

# Detecting financial crime using an Azure advanced analytics platform and MLOps approach



Lars Haringa, Data Scientist, ABN AMRO Bank

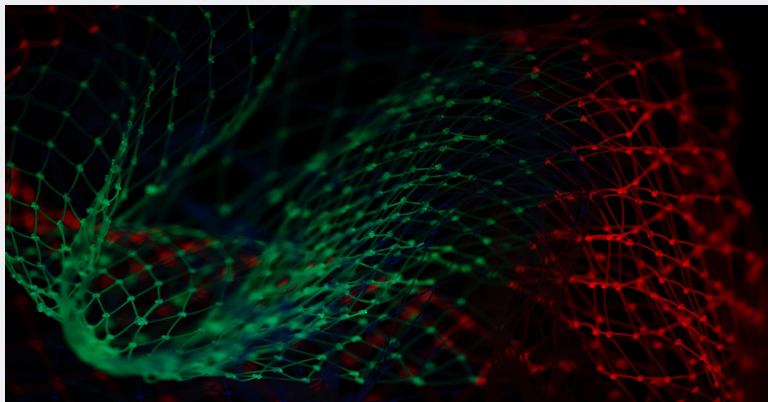


Saman Amini, ML Engineer, ABN AMRO Bank

# Outline

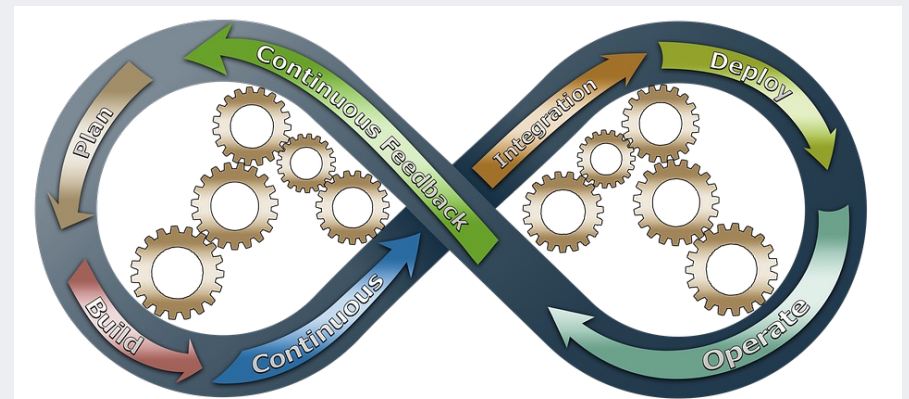
## Transaction Monitoring with Machine Learning

*Lars Haringa*



## MLOps

*Saman Amini*



# Gatekeepers of the financial system

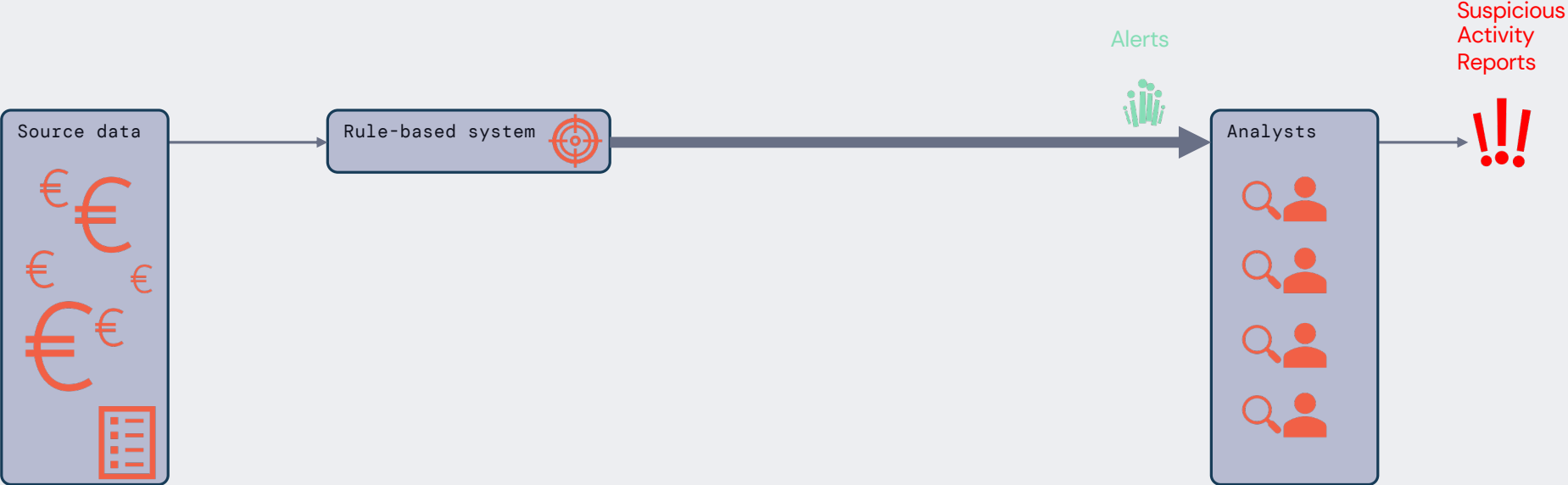


**ABN·AMRO**

- 1/4 Systemically Important Banks banks in NL
- Many millions of transactions per day
- Strictly regulated

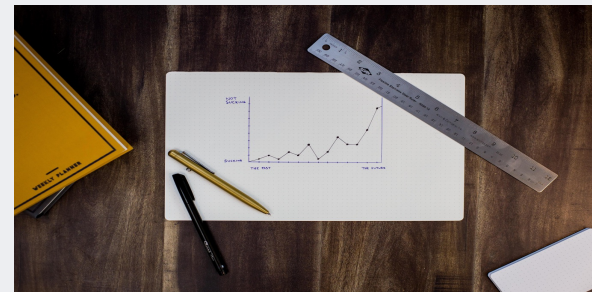
- Legal obligation for Transaction Monitoring (TM) ← profits of organised crime
- Unique position for detecting financial crime (DFC)
- Costly operation

# Rule-based TM



# From rule-based TM to TMML

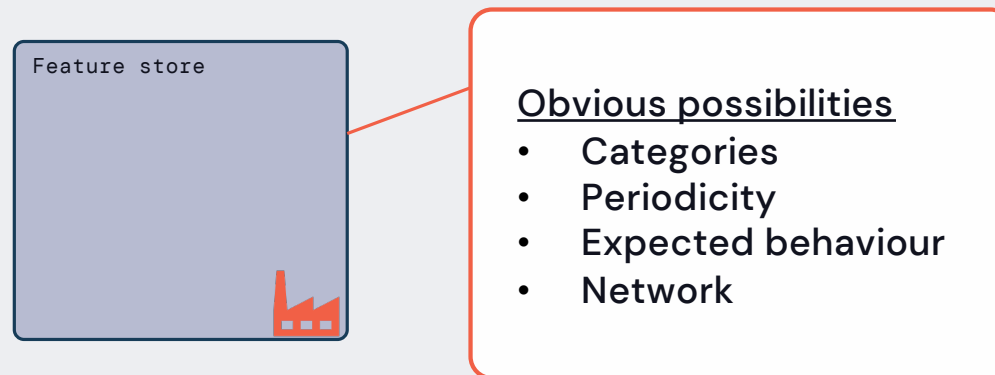
- Hand-built (a priori)
- Simple
- Many false positives
- *E.g. if deposit > threshold, investigate*



- Data-driven Transaction Monitoring Machine Learning (TMML)
- Complex: 100s simultaneous decisions
- Efficient

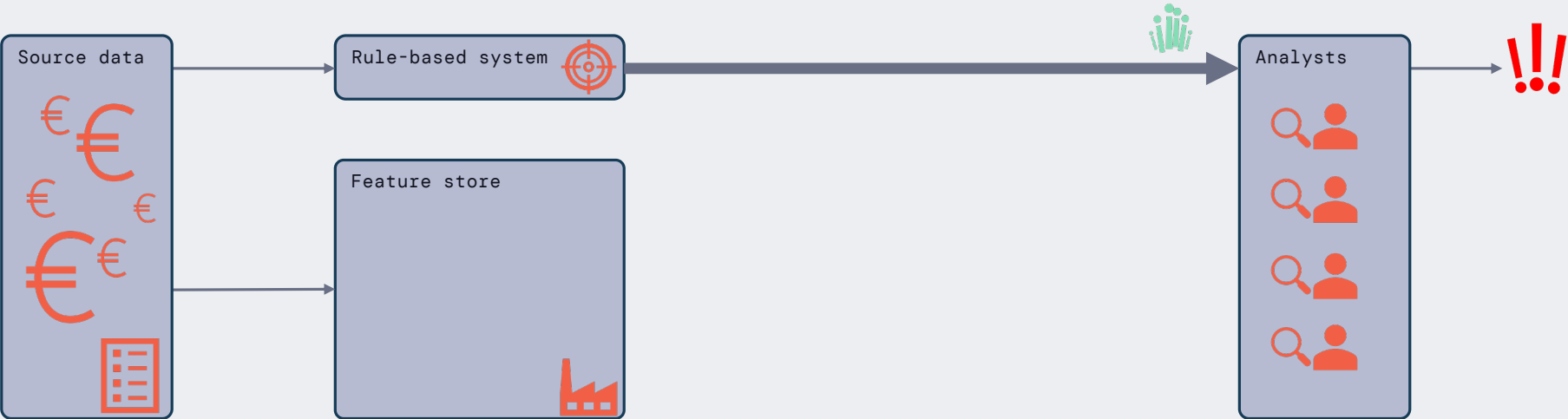
# Feature store

- Transaction data is rich (e.g. sensitive)

