Unsupervised Anomaly Detection for Intricate KPIs via Adversarial Training of VAE

第一个窗口

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Background

Challenges

Ideas

Experiments

Background

Challenges

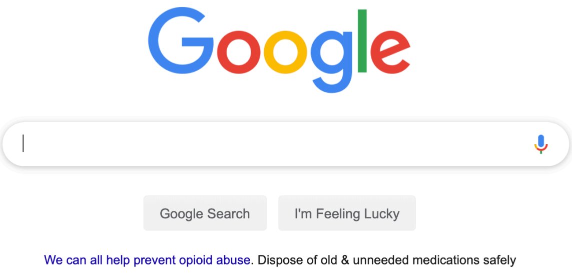
Ideas

Experiments

Key Performance Indicators

Fig1: Web Applications

Key Performance Indicators



Request

Fig2: From user to server

Monitor

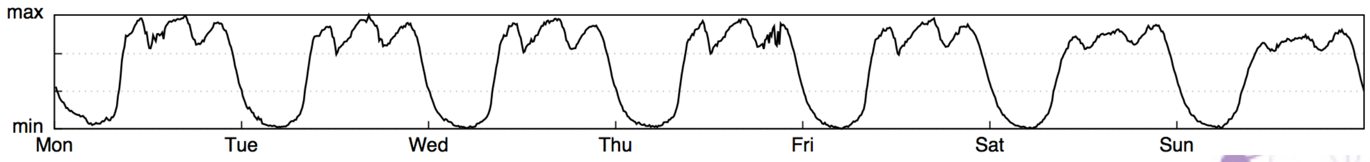


Fig3: Page view

It is stable?

Key Performance Indicators

Smooth KPIs: e.g, The respond time of server, and page view

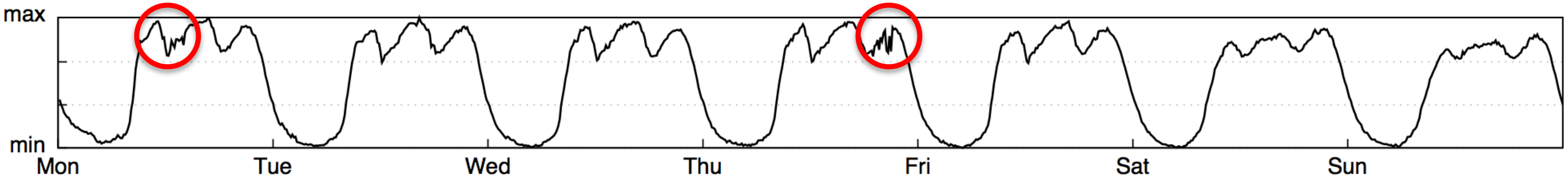


Fig4: An example of Anomalies in page view

Intricate KPIs: e.g, The query per second and transaction per second

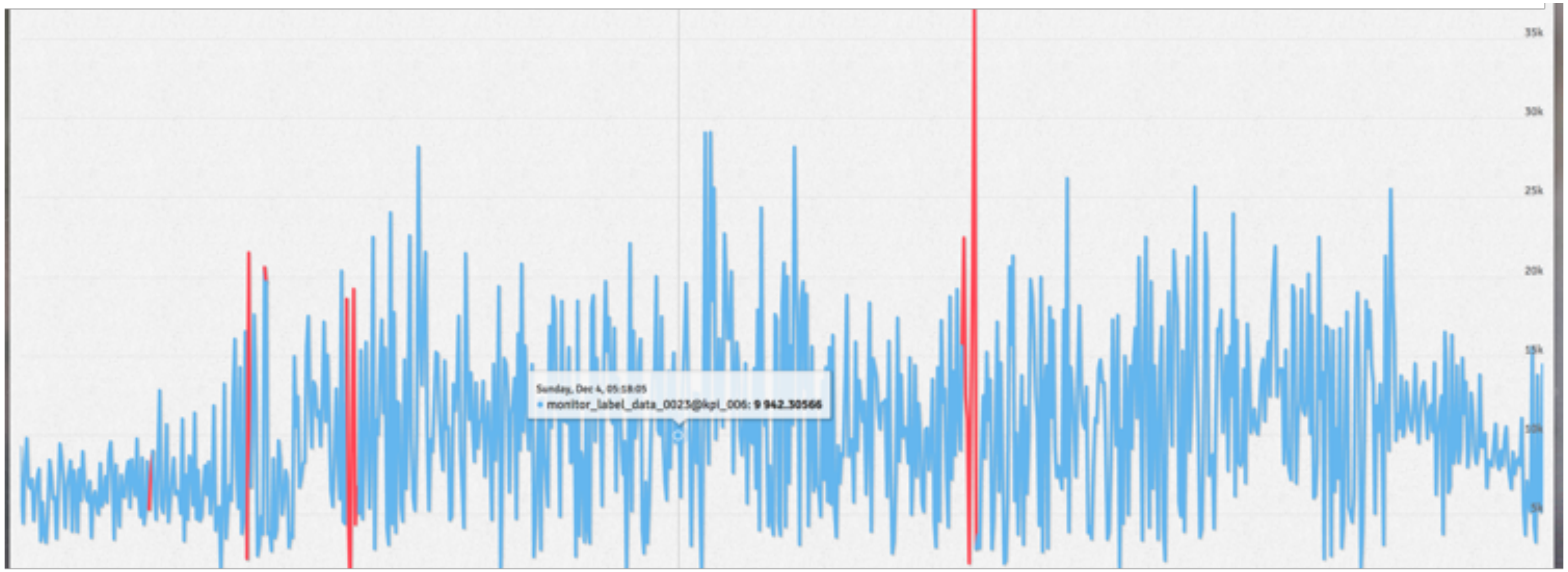


Fig5: An example of Anomalies in database

Existing Method

- Statistical
  - Anomaly detectors based on traditional statistical models [INFOCOM2012]
- Supervised
  - Supervised ensemble learning with above detectors – Opprentice[IMC2015]
- Unsupervised
  - Unsupervised anomaly detection based on VAE – Donut [WWW2018]

They can only work on smooth KPIs.

Smooth KPIs

Original data

Smooth Curve

Gaussian Noise

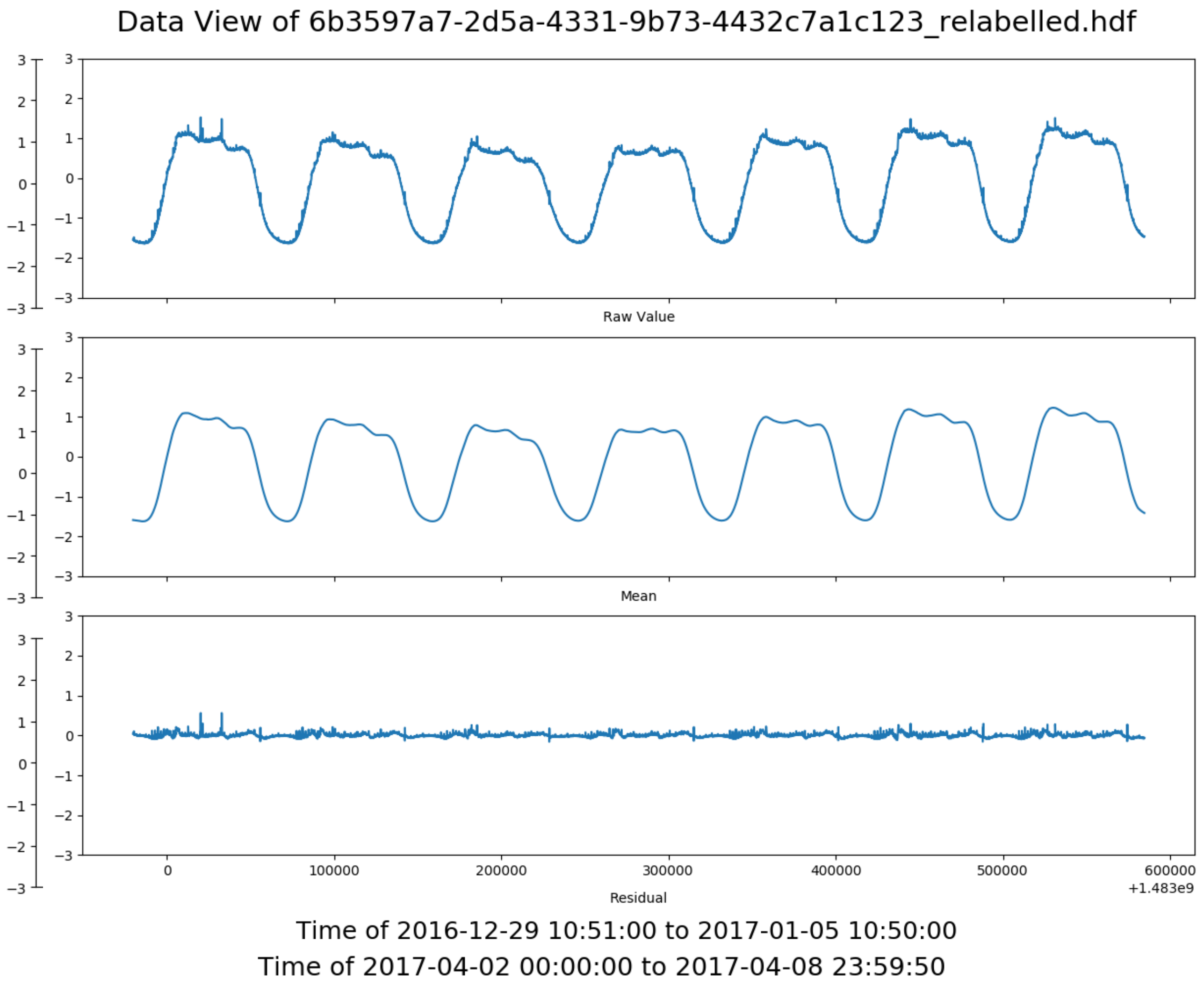
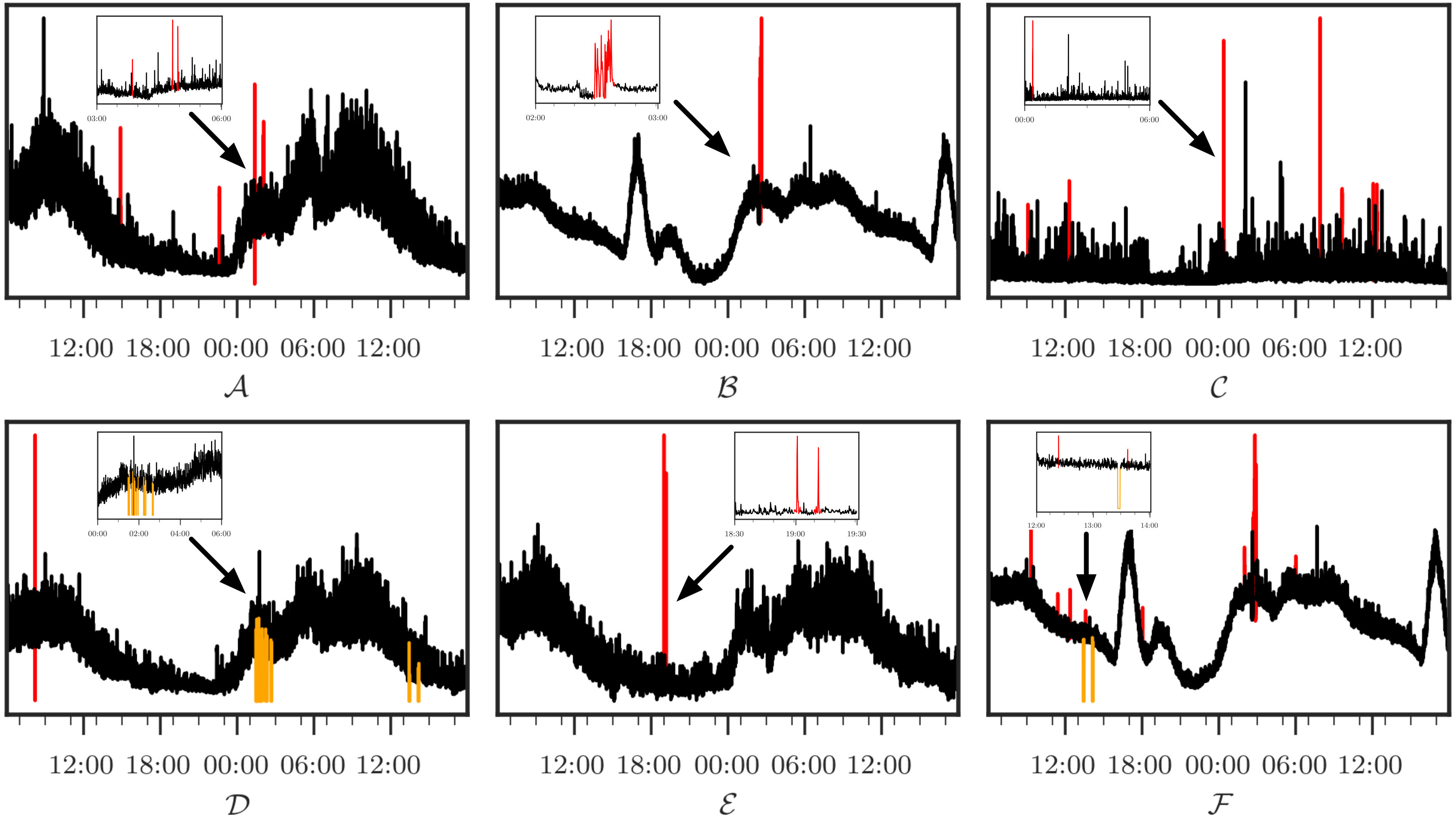


