CycleGAN-Based Data Augmentation for Enhanced Remaining Useful Life Prediction under Unsupervised Domain Adaptation

- Annual Conference of the PhM Society 2024 -

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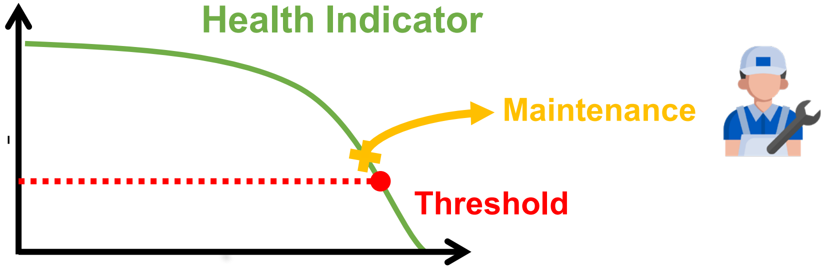
Introduction – Predictive Maintenance

CMMS



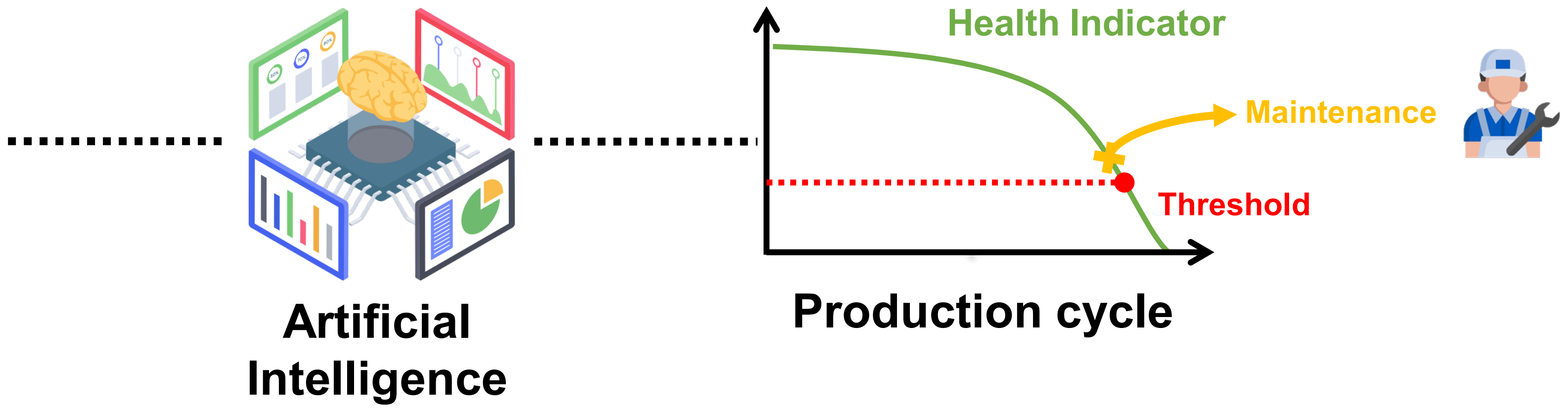
Production cycle

➢Enhance Operational Efficiency

➢Reduce cost

Industry 4.0 manufacturing pipeline

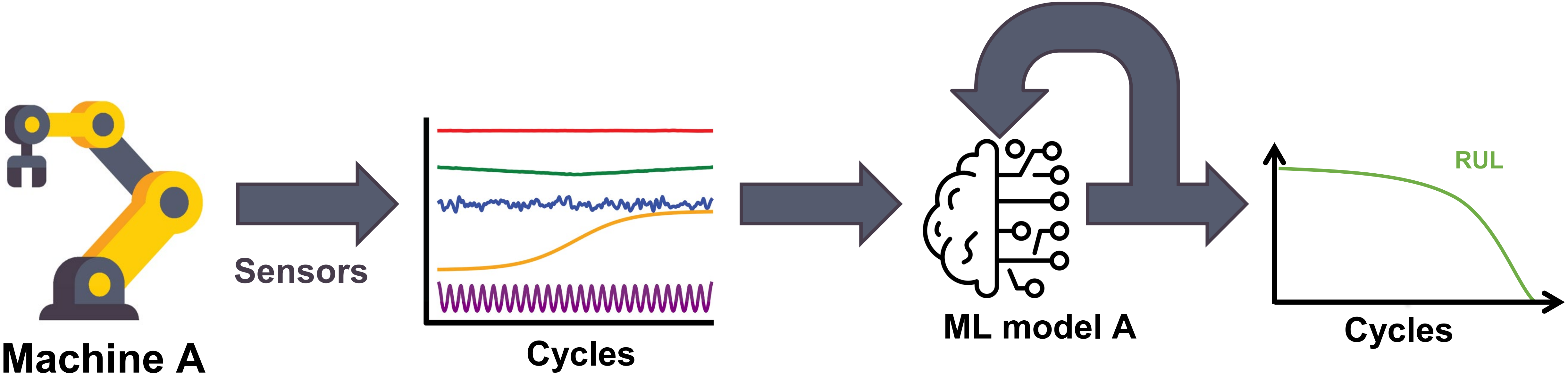
Introduction – Predictive Maintenance



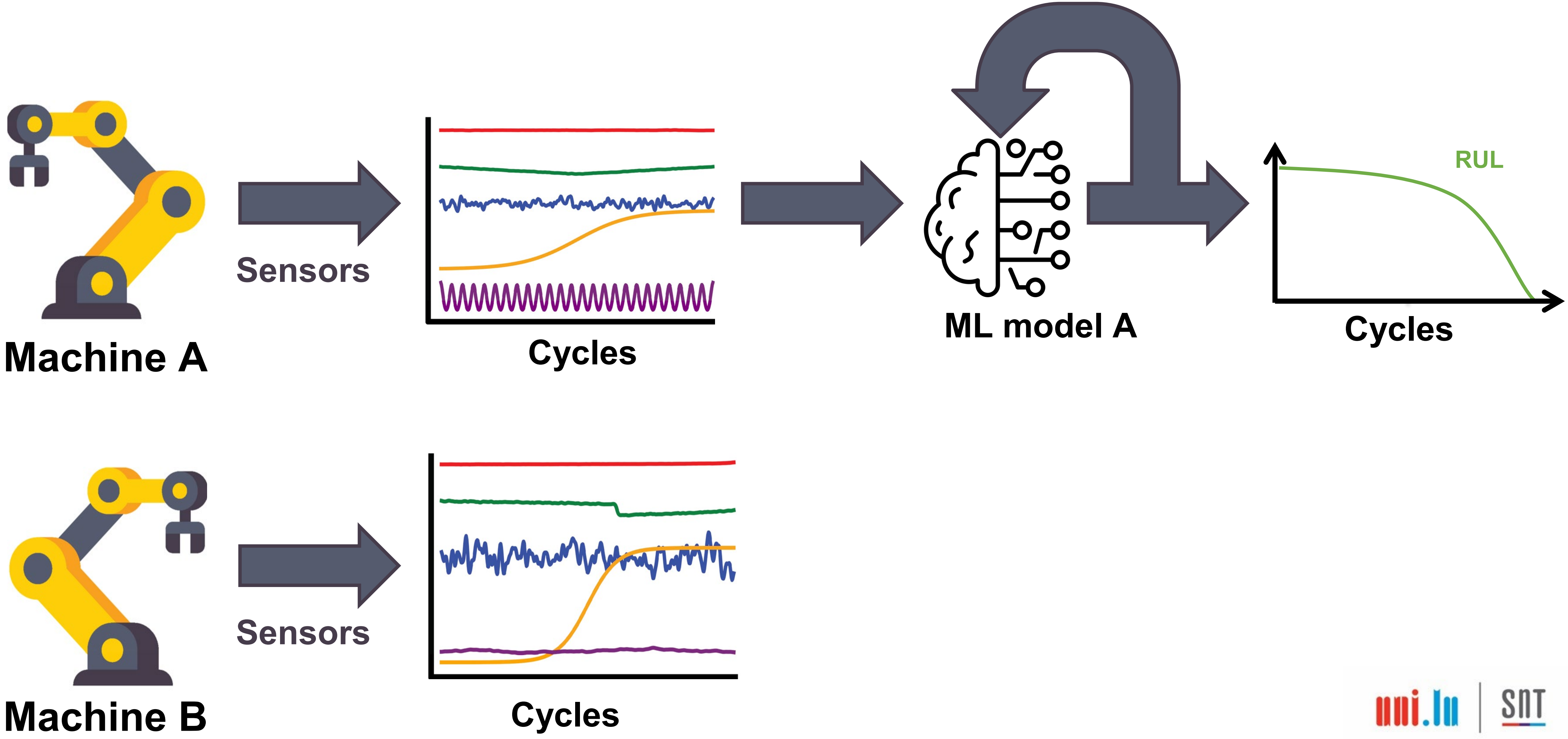
- ➢Enhance Operational Efficiency
- ➢Reduce cost

