

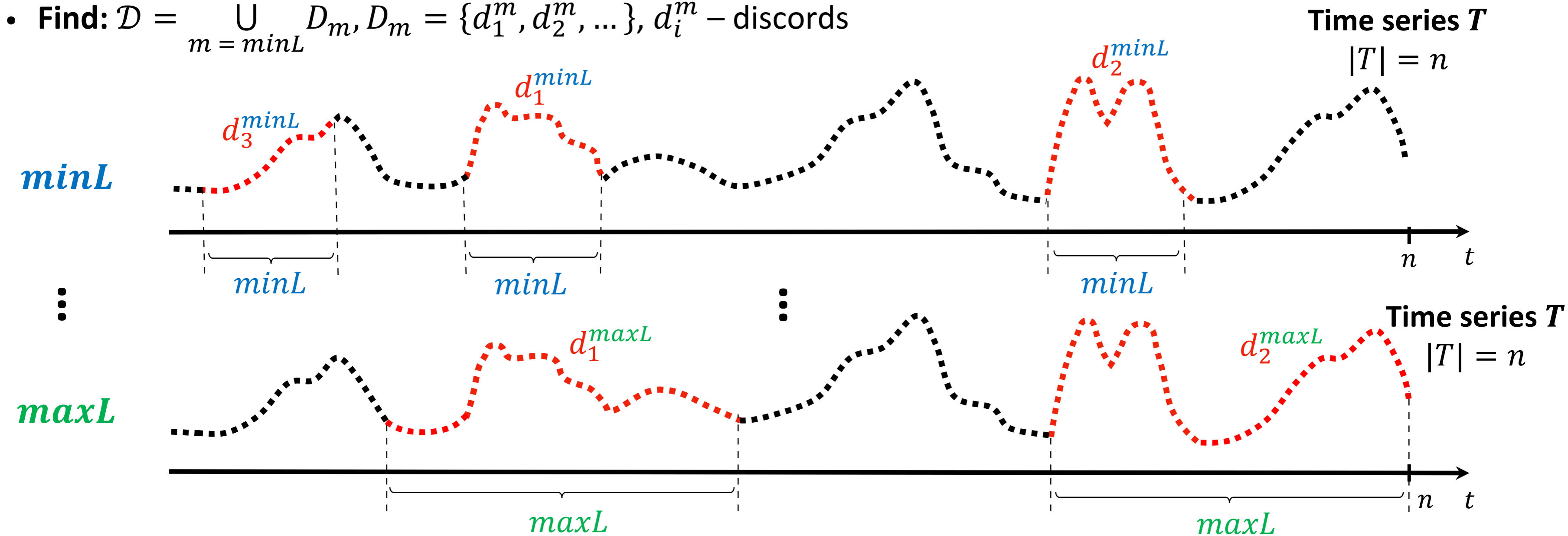
Current results of the project
“Development of models, methods and algorithms
for time series anomaly discovery”

Yana Kraeva, Mikhail Zymbler

Task of arbitrary length discord discovery¹⁾

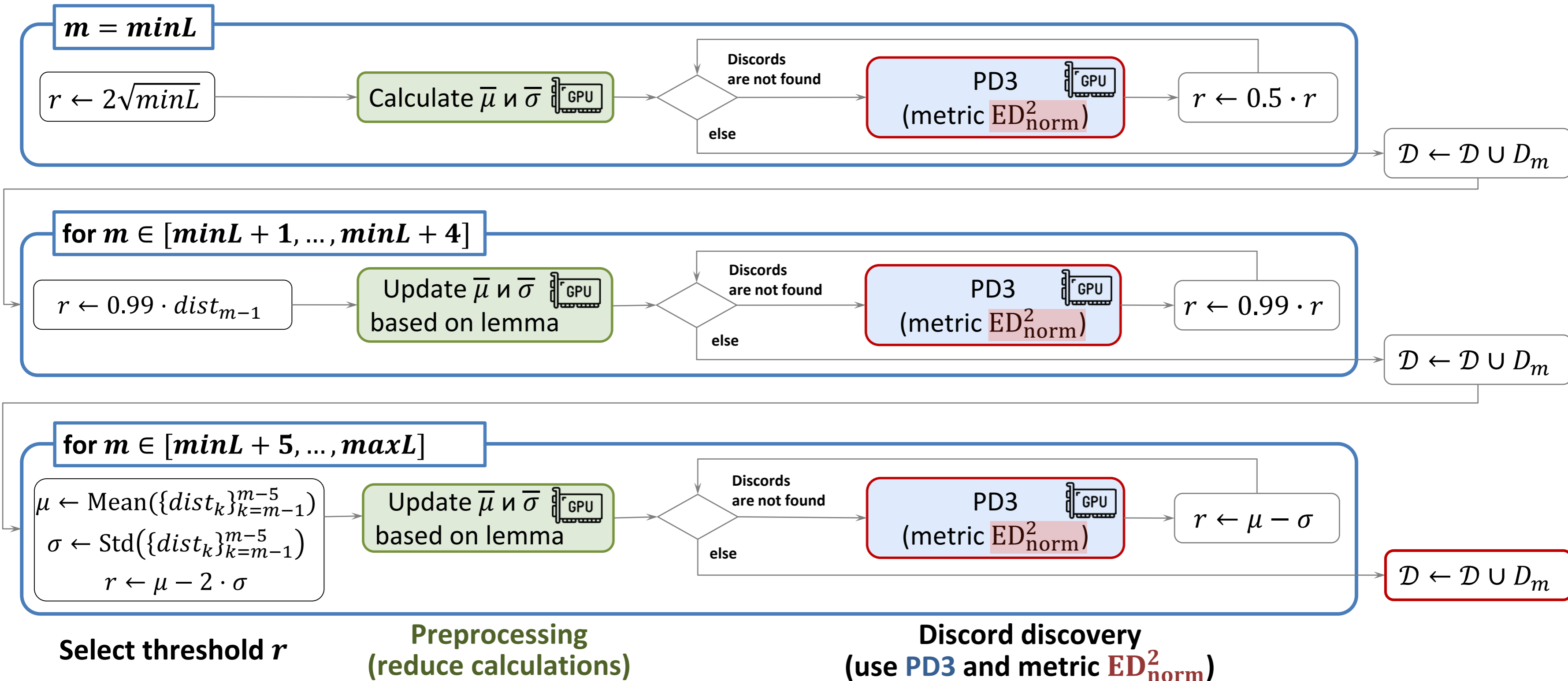
- **Discord** is a subsequence of a given length whose nearest neighbor is at least at a given threshold far away
- **Given:** time series T , discord length range $minL, \dots, maxL$

- **Find:** $\mathcal{D} = \bigcup_{m=minL}^{maxL} D_m, D_m = \{d_1^m, d_2^m, \dots\}, d_i^m$ – discords



¹⁾ Nakamura T., *et al.* MERLIN: parameter-free discovery of arbitrary length anomalies in massive time series archives. IEEE ICDM 2020. pp. 1190-1195.

PALMAD (Parallel Arbitrary Length MERLIN-based Anomaly Discovery)¹⁾

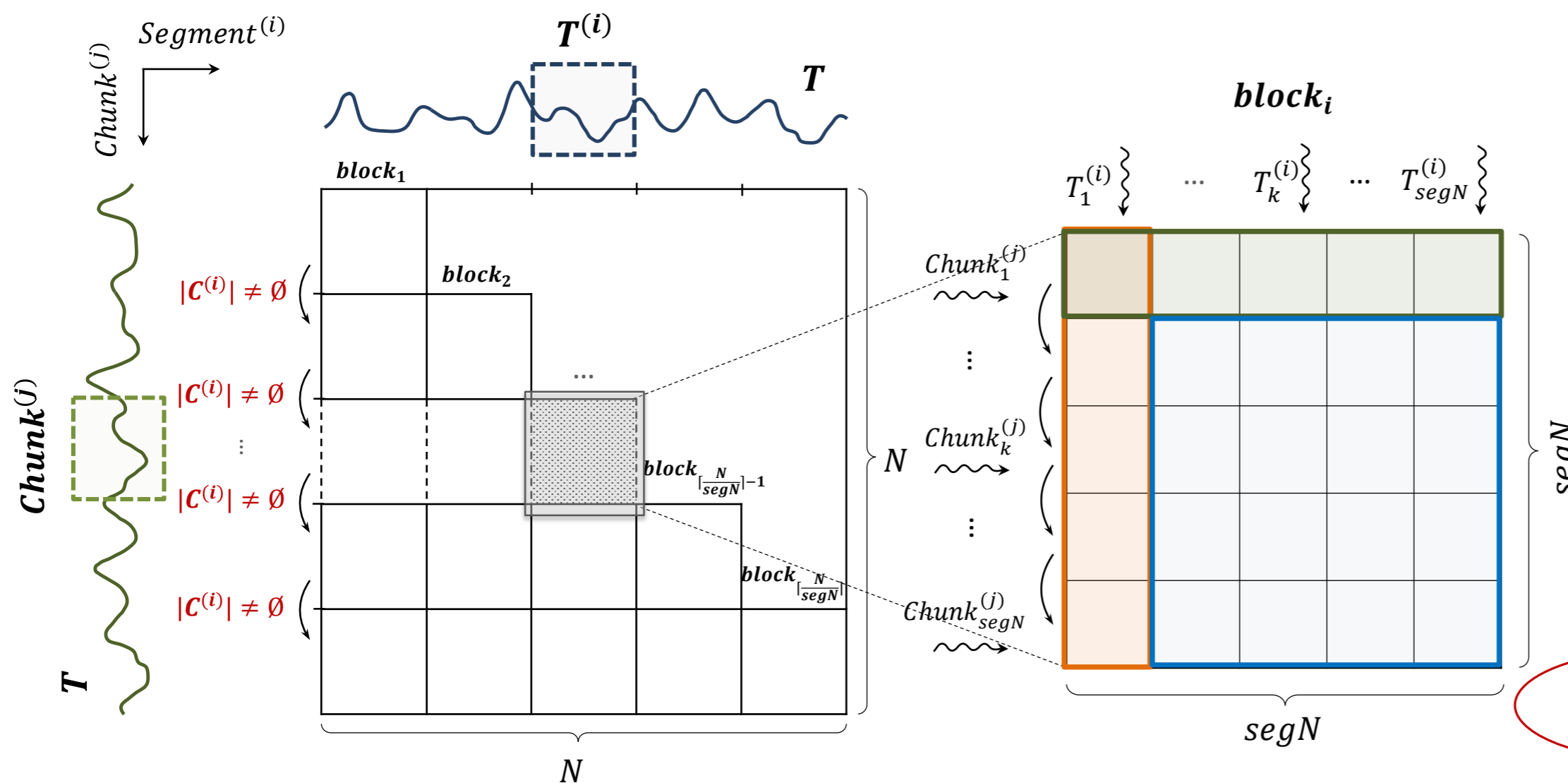


¹⁾ Zymbler M., Kraeva Y. High-performance Time Series Anomaly Discovery on Graphics Processors. CoRR. 2023. Vol. abs/2304.01660. arXiv: 2304.01660.

PD3: Parallel DRAG-based Discord Discovery¹⁾

1. Two phases: the candidate selection and discords refinement
2. Data parallelism: SIMT (Single Instruction Multiple Threads)
3. Efficient calculations of scalar products $T_{i,m} \cdot T_{j,m}$

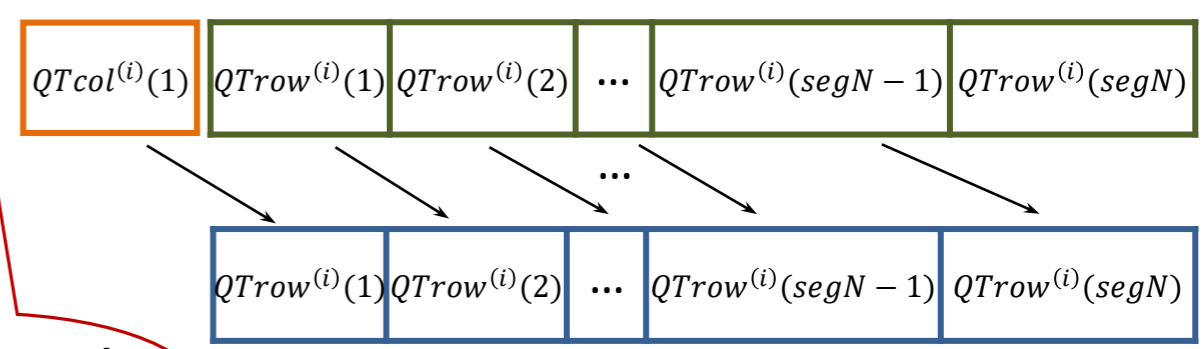
$$ED_{\text{norm}}^2(T_{i,m}, T_{j,m}) = 2m \left(1 - \frac{T_{i,m} \cdot T_{j,m} - m\mu_i\mu_j}{m\sigma_i\sigma_j} \right)$$



$$QTrow^{(i)}(tid) = \sum_{k=1}^m T_{tid}^{(i)}(k) \cdot Chunk_1^{(j)}(k)$$

$$QTcol^{(i)}(tid) = \sum_{k=1}^m T_1^{(i)}(k) \cdot Chunk_{tid}^{(j)}(k)$$

$$QTrow^{(i)}(tid) = QTrow^{(i)}(tid - 1) - T_{tid-1}^{(i)}(1) \cdot Chunk_{tid-1}^{(j)}(1) + T_{tid}^{(i)}(m) \cdot Chunk_{tid}^{(j)}(m)$$

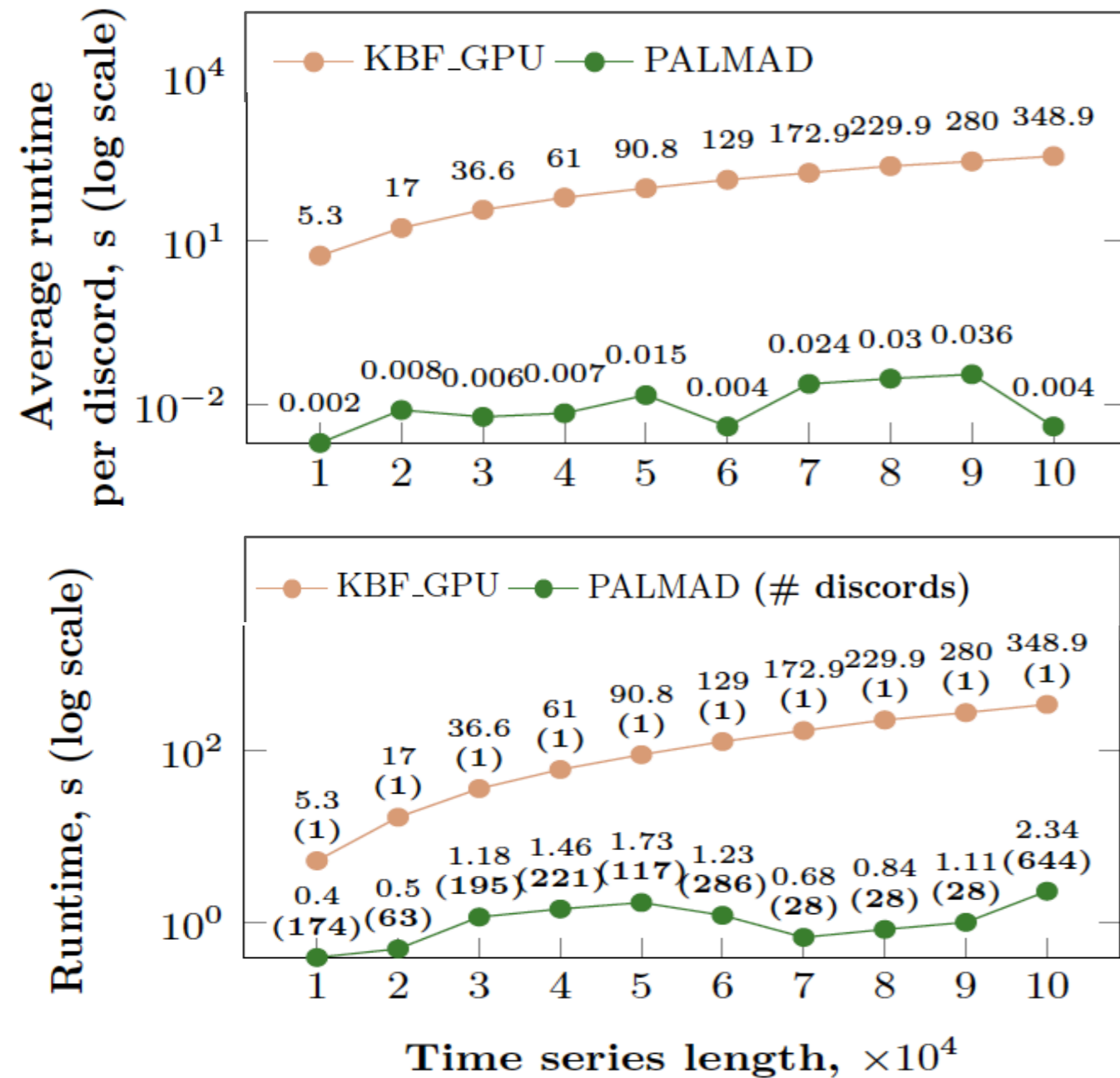


$O(1)$ instead of $O(m)$!

