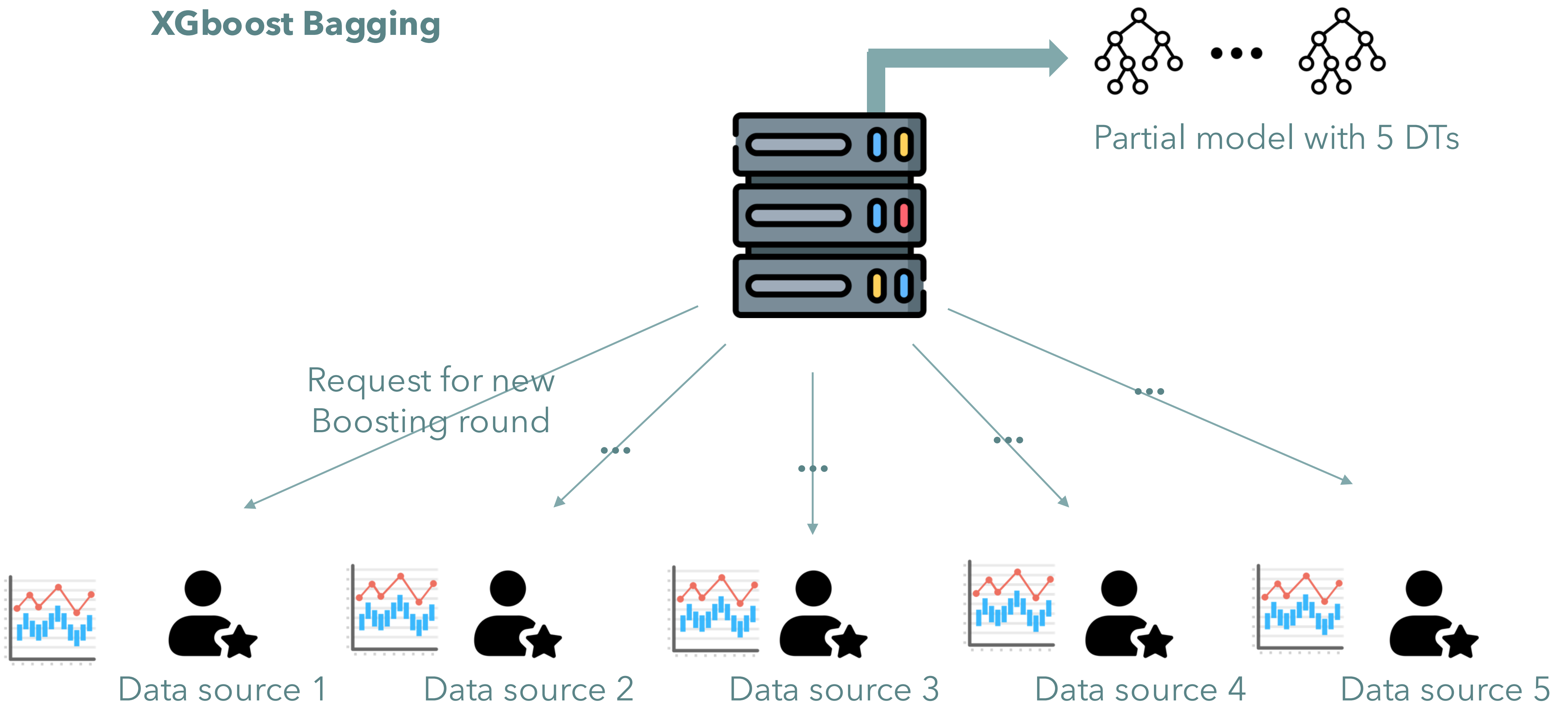

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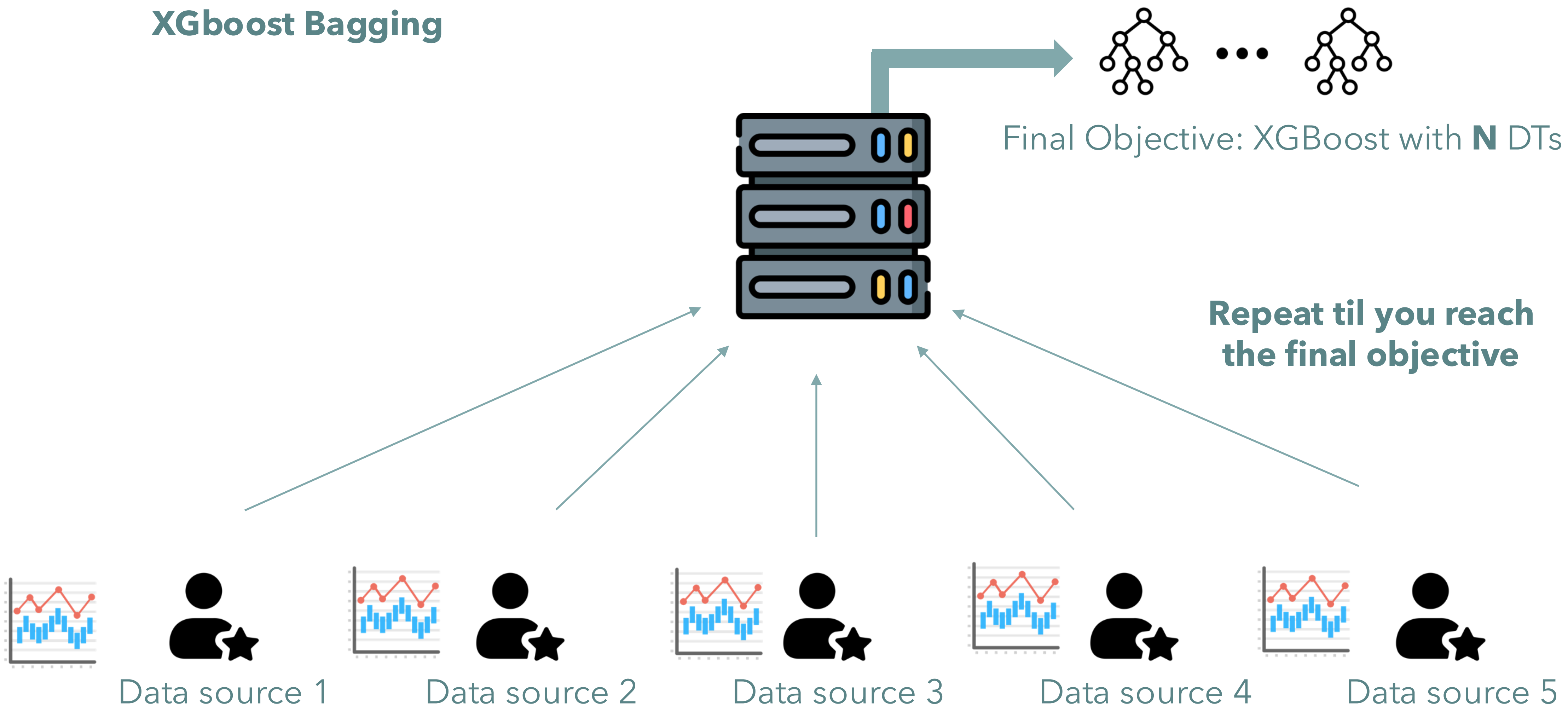