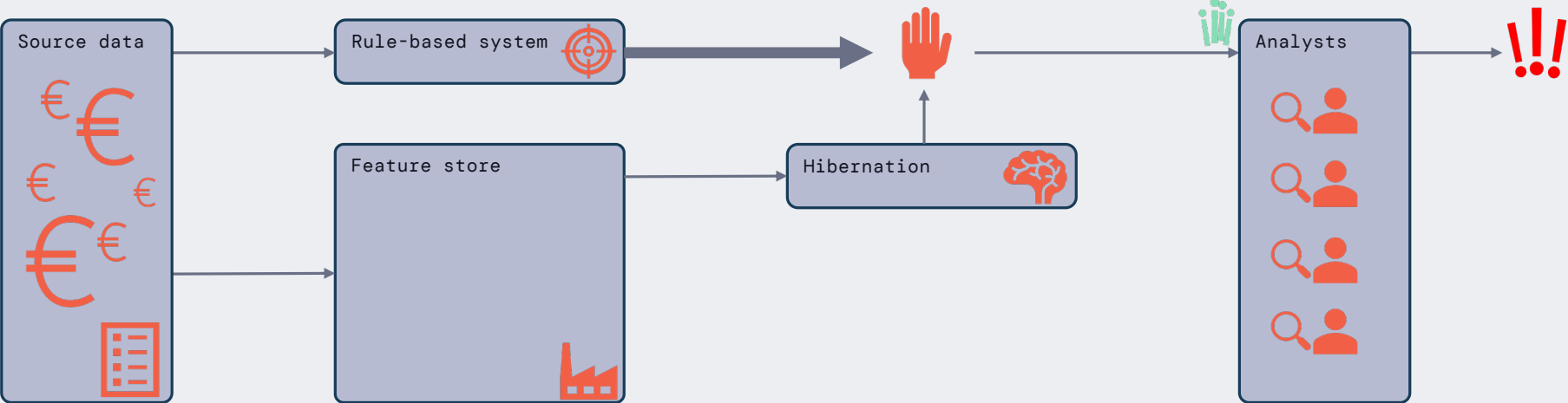


- IT to combine and transform various sources continuously

# Feature store

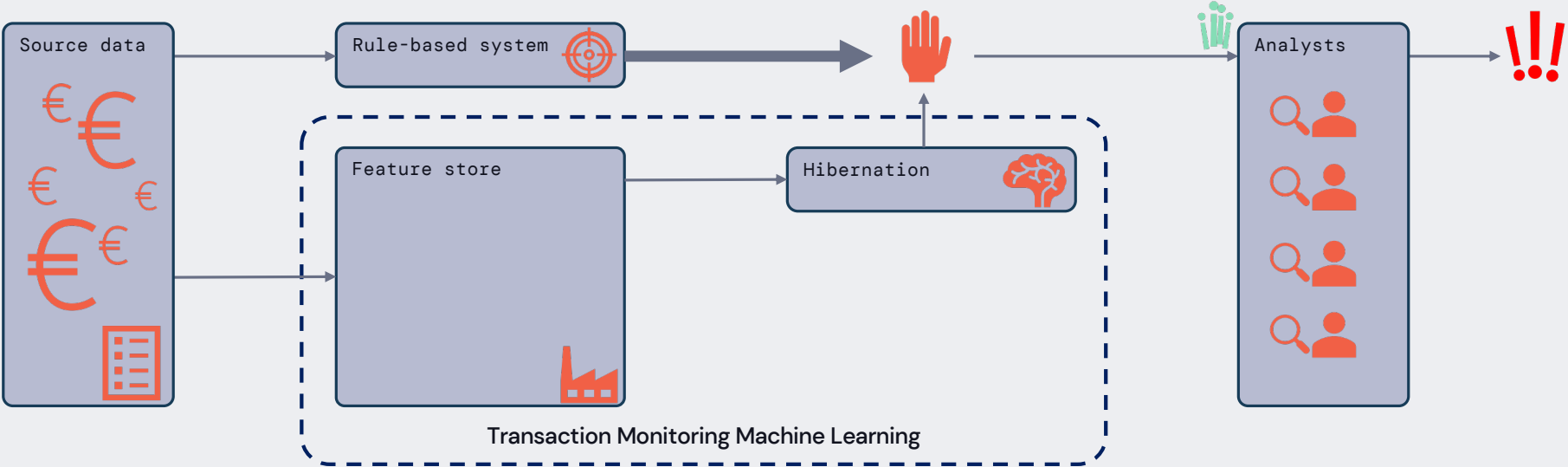


# Supervised model – reducing false positives

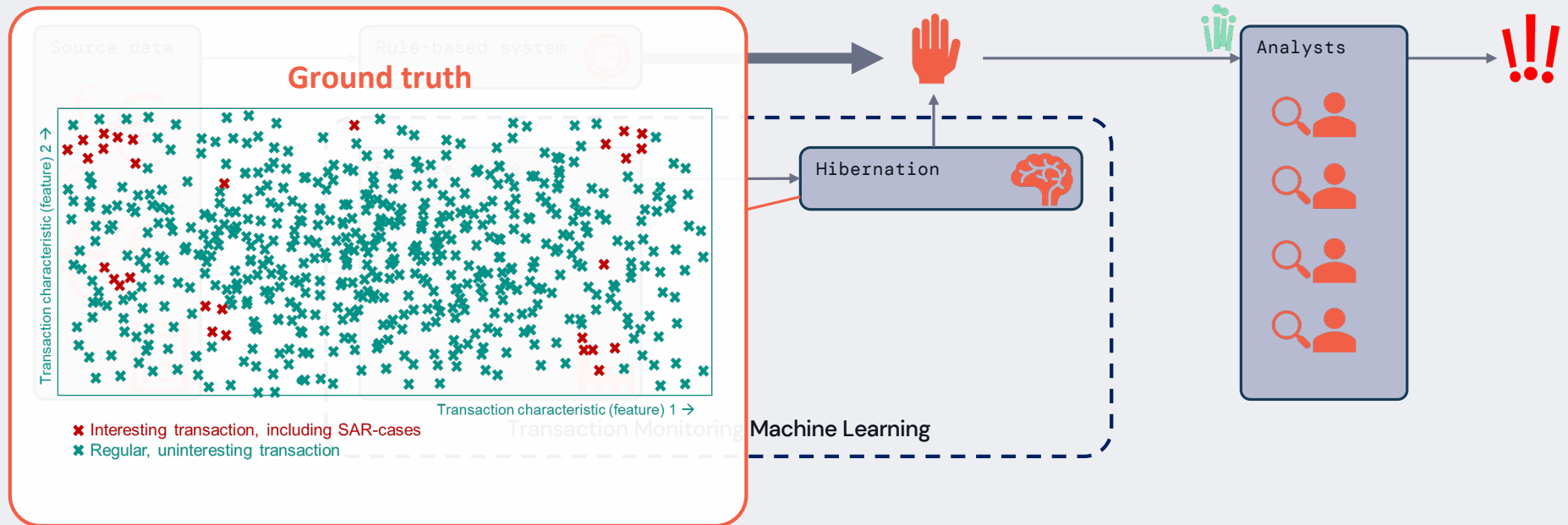




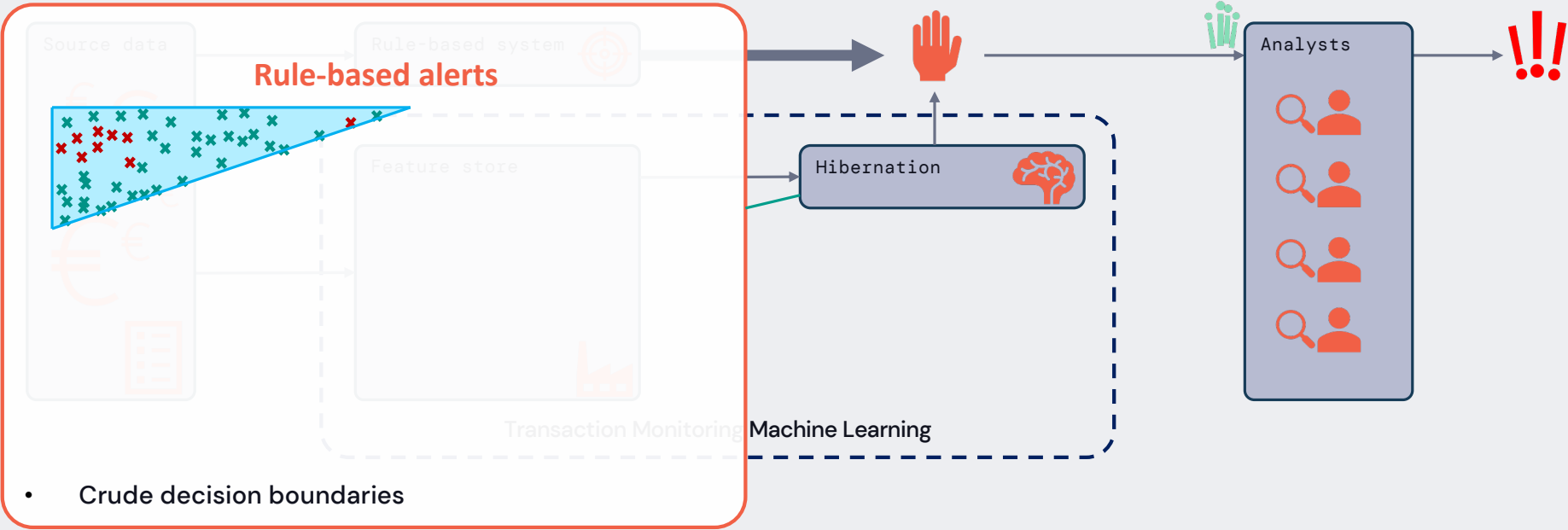
# Supervised model – reducing false positives



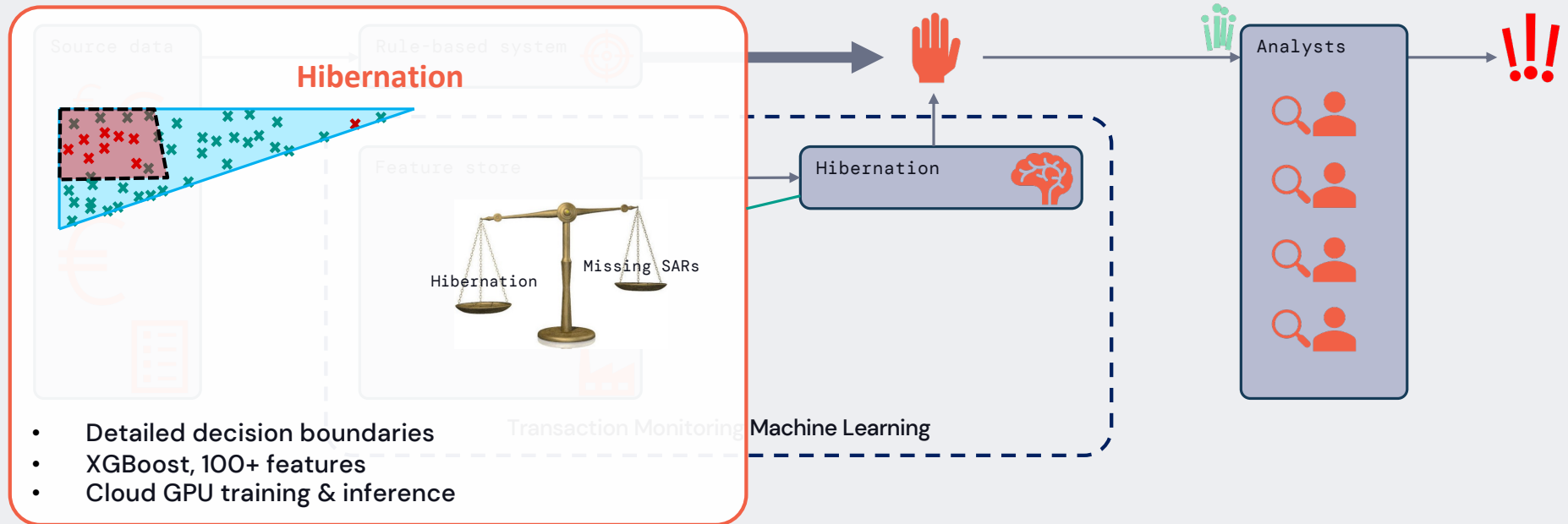
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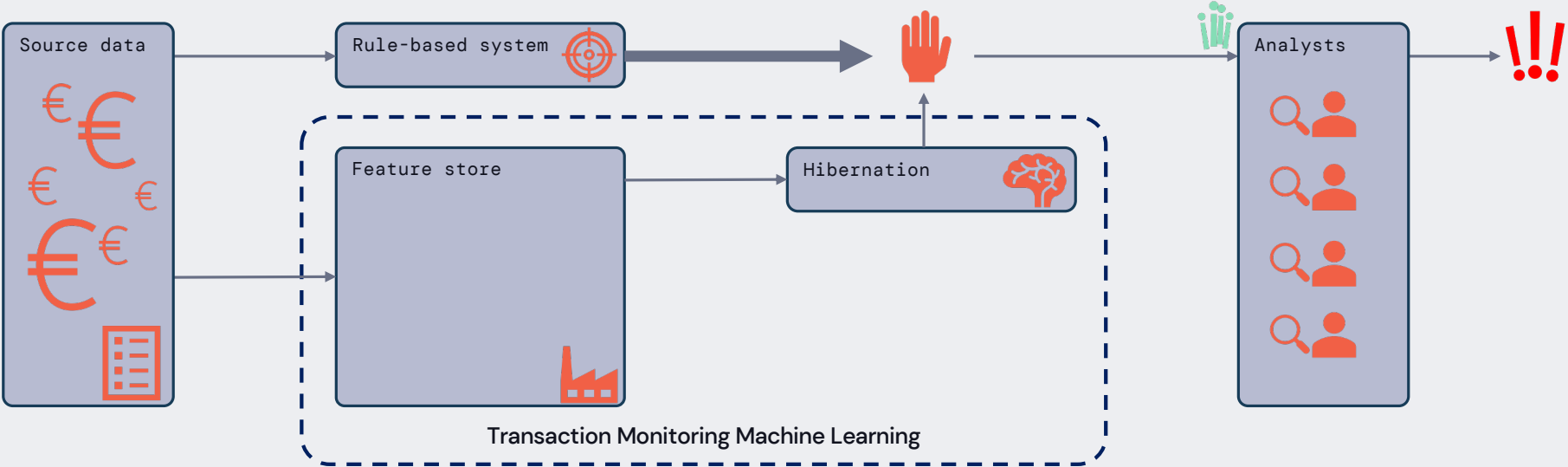
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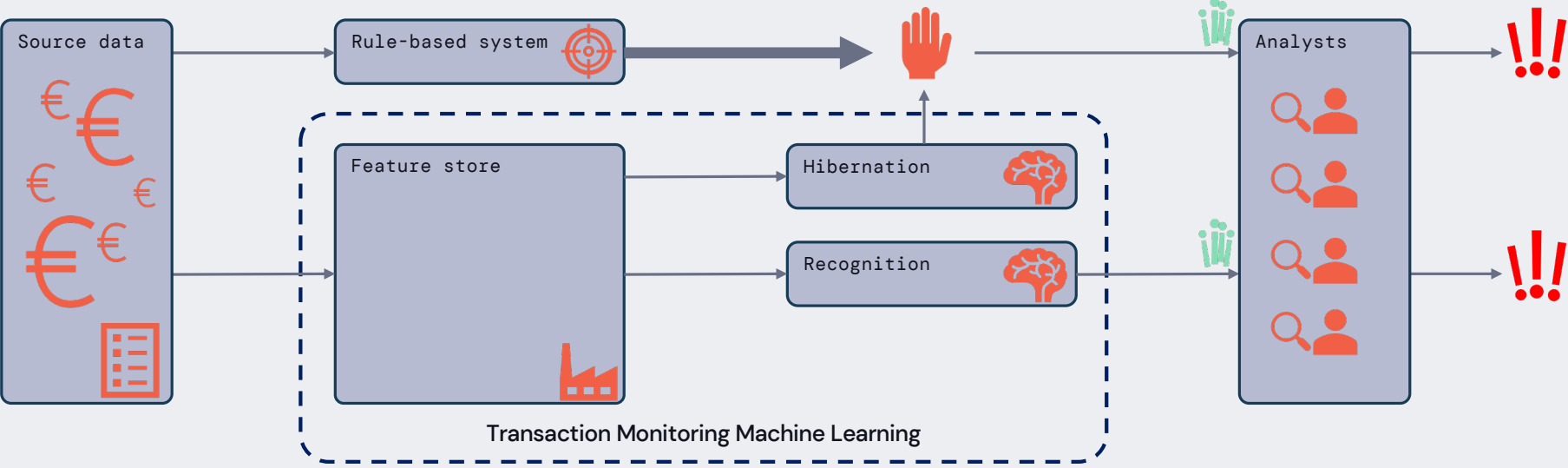
# Supervised model – reducing false positives