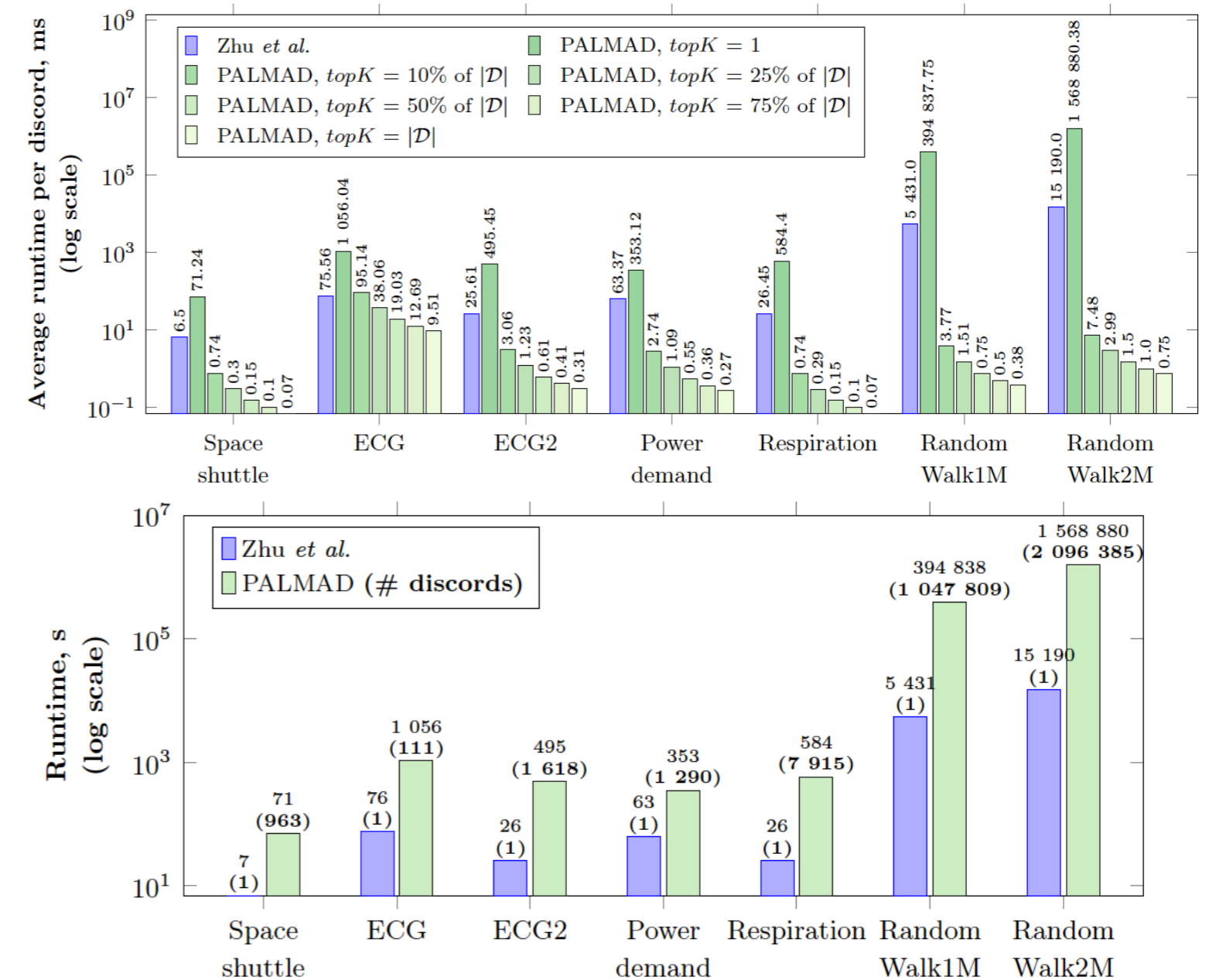
¹⁾ Kraeva Y., Zymbler M. Parallel algorithm for time series discord discovery on a graphics processor. Pattern Recognition and Image Analysis. 2023. Vol. 33, no. 2. Accepted for publication.

Experiments: Comparison with analogs

• KBF_GPU



• Zhu et al.



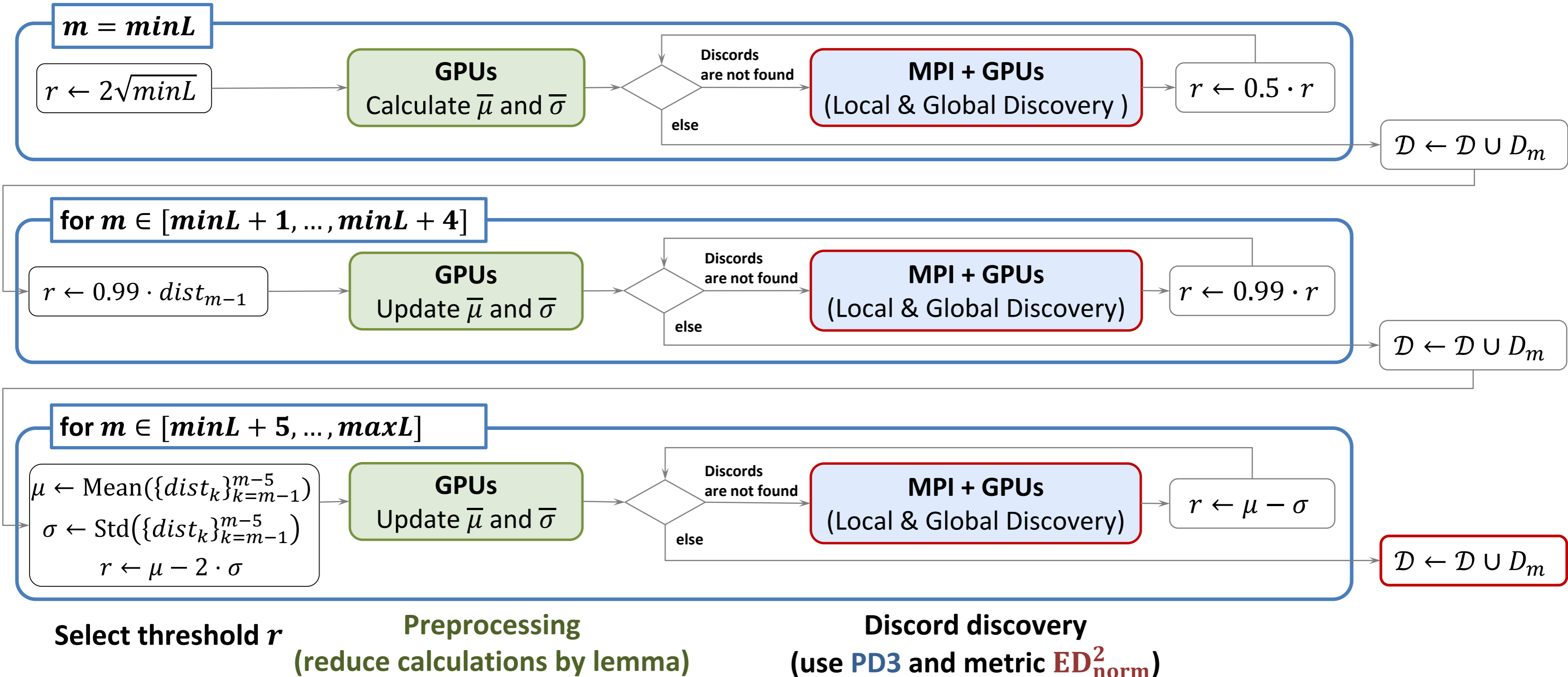
PALMAD significantly outruns KBF_GPU

PALMAD significantly outruns Zhu et al. w.r.t. the average running time to discover one discord

PALMAD **cannot**

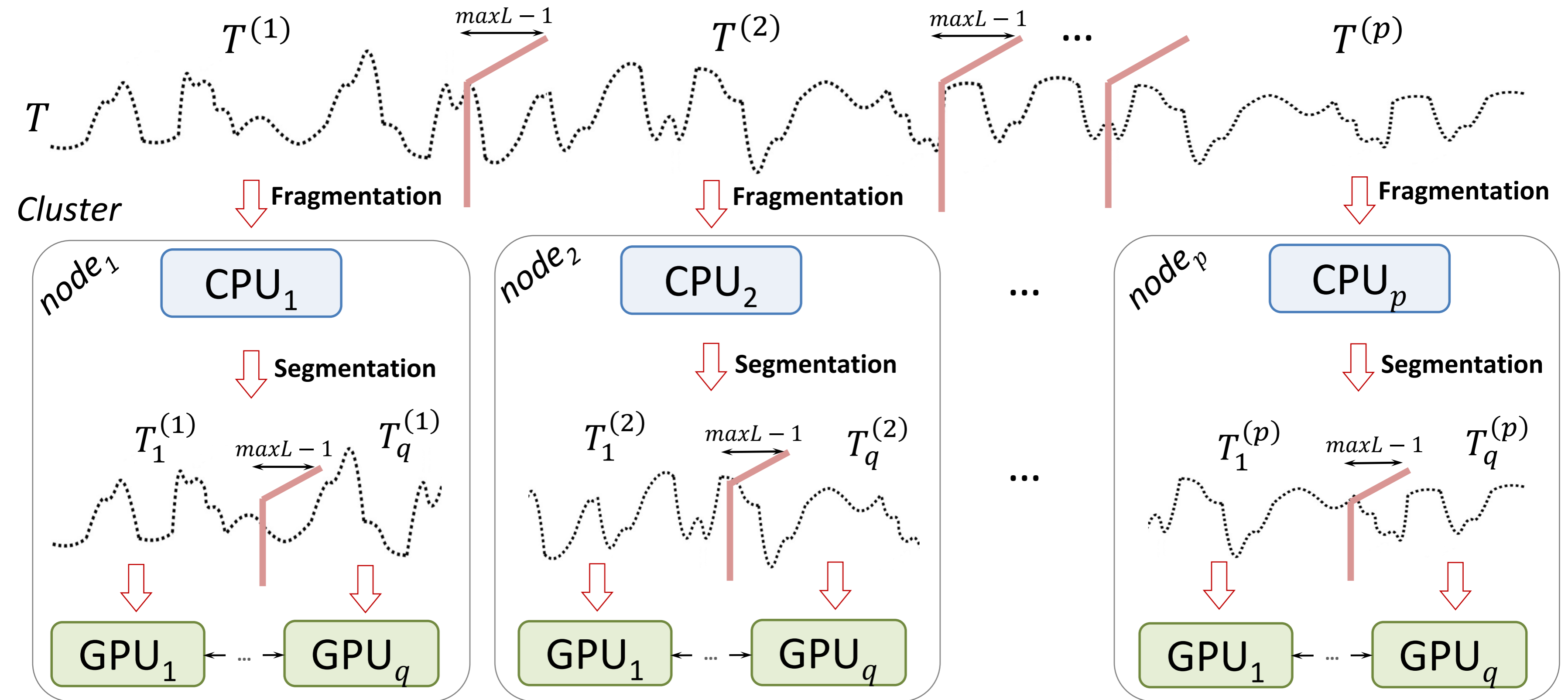
- **deal with a time series that larger than RAM of a GPU**
- discover anomalies online

From PALMAD to PADDi (PALMAD-based Anomaly Discovery on Distributed GPUs)

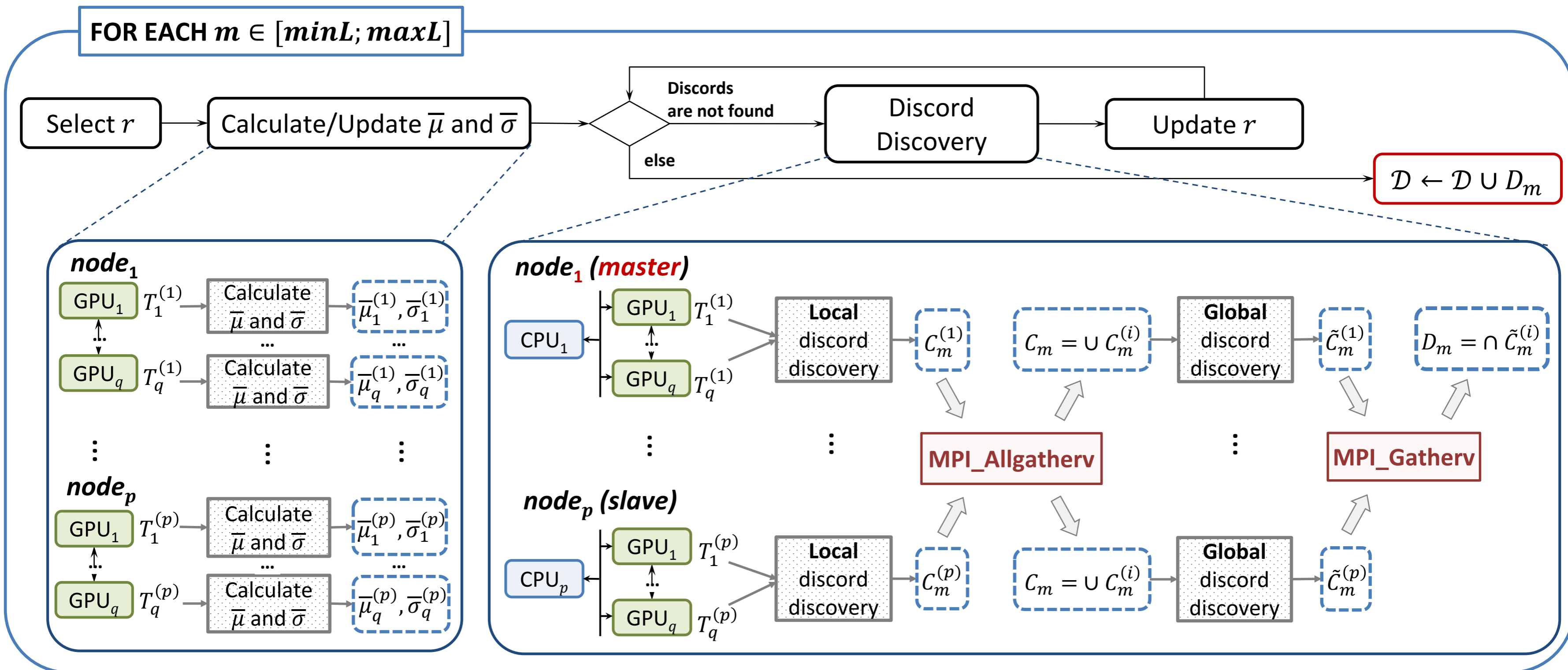


¹⁾ Zymbler M., Kraeva Y. High-performance Time Series Anomaly Discovery on Graphics Processors. CoRR. 2023. Vol. abs/2304.01660. arXiv: 2304.01660.

