#### ZABBIX '25 CONFERENCE GERMANY

Al-based **Anomaly Detection** in Zabbix



0.//%

70%

90%

100%

Disk IO utilization

Temperature

7.14 %

90%

100%

and Reckoner

class: os class: software environment: product

ZBX SNMF

Template W... Zabbix Serv. Linux by Za..., Nebula

 $A_{Vailabilit_{\mathcal{Y}}}$ 

Monitored by

Templates

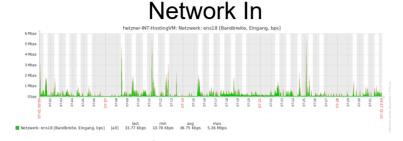
#### Zabbix meets Al

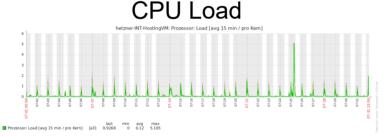
# The idea of anomaly detection

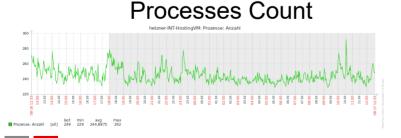




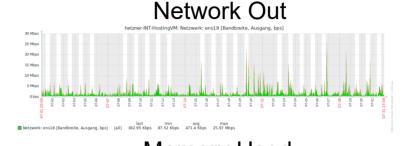
## The idea of anomaly detection

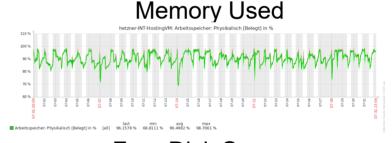


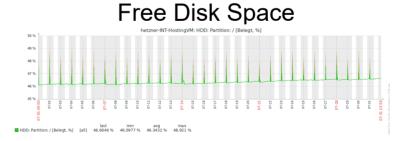




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#### The idea of anomaly detection

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

- Instead of looking to one metric at a time, have a system that looks at multiple metrics at once
- Instead of using simple trigger 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
- Allow this concept to be used across multiple hosts





#### The idea of anomaly detection

#### Examples

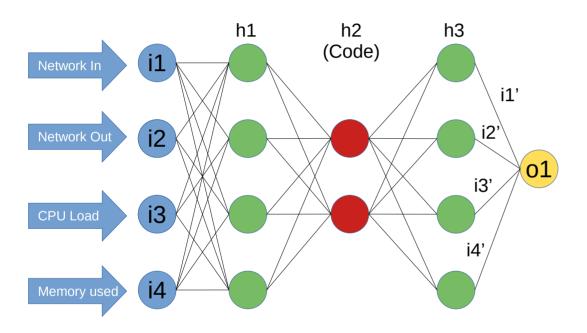
- Monitoring server rooms:
   Pay attention not only to the temperature, but also relate it to the power consumption of the systems, air conditioning, etc.
- Server utilization:
   Pay attention not only to CPU utilization, but also to memory usage, the number of users, network traffic, etc.





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

#### Long short-term memory based Autoencoder



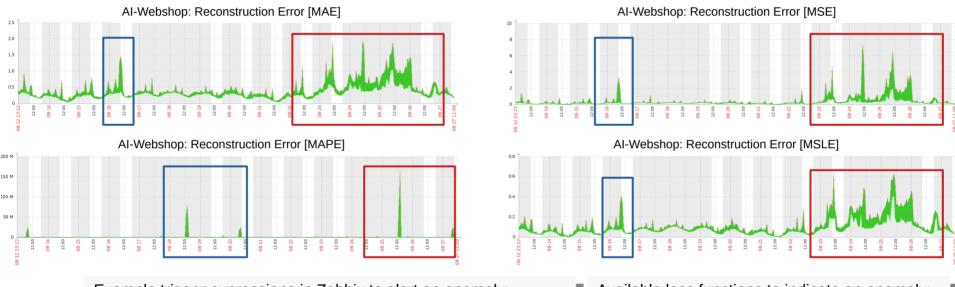
- Incoming data is connected to i1 to i4 (ix)
- Hidden layer "h1" acts as an encoder to extract the features of that data
- Hidden layer "h2" is much smaller and extracts the essence of these features
- Hidden layer "h3" acts as an decoder to reconstruct the original data
- If there is a problem, hidden layer "h3" will cause a data reconstruction error
- This error is calculated as an anomaly using a "loss function" in "o1"