Industry 4.0 manufacturing pipeline

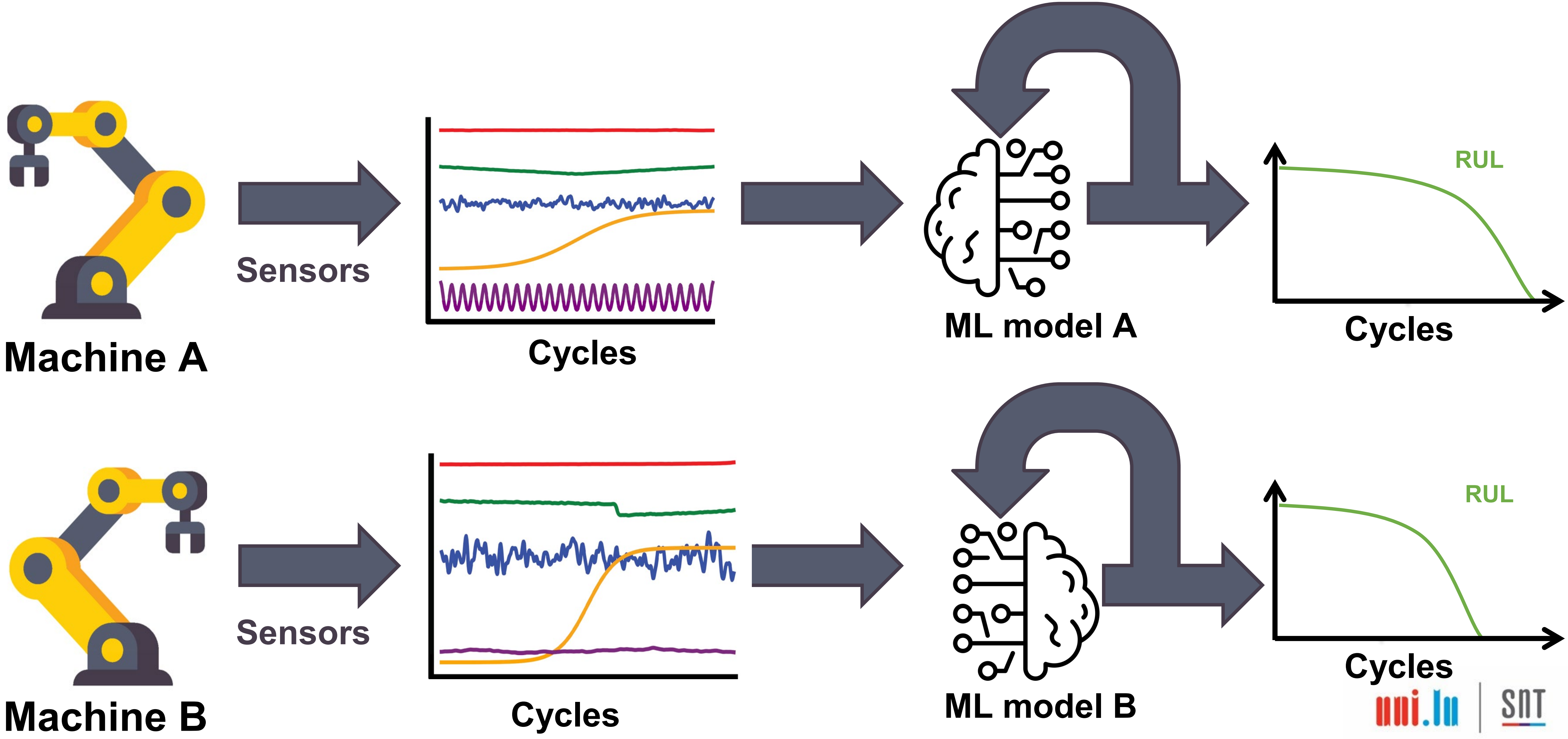
Introduction – Standard ML process



Introduction – Standard ML process



Introduction – Standard ML process



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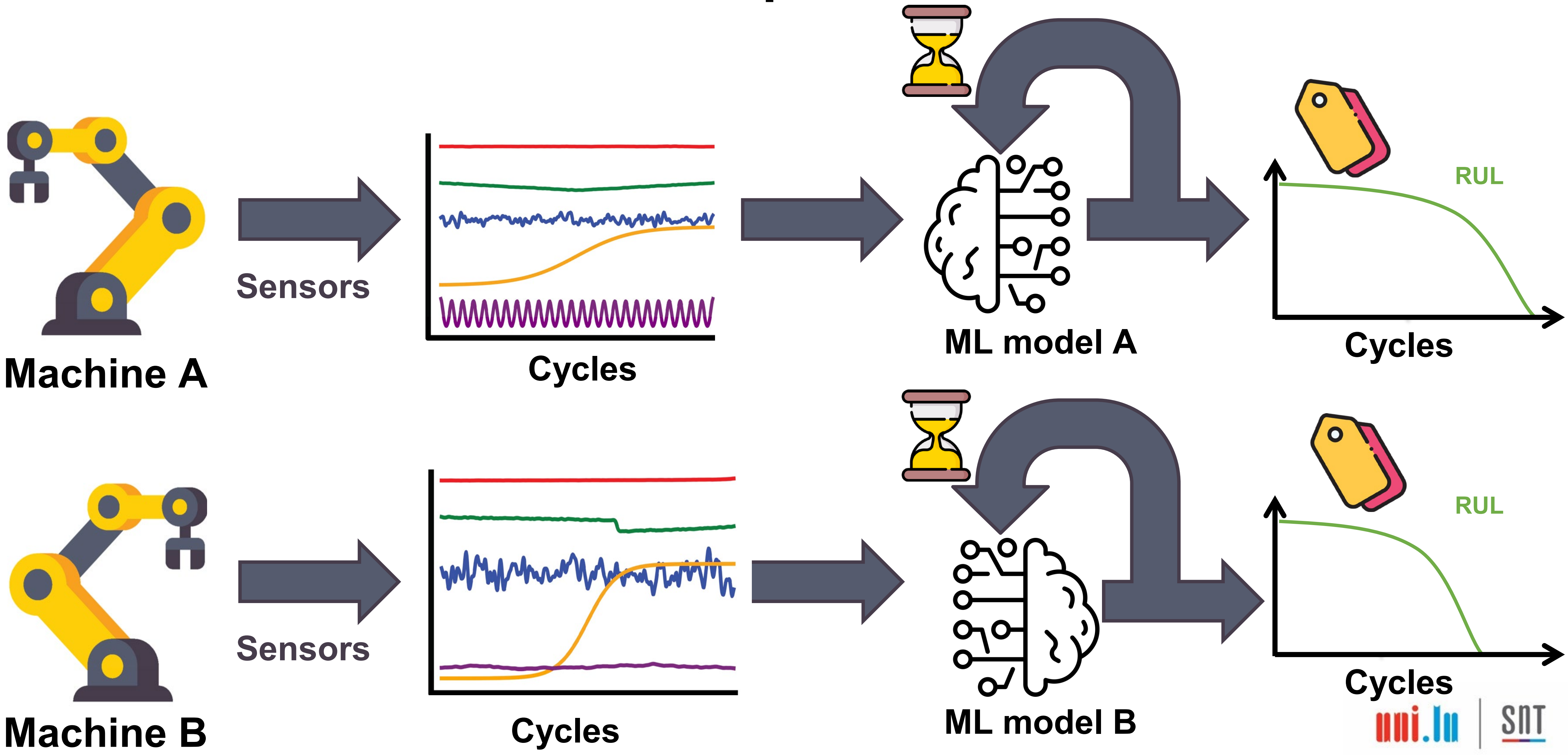
Introduction – Standard ML process



