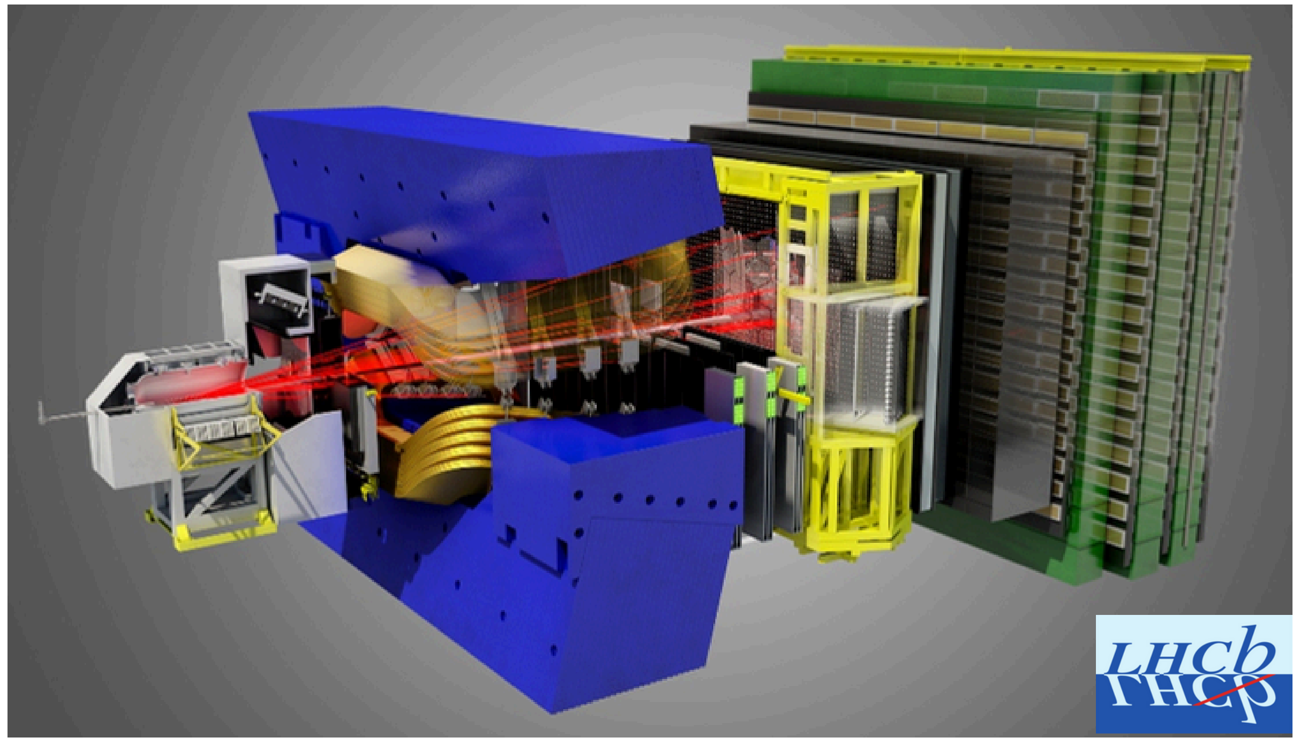
MONITORING EVALUATION FOR LARGE-SCALE ENVIRONMENTS AND OPTIMIZING DATA SYSTEM HEALTH

Supervisor: Apostolos Karvelas

Anastasiia Petrovych

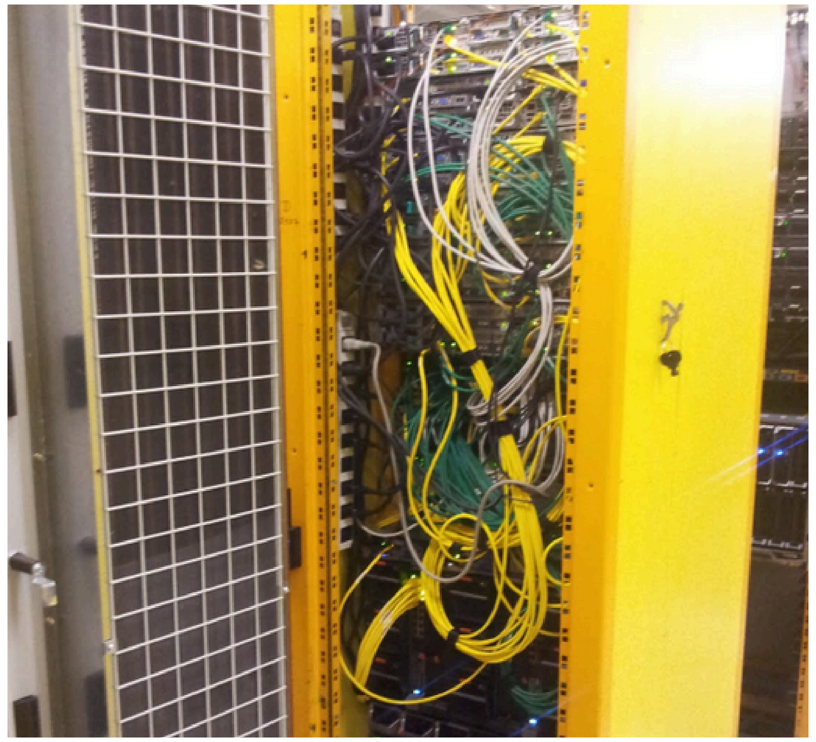
AGENDA OVERVIEW

PROJECT BACKGROUND



LHCb experiment

Data centers



Data farms

PROBLEM STATEMENT

How to detect anomalies in servers?

Problems

- Hardware Failures
- Software Issues
- Resource Constraints
- Environmental Factors

Consequences

- Data Loss
- Downtime
- Data Inconsistency
- Inefficient use of resources

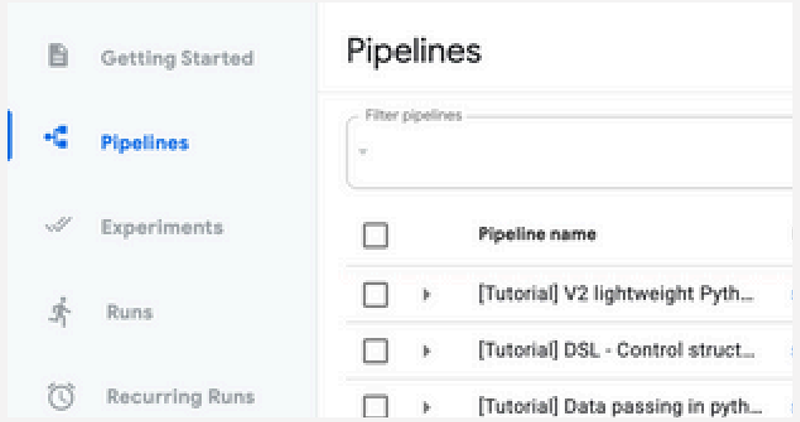
FRAMEWORK

Kubeflow

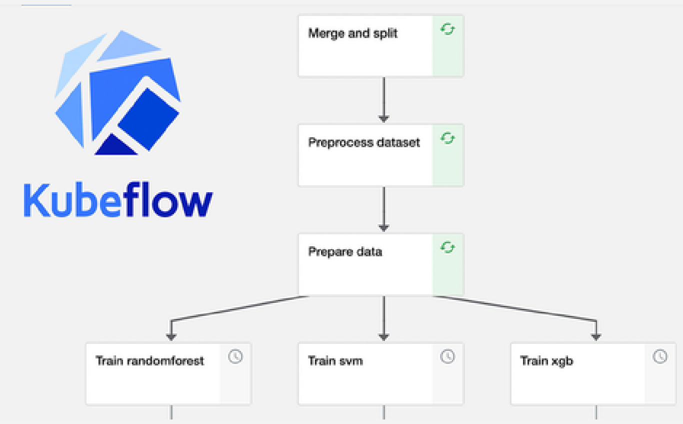
an **open-source** platform for machine learning and **MLOps** on Kubernetes