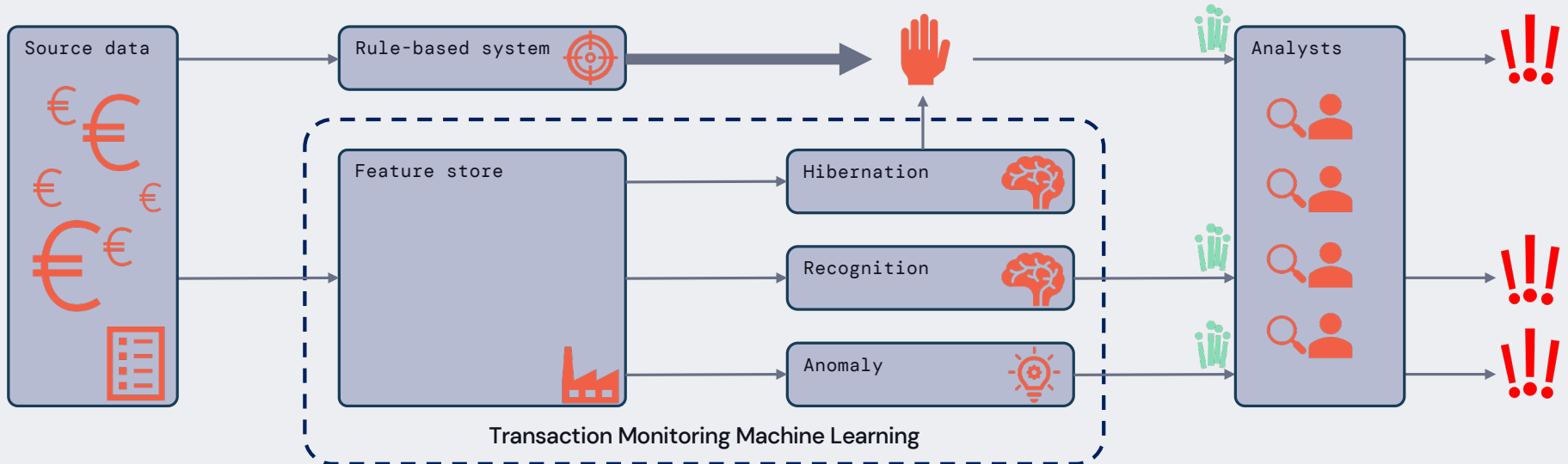
# Supervised model – reducing false positives



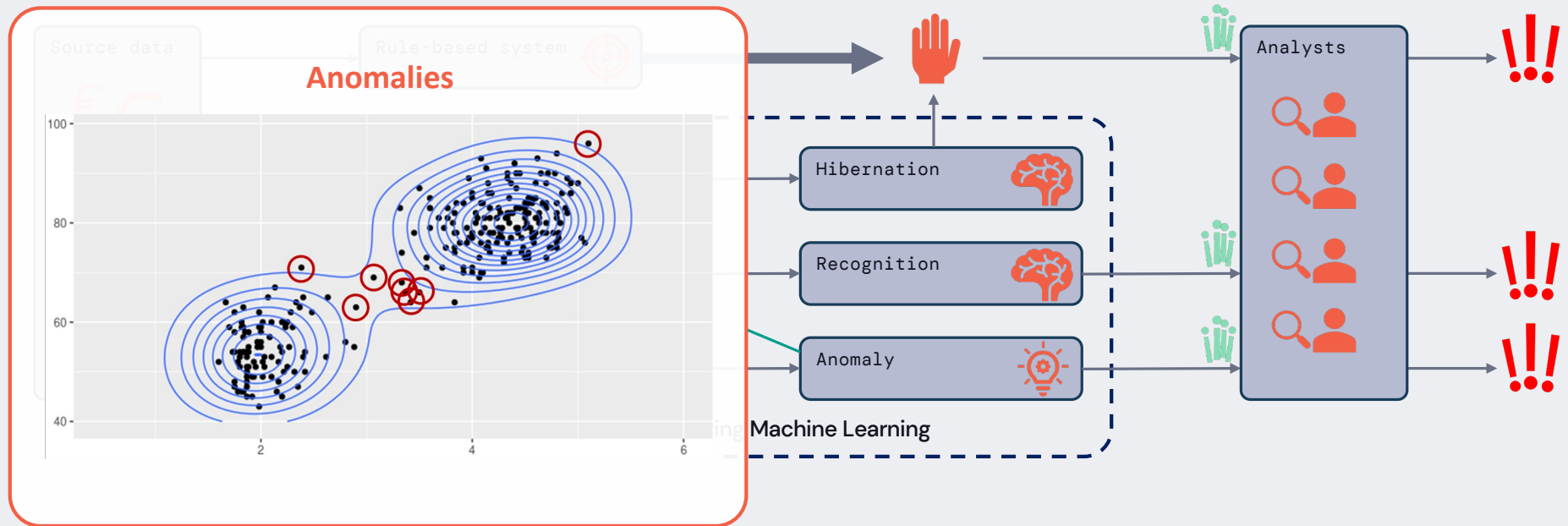
# Supervised model – detecting similar cases



