Zabbix meets AI
-
Leverage machine learning for detecting anomalies

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Zabbix meets AI

First of all
This talk is not about ChatGPT ;-)

Nevertheless – ChatGPT is a great product

Zabbix meets AI

Time travel

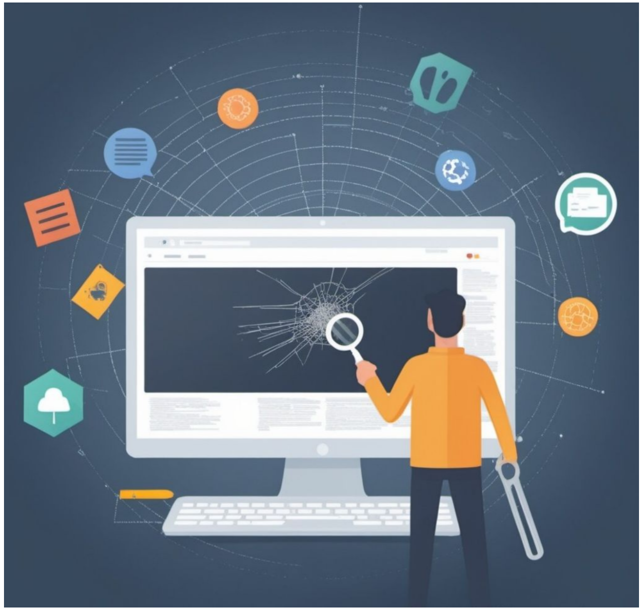
-

Back to the year 2020

Zabbix meets AI

It all started in May 2020

- One of our customers operates webshops
- These webshops are monitored by Zabbix
- On May 19th 2020 our customer found out that one of the webshops had been hacked
- Zabbix did not alert the hack
- The customer was not happy about this...



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Zabbix meets AI

Customer:

“Why did the network monitoring not alert that the webshop was hacked?”

We:

“Because Zabbix was not configured for this specific scenario.”

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Zabbix meets AI

Customer:

“If a doctor takes a blood screen, he can determine whether something is wrong, why can't Zabbix network monitoring do that?”

We:

“Again, because Zabbix was not configured for this specific scenario.”

“But wait, **maybe** there is a way for Zabbix to learn about the special features of a particular environment and then detect that something is `different`.”

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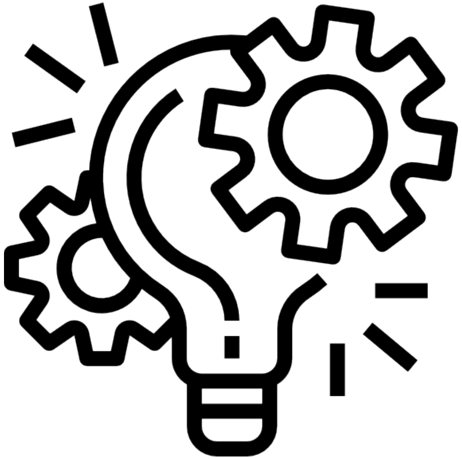
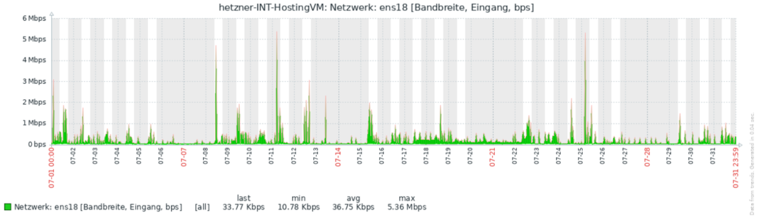
The idea of anomaly detection

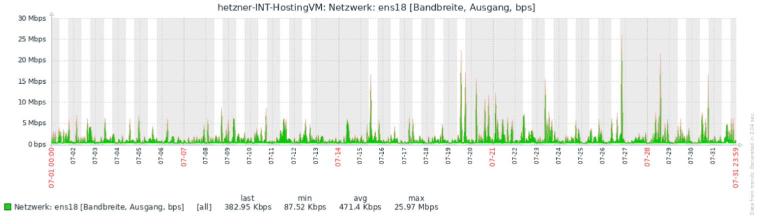


Zabbix meets AI – The idea of anomaly detection

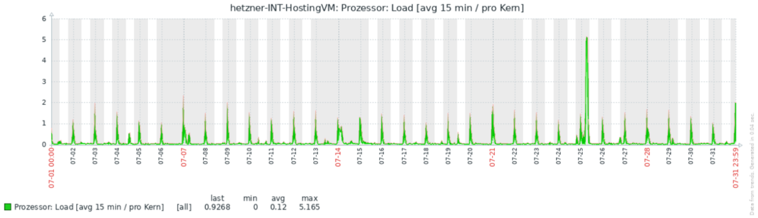
Network In



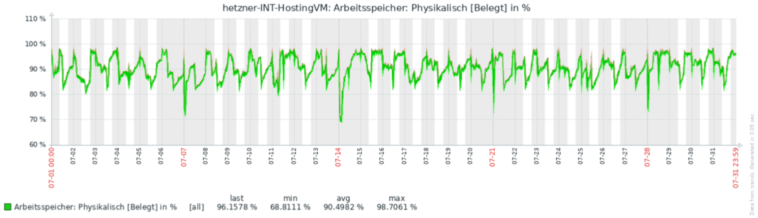
Network Out



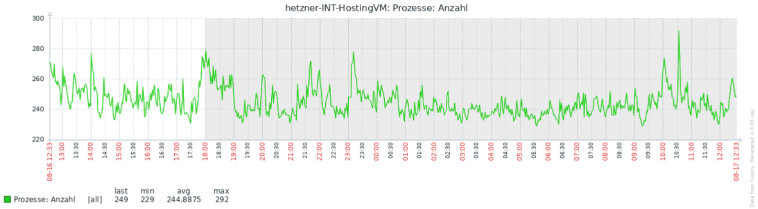
CPU Load



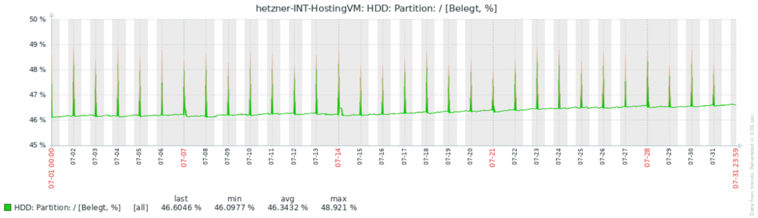
Memory Used



Processes Count



Free Disk Space



Simple “Blood screen” of a system

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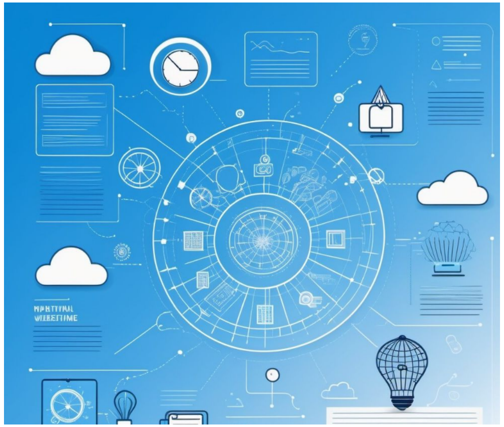
Zabbix meets AI – The idea of anomaly detection

Place individual metrics in a system-specific context to detect anomalies

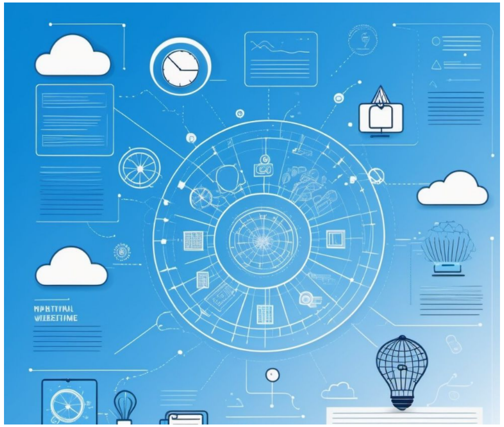
- Instead of having one trigger that looks at one metric at a time, have a system that looks at multiple metrics at once
- Instead of using simple trigger functions or simple aggregate functions, look at the data as a whole over a period of time
- Instead of using triggers with static conditions, let the system "learn" the specific characteristics over time with variable conditions



Zabbix meets AI – The idea of anomaly detection

Examples

- Monitoring server rooms:
  Do not only pay attention to the temperature, but put it in context with the power consumption of the systems, the air conditioning system etc.
- Server utilization:
  Do not only pay attention to the CPU utilization, but put it in a context with the number of users, the memory utilization, the network traffic etc.