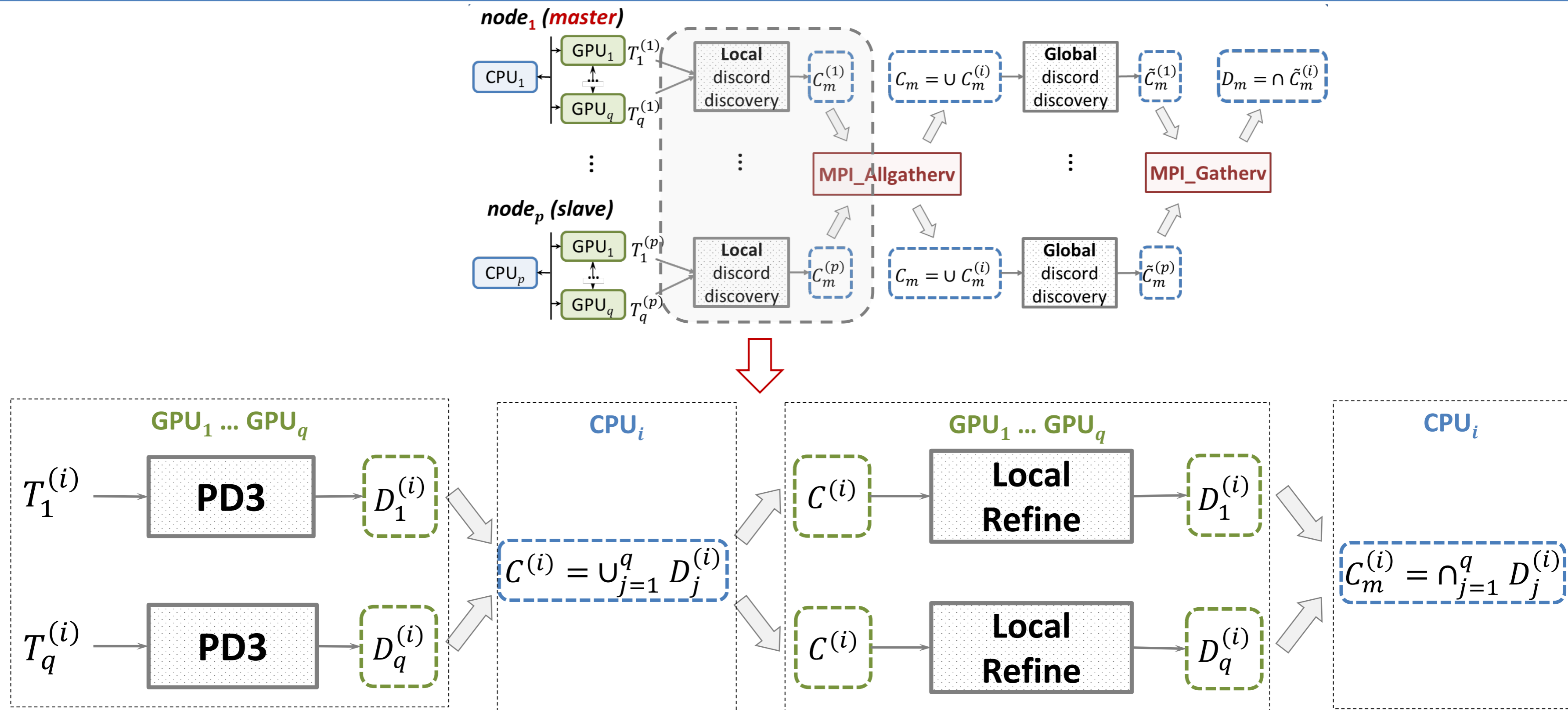
PADDi: Fragmentation and segmentation



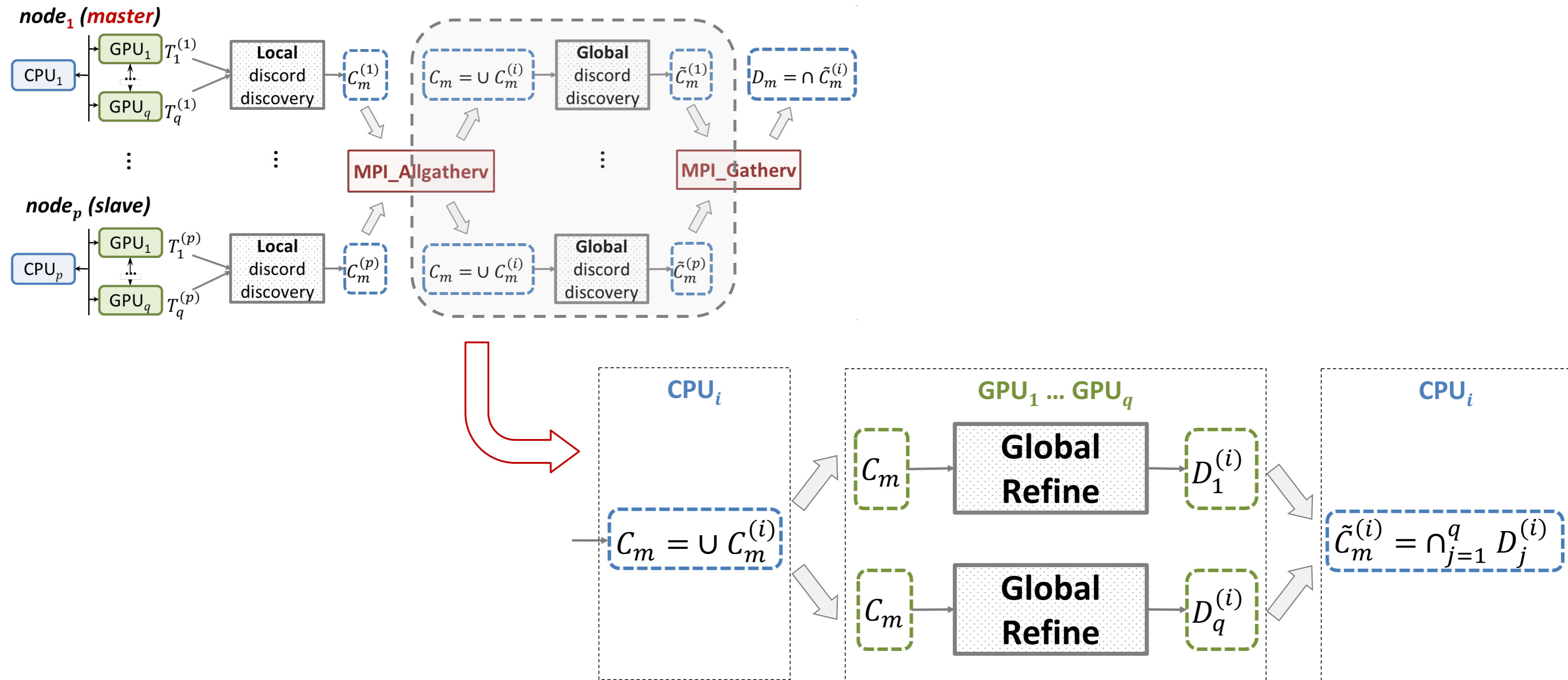
PADDi: General scheme



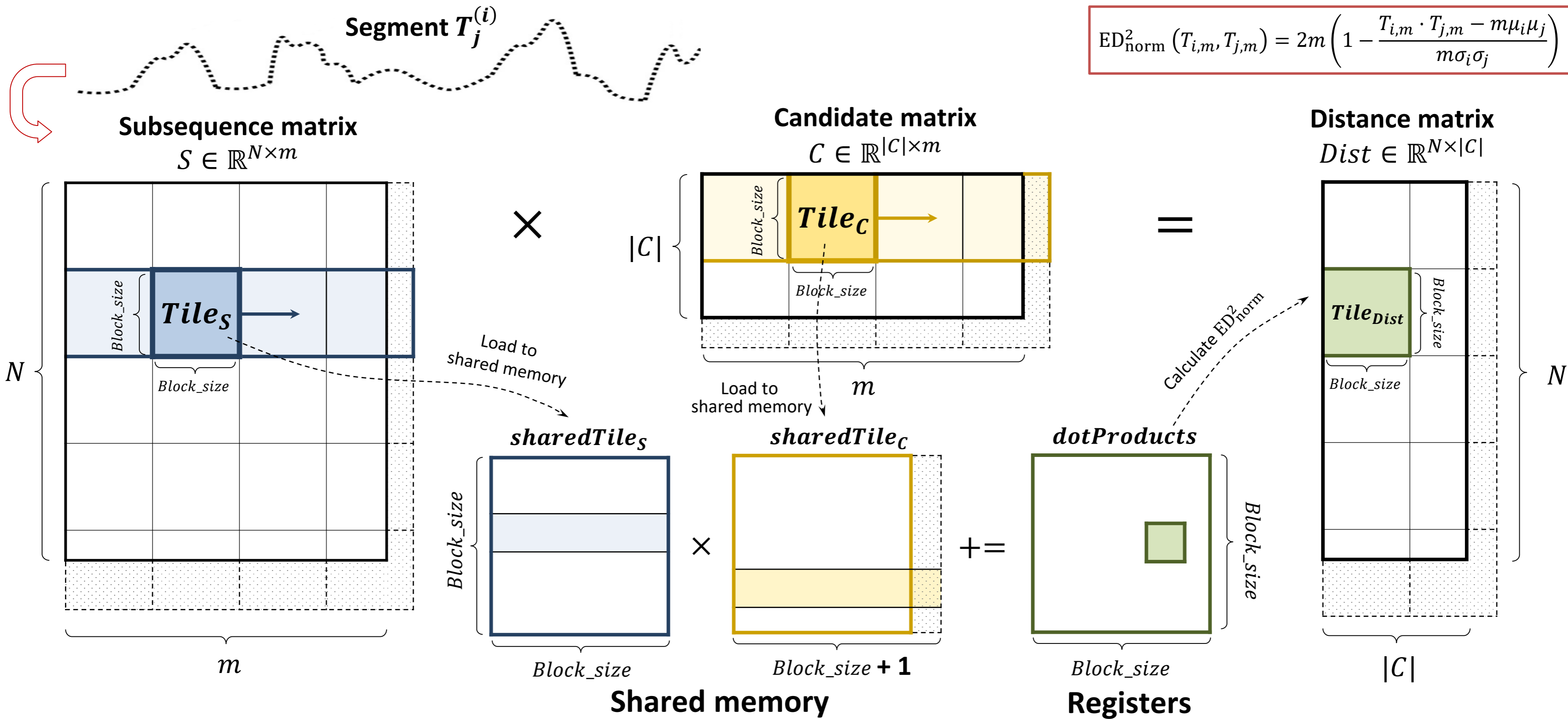
PADDi: Local Discord Discovery



PADDi: Global Discord Discovery



Local/Global Discord Refinement



Experiments

- **Hardware**

- Cluster: Lomonosov-2, MSU
- Node: 1 x Xeon Gold 6126 with 2 x NVIDIA Tesla P100 (3 584 CUDA-cores, @1.19 GHz, 4 TFLOPS)

- **Datasets**

Time series	Time series length, n	Discord length range, $minL..maxL$	Domain
ECG ¹⁾	$4 \cdot 10^6$	64..128	Electrocardiogram of an adult patient
GAP ²⁾	$2 \cdot 10^6$	256..512	Power demand in France

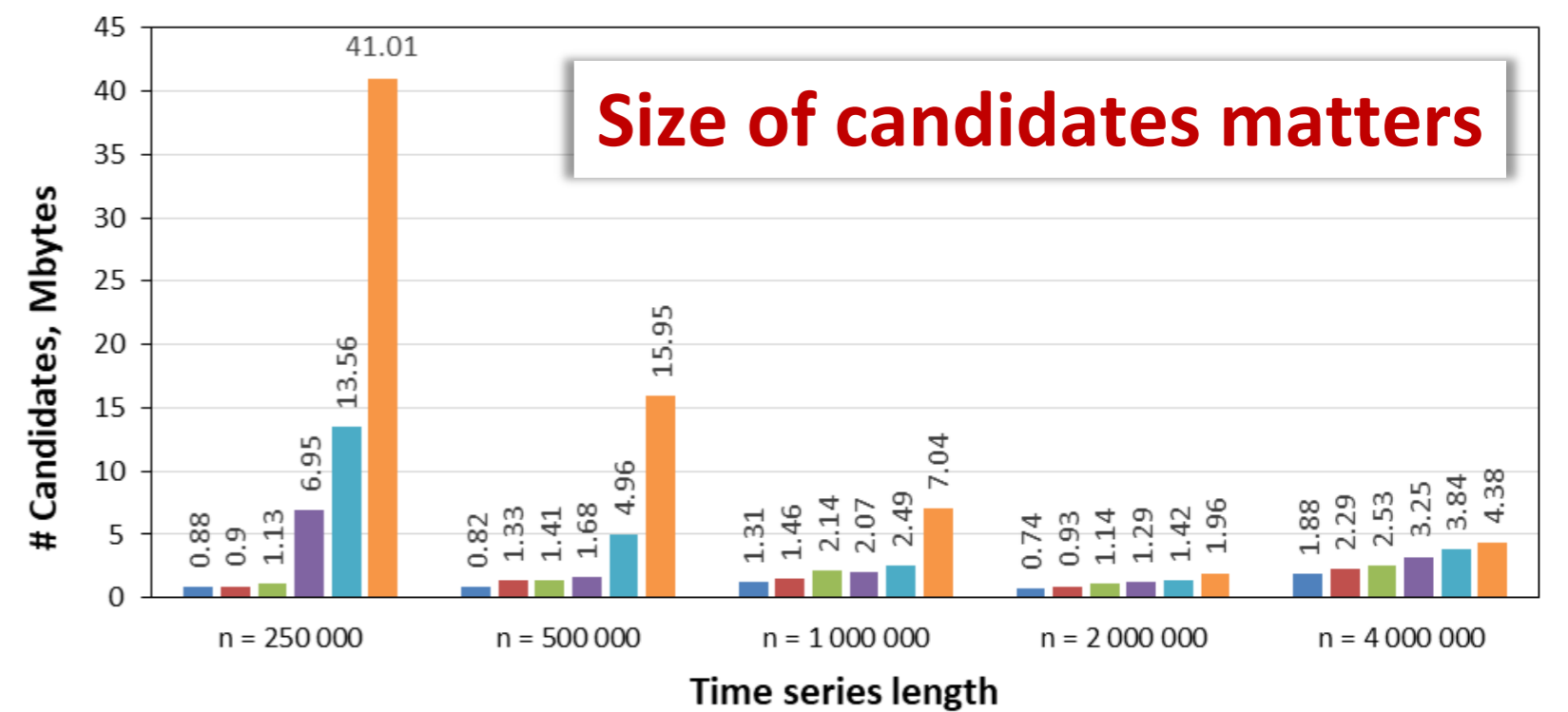
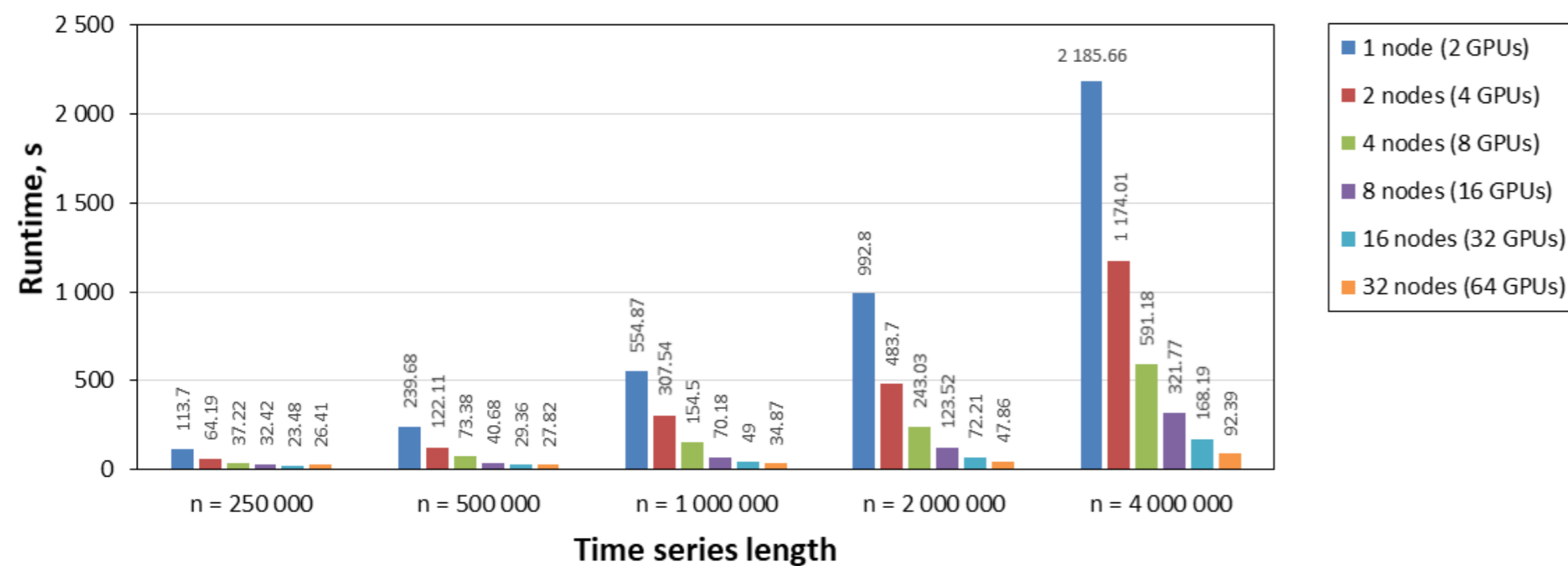
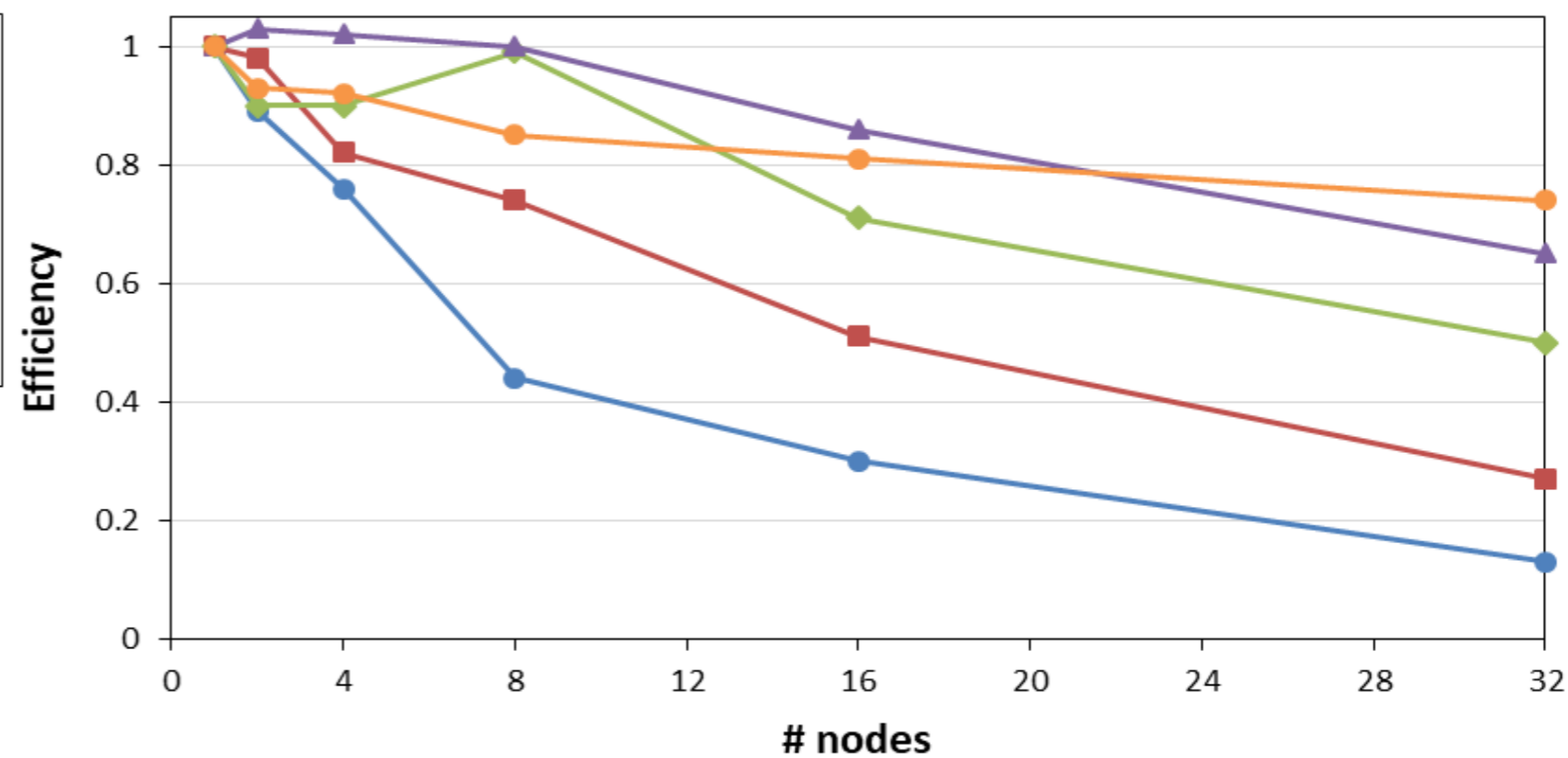
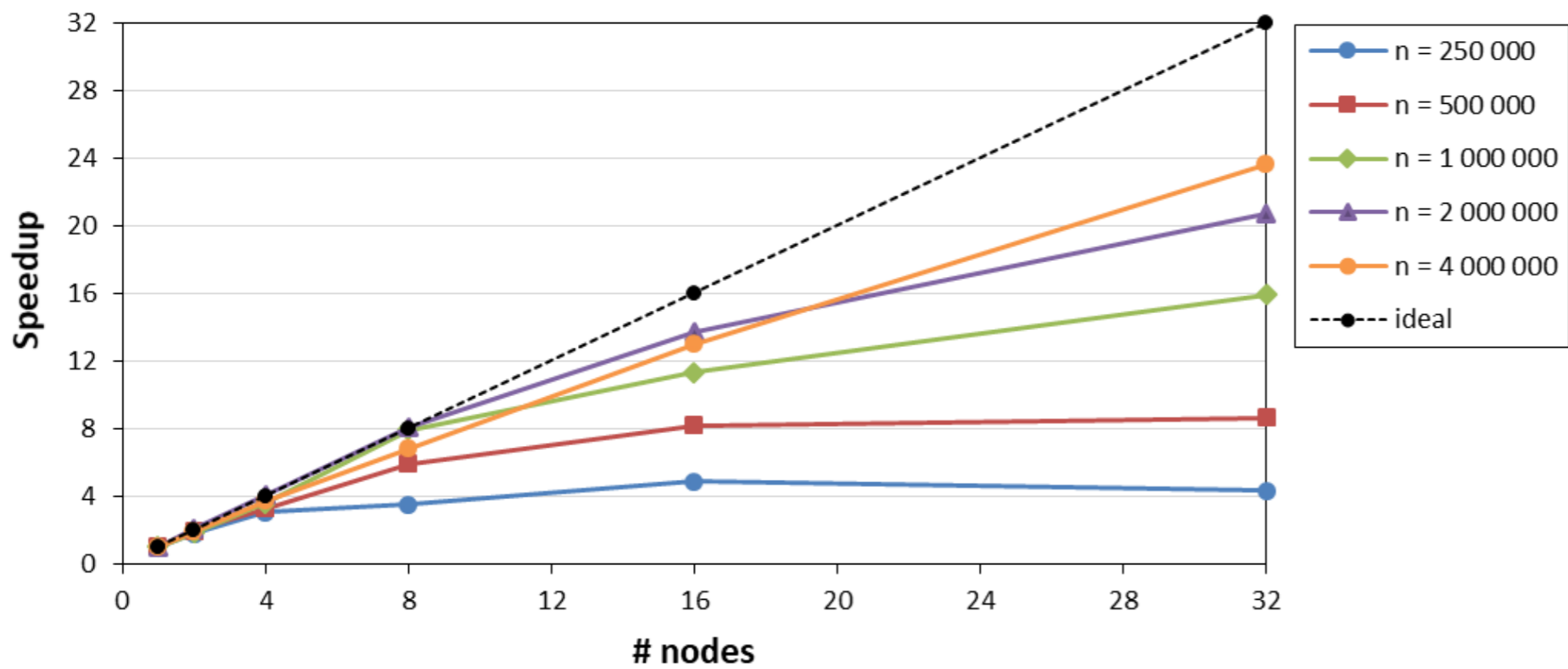
- **Measures**

