Sequential Latent Variable Models for Prognostics and Health Management

Final Presentation - 08.11.2019

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Agenda

1. Introduction
2. Datasets
3. Sequential Latent Variable Models
4. Anomaly Detection
5. Prognostics
6. Conclusion & Future Work

Prognostics and Health Management

- Includes several sub fields such as anomaly detection, prognostics and fault diagnostics
- Its objective is to increase system reliability, availability, and safety to reduce maintenance costs
- Each subfield has its own methods (which are similar in several cases)

⇒ No method has been applied to multiple fields

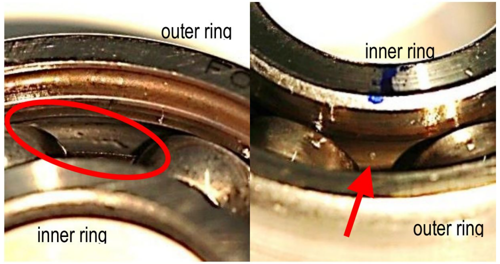
Contributions

- Build upon work of Max using STORN for anomaly detection
- Extend method to other sequential latent variable model (DVBF)
- Introduce novel anomaly detection method relying on latent space representations
- Adapt method to prognostics

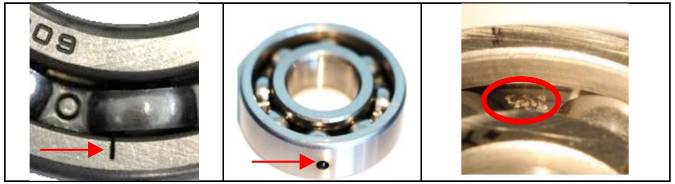
Datasets

Paderborn Dataset

- Vibration data of bearings collected using accelerometer
- Data consists of **6 normal** and **26 anomalous** trajectories
  - 4 operating conditions
  - 12 artificially damaged trajectories
  - 14 trajectories with real damage
  - 3 fault locations (inner race, outer race, and both)
  - Several different fault types, different severity
  - ~31.4million normal and ~125.5million anomalous data points
- Faults are introduced using EDM, drilling, and pitting



Real Damages [9]



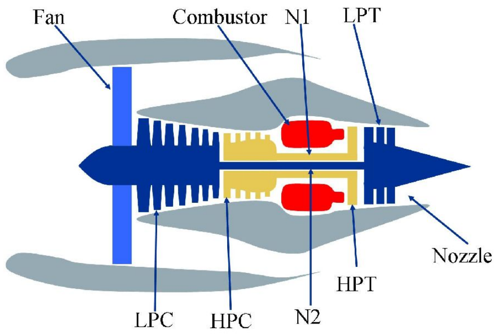
Artificial Damages [9]

CMAPSS Dataset

- Several sensor readings of simulated turbofan engines
- One timestep = Snapshot during one particular flight
- Multiple independent datasets available:

Dataset	FD001	FD002	FD003	FD004
# Full Traject. (Train)	100	260	100	249
# Cropped Traject. (Test)	100	259	100	248
# Conditions	1	6	1	6
# Fault Types	1	1	2	2

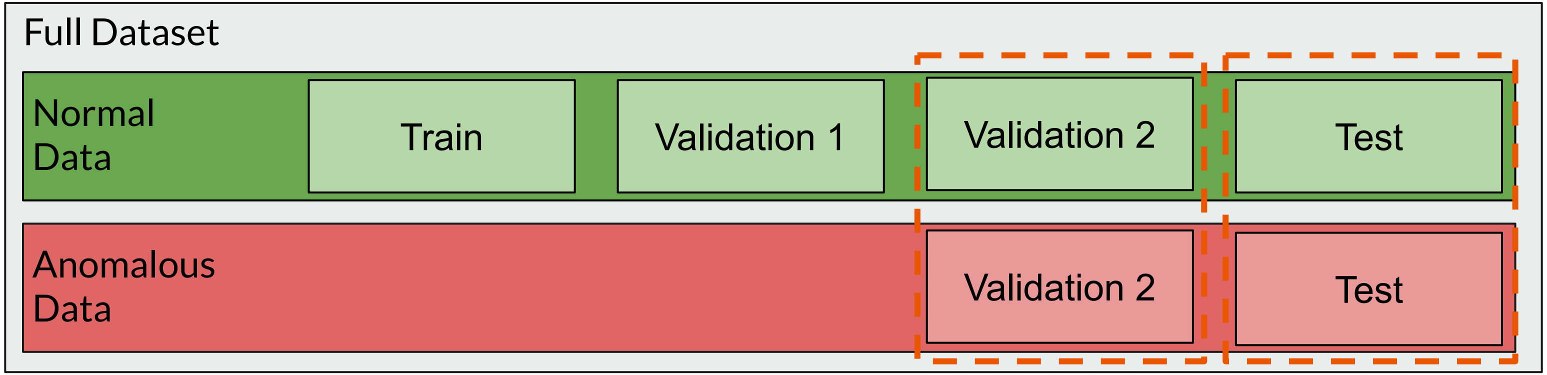
- For anomaly detection data is split:
  - RUL > 130 -> Normal
  - RUL < 50 -> Anomalous



Turbofan Engine [10]

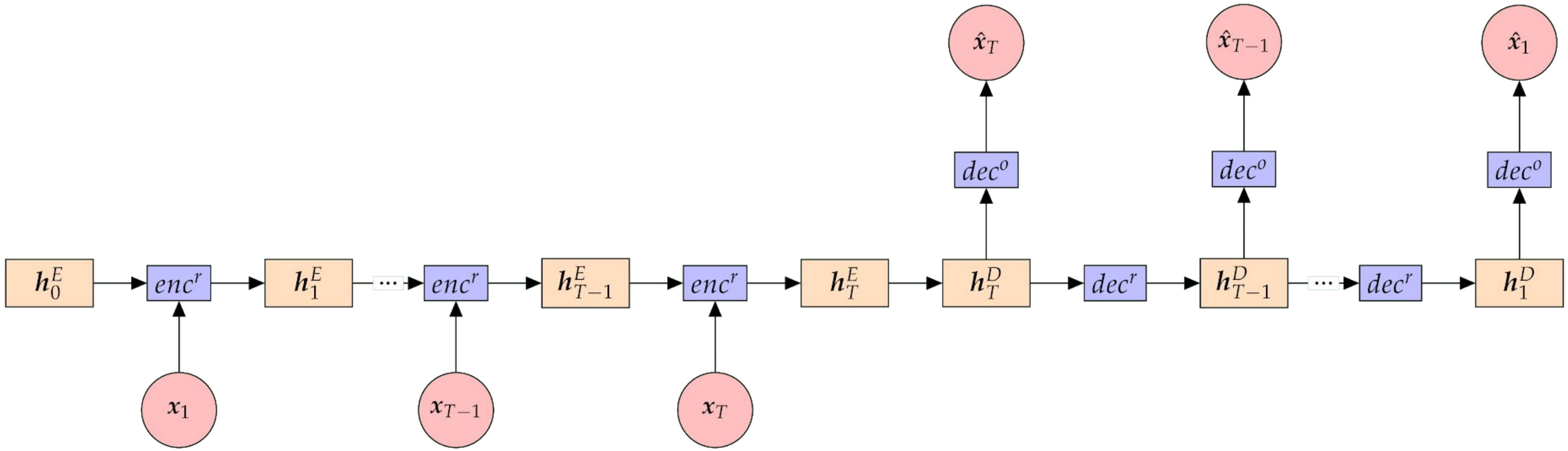
Dataset Split

Dataset needs to be split into different parts:

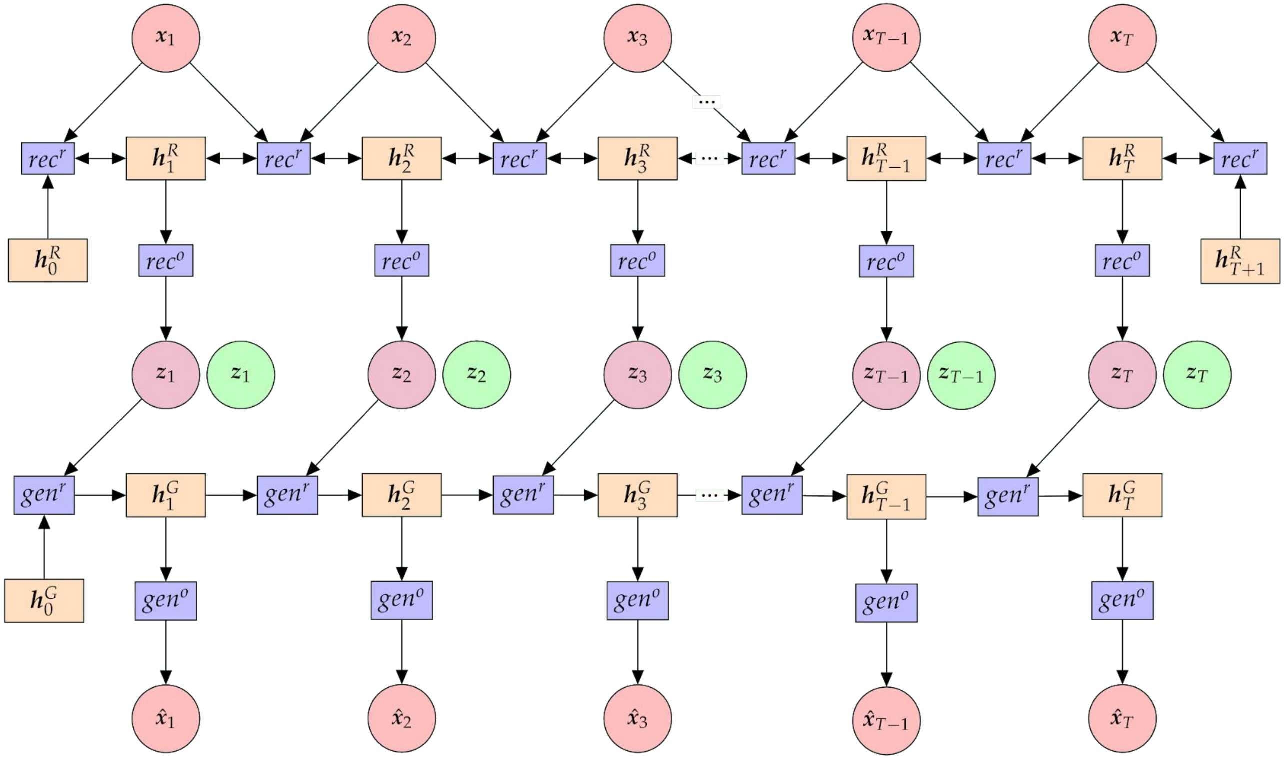


Sequential Latent Variable Models

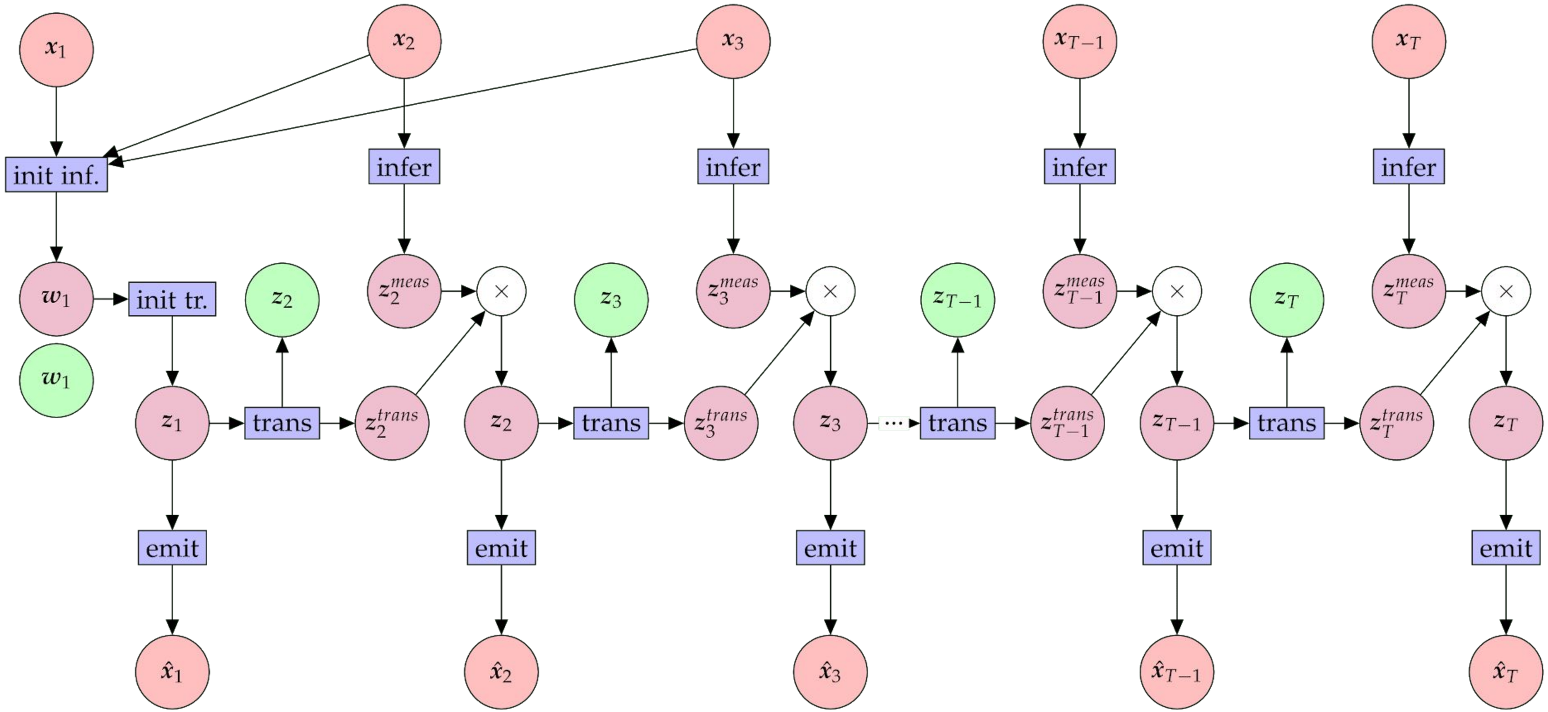
Encoder-Decoder Model (EncDec) [1]



Stochastic Recurrent Network (STORN) [2]



Deep Variational Bayes Filter (DVBF) [3]



Anomaly Detection

Overview

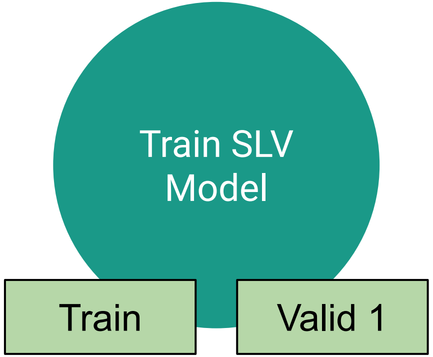
General

- Detection of previously unseen patterns that do not match expected behavior
- Applicable to detect anomalies such as credit card fraud or mechanical faults
- Can prevent total system failures by early detection

Difficulties

- Definition of normality often not straightforward
- Boundary between normal and anomalous behavior often not precisely defined
- Anomalous data hard to obtain
- Noise in data might be mistaken as anomaly

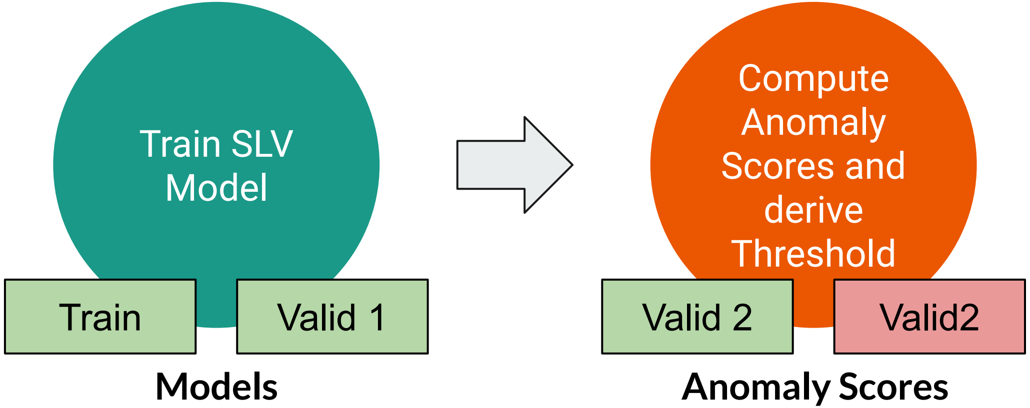
Methods



Models

- EncDec Model
- STORN
- DVBF

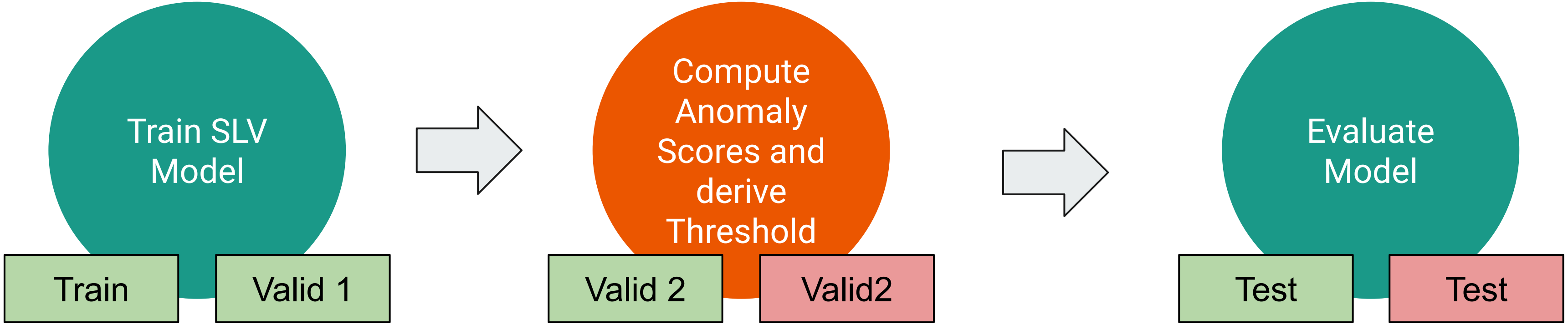
Methods



- EncDec Model
- STORN
- DVBF

- Reconstruction-based methods
- ELBO-based methods
- Latent space methods

Methods



Models

- EncDec Model
- STORN
- DVBF

Anomaly Scores

- Reconstruction-based methods
- ELBO-based methods
- Latent space methods

Evaluation Metrics

- F1 Score
- Recall, Precision
- ROC-AUC

Methods - Reconstruction-based methods

Rely on difference between observation and emission

Global One-Step Prediction Error Threshold [4]