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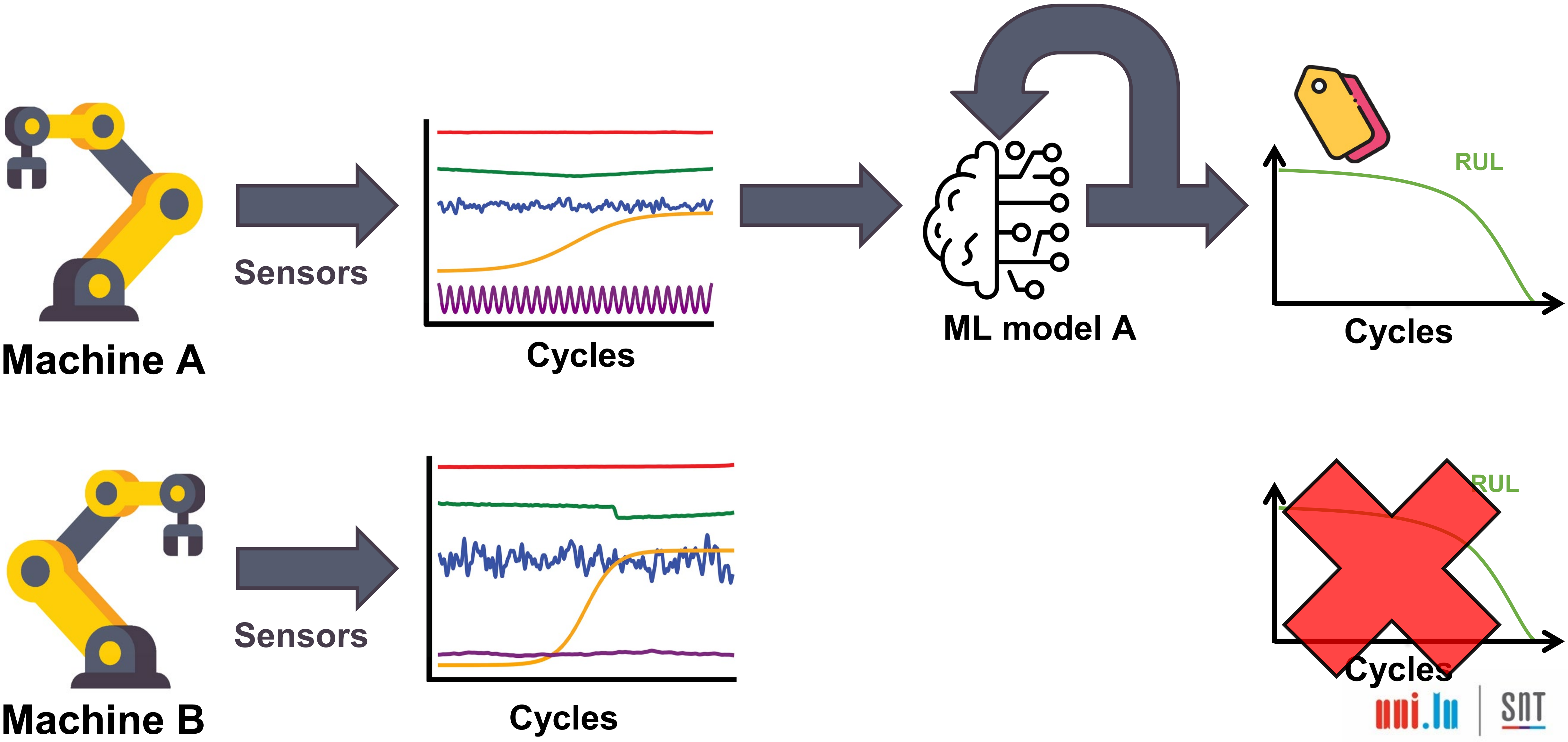
Introduction – Unsupervised Domain Adaptation (UDA)



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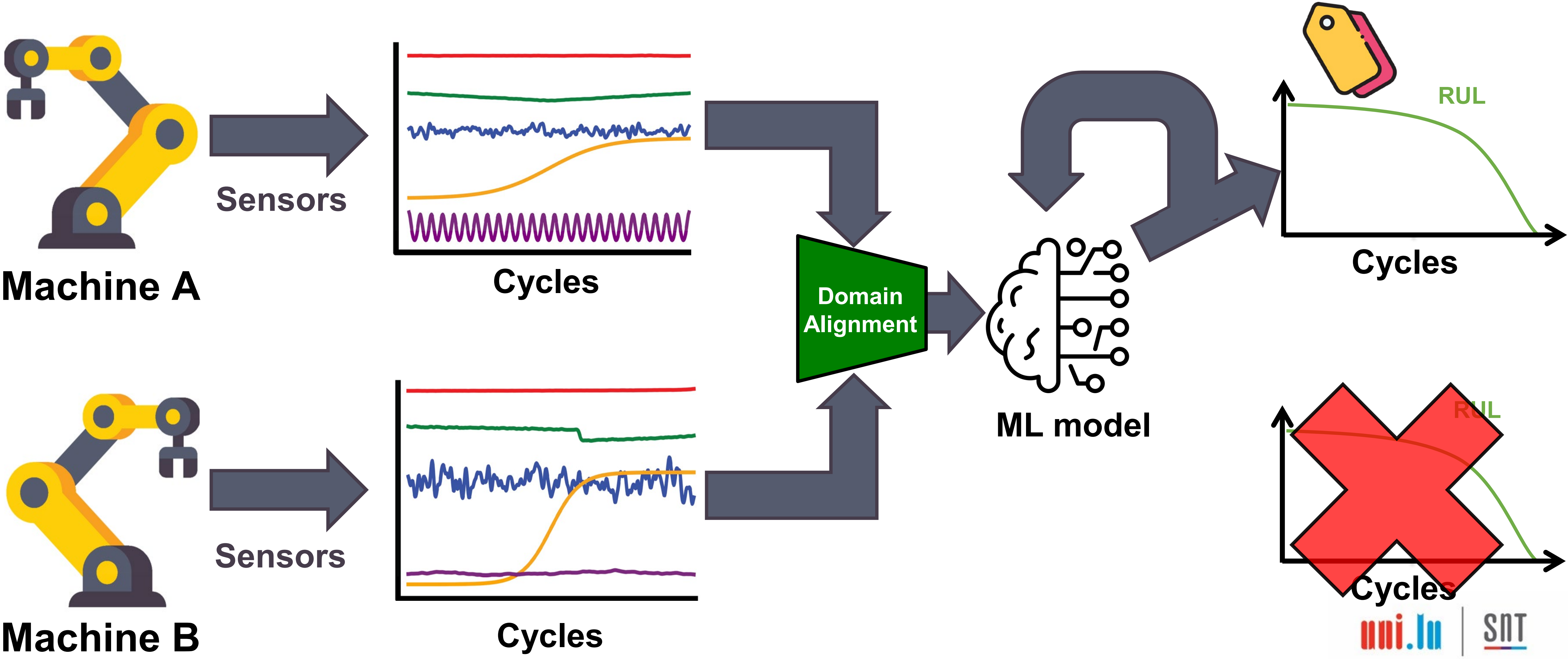
Unsupervised Domain Adaptation (UDA)