1.Define pipeline components

2. Compile to YAML file

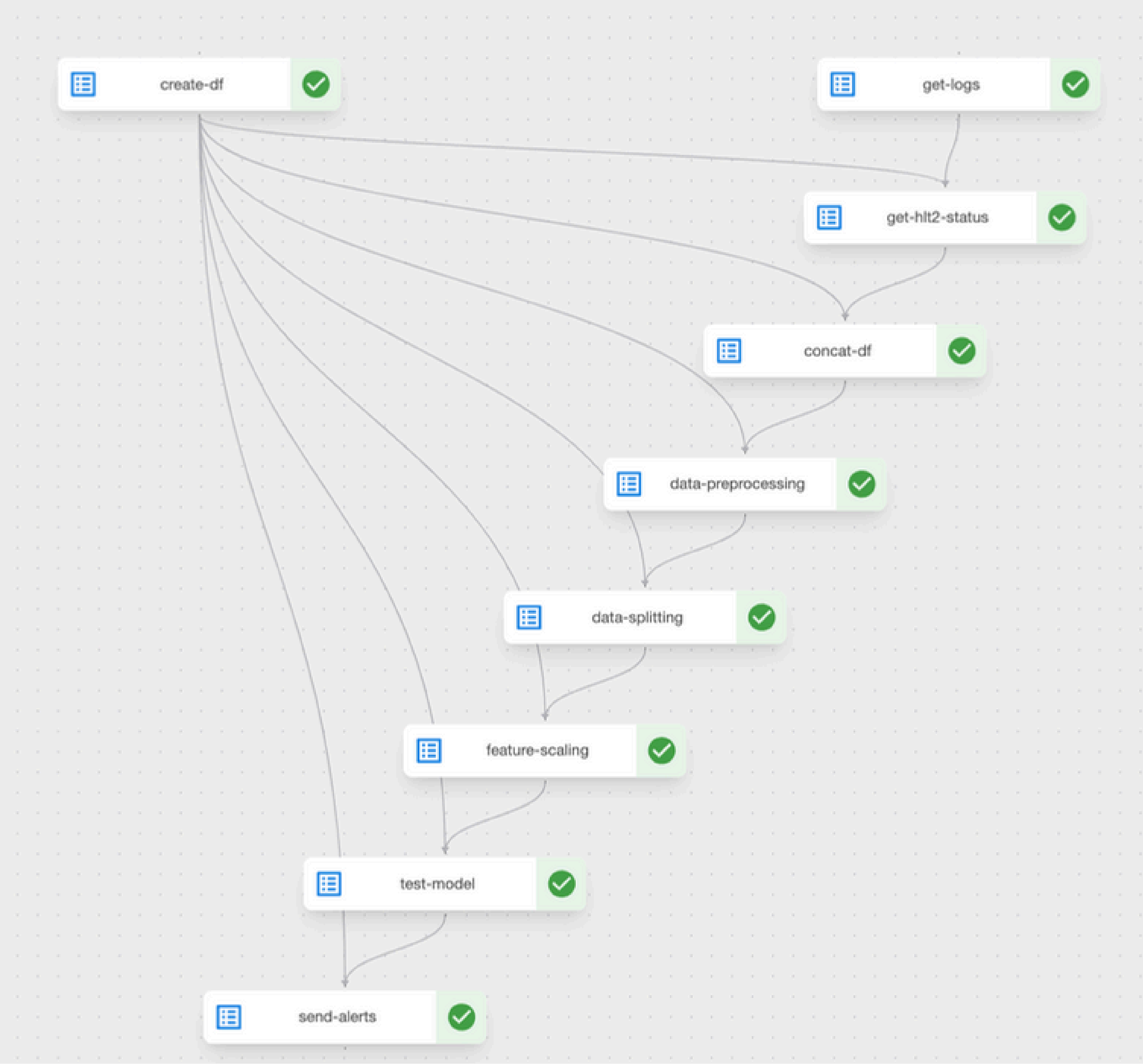


3. Create pipeline in Kubeflow Central Dashboard

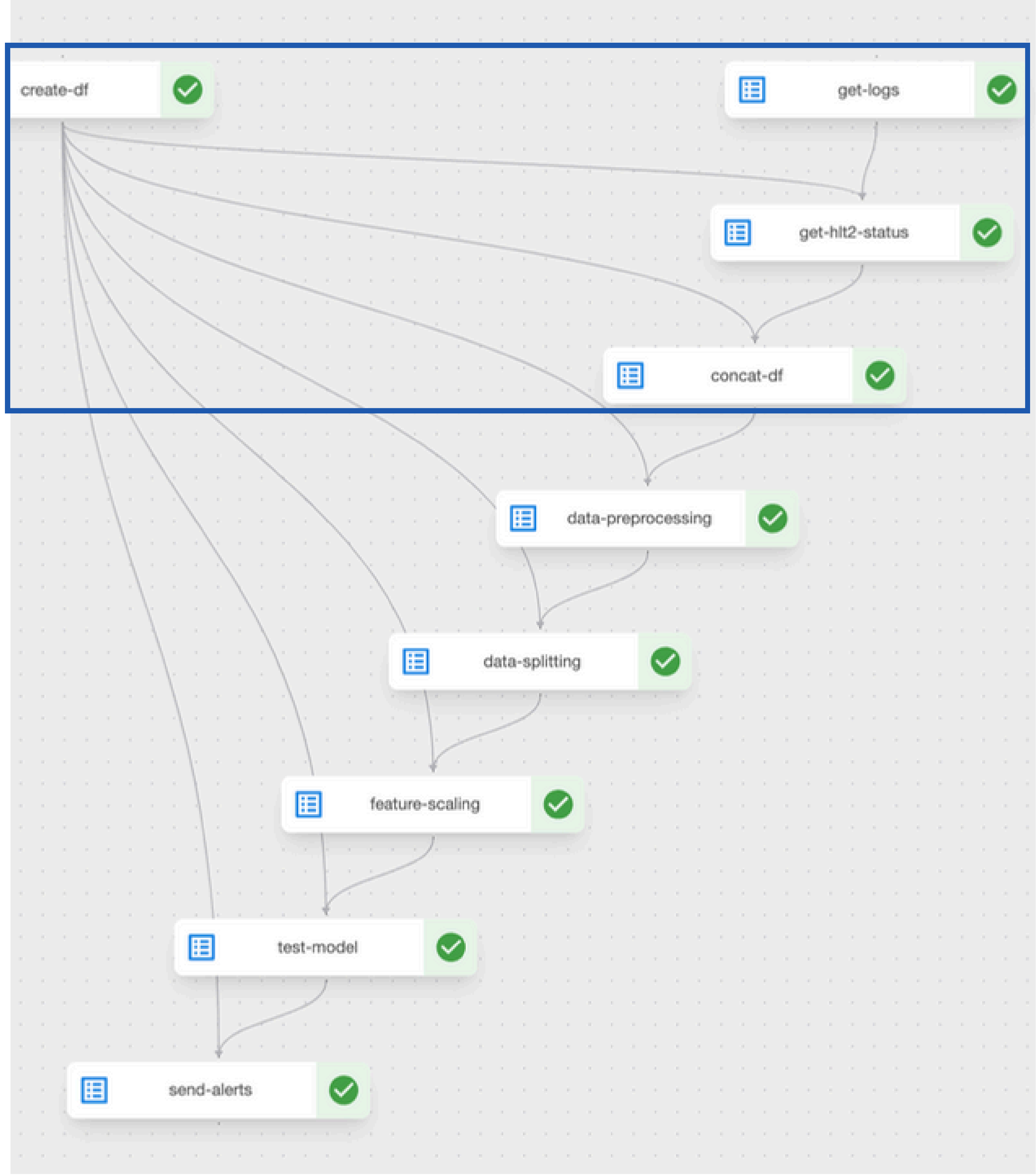


4. Run recurrent calls

PIPELINE


create-df
get-logs
get-hlt2-status
concat-df
data-preprocessing
data-splitting
feature-scaling
test-model
send-alerts

DATA COLLECTION



Prometheus

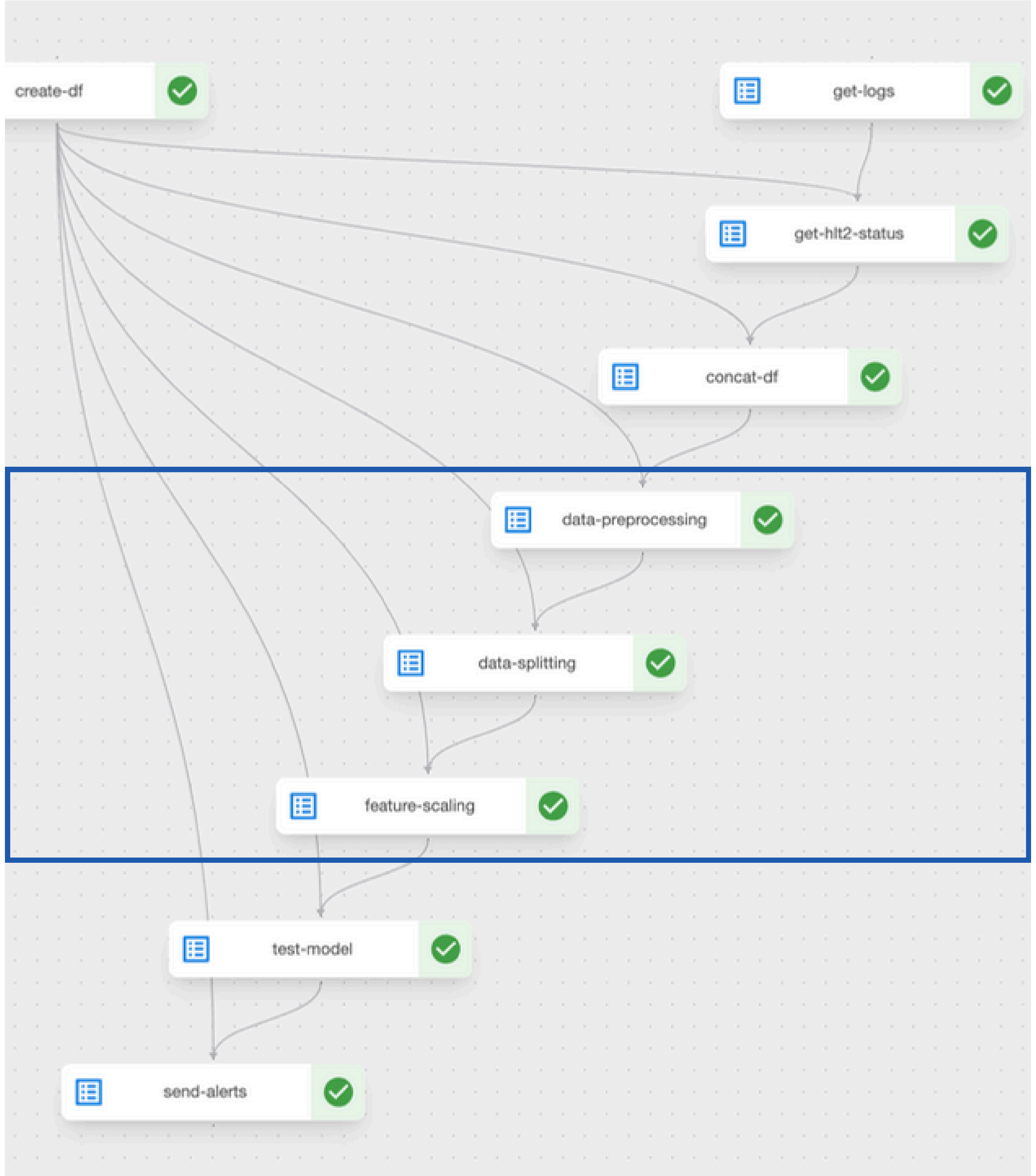
HLT20319_2> in state <PAUSED>
HLT20303_2> in state <PAUSED>
HLT20329_2> in state <PAUSED>
HLT20333_2> in state <PAUSED>

Logs

event monitoring
and alerting

Metrics

CPU Utilization
Disk I/O
Memory
Network
System Overview



DATA PREPROCESSING

Fill missing values and choose important feature

Split dataset into train and validation

Feature scaling

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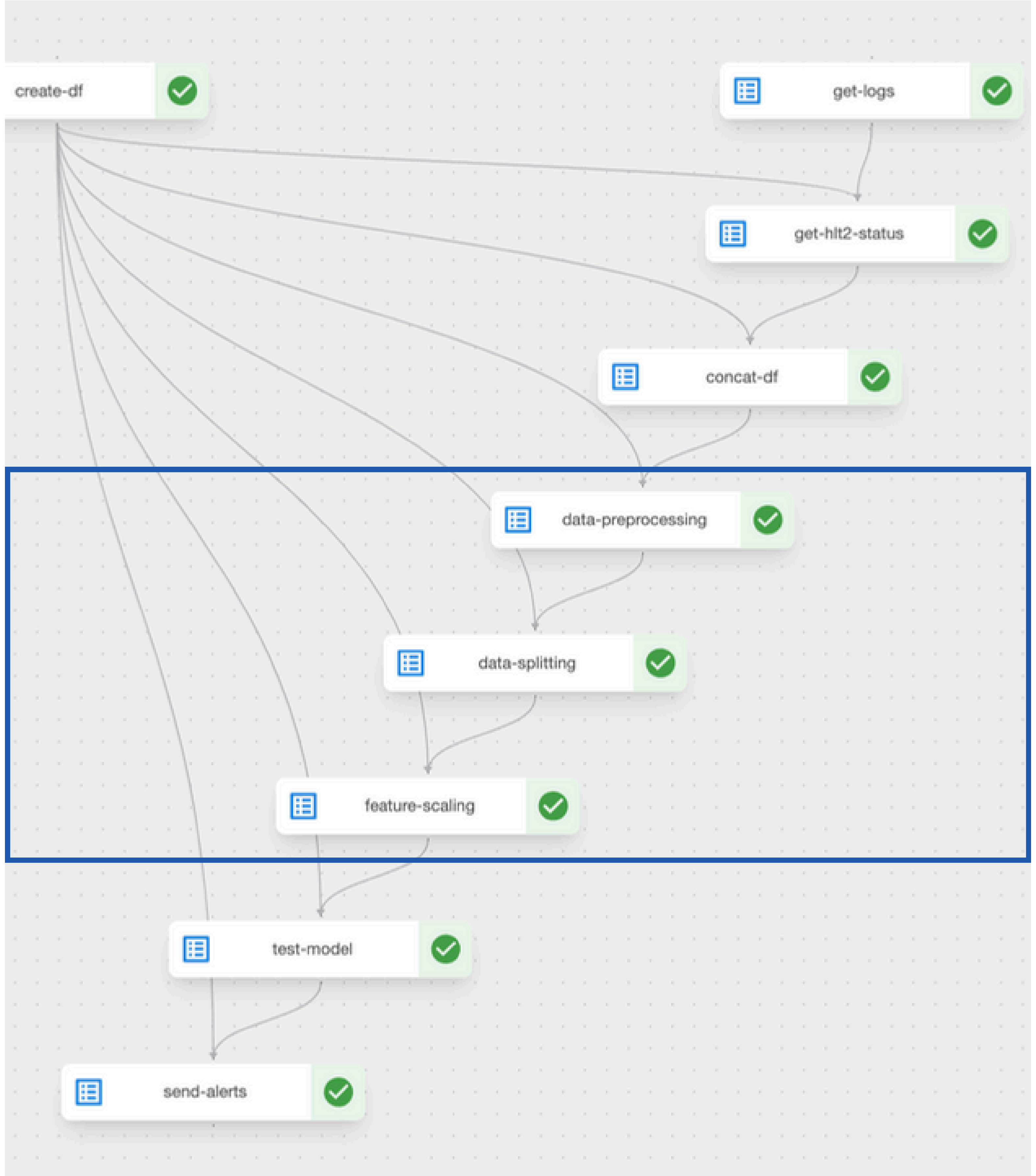