- Performance: 10-runs averaged runtime without I/O
- Speedup: $s(p) = t_1/t_p$, where t_1 – runtime on one node, t_p – runtime on p nodes
- Parallel efficiency: $e(p) = s(p) / p$

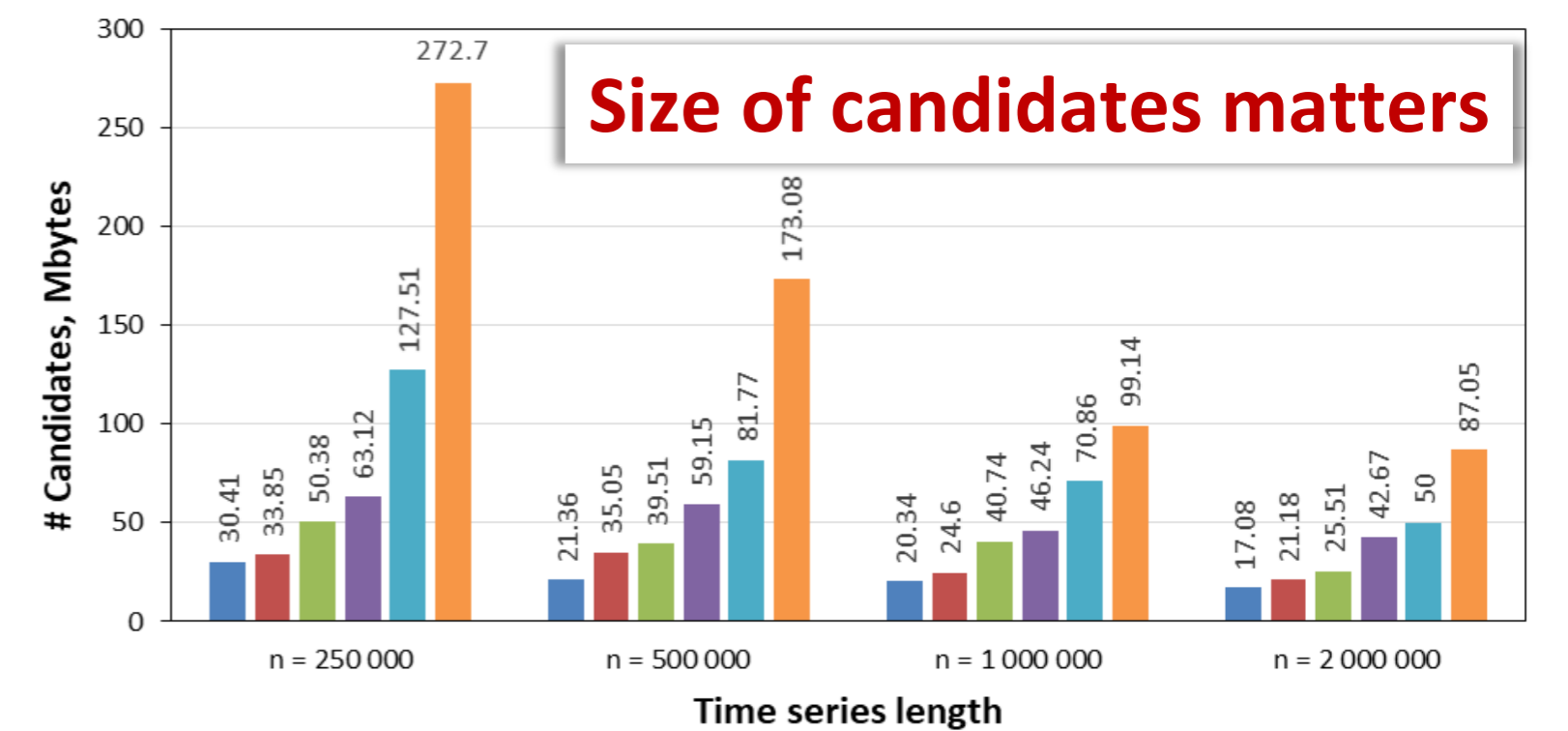
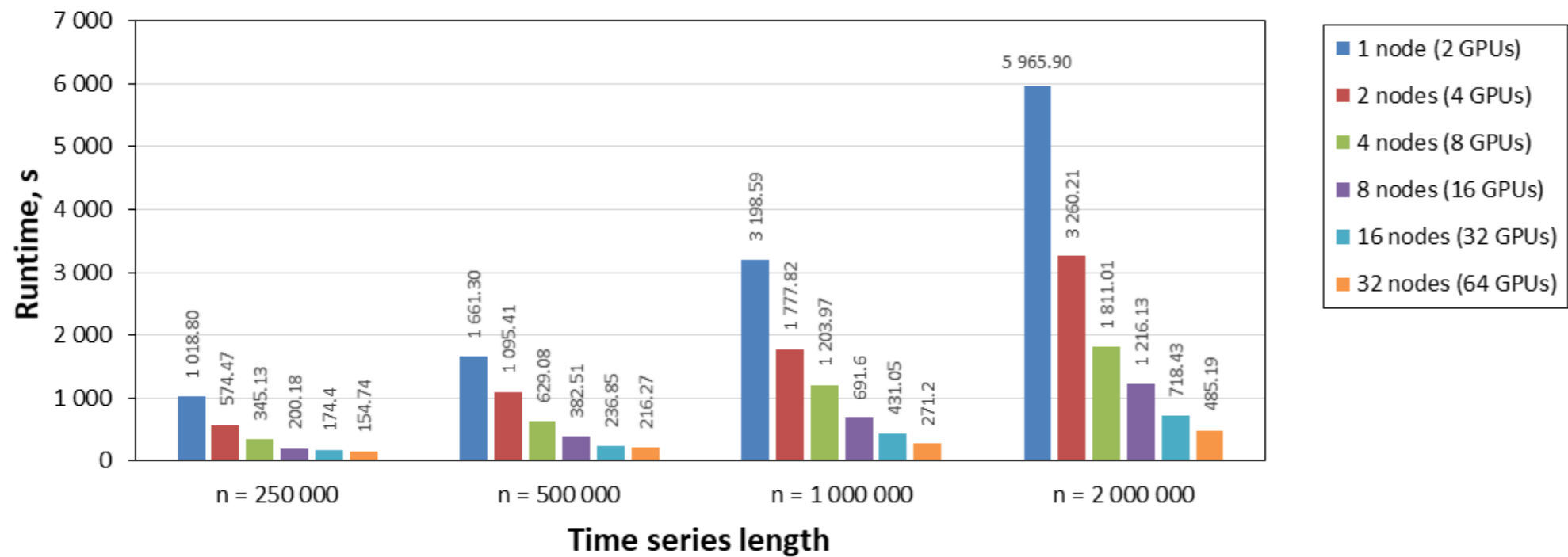
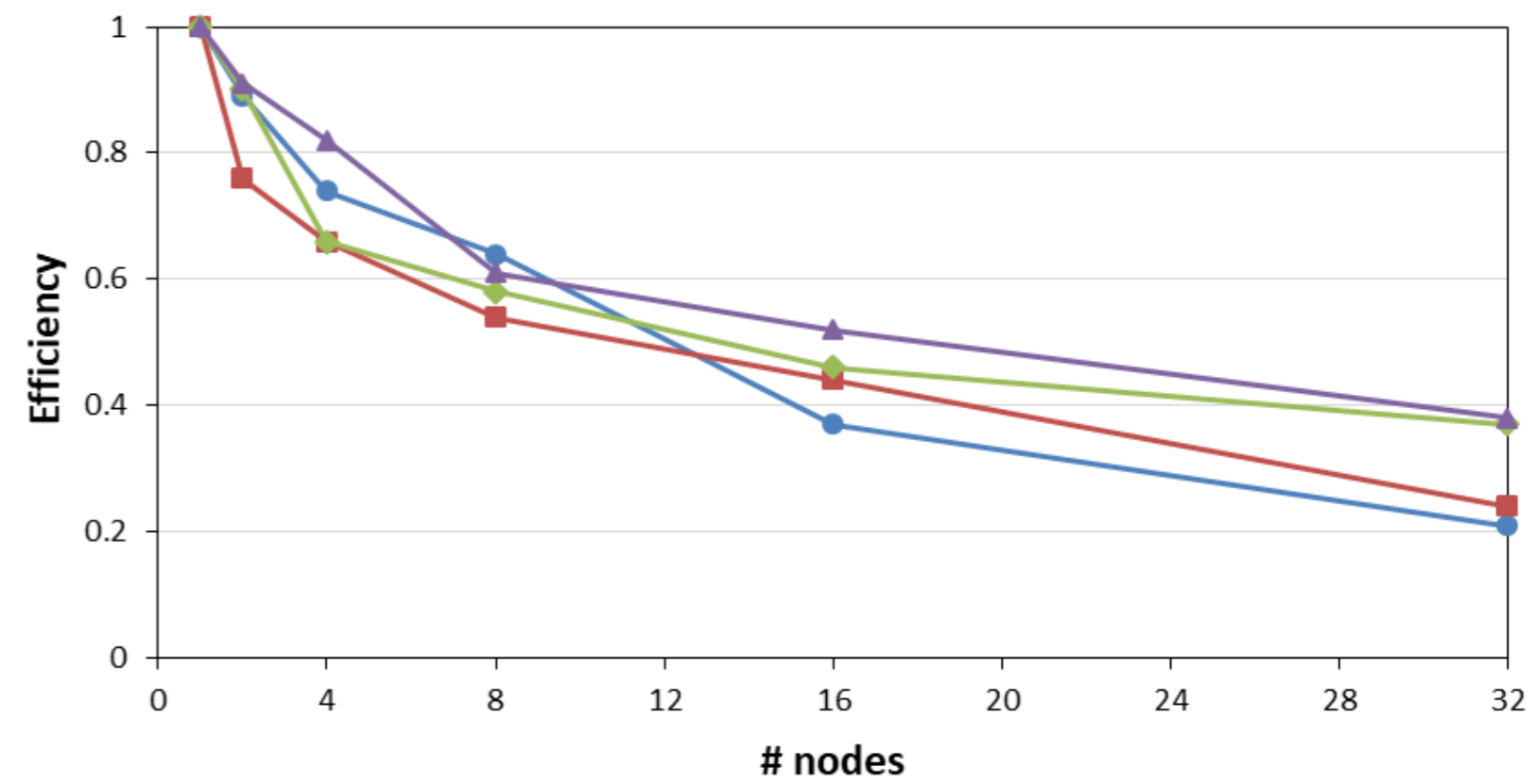
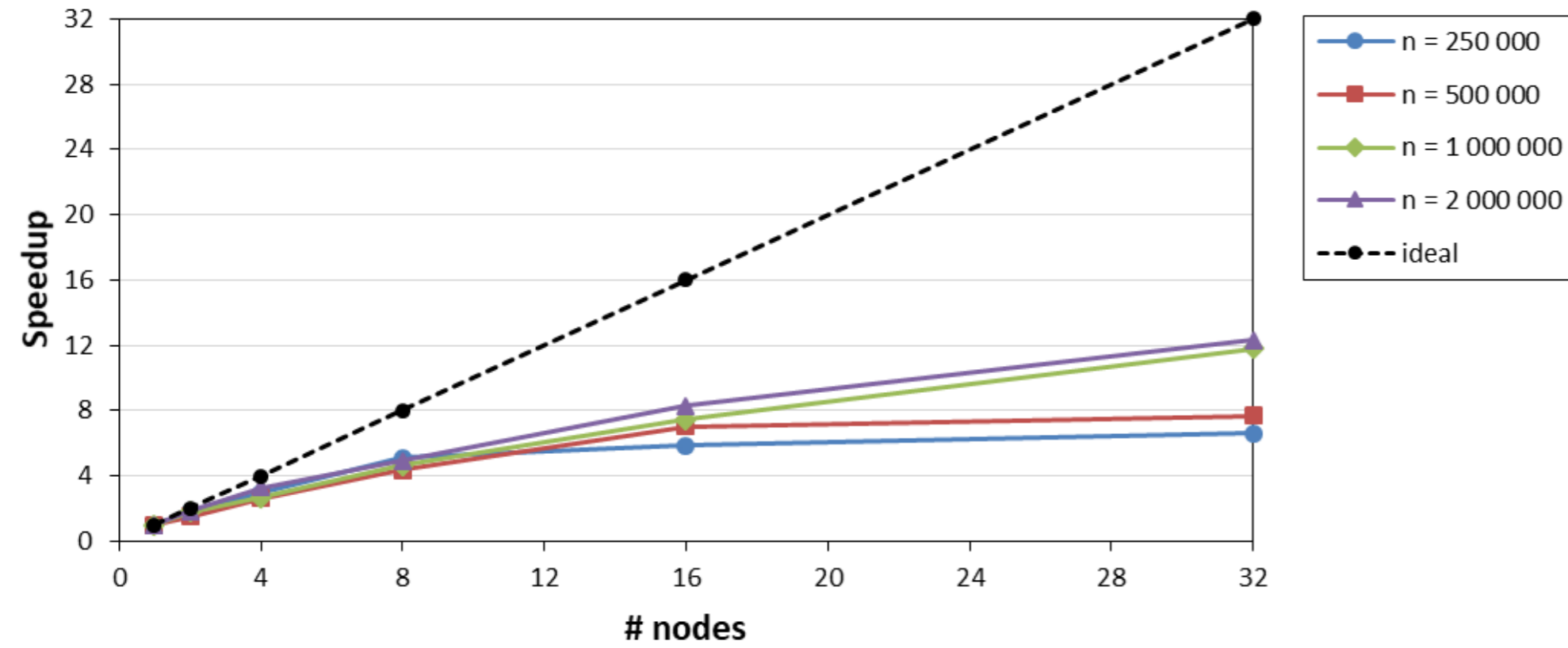
¹⁾ Lu Y. et al. Matrix Profile XXIV: Scaling Time Series Anomaly Detection to Trillions of Datapoints and Ultra-fast Arriving Data Streams. ACM SIGKDD 2022. pp. 1173-1182.

²⁾ Linardi M. et al. Matrix Profile X: VALMOD - Scalable Discovery of Variable-Length Motifs in Data Series. SIGMOD 2018. pp. 1053-1066.

Scalability: ECG



Scalability: GAP



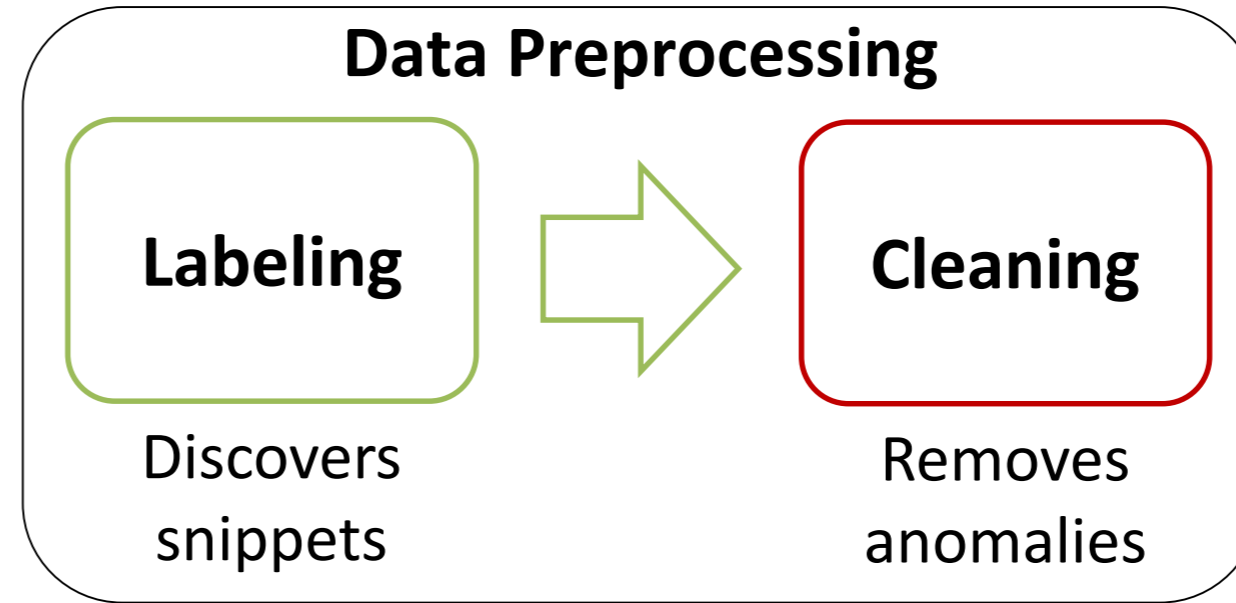
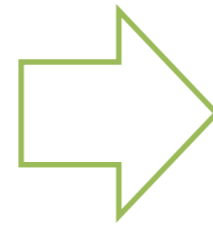
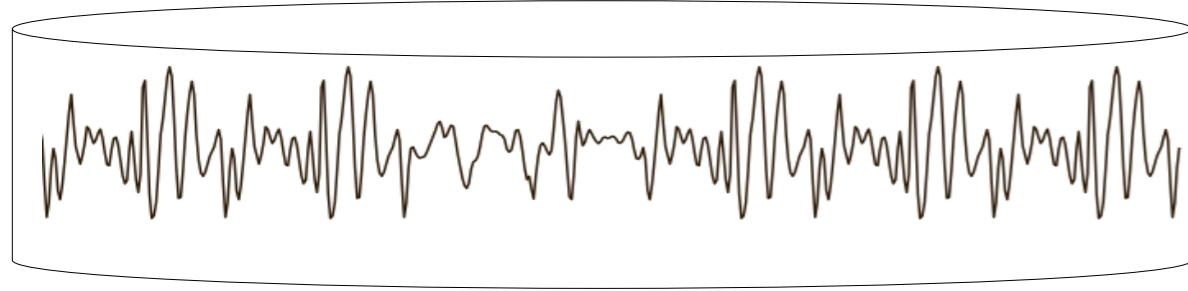
Limitations of PALMAD