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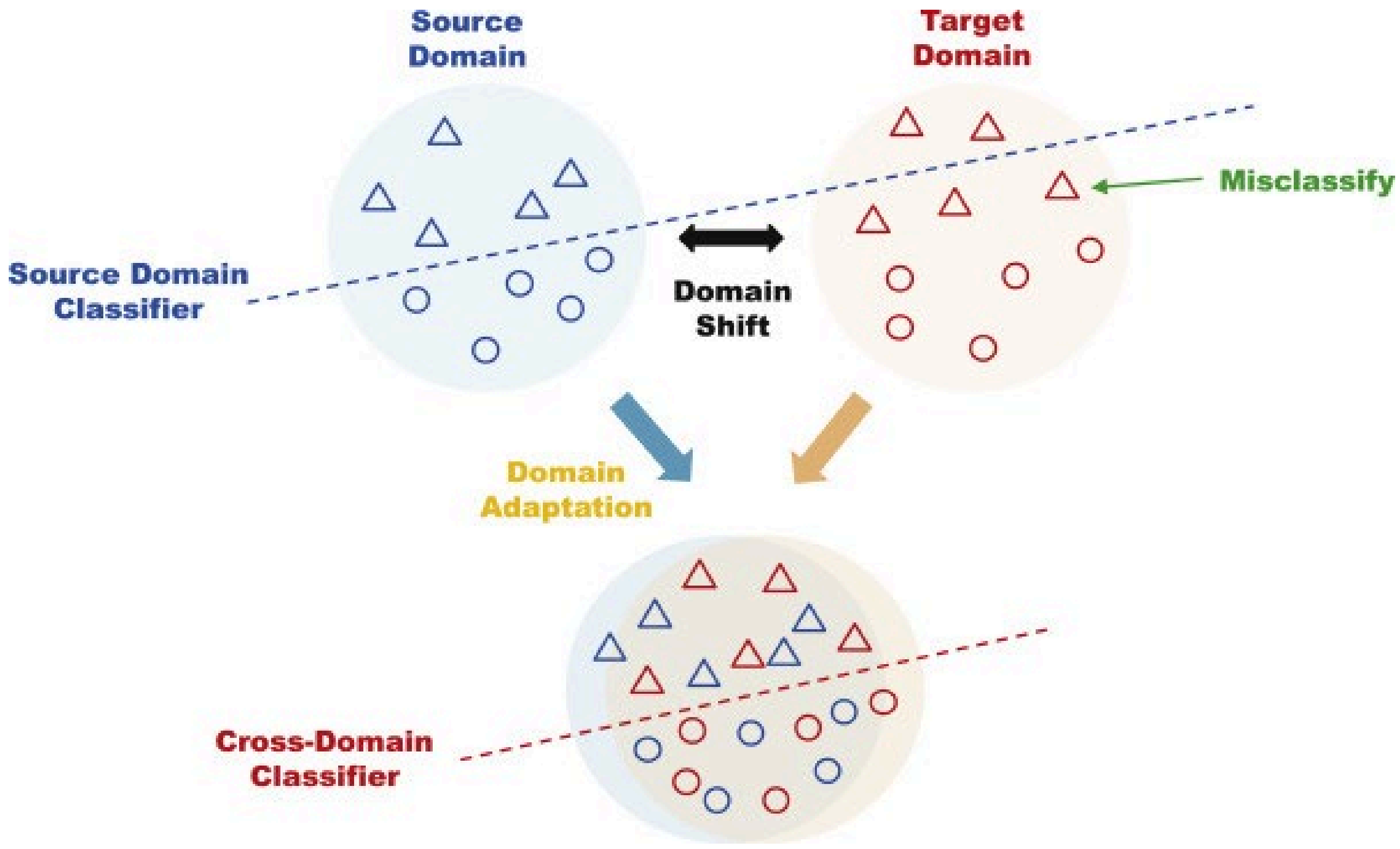
Unsupervised Domain Adaptation (UDA)



Li X., Et al.(2019). Multi-layer domain adaptation method for rolling bearing fault diagnosis. Signal processing, 157, 180-197.

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Unsupervised Domain Adaptation (UDA)

Problems:

- **Domain alignment** might **struggle** when there is a **large gap** between **source** and **target** domain
- **Real-world data** often exhibit **high variability** in **operational conditions** and **failure modes**
- **UDA** models risk **overfitting** to source data when **target domain** information is **insufficient**

Unsupervised Domain Adaptation (UDA)

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- **UDA** models risk **overfitting** to source data when **target domain** information is **insufficient**

Our work:

Use **Data Augmentation** to generate **realistic synthetic data** in the **target domains** to help UDA to **better aligns the domains**