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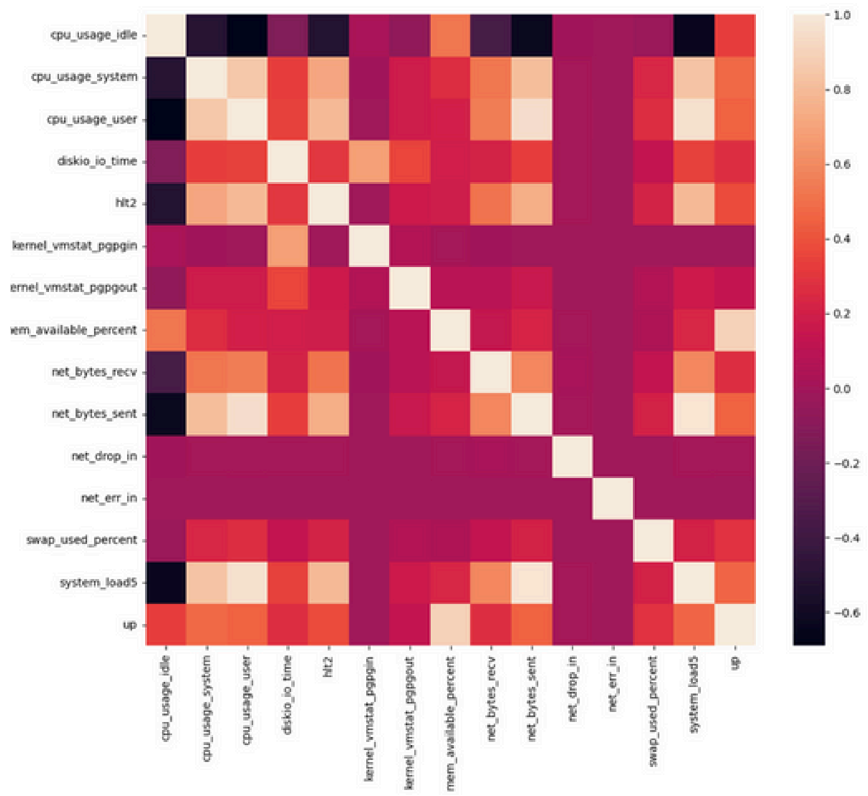
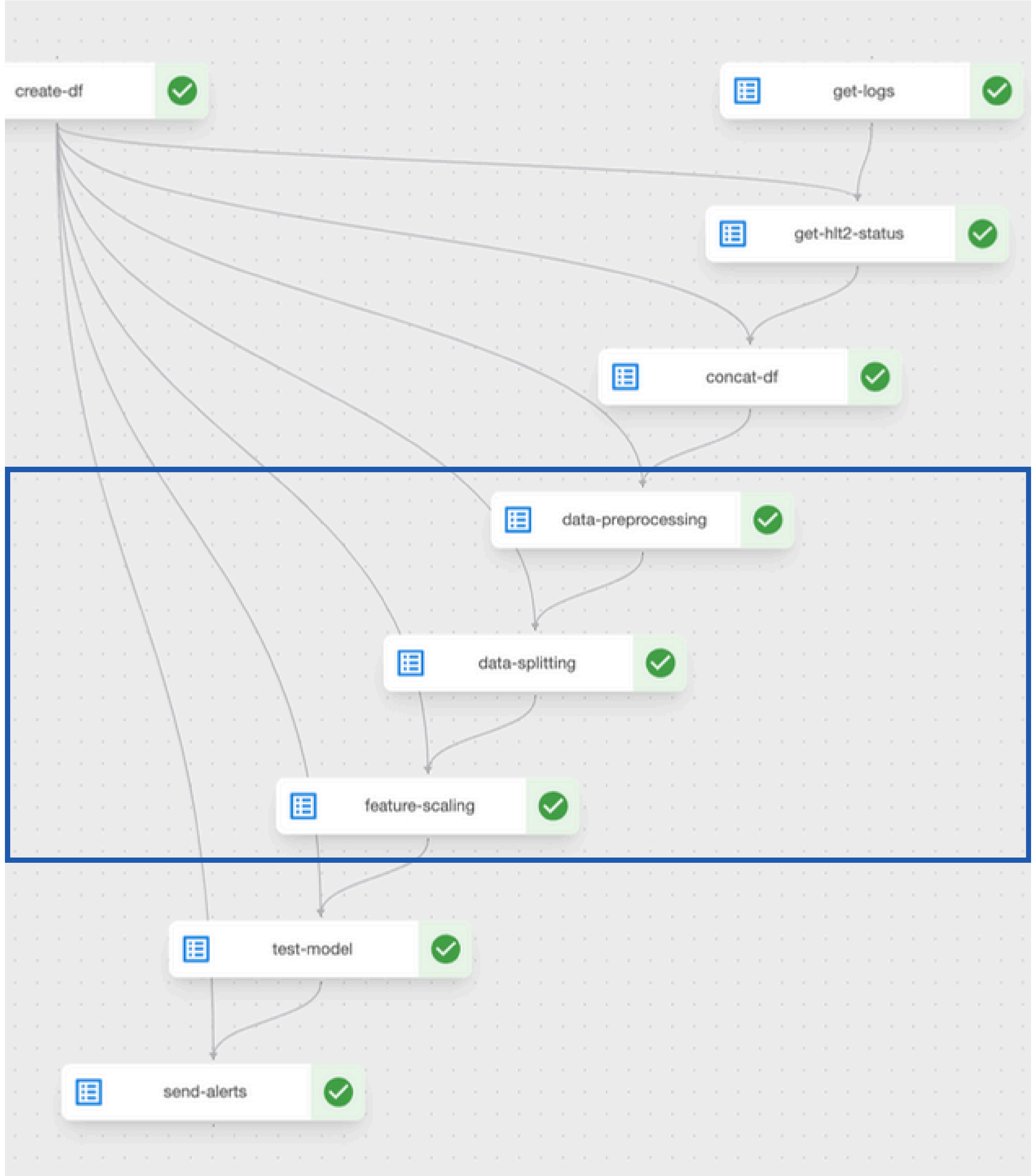


Correlation matrix



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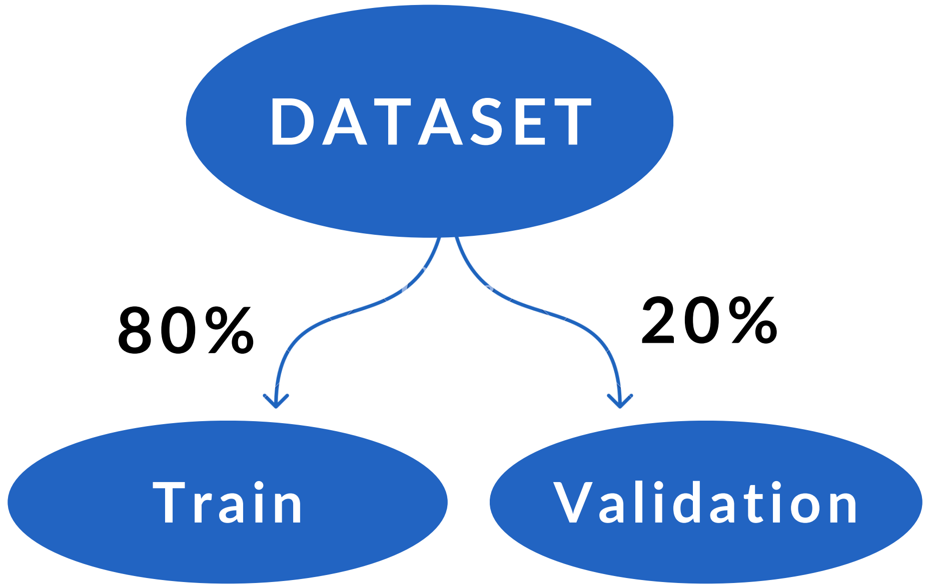