PALMAD **cannot**

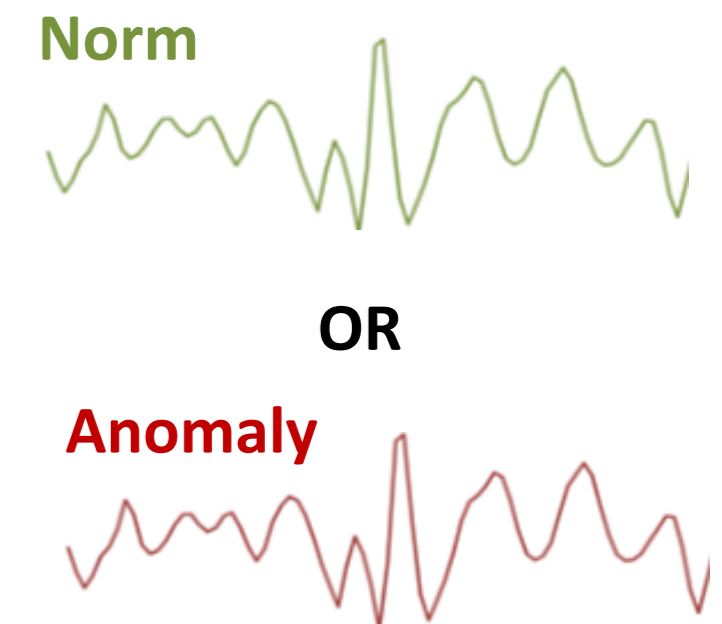
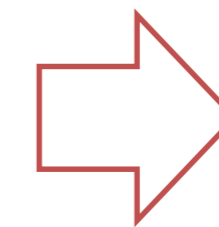
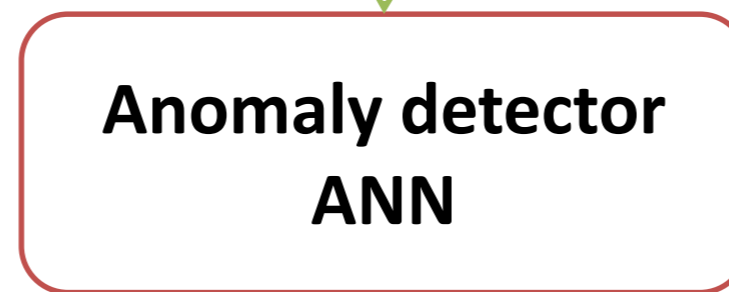
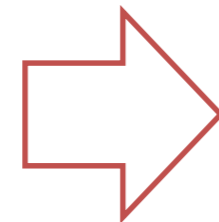
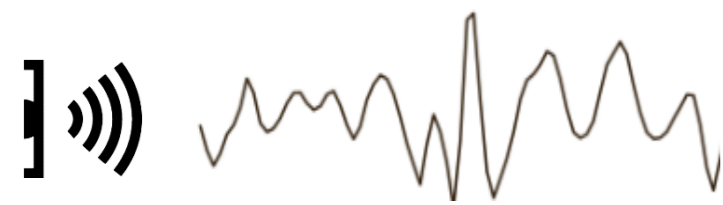
- deal with a time series that larger than RAM of a GPU
- **discover anomalies online**

Discover anomalies online: DiSSiD (Discord, Snippet, and Siamese Net-based Detector)

Representative fragment of time series

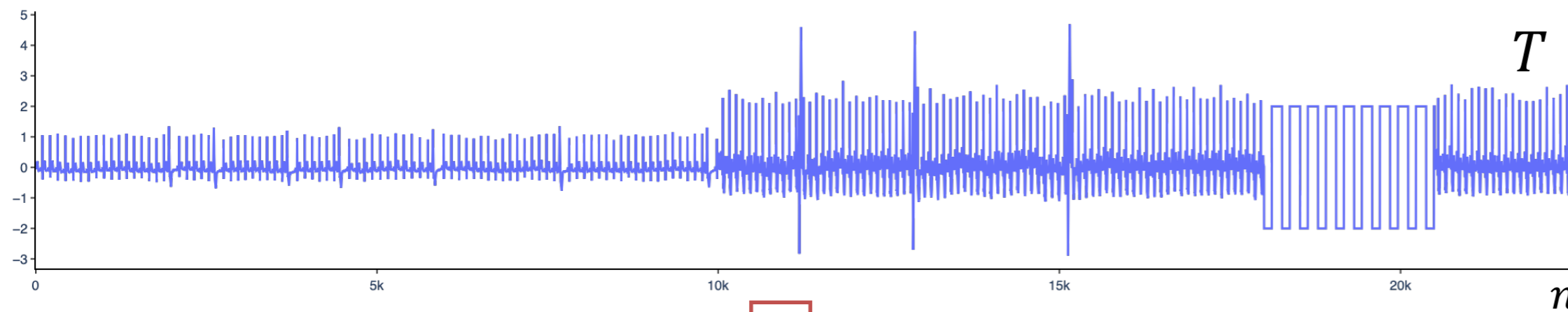


Potentially anomalous subsequence

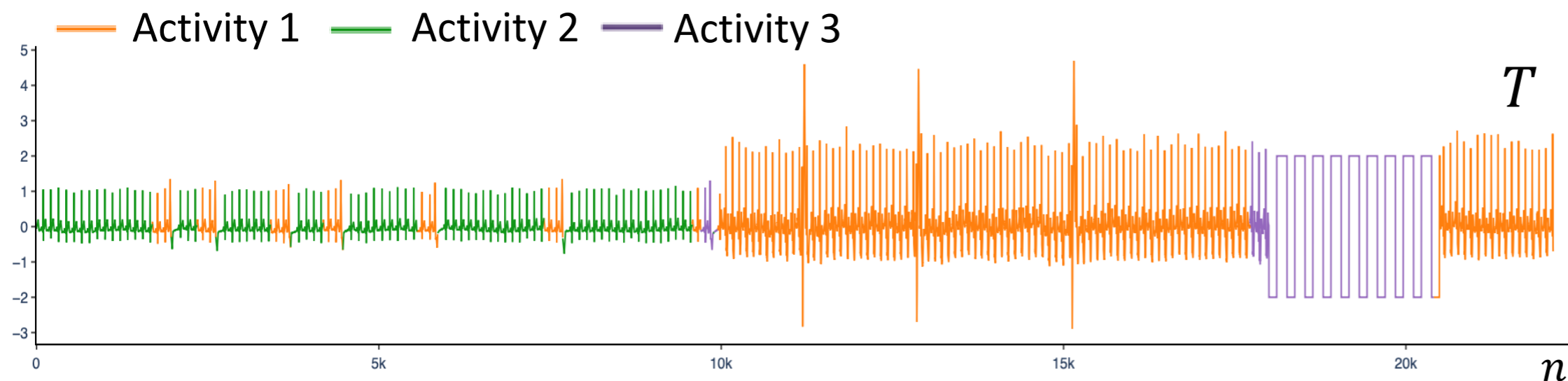


DiSSiD: Labeling

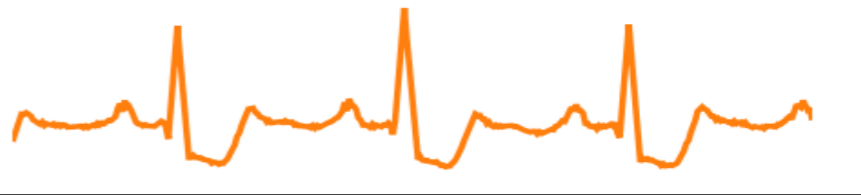

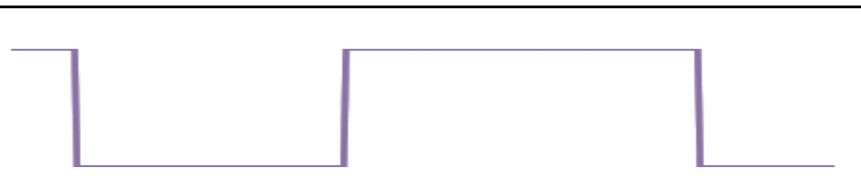
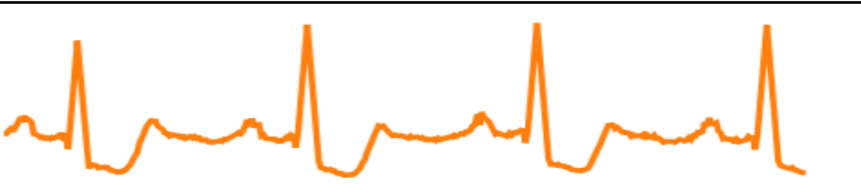
- Labeling is based on the snippet concept¹⁾
- PSF (Parallel Snippet Finder)²⁾ is applied for snippet discovery



PSF



Labeled set L

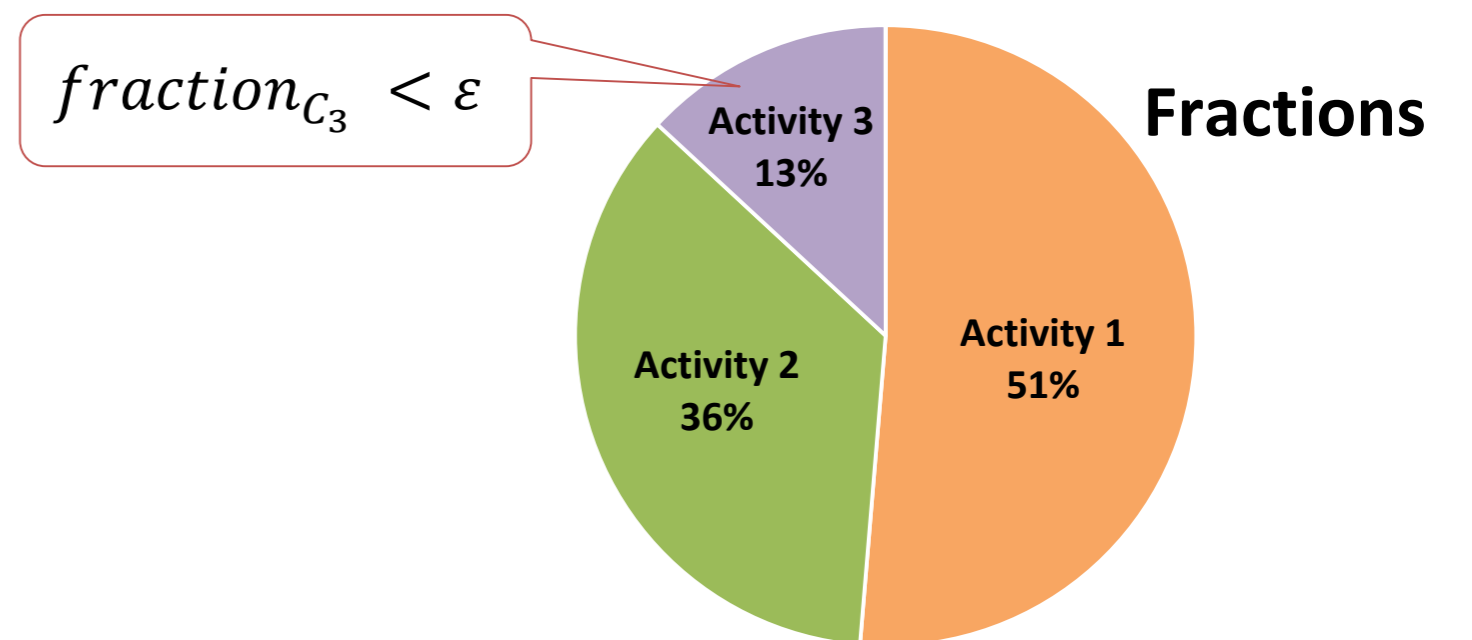
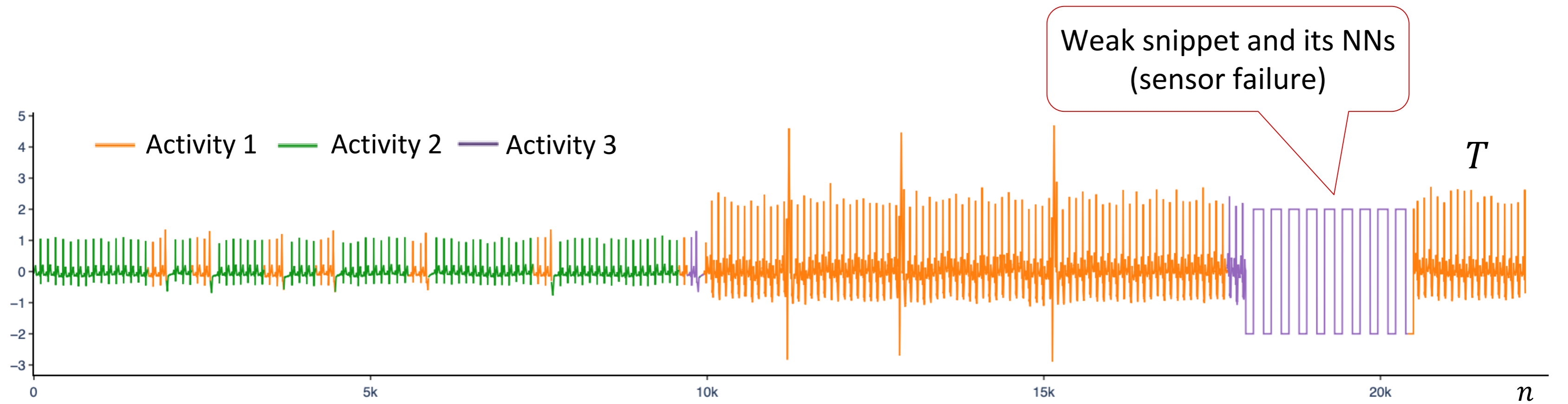
Subsequence	Label
	1
	2
	3
...	...
	1

m

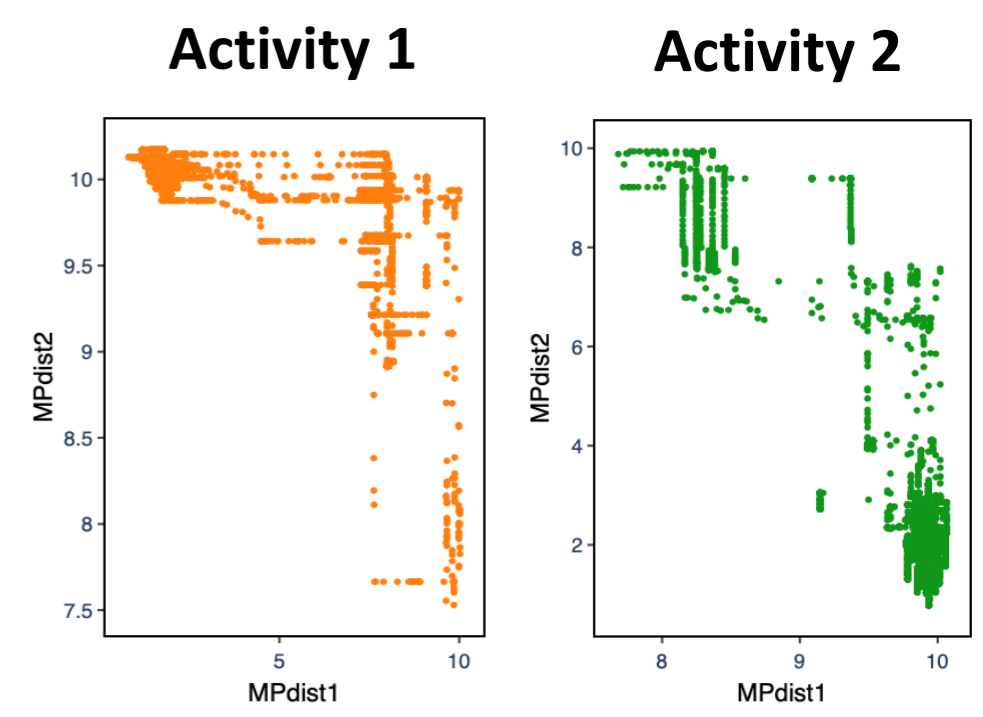
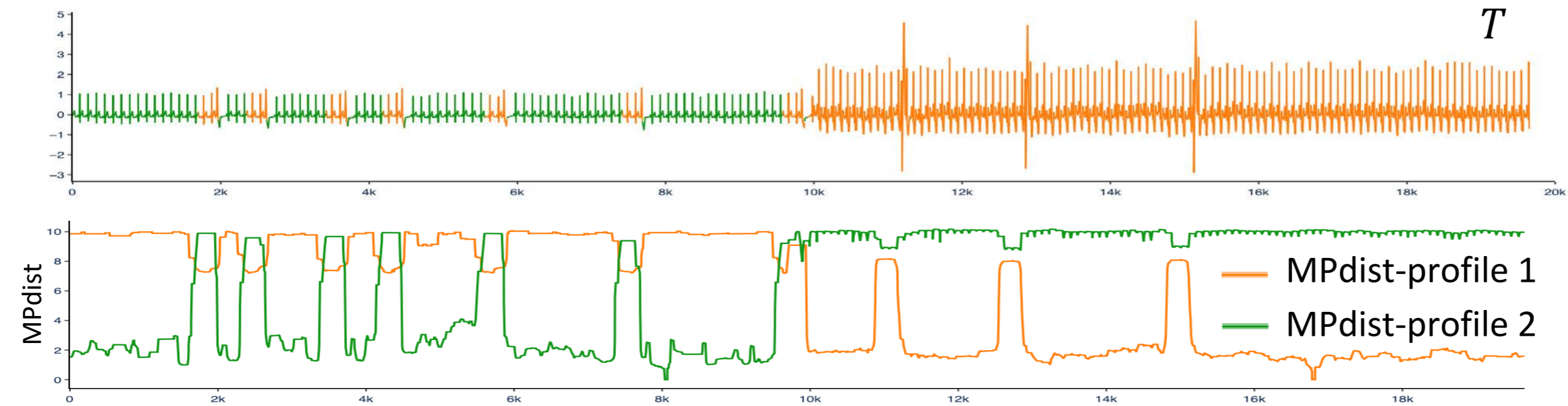
¹⁾ Imani S., et al. Introducing time series snippets: a new primitive for summarizing long time series. Data Min. Knowl. Discov. 34(6): 1713-1743 (2020). DOI: [10.1007/s10618-020-00702-y](https://doi.org/10.1007/s10618-020-00702-y)

²⁾ Zymbler M., Goglavchev A. Fast Summarization of Long Time Series with Graphics Processor. Mathematics 10(10). Article 1781. 2022. DOI: [10.3390/math10101781](https://doi.org/10.3390/math10101781)