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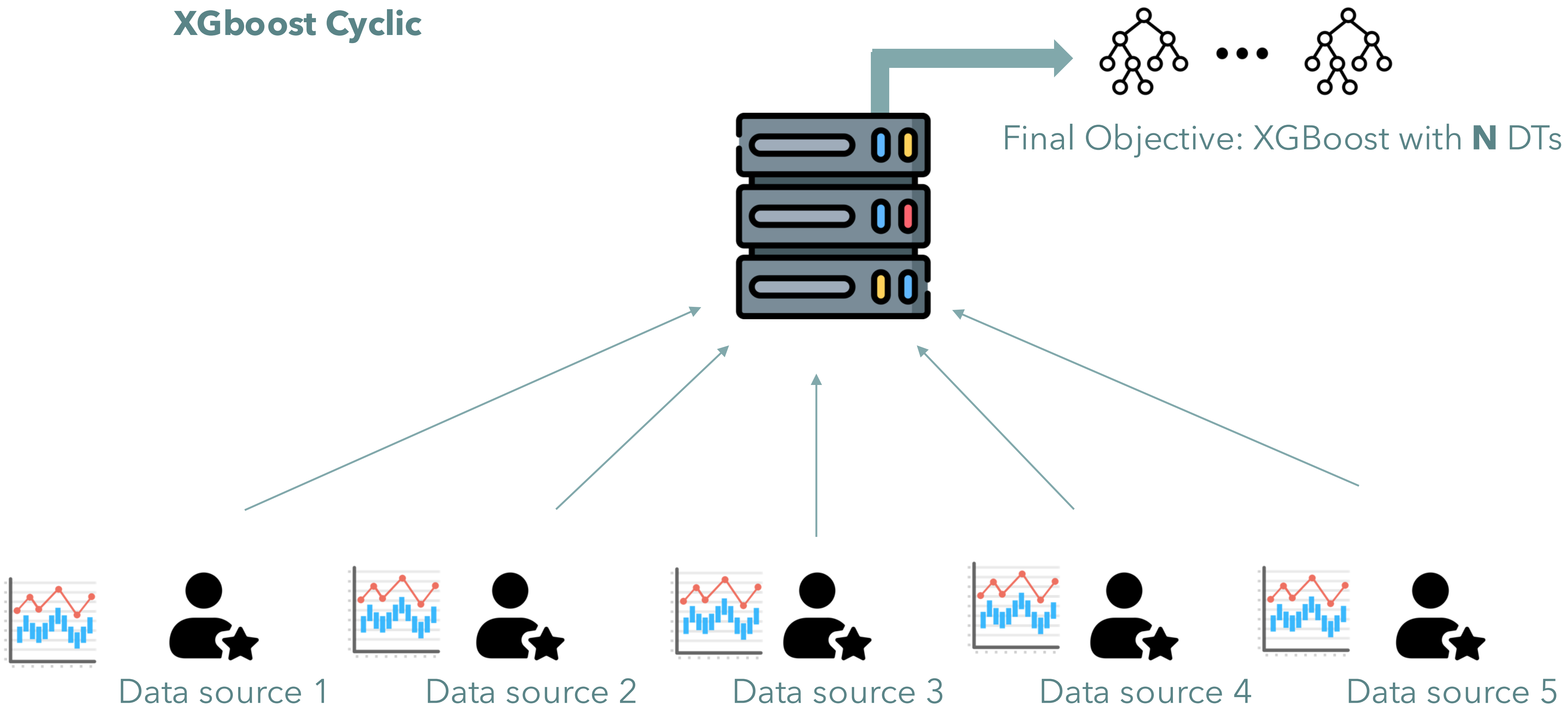

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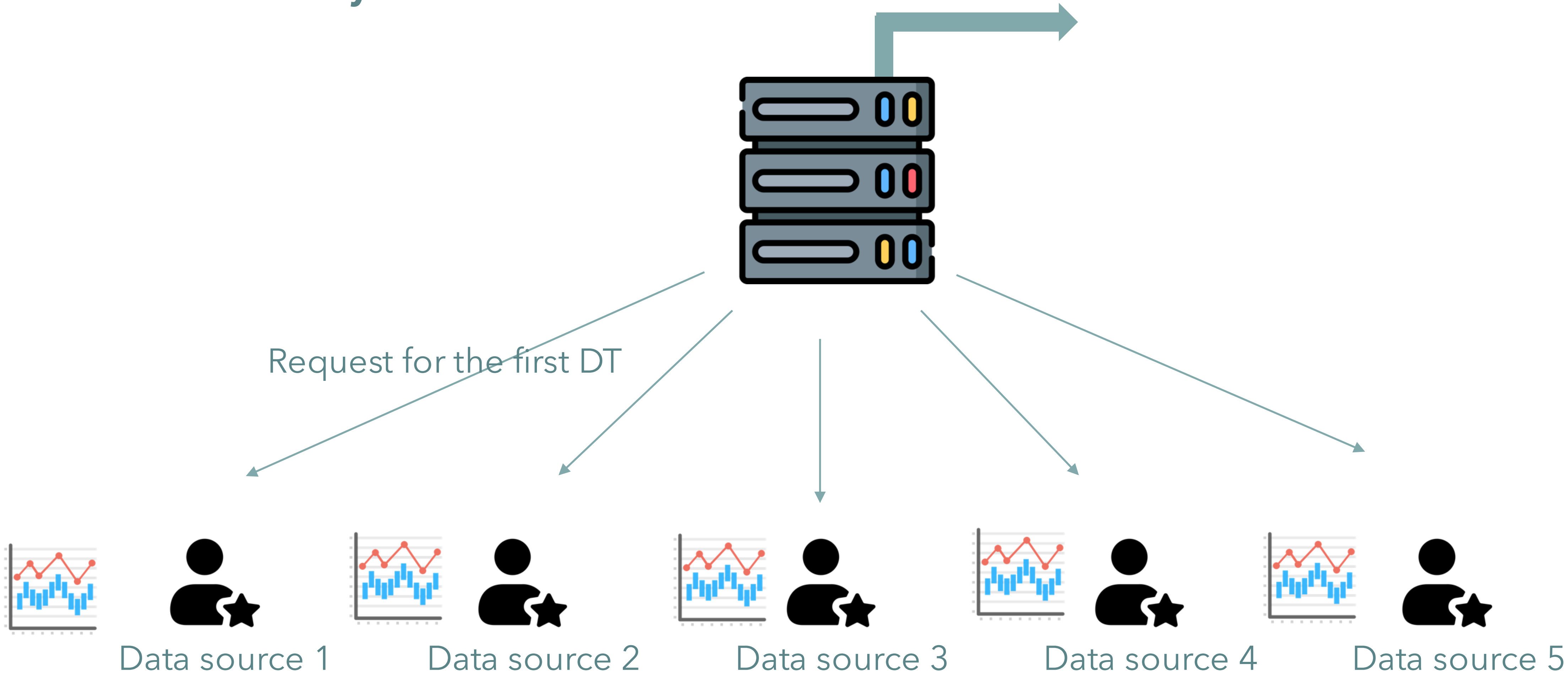
Horizontal Federated Learning – DT Ensembles

XGboost Cyclic



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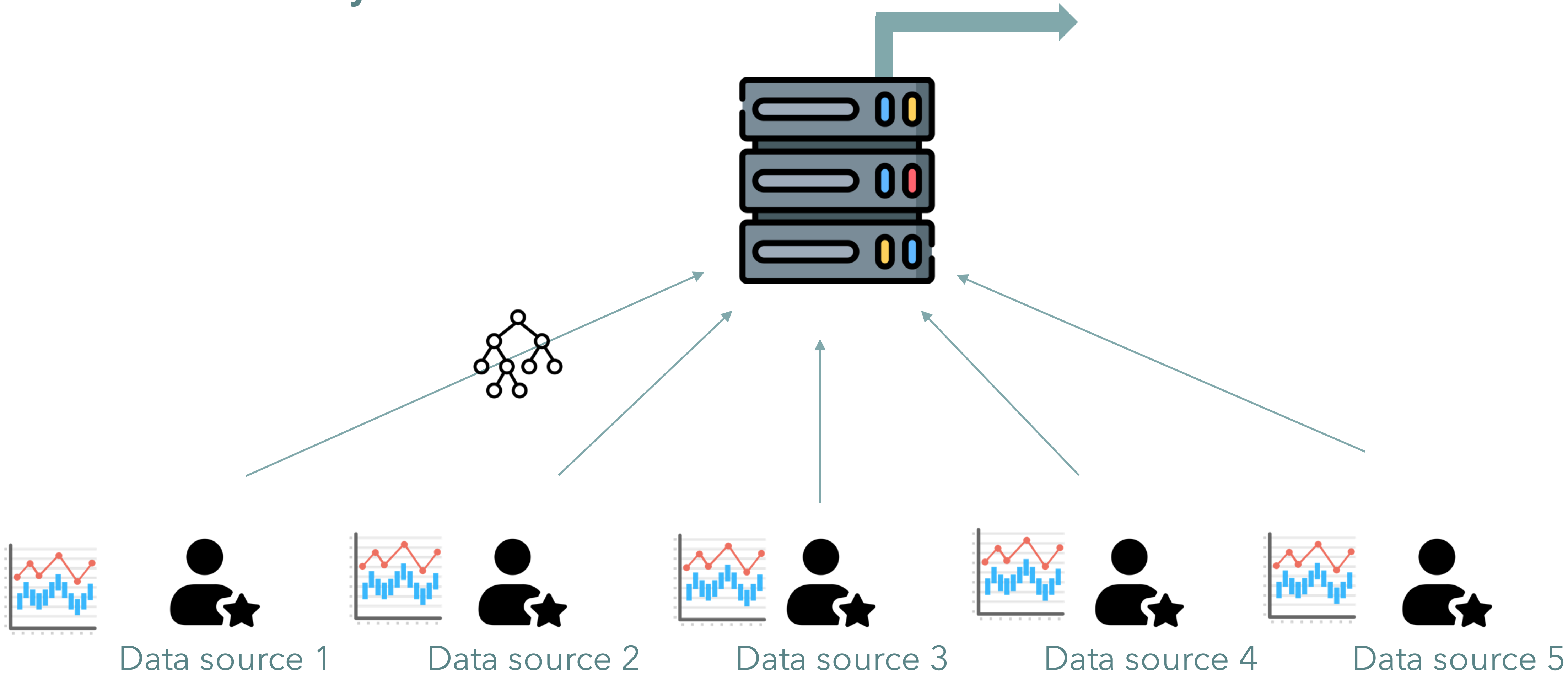