Simplified schematic representation of an Autoencoder neural network

#### Using a model in production

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





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 - Mean Absolute Error

MAPE - Mean Absolute Percentage Error

MSE - Mean Squared Error

MSLE - Mean Squared Logarithmic Error

#### Al-based anomaly detection

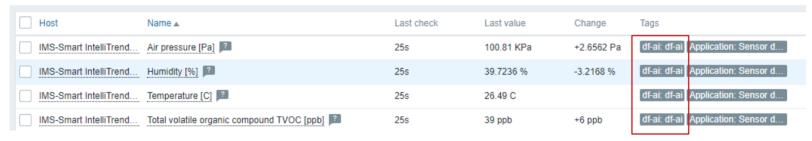
# Integration with Zabbix





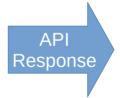
#### Data extraction from Zabbix

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





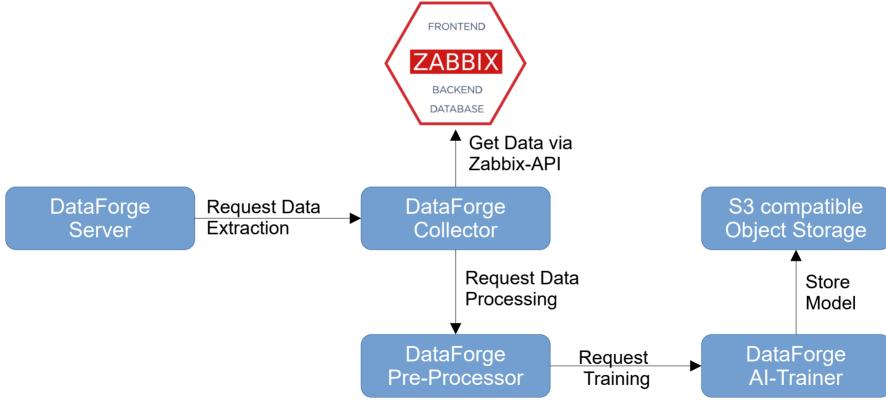
```
"jsonrpc": "2.0",
    "method": "history.get",
    "params": {
        "output": "extend",
        "history": 0,
        "itemids": "912257",
        "sortfield": "clock",
        "sortorder": "DESC",
        "limit": 10
},
    "id": 1
}
```





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

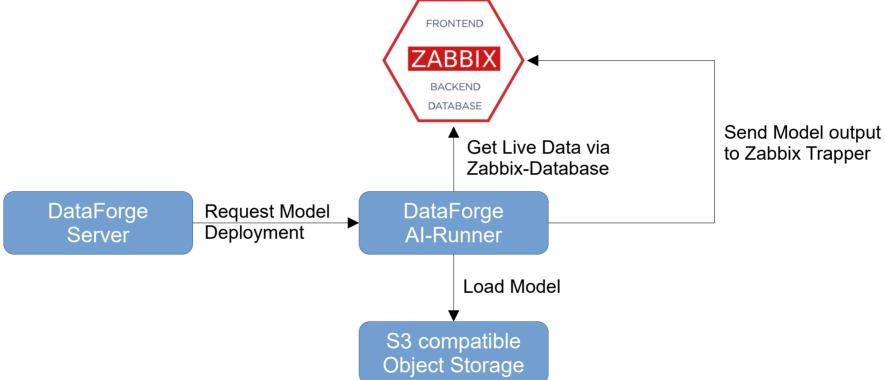
## Integration with Zabbix - Training





No changes to Zabbix Source code required

#### Integration with Zabbix - Inference





No changes to Zabbix Source code required



## Al-based anomaly detection

# Detecting simple anomalies





## Detecting simple anomalies

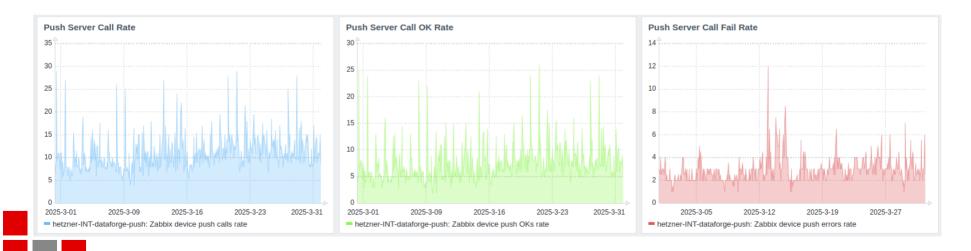
These are the three most important metrics of our Push Notification Server:

"Call Rate", "Call OK Rate" and "Call Fail Rate"

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These rates indicate the number of attempted, successful and failed push notification requests over time

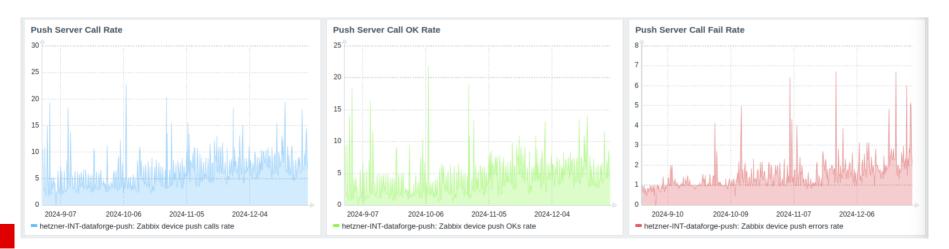
The failure rate of around 20%-30% is based on users who reinstall / uninstall the app, but leave the mediatype configuration as is on their Zabbix user account