Fig6: Smooth KPI

Intricate KPIs



- micro-congestion
- fine granularity
- prevalent and important (e.g, database, server)
- little studied

Fig7: Intricate KPIs

Intricate KPIs

Original data

Smooth Curve

Noise

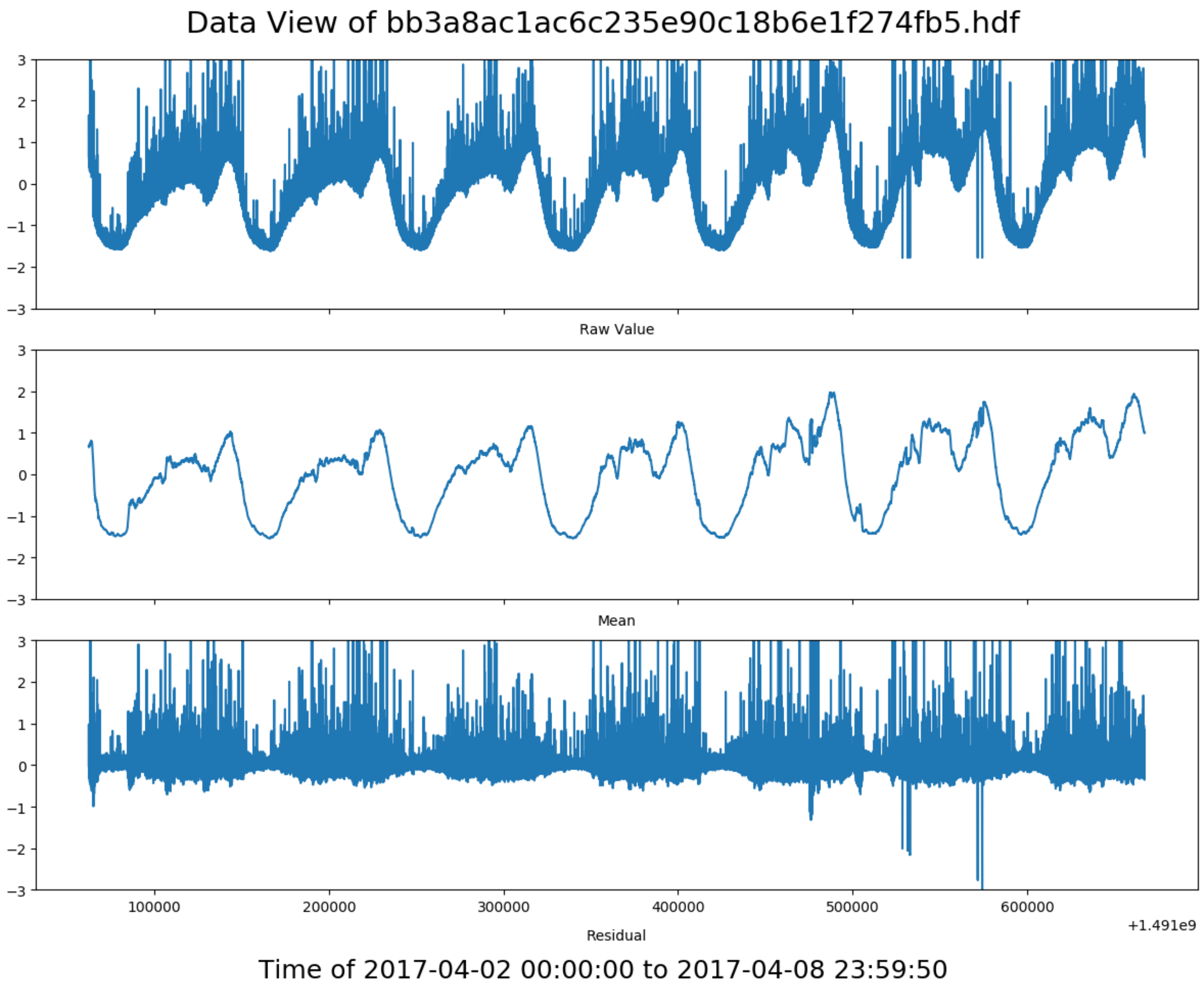


Fig8: KPI A

- non-Gaussian noises
- hard to model

Intricate KPIs

Original data

Smooth Curve

Noise

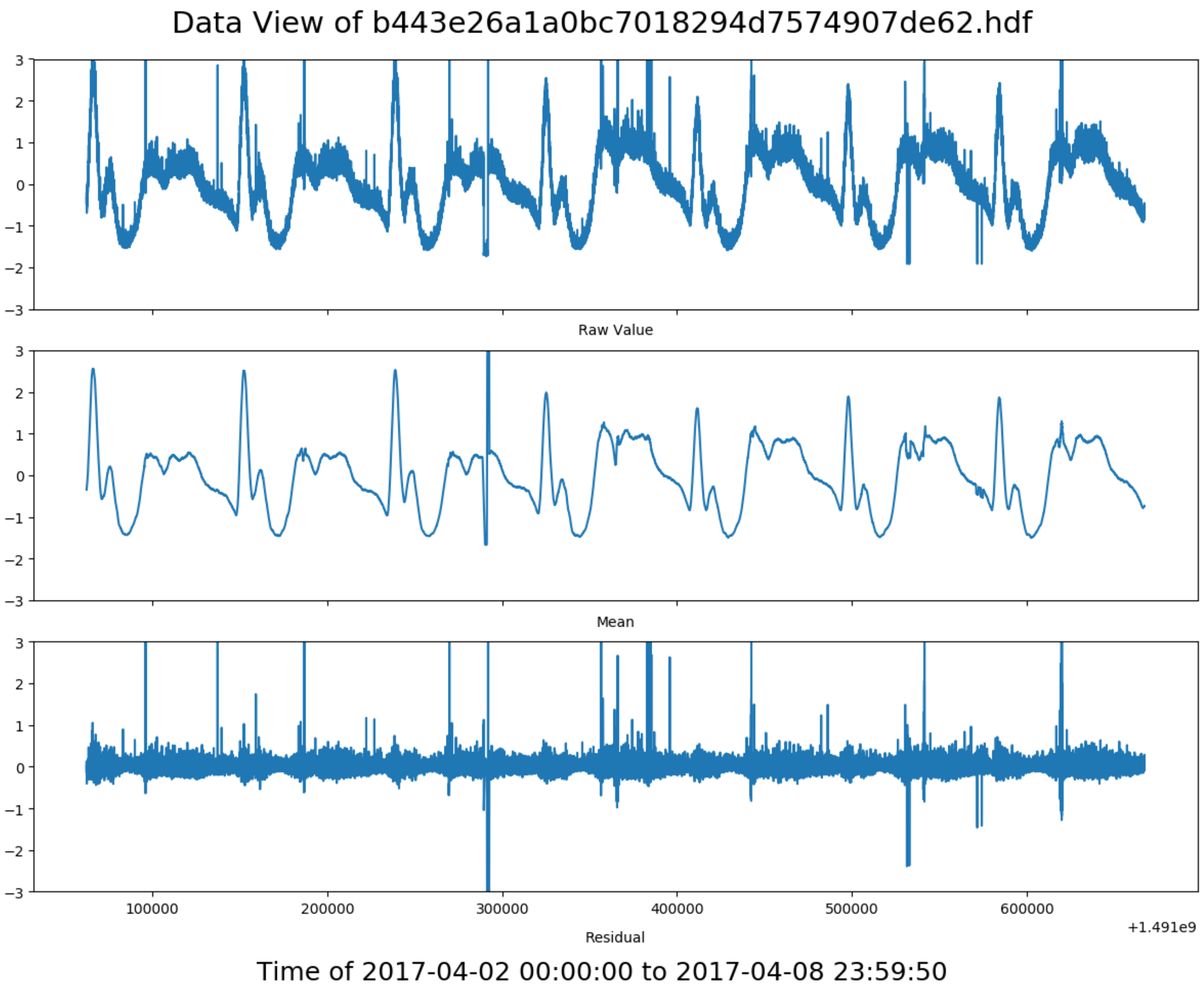


Fig9: KPI B

- non-Gaussian noises
- hard to model

Intricate KPIs

Original data

Smooth Curve

Noise

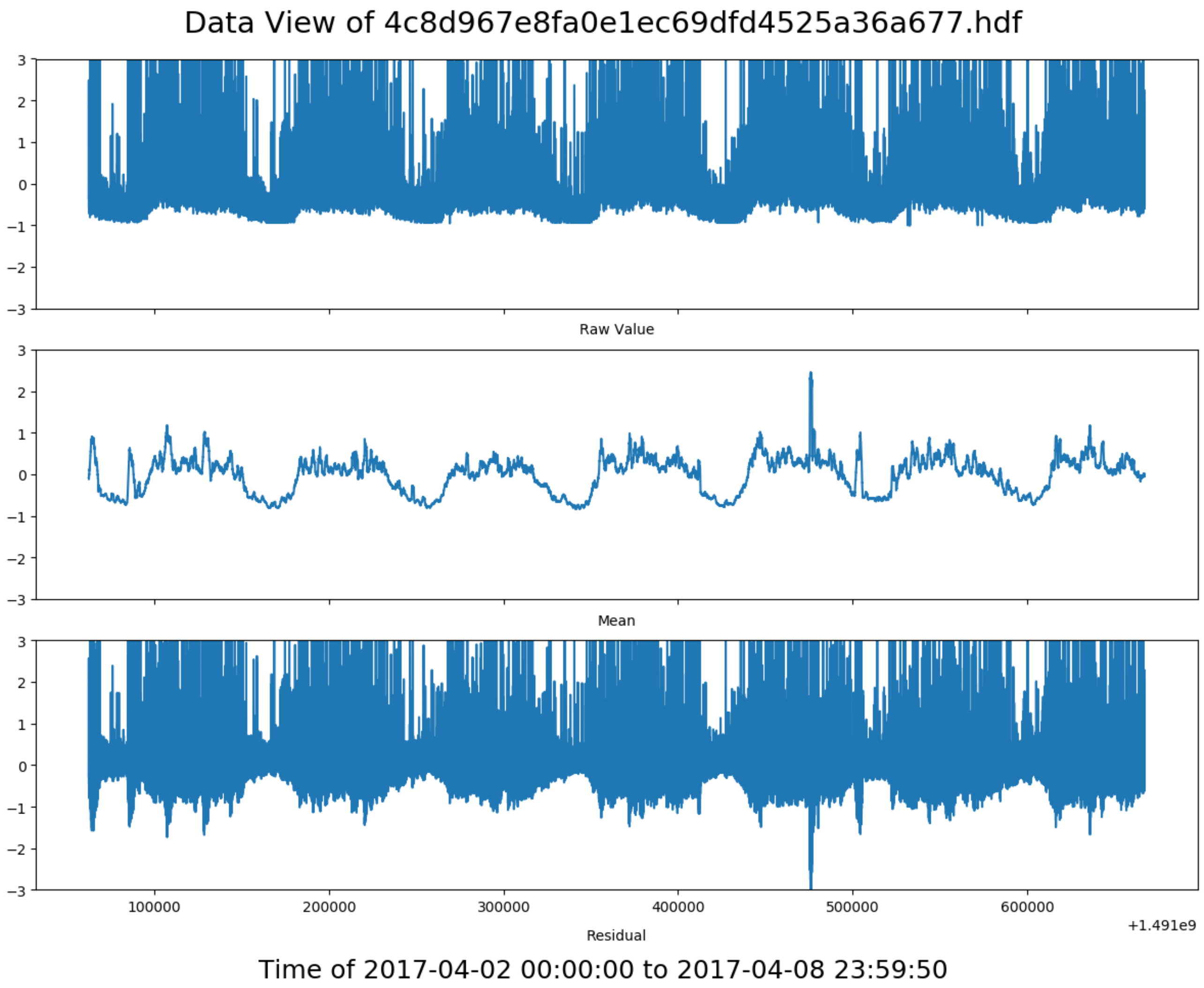


Fig10: KPI C

- non-Gaussian noises
- hard to model

Donut

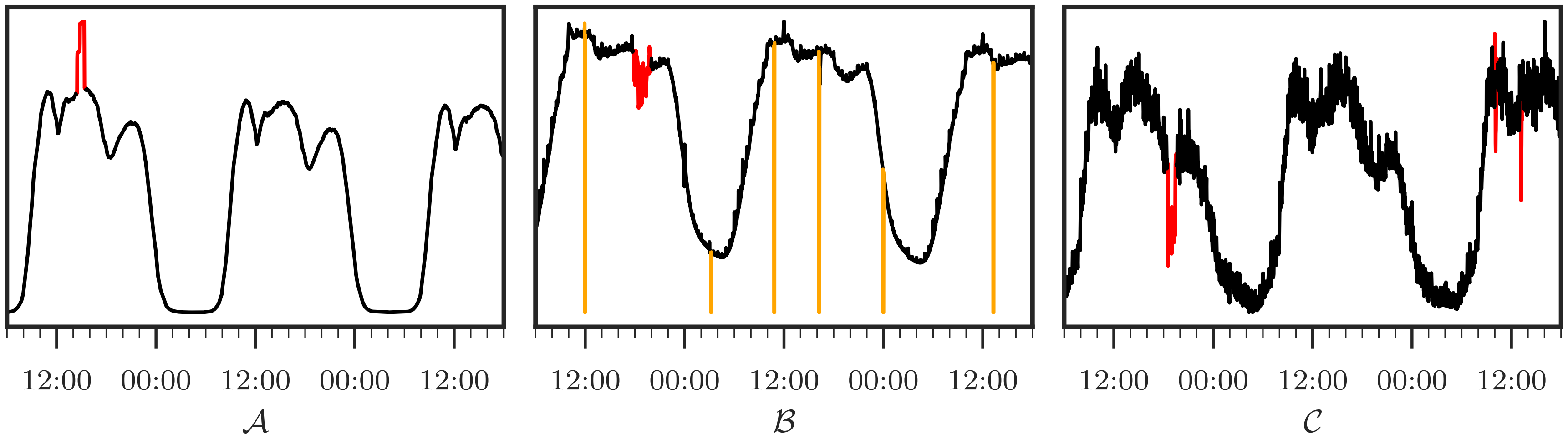


Fig11: The Dataset of Donut

Donut

- A recent future of W data points at time t is called a window at time t. Donut tries to model the distribution of normal windows by VAE(Variational Auto Encoder) and find anomalies by likelihood.

- The training objective of VAE, is the evidence lower bound of likelihood(ELBO).

$$\mathcal{L}_{vae} = \mathbb{E}_{p(\mathbf{x})}\left[\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \mathrm{KL}\left[q_\phi(\mathbf{z}|\mathbf{x}) \,\|\, p_\theta(\mathbf{z})\right]\right]$$

- In Donut, $p_\theta(\mathrm{x}|\mathrm{z})$ is diagonal multivariate gaussian distribution and it works well on seasonal smooth KPIs.

Donut

- Element-wise posterior:
  - $\ln p_\theta(\mathrm{x}|\mathrm{z}) = \sum_i \ln p_\theta(\mathrm{x}_i|\mathrm{z})$

- It is useful for smooth KPIs but not for Intricate KPIs.

Out of Expectation

- Donut assumes that the data is seasonal smooth with diagonal gaussian noise but the intricate KPIs are not.
- VAE will only learn the mean and variance locally.

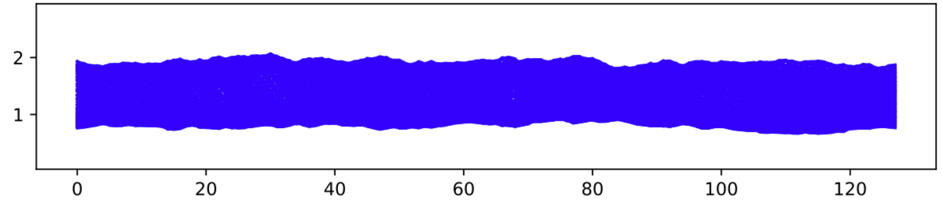


Fig12: Reconstructed element-wise gaussian distribution

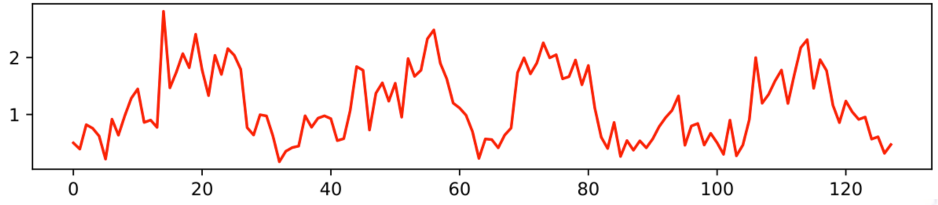
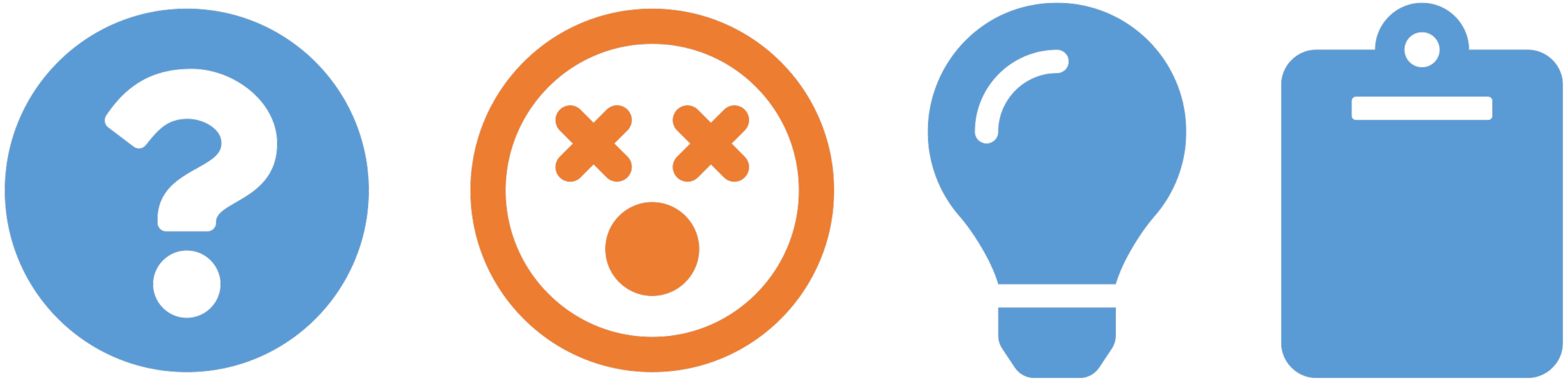


Fig13: Original curve



Background | Challenges | Ideas | Experiments

Challenges

Dataset is too intricate for VAE to learn

Element-wise gaussian posterior is not appropriate

Reconstruction loss is too hard to learn

The limit of training method

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Challenges

$$\mathcal{L}_{vae} = \mathbb{E}_{p(\mathbf{x})}\left[\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})] - \mathrm{KL}\left[q_\phi(\mathbf{z}|\mathbf{x}) \,\|\, p_\theta(\mathbf{z})\right]\right]$$

- $\mathbb{E}_{p(\mathbf{x})}\left[\mathbb{E}_{q_\phi(\mathbf{z}|\mathbf{x})}[\log p_\theta(\mathbf{x}|\mathbf{z})]\right]$ is called reconstruction loss.
- ELBO is a trade-off and when the reconstruction loss is hard to learn (nearly no gradient from it), our model tends to learn another term.