- Compute reconstruction error:

$$a_t = ||x_t - \hat{x}_t||^2$$

- Take 0.995 percentile across time for final anomaly score

Methods - Reconstruction-based methods

Rely on difference between observation and emission

Global One-Step Prediction Error Threshold [4]

- Compute reconstruction error:

$$a_t = ||x_t - \hat{x}_t||^2$$

- Take 0.995 percentile across time for final anomaly score

Global Prediction Error Threshold

- Use sum instead of percentile to compute anomaly score:

$$\delta = \sum_{t=0}^{T} ||x_t - \hat{x}_t||^2$$

Methods - ELBO-based methods

Rely on lower bound as it is an approximation of true data likelihood

Global Stepwise Lower Bound Threshold [4]

- Similar to Global One-Step Prediction Error Threshold
- Take 0.005 percentile of stepwise lower bound values

Methods - ELBO-based methods

Rely on lower bound as it is an approximation of true data likelihood

Global Stepwise Lower Bound Threshold [4]

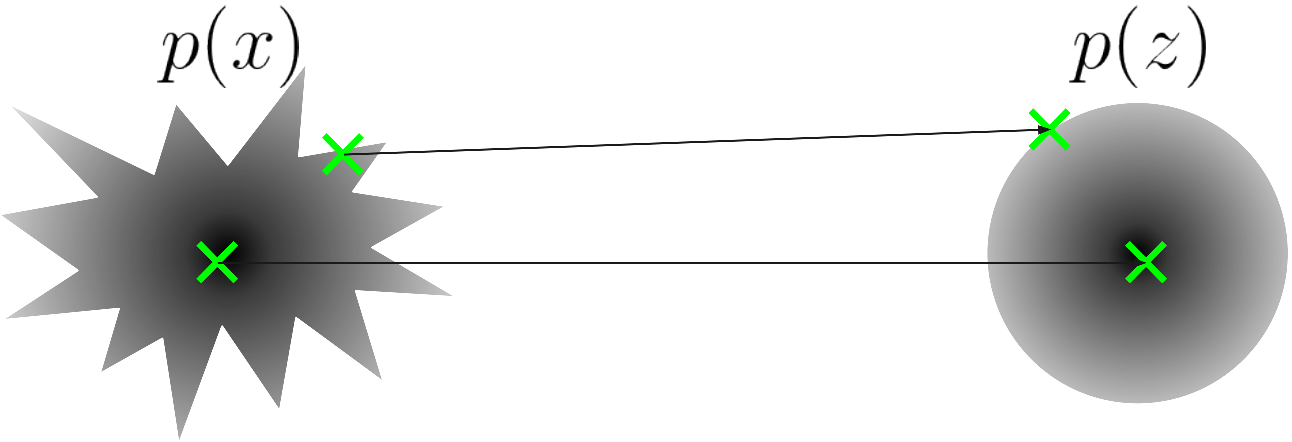
- Similar to Global One-Step Prediction Error Threshold
- Take 0.005 percentile of stepwise lower bound values

Lower Bound [4]

- Similar to Global Prediction Error Threshold
- Sum stepwise lower bounds instead of taking percentile

Methods - Latent space methods

Rely on latent space representation for anomaly detection

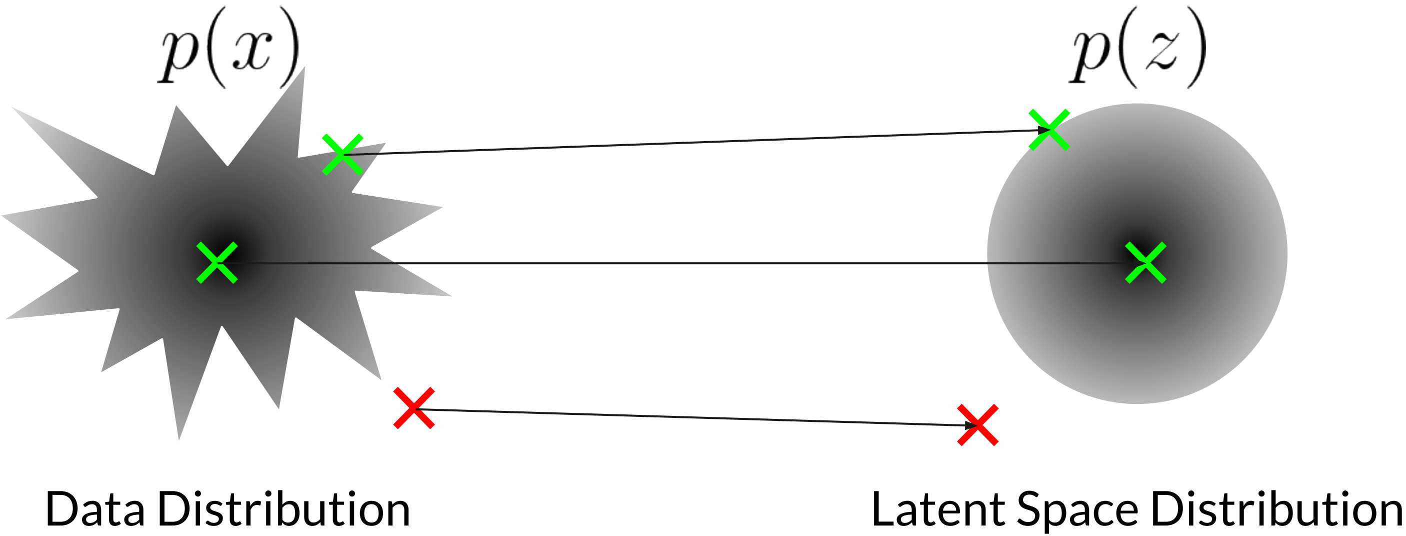


Data Distribution

Latent Space Distribution

Methods - Latent space methods

Rely on latent space representation for anomaly detection



Methods - Latent space methods

Rely on latent space representation for anomaly detection

One-Class Classifier

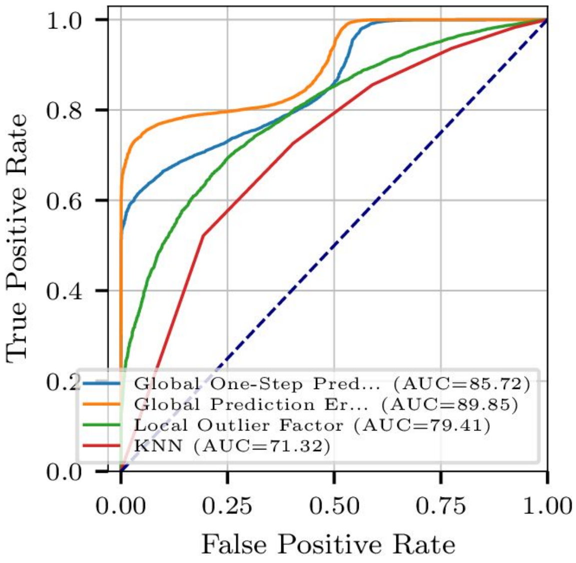
- Only trained on normal data
- Draw boundary around normal samples
- Output of decision function used as anomaly score
- Local Outlier Factor, One-Class SVM, ...

Two-Class Classifier

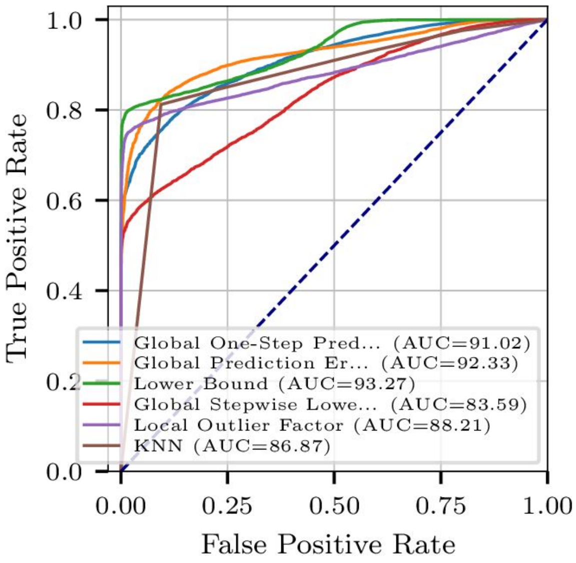
- Trained on normal and anomalous data
- Discriminate between normal and anomalous samples
- Output of decision function used as anomaly score
- KNN, Decision Trees, SVM, ...