Do this with series of values over time, not with single values per metric

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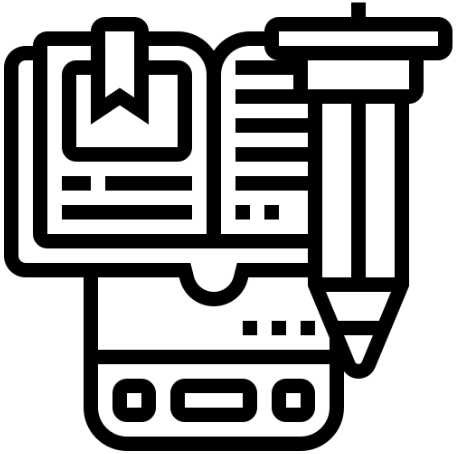
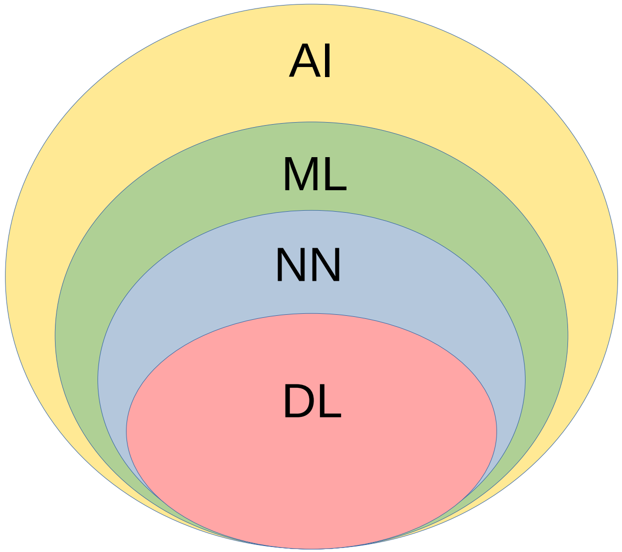
Machine learning and neural networks



Machine learning and neural networks

- Artificial intelligence (AI) is the overarching term
- Machine learning (ML) is a sub-area of AI
- Neural network (NN) is a sub-area of ML and also forms the backbone of deep learning algorithms (sometimes called ANN – Artificial neural network)
- Deep learning (DL) is a sub-area of ML where the number of node layers or depth is higher than in a single neural network
(sometimes called DNN – Deep neural network)



Machine learning is not necessarily based on NN or DL

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Machine learning and neural networks

Example of trigger function in Zabbix using machine learning:

```
trendstl(/host/key,eval period:time shift,detection period,season,
<deviations>,<devalg>,<s window>)
```

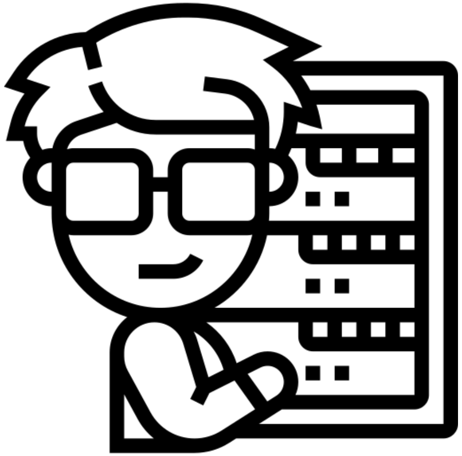
Returns the rate of anomalies during the detection period

```
eval period - the time period that must be decomposed
detection period - the time period before the end of eval period
season - the shortest time period where a repeating pattern is expected
deviations - the number of deviations to count as anomaly
devalg - the deviation algorithm, can be stddevpop, stddevsamp or mad
s window - the span of the loss window for seasonal extraction
```

These functions are designed to work with time series data of a single metric, therefore there is no context to other related metrics

Zabbix meets AI

Simple Data vs. Time series data
Univariate vs. Multivariate data



Machine learning and neural networks

Difference between univariate and multivariate data / simple and time-series data

- Univariate simple data: One value
  Example: Temperature: 23 C
- Univariate time series data: List of values
  Example: 23 C, 24 C, 25 C

- Multivariate simple data: Multiple metrics, one value per metric
  Example: Temperature: 23 C, Humidity: 56 %, Air Pressure: 998 mbar
- Multivariate time series data: Multiple metrics, list of value sets
  Example: 23 C/56 %/998 mbar, 24 C/55 %/1002 mbar, 25 C/54 %/1004 mbar

We want multivariate time-series data because we need contextual relationships and temporal context

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Machine learning and neural networks

Univariate times-series data

[{"temp":23, "time":1723988060},
{"temp":24, "time":1723988120},
{"temp":25, "time":1723988180}]

[{"apress":998, "time":1723988060},
{"apress":1002, "time":1723988120},
{"apress":1004, "time":1723988180}]

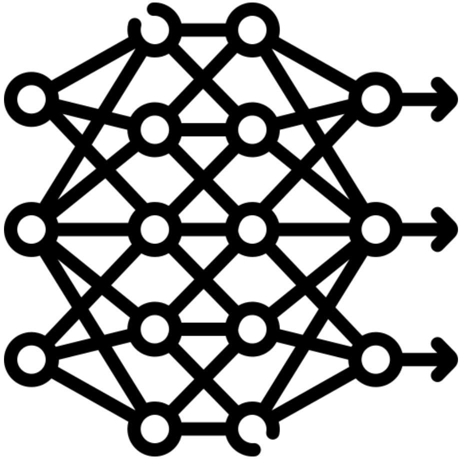
[{"humidity":56, "time":1723988060},
{"humidity":55, "time":1723988120},
{"humidity":54, "time":1723988180}]

Multivariate times-series data

[{"temp":23, "hum":56, "apress":998, "time":1723988060},
{"temp":24, "hum":55, "apress":1002, "time":1723988120},
{"temp":25, "hum":54, "apress":1004, "time":1723988180}]

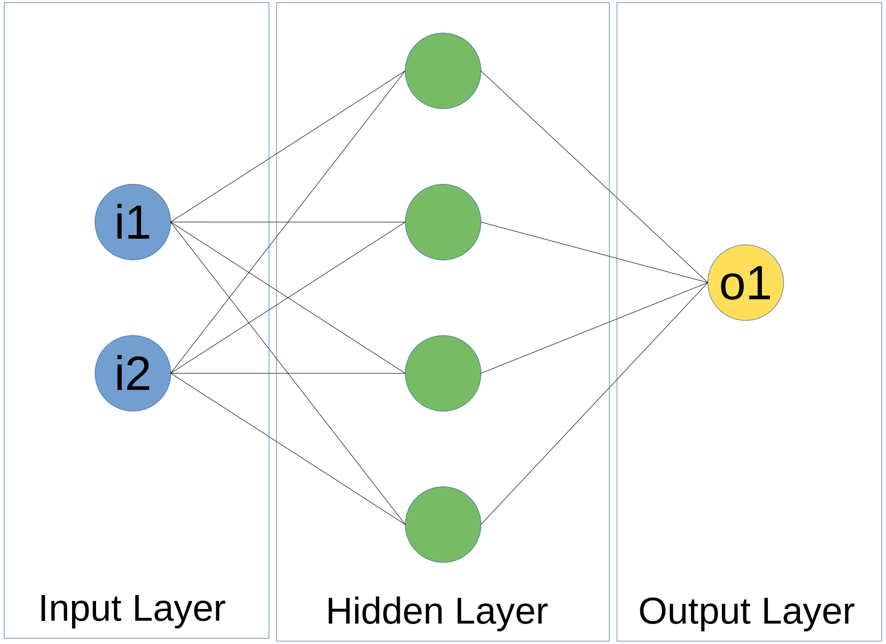
Convert univariate times-series data into multivariate time-series data sets