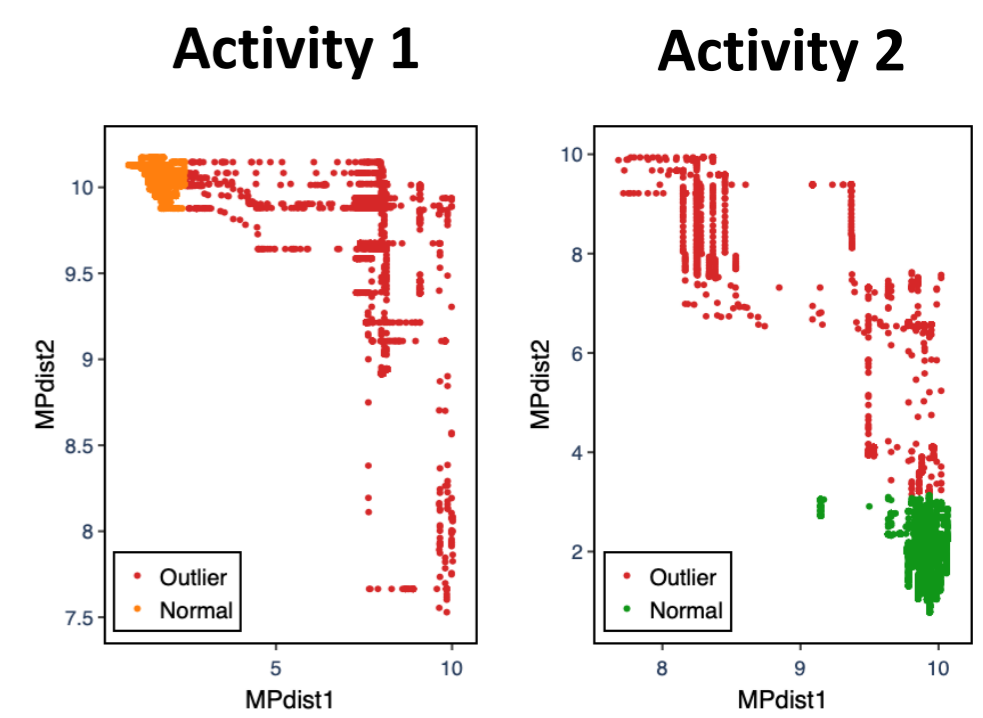
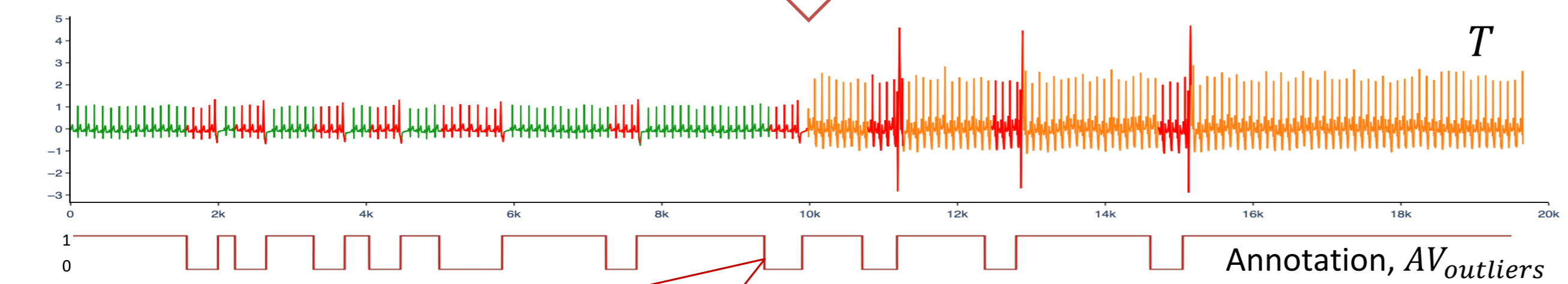
DiSSiD: Cleaning by removing weak snippets (rare activities)



DiSSiD: Cleaning by removing outlier neighbors

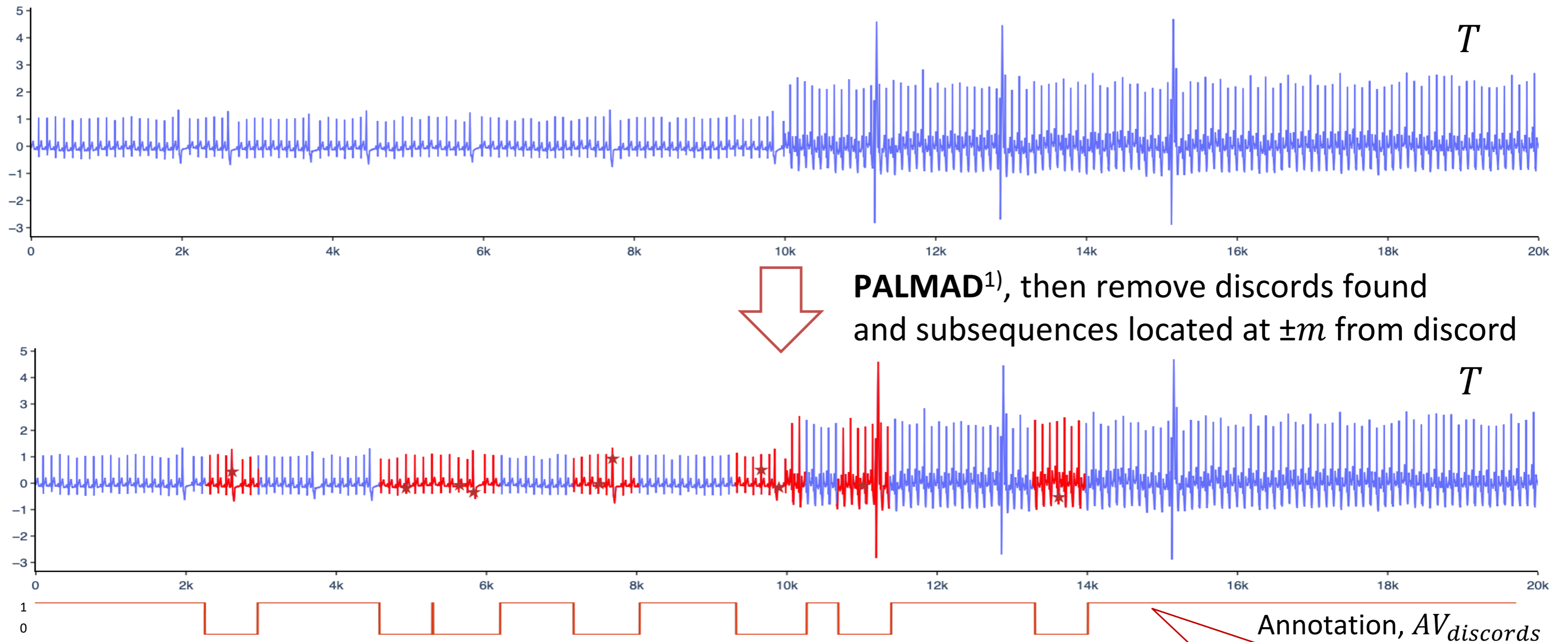


Outlier detection in \mathbb{R}^K



$$AV_{outliers}[i] = \begin{cases} 0, & T_{i,m} \text{ is outlier} \\ 1, & \text{otherwise} \end{cases}$$

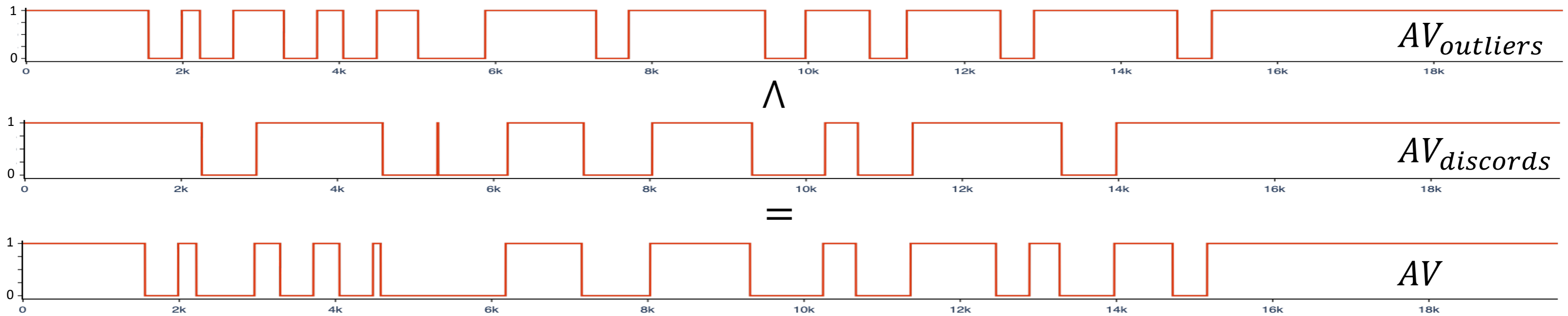
DiSSiD: Cleaning by removing discords and their trivial matches



$$AV_{discords}[i] = \begin{cases} 0, & T_{i,m} \in D \\ 1, & otherwise \end{cases}$$

¹⁾ Zymbler M., Kraeva Y. High-performance Time Series Anomaly Discovery on Graphics Processors. CoRR. 2023. Vol. abs/2304.01660. arXiv: 2304.01660.

DiSSiD: Cleaning



Labeled set L

Subsequence	Label
	1
	2
...	...
	1

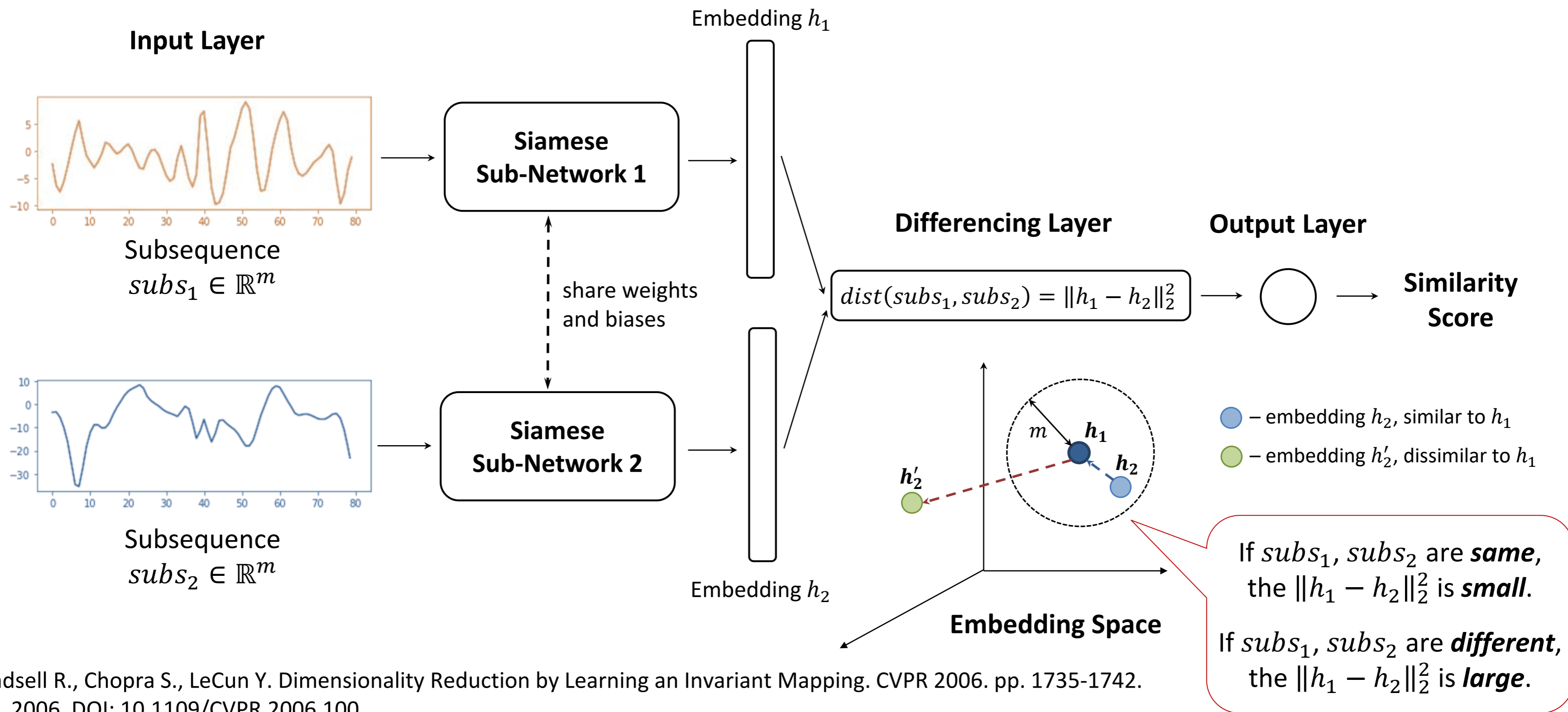
Anomaly set $\{s_i \in L \mid AV(i) = 0\}$

Subsequence
...

“Normalized” set L

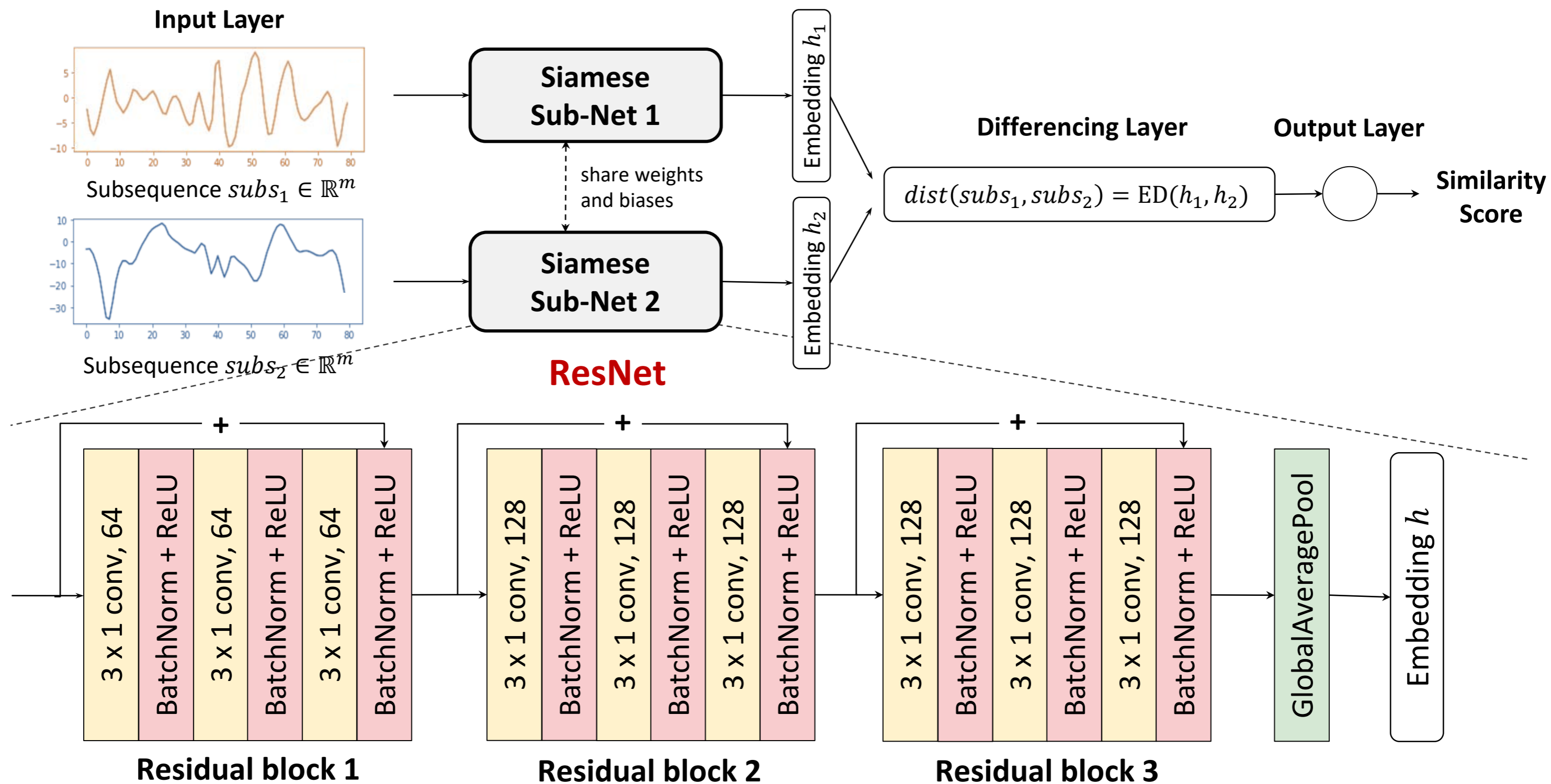
Subsequence	Label
	1
	2
...	...
	2

DiSSiD: Siamese Network*



* Hadsell R., Chopra S., LeCun Y. Dimensionality Reduction by Learning an Invariant Mapping. CVPR 2006. pp. 1735-1742. IEEE, 2006. DOI: 10.1109/CVPR.2006.100.

DiSSiD: ResNet*

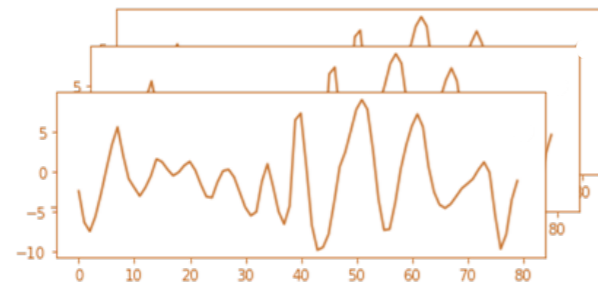
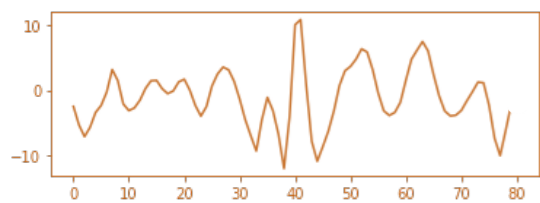


* Wang Z., et al. Time series classification from scratch with deep neural networks: A strong baseline. IJCNN 2017. pp. 1578-1585. IEEE, 2017. DOI: 10.1109/IJCNN.2017.7966039.