# Unsupervised model – anomaly detection

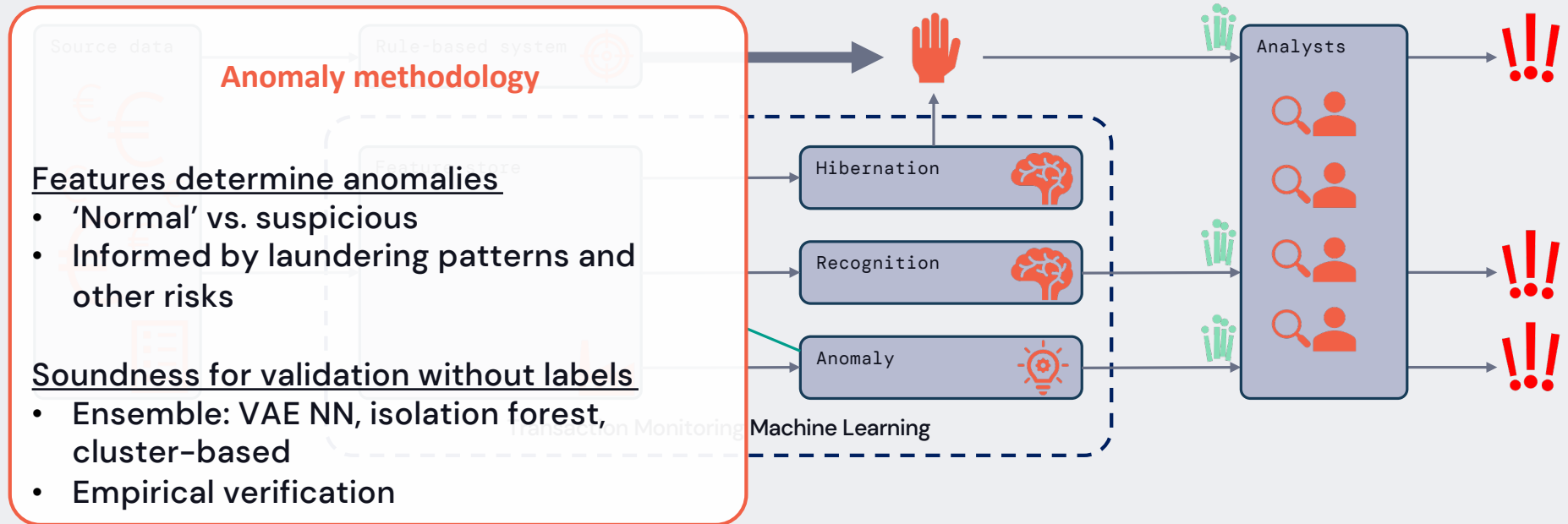


# Unsupervised model – anomaly detection

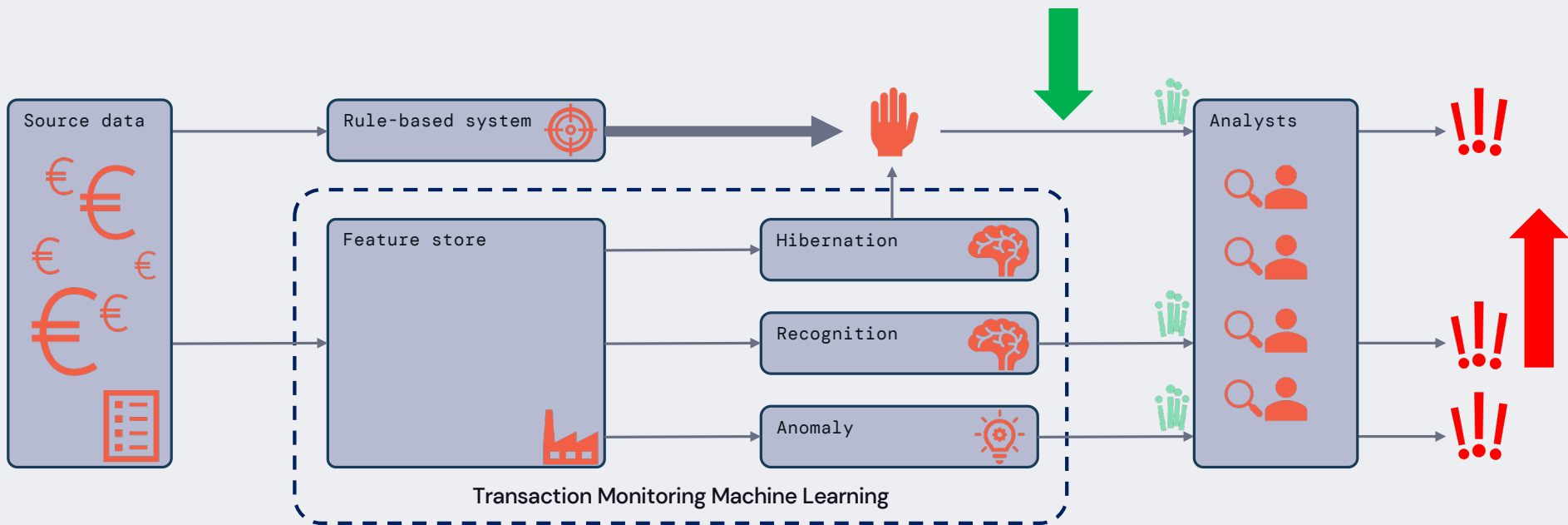




# Unsupervised model – anomaly detection



# Results



- Less false positives, more Suspicious Activity Reports

# Results – business value



## False positive reduction: refocus work

- Analyst capacity is needed elsewhere (e.g. anomalies, new models)
- Hibernating false positives saves analysts unrewarding, repetitive work
- Analysts need exposure to actual suspicious behaviour

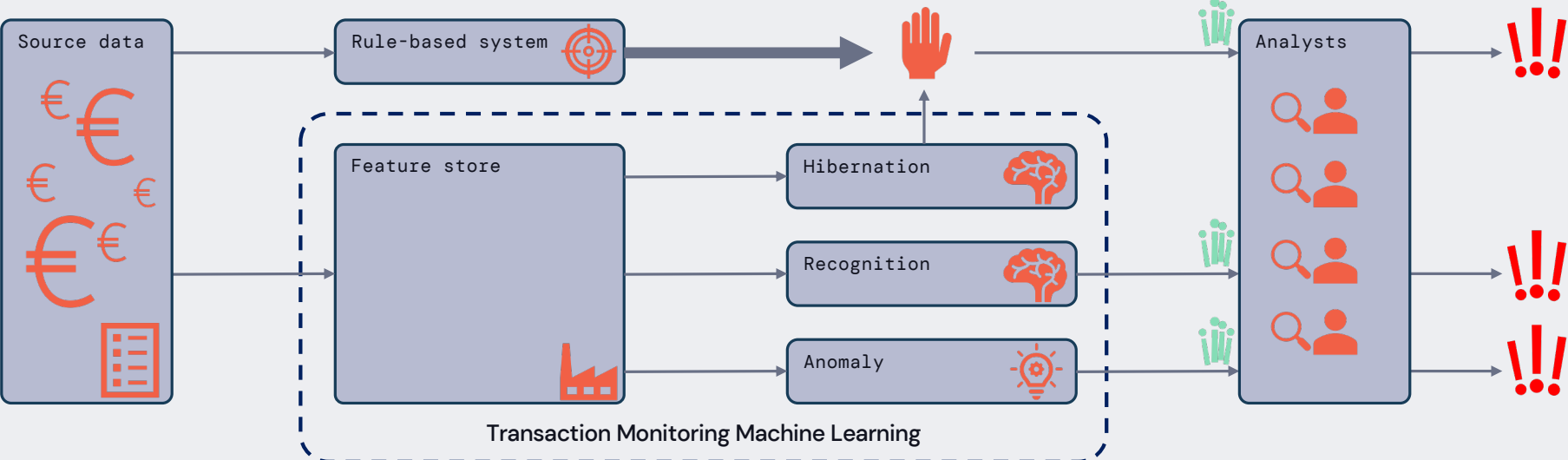


## Increased vigilance

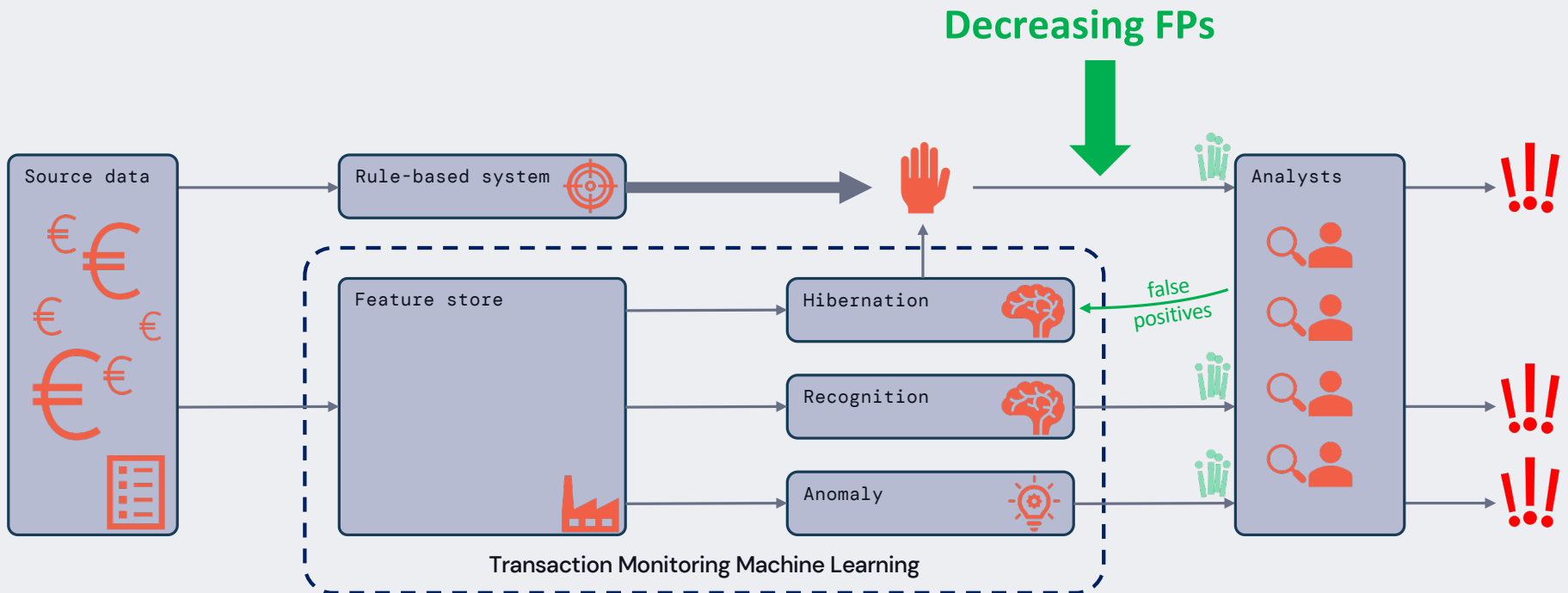
- Recognition model extrapolates existing knowledge of SAR-filings
- Anomaly model expands existing knowledge, searching for 'unknown unknown' suspicious behaviour