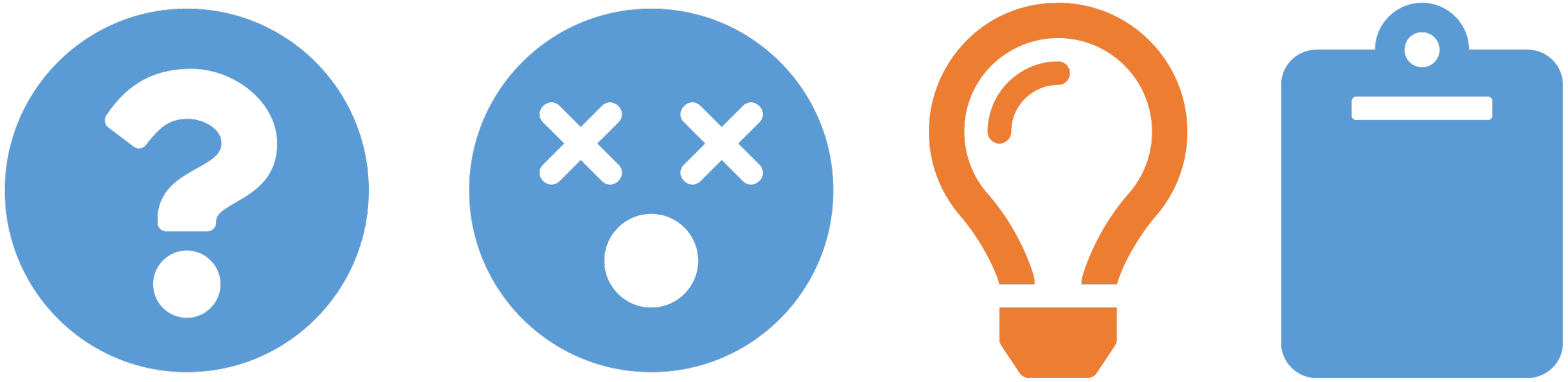
Challenges

Dataset is too intricate for VAE to learn

Element-wise gaussian posterior is not appropriate

Reconstruction loss is too hard to learn

The limit of training method



Background Challenges Ideas Experiments

Ideas

Problem	Solution
Element-wise gaussian posterior is not appropriate	Choose another posterior which is not element-wise
Reconstruction loss is too hard to learn	Relax the constraint of reconstruction loss
The limit of training method	Use adversarial training

Ideas

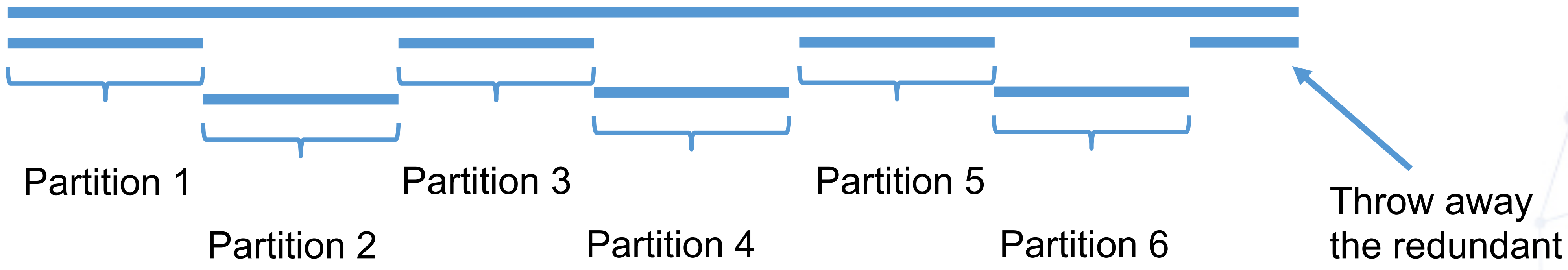
Choose another posterior which is not element-wise

- $p_\theta(\mathrm{x}|\mathrm{z}) = \frac{1}{Z(\lambda)} e^{-\lambda\|\mathrm{x}-G(z)\|}$
- $G(z)$ is the generative network and λ is a learnable variable.
- $Z(\lambda)$ can be simply calculated when λ is fixed.
- It is easy to check that it is not element-wise.

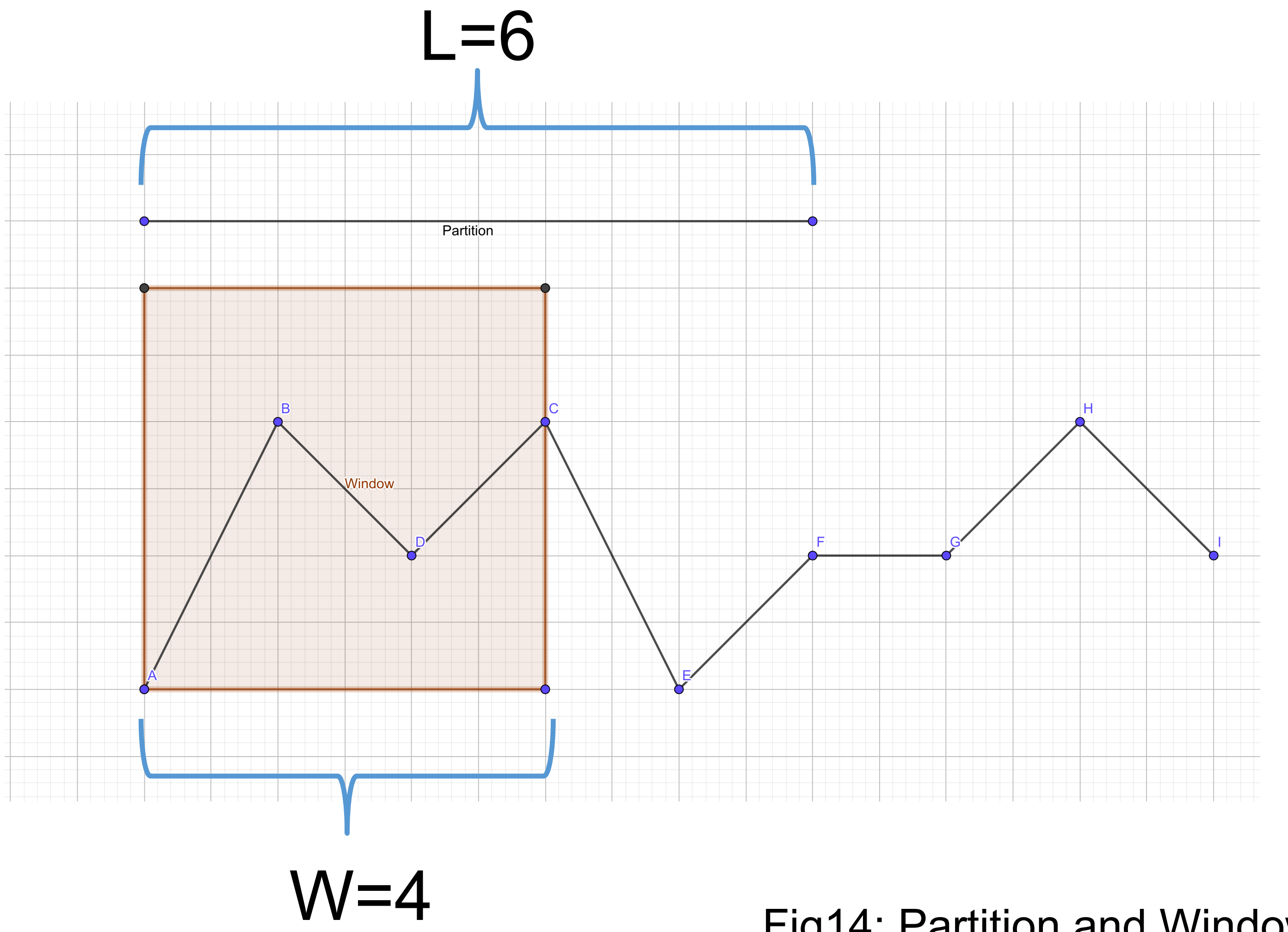
Ideas

Relax the constraint of reconstruction loss

- Introduce a new notion: Partition
- Divide the whole KPI into several partitions, whose length are all L