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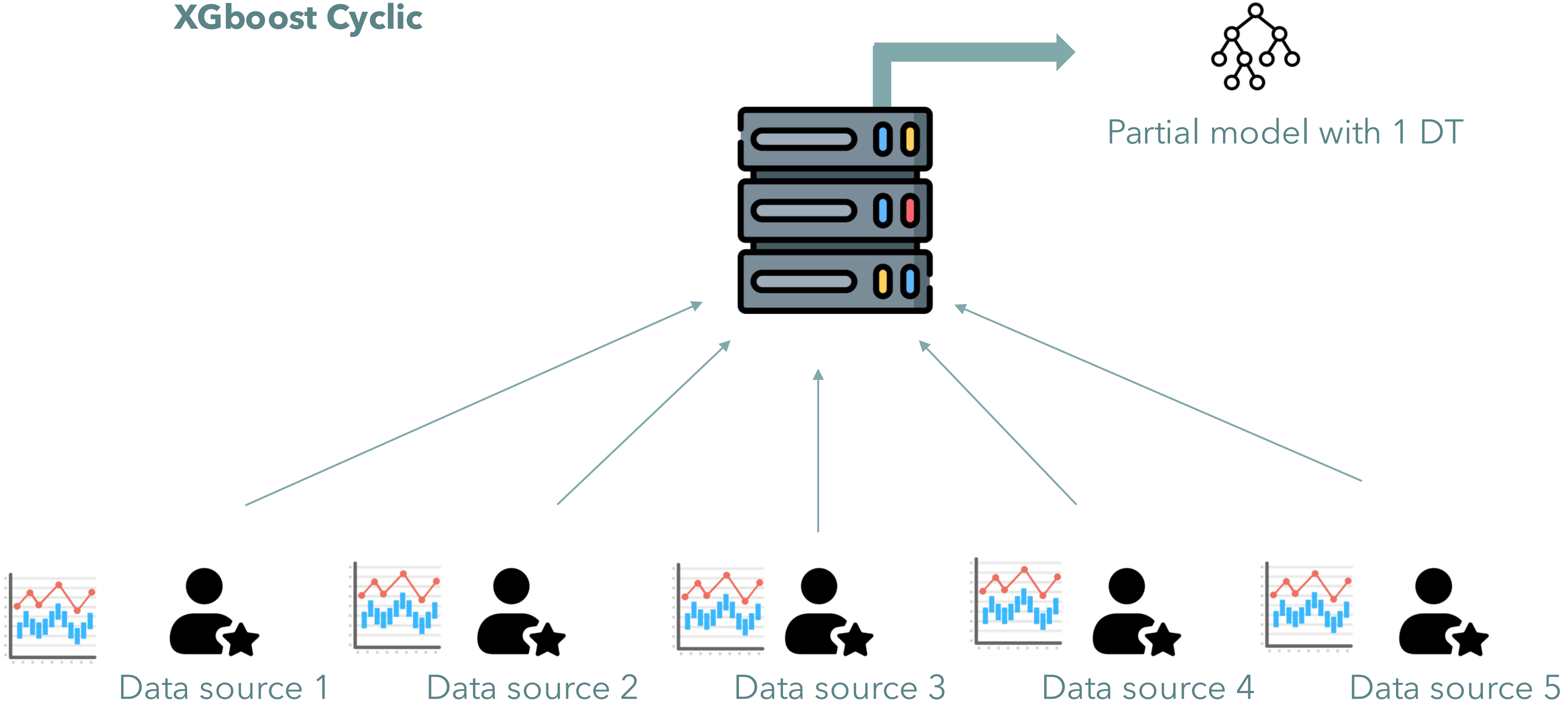

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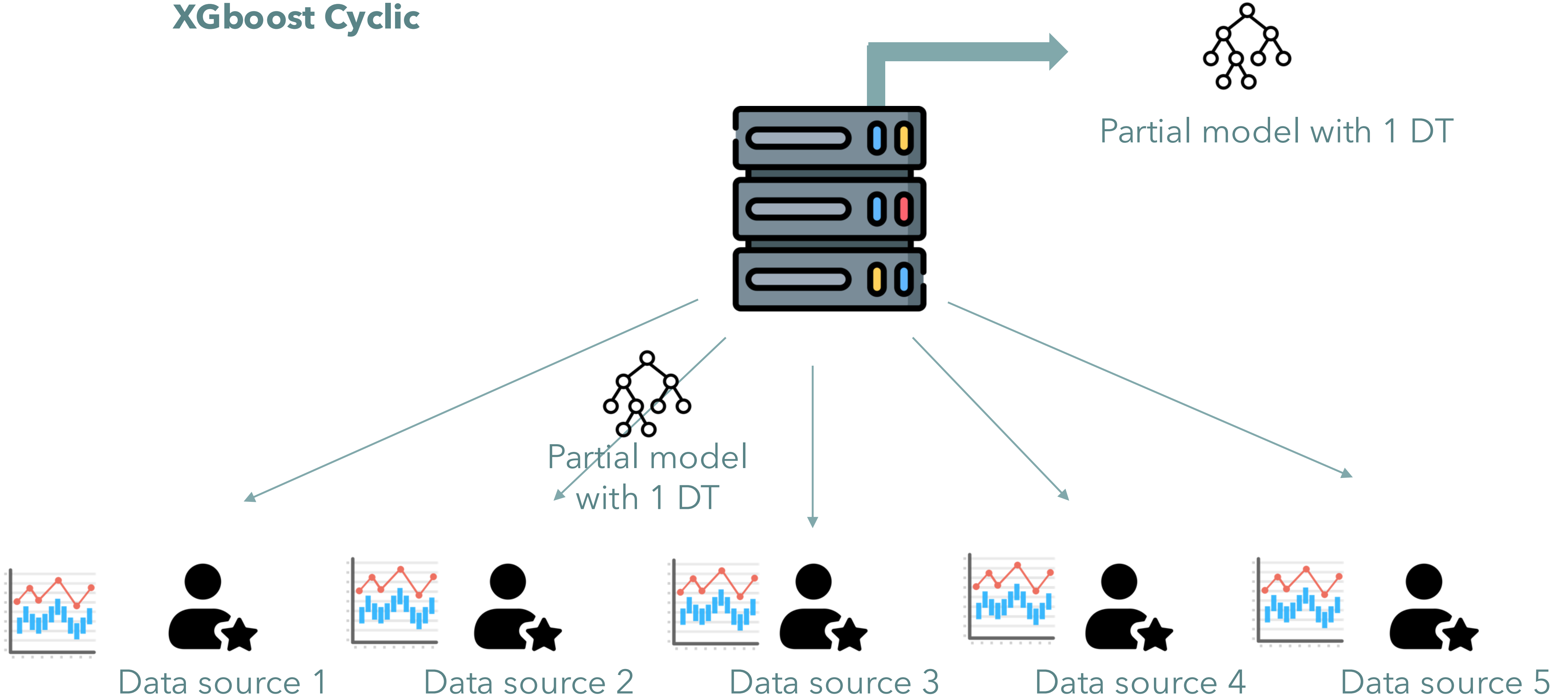