## Detecting simple anomalies

Writing a trigger for these metrics is non-trivial:

- Large spikes can be expected when a customer has a large number of issues that trigger many push notifications
- Looking at a longer time interval all metrics are trending upwards as the application gains users





## Al-based anomaly detection

## How can we solve this with AI?





#### From data to model

- Create a training dataset with history data from Zabbix
- Create one or more test datasets with history data from Zabbix
- Create a model configuration
- Create / Train a model
- Test the model
- Assign the the model to an Al-Runner



#### Al-based anomaly detection

#### **Datasets**





#### Tagging Items for Data Extraction

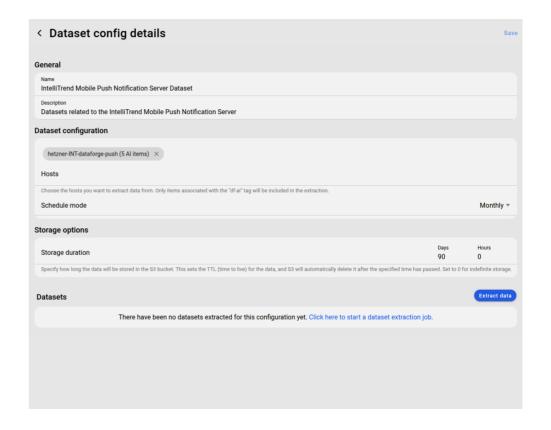
- Mark metrics that AI should use by assigning the tag "df-ai" to relevant items in Zabbix
- These tags will be used to extract the data from Zabbix for:
  - Training the model
  - Testing the model
  - Using the model in production (Inference)

	Name ▲	Triggers	Key	Interval	History	Trends	Туре	Status	Tags II
•••	DataForge Push Server: Push server raw data: Zabbix device push calls rate	Triggers 2	dfpush.zabbix_device_push_calls_rate		90d	365d	Dependent item	Enabled	df-ai
•••	DataForge Push Server: Push server raw data: Zabbix device push errors/calls absolute ratio	Triggers 2	dfpush.zabbix_device_push_errors_calls_ratio		90d	365d	Dependent item	Enabled	df-ai
•••	DataForge Push Server: Zabbix device push errors/calls recent ratio	Triggers 2	dfpush.zabbix_device_push_errors_calls_recent_ratio	1m	90d	365d	Calculated	Enabled	df-ai
•••	DataForge Push Server: Push server raw data: Zabbix device push errors rate		dfpush.zabbix_device_push_errors_rate		90d	365d	Dependent item	Enabled	df-ai



#### Creating a dataset

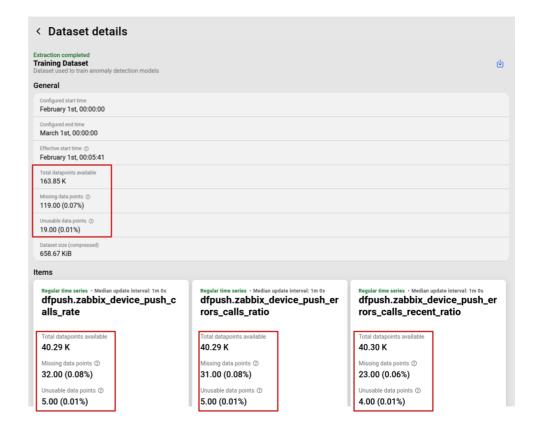
- Add host(s) with tagged items
- Choose scheduling mode for automatic update
- Set storage duration for house keeping
- Datasets needs to be created for:
  - Training
  - Testing





#### Creating a dataset

- After the data extraction process finished, dataset details are updated
- The analysis is helpful to decide whether the dataset will be useful in a training or in a test
- Datasets can be be downloaded, decompressed and converted to a variety of formats for further processing in 3th party applications

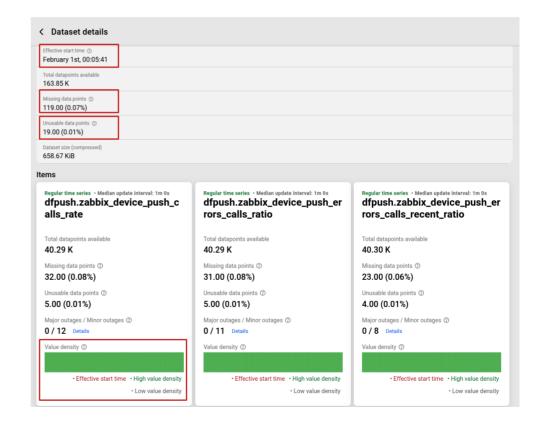




#### Dataset – Quality of data

#### Analysis of the dataset:

- This dataset has a high value density and looks healthy
- Very few datapoints are missing or unusable
- All of the time series were detected as having a consistent update interval
- There are no major outages and an evenly distributed value density
- The effective start time of the dataset (the time at which each time series had at least one value) is only 5m41s after the configured start time