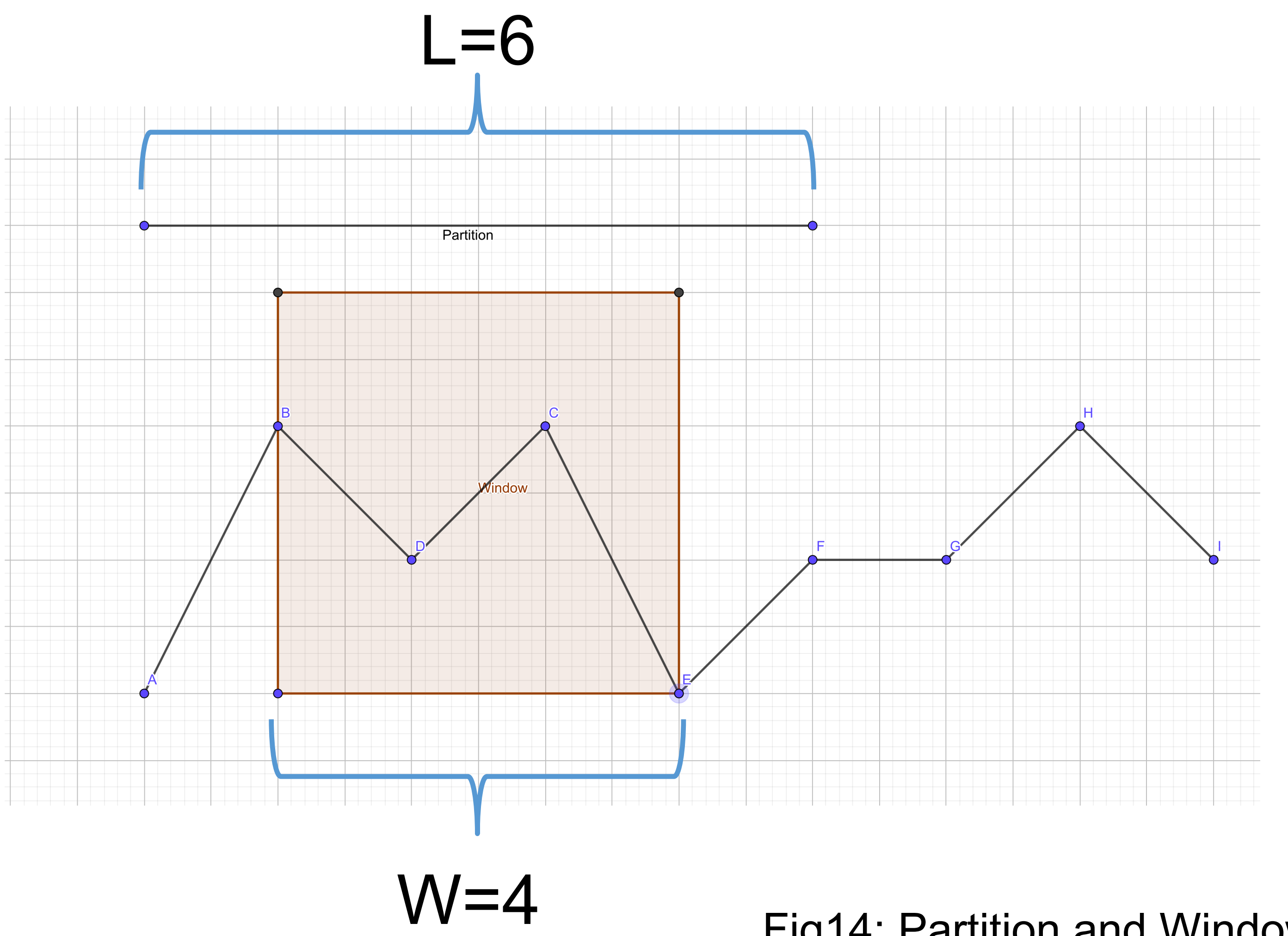
Partition and Window



Window 1

Fig14: Partition and Window

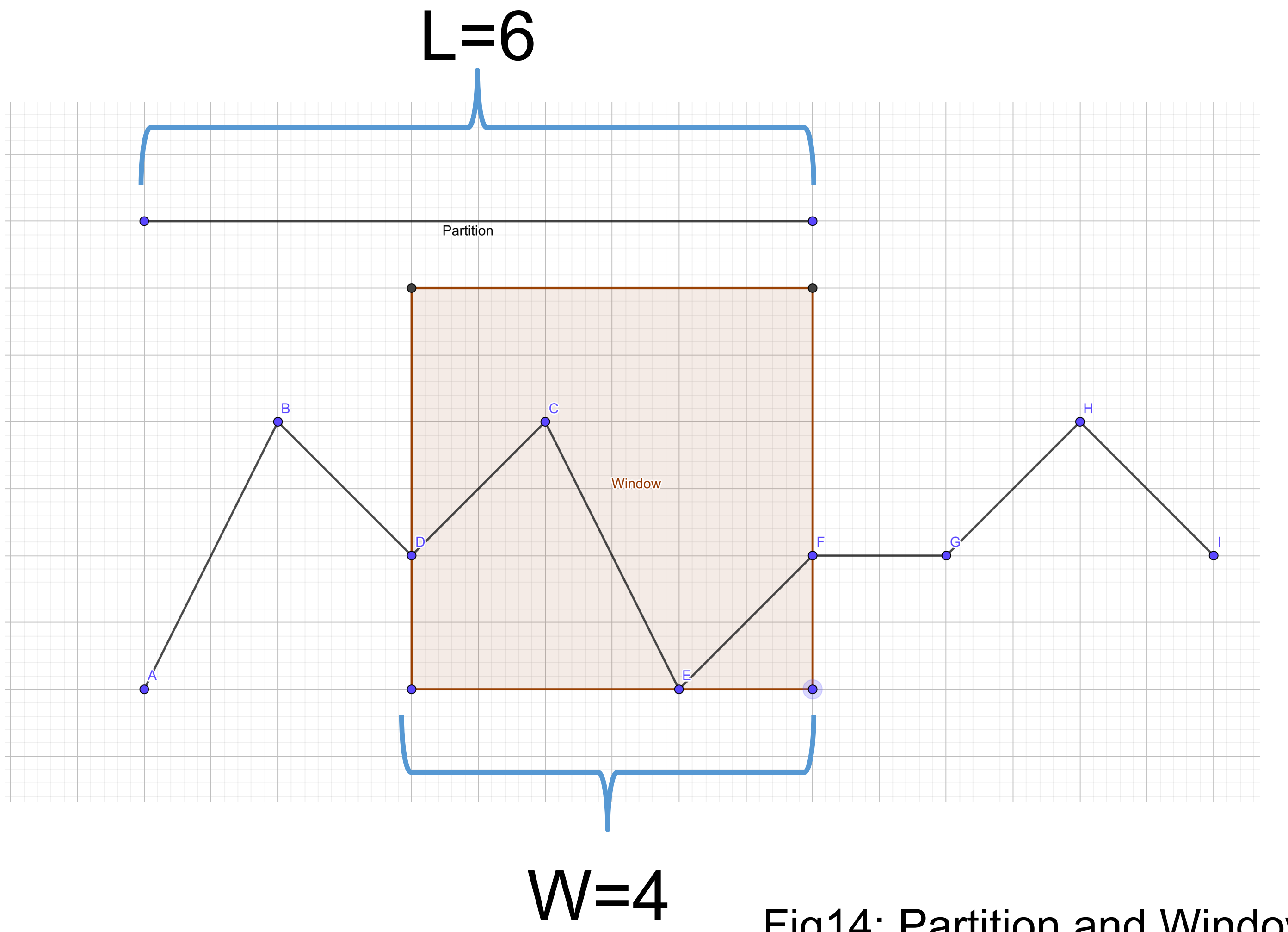
Partition and Window



Window 2

Fig14: Partition and Window

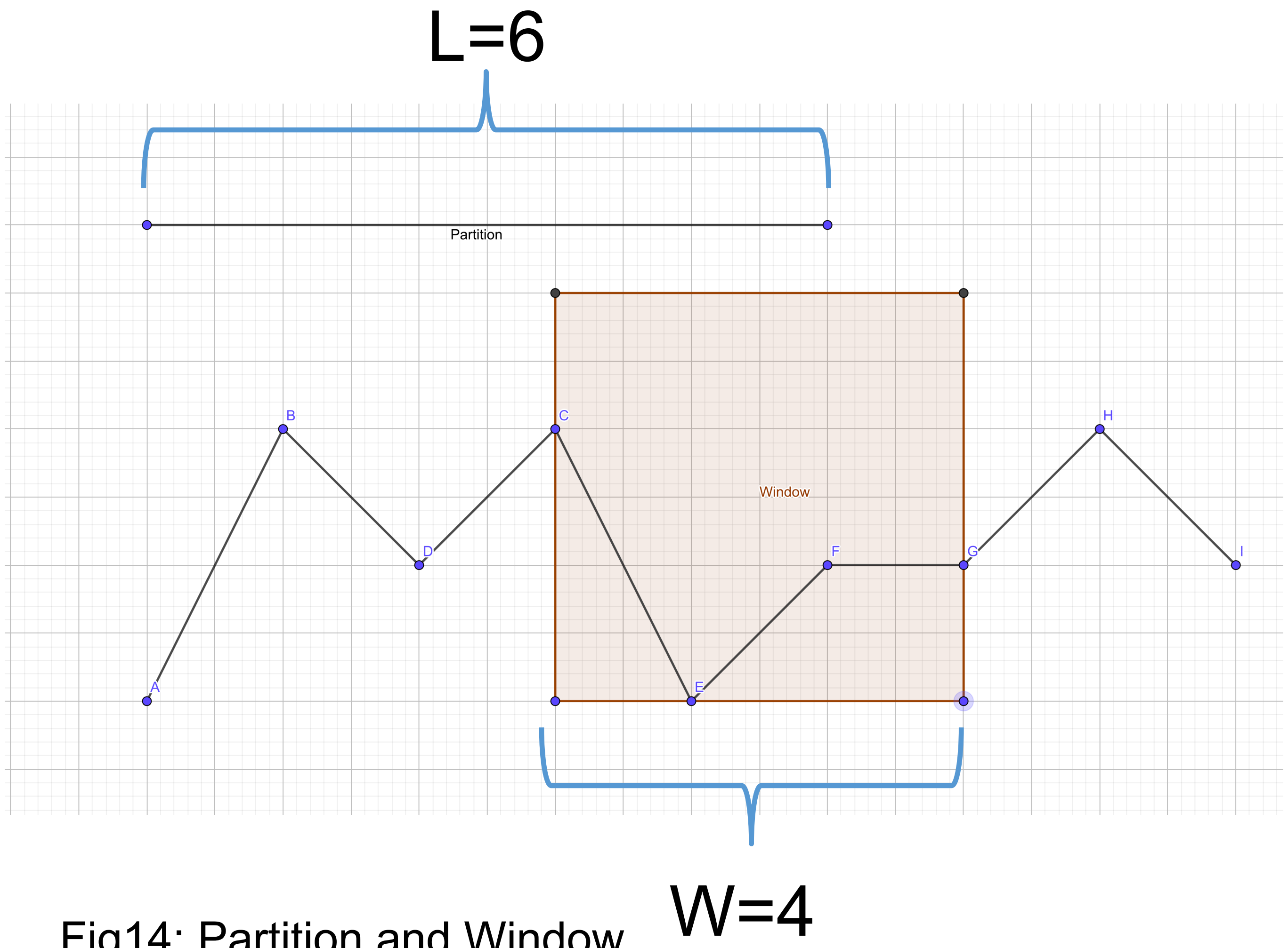
Partition and Window



Window 3

Fig14: Partition and Window

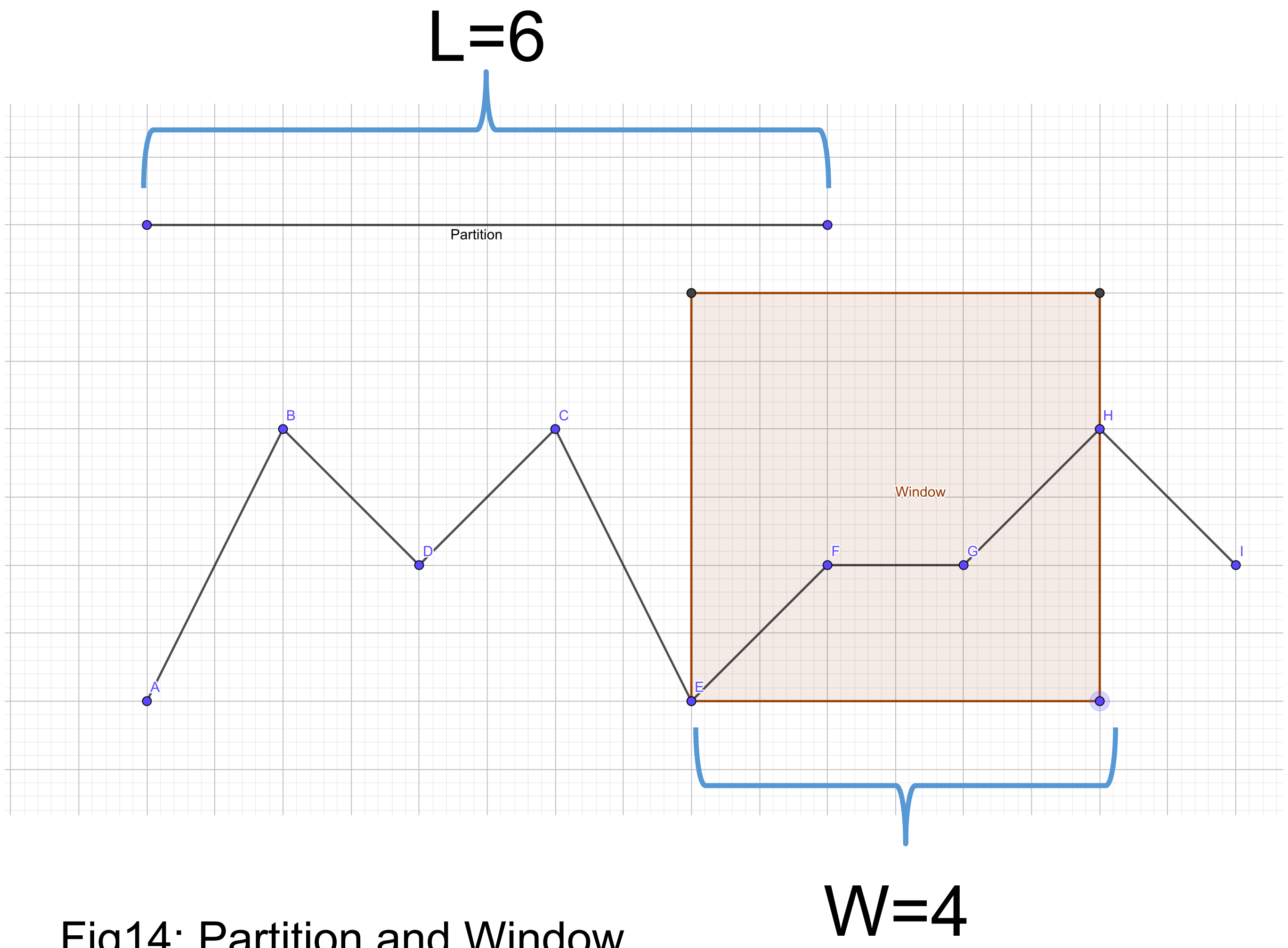
Partition and Window



Window 4

Fig14: Partition and Window

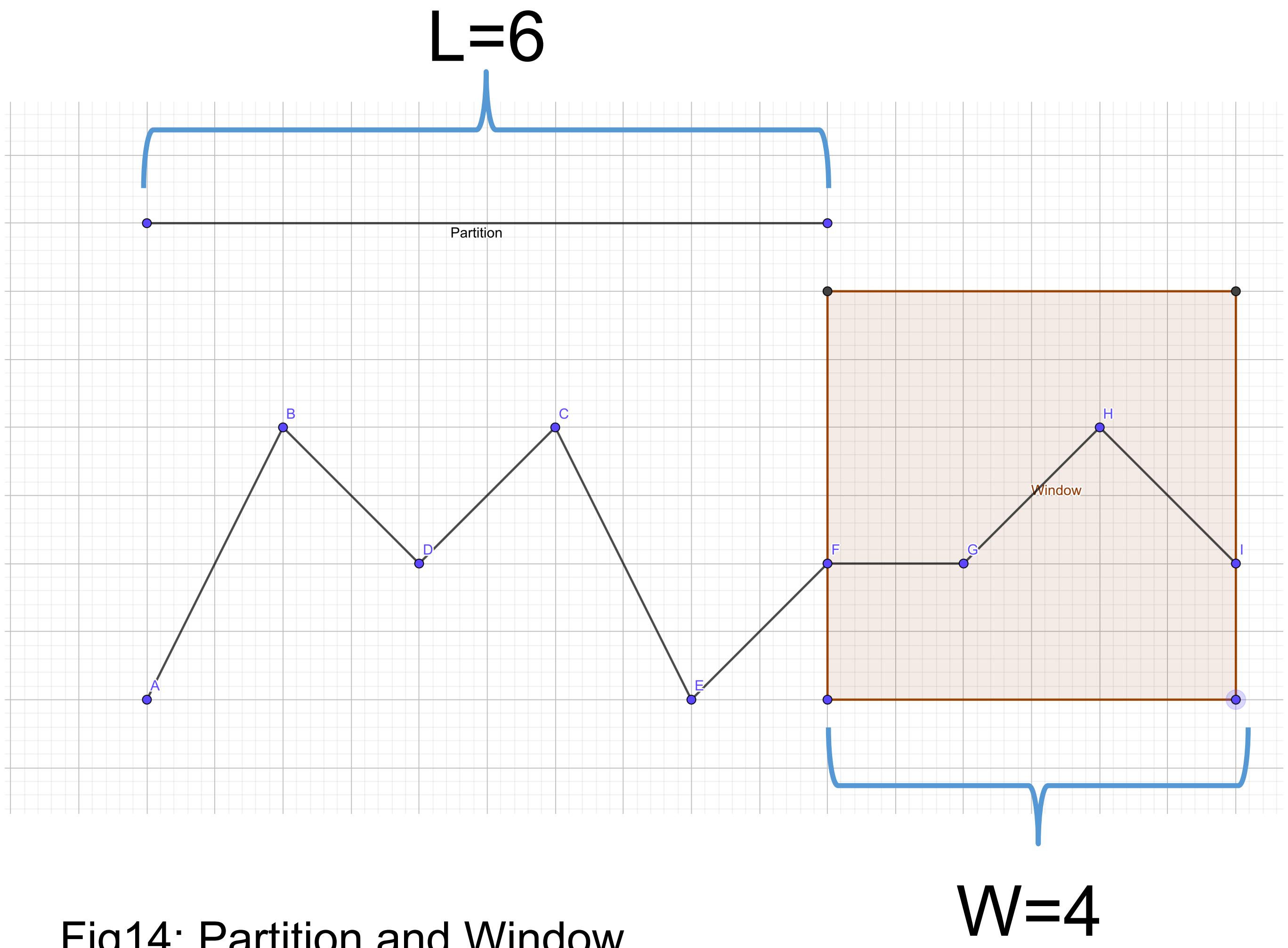
Partition and Window



Window 5

Fig14: Partition and Window

Partition and Window

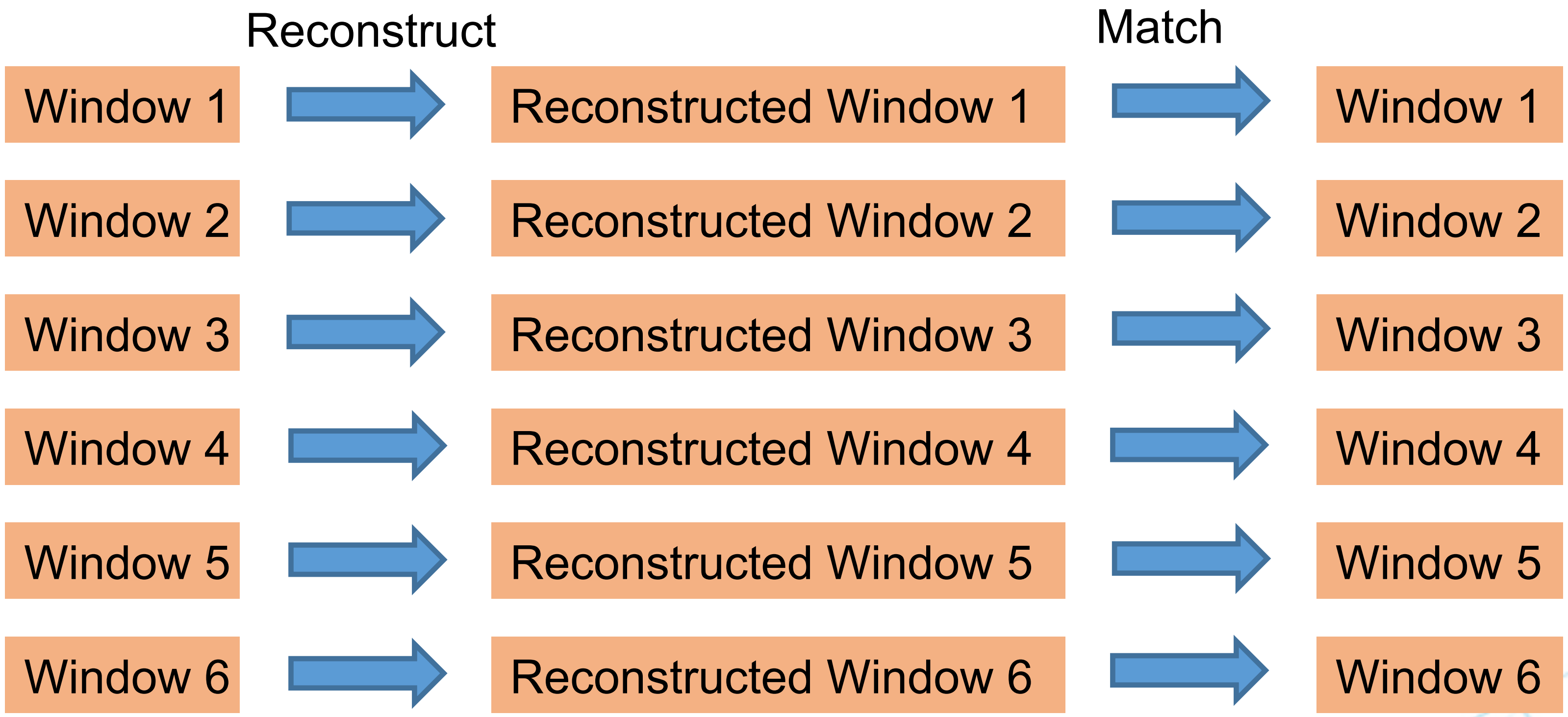


Window 6

Fig14: Partition and Window

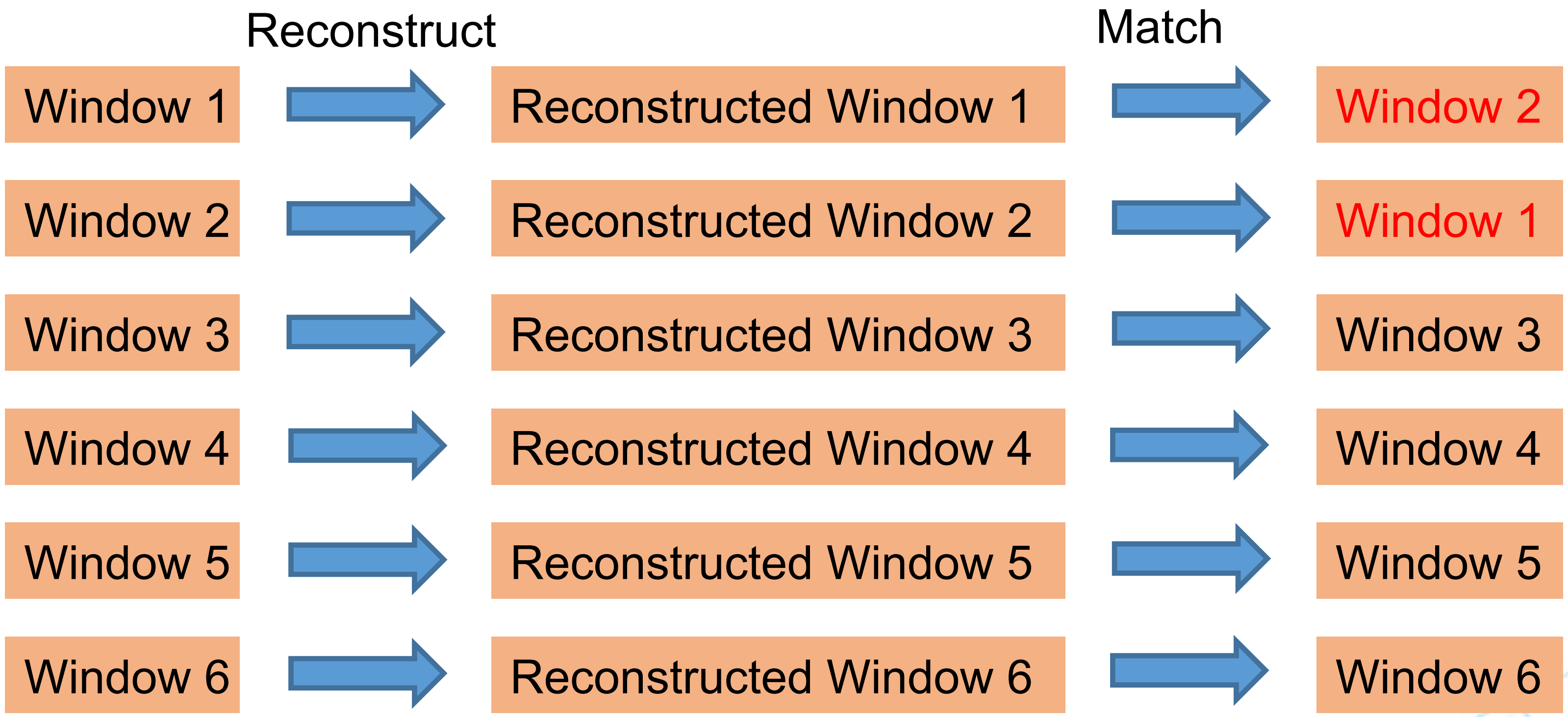
Match

- In a partition, we regard the reconstruction loss as distance between reconstructed window and original window.



Match

- We relax the reconstruction loss by following way: we permit each reconstructed window to match one window in this partition and compute the sum of the distance between each pair.



