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Deep Autoencoders for Anomaly Detection in Electricity Consumption of Buildings

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The problem of energy wastes in buildings

- Topics of environmental pollution and energy saving are among the most discussed in the recent years

- According to the United Nations Environment Programme, buildings are responsible for 38% of the global energy use [1]

- This, combined with the rising costs of energy, provides us a good reason to devise effective new ways to **prevent energy wastes in buildings**

[1] United Nations Environmental Programme (UNEP). 2021 Global Status Report for Buildings and Construction: Towards a Zero-emission, Efficient and Resilient Buildings and Construction Sector, 2021.

The problem of energy wastes in buildings

- One of the possible ways to reduce energy wastes in buildings is to detect faults and abnormal patterns in the electricity consumption
- To detect faults and abnormal patterns in the electricity consumption of buildings, **anomaly detection algorithms** can be used

The problem of energy wastes in buildings

- This thesis focuses on data-driven approaches
- In particular, it focuses on **autoencoders**, semi-supervised deep learning neural networks that provide state-of-the-art detection performance
- The state-of-the-art for anomaly detection in the electricity consumption of buildings is *variational autoencoder with variational self-attention mechanism* [1]

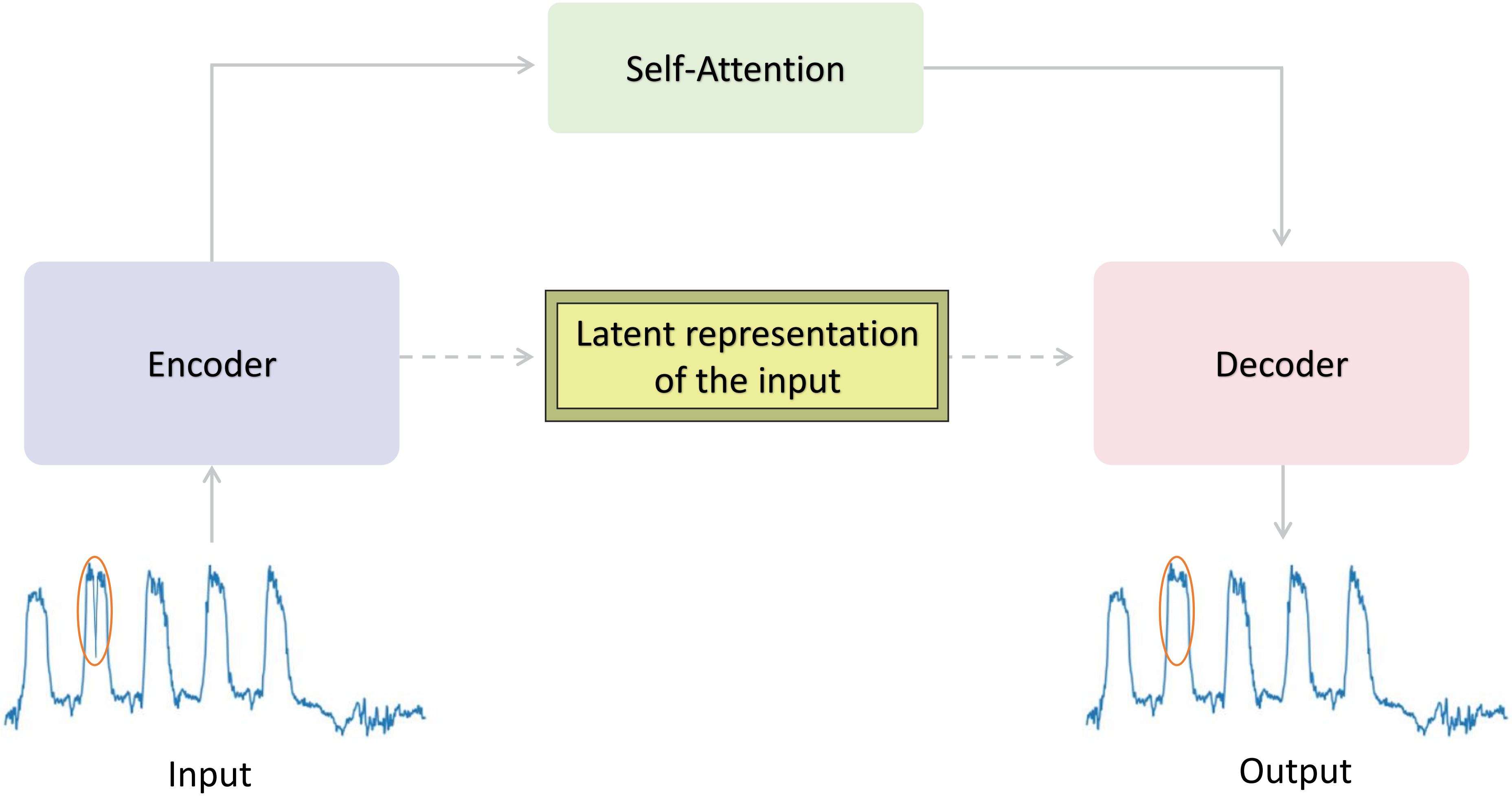
[1] Joao Pereira and Margarida Silveira. Unsupervised anomaly detection in energy time series data using variational recurrent autoencoders with attention. In Proc. ICMLA, pages 1275–1282, 2018.