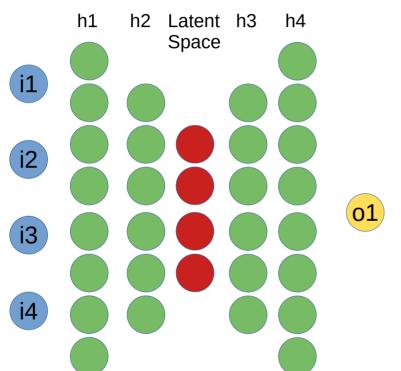
#### Al-based anomaly detection

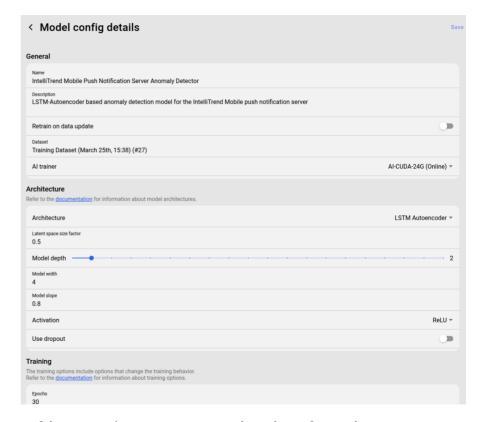
# Creating a Model





#### Model configuration

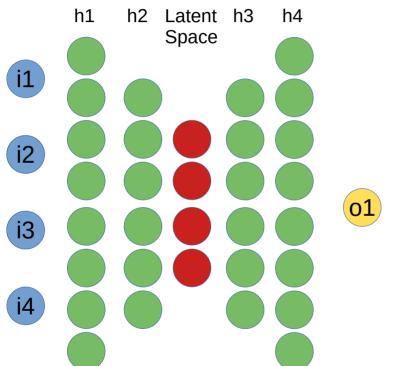


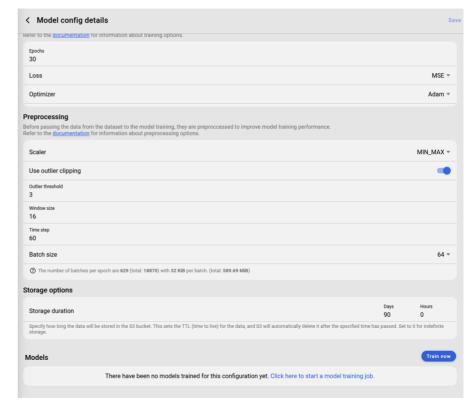




Architecture defines model type, number of layers / neurons, activation function etc.

#### Model configuration



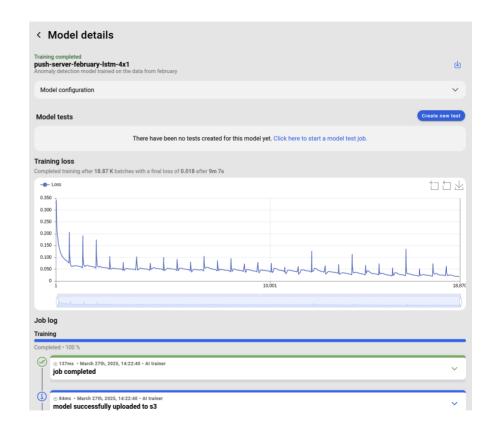




Preprocessing defines operations on the dataset for training including batch size

#### Model creation

- Model is created based on model configuration and training dataset
- The number of selected metrics (items) effected the number of neurons
- Model details show the training loss during the training process





#### Model test

- After the model is created, it can be tested using datasets
- Typically there is a baseline test and also validation tests
- Any number of datasets can be created from Zabbix history data
- Different loss functions can be used

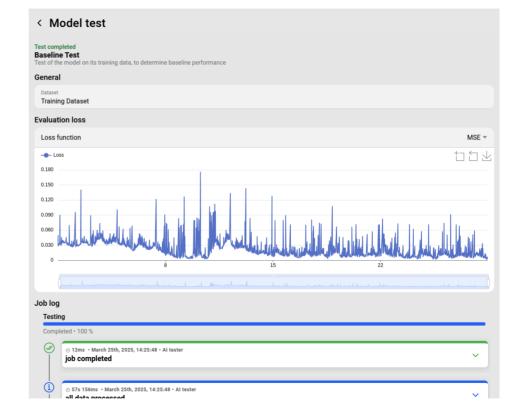
Available loss functions to indicate an anomaly:

MAE - Mean Absolute Error

MAPE - Mean Absolute Percentage Error

MSE - Mean Squared Error

MSLE - Mean Squared Logarithmic Error





#### Al-based anomaly detection

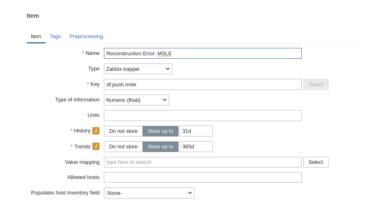
# Using the model





#### Creating output items

- The result of the model evaluation is sent to Zabbix using items
- Item type must be trapper with type numeric (float)
- The item keys must use a consistent prefix and then be suffixed with the appropriate loss metric like "df.push.msle"

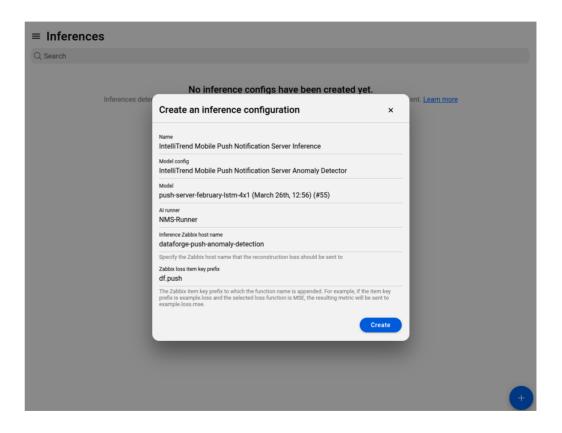


	Name ▲	Triggers	Key	Interval	History	Trends	Туре	Status	Т
	Reconstruction Error: MAE		df.push.mae		31d	365d	Zabbix trapper	Enabled	
•••	Reconstruction Error: MAPE		df.push.mape		31d	365d	Zabbix trapper	Enabled	
000	Reconstruction Error: MSE		df.push.mse		31d	365d	Zabbix trapper	Enabled	
•••	Reconstruction Error: MSLE		df.push.msle		31d	365d	Zabbix trapper	Enabled	



## Deploying the model

- The process of actually using a model is called inference
- The inference configration defines the model, Al-Runner and the host in Zabbix to receive the model output

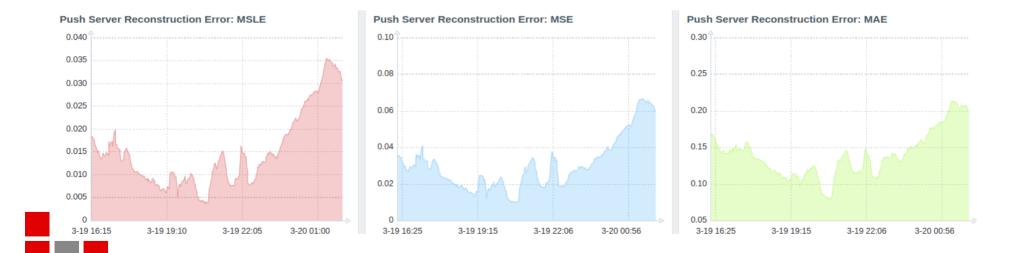




#### Deploying the model

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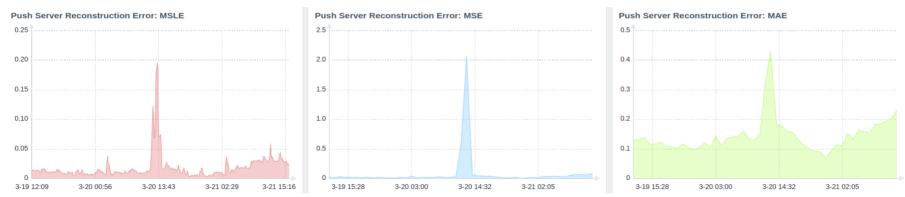
- After deploying the model, the output for each loss function shows up as item in Zabbix
- These items can be used with any trigger function in Zabbix to detect an anomaly



## Detecting an anomaly

When an anomaly is detected, the values of the loss functions change significantly

For example MSE (Mean Squared Error) is more sensible than MAE (Mean absolute Error)







## Al-based anomaly detection

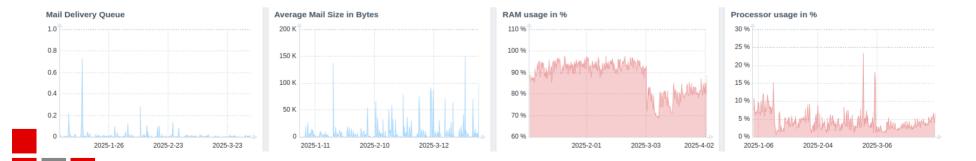
# Lets look at more examples





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- Below some KPI's from a Microsoft Exchange Server
- The graphs show the mail queue, average mail size in bytes and %ram and %cpu usage
- There are 17 additional items that will be used for training for a total of 21 items