Whole Process

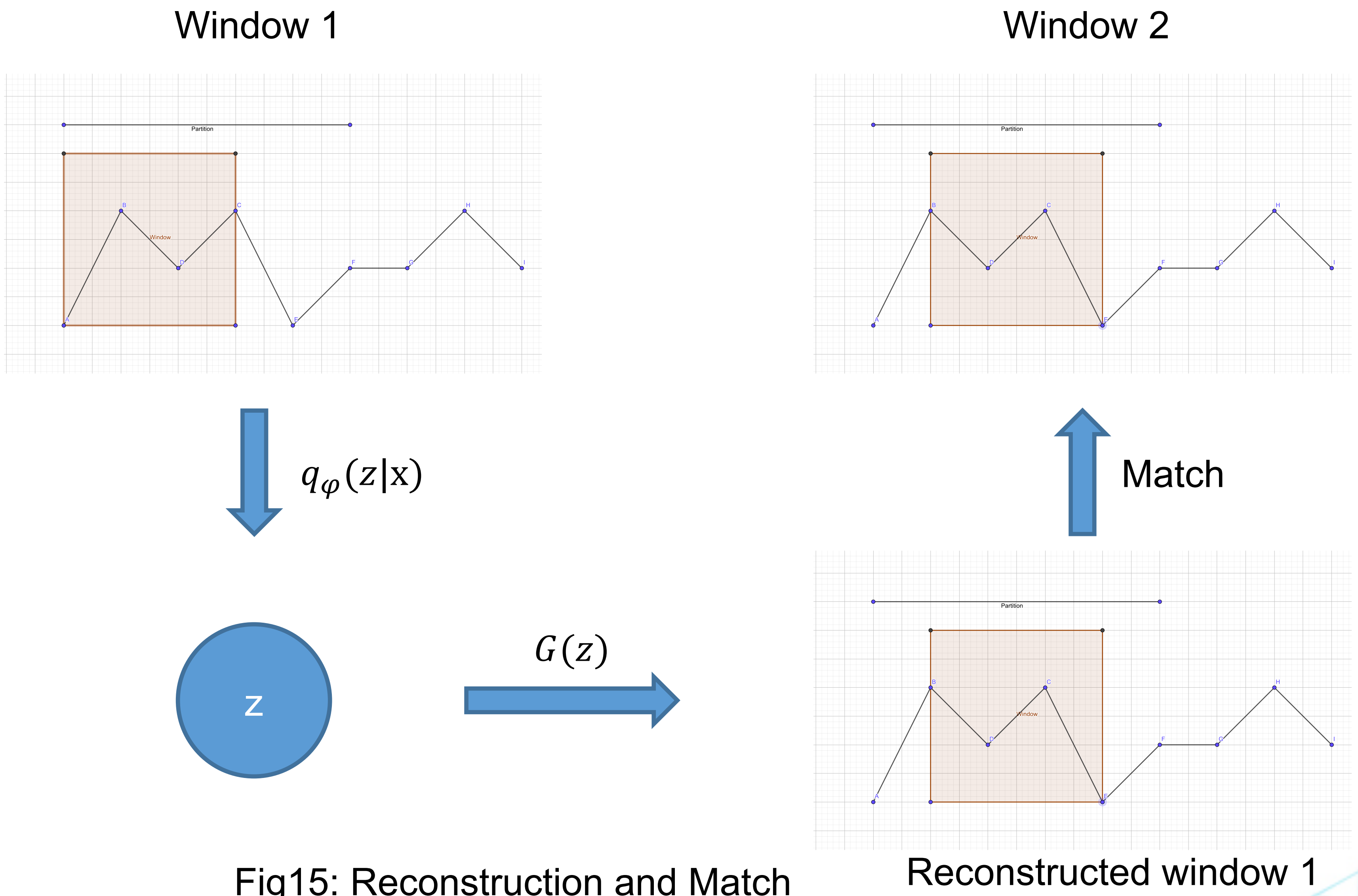


Fig15: Reconstruction and Match

Relationship

- It is easy to see that match reconstruction loss is less than reconstruction loss (just trivial match).

- Reconstruction loss is the special case: L=1

- Understand it intuitively: L is our tolerance. We tolerate some errors of reconstruction.

Ideas

Use adversarial training

- A **generative adversarial network** (**GAN**) is a class of machine learning systems. Two neural networks contest with each other in a zero-sum game framework.

- It works very well in image generation.

Wasserstein distance

- **Wasserstein distance** used by WGAN[ICML2017].

$$W^1[P(\mathbf{x}|w)\|P_G(\mathbf{y}|w)] = \inf_{\gamma\in\Gamma_w}\int_{\mathcal{X}\times\mathcal{X}}\|\mathbf{x}-\mathbf{y}\|\mathrm{d}\gamma(\mathbf{x},\mathbf{y})$$