Goal of the thesis

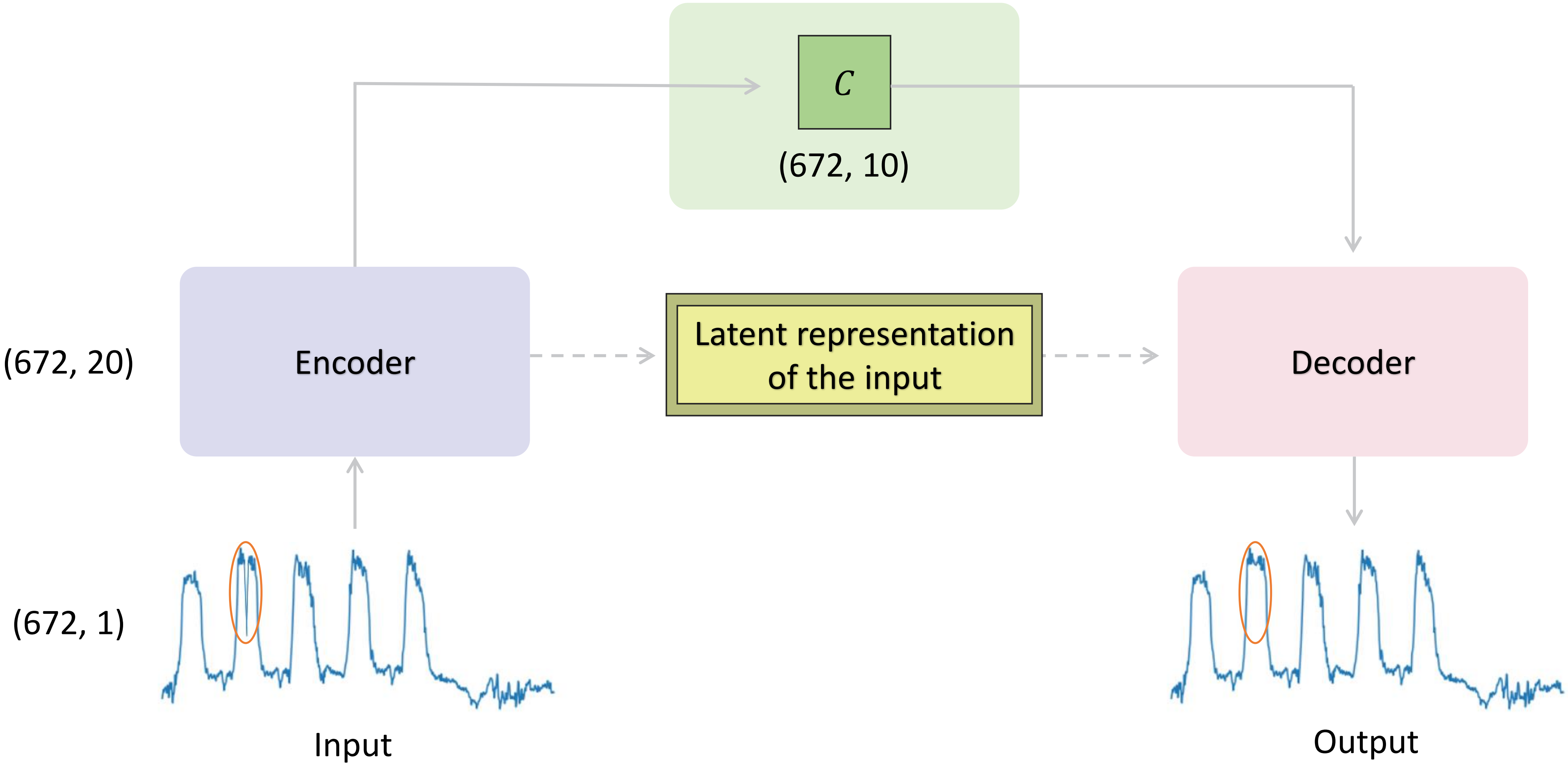
The goals of this thesis are:

- to present an **innovative autoencoder** for anomaly detection in electricity consumption of buildings that outperforms the state-of-the-art
- to present an **extensive experimental comparison** of 8 autoencoders on 2 datasets