Name ▲	Last check	Last value	Change	Tags
Arbeitsspeicher: Physikalisch [Belegt] in %	1m 47s	87.7376 %	+0.4971 %	df-ai
Arbeitsspeicher: Swap [Belegt] in %	1m 47s	41.9535 %	-0.011 %	df-ai
Exchange: MSExchange-Datenbank [Information Store / Protokoll: Generierte Bytes/s]	53s	0		df-ai
Exchange: MSExchange-Datenbank [Information Store / Protokoll: Schreiben Bytes/s]	16s	0		df-ai
Exchange: MSExchange-Datenbank [Information Store I/O / Datenbanklesevorgänge/s]	1m 30s	0		df-ai
Exchange: MSExchange-Datenbank [Information Store I/O / Datenbankschreibvorgänge/s]	1m 39s	0.9874	-0.000143	df-ai
Exchange: MSExchangeTransport [SMTP-Empfang(_total) / Aktuelle Verbindungen]	53s	2		df-ai
Exchange: MSExchangeTransport [SMTP-Empfang(_total) / Empfangene Bytes/s]	16s	41373.7277	-116681.7052	df-ai
Exchange: MSExchangeTransport [SMTP-Empfang(_total) / Empfangene Nachrichten / Delta]	1m 30s	7	-4	df-ai
Exchange: MSExchangeTransport [SMTP-Empfang(_total) / Empfangene Nachrichten/s]	4s	0		df-ai
Exchange: MSExchangeTransport [SmtpSend(_total) / Aktuelle Verbindungen]	1m 42s	0		df-ai
Exchange: MSExchangeTransport [SmtpSend(_total) / Gesendete Bytes/s]	53s	408635.0496	+378003.4473	df-ai
Exchange: MSExchangeTransport [SmtpSend(_total) / Gesendete Nachrichten / Delta]	4s	14	-2	df-ai
Exchange: MSExchangeTransport [SmtpSend(_total) / Gesendete Nachrichten/s]	11s	1.9698	+0.000057	df-ai
Exchange: MSExchangeTransport [Zustellungswarteschlange / Warteschlangen extern]	1m 30s	0		df-ai
Exchange: MSExchangeTransport [Zustellungswarteschlange / Warteschlangen intern]	53s	0		df-ai
Exchange: MSExchange [Client Type / Messages opened/sec]	1m 42s	2.9536	+2.9536	df-ai
Exchange: MSExchange [IS Store / Messages opened/sec]	1m 41s	0	-0.9906	df-ai
Exchange: MSExchange [MapiHttp Emsmdb / aktive Benutzer / Anzahl]	1m 42s	2	+1	df-ai
Netzwerk: Ping [Antwortzeit]	1m 31s	0.53ms	+0.054ms	df-ai
Netzwerk: Ping [Status]	1m 31s	Up (1)		df-ai

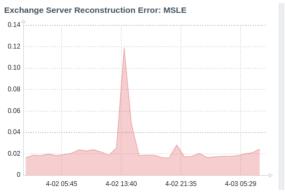


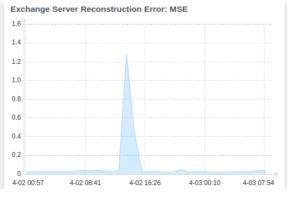
- The training dataset contains 405K datapoints obtained from 21 items over a duration of one month
- The validation dataset contains 464K datapoints obtained from 21 items over a duration of one month
- During the training process with 100 epochs, the dataset will be expanded to 4.8GiB

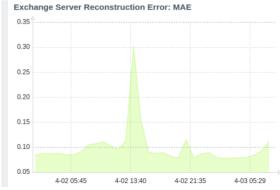
Extraction completed Validation Dataset	Extraction completed Training Dataset				
General	General				
Configured start time March 1st, 00:00:00	Configured start time February 1st, 00:00:00				
Configured end time April 1st, 00:00:00	Configured end time February 28th, 00:00:00				
Effective start time ⑦ March 1st, 00:01:56	Effective start time ⑦ February 1st, 00:01:44				
Total datapoints available 464.42 K	Total datapoints available 405.12 K				
Missing data points ⑦ 183.00 (0.04%)	Missing data points ⑦ 223.00 (0.06%)				
Unusable data points ⑦ 0 (0.00%)	Unusable data points ⑦ 0 (0.00%)				
Dataset size (compressed) 1.67 MiB	Dataset size (compressed) 1.44 MiB				



- We now have created one trigger that monitors a total of 21 related items
- If any of these items shows an unexpected behavior over time or in relation to other items, this trigger will fire
- To get the root cause, further investigation is needed
- If required, specific triggers can be added