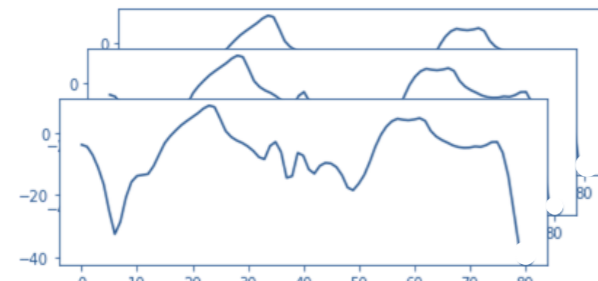
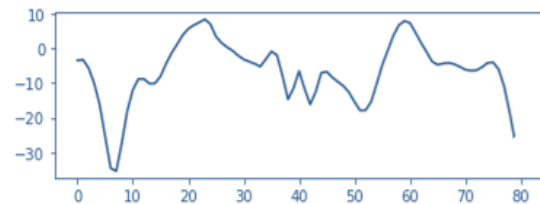
DiSSiD: Model training

“Normalized” set L

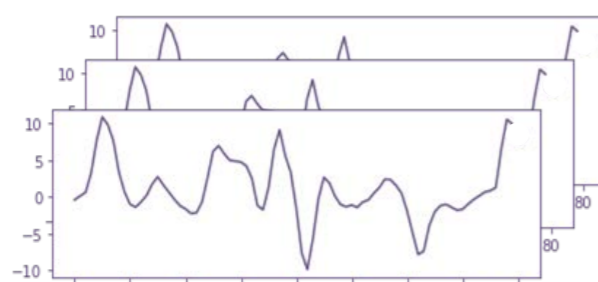
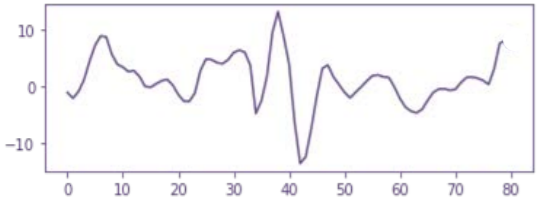
Snippet₁ and its Nearest Neighbors



Snippet₂ and its Nearest Neighbors

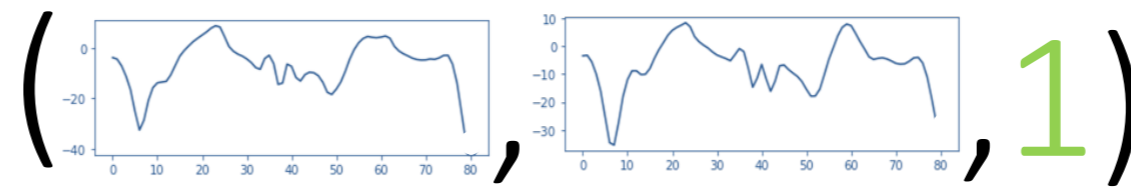


Snippet₃ and its Nearest Neighbors

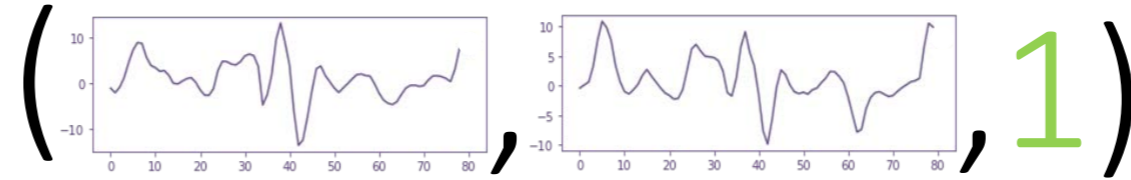


Training set

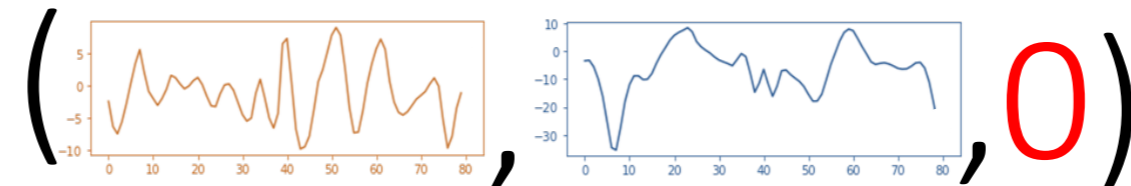
Positive samples



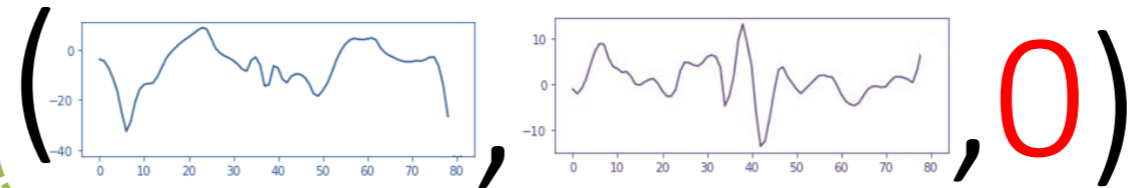
⋮



Negative samples



⋮



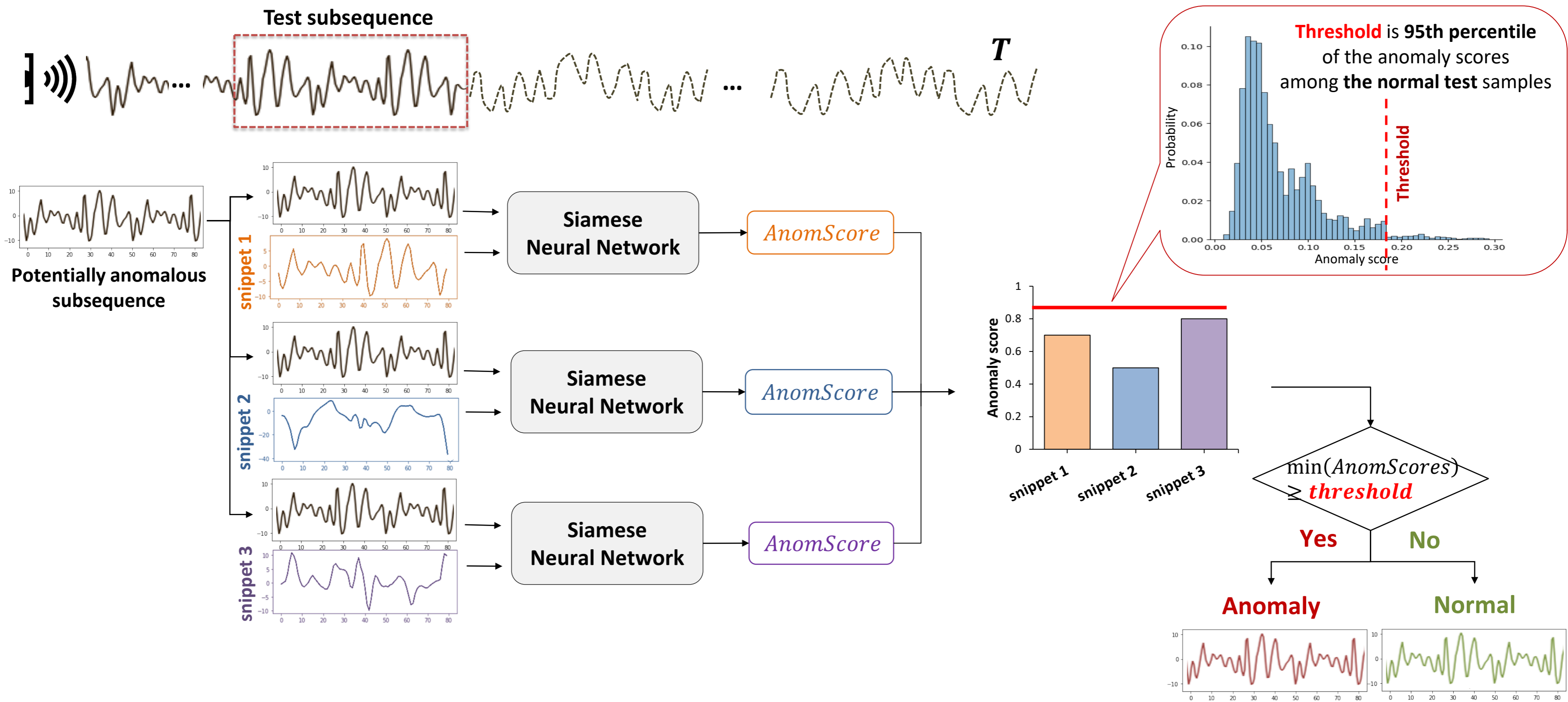
Max # **positive** pairs =

$$= \sum_{i=1}^K \binom{|C_i \cdot NN|}{2}$$

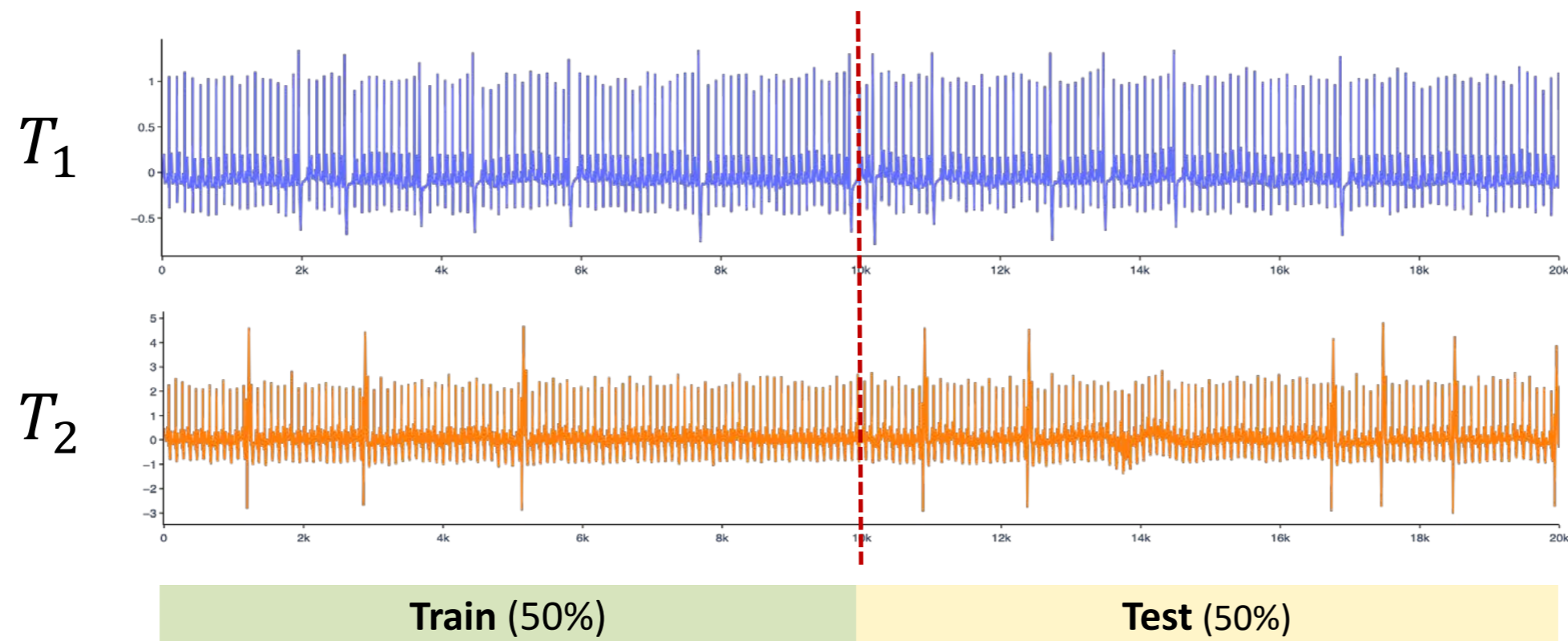
Max # **negative** pairs =

$$= \sum_{i=1}^K \sum_{j=i}^K |C_i \cdot NN| \cdot |C_j \cdot NN|$$

DiSSiD: Online anomaly detection



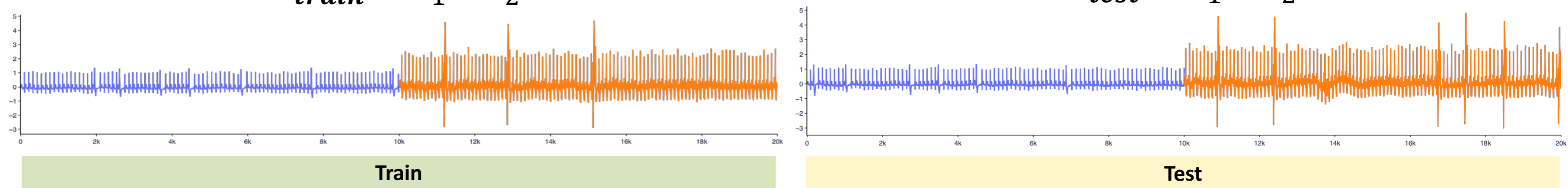
Experiments: Data generation



Concatenate
the corresponding parts
of time series

$T_{train} = T_1^1 \cdot T_2^1$

$T_{test} = T_1^2 \cdot T_2^2$



Experiments: Setup

- **Hardware:** Neurocomputer SUSU, NVIDIA Ampere A100 PCIe (6 912 CUDA-cores, 9.7 TFLOPS)
- **Data:** MIT-BIH Arrhythmia Database¹⁾
 - For generating the labeled set:

Time series	Training time series length, n_{train}	Test time series length, n_{test}	Snippet length, m	Subsequence length, l	Snippet number, K	Discord fraction, α
ECG_803_805	$5 \cdot 10^4$	$5 \cdot 10^4$	350	75	2	0.0002
ECG_803_806	$5 \cdot 10^4$	$5 \cdot 10^4$	350	75	2	0.0002

– For neural network learning: generate 170 000 pairs (2 positive + 2 negative pairs per 1 subsequence)

- **Measure:** $Precision = \frac{TP}{TP+FP}$, TP – true anomalies detected, FP – false positive anomalies detected

- **Neural Network Hyperparameters:**

– **Loss function:** contractive loss

$$L(x_i, x_j, z_{i,j}) = z_{i,j} ED^2(h_i, h_j) + (1 - z_{i,j}) \max\left(0, \tau - ED(h_i, h_j)\right)^2,$$

where τ – margin between samples of different classes

– **Optimizer:** Adam

– **# Epochs:** 40

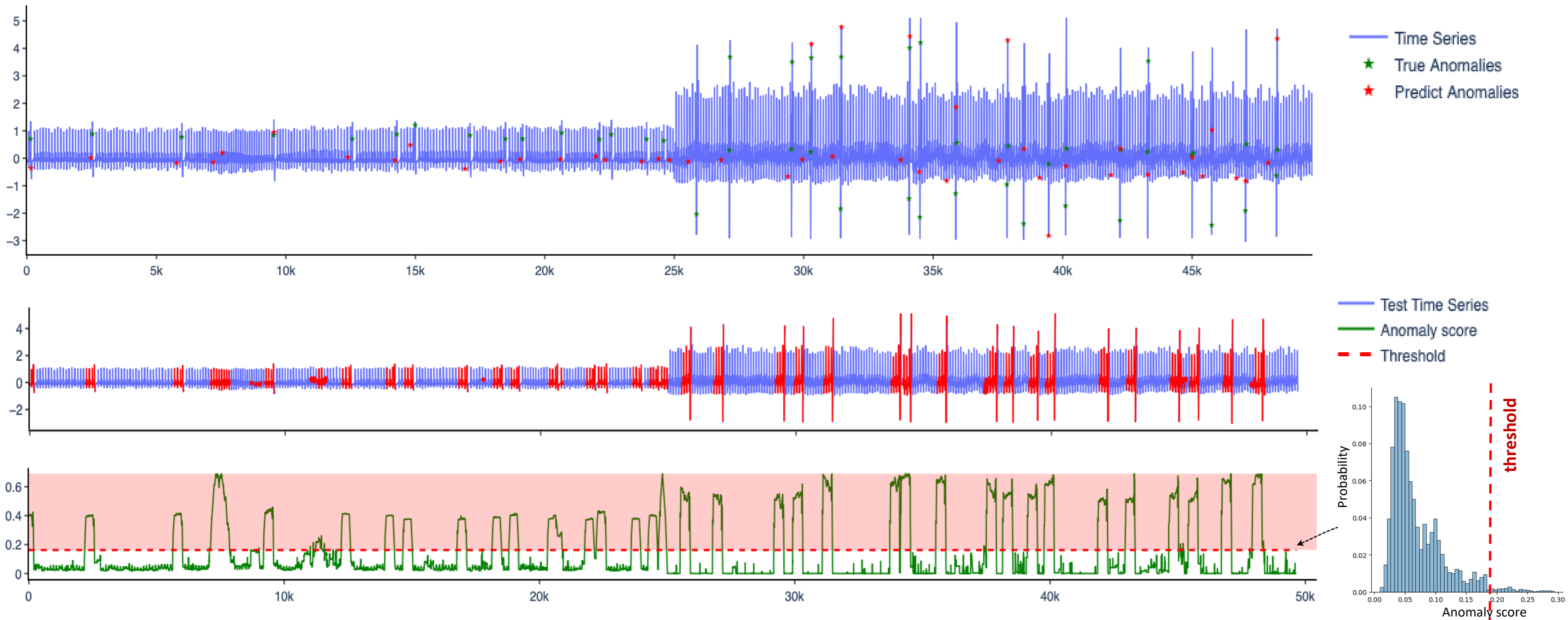
– **Batch size:** 128

– **Learning rate:** $1 \cdot 10^{-3}$

– **Embedding size:** 128

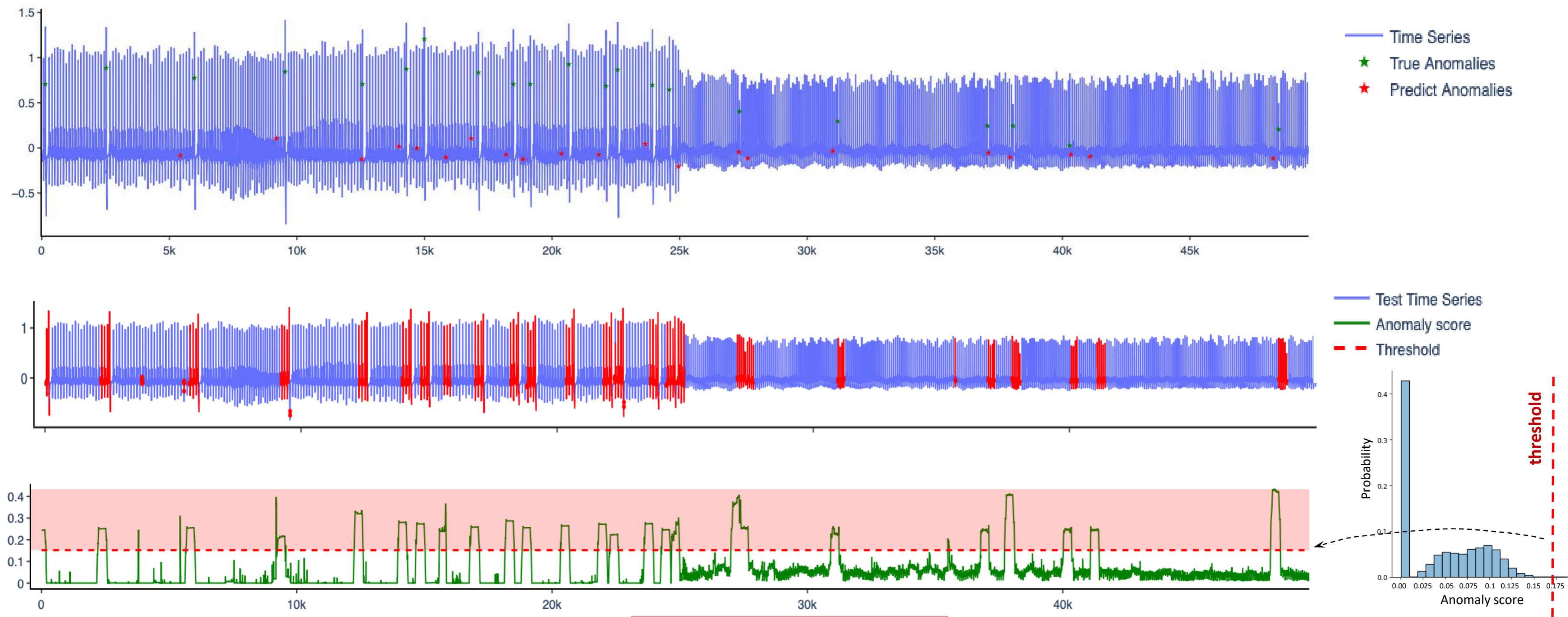
¹⁾ Goldberger A. L., et al. PhysioBank, PhysioToolkit, and PhysioNet components of a new research resource for complex physiologic signals. Circulation 101(23): 215-220. 2000.