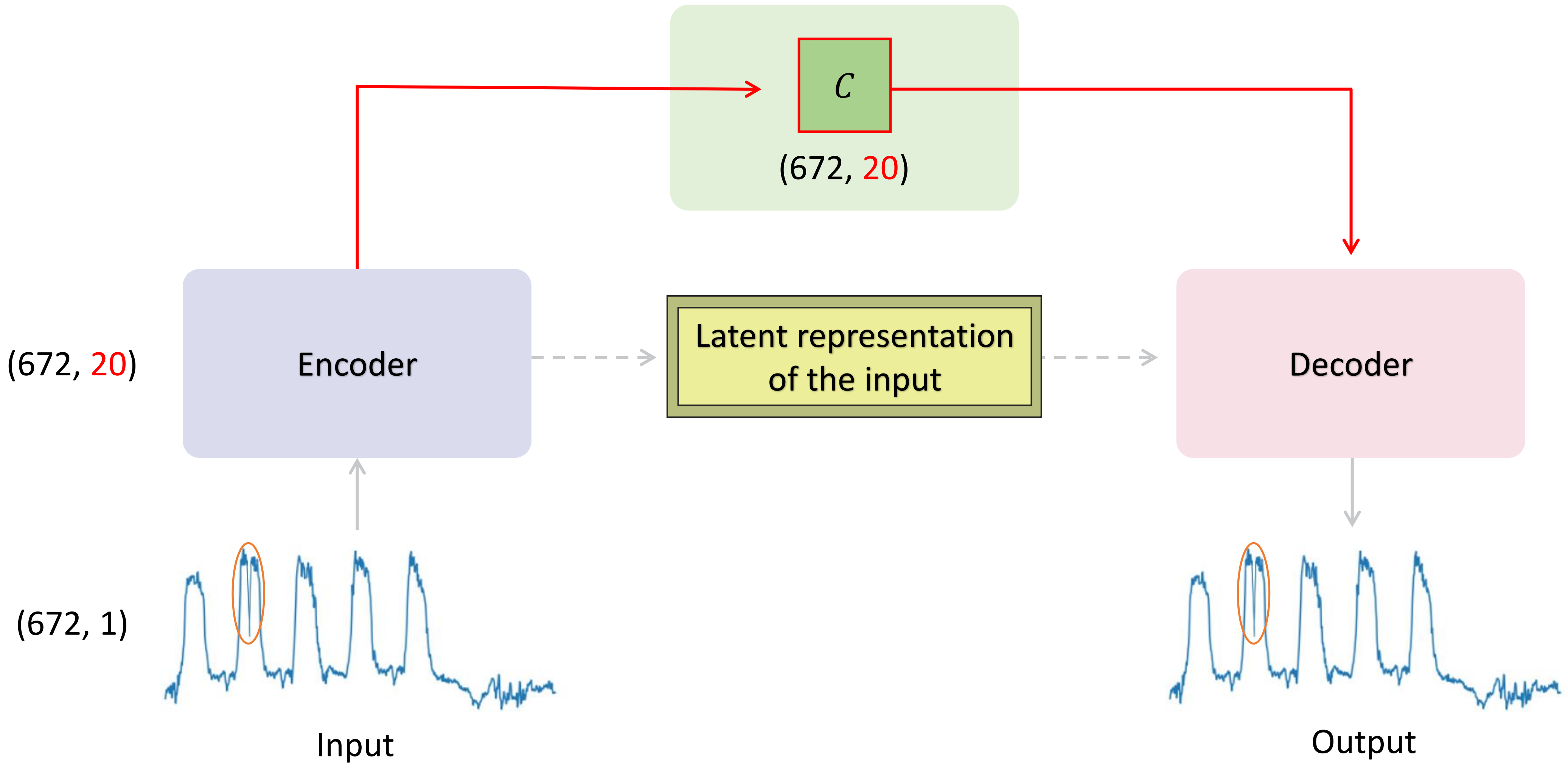
Variational Autoencoders with Self-Attention Mechanism