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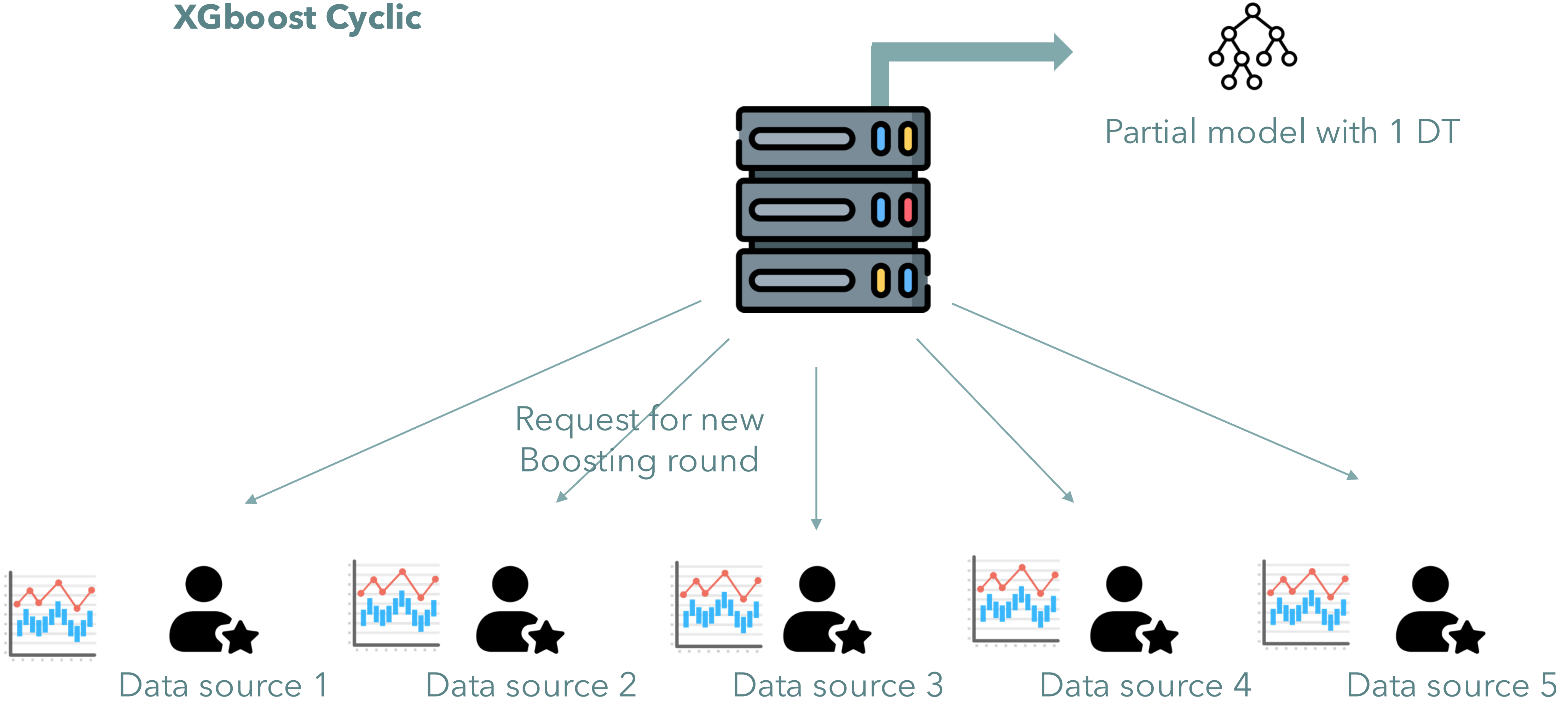

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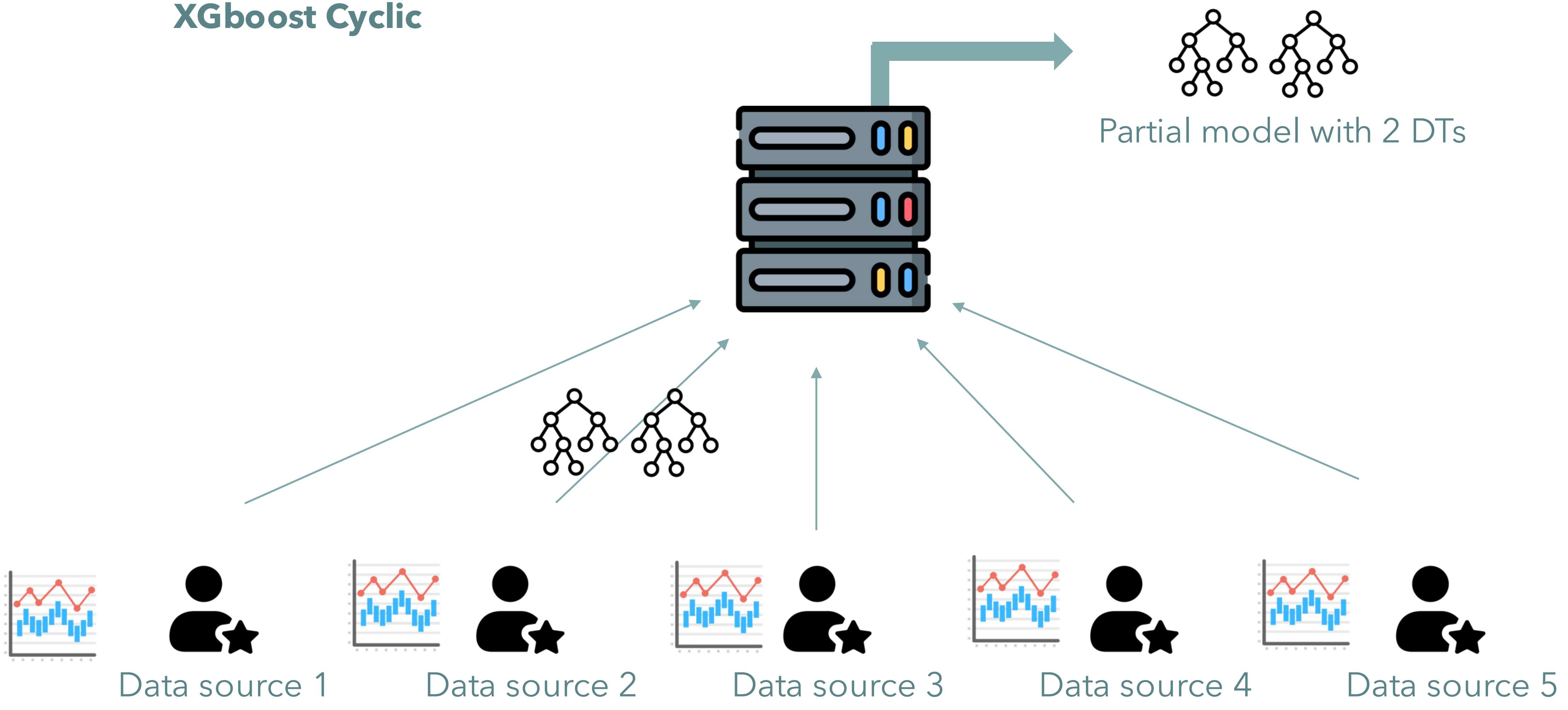