Experiments: ECG_803_805



Precision = 0.915

Experiments: ECG_803_806



Precision = 0.81

Conclusions

- The results obtained:
 - parallel algorithm for discord discovery on HPC cluster with multi-GPU nodes
 - method for online anomaly detection
- Further research:
 - extensive experiments: time series from various domains, rivals, etc.
 - upgrade the method to make it adaptive

Thank you for your attention! Questions?

Kraeva Yana

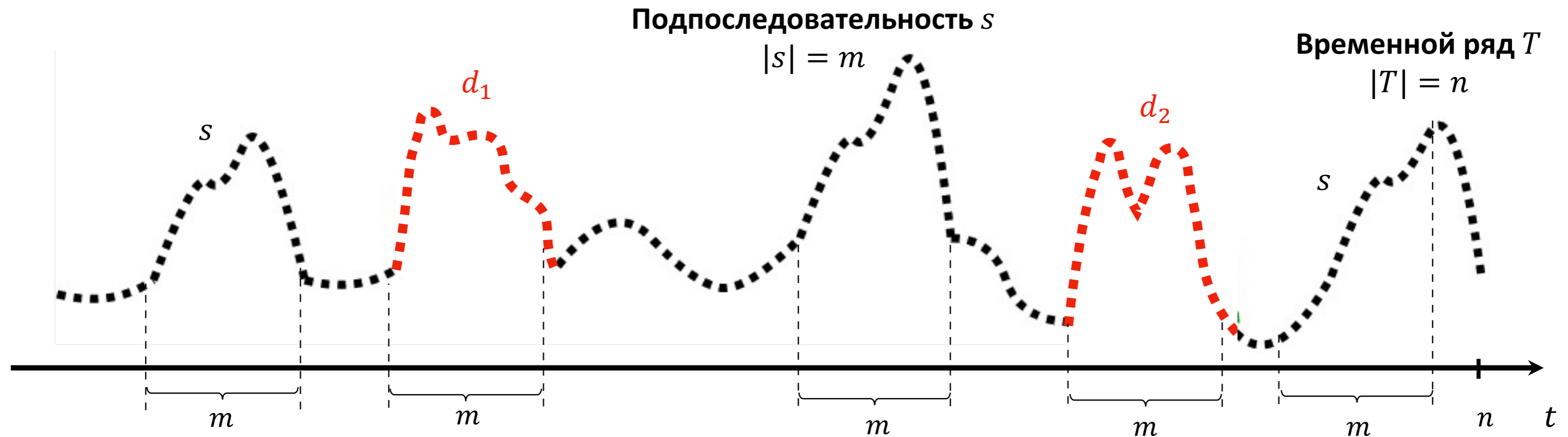
kraevaya@susu.ru

Основные работы по теме исследования

Алгоритм	Платформа	Критика
Последовательный алгоритм		
Nakamura T., <i>et al.</i> MERLIN : parameter-free discovery of arbitrary length anomalies in massive time series archives. IEEE ICDM 2020. pp. 1190-1195.	CPU	Квадратичная сложность от длины ряда
Параллельные алгоритмы		
DRAG : Yankov D., <i>et al.</i> Disk aware discord discovery: finding unusual time series in terabyte sized datasets. Knowl. Inf. Syst. 17(2): 241-262. 2008.	CPU	Симуляция MapReduce
PDD : Huang T., <i>et al.</i> Parallel discord discovery. PAKDD 2016. LNCS 9652. Springer, 2016. pp. 233-244.	Spark	Низкая производительность ввиду большого количества обменов между узлами
PhiDD : Zymbler M., <i>et al.</i> A Parallel Approach to Discords Discovery in Massive Time Series Data. Computers, Materials & Continua 66(2): 1867-1876. 2021.	Кластер Intel Xeon Phi	Квадратичная пространственная сложность от длины ряда
KBF_GPU : Thuy T.T.H., <i>et al.</i> A new discord definition and an efficient time series discord detection method using GPUs. ICSED 2021. pp. 63-70.	GPU	Полный перебор подпоследовательностей ряда
Zhu B., et al. A GPU Acceleration framework for motif and discord based pattern mining. IEEE Trans. on Parallel and Distr. Systems 32(8): 1987-2004. 2021.	GPU	Поиск одного (самого важного) диссонанса ряда
PD3 : Zymbler M., Kraeva Ya. Parallel algorithm for time series discord discovery on a graphics processor. Pattern Recognition and Image Analysis 33(2). 2023.	GPU	Ручной подбор длины диссонанса и порога

Постановка задачи

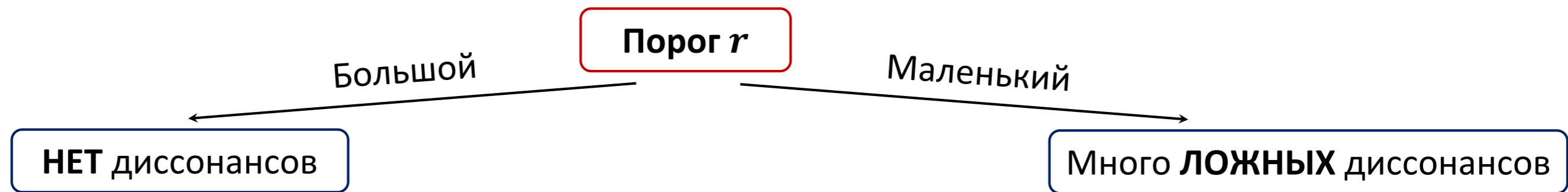
- **Диссонанс**¹⁾ – подпоследовательность ряда, расстояние от которой до ближайшего соседа не ниже порога r
- **Дано:** временной ряд T , длина диссонанса m , порог r
- **Найти:** $D = \{d_1, d_2, \dots\}$, $d_i \in D \Leftrightarrow \forall s \in T \min_{s \cap d_i = \emptyset} \text{dist}(d_i, s) \geq r$



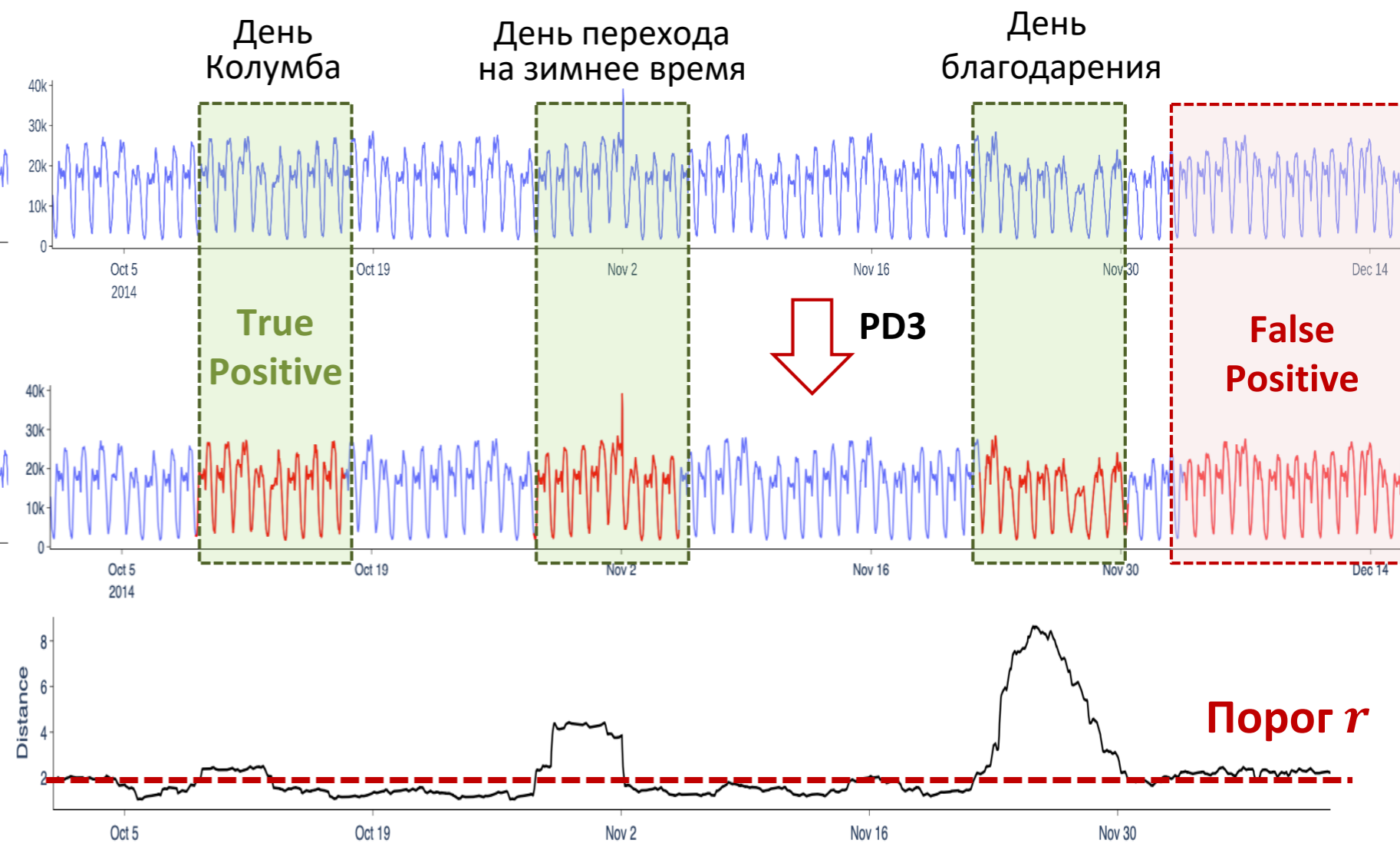
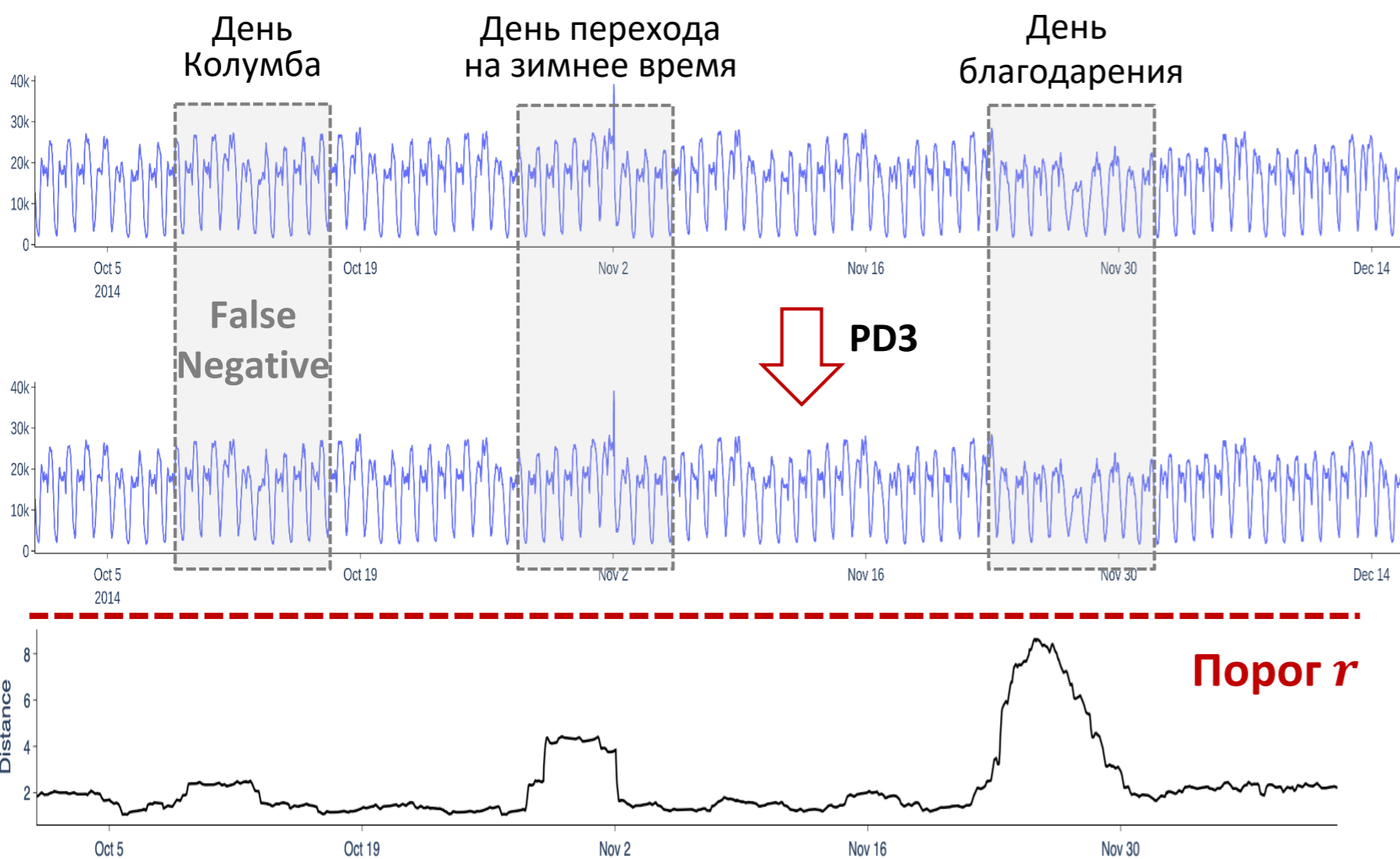
Количество подпоследовательностей: $N = n - m + 1$

¹⁾ Yankov D., Keogh E.J., Rebbapragada U. Disk aware discord discovery: finding unusual time series in terabyte sized datasets. Knowl. Inf. Syst. 17(2): 241-262. 2008.

PD3 (Parallel DRAG-based Discord Discovery): Ручной подбор r

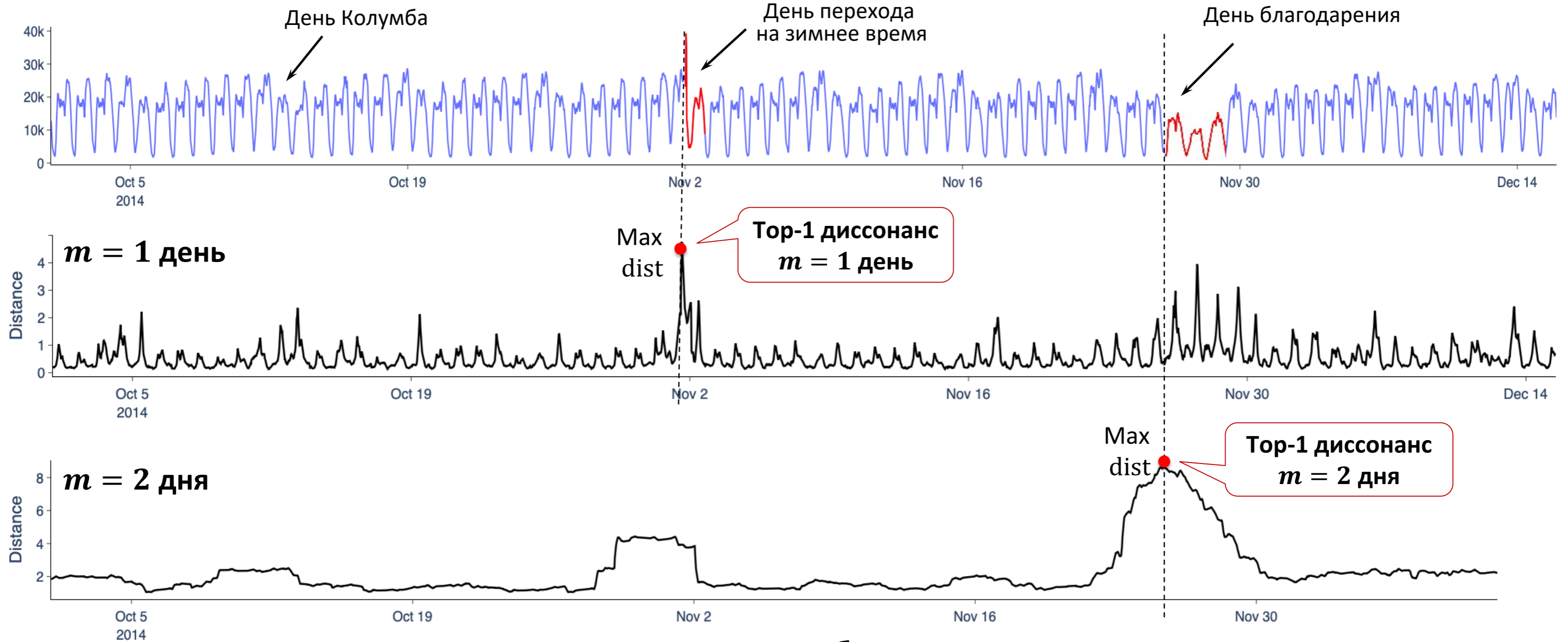


Среднее число пассажиров NY такси (осень 2014 г., каждые полчаса)



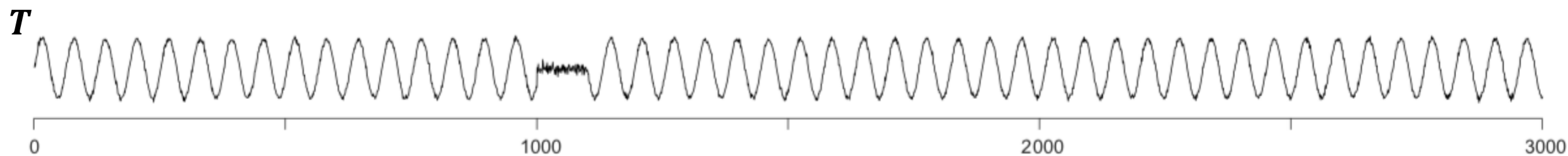
PD3 (Parallel DRAG-based Discord Discovery): Ручной подбор m

Среднее число пассажиров NY такси
(осень 2014 г., каждые полчаса)