Standard Self-Attention Mechanism

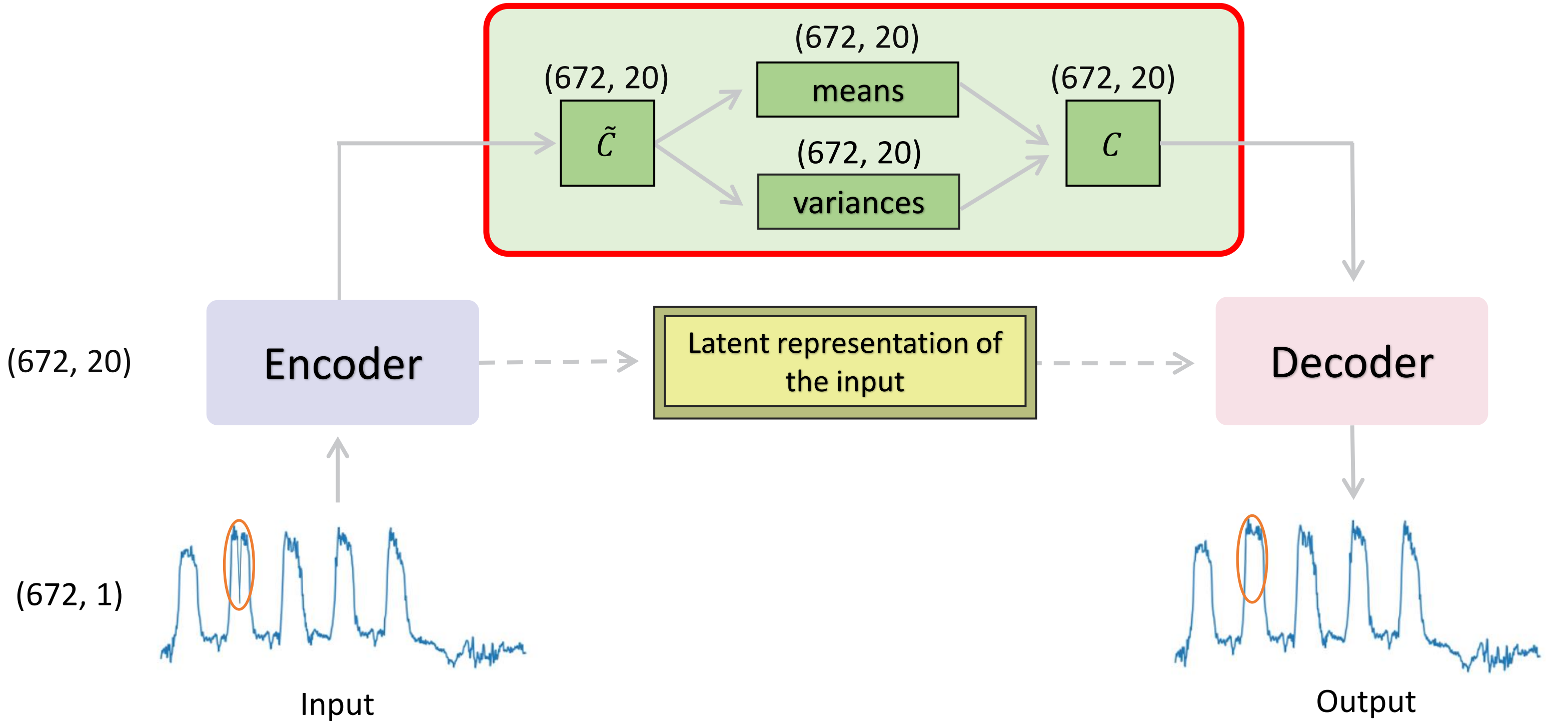


Standard Self-Attention Mechanism



Variational Self-Attention Mechanism

Context vectors C are modelled as **random** variables sampled from a Gaussian Distribution [1]