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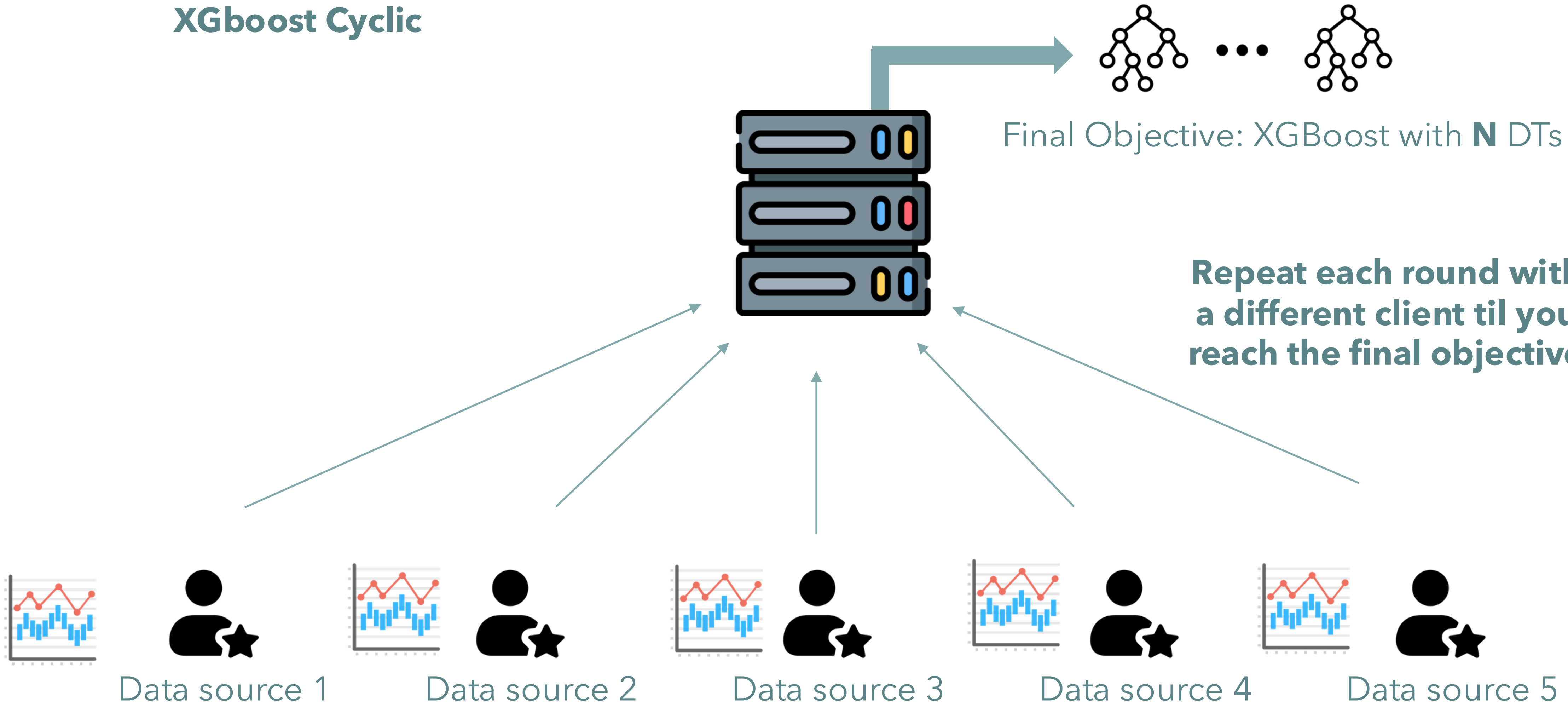
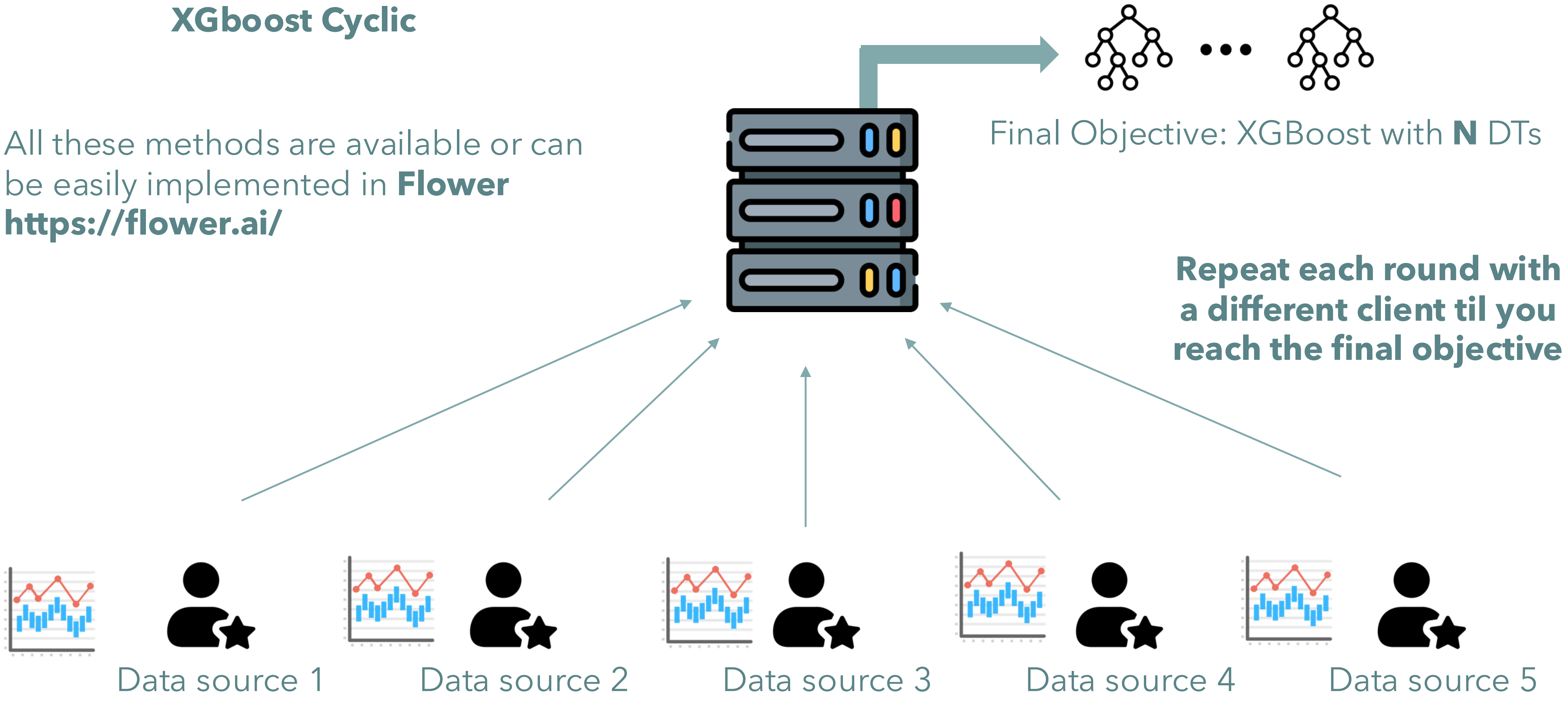


Repeat each round with a different client til you reach the final objective

Horizontal Federated Learning – DT Ensembles

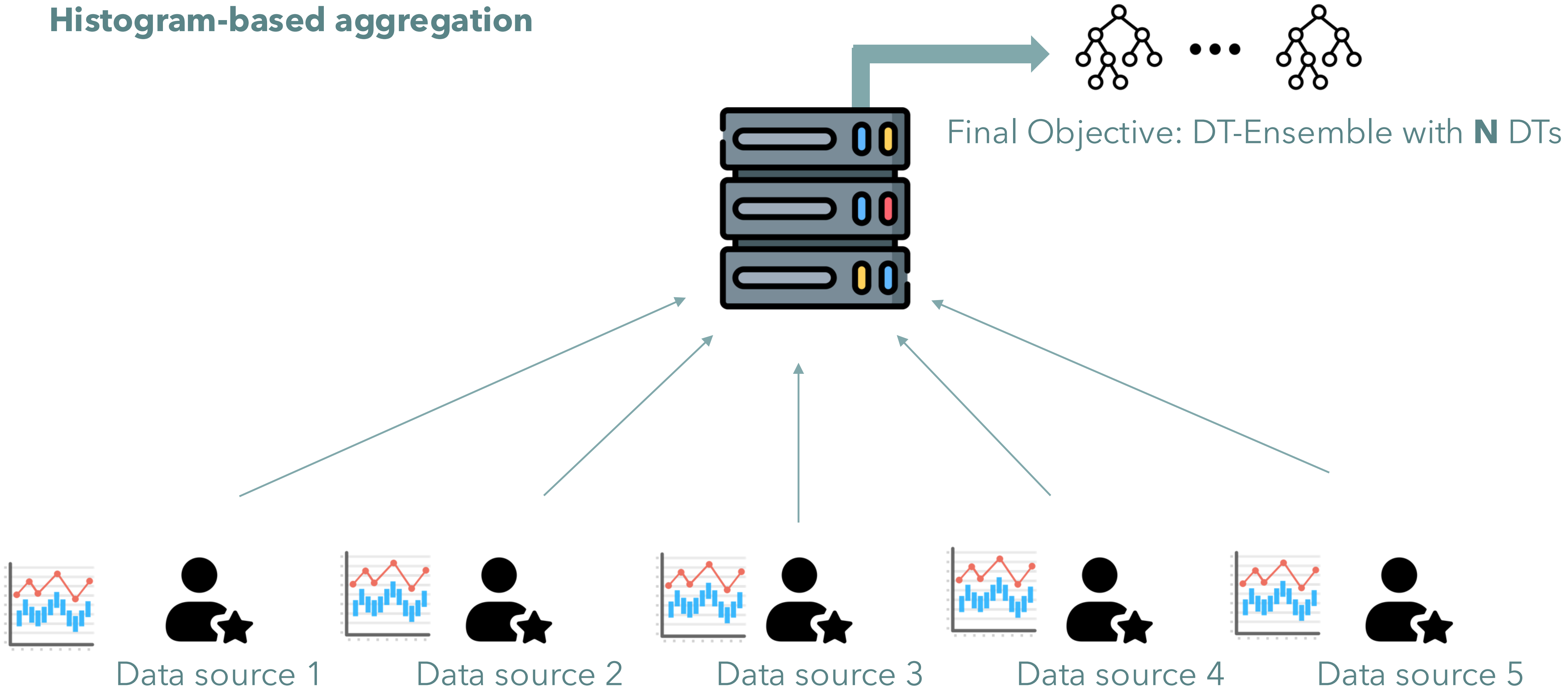
XGboost Cyclic

All these methods are available or can be easily implemented in **Flower** **https://flower.ai/**