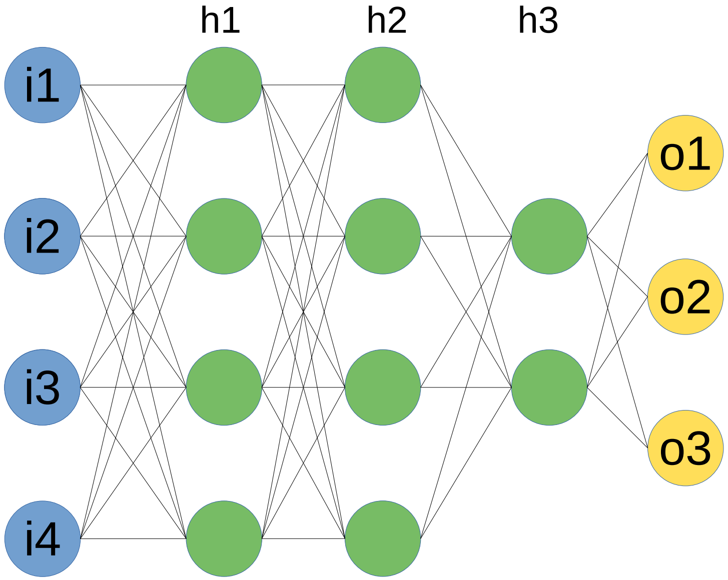
Anatomy of Neural networks



Machine learning and neural networks

Each line represents a connection to an artificial neuron with individual “Weights”





Simple example with 46 trainable weights (without biases)
Each line represents a weight

Basic design of neural networks

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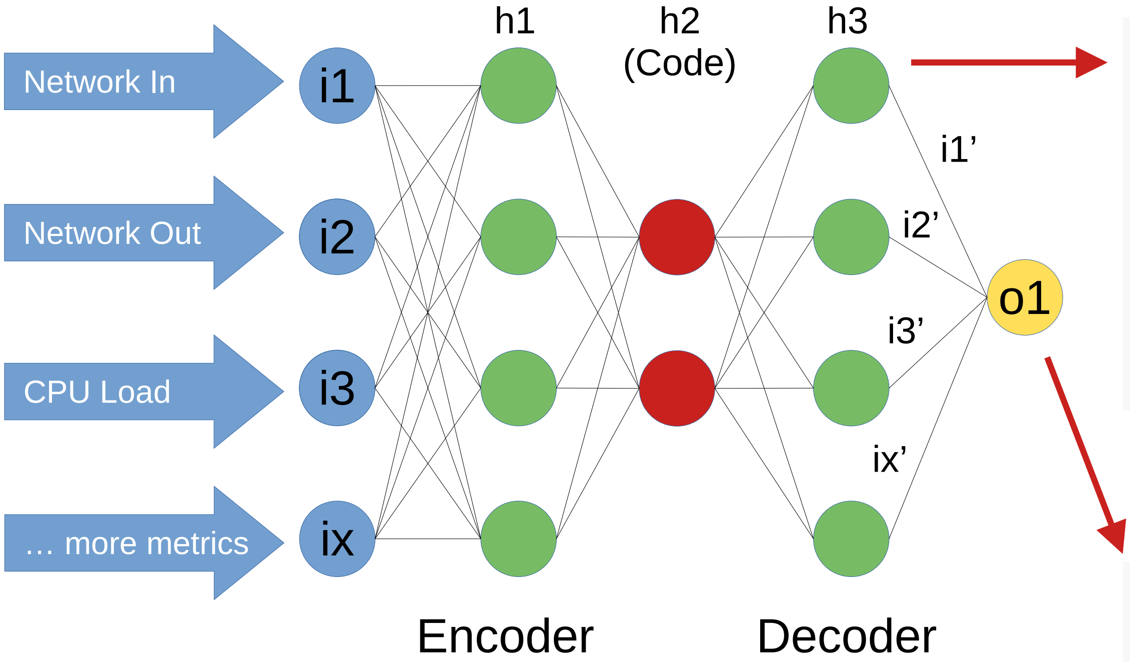
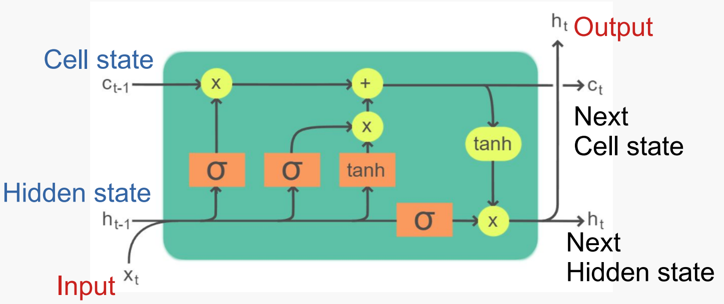
Deep neural networks - Autoencoder

Deep neural network to detect anomalies in multivariate time-series data using LSTM cells



LSTM cell memorizes previous states



Output provides the decoding error, which is an indication for an anomaly

Autoencoders have an encoder and decoder, acting as a data compressor

Deep neural networks - Autoencoder

With an Autoencoder using Long Short-Term Memory cells (LSTM) there is support for:

- ✅ Multivariate data
- ✅ Times-series data
- ✅ Temporal context
- ✅ Contextual relationships

What about training?

- To train a model, training data is required
- Usually supervised learning requires labeled data, which is is not always easy to get
- However, the Autoencoder architecture allows unsupervised training with unlabeled data which is great for this use-case

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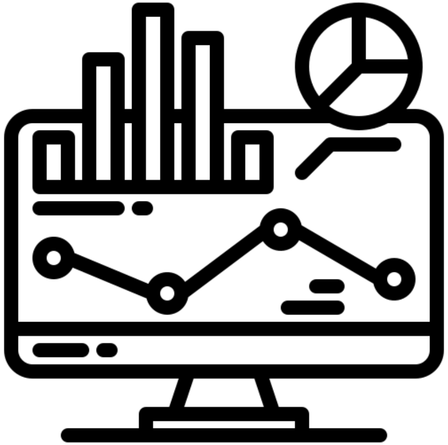
Preparing the data for training, testing and inference



Preparing the data – Training and inference

- **Training**: Train a model with training data so it “learns” features
- **Inference**: Use a trained model with production data

How to prepare the data for training, testing and inference?

- ► **Extraction**: Data needs to be extracted from Zabbix, using the Zabbix-API or Zabbix database
- ► **Data Enrichment**: To provide additional context, certain metrics, such as timestamps, need to be pre-processed by creating additional inputs like hour/minute, day of the week, month of the year
- ► **Normalization**: Neural networks prefer a min-max normalization of the values in the datasets in the range of [0, 1] or [-1, 1]
- ► **Windowing**: Divide multivariate time-series data into a sliding window of data

Preparing the data – Extraction

Use of tags to identify the items that should be used for training and later for inference

	Host	Name ▲	Last check	Last value	Change	Tags
☐	IMS-Smart IntelliTrend...	Air pressure [Pa] ?	25s	100.81 KPa	+2.6562 Pa	df-ai: df-ai Application: Sensor d...
☐	IMS-Smart IntelliTrend...	Humidity [%] ?	25s	39.7236 %	-3.2168 %	df-ai: df-ai Application: Sensor d...
☐	IMS-Smart IntelliTrend...	Temperature [C] ?	25s	26.49 C		df-ai: df-ai Application: Sensor d...
☐	IMS-Smart IntelliTrend...	Total volatile organic compound TVOC [ppb] ?	25s	39 ppb	+6 ppb	df-ai: df-ai Application: Sensor d...