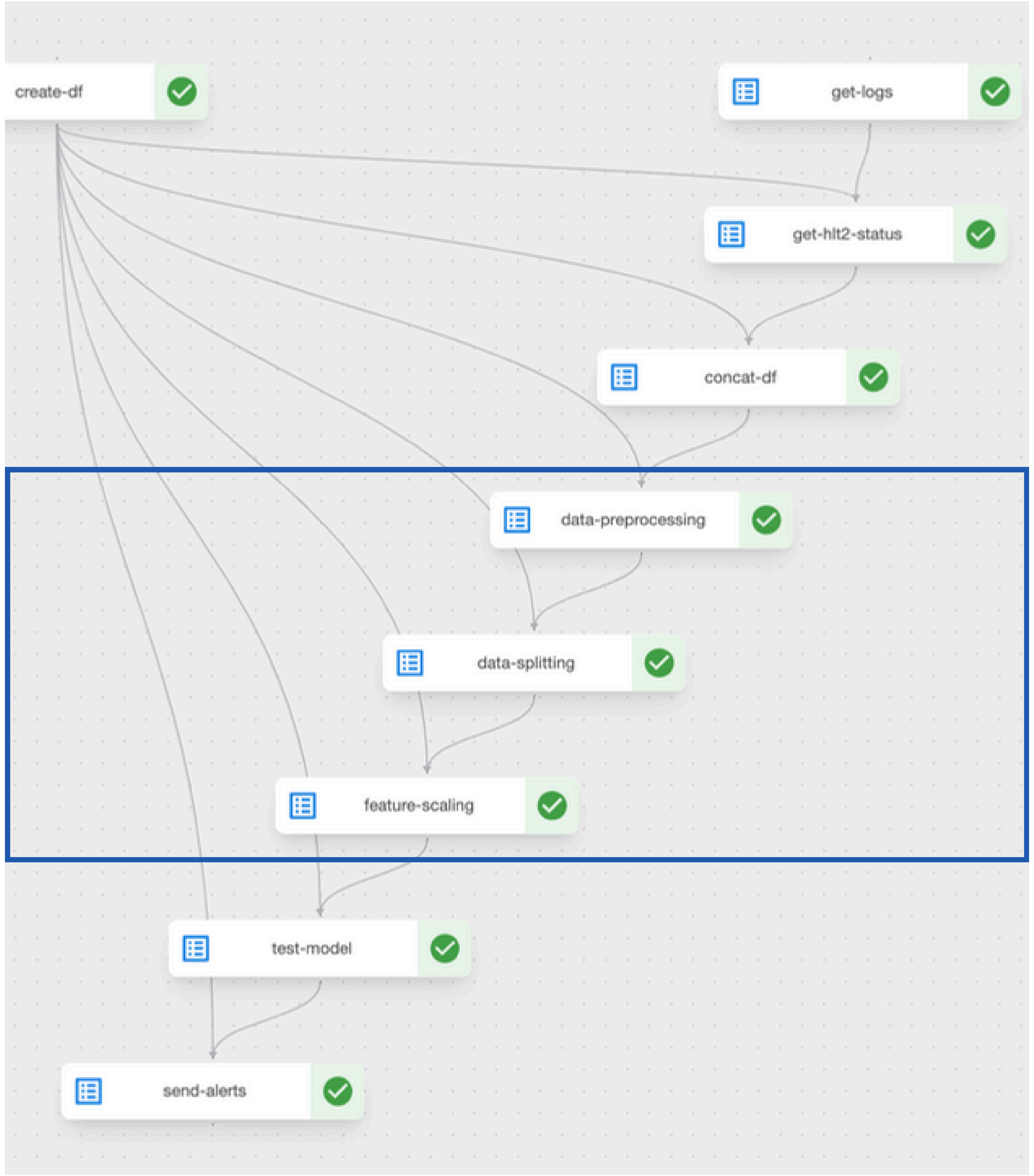

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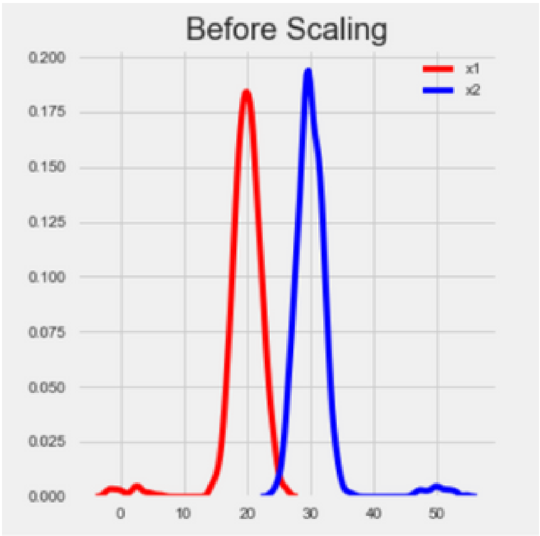
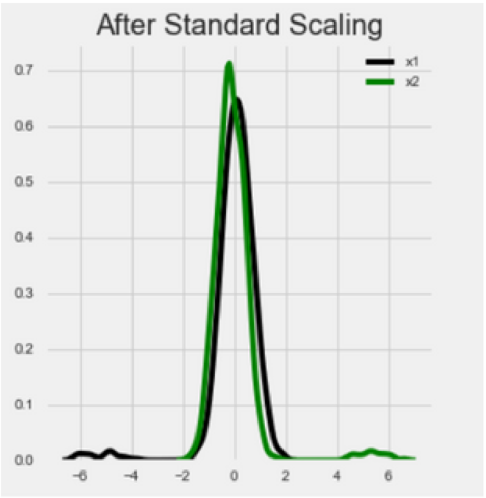
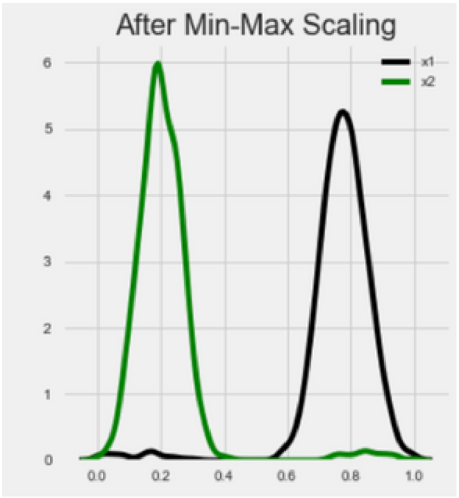
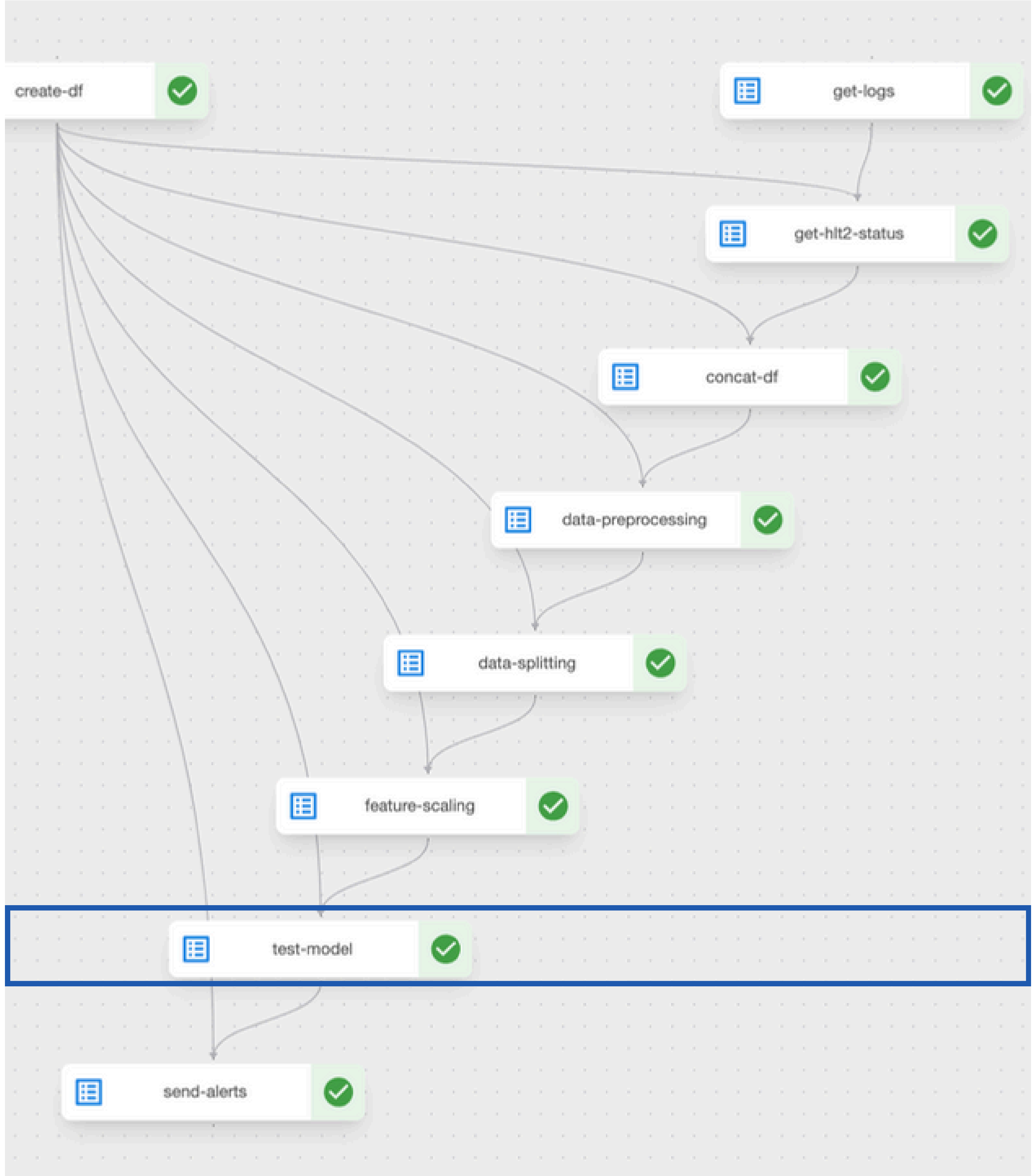