Horizontal Federated Learning – DT Ensembles

Histogram-based aggregation



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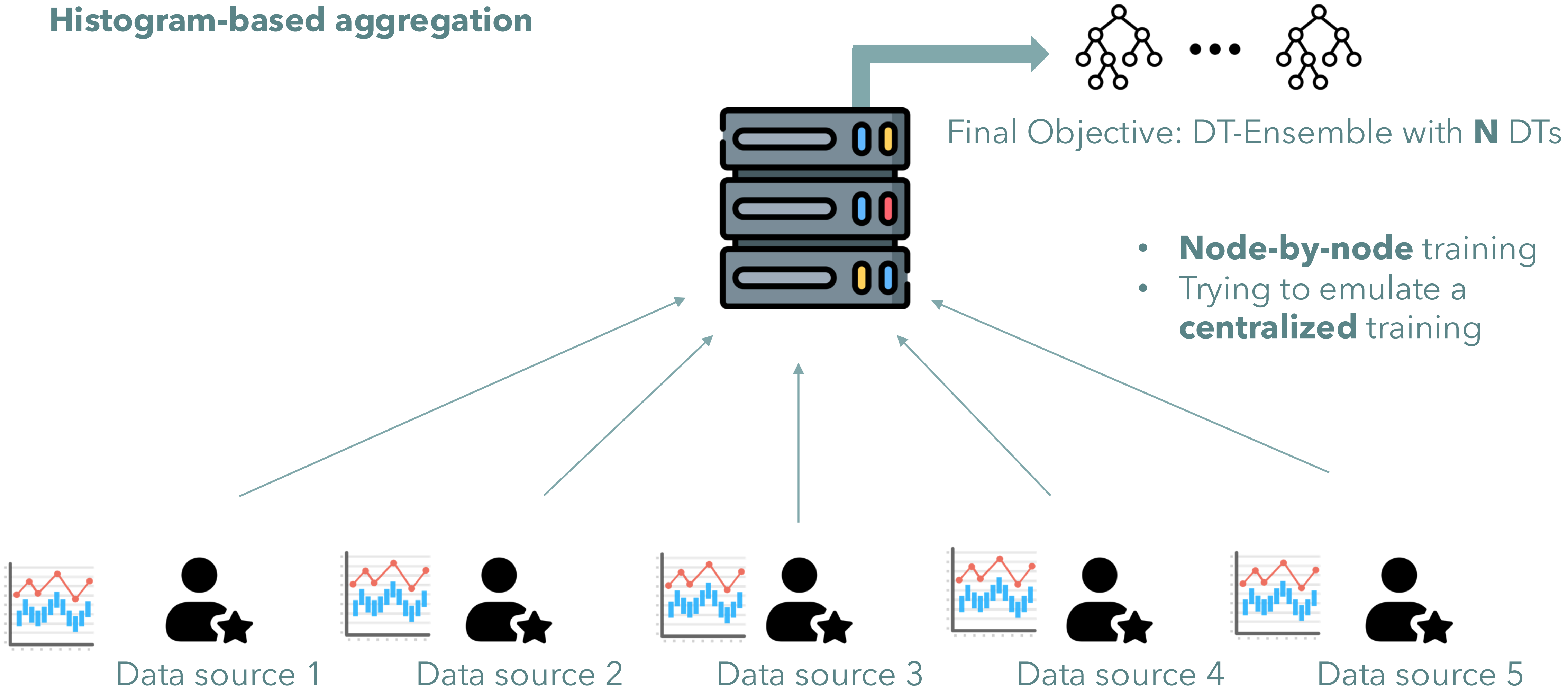
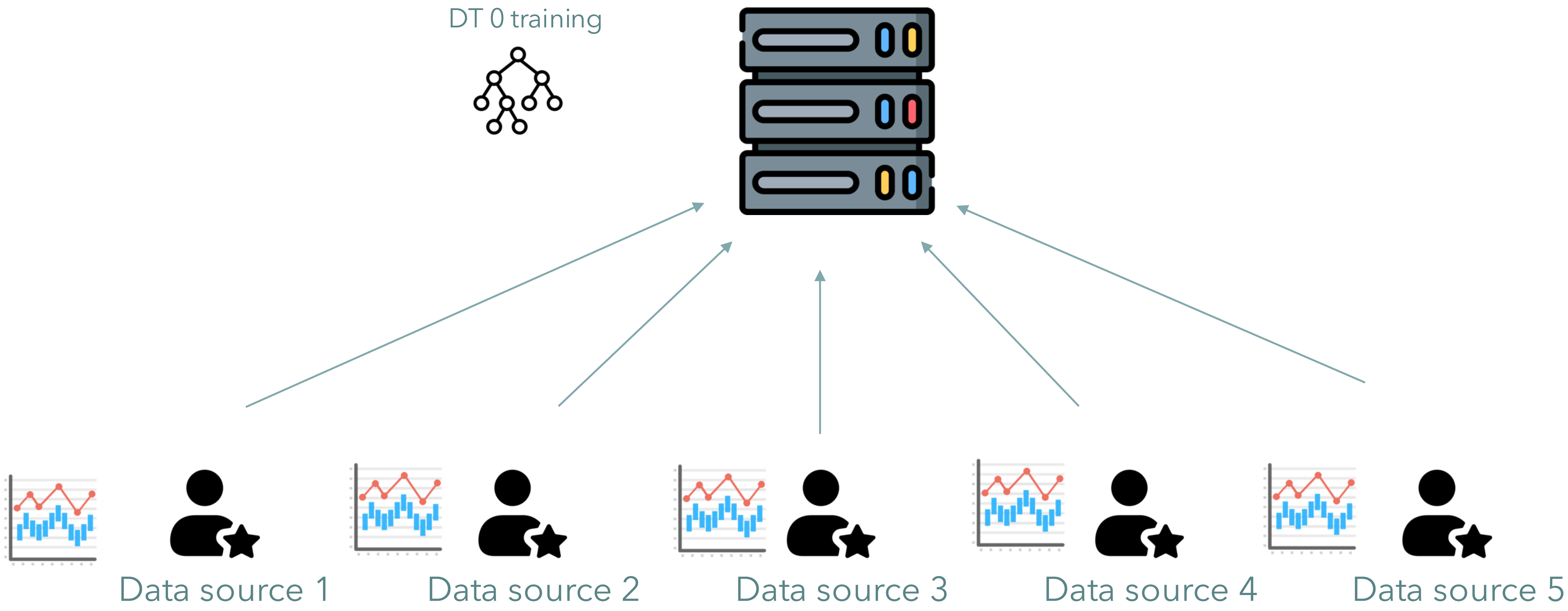


- **Node-by-node** training
- Trying to emulate a **centralized** training

Horizontal Federated Learning – DT Ensembles

Histogram-based aggregation



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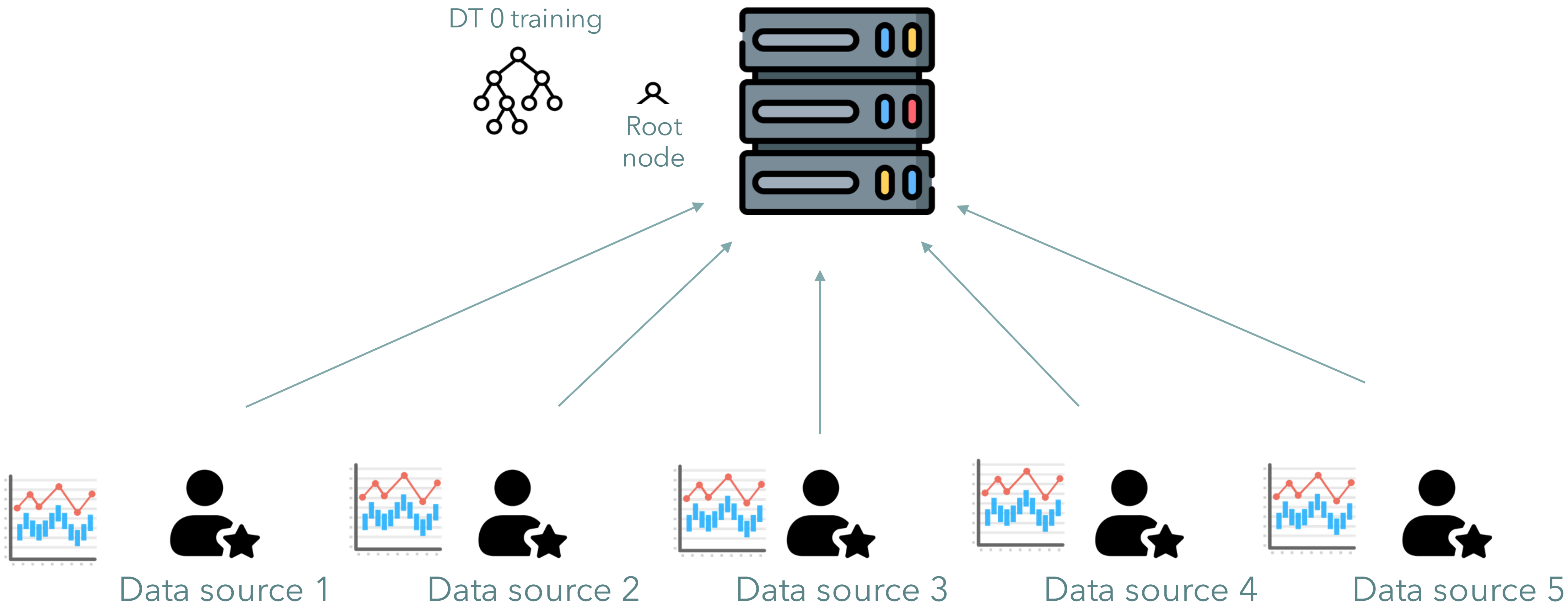