Results Paderborn

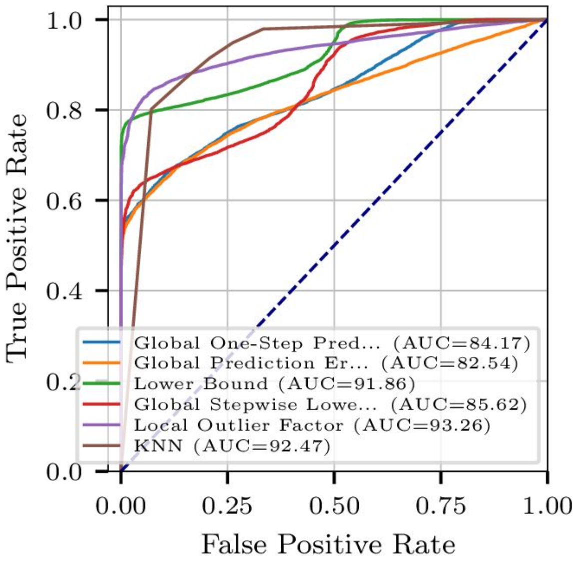
Results - Paderborn



EncDec Model

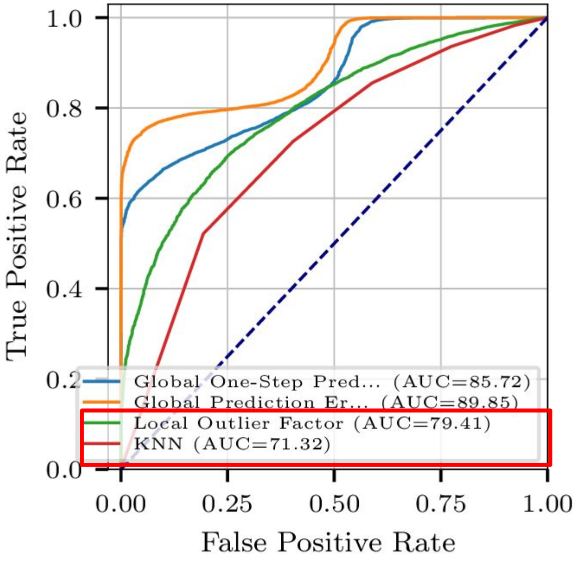


STORN

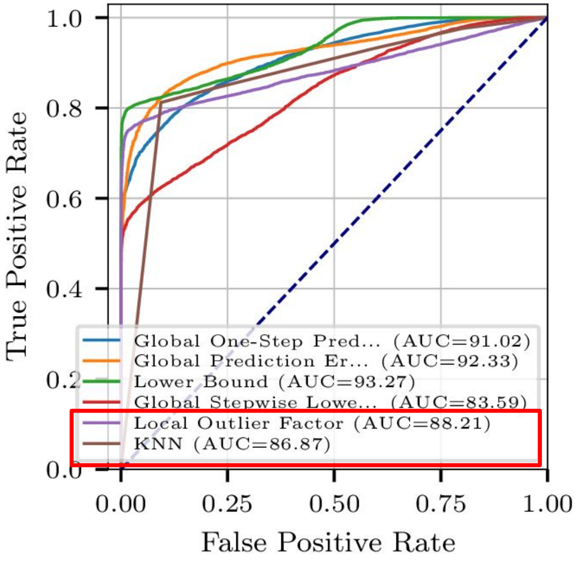


DVBF

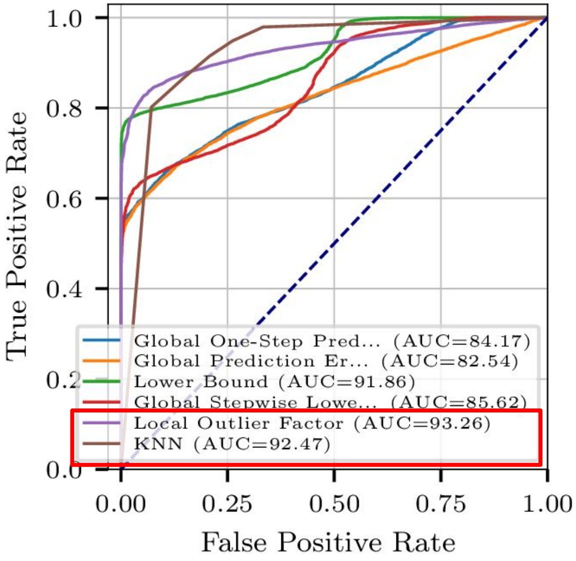
Results - Paderborn



EncDec Model



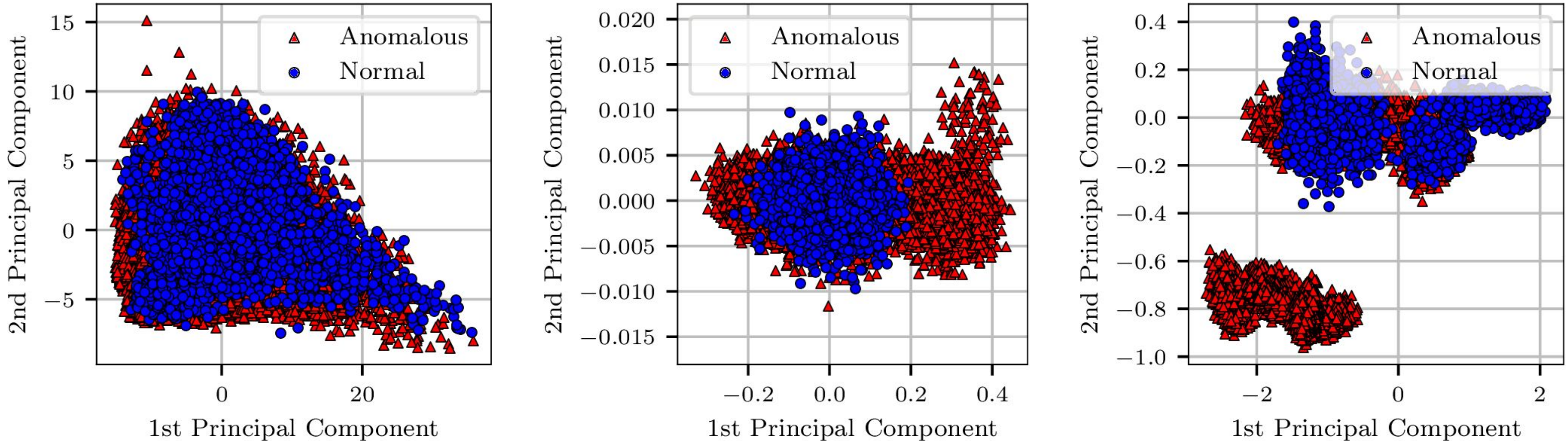
STORN



DVBF

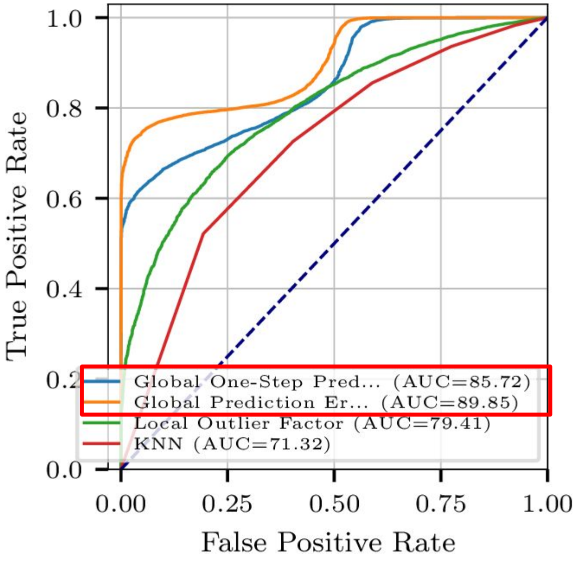
Results - Paderborn

Latent space of different models:

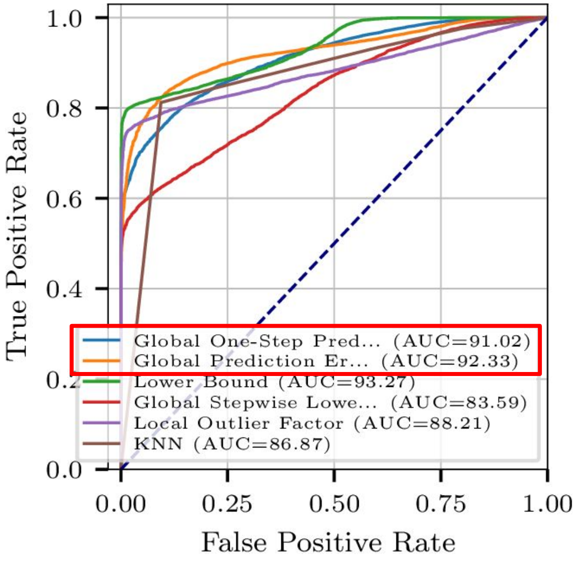


EncDec Model STORN DVBF

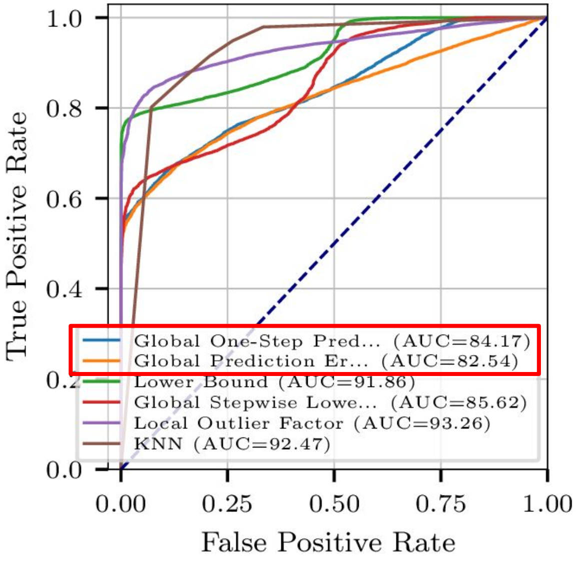
Results - Paderborn



EncDec Model



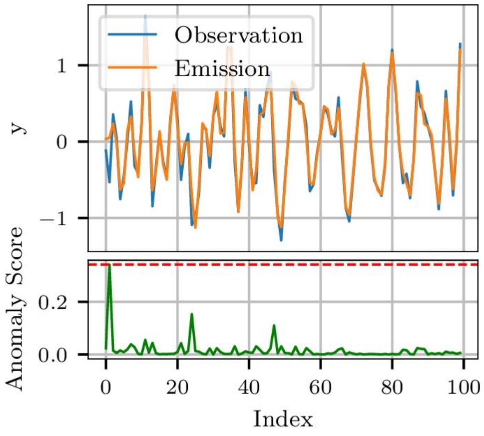
STORN



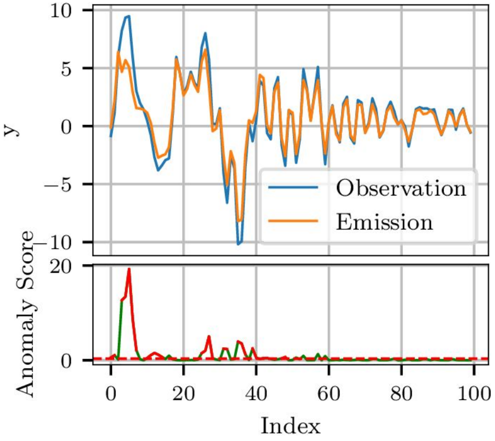
DVBF

Results - Paderborn

Global One-Step Prediction Error Threshold using STORN:

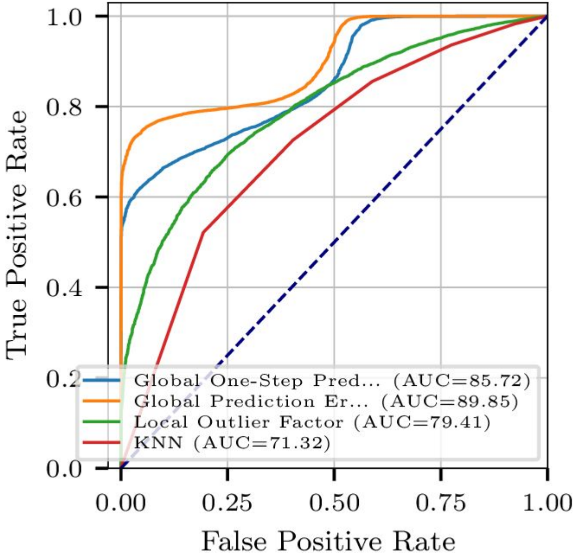


Normal Sample

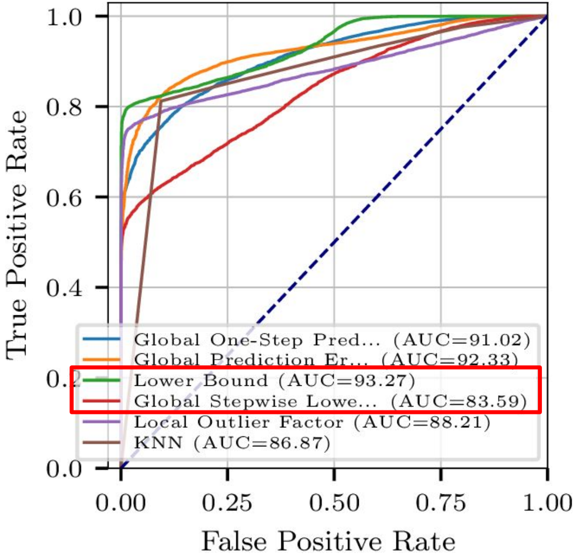


Anomalous Sample

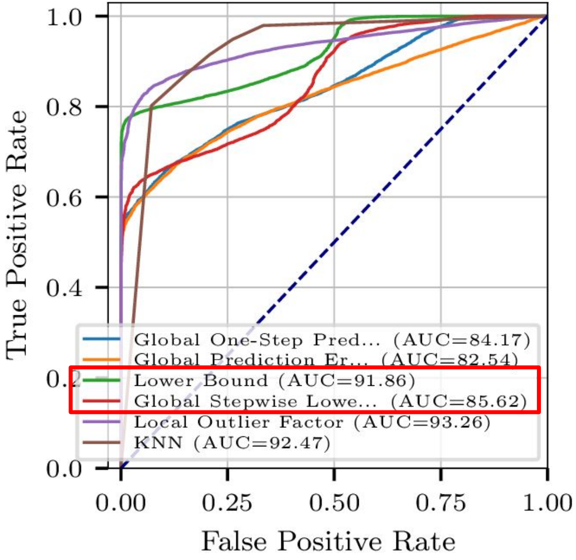
Results - Paderborn



EncDec Model



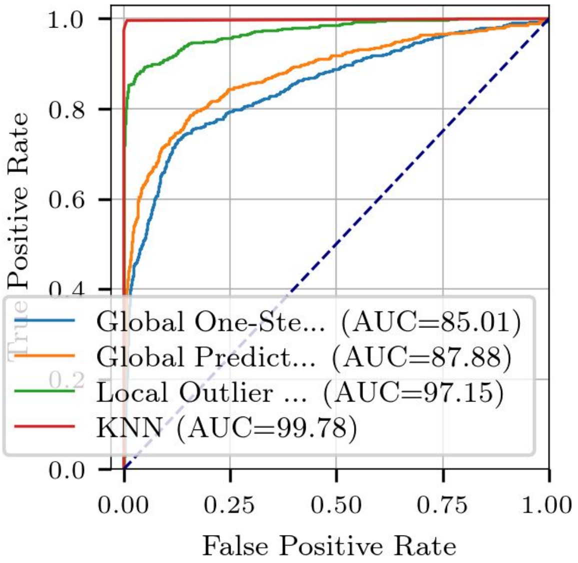
STORN



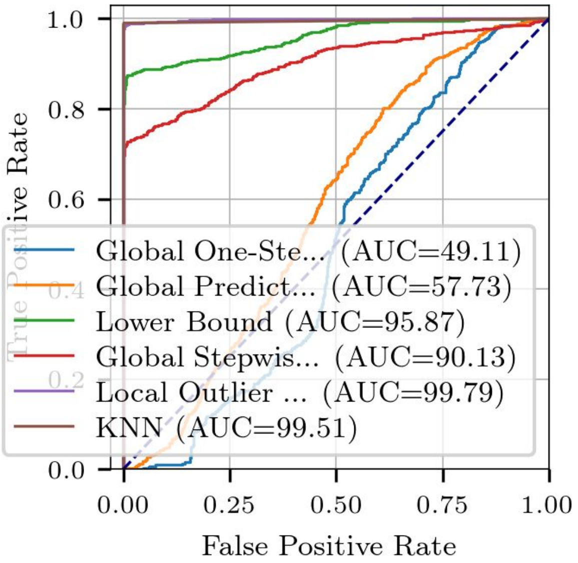
DVBF

Results CMAPSS

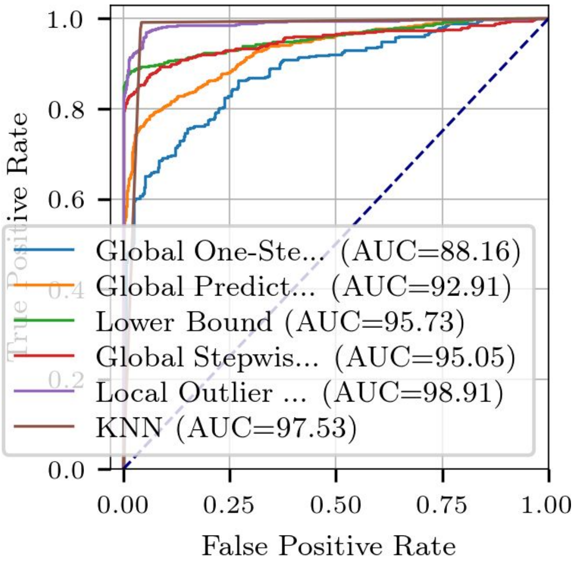
Results - CMAPSS FD001



EncDec Model

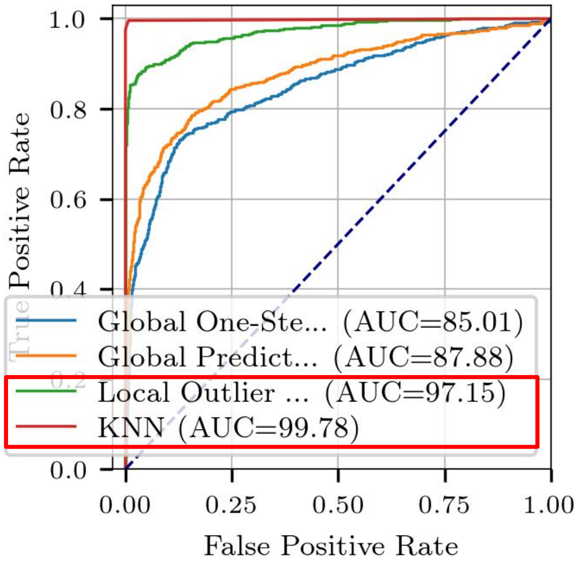


STORN

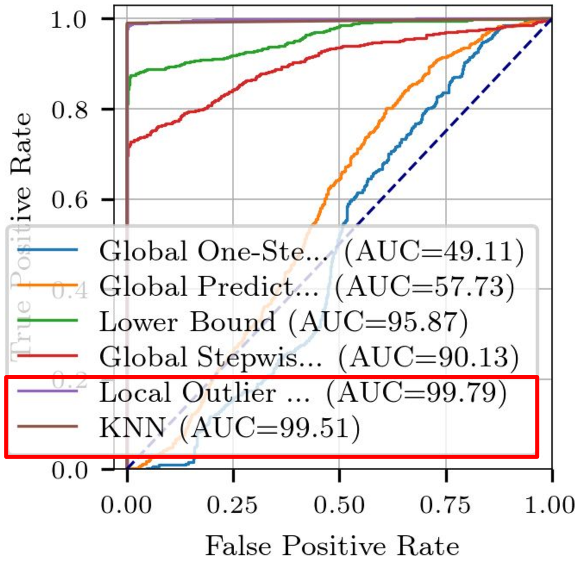


DVBF

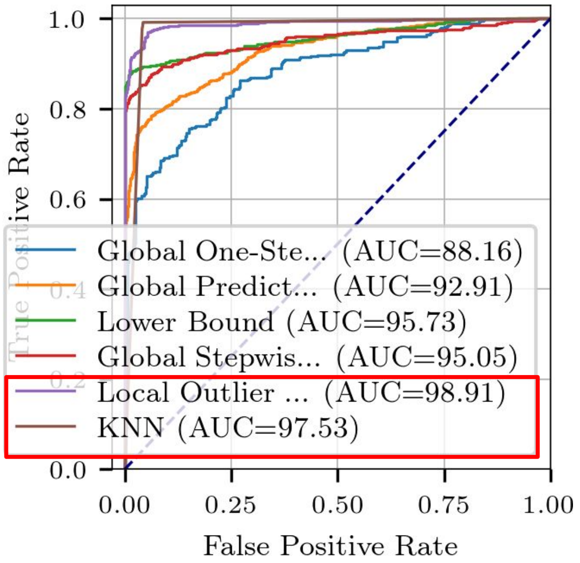
Results - CMAPSS FD001



EncDec Model



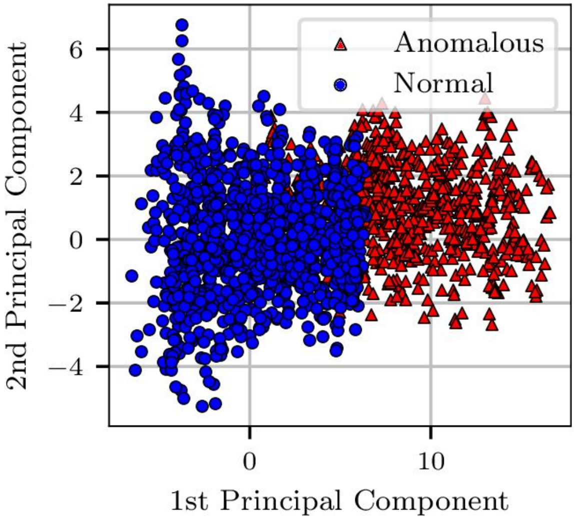
STORN



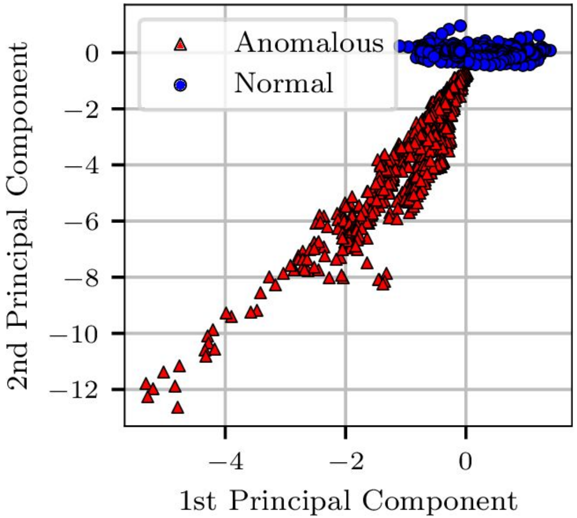
DVBF

Results - CMAPSS FD001

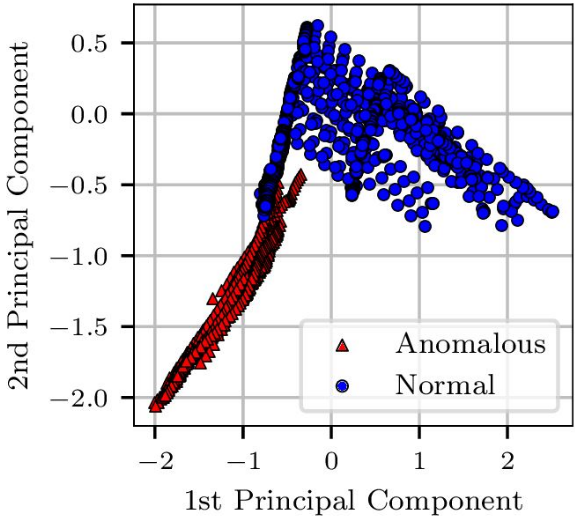
Latent Space of different models:



EncDec Model

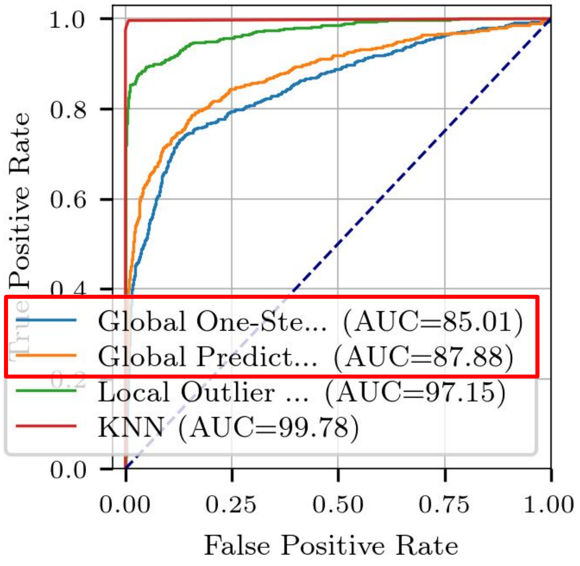


STORN

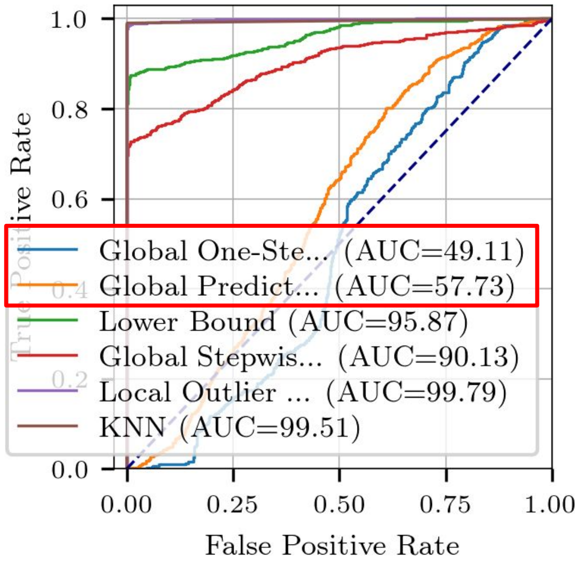


DVBF

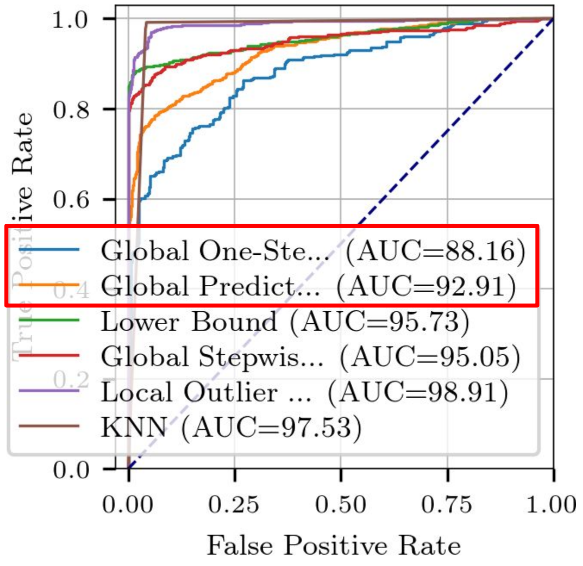
Results - CMAPSS FD001



EncDec Model



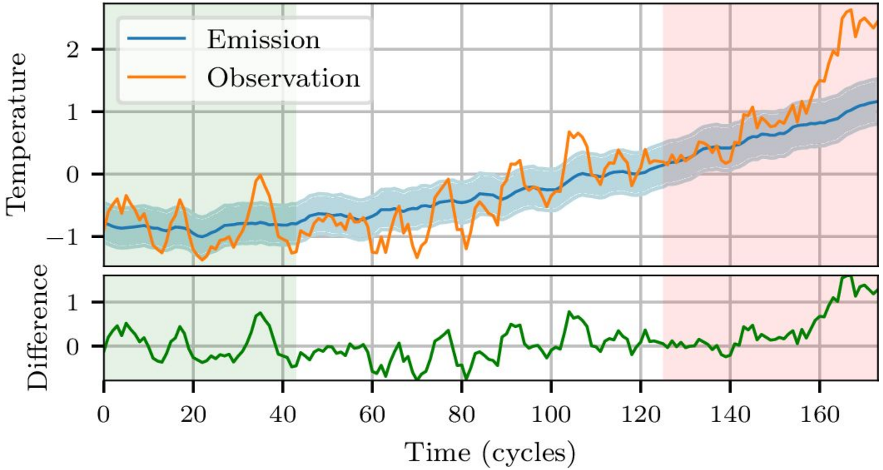
STORN



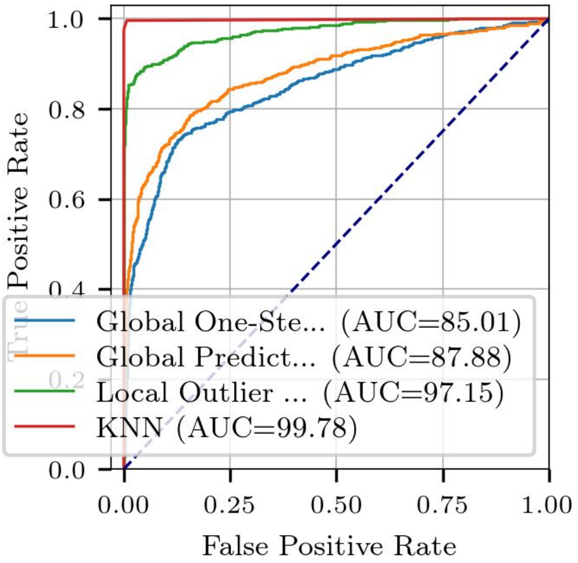
DVBF

Results - CMAPSS FD001

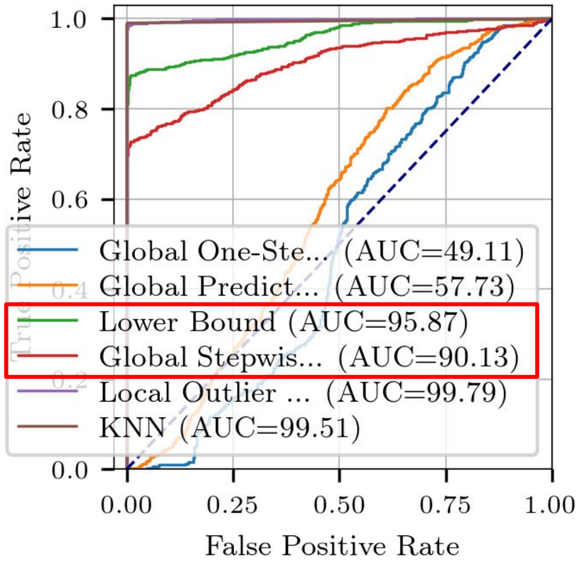
Difference between observation and emission using DVBF:



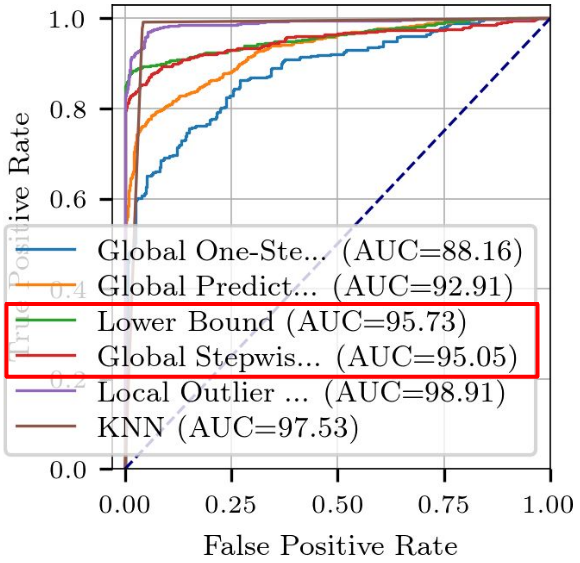
Results - CMAPSS FD001



EncDec Model



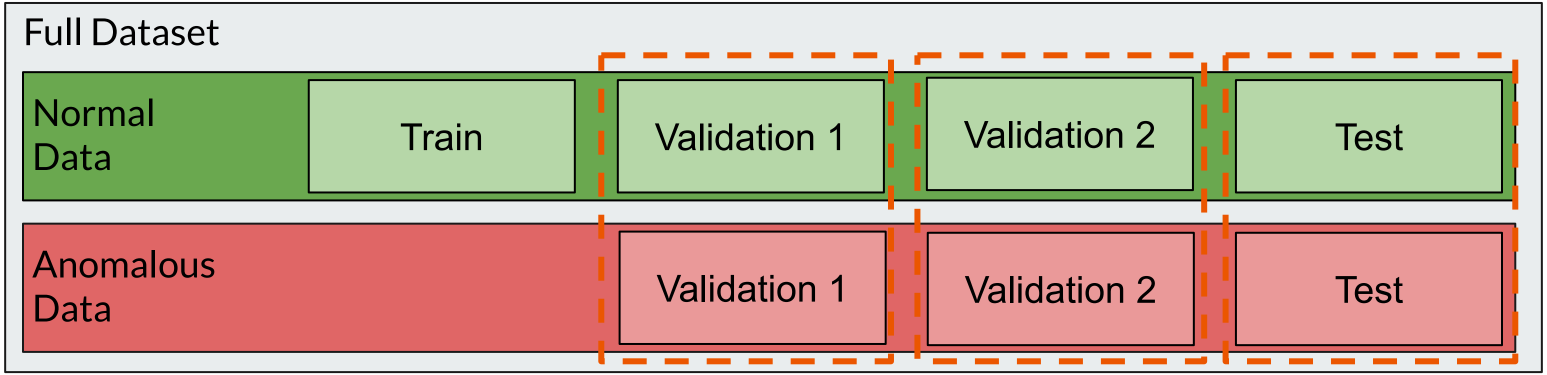
STORN



DVBF

Methods - Model selection

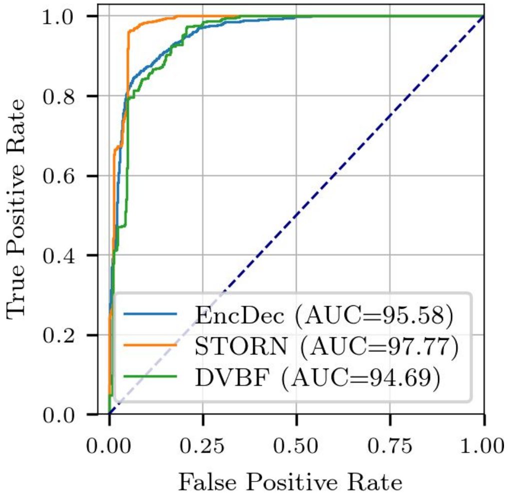
Do model selection directly based on anomaly detection performance:



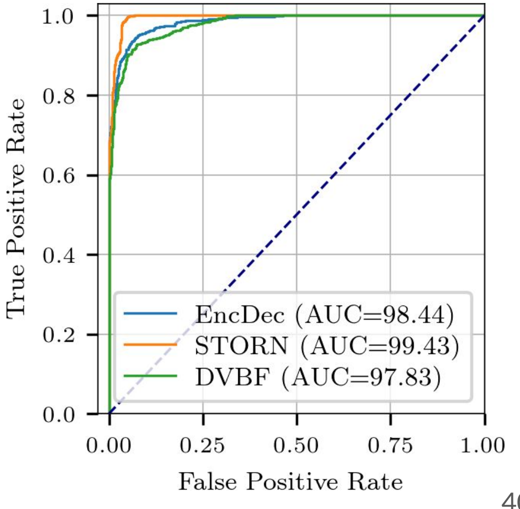