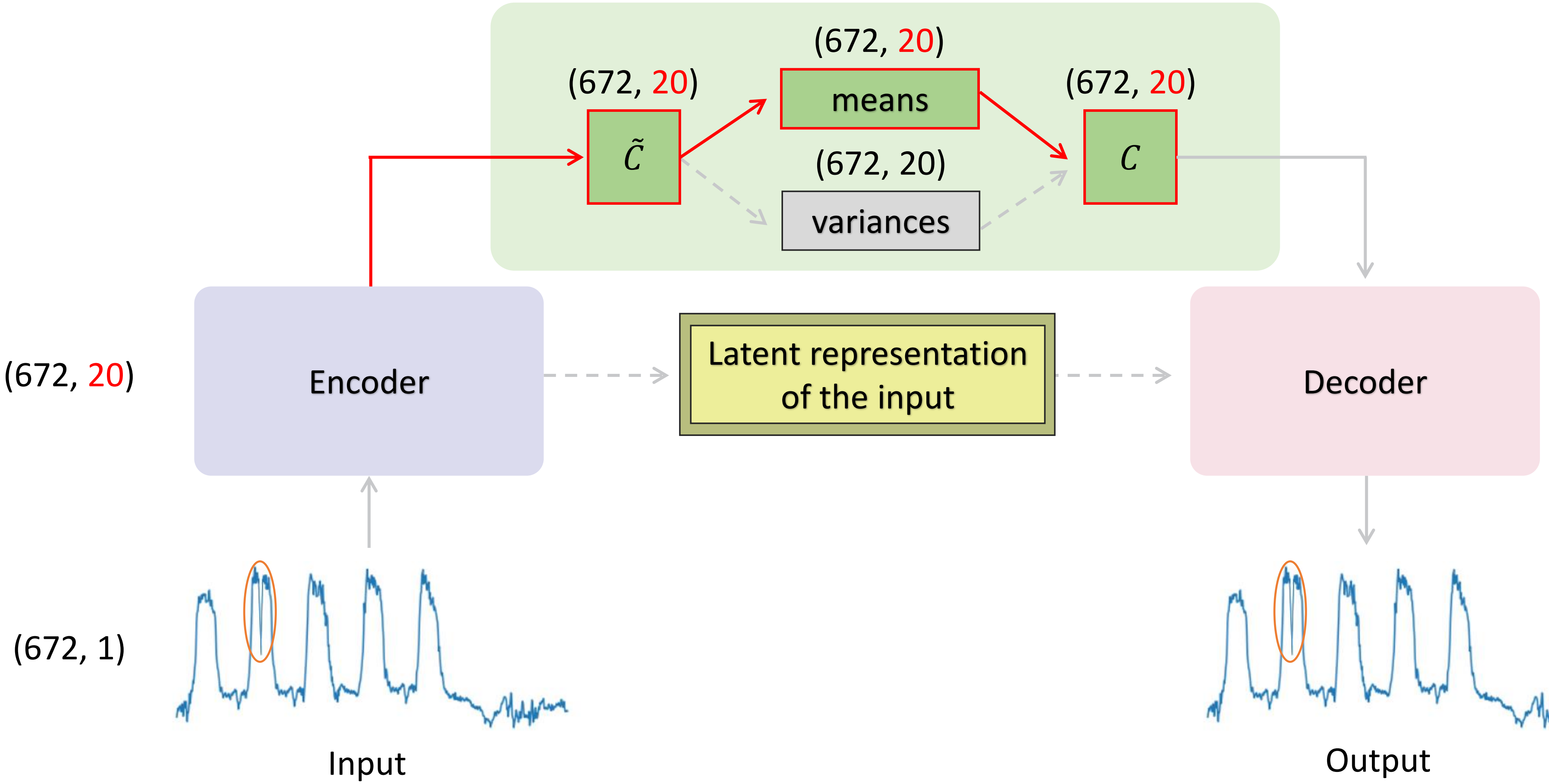


[1] Joao Pereira and Margarida Silveira. Unsupervised anomaly detection in energy time series data using variational recurrent autoencoders with attention. In Proc. ICMLA, pages 1275–1282, 2018.