*Business value supports data science + developer teams*

# Continuous retraining

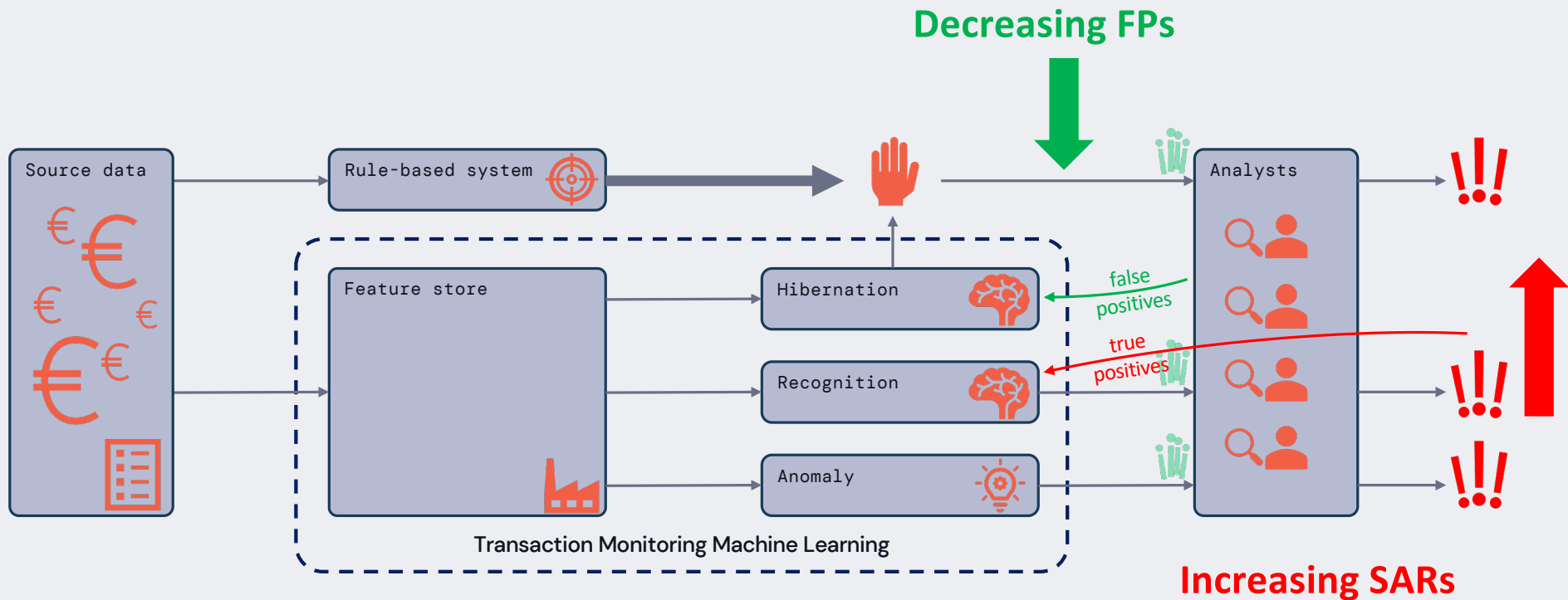


# Continuous retraining – human-in-the-loop



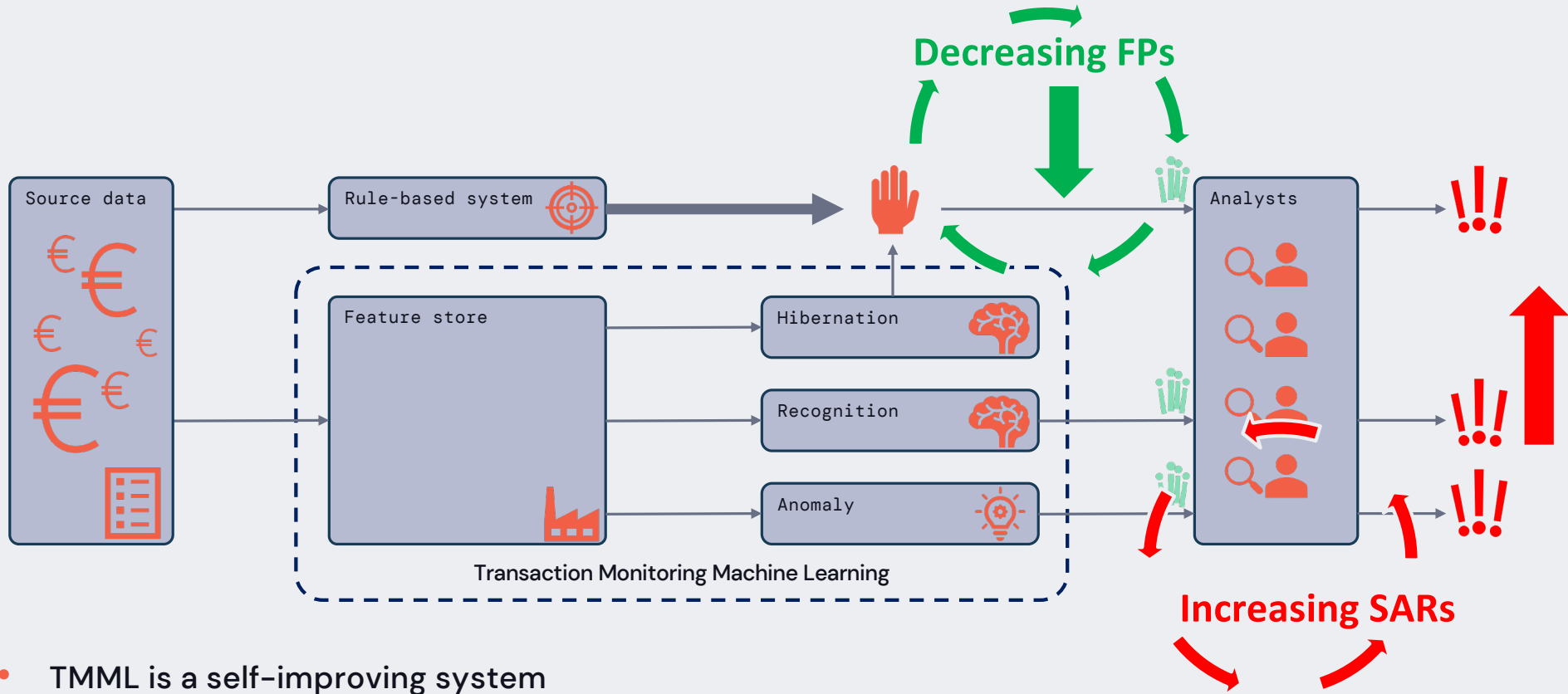
- Rule-based system + hibernation is self-correcting