$$= \sup_{Lip(f)\leq 1}\left\{\int_{\mathcal{X}} f(\mathbf{x})p(\mathbf{x}|w)\mathrm{d}\mathbf{x} - \int_{\mathcal{X}} f(\mathbf{y})p_G(\mathbf{y}|w)\mathrm{d}\mathbf{y}\right\}$$

- $P(\mathrm{x}|\omega)$ is the distribution of windows in Partition ω
- $P_G(\mathrm{y}|\omega)$ is the distribution of reconstructed windows in Partition ω
- γ represents the matches

Training

$$W^1[P(\mathbf{x}|w)\|P_G(\mathbf{y}|w)] = \inf_{\gamma\in\Gamma_w}\int_{\mathcal{X}\times\mathcal{X}} \|\mathbf{x}-\mathbf{y}\|\mathrm{d}\gamma(\mathbf{x},\mathbf{y})$$

$$= \sup_{Lip(f)\leq 1}\left\{\int_{\mathcal{X}} f(\mathbf{x})p(\mathbf{x}|w)\mathrm{d}\mathbf{x} - \int_{\mathcal{X}} f(\mathbf{y})p_G(\mathbf{y}|w)\mathrm{d}\mathbf{y}\right\}$$

- We train another network $D(\mathrm{x})$ to find the optimal f above, with a penalty on the gradient norm for random samples (WGAN-GP[NIPS2017]).
- Decrease the size of each partition during training.
- We complete an adversarial training algorithm of VAE.