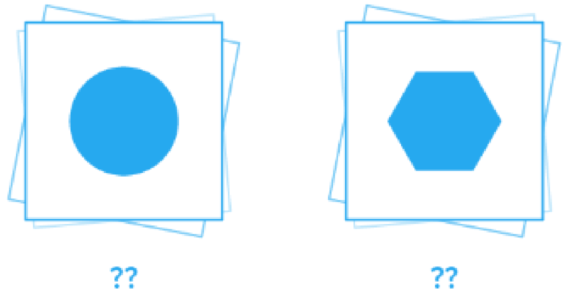
Standard scaler



Min-Max scaler

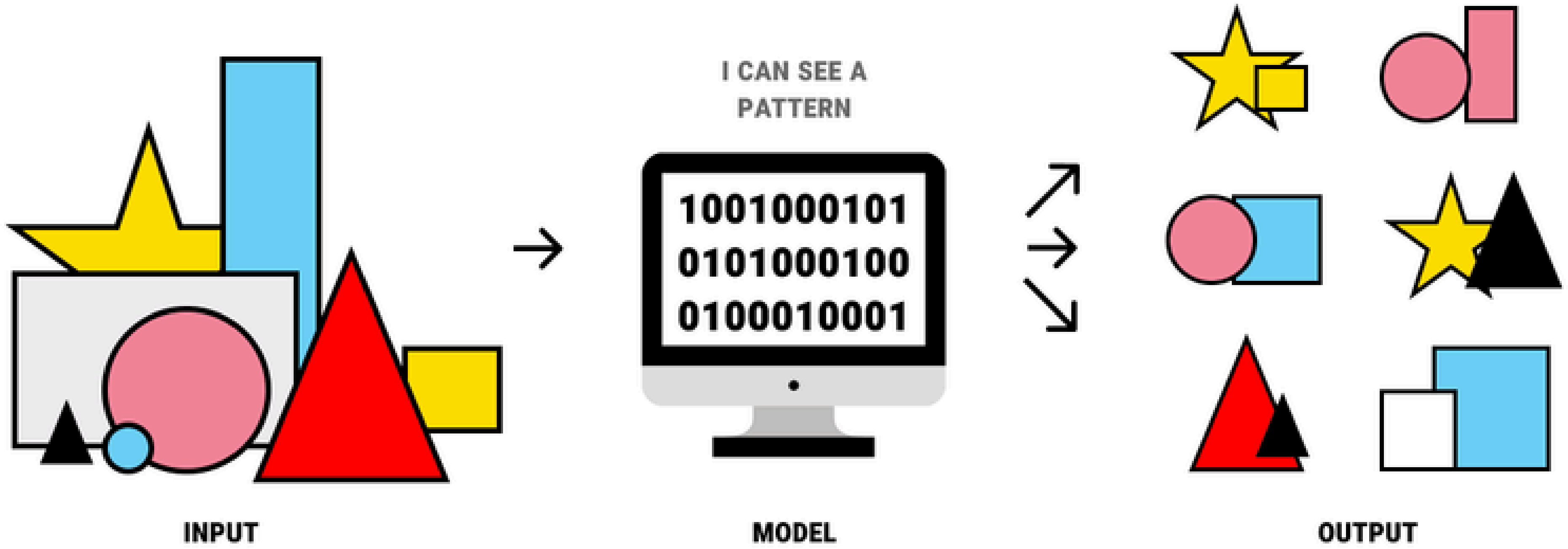


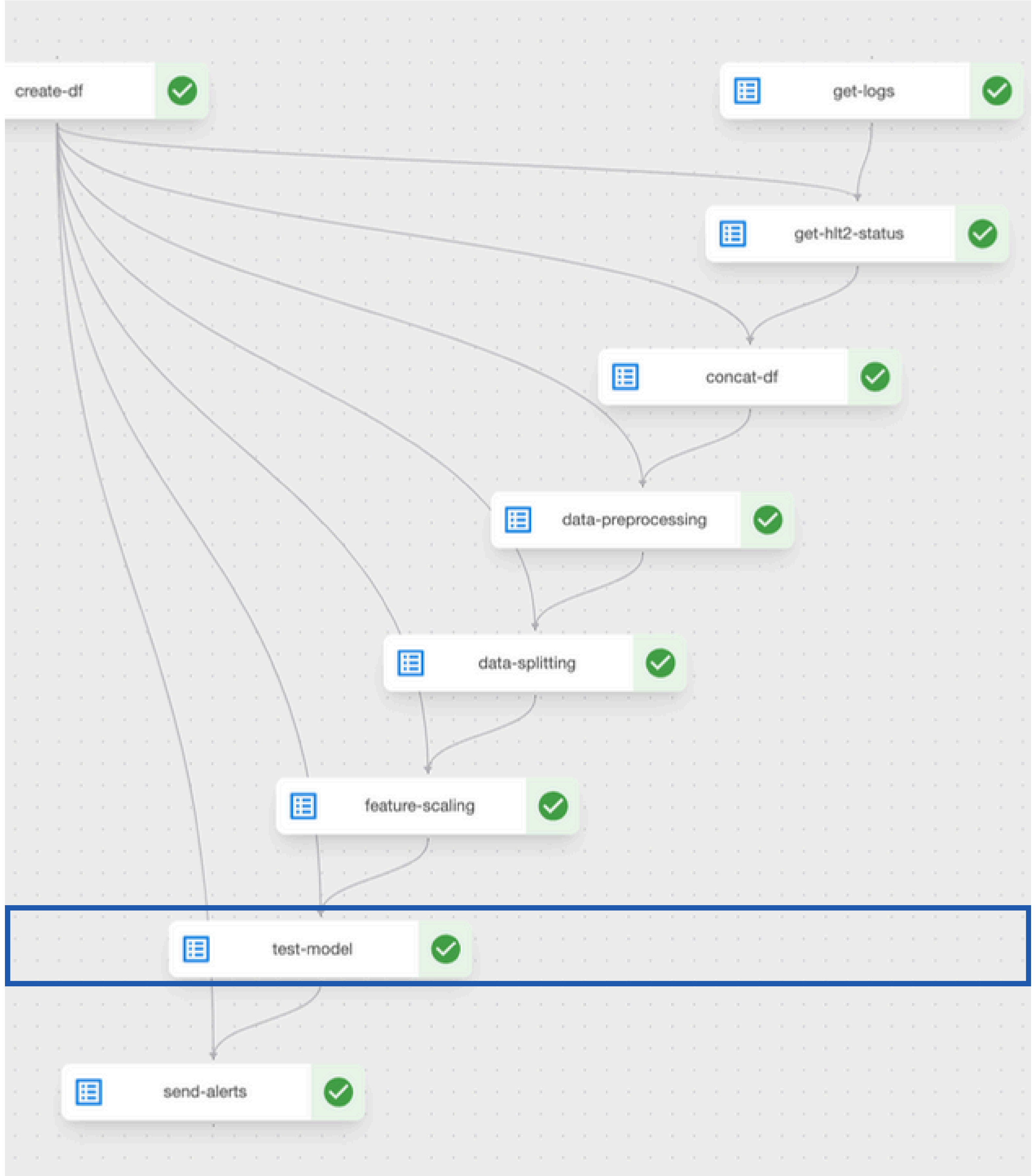
MODEL TRAINING



unlabeled data

Unsupervised learning





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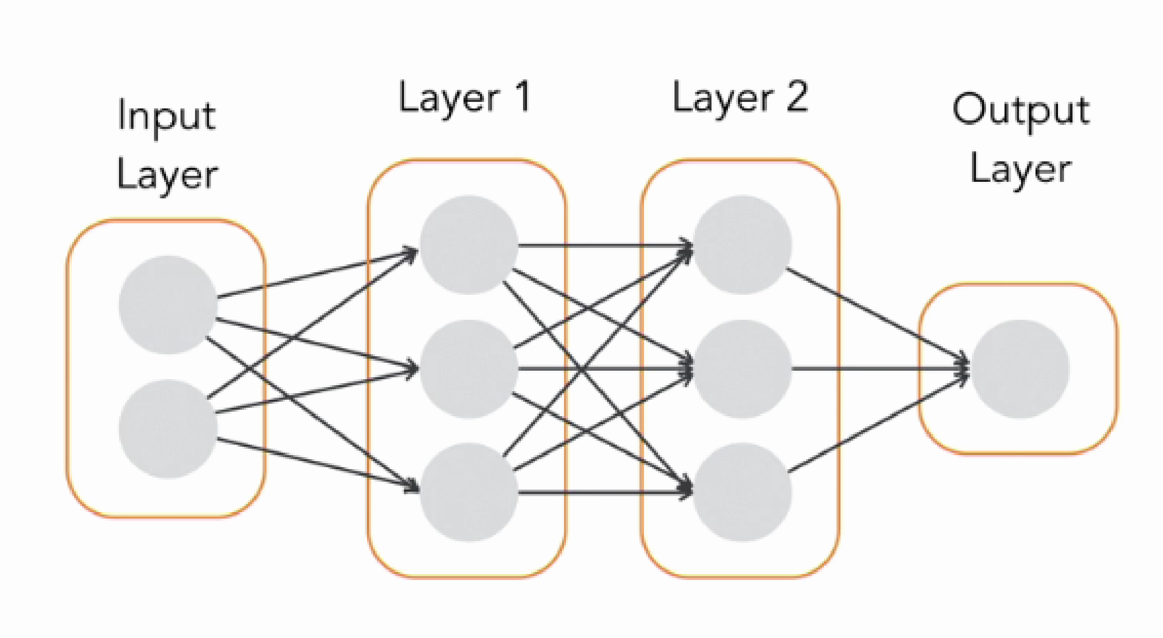
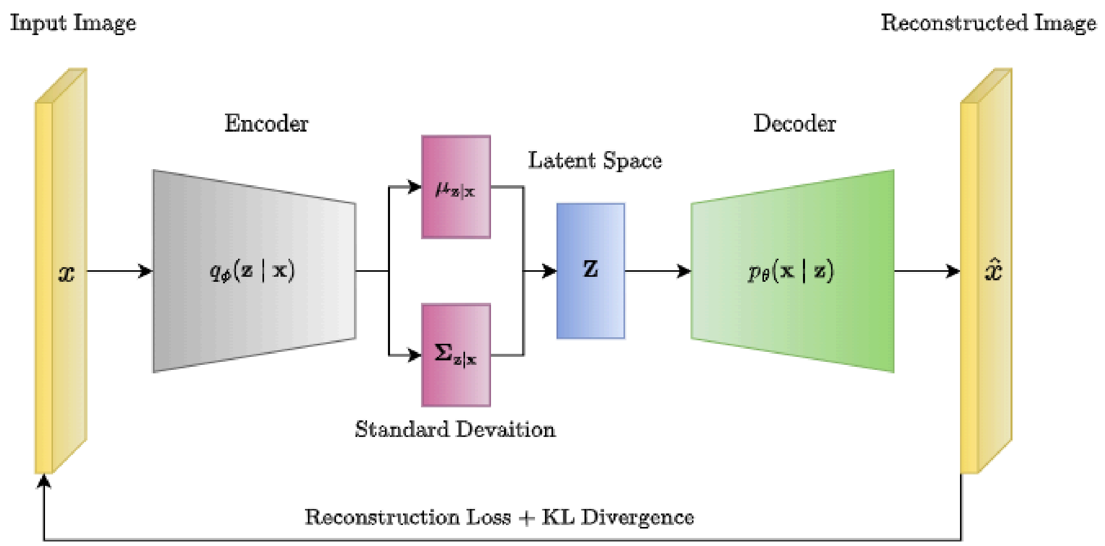
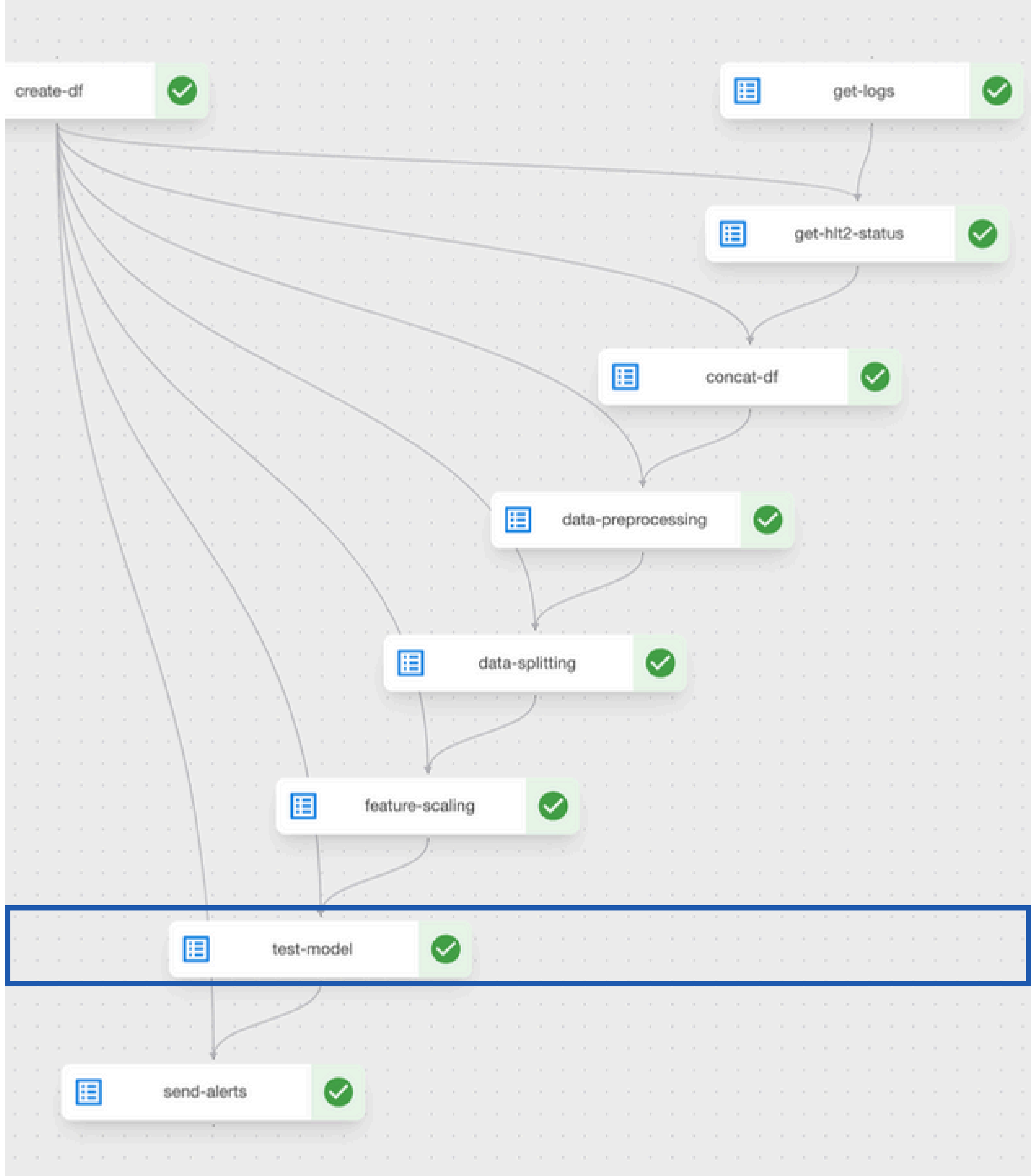