API Request

```
{
    "jsonrpc": "2.0",
    "method": "history.get",
    "params": {
        "output": "extend",
        "history": 0,
        "itemids": "912257",
        "sortfield": "clock",
        "sortorder": "DESC",
        "limit": 10
    },
    "id": 1
}
```

API Response

```
{
  "jsonrpc": "2.0",
  "result": [
    {
      "itemid": "912257",
      "clock": "1724588945",
      "value": "26.31999969",
      "ns": "227934509"
    },
    {
      "itemid": "912257",
      "clock": "1724588885",
      "value": "26.32999992",
      "ns": "87916196"
    },
```

Using the Zabbix-API to get univariate time-series data for a given item

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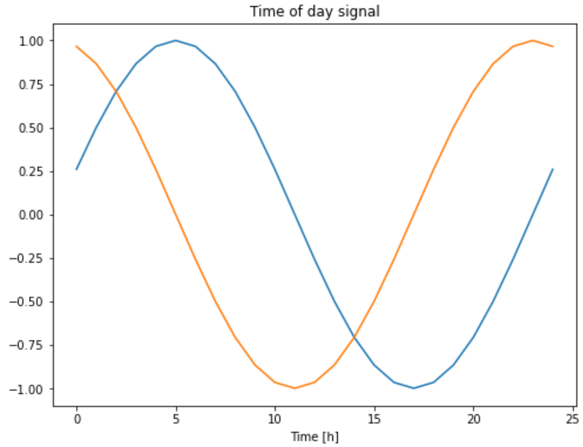
Preparing the data – Data Enrichment

```
{
  "itemid": "912257",
  "clock": "1724588945",
  "value": "26.31999969",
  "ns": "227934509"
}
```

- Timestamps always increase their value per second (monotonic increasing function)
- They need to be transformed into something that changes periodically over time
- Both sine and cosine are required to differentiate between positions with the same values

```
# Timestamp conversion to single features
day = 24*60*60
year = (365.2425)*day
ts['day_sin']  = sin(timestamp * (2*pi/day))
ts['day_cos']  = cos(timestamp * (2*pi/day))
ts['year_sin'] = sin(timestamp * (2*pi/year))
ts['year_cos'] = cos(timestamp * (2*pi/year))
```



Adding features from timestamps so that the network learns the periodicity in the data

Preparing the data – Normalization


```
{
  "jsonrpc": "2.0",
  "result": [
    {
      "itemid": "912257",
      "clock": "1724588945",
      "value": "26.31999969",
      "ns": "227934509"
    },
    {
      "itemid": "912257",
      "clock": "1724588885",
      "value": "26.32999992",
      "ns": "87916196"
    },
```


Min-Max Normalization


```
[
    {
      "itemid": "912257",
      "clock": "1724588945",
      "value": "0.7576",

    },
    {
      "itemid": "912257",
      "clock": "1724588885",
      "value": "0.8245",
    },
```


Challenges:

- With large datasets, min-max normalization can take some time and resources
- Detecting outliers is difficult, because they could be valid data points in the dataset

Normalize data using min-max normalization and clip outliers

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Preparing the data – Windowing

```
...
...
{"temp":0.75, "hum":0.56, "apress":0.79, "ts_ds":0.50, ts_dc:0.34},
{"temp":0.82, "hum":0.55, "apress":0.80, "ts_ds":0.64, ts_dc:0.77},
{"temp":0.84, "hum":0.54, "apress":0.86, "ts_ds":0.77, ts_dc:0.64},
{"temp":0.83, "hum":0.53, "apress":0.88, "ts_ds":0.87, ts_dc:0.50},
...
...
```

0.75	0.82	0.84
0.56	0.55	0.54
0.79	0.80	0.86
0.50	0.64	0.77
0.34	0.77	0.64

```
...
...
{"temp":0.75, "hum":0.56, "apress":0.79, "ts_ds":0.50, ts_dc:0.34},
{"temp":0.82, "hum":0.55, "apress":0.80, "ts_ds":0.64, ts_dc:0.77},
{"temp":0.84, "hum":0.54, "apress":0.86, "ts_ds":0.77, ts_dc:0.64},
{"temp":0.83, "hum":0.53, "apress":0.88, "ts_ds":0.87, ts_dc:0.50},
...
...
```

0.82	0.84	0.83
0.55	0.54	0.53
0.80	0.86	0.88
0.64	0.77	0.87
0.77	0.64	0.50

Prepare an overlapping window with multivariate time-series data with a constant size

Preparing the data – Final windows of data

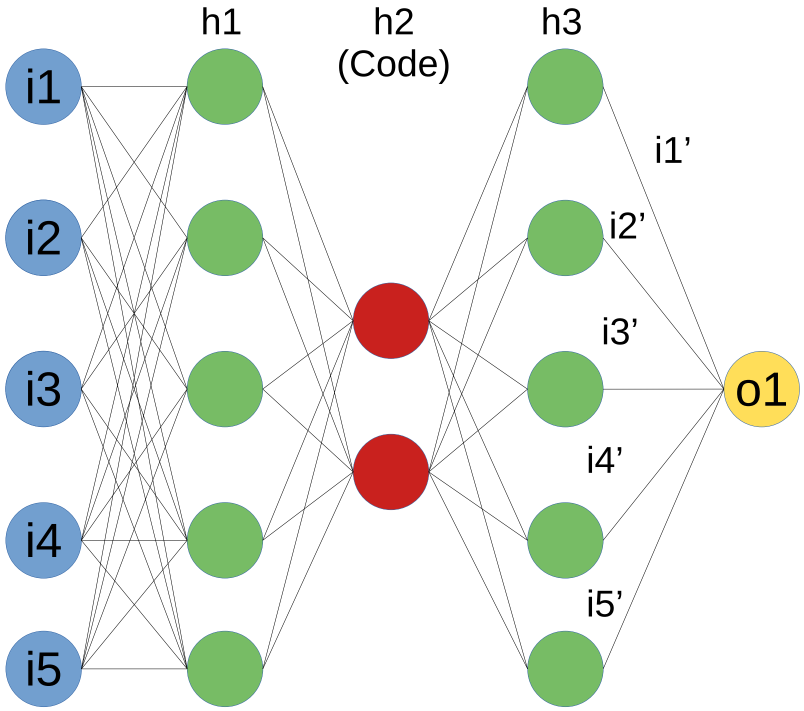
Batch of windowed data

0.82	0.84	0.83
0.55	0.54	0.53
0.80	0.86	0.88
0.64	0.77	0.87
0.77	0.64	0.50

Windowed data

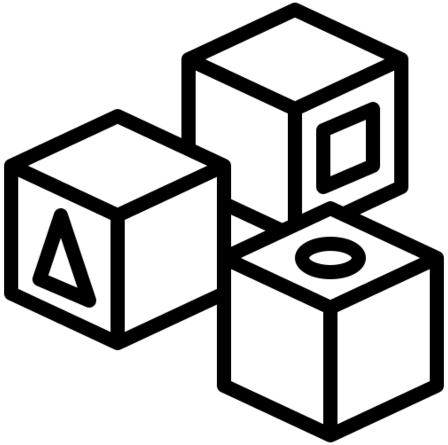
0.75	0.82	0.84
0.56	0.55	0.54
0.79	0.80	0.86
0.50	0.64	0.77
0.34	0.77	0.64