# Continuous retraining – human-in-the-loop



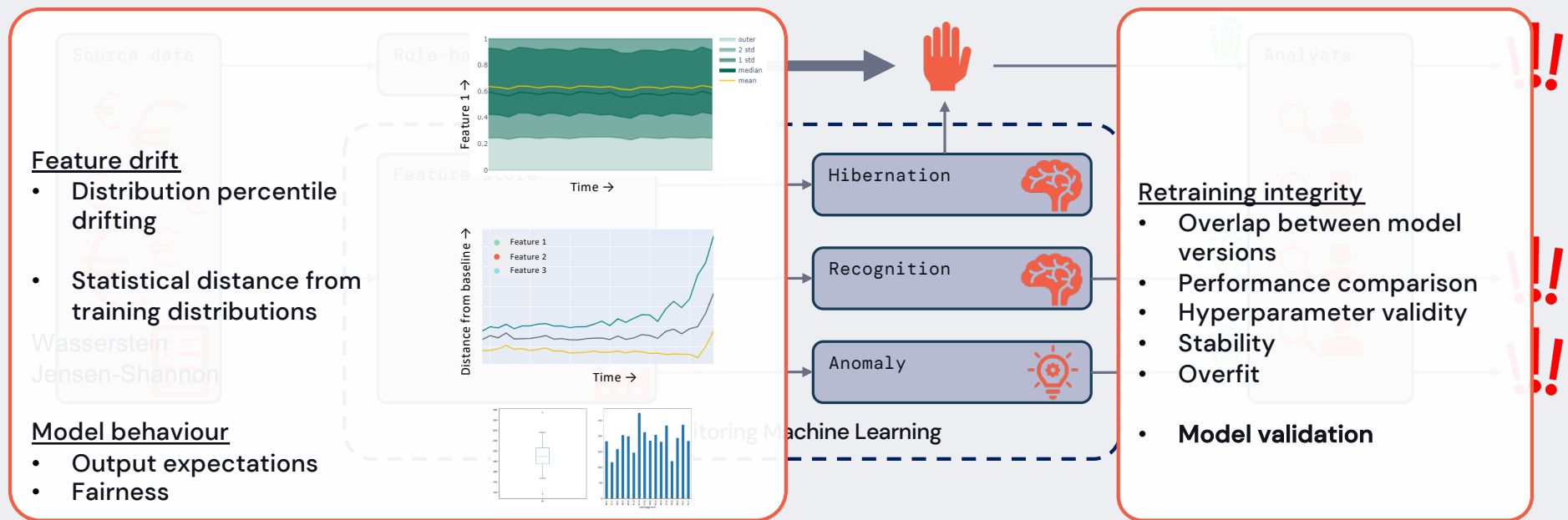
- TMML memory grows

# Continuous retraining – human-in-the-loop

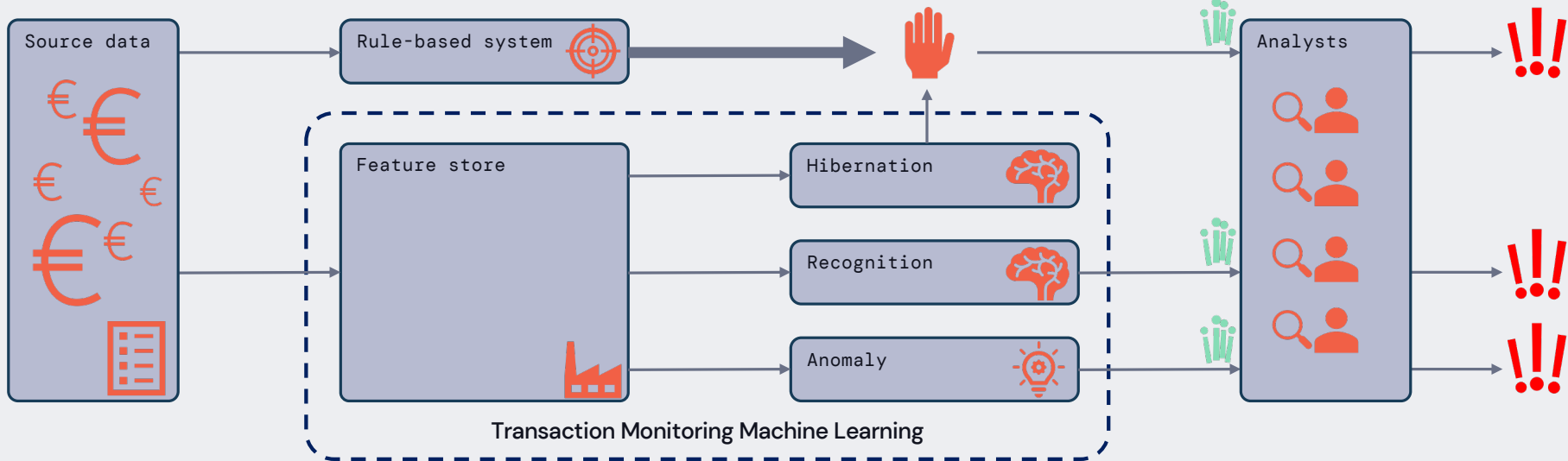


- TMML is a self-improving system

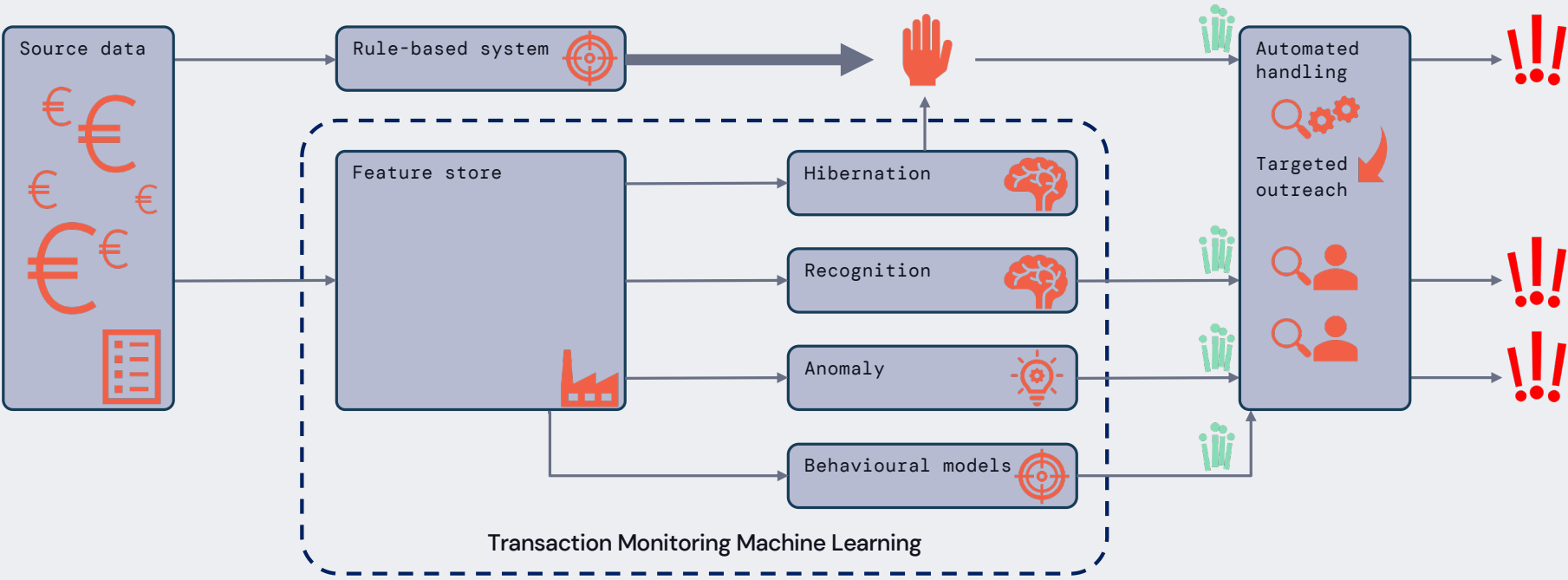
# Continuous retraining – monitoring



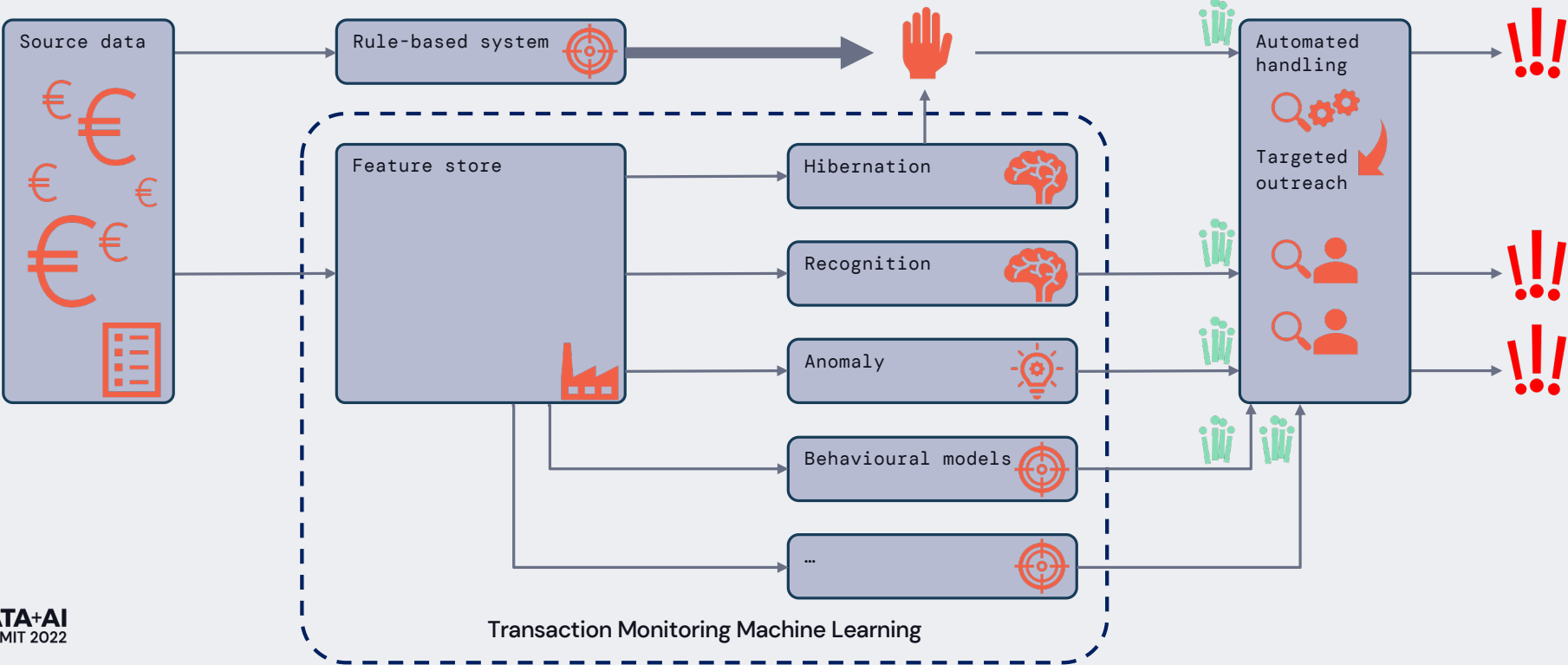


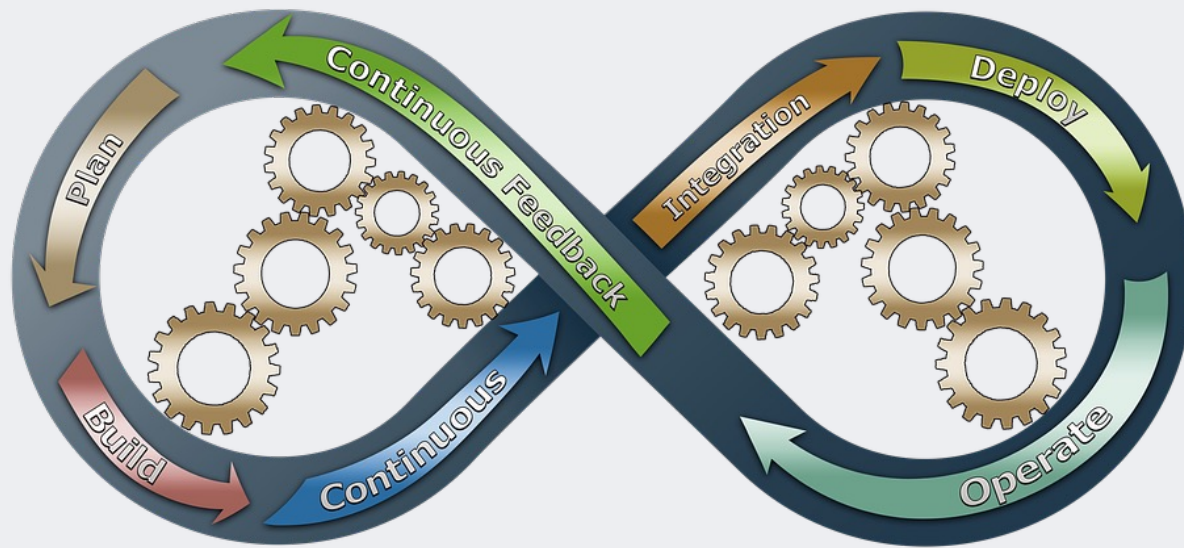


# Flexible setup – expandability



# Flexible setup – expandability





# Delivering business value by data science



Approaching data science  
from a scientific and  
experimental perspective



Delivering business value  
by bringing data science  
solutions into production

# A Common Story



# Challenges associated with model productionalization



Lack of suitable infrastructure



Lack of a central model registry



Alignment between IT engineers and data scientists



Lack of multidisciplinary team



Versioning and reproducibility



Feedback and iteration

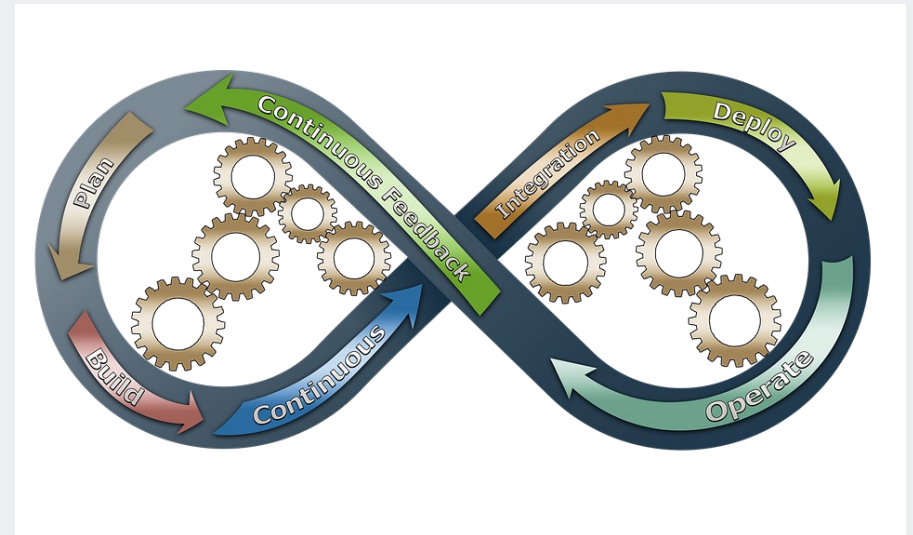


Sharing and reusing features



# DevOps principles

- Fast flow from Development to Operations
- Shorten and amplify feedback between teams
- Foster a culture of continual experimentation and learning





# What is MLOps

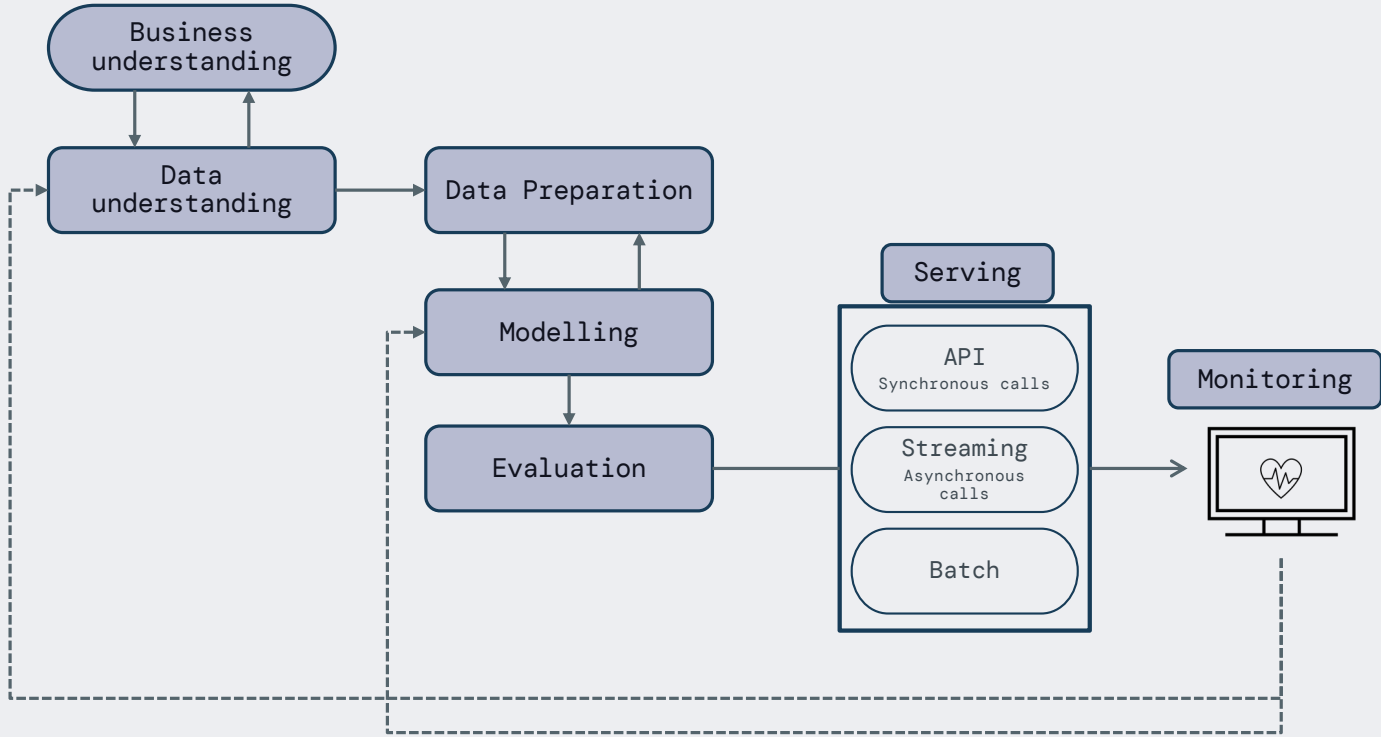


- Agile ML engineering approach inspired by DevOps
- An approach in which a multi-disciplinary team develops and operationalizes machine learning solutions based on code, data, and models in small increments
- Fully automated deployment of ML model into production
- Reproducible and reliable workflows

# Why did we adopt MLOps

- Productionalizing an increasing number of models without having a standardized framework was challenging.
- Retraining and monitoring of existing models, became an increasing bottleneck for data scientists.
- Lack of a framework to implement organizational quality gates.