Sequential model



VAE



TESTING

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}|$$

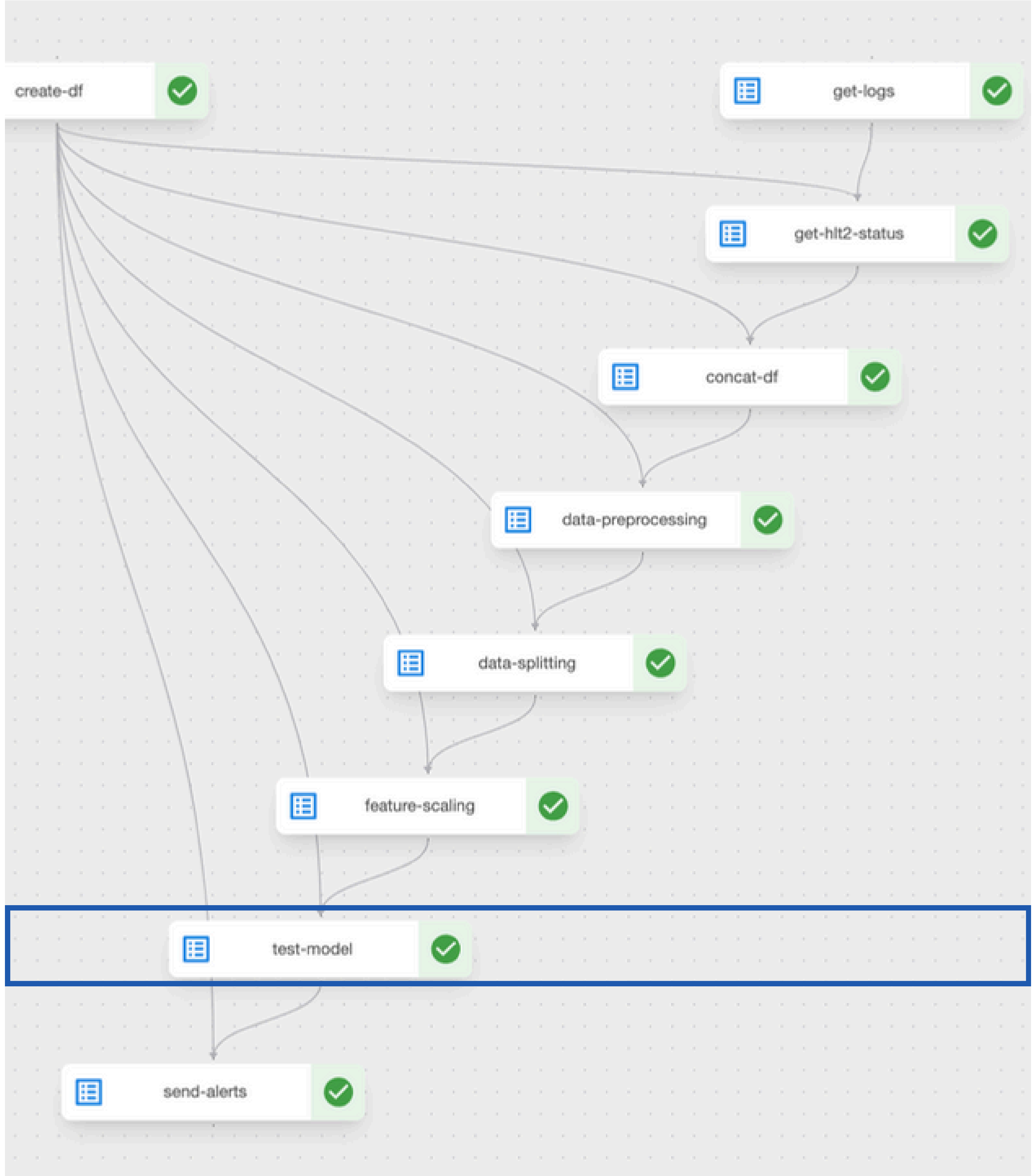
$$MSE = \frac{\Sigma(y_i - \hat{y}_i)^2}{n}$$

where,

n: *number of observation*

y_i: *the actual value of the* i^{th} *observation*

$\widehat{y_i}$: *the predicted value of the* i^{th} *observation*



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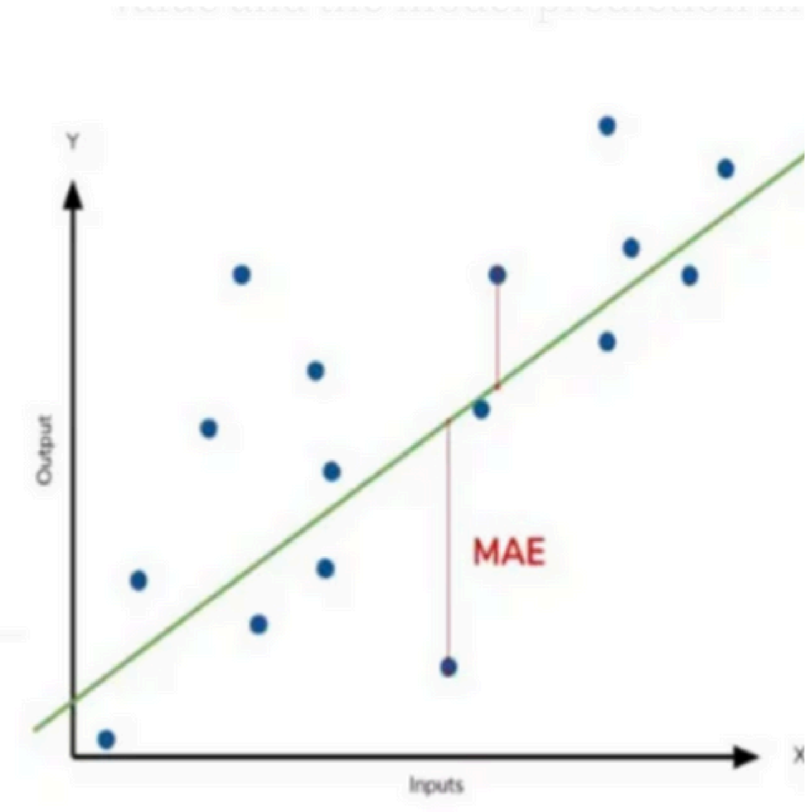
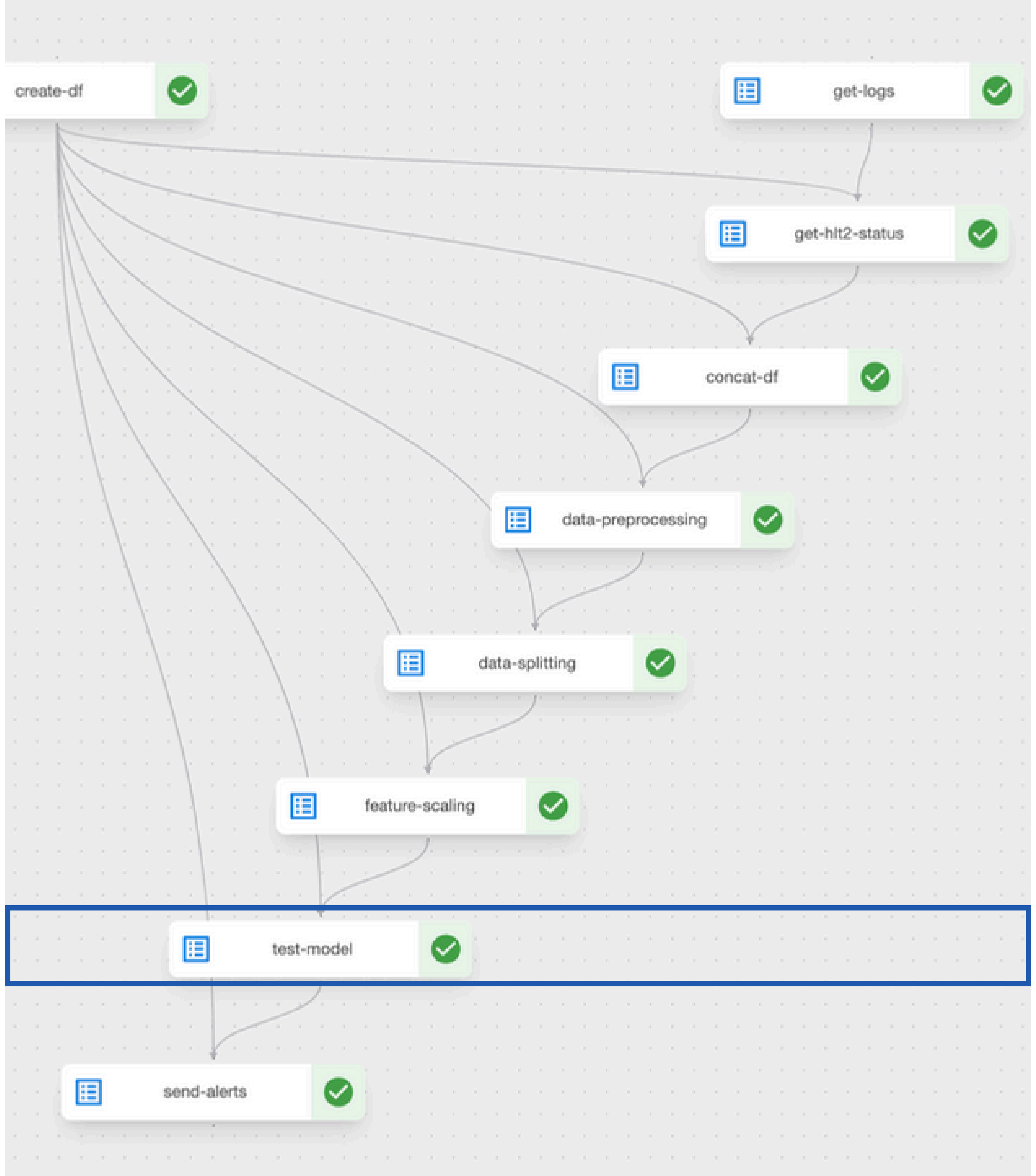


difference between the actual value and the model prediction over the entire data set



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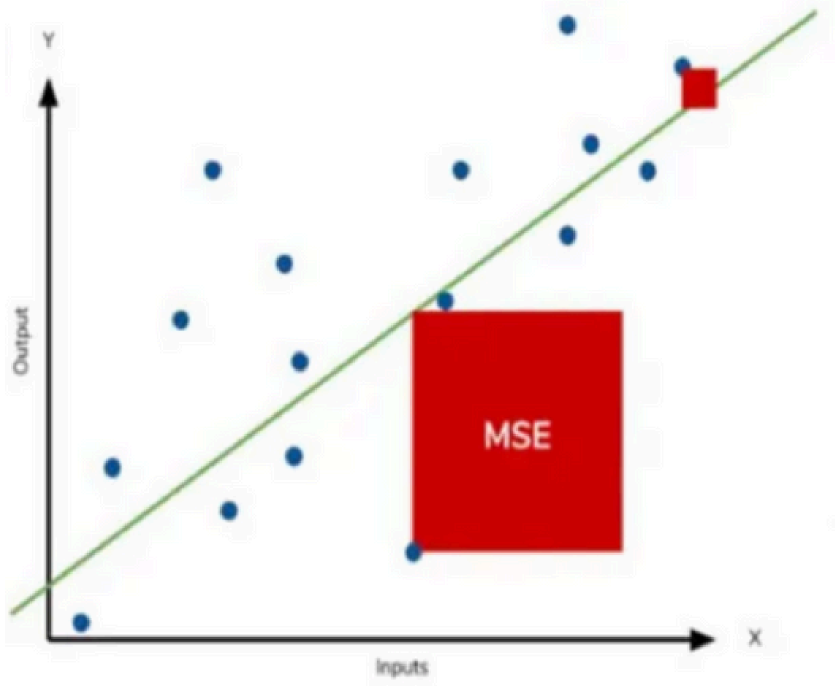
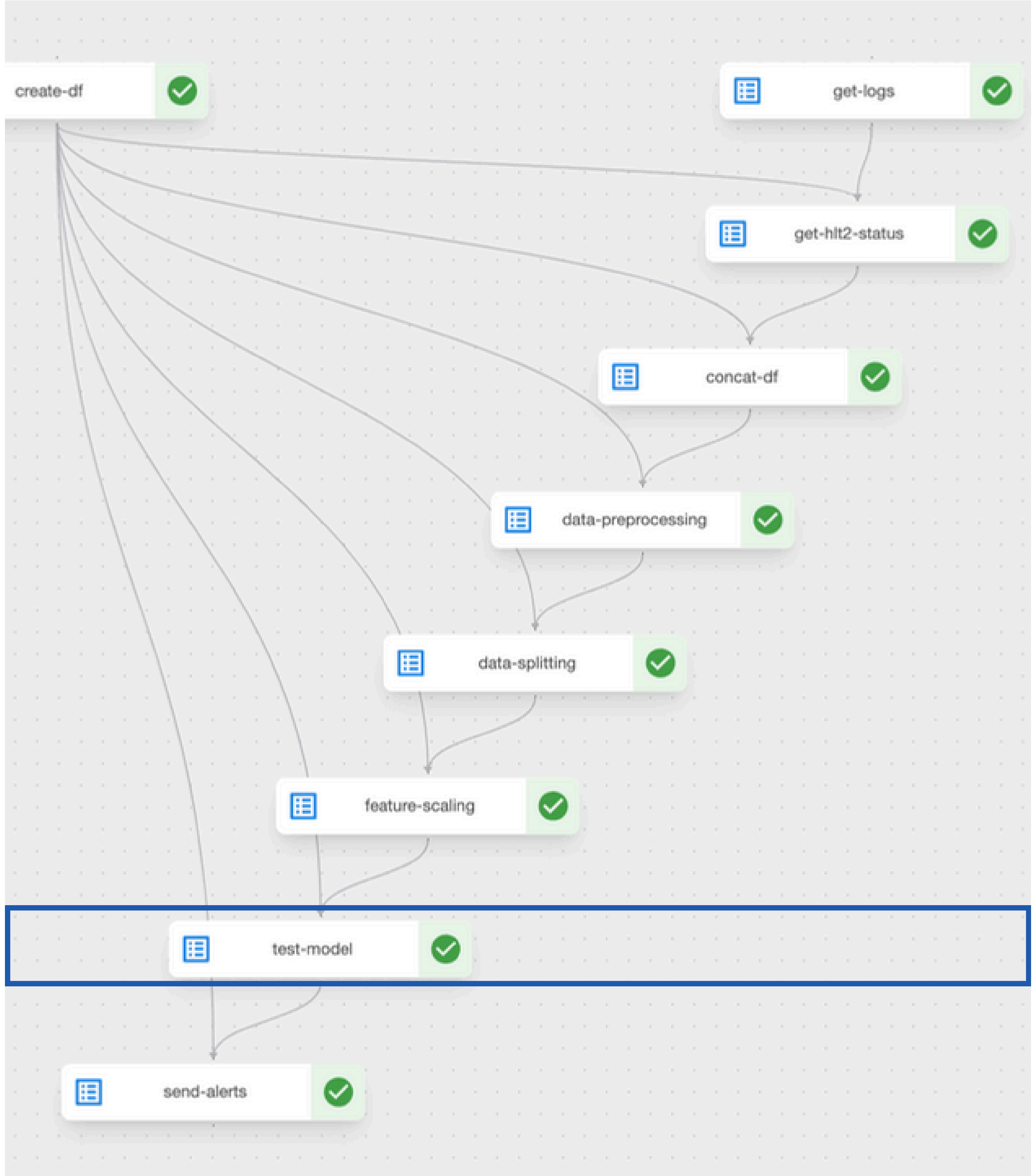