Variational Self-Attention Mechanism

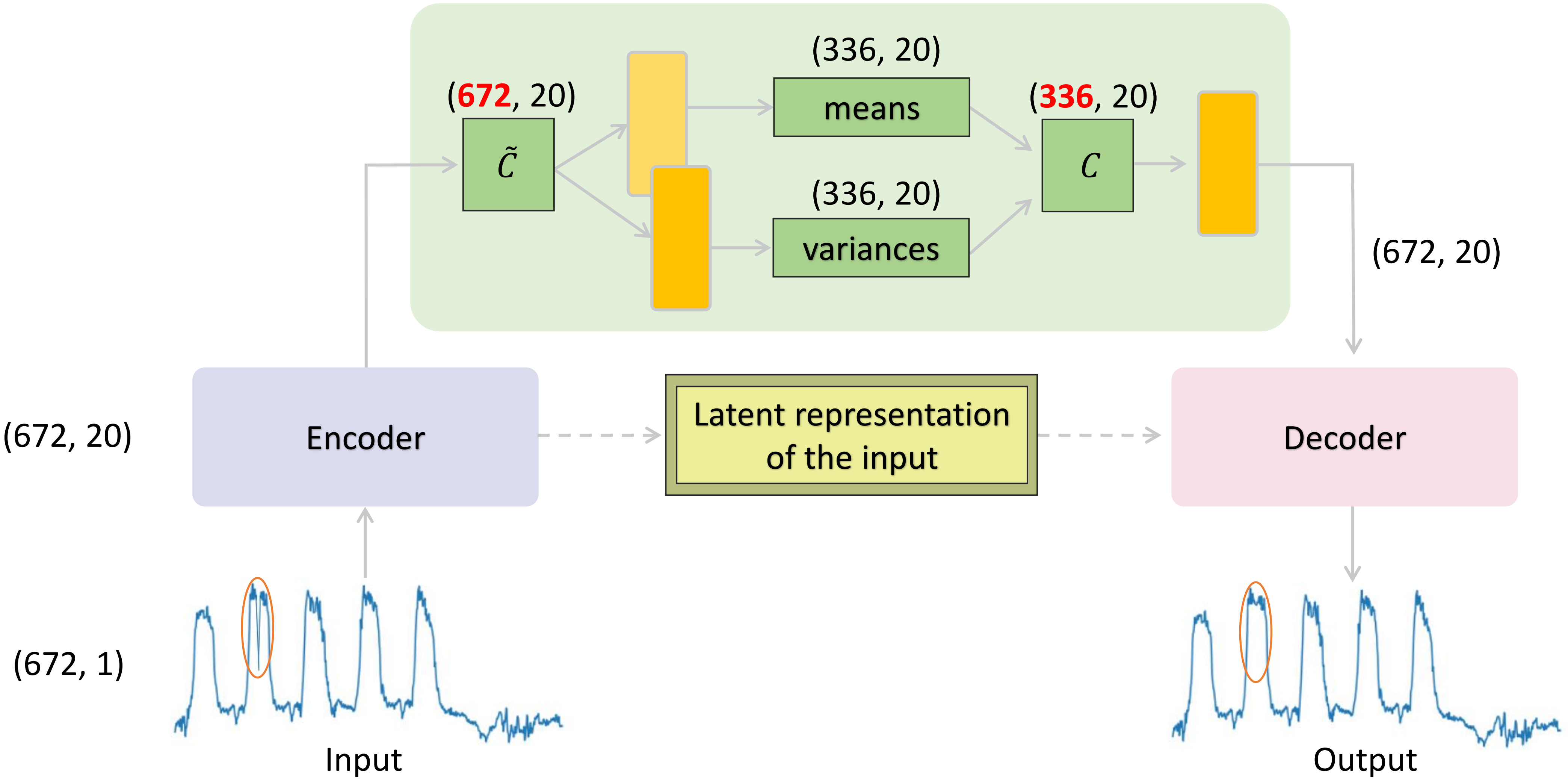
- A **dedicated term** is added to the loss function used to train the model
- If the loss function contains many terms, not all of them are properly minimized during the training
- If the dedicated term is not properly minimized, the bypassing phenomenon is not properly solved and there is a deterioration in performance

Variational Self-Attention Mechanism



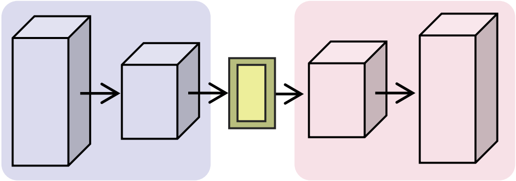
- The bypassing phenomenon is avoided by modifying the autoencoder architecture
- $\boldsymbol{C}$ **and** $\widetilde{\boldsymbol{C}}$ **have different shapes**, so the bypassing phenomenon cannot occur
- Performance does not deteriorate when the loss function consists of many terms