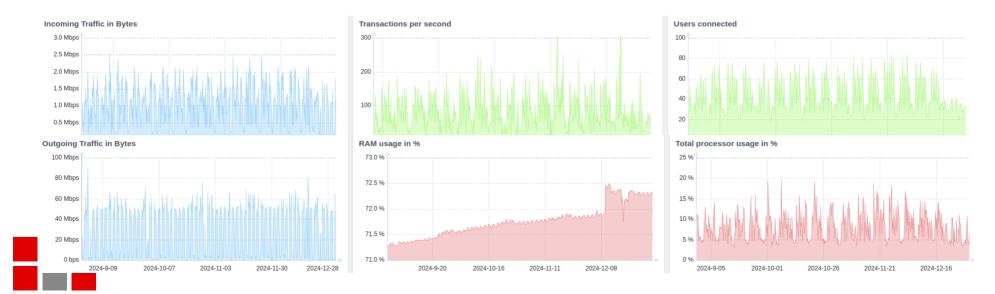




#### Example MS-SQL Server

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- Below some KPI's from a Microsoft SQL Server
- There are 56 additional items that will be used for training for a total of 62 items

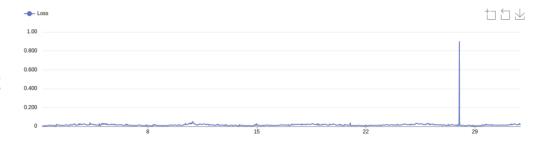


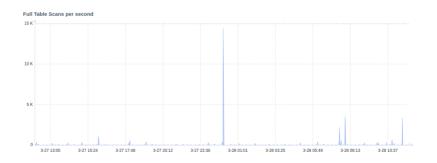


#### **Example MS-SQL Server**

- At 3-27 the model detected an anomaly
- After reviewing the metrics, the culprit was found quickly
- The number of full table scans per second spiked to almost 15.000 while the number of log truncations also spiked at around 480









### Al-based anomaly detection

## Combine AI with regular trigger



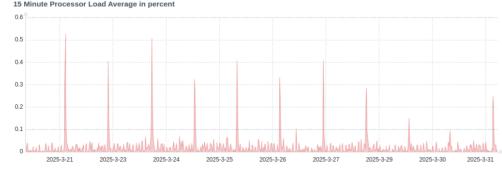


#### Challenge

- Every evening at around 21:00, Zabbix sends an alert
- Reason: Processor load gets high

#### **Possible solutions**

- Schedule periodic maintenance
- Use time() function
- ... combine with anomaly detection





#### Mark items, create dataset, train model

	Name ▲	Triggers	Key	Interval	History	Trends	Туре	Status	Tags	Info
•••	TPL: OS_Linux [Server, All] [Basic]: Arbeitsspeicher: Physikalisch [Belegt] in %	Triggers 2	vm.memory.size[pused]	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Arbeitssp	
•••	TPL: OS_Linux [Server, All] [Basic]: Arbeitsspeicher: Physikalisch [FREI] in %		vm.memory.size[pavailable]	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Arbeitssp	
•••	TPL: OS_Linux [Server, All] [Basic]: Arbeitsspeicher: Swap [Belegt] in %	Triggers 2	system.swap.size[,pused]	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Arbeitssp	
•••	TPL: OS_Linux [Server, All] [Basic]: Arbeitsspeicher: Swap [Frei] in %		system.swap.size[,pfree]	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Arbeitssp	
•••	TPL: Netzwerk Ping [All] [basic]: Netzwerk: Ping [Antwortzeit]		icmppingsec	2m	30d	365d	Simple check	Enabled	df-ai Application: Netzwerk	
•••	TPL: Netzwerk Ping [All] [basic]: Netzwerk: Ping [Status]	Triggers 1	icmpping	2m	30d	365d	Simple check	Enabled	df-ai Application: Netzwerk	
•••	TPL: OS_Linux [Server, All] [Basic]: Prozesse: Anzahl [aktiv]		proc.num[,,run]	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Prozesse	
•••	TPL: OS_Linux [Server, All] [Basic]: Prozessor: Auslastung [Gesamt] in %	Triggers 2	system.cpu.util[,total]	2m	30d	365d	Calculated	Enabled	df-ai Application: Prozessor	
•••	TPL: OS_Linux [Server, All] [Basic]: Prozessor: Context switches [/sec]		system.cpu.switches	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Prozessor	
•••	TPL: OS_Linux [Server, All] [Basic]: Prozessor: Interrupts [/sec]		system.cpu.intr	2m	30d	365d	Zabbix agent	Enabled	df-ai Application: Prozessor	



#### Baseline test



#### Validation test

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Training looks good, no anomaly at 21:00 during backup