Review

Use adversarial training

Which

Choose another posterior which is not diagonal

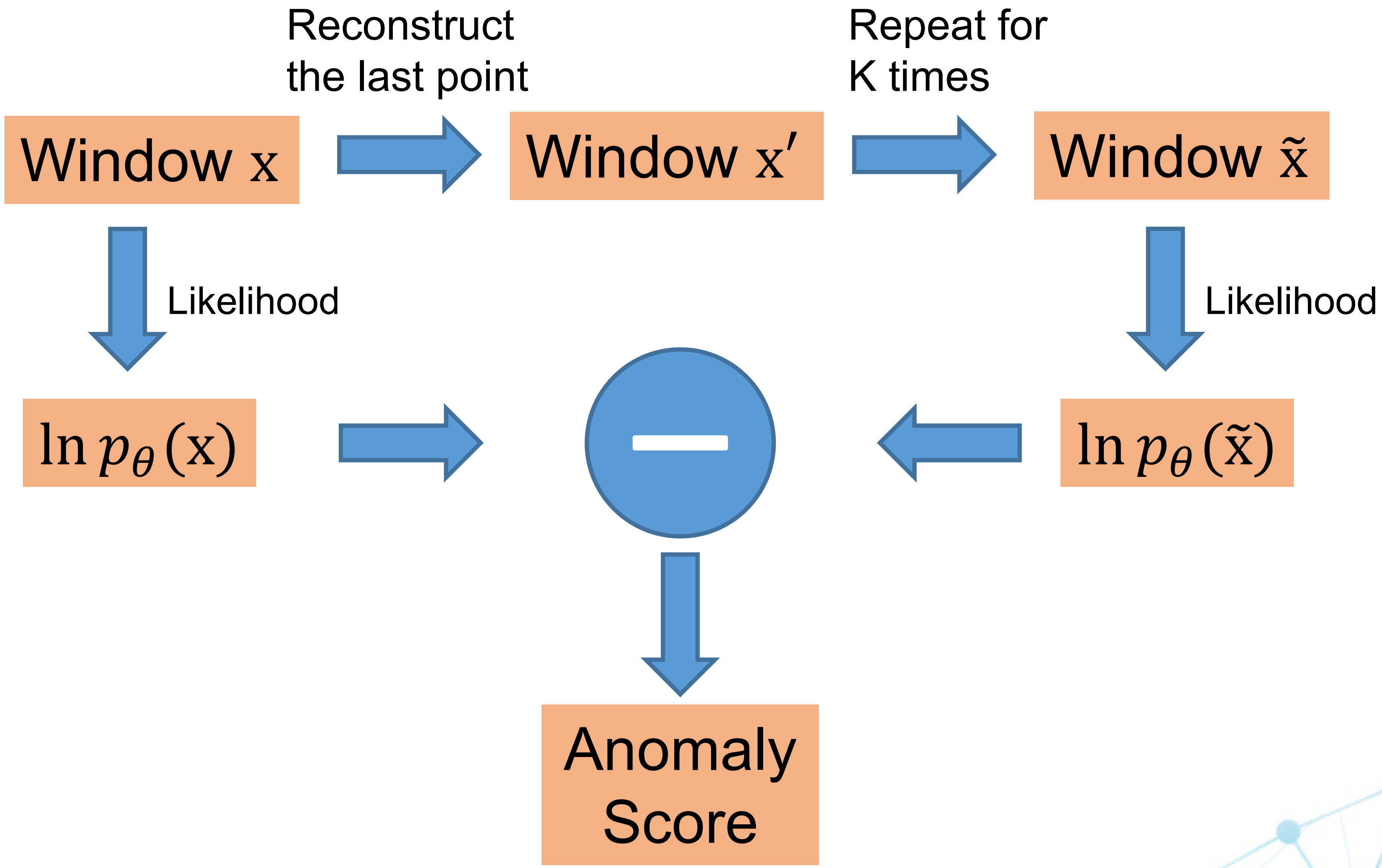
1-Wasserstein Distance

degenerate

Exponential posterior distribution

Robust metric

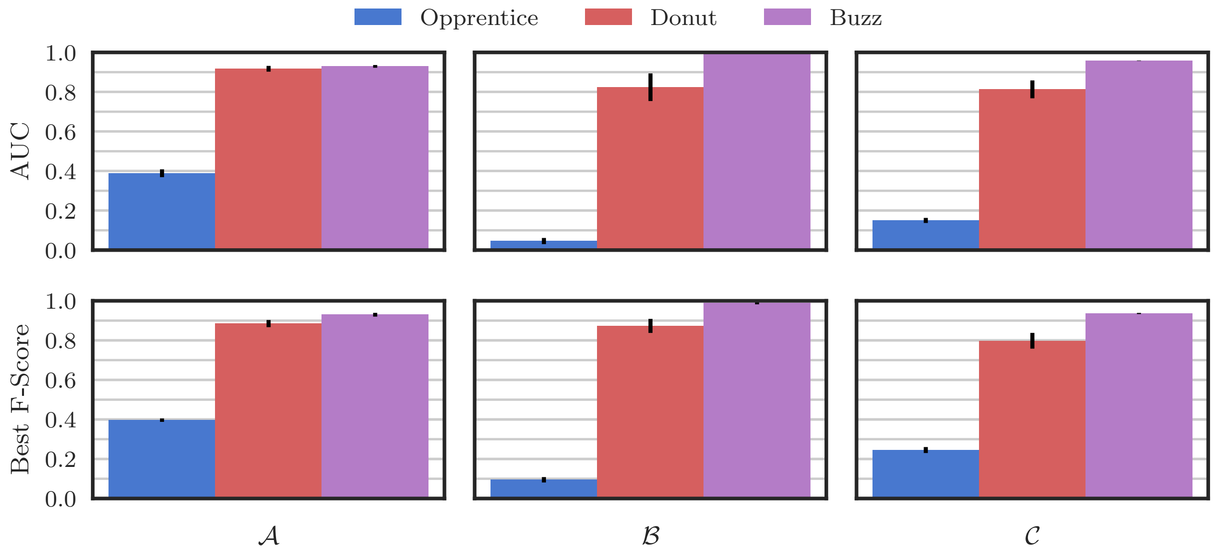
Detection



Reconstruct
the last point
Repeat for
K times
Window x
Window x'
Window $\tilde{\mathrm{x}}$
Likelihood
Likelihood
$\ln p_\theta(\mathrm{x})$
$\ln p_\theta(\tilde{\mathrm{x}})$
Anomaly
Score

Background Challenges Ideas Experiments

Experiments



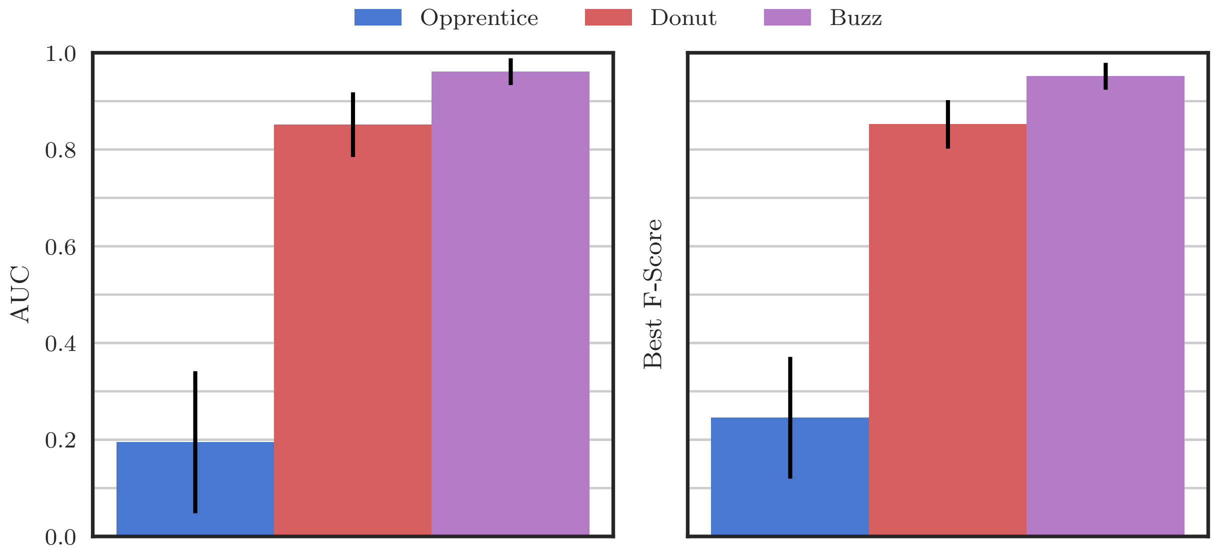


Fig16: Performance

Experiments

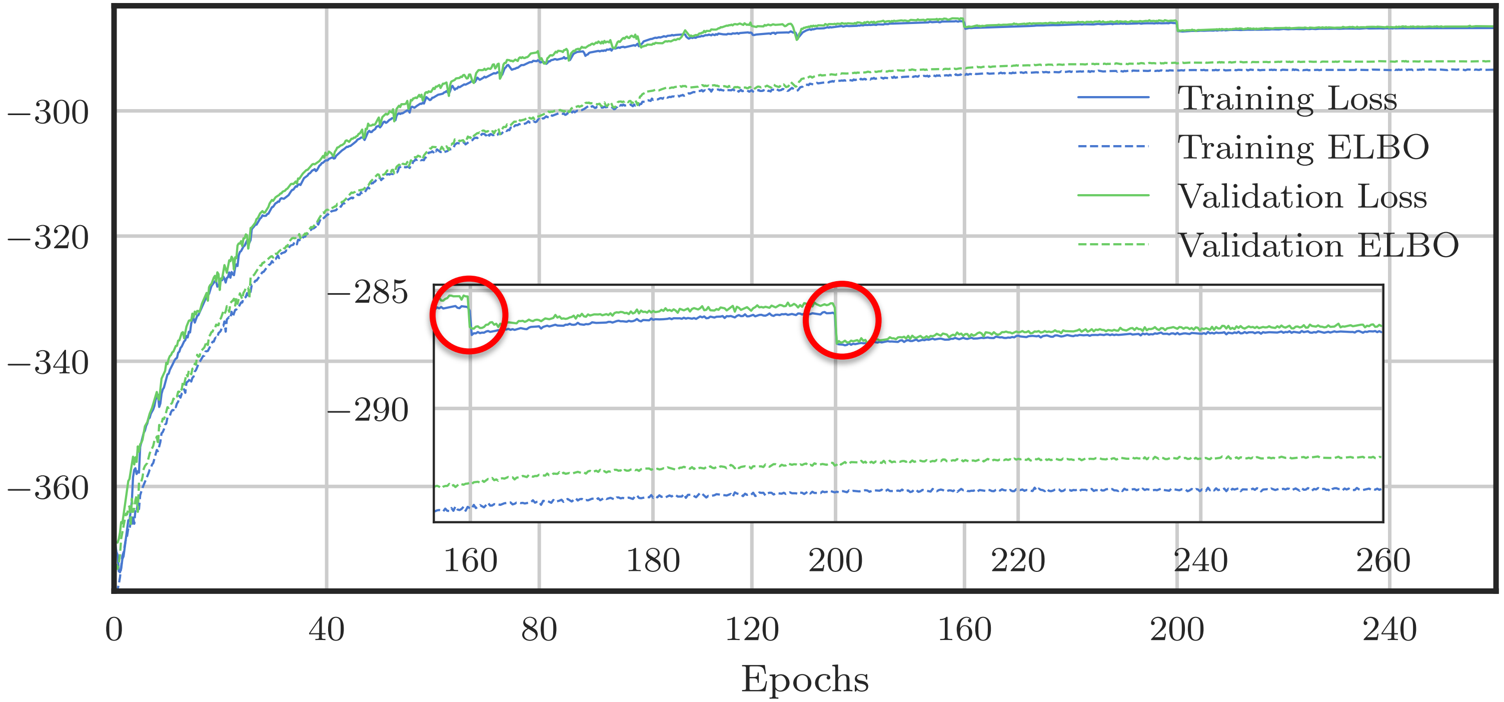


Fig17: Loss and ELBO

The fact that ELBO increases during the training, indicates that our model maximizes the ELBO indeed.

Conclusion

- The first unsupervised anomaly detection algorithm via deep generative model on intricate KPIs

- The first adversarial training method for VAE, based on partitions analysis

- Our deduction build the bridge between VAE and Wasserstein Distance

Thank you

Q&A