Windowed data



Transfer of batches of windowed time series data to the deep learning model

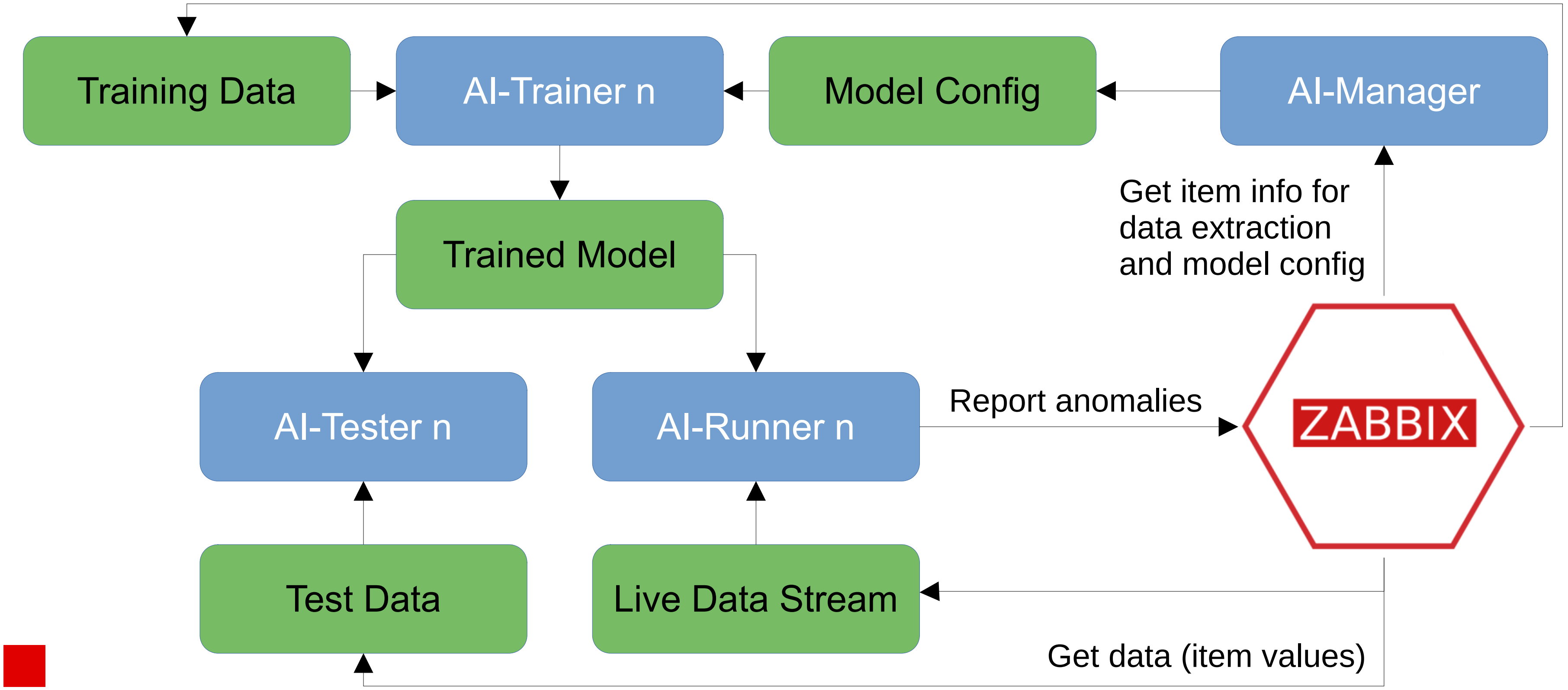
Building blocks to integrate AI into Zabbix



Zabbix meets AI – Building blocks

- **Create a model configuration**: Select model type and define model hyperparameters
- **Extract training and test data**: Select data from Zabbix history/trends for specific items
- **Create and train the model**: Model inputs will be adjusted to match items from Zabbix
- **Test the model**: Test the model based on existing historical data from Zabbix
- **Use the model with live data**: Continuously extract and prepare the values for selected items and pass them to the model for evaluation
- **Pass the result of the evaluation back to Zabbix**: The anomaly probability should be send to Zabbix as an item, so mechanisms like trigger, actions, alerts etc. could be used
- **Support multiple models**: To detect anomalies across multiple different systems, multiple models must be usable at the same time

Zabbix meets AI – Building blocks



Number of n AI Trainer/Tester/Runner need to scale horizontally like Zabbix Proxies

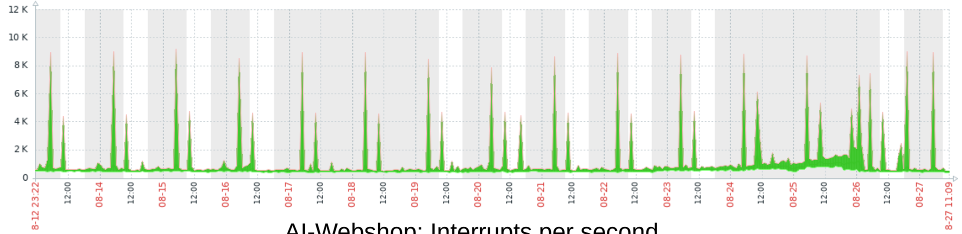
Zabbix meets AI

Do you remember
the
time travel?

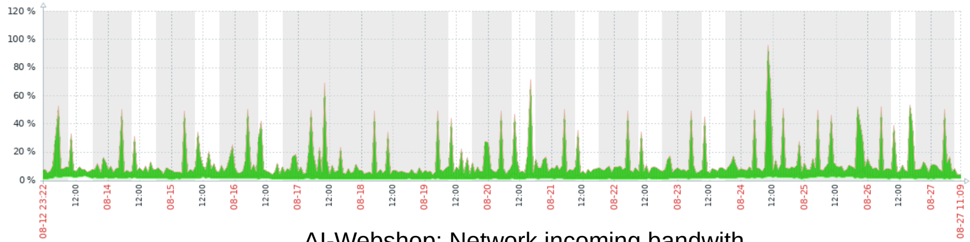
Zabbix meets AI – Data from the time travel

Some metrics of the system in question ...

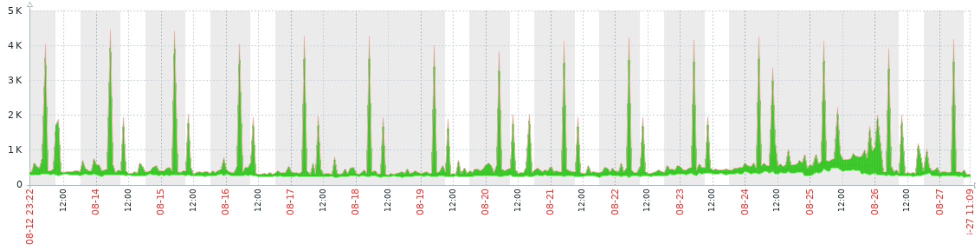
AI-Webshop: Context switches



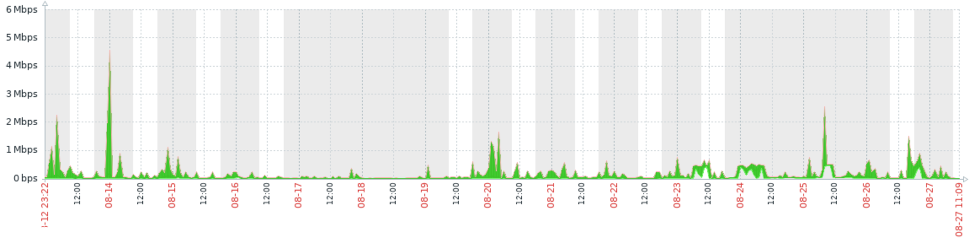
AI-Webshop: CPU usage all



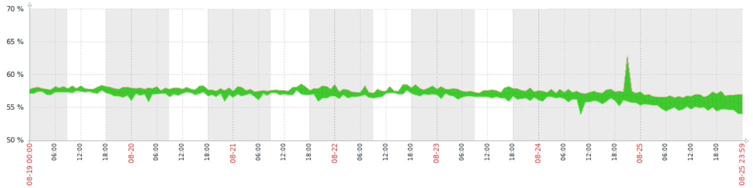
AI-Webshop: Interrupts per second



AI-Webshop: Network incoming bandwith



AI-Webshop: Memory free



It is difficult for a human being to recognize anomalies in this type of data

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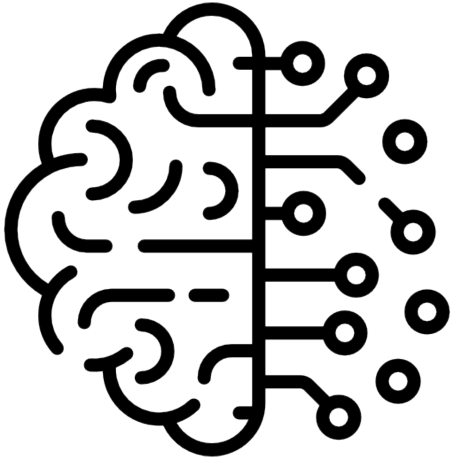
Creating the model