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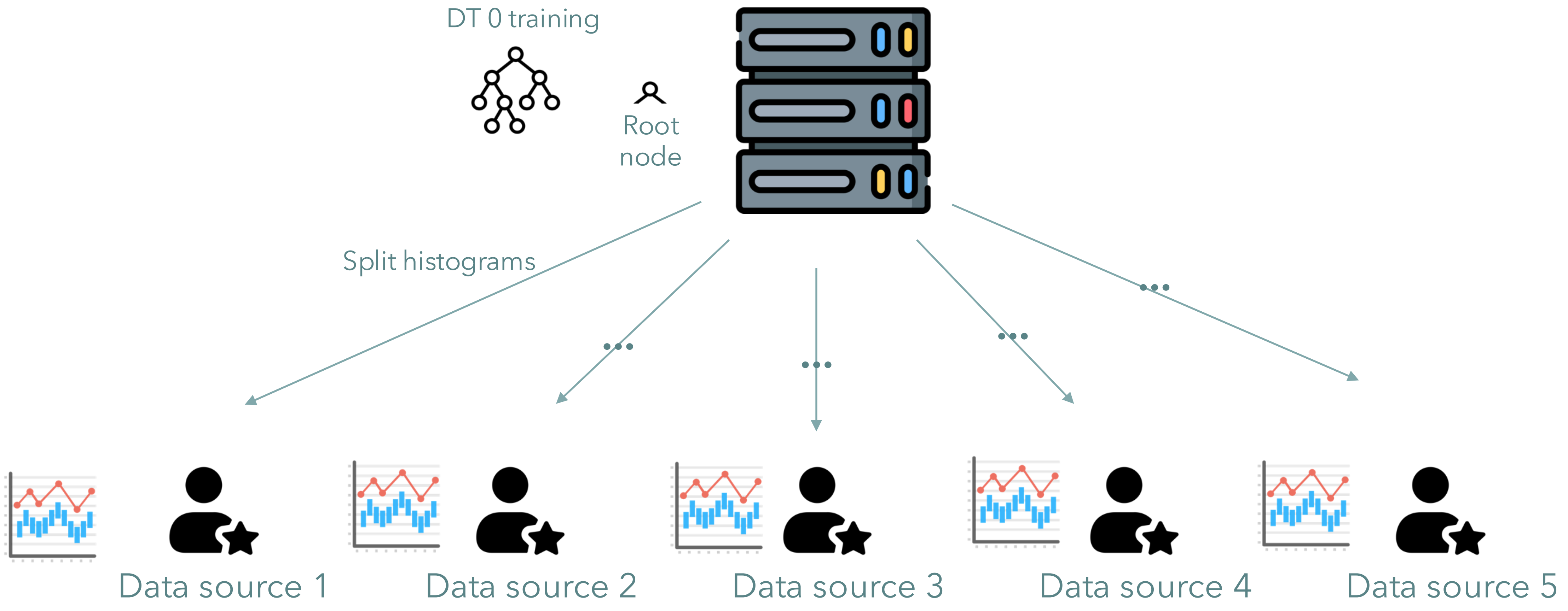

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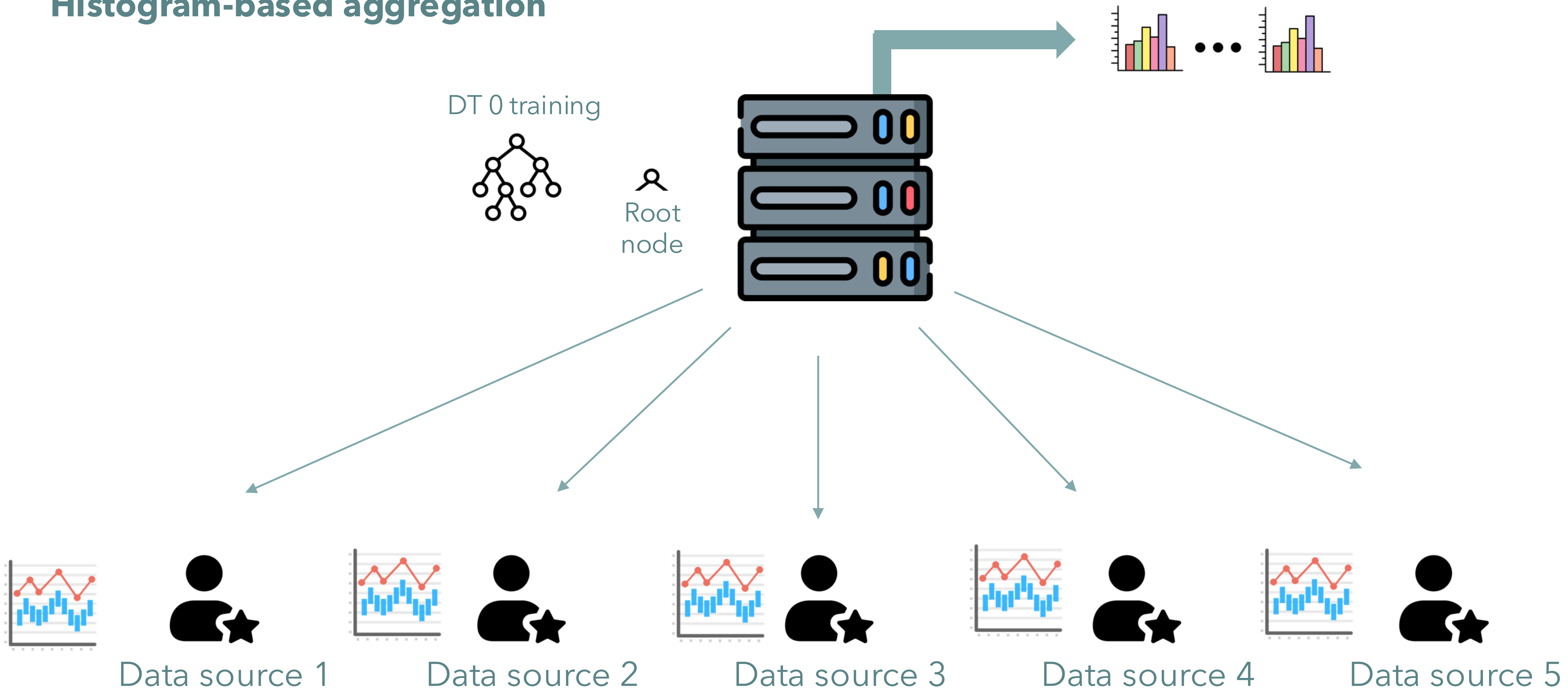

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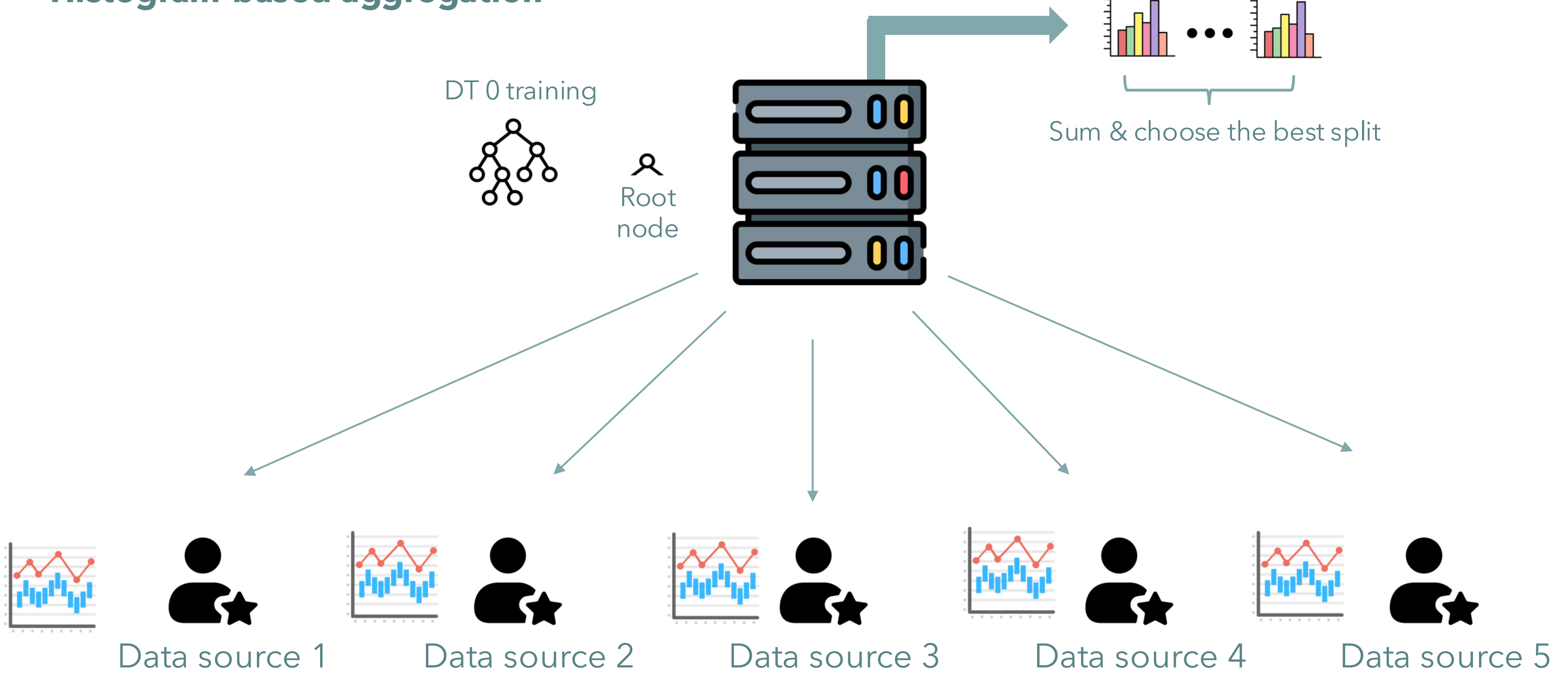