Results - CMAPSS FD001

Anomaly detection performance using Global One-Step Prediction Error Threshold ROC-AUC during model selection:

Global One-Step Prediction Error Threshold:



Global Prediction Error Threshold:



Summary

- Latent space approaches achieved best result on both datasets
- ELBO-based methods consistently outperform reconstruction-based methods
- Global approaches better than stepwise approaches
- Performance of methods varies across different models

Prognostics

Overview

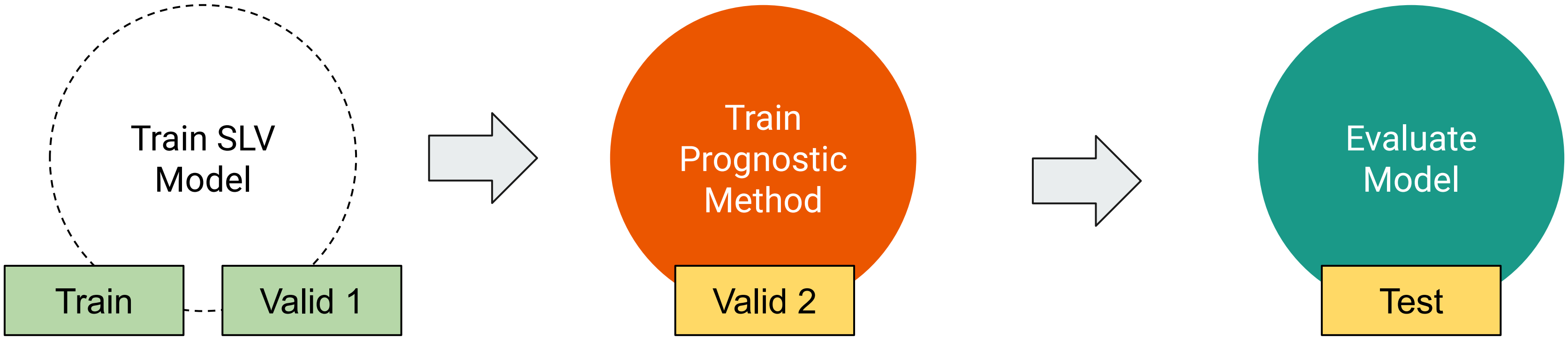
General

- Estimation of remaining useful life (RUL)
- Applicable for example to medical equipment, bearings, engines
- Can prevent total system failures by early detection