Zabbix meets AI – Creating a model

Item selection for the AI model is based on tags and hosts in Zabbix

Name ▲	Triggers	Key	Interval	History	Trends	Type	Status	Tags	Info
Template AI-Webshop: Context switches		contextSwitches		90d	365d	Zabbix Agent	Enabled	df-ai	
Template AI-Webshop: CPU usage all		cpuPUsageAll		90d	365d	Zabbix Agent	Enabled	df-ai	
Template AI-Webshop: Interrupts per second		interruptsPerSec		90d	365d	Zabbix Agent	Enabled	df-ai	
Template AI-Webshop: Memory free		memoryPFree		90d	365d	Zabbix Agent	Enabled		
Model One: Reconstruction Error [MAE]		m1.loss.mae		90d	365d	Zabbix trapper	Enabled		
Model One: Reconstruction Error [MAPE]		m1.loss.mape		90d	365d	Zabbix trapper	Enabled		
Model One: Reconstruction Error [MSE]		m1.loss.mse		90d	365d	Zabbix trapper	Enabled		
Model One: Reconstruction Error [MSLE]		m1.loss.msle		90d	365d	Zabbix trapper	Enabled		
Model Two: Reconstruction Error [MAE]		m2.loss.mae		90d	365d	Zabbix trapper	Enabled		
Model Two: Reconstruction Error [MAPE]		m2.loss.mape		90d	365d	Zabbix trapper	Enabled		
Model Two: Reconstruction Error [MSE]		m2.loss.mse		90d	365d	Zabbix trapper	Enabled		
Model Two: Reconstruction Error [MSLE]		m2.loss.msle		90d	365d	Zabbix trapper	Enabled		
Template AI-Webshop: Network incoming bandwith		ifInBps		90d	365d	Zabbix Agent	Enabled	df-ai	
Template AI-Webshop: Process count		processCount		90d	365d	Zabbix Agent	Enabled	df-ai	

Reconstruction error is sent by the AI-Runner as an indication of an anomaly per model

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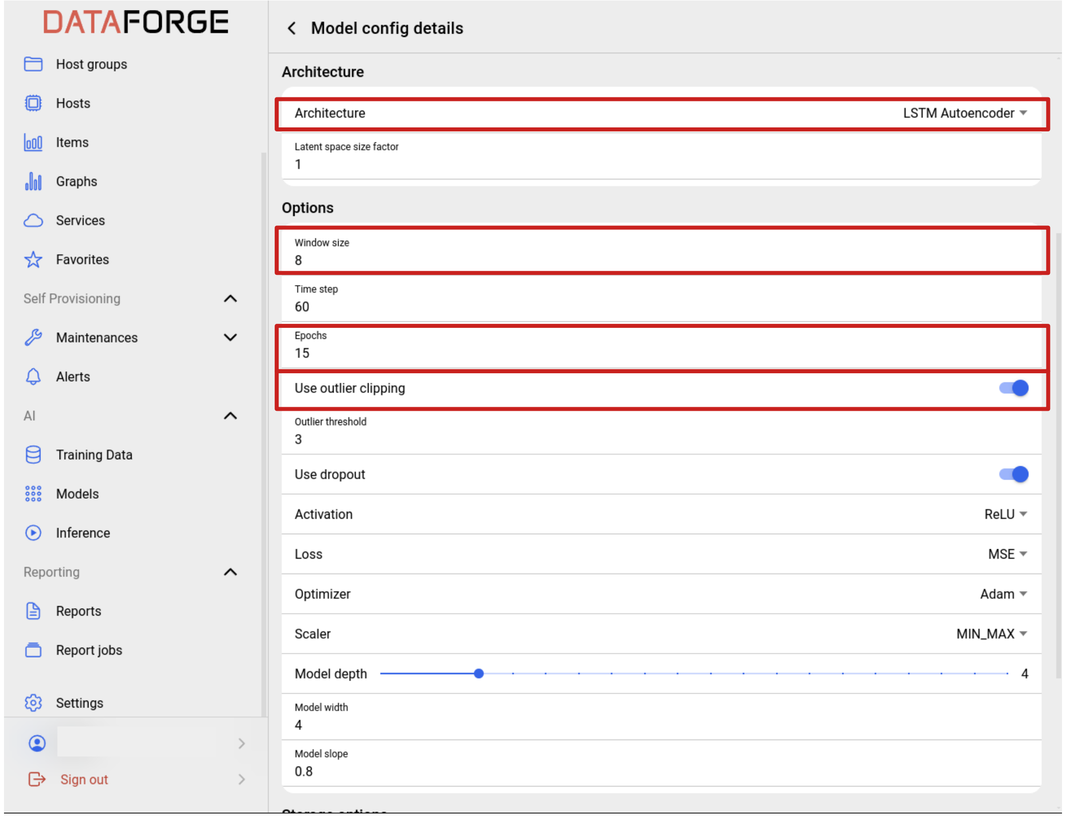
Zabbix meets AI – Creating a model

Model configuration with preferences using DataForge with Zabbix



Global model parameters:

- Architecture
- Windows Size
- Epochs
- Outlier clipping
- ...
- other model hyperparameters

Expected weights count:
35.000 – 40.000 Parameter

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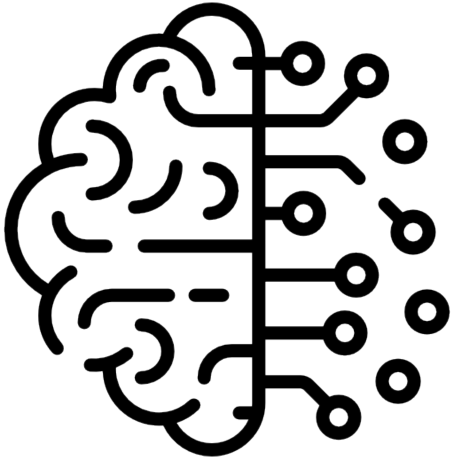
Training and testing the model