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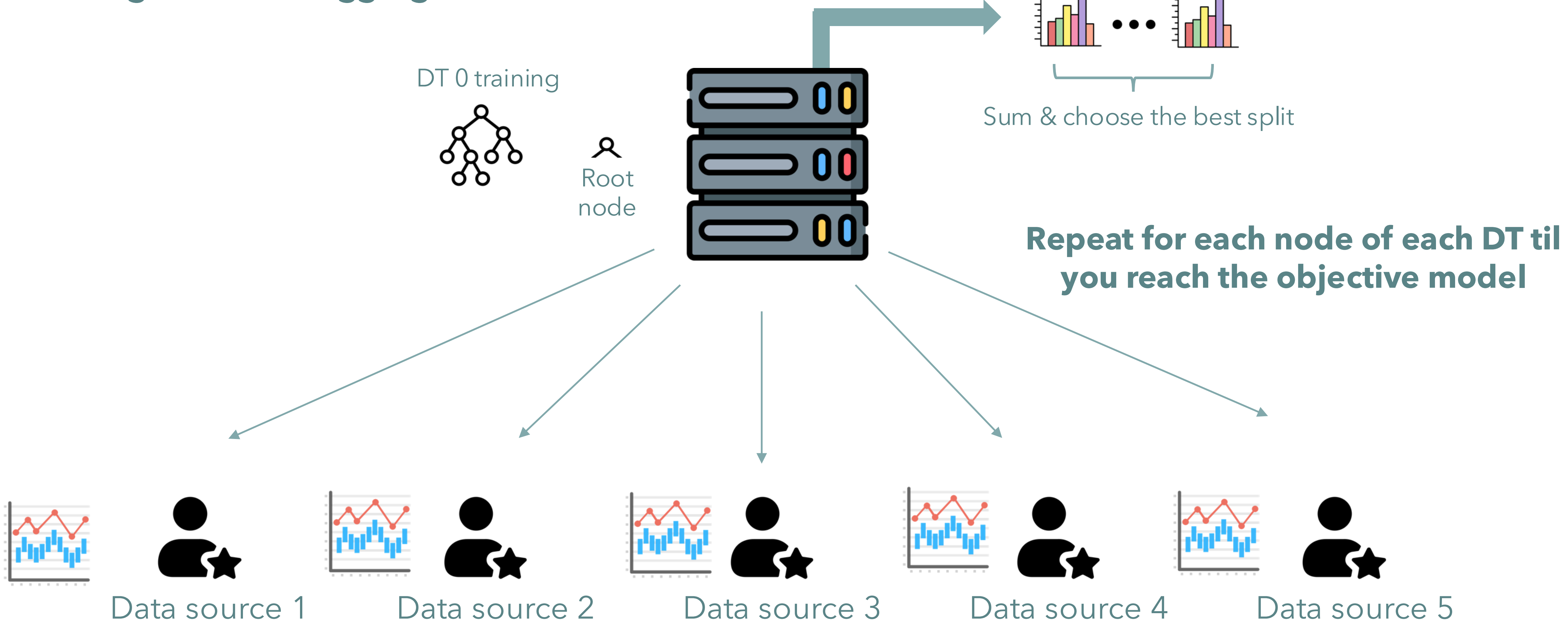
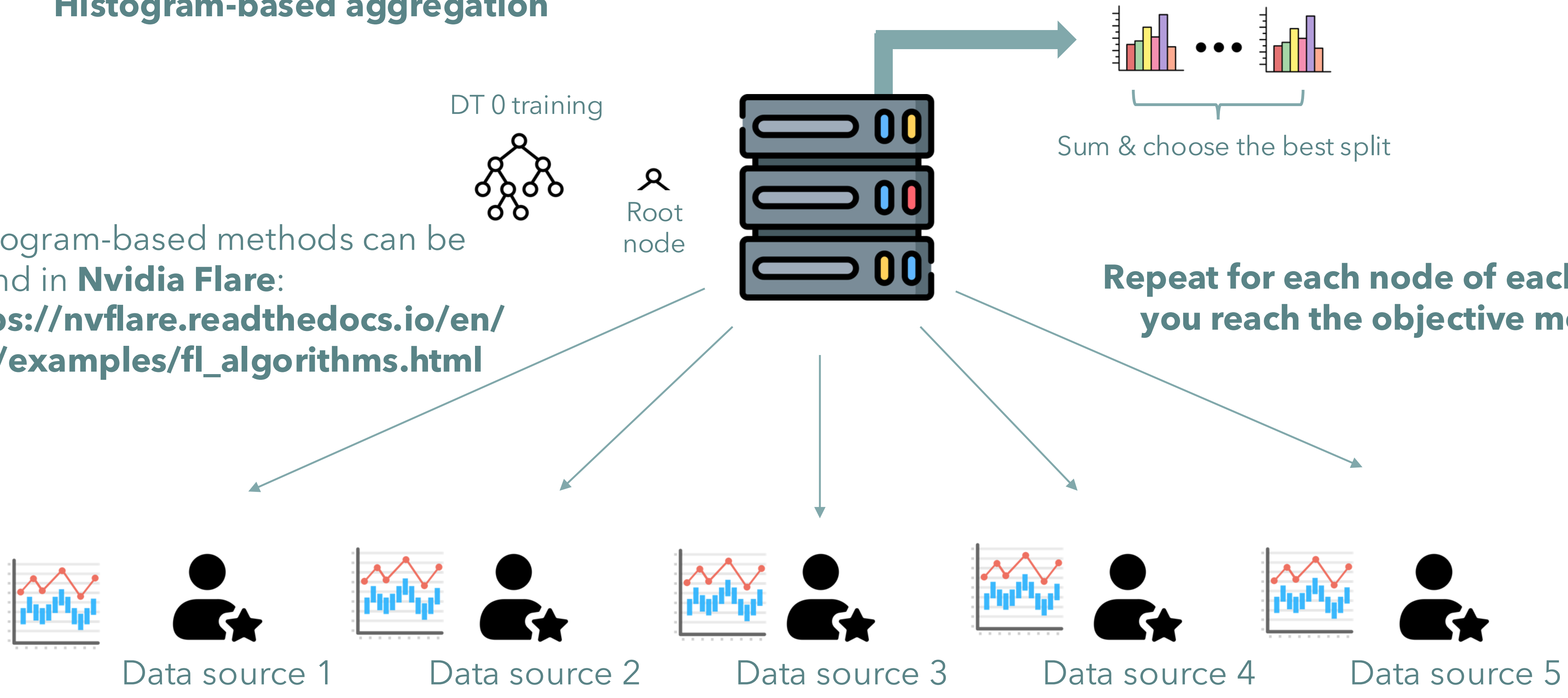


Horizontal Federated Learning – DT Ensembles

Histogram-based aggregation

Histogram-based methods can be found in **Nvidia Flare**: **https://nvflare.readthedocs.io/en/2.4/examples/fl_algorithms.html**



Repeat for each node of each DT til you reach the objective model

Horizontal Federated Learning – DT Ensembles

Traditional aggregation methods

Pros
- Fast and simple implementation
- Low communication overhead

Cons
- Accuracy decrease
- Low security w.r.t. malicious attacks

Histogram aggregation methods

Pros
- Accuracy close to centralized training
- High security w.r.t. malicious attacks

Cons
- Harder to implement
- High communication overhead

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Creativity, Science and **Innovation**

Thank you for your attention

December 1^{st}, 2025

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