the average *squared* difference between the <u>estimated</u> values and the <u>actual</u> value

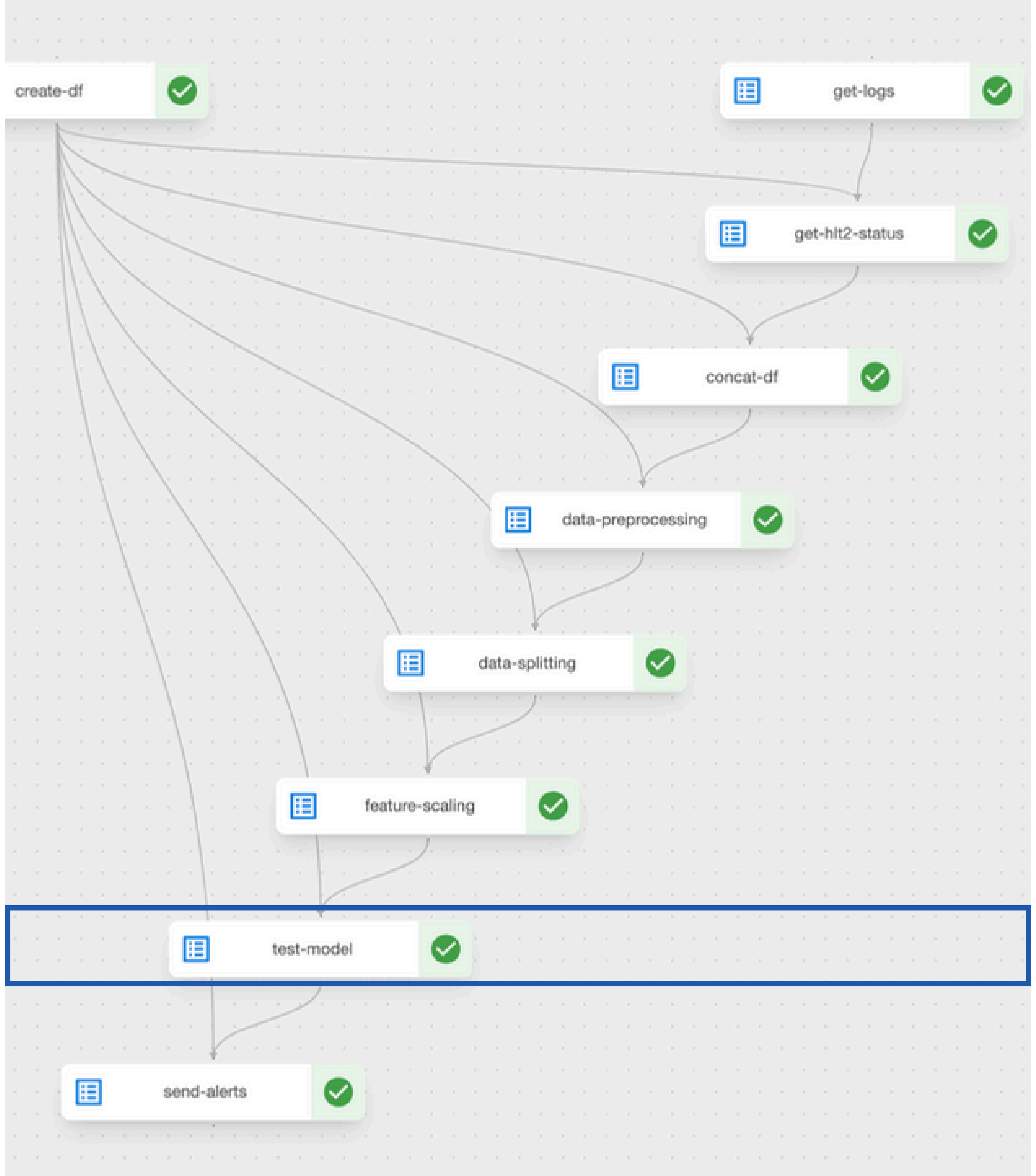


DETECT ANOMALIES

Reconstruct loss on predicted data

Find threshold as 99.9th percentile

Identify anomalies



DETECT ANOMALIES

Reconstruct loss on predicted data

$$L = \frac{1}{n}\sum_{i=1}^{n} |y_i - \tilde{y}_i|$$

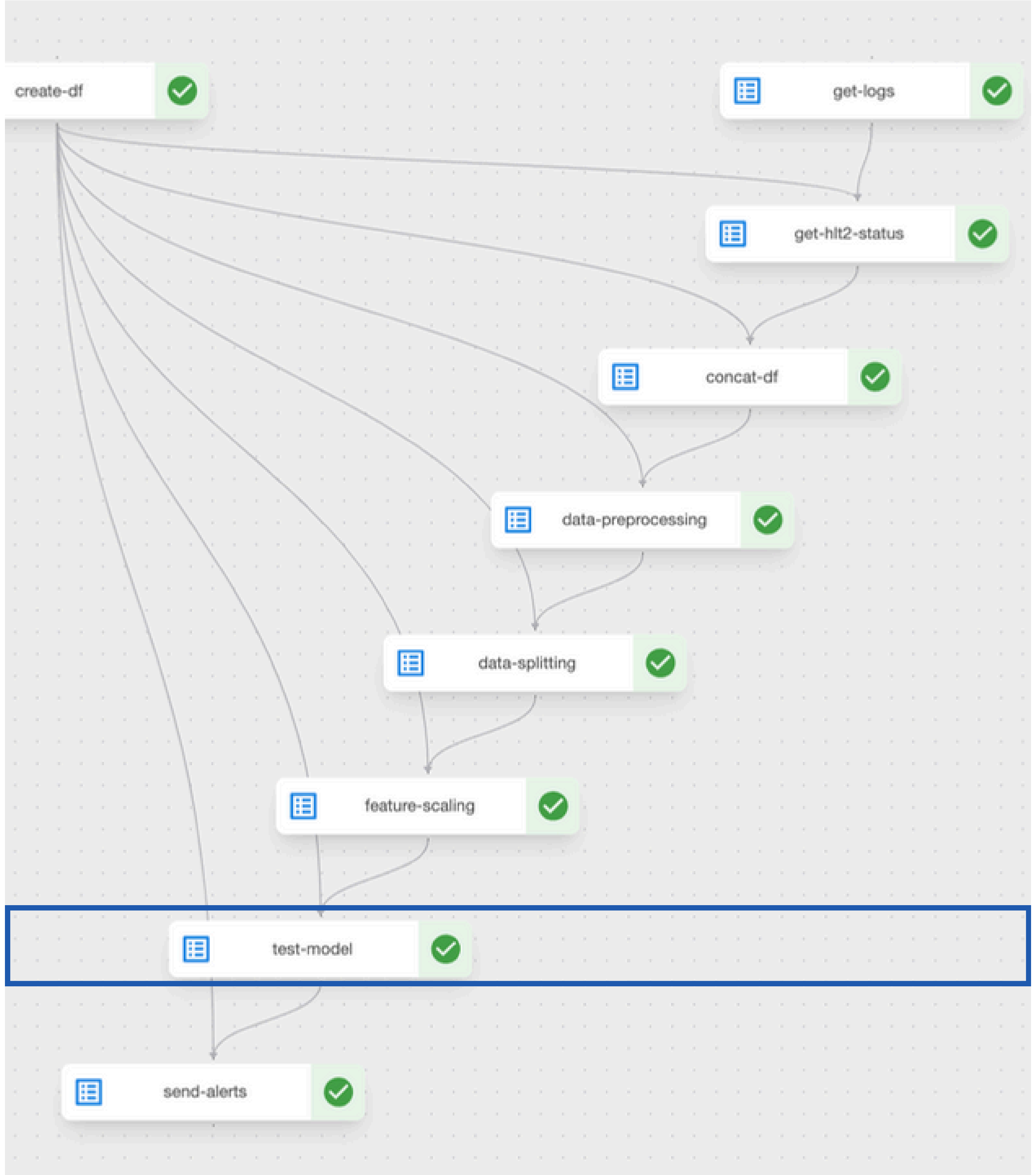
y_i is the original data point.

$\tilde{y}_i$ is the reconstructed data point.