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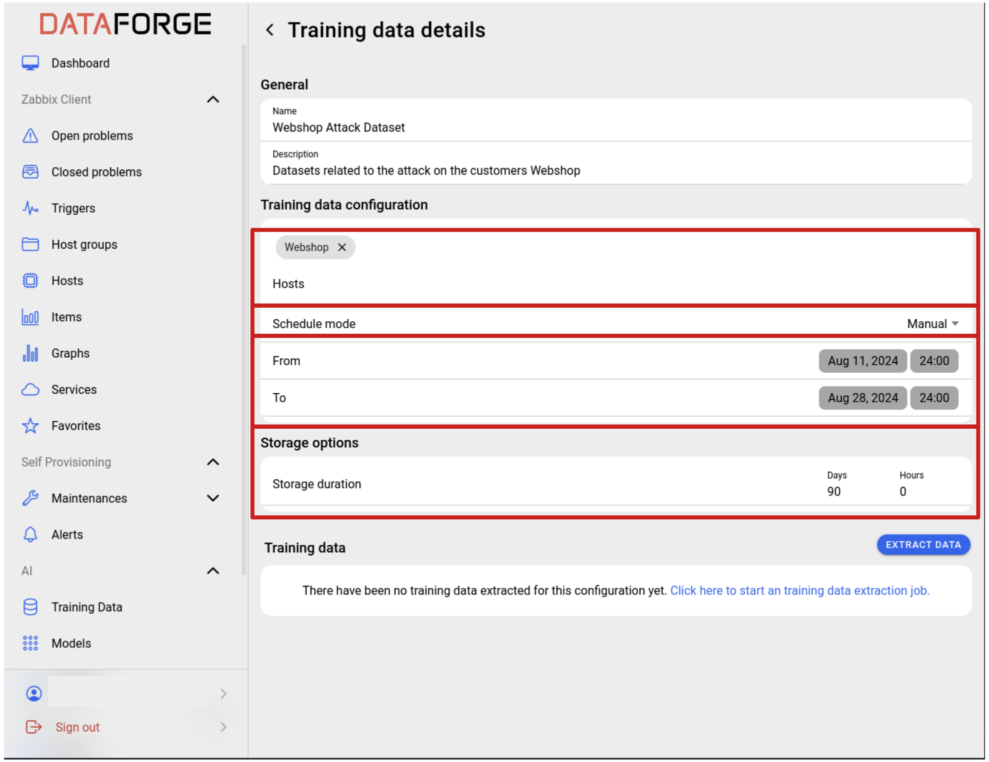
Zabbix meets AI – Training a model

Create training or test data



Training and test datasets

- One or multiple hosts
- When to create/update data
- Time period
- Data storage period

The data is extracted from items that have a corresponding tag in Zabbix

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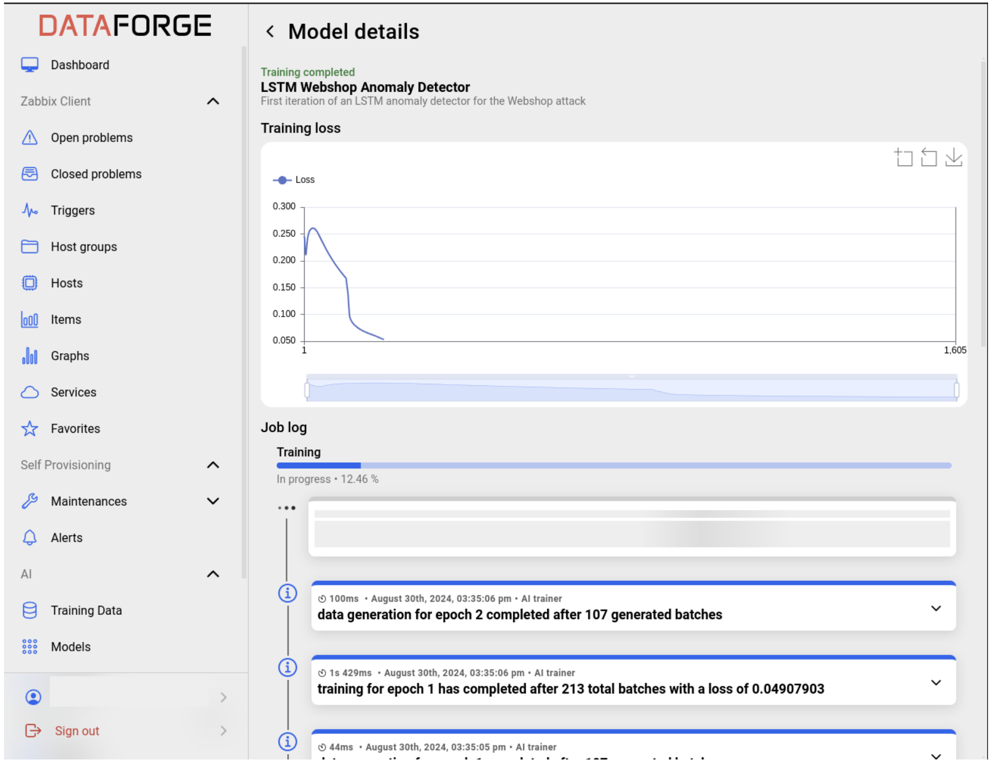
Zabbix meets AI – Training a model

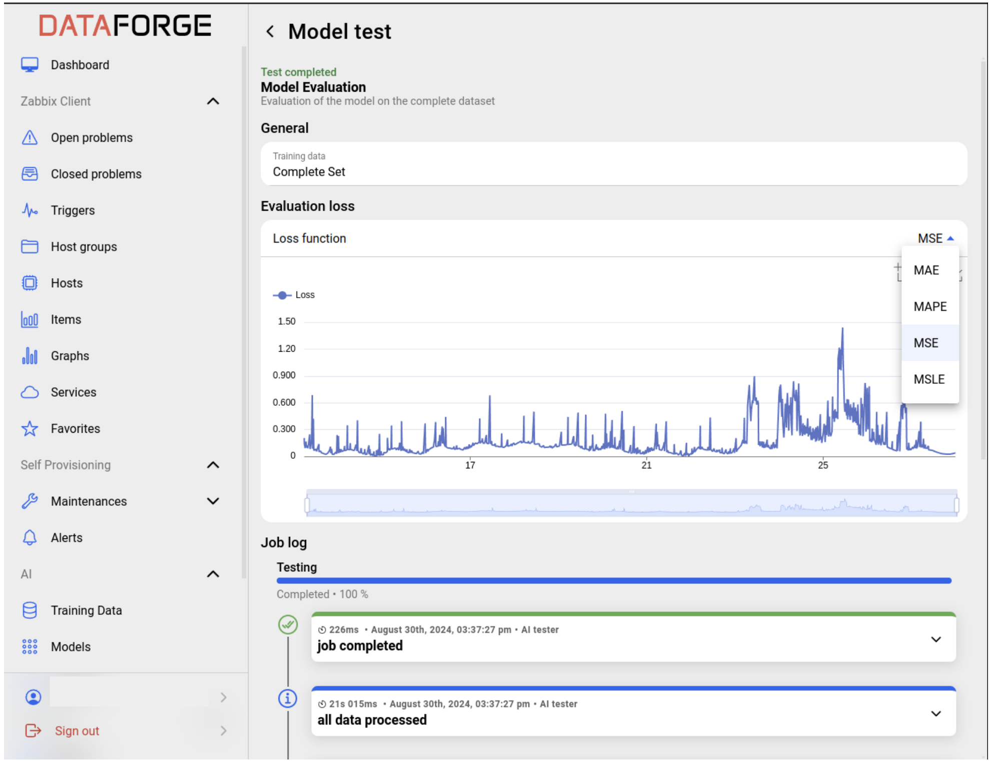
Training with created training data set and model configuration



- Training loss graph and progress is streamed in realtime
- Loss graphs gives an estimation of the quality of the model

Zabbix meets AI – Test a model

Testing a model is similar to training, except that it uses a different dataset



- Loss graphs shows the performance on historical data selected from Zabbix
- Different loss functions are available to calculate the value of the anomaly
- The output of these functions is available in Zabbix as an item and can be used with a trigger
- Testing a model with real data is a good way to test the performance before going live