Data Augmentation

Artificially generating new data from existing data

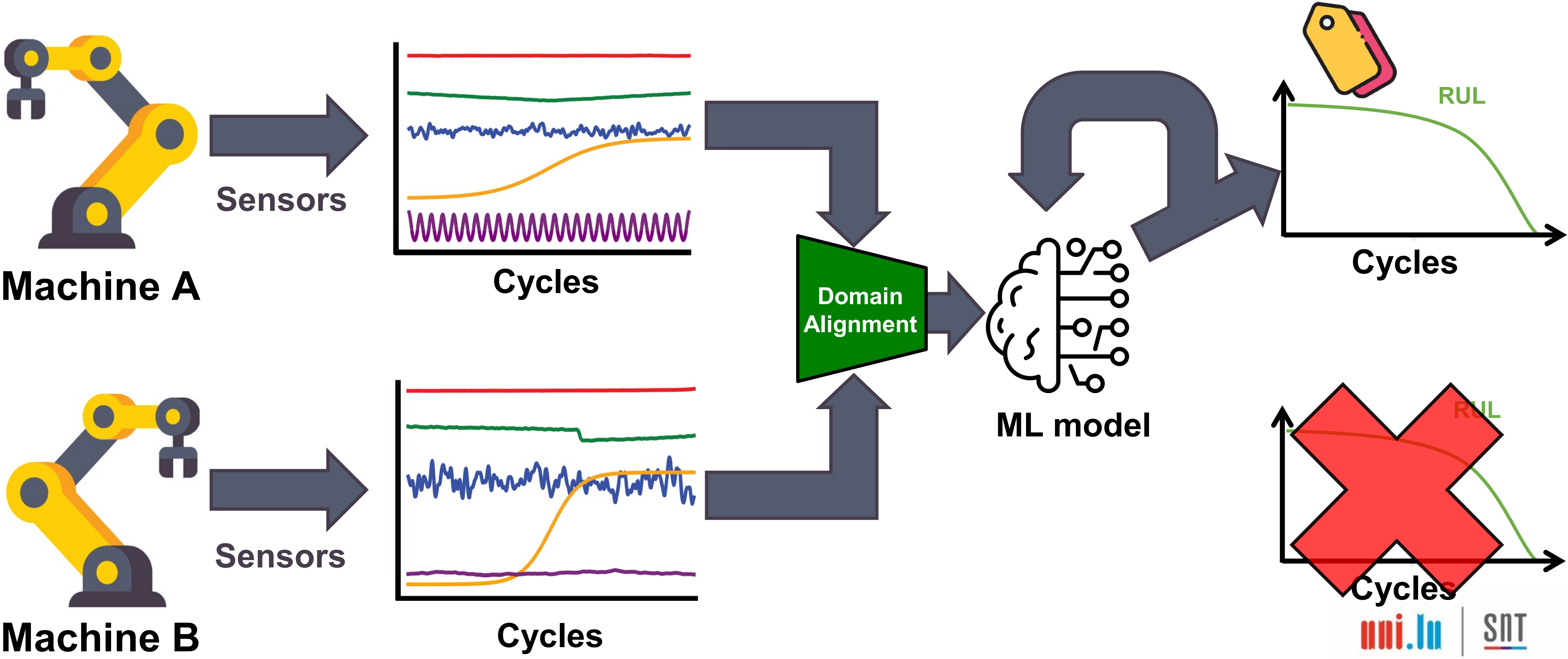
Label: **Cat**

Label: **Cat**

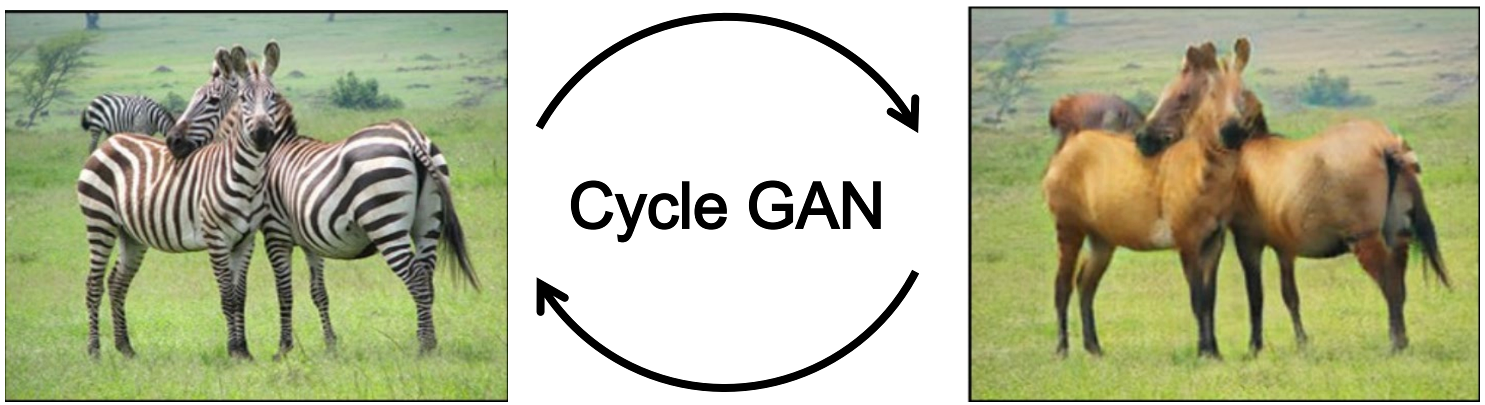
RUL: **10 Cycles**

RUL: **10 Cycles**

Unsupervised Domain Adaptation (UDA)

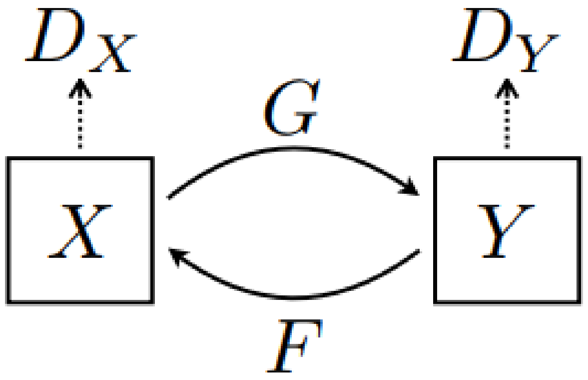


Data Augmentation – Cycle GAN

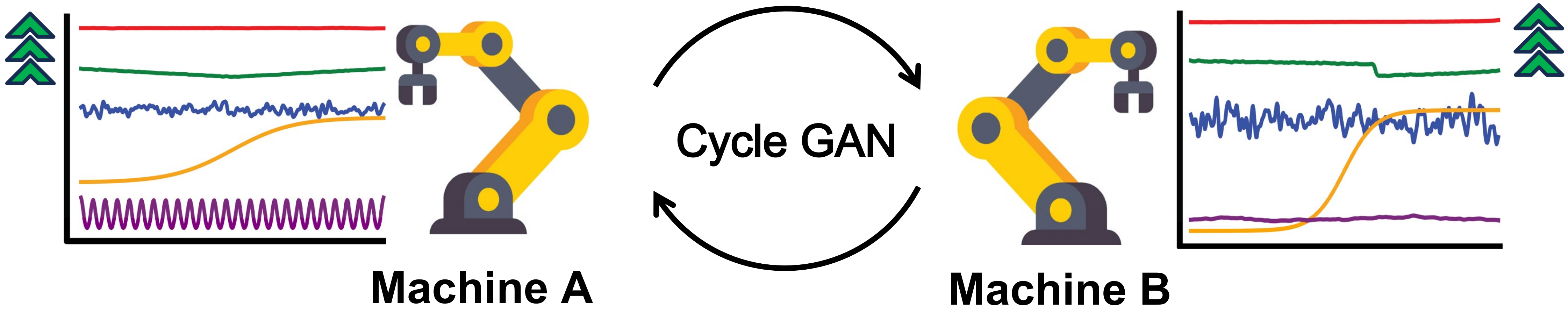


Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." Proceedings of the IEEE international conference on computer vision. 2017.

- **No need for paired data**
- **No need for labels**



Data Augmentation – Cycle GAN



Saravanan, et al. "TSI-GAN: Unsupervised Time Series Anomaly Detection Using Convolutional Cycle-Consistent Generative Adversarial Networks." Pacific-Asia Conference on Knowledge Discovery and Data Mining. Cham: Springer Nature Switzerland, 2023.

*

Pu, Ziqiang, et al. "Sliced Wasserstein cycle consistency generative adversarial networks for fault data augmentation of an industrial robot." Expert Systems with Applications 222 (2023): 119754.

Schockaert, Cedric, and Henri Hoyez. "Mts-cyclegan: An adversarial-based deep mapping learning network for multivariate time series domain adaptation applied to the ironmaking industry." arXiv preprint arXiv:2007.07518 (2020).