$|y_i - \tilde{y}_i|$ is the absolute difference

Find threshold as 99.9th percentile

Identify anomalies



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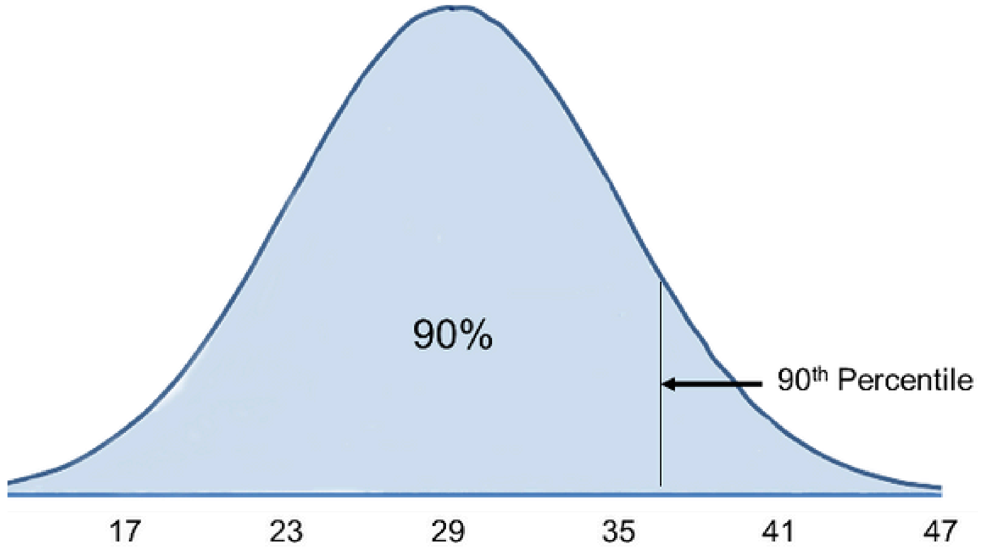

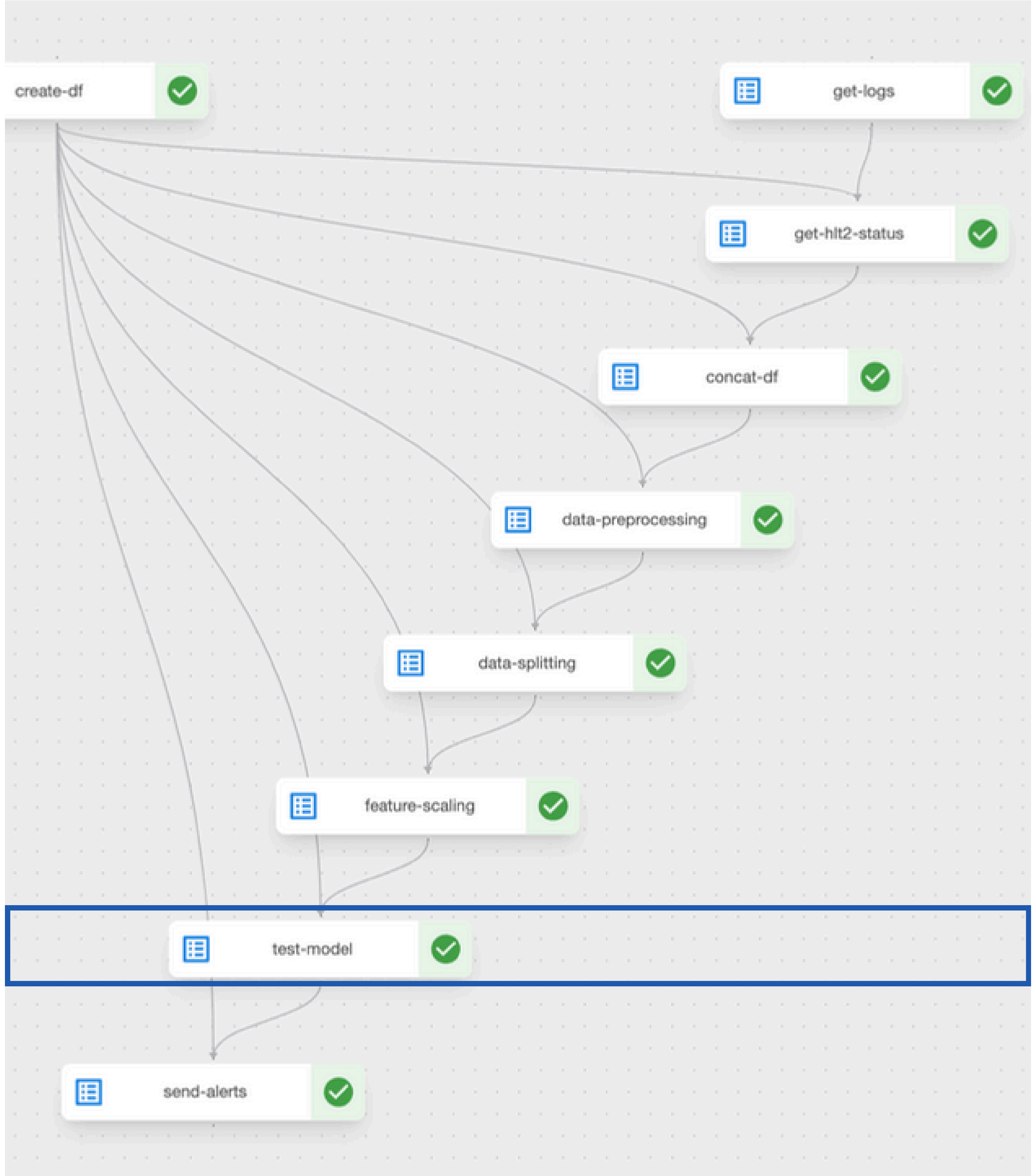

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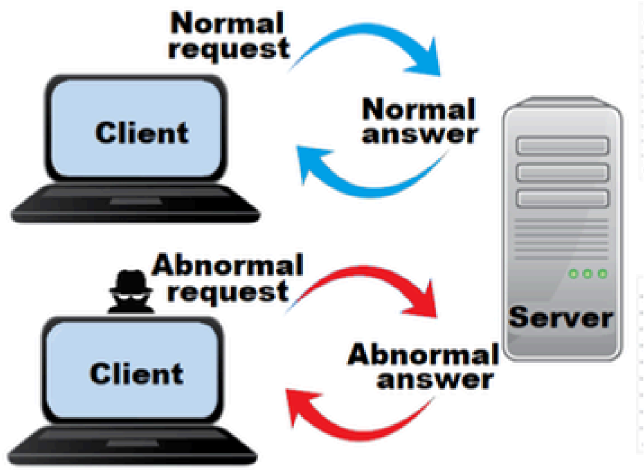
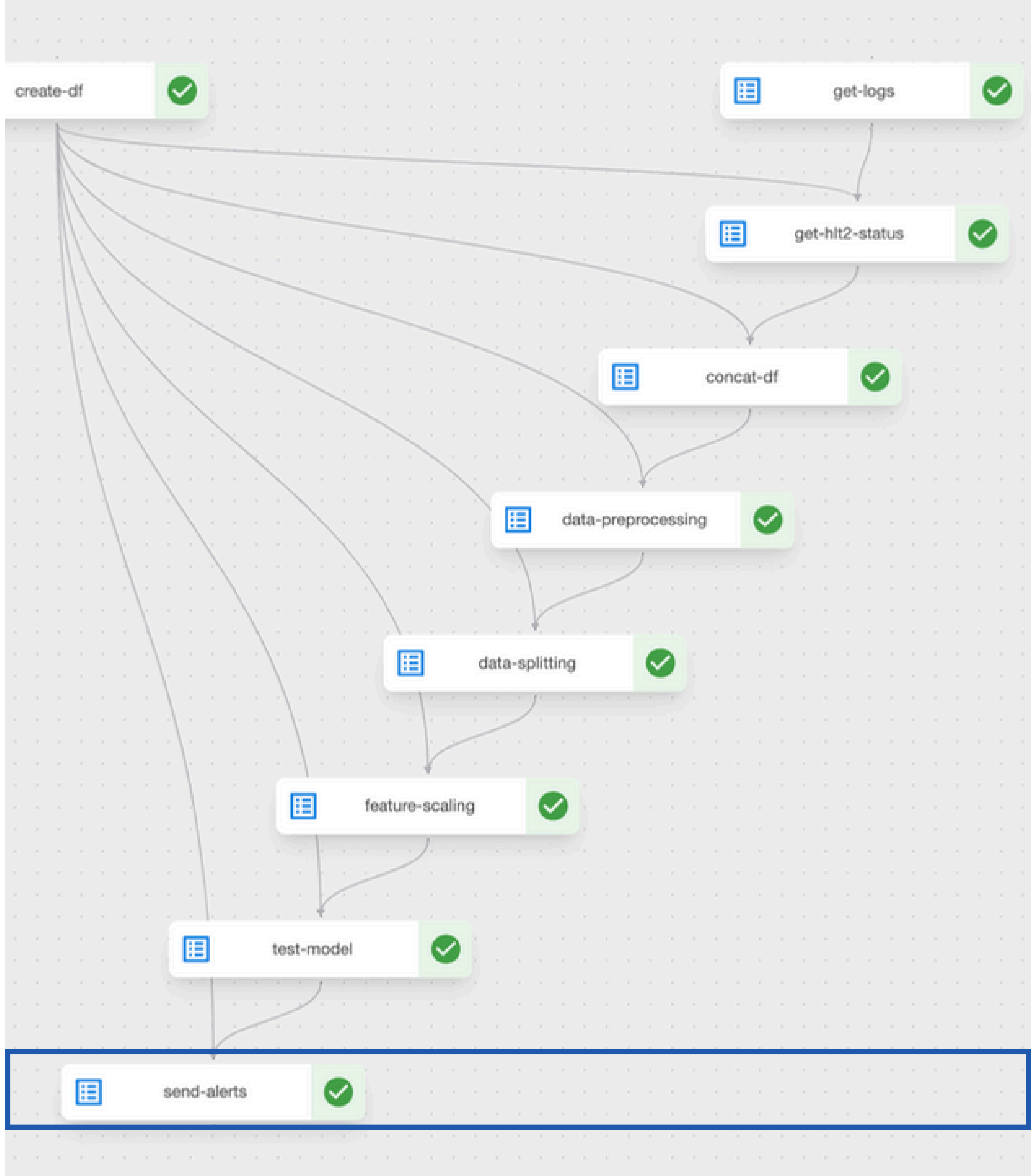


when the reconstruction loss exceeds the threshold

SEND ALERTS



Recurring Runs

Status	Trigger
ENABLED	Every 1 days

Gmail

Anomaly Detection Report

1 message

anastasiia.petrovych@cern.ch <anastasiia.petrovych@cern.ch>
To: anastasiyapetrovych25@gmail.com

Dear Colleague,

This is the detected anomaly report for the past day. Please find the details below:

Anomalies detected:
- Node n2011704 has 1 windows with high anomaly scores.
- Node n2012503 has 1 windows with high anomaly scores.
- Node n2020501 has 1 windows with high anomaly scores.
- Node n2020504 has 1 windows with high anomaly scores.
- Node n2020901 has 1 windows with high anomaly scores.
- Node n2022501 has 2 windows with high anomaly scores.
- Node n2022504 has 1 windows with high anomaly scores.
- Node n2022901 has 1 windows with high anomaly scores.
- Node n2024101 has 1 windows with high anomaly scores.
- Node n2024104 has 1 windows with high anomaly scores.
- Node n2024304 has 1 windows with high anomaly scores.
- Node n2024503 has 2 windows with high anomaly scores.
- Node n2040102 has 1 windows with high anomaly scores.
- Node n2040104 has 1 windows with high anomaly scores.
- Node n2040304 has 1 windows with high anomaly scores.
- Node n2040703 has 1 windows with high anomaly scores.
- Node n2041501 has 1 windows with high anomaly scores.
- Node n2041503 has 1 windows with high anomaly scores.
- Node n2044302 has 4 windows with high anomaly scores.
- Node n2052504 has 1 windows with high anomaly scores.
- Node n2053901 has 3 windows with high anomaly scores.
- Node n2054301 has 5 windows with high anomaly scores.
- Node n2062502 has 1 windows with high anomaly scores.
- Node n2062702 has 3 windows with high anomaly scores.

Regards,
LHCb team.

CONCLUSION

- Automated the anomaly detection process and increased efficiency
- Improved the accuracy and reliability of the whole pipeline
- Implemented daily monitoring for continuous detection and timely alerts

THANK YOU!

Anastasiia Petrovych