# A typical flow of model development and serving



# Our tech stack



**Databricks:** Notebooks, clusters, Repos, spark, ...



**MLflow:** tracking experiments, central model registry



**Azure repos:** version control codebase



**Azure pipelines:** automated build and deploy pipelines

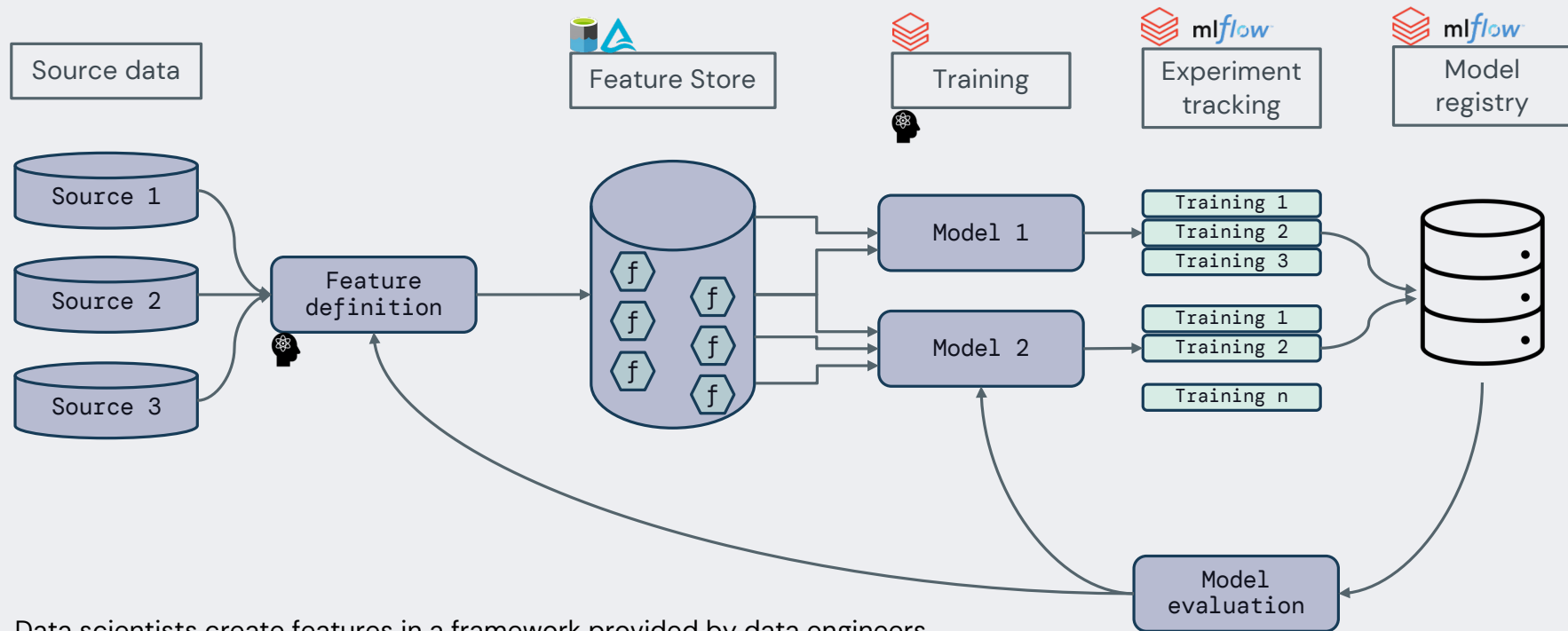


**Azure Data Lake storage Gen2 and Delta Lake:** feature store implementation



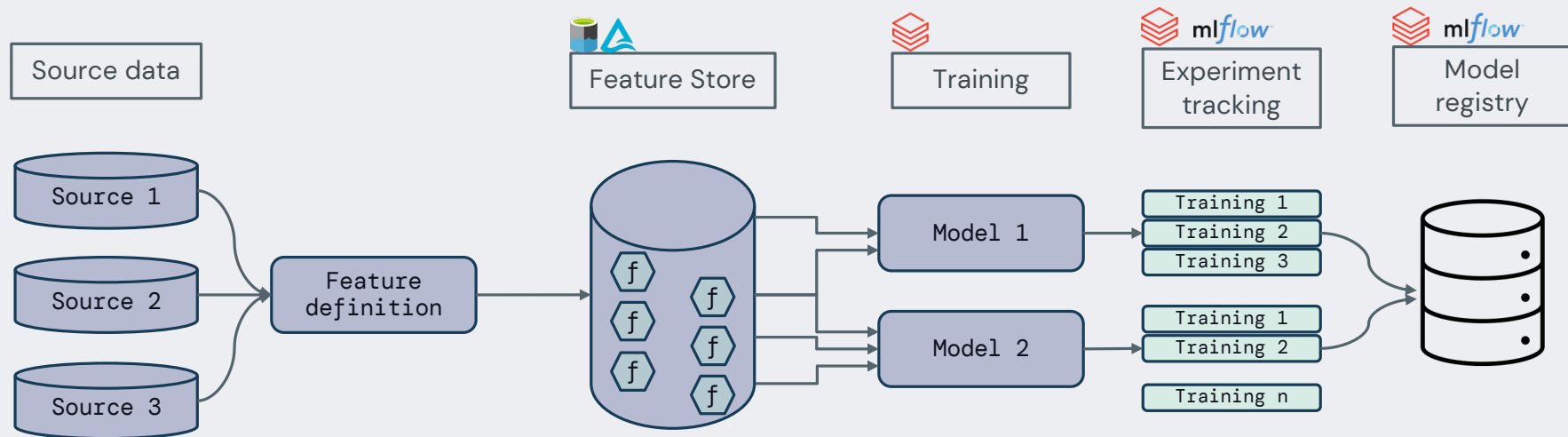
**Azure Data Factory:** orchestrating data movement and transforming data at scale

# Exploration environment

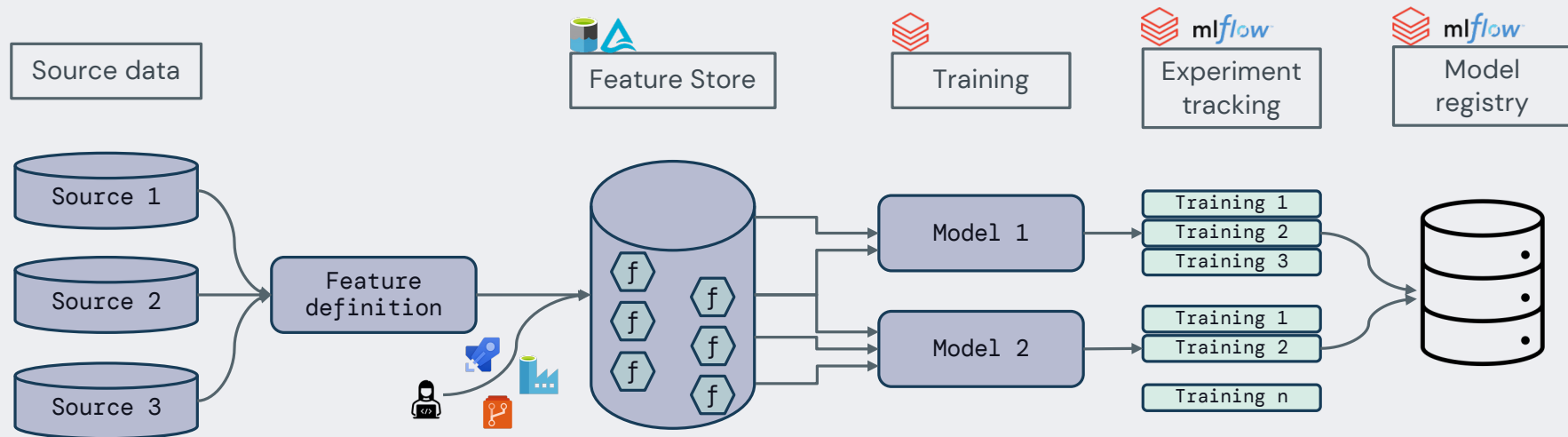


- Data scientists create features in a framework provided by data engineers
- Data scientists develop models in a framework provided by ML engineers

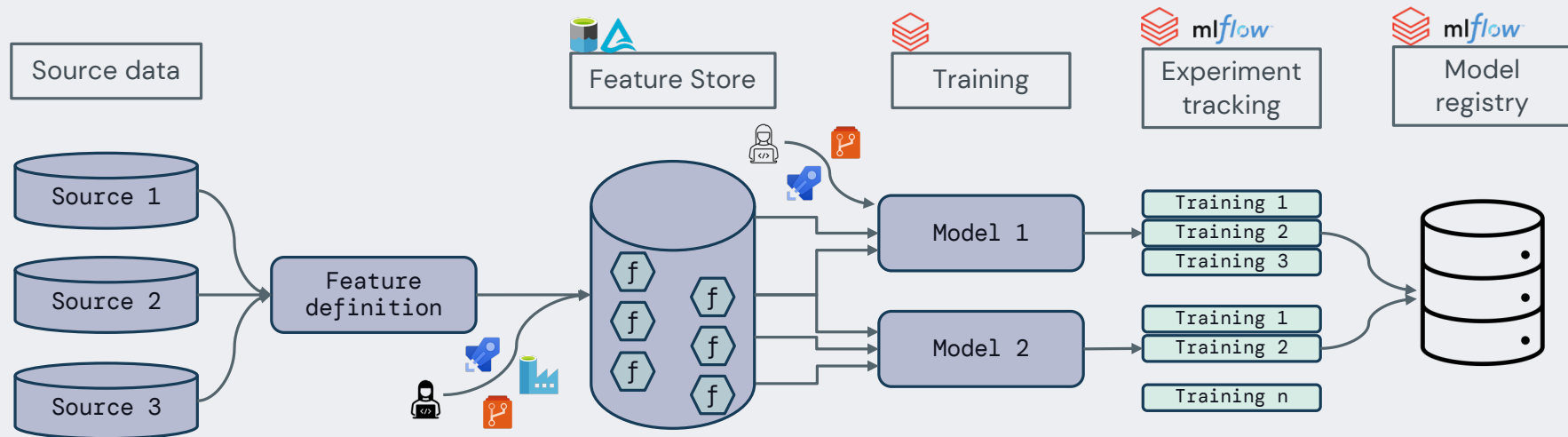
# DTAP environment



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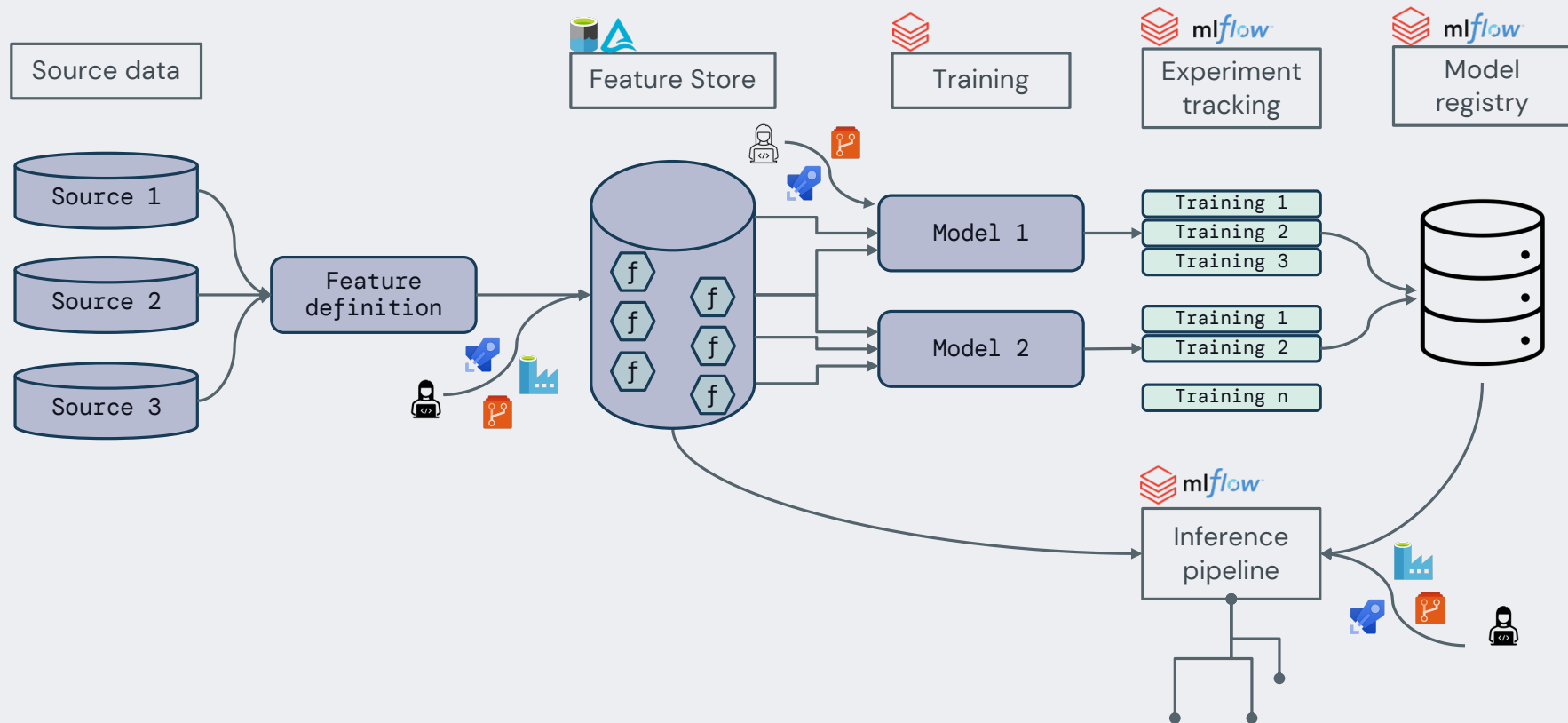
# DTAP environment