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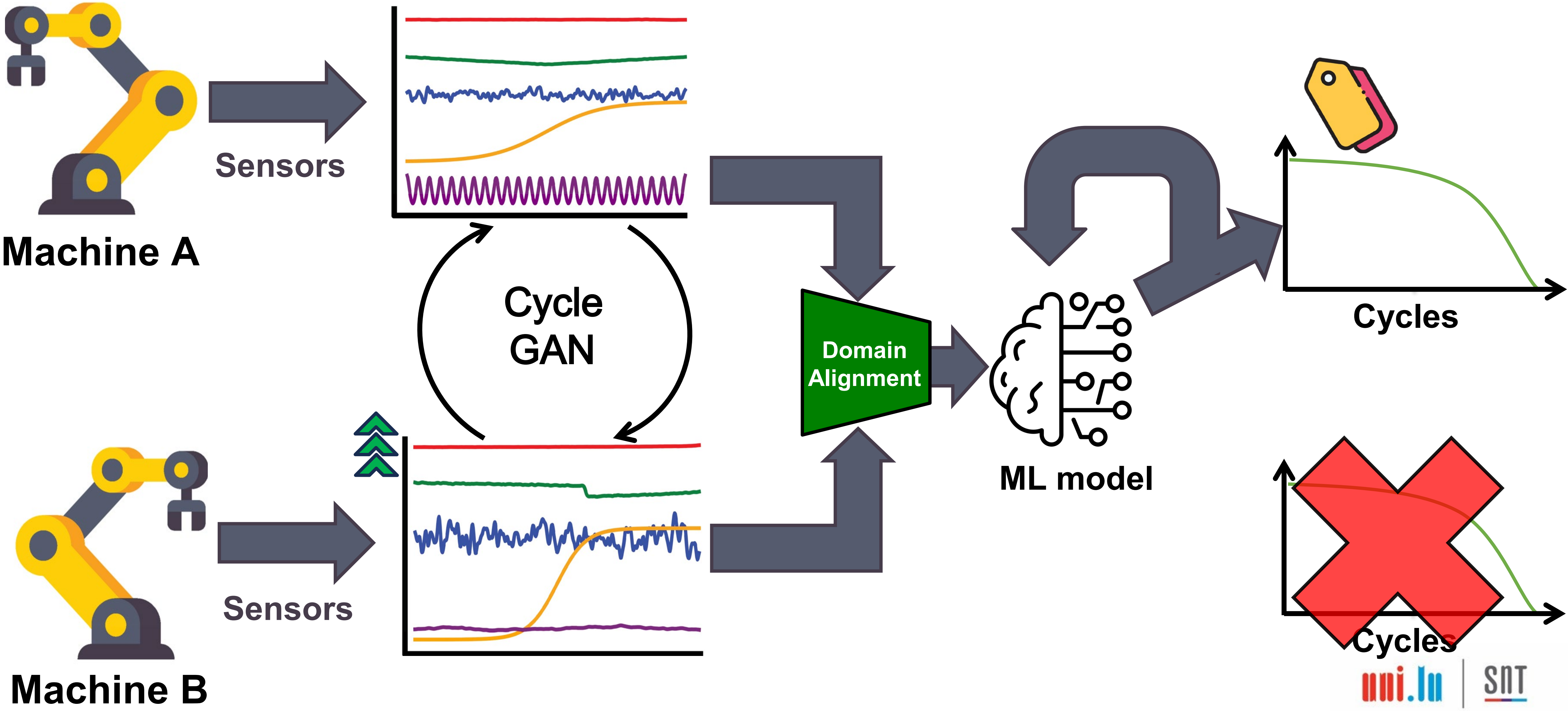
Workflow



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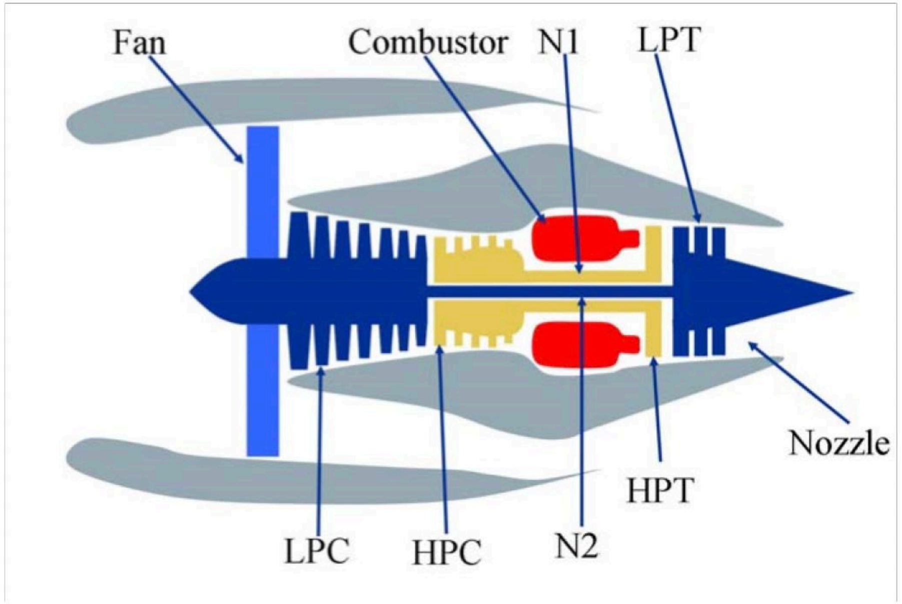
Experimental setup

Dataset: NASA C-MAPSS

Data	FD001	FD002	FD003	FD004
Engines: Train	100	260	100	249
Engines: Test	100	259	100	248
Op. Conditions	1	6	1	6
Fault Modes	1	1	2	2

Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)



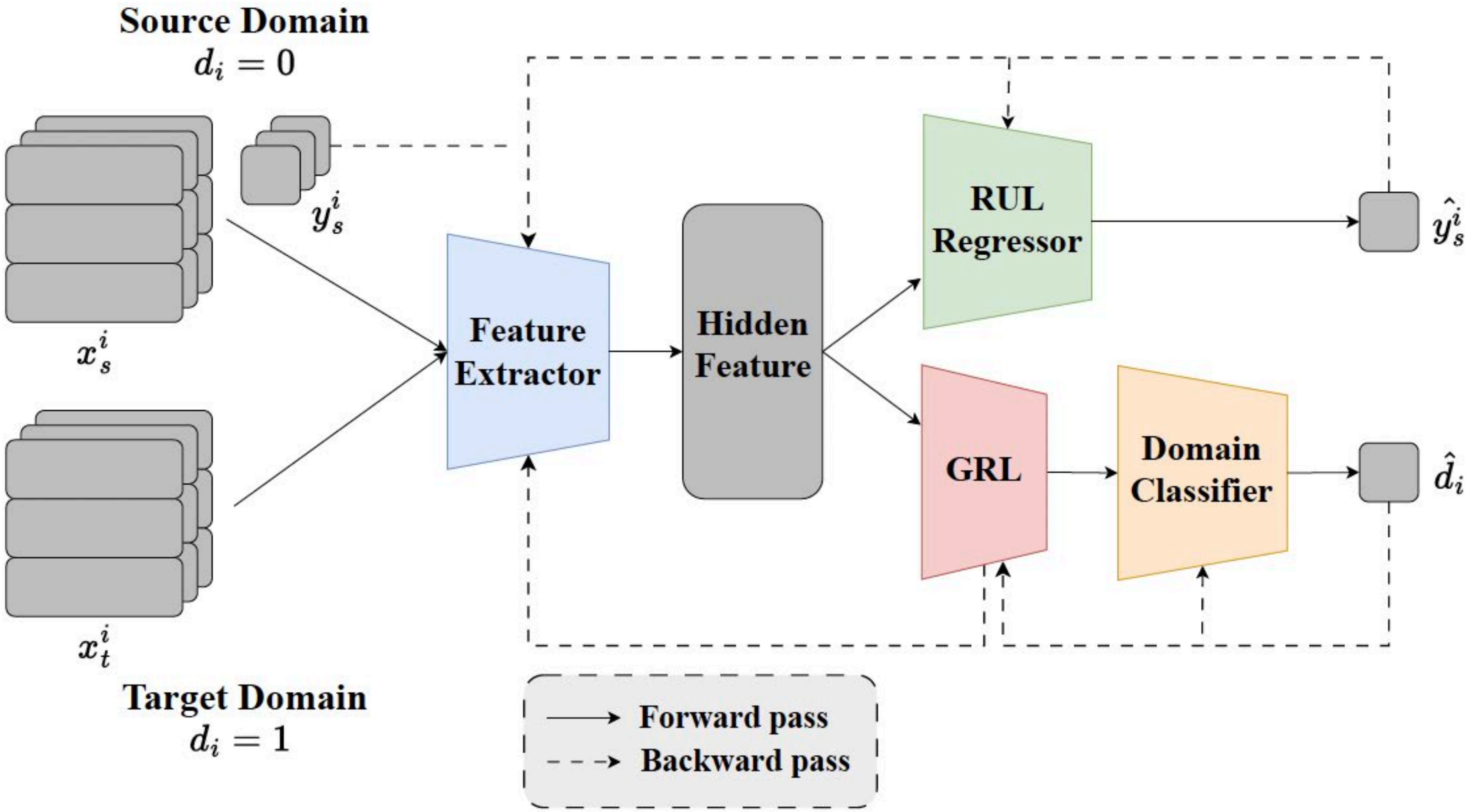
Saxena, A., et al. (2008). Damage propagation modeling for aircraft engine run to failure simulation. In 2008 international conference on prognostics and health management (pp. 1–9)