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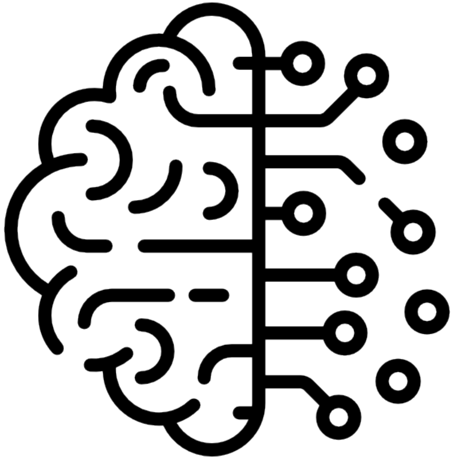
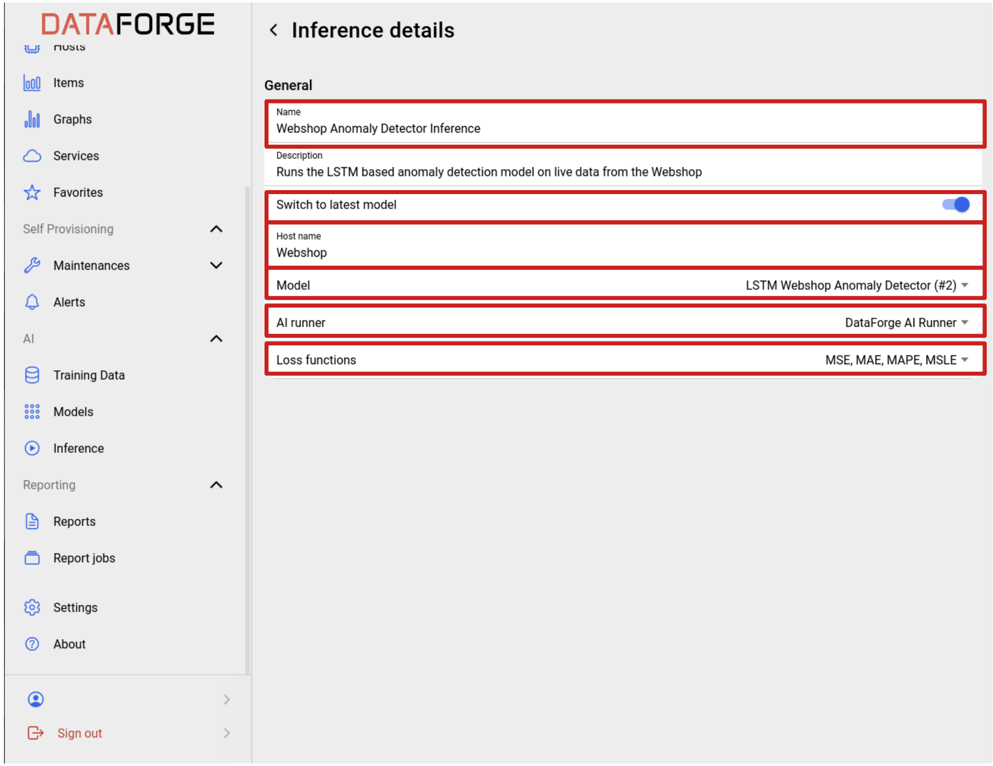
Using the model - Inference



Zabbix meets AI – Using a model in production



- Set a name to identify the model
- Select whether the model update should be provisioned automatically
- Select the host(s) the model should be used with
- Select the AI Runner instance to be used
- Select the loss functions that are to be used to calculate the anomalies and sent to Zabbix

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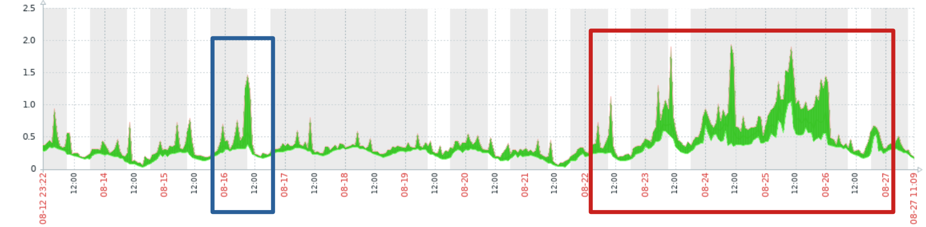
Zabbix meets AI – Using a model in production

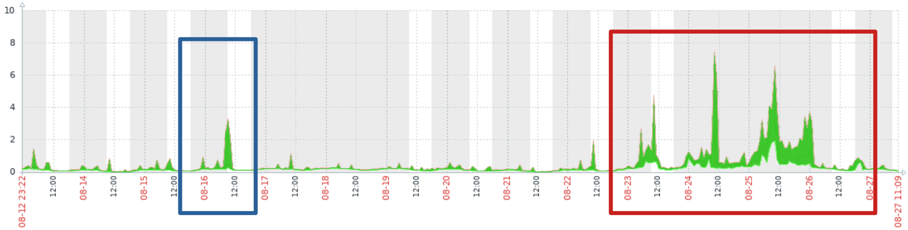
Model output with various loss functions as items in Zabbix based on the webshop data

Reconstruction errors represent the probabilities for anomalies based on their loss function

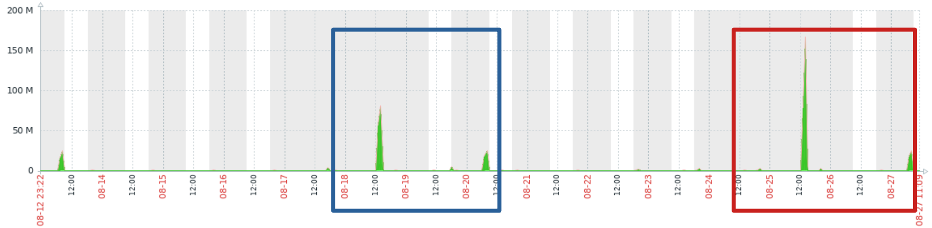
AI-Webshop: Reconstruction Error [MAE]



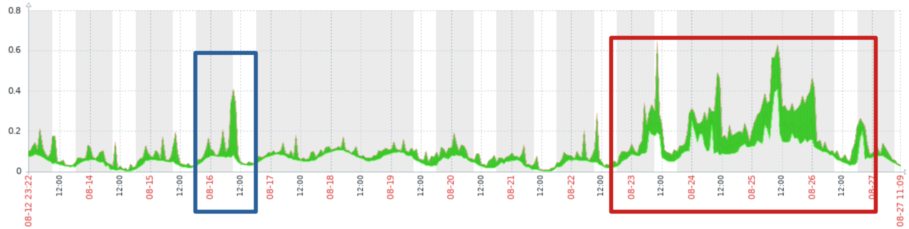
AI-Webshop: Reconstruction Error [MSE]



AI-Webshop: Reconstruction Error [MAPE]



AI-Webshop: Reconstruction Error [MSLE]



Example trigger expressions in Zabbix to alert an anomaly:

```
avg(/AI-Webshop/1.loss.mae,600)  >={$MIN_ANOMALY_MAE}
last(/AI-Webshop/m1.loss.mape)   >={$MIN_ANOMALY_MAPE}
min(/AI-Webshop/1.loss.mse,300)  >={$MIN_ANOMALY_MSE}
min(/AI-Webshop/1.loss.msle,300)>={$MIN_ANOMALY_MSLE}
```

Available loss functions to indicate an anomaly:

MAE	- **M**ean **A**bsolute **E**rror
MAPE	- **M**ean **A**bsolute **P**ercentage **E**rror
MSE	- **M**ean **S**quared **E**rror
MSLE	- **M**ean **S**quared **L**ogarithmic **E**rror

Summary

Zabbix meets AI – Summary

- Deep neural network are a great way to detect anomalies in time-series data due to their ability to maintain temporal context
- They excel at analyzing multiple metrics simultaneously, enabling the creation of contextual relationships between data from various sources
- Zabbix’s flexible architecture and robust API make it an ideal platform for integrating AI
- By combining metrics from multiple hosts into a single model, anomaly detection becomes even more powerful, particularly when monitoring entire services
- The results of these AI-driven detections can be seamlessly fed back into Zabbix as items, allowing to leverage any of Zabbix’s trigger functions to generate alerts
- Zabbix's versatility in metric collection extends beyond just computer and network metrics, making AI-based anomaly detection applicable to a wide range of domains

  Whether it's monitoring sales and visitor traffic for an online shop, or tracking the power generation of a solar park, any metric that can be collected in Zabbix can be utilized for anomaly detection

Zabbix meets AI
-
Leverage machine learning for detecting anomalies

Thank You!

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