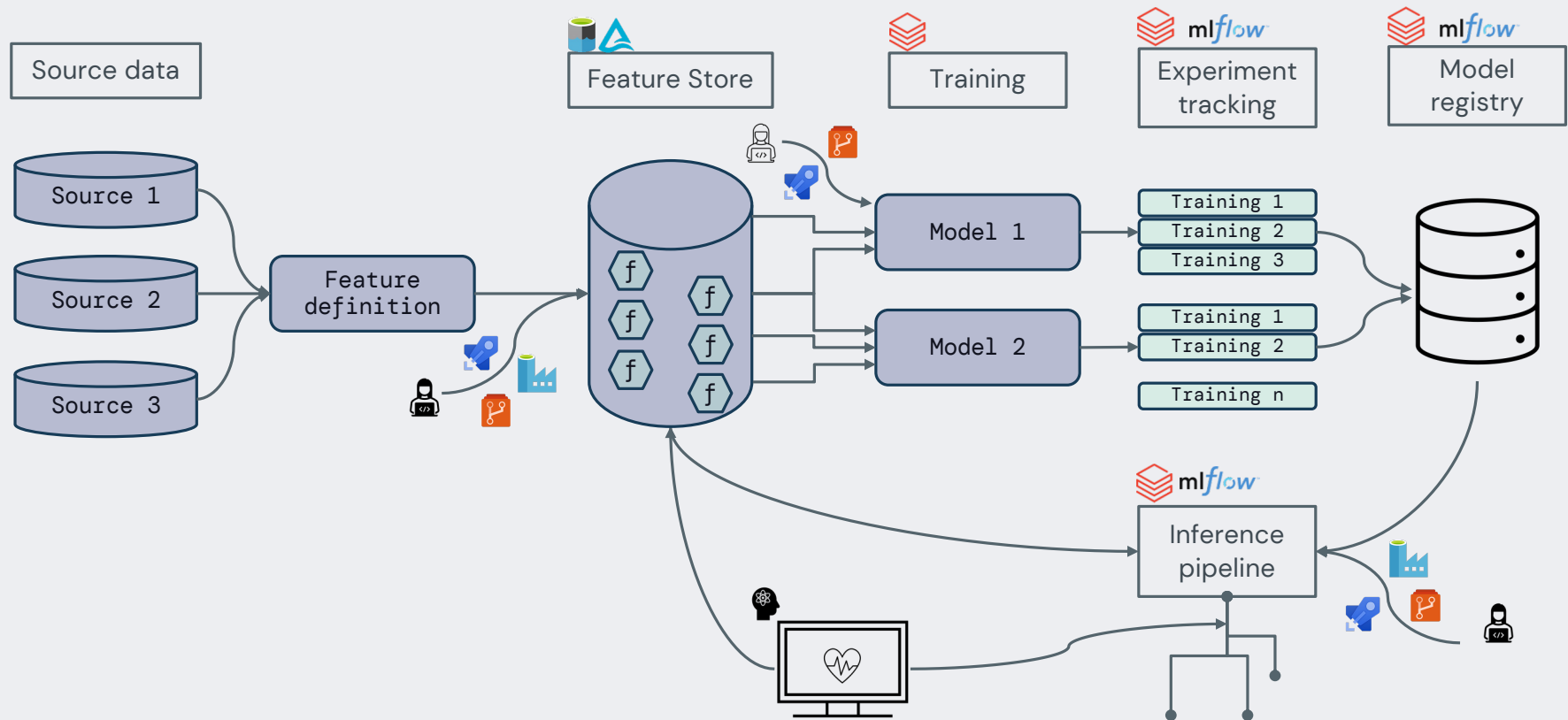
- New model implementations are shared with MLEs via pull requests



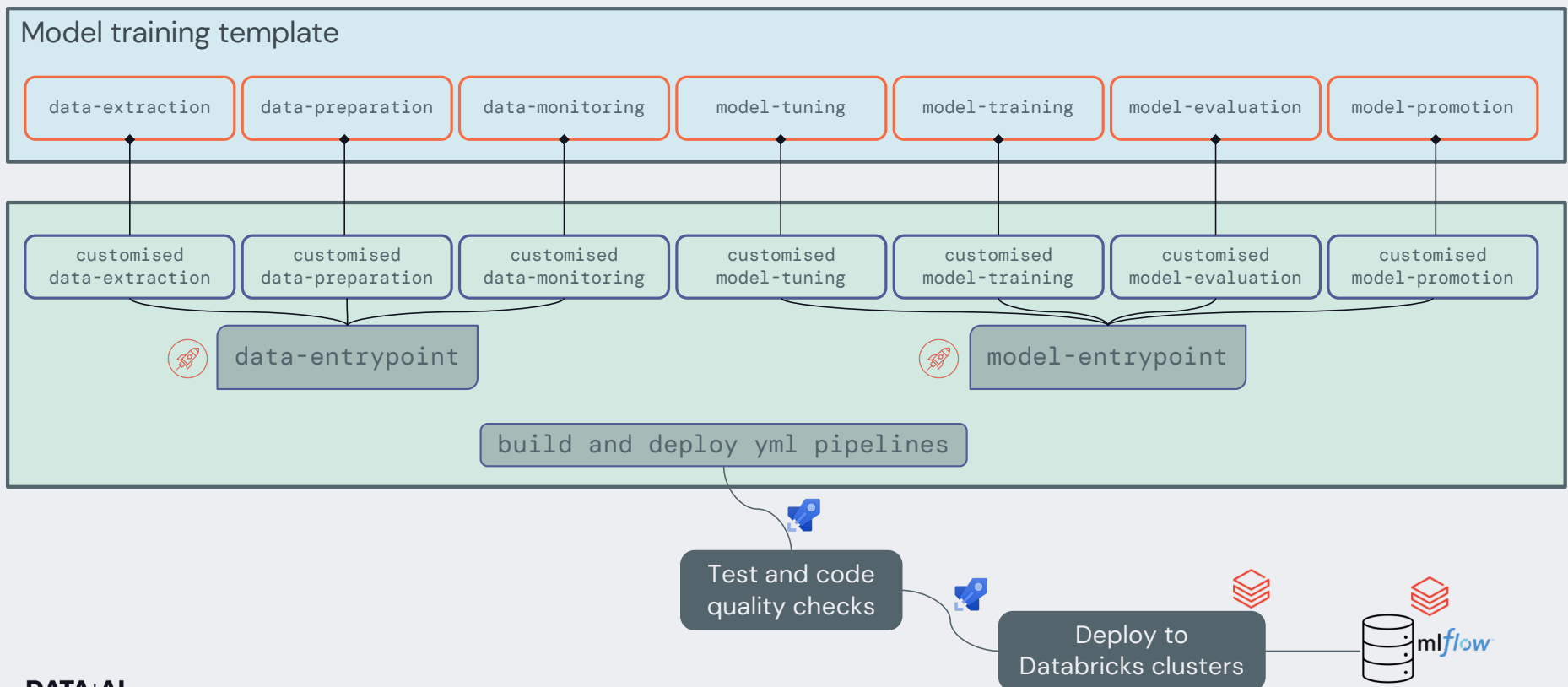
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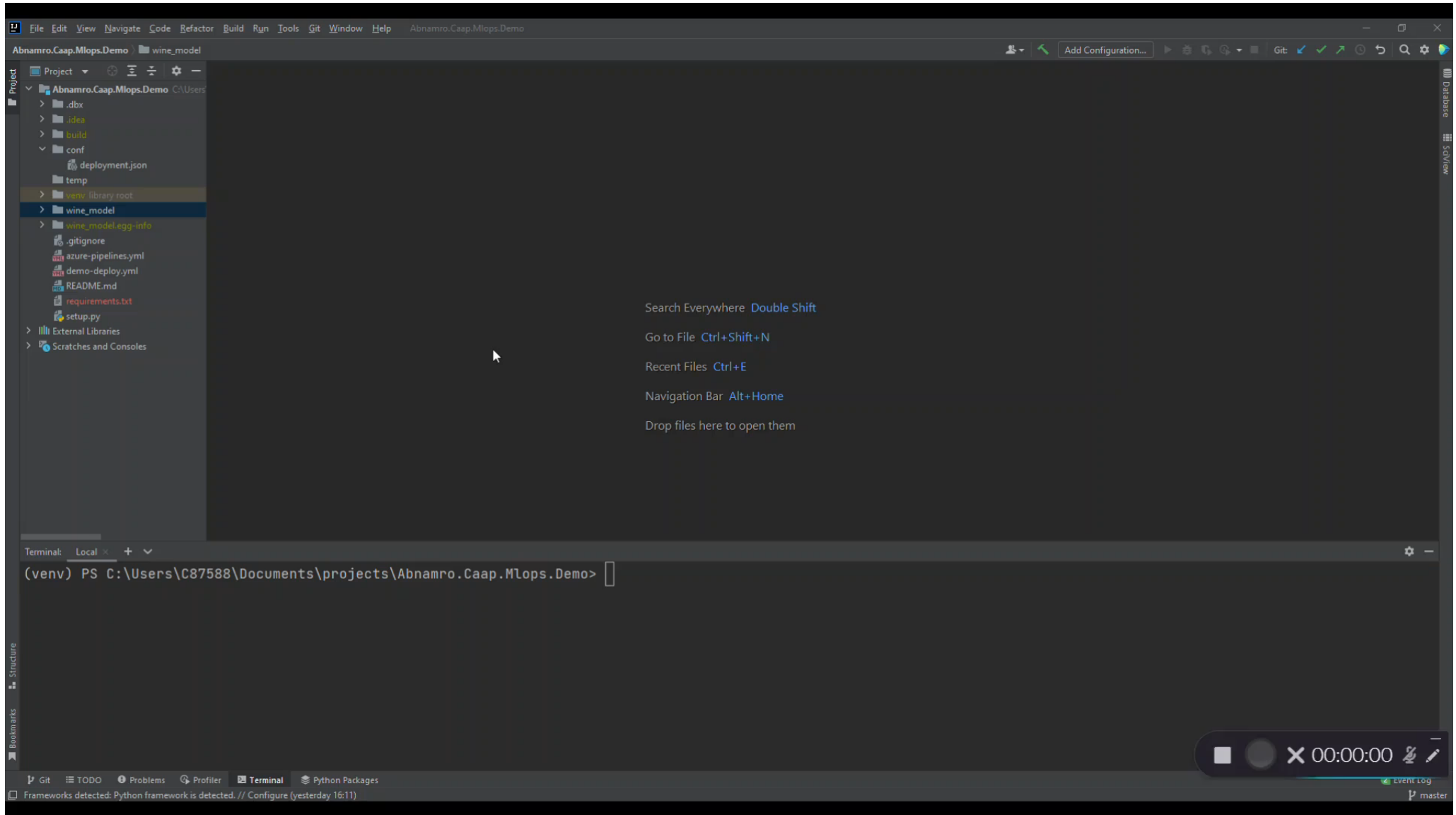


# DTAP environment



# Standardized training template





# Values delivered by applying MLOps

standardization of model development

standardization of quality checks

built-in reproducibility

built-in traceability

automated retraining

semi-automated monitoring

built-in quality assurance

centralized model management

faster productionalization

**DATA+AI**  
SUMMIT 2022

# Thank you



Lars Haringa, Data Scientist, ABN AMRO Bank



Saman Amini, ML Engineer, ABN AMRO Bank