Preprocessing:

- Normalization in [-1;1]
- Sliding window of length 50

Experimental setup - DANN

Domain Adaptation (1)



Inspired from *Nejjar, Ismail, et al. "Domain adaptation via alignment of operation profile for Remaining Useful Lifetime prediction." Reliability Engineering & System Safety 242 (2024): 109718.*

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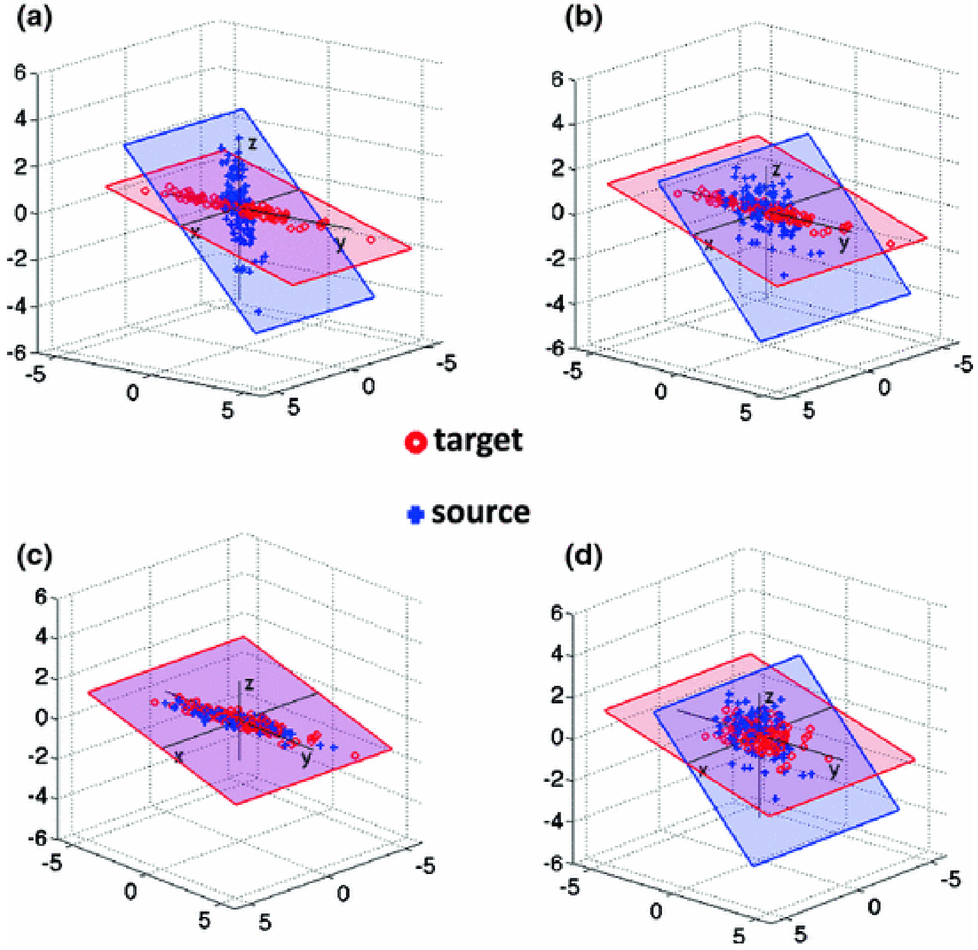
Experimental setup - CORAL

Domain Adaptation (2)



Sun, Baochen et al. "Correlation alignment for unsupervised domain adaptation." Domain adaptation in computer vision applications (2017): 153-171.

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Experimental setup - Metrics

RUL prediction

Lower is better

- $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y^i} - y^i)^2}$

- $Score = \sum_{i=1}^{n} e^{\alpha(|\hat{y^i} - y^i|)}$

where

$$\alpha = \begin{cases} 1/10 & \text{if} \quad \hat{y^i} - y^i > 0 \\ 1/13 & \text{else} \end{cases}$$