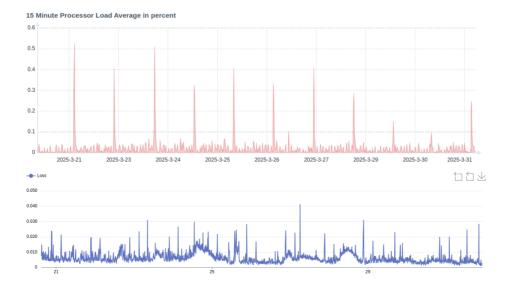
Reconfigure the trigger – only fire if there is also an anomaly

* Name	$\label{eq:alignment} \mbox{Al: \{HOST.NAME\} - Prozessor: Auslastung > \{\$CPU\_USED\_WARNING\_MAX\} \% [t] } \label{eq:alignment}$	
Event name	AI: {HOST.NAME} · Prozessor: Auslastung > {\$CPU_USED_WARNING_MAX} % [Über {\$CPU_USED_INTERVAL} Sekunden]	
perational data		
Severity	Not classified Information Warning Average High Disaster	
* Expression	Edit Insert expression	
	And Or Replace	
	A and ((B and C) or (D and E))	
	Target Expression	Action Info
	✓ And	Remove
	A last(/hetzner-INT-dataforge/df.hetzner.mse)>0.06	Remove
	∟ Or	Remove
	- And	Remove
	B {TRIGGER.VALUE}=0	Remove
	☐ C min(/hetzner-INT-dataforge/system.cpu.util[,total],{\$CPU_USED_INTERVAL})>{\$CPU_USED_WARNING_MAX}	Remove
	L And	Remove
	- D (TRIGGER.VALUE)=1	Remove
	LE min(/hetzner-INT-dataforge/system.cpu.util[.total].{\$CPU_USED_INTERVAL}}>{\$CPU_USED_WARNING_OK}	Remove
	Test	



#### It works – no alarm sent during the backup at 21.00

Averaç	e OK	AI: {HOST.NAME} - Prozessor: Auslastung > {\$CPU_USED_WARNING_MAX} % [Über {\$CPU_USED_INTERVAL} Sekunden]	last(/hetzner-INT-dataforge/df.hetzner.mse)>0.1 and (({TRIGGER.VALUE}=0 and min(/hetzner-INT-dataforge/system.cpu.util[,total], {\$CPU_USED_INTERVAL}}>{\$CPU_USED_WARNING_MAX}) or ({TRIGGER.VALUE}=1 and min(/hetzner-INT-dataforge/system.cpu.util[,total], {\$CPU_USED_INTERVAL}}>{\$CPU_USED_WARNING_OK}))	Ena
Averaç	PROBLEM	{HOST.NAME} - Prozessor: Auslastung > {\$CPU_USED_WARNING_MAX} % [Über {\$CPU_USED_INTERVAL} Sekunden]	({TRIGGER.VALUE}=0 and min(/hetzner-INT-dataforge/system.cpu.util[.total],{\$CPU_USED_INTERVAL}})>{\$CPU_USED_WARNING_MAX}) or ({TRIGGER.VALUE}=1 and min(/hetzner-INT-dataforge/system.cpu.util[.total],{\$CPU_USED_INTERVAL}})>{\$CPU_USED_WARNING_OK})	Ena





But – It sents alarms when the load is at an unusal time like here at 11:18







### Al-based anomaly detection

# Hardware requirements





### Hardware requirements

Hardware requirements for these autoencoder models are quite moderate. As an example we will use the 100 epoch MS-SQL server model with 62 items and one month of data:

- NVIDIA RTX-4090: Training process used 1.3GiB of DRAM and 458MiB of VRAM with the GPU hovering around 60% utilization and the CPU loading 2 cores for the training process.
   Training took 6m 32s or 3.92s per epoch using this setup.
- AMD R9 7950X3D CPU: Training process used 533MiB of DRAM with the CPU loading 8 cores for the training process.
   Training took 20m 42s or 12.42s per epoch using this setup.
- AMD R7 3700U CPU: Training process used 510MiB of DRAM with the CPU loading 4 cores for the training process.
   Training took 8h 53m or 5m 32s per epoch using this setup.
- Inference does not require a GPU. For example an AMD R9 7950X3D CPU can handle upto 560 NVPS. The MS-SQL server model with 62 items equals to 0.51 NVPS.



### Al-based anomaly detection

# Summary





#### Summary

#### Al-based anomaly detection systems can:

- ... learn simple and complex threshold values
- ... learn temporal dependencies (Certain values are expected at certain times)
- ... learn value dependencies (Certain values must maintain a mathematical relationship between each other)
- ... learn dependencies across multiple systems and services
- ... improve monitoring setups by looking into anomalies across many items at once
- ... express the magnitude of an anomaly using the value of reconstruction error instead of just true/false



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# Thank you





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