Convolutional Variational Self-Attention Mechanism

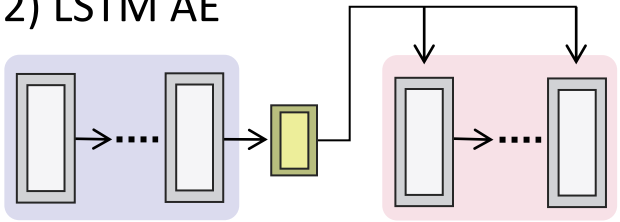


Experimental setting

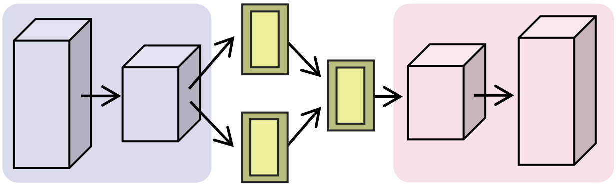
1) CNN AE



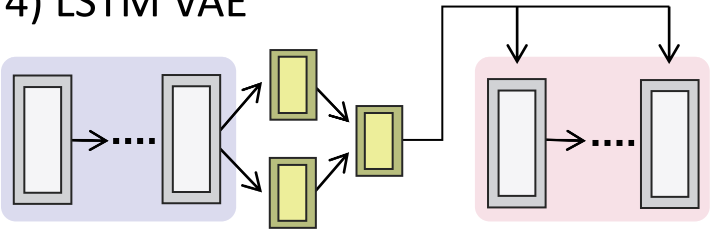
2) LSTM AE



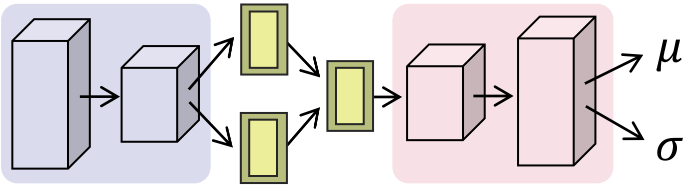
3) CNN VAE



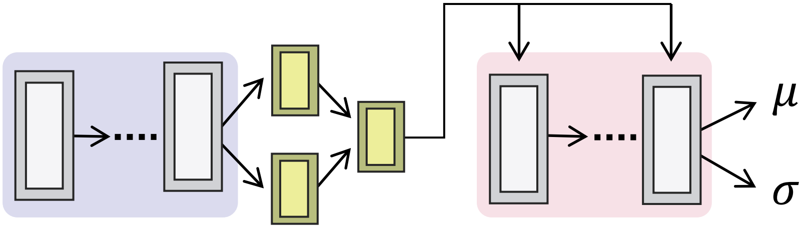
4) LSTM VAE



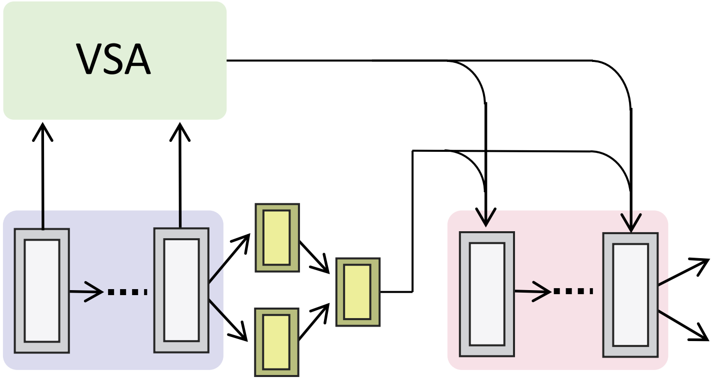
5) CNN VAE + Rec.Prob. [1]



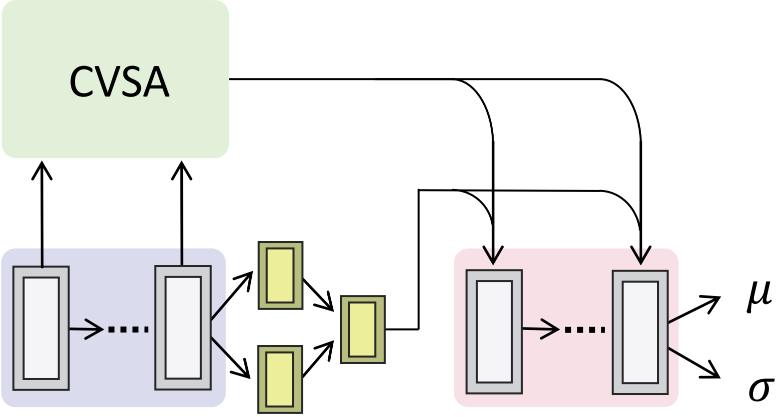
6) LSTM VAE + Rec.Prob. [1]



7) LSTM VAE + Var.Self.Att. + Rec.Prob. [2]



8) LSTM VAE + Conv.Var.Self.Att. + Rec.Prob.

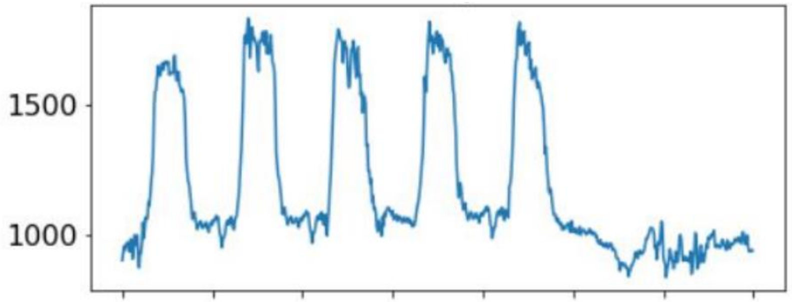


[1] Jinwon An. Variational autoencoder based anomaly detection using reconstruction probability. Special Lecture on IE, 2(1):1–18, 2015.

[2] Joao Pereira. Unsupervised anomaly detection in energy time series data using variational recurrent autoencoders with attention. In Proc. ICMLA, pages 1275–1282, 2018.