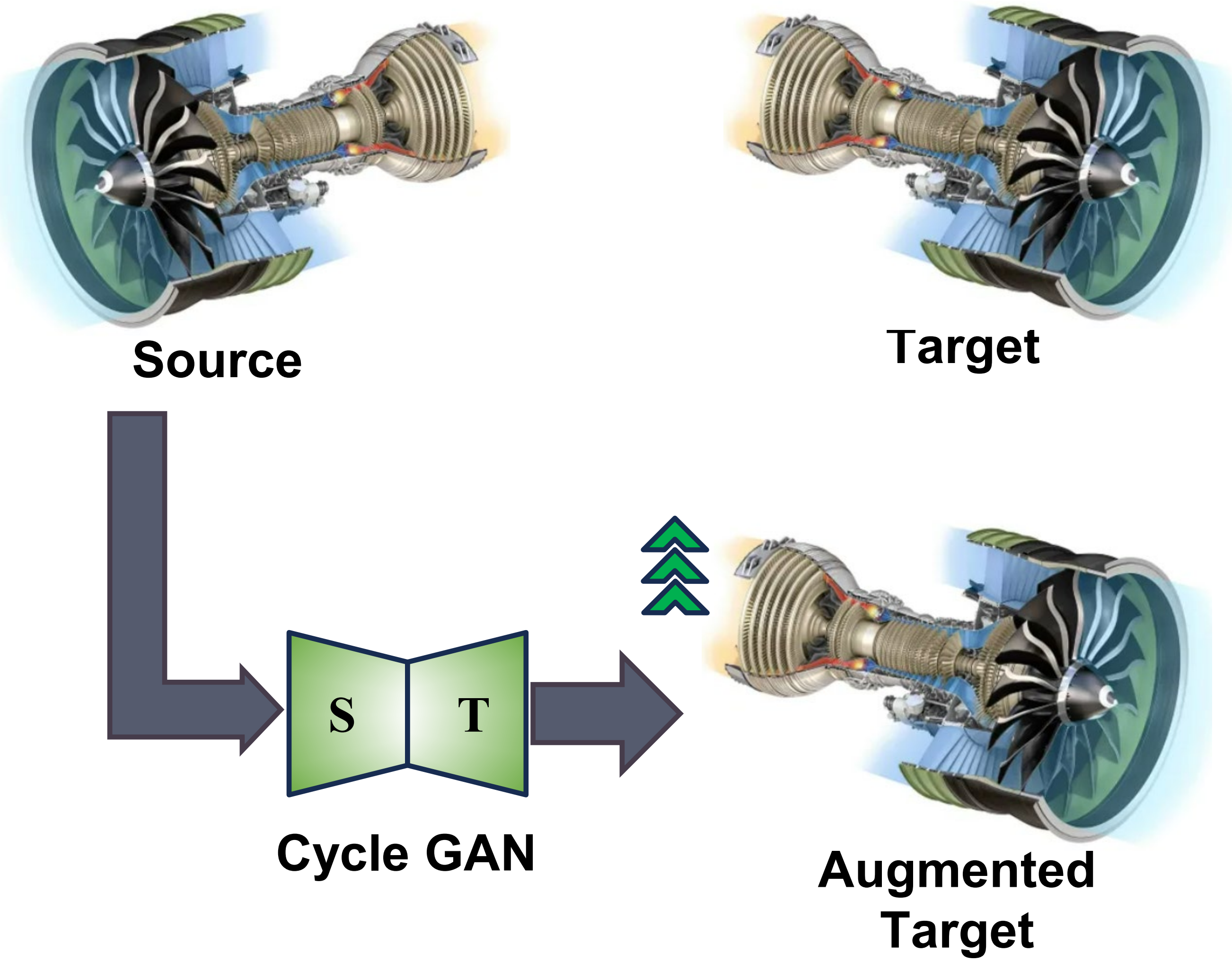
Data Augmentation Quality

Lower is better

- $W(\mathcal{S},\mathcal{T}) = \inf_{\gamma \in \Pi(\mathcal{S},\mathcal{T})} \int_{\Omega^2} D(x_s, x_t)\, d\gamma(x_s, x_t)$

where $\Pi(\mathcal{S},\mathcal{T})$ is the joint distribution of source and target, D a distance and $\gamma(x_s, x_t)$ represents the amount of "information" transported from x_s in $\mathcal{S}$ to x_t in $\mathcal{T}$.

Results – Data Augmentation Quality



Data	FD001	FD002	FD003	FD004
Engines: Train	100	260	100	249
Engines: Test	100	259	100	248
Op. Conditions	1	6	1	6
Fault Modes	1	1	2	2

Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Source → Target	$W(\mathcal{S}, \mathcal{T})$	$W(\mathcal{T}, \mathcal{T}_{aug})$
FD001 → FD002	0.35	**0.20**
FD001 → FD003	**0.04**	0.09
FD001 → FD004	0.36	**0.15**
FD002 → FD001	0.35	**0.23**
FD002 → FD003	0.33	**0.24**
FD002 → FD004	**0.01**	0.11
FD003 → FD001	**0.04**	0.08
FD003 → FD002	0.33	**0.14**
FD003 → FD004	0.33	**0.19**
FD004 → FD001	0.36	**0.16**
FD004 → FD002	**0.01**	0.11
FD004 → FD003	0.33	**0.10**

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Results – RUL Prediction

Source → Target	DANN	DANN w/ Aug
FD001 → FD002	**55.6** (±1.2)	56.0 (±2.3)
FD001 → FD003	39.8 (±1.5)	**37.5** (±1.3)
FD001 → FD004	**46.6** (±2.9)	49.2 (±1.7)
FD002 → FD001	33.0 (±5.8)	**27.1** (±3.7)
FD002 → FD003	44.5 (±4.0)	**42.8** (±2.7)
FD002 → FD004	43.6 (±1.3)	**42.2** (±0.5)
FD003 → FD001	29.2 (±2.9)	**23.7** (±1.9)
FD003 → FD002	**57.1** (±0.6)	57.8 (±1.4)
FD003 → FD004	46.5 (±0.6)	**46.2** (±0.4)
FD004 → FD001	41.7 (±13.7)	**41.1** (±7.1)
FD004 → FD002	40.0 (±6.9)	**23.7** (±0.9)
FD004 → FD003	40.6 (±2.8)	**38.8** (±4.4)

Data	FD001	FD002	FD003	FD004
Engines: Train	100	260	100	249
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Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Same Op. Conditions

1 FM -> 2 FM : No improvement

Results – RUL Prediction

Source → Target	DANN	DANN w/ Aug
FD001 → FD002	**55.6** (±1.2)	56.0 (±2.3)
FD001 → FD003	39.8 (±1.5)	**37.5** (±1.3)
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Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Same Op. Conditions

2 FM -> 1 FM : Improvmement

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Results – RUL Prediction

Source → Target	DANN	DANN w/ Aug
FD001 → FD002	**55.6** (±1.2)	56.0 (±2.3)
FD001 → FD003	39.8 (±1.5)	**37.5** (±1.3)
FD001 → FD004	**46.6** (±2.9)	49.2 (±1.7)
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Data	FD001	FD002	FD003	FD004
Engines: Train	100	260	100	249
Engines: Test	100	259	100	248
Op. Conditions	1	6	1	6
Fault Modes	1	1	2	2

Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Single to Multiple Op. Conditions

No improvement / Worsen

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Results – RUL Prediction

Source → Target	DANN	DANN w/ Aug
FD001 → FD002	**55.6** (±1.2)	56.0 (±2.3)
FD001 → FD003	39.8 (±1.5)	**37.5** (±1.3)
FD001 → FD004	**46.6** (±2.9)	49.2 (±1.7)
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Data	FD001	FD002	FD003	FD004
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Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Multiple to Single Op. Conditions

Improvement
(no improvement ?)

Results – RUL Prediction

Source → Target	CORAL	CORAL w/ Aug
FD001 → FD002	64.0 (±4.8)	**64.0** (±1.9)
FD001 → FD003	41.2 (±1.7)	**39.2** (±1.0)
FD001 → FD004	**55.0** (±6.0)	55.5 (±5.3)
FD002 → FD001	**41.1** (±3.3)	42.5 (±1.9)
FD002 → FD003	42.3 (±8.2)	**40.3** (±5.0)
FD002 → FD004	55.3 (±6.5)	**55.2** (±3.0)
FD003 → FD001	**46.9** (±0.8)	44.4 (±1.6)
FD003 → FD002	57.0 (±3.3)	**55.7** (±4.1)
FD003 → FD004	57.5 (±1.3)	**55.4** (±1.8)
FD004 → FD001	70.6 (±6.7)	**68.7** (±5.4)
FD004 → FD002	46.9 (±3.1)	**46.3** (±2.9)
FD004 → FD003	48.5 (±1.8)	**46.7** (±1.9)

Data	FD001	FD002	FD003	FD004
Engines: Train	100	260	100	249
Engines: Test	100	259	100	248
Op. Conditions	1	6	1	6
Fault Modes	1	1	2	2

Table 1. C-MAPSS datasets descriptions (Saxena & Goebel, 2008)

Likely the same conclusions

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Thank you!

Contact:

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