Difficulties

- Full run-to-failure time series hard to obtain
- Data often noisy aggravating accurate RUL estimation

Methods



Models

- EncDec Model
- STORN
- DVBF

RUL Estimation

- Latent space methods

Evaluation Metrics

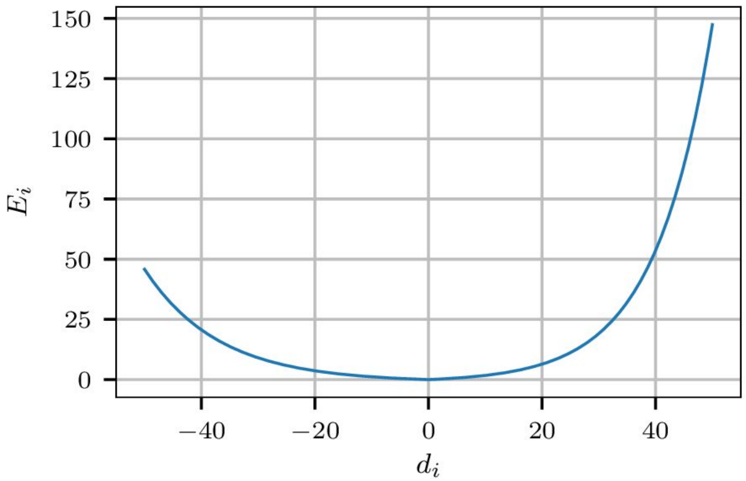
- RMSE
- Timeliness Score

Timeliness Score

- Penalizes late predictions more
- Score grows exponentially with difference

$$E^{(i)} = \begin{cases} e^{-\frac{d^{(i)}}{13}} - 1 & \text{for } d^{(i)} < 0 \\ e^{\frac{d^{(i)}}{10}} - 1 & \text{for } d^{(i)} \geq 0, \end{cases}$$

$$d^{(i)} = \hat{\mathrm{RUL}}^{(i)} - \mathrm{RUL}^{(i)}$$



Methods - Latent space methods

Rely on latent space representation for prognostics

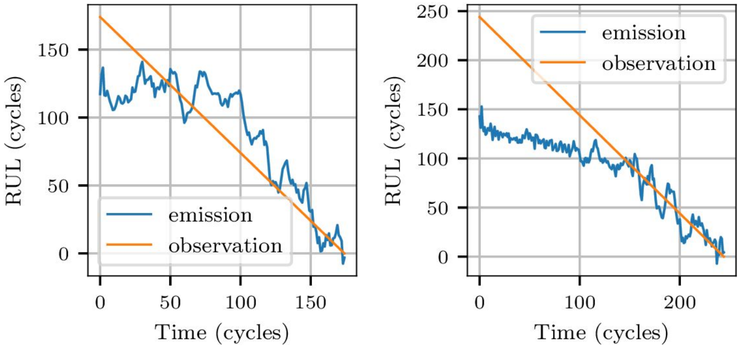
Regression Model

- Trained on latent space of full run-to-failure trajectories
- Outputs RUL estimate for sequence
- Linear Regression, Random Forests

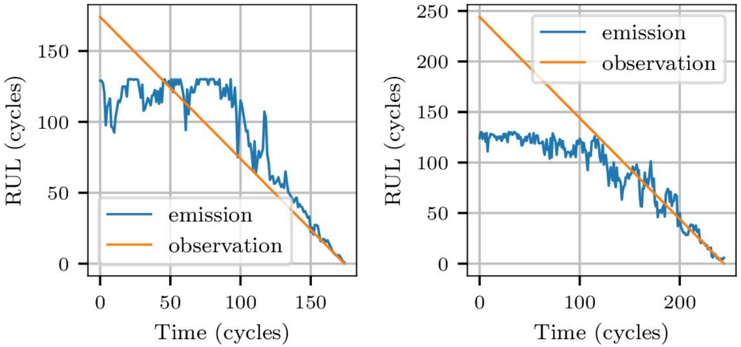
Results CMAPSS

Results - CMAPSS FD001

RUL prediction using DVBF:



Linear Regression



Random Forest

Results - CMAPSS FD001

Results using ELBO for model selection during HPS:

Model	Method	RMSE	Timeliness Score
EncDec	Linear Regression	18.32	1202.13
	Random Forest	20.51	1537.29
STORN	Linear Regression	18.21	997.11
	Random Forest	**18.16**	1252.72
DVBF	Linear Regression	18.51	**858.84**
	Random Forest	20.34	1242.52

Results - CMAPSS FD001

Results using RMSE for Linear Regression for model selection during HPS:

Model	Method	RMSE	Timeliness Score
EncDec	Linear Regression	19.89	1684.91
STORN	Linear Regression	**17.10**	**635.47**
DVBF	Linear Regression	17.77	879.08

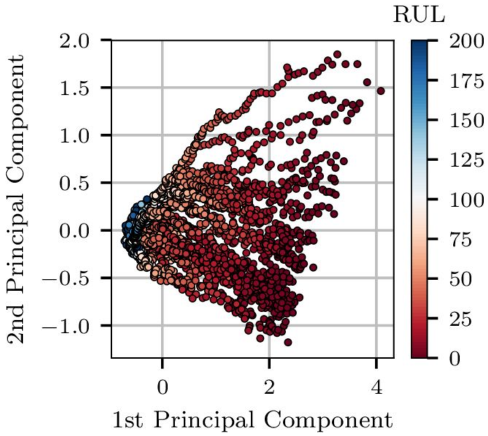
Results - CMAPSS FD001-FD004

RMSE results on all CMAPSS datasets using RMSE for Linear Regression during model selection:

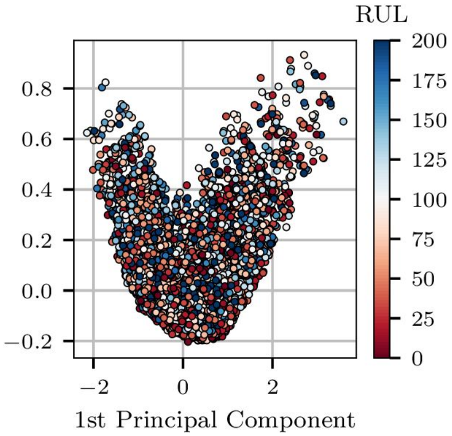
Model	FD001	FD002	FD003	FD004
EncDec + Linear Regression	19.89	**30.05**	20.35	32.60
STORN + Linear Regression	**17.10**	31.06	**17.56**	31.67
DVBF + Linear Regression	17.77	34.44	31.81	**30.54**

Results - CMAPSS FD001-FD004

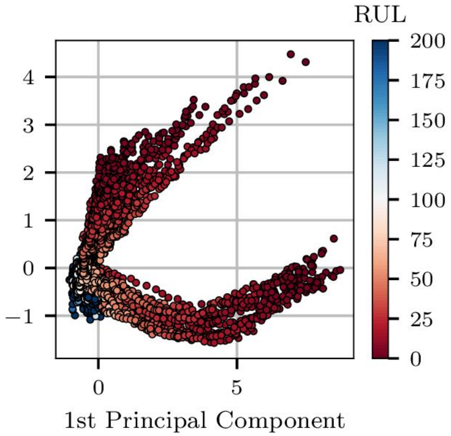
Latent space using STORN:



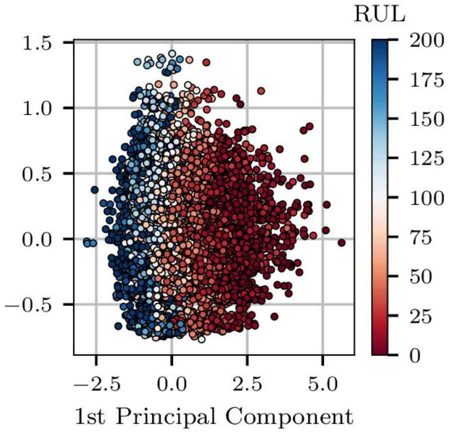
FD001



FD002



FD003



FD004

Results - CMAPSS FD001-FD004

RMSE on all CMAPSS datasets:

Model	FD001	FD002	FD003	FD004
EncDec + Linear Regression	19.89	30.05	20.35	32.60
STORN + Linear Regression	17.10	31.06	17.56	31.67
DVBF + Linear Regression	17.77	34.44	31.81	30.54
CNN [5]	18.45	30.29	19.82	29.16
DLSTM [6]	18.33	-	19.78	-
RBM + LSTM [7]	**12.56**	**22.73**	**12.10**	**22.66**

Summary

- Linear Regression generally outperforms Random Forests
- Performance varies significantly depending on number of operating conditions/faults
- Performance can be improved using RMSE for model selection
- Methods outperformed several supervised CNN/LSTM-based approaches
- There is still a gap between our methods and the state-of-the-art results

Conclusion & Future Work

Conclusion

- Novel method applicable to both prognostics and anomaly detection
- Extended anomaly detection with STORN to DVBF
- STORN and DVBF outperformed the EncDec model
- Introduced latent space anomaly detection which achieved best results on Paderborn and CMAPSS FD001 dataset
- Introduced Global Prediction Error Threshold which consistently outperforms the Global One-Step Prediction Error Threshold

Future Work

- Use other sequential latent variable models (SRNN, VRNN, DKF)
- Apply methods to fault diagnostics (also part of PHM framework)
- Novel prognostics methods using reconstruction-based and ELBO-based approaches
- Instead of direct mapping to RUL, use health index and similarity matching

Questions

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