Experimental results – Univariate dataset

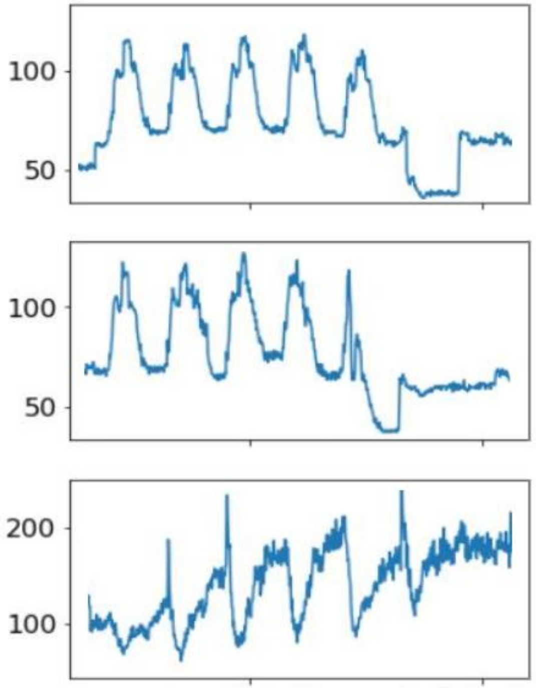
- Univariate dataset containing data on the electricity consumption of a research facility in the Netherlands
- Low-noise dataset



	F1 score
CNN **AE**	82.32
LSTM **AE**	87.73
CNN **VAE**	85.44
LSTM **VAE**	88.21
CNN VAE + **Rec.Prob.**	86.78
LSTM VAE + **Rec.Prob.**	90.13
LSTM VAE + **Var.Self.Att.** + Rec.Prob.	89.55
LSTM VAE + **Conv.Var.Self.Att.** + Rec.Prob.	91.48

Experimental results – Multivariate dataset

- Multivariate dataset containing data on the electricity consumption of a office building in the North of Italy
- High-noise dataset



	F1 score
CNN **AE**	39.76
LSTM **AE**	65.31
CNN **VAE**	48.93
LSTM **VAE**	61.15
CNN VAE + **Rec.Prob.**	47.99
LSTM VAE + **Rec.Prob.**	57.97
LSTM VAE + **Var.Self.Att.** + Rec.Prob.	40.13
LSTM VAE + **Conv.Var.Self.Att.** + Rec.Prob.	44.79

Conclusion

- An innovative autoencoder for anomaly detection in electricity consumption of buildings has been presented

- The proposed autoencoder outperforms the state-of-the-art by solving the bypassing phenomenon caused by the variational self-attention mechanism

- The bypassing phenomenon has been solved introducing the **convolutional variational self-attention mechanism**

Future work

- To test the proposed autoencoder on data streams instead of a static dataset to simulate sensors readings using Apache Kafka and Apache Spark

- Some parts of this thesis are included in an article titled "Empirical Evaluation of Deep Autoencoders for Anomaly Detection in Electricity Consumption of Buildings", currently under major revision for IEEE Intelligent Systems

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Thank you for your attention

Loss function

$$\boldsymbol{Loss\ function} = \boldsymbol{\alpha} * \boldsymbol{likelihood} + \boldsymbol{\beta} * \boldsymbol{reconstruction\ loss} + \boldsymbol{\delta} * (\boldsymbol{KL\ Loss\ Z} + \boldsymbol{\gamma} * \boldsymbol{KL\ Loss\ C})$$

- **Likelihood**: probability that the input could be sampled from a Laplace distribution characterized by the means and the scales that the model return as output
- **Reconstruction loss**: computed considering the input and a reconstruction of it obtained by sampling from a Laplace distribution characterized by the means and the variances that the models returns as outputs
- **KL Loss Z**: KL divergence computed considering the latent space associated to the latent representation of the input
- **KL Loss C**: KL divergence computed considering the latent space associated to the Self-Attention

Reconstruction probability

$$Rec.Prob. = \ p_{\theta}(\mathrm{x(i)} \mid \mu_{x(i)}\ ,\ \sigma_{x(i)})$$

- For each input data point $x(i)$, p_{θ} is the probability for $x(i)$ to be sampled from a distribution having parameters $\mu_{x(i)}$ and $\sigma_{x(i)}$
- $\mu_{x(i)}$ and $\sigma_{x(i)}$ are the parameters that the autoencoder returns as output when $x(i)$ is provided as input

Noisy datasets, high variances and deterioration in performances

Having higher variances entail that:

- **The value of the reconstruction probability associated to anomalous data points is higher than it should** (as the probability of having sampled that anomalous data point from a distribution having a certain mean and an higher variance is higher)
- **The value of the reconstruction probability associated to nominal data points is lower than it should** (as the probability of having sampled that nominal data point from a distribution having a certain mean and a higher variance is lower)

F1 score

$$F1\ score = \frac{2\ *Recall\ *Precision}{Recall + Precision}$$

- **Precision** is given by the number of real anomalies correctly identified divided by the number of data points classified as anomalous
- **Recall** is given by the number of real anomalies correctly identified divided by the total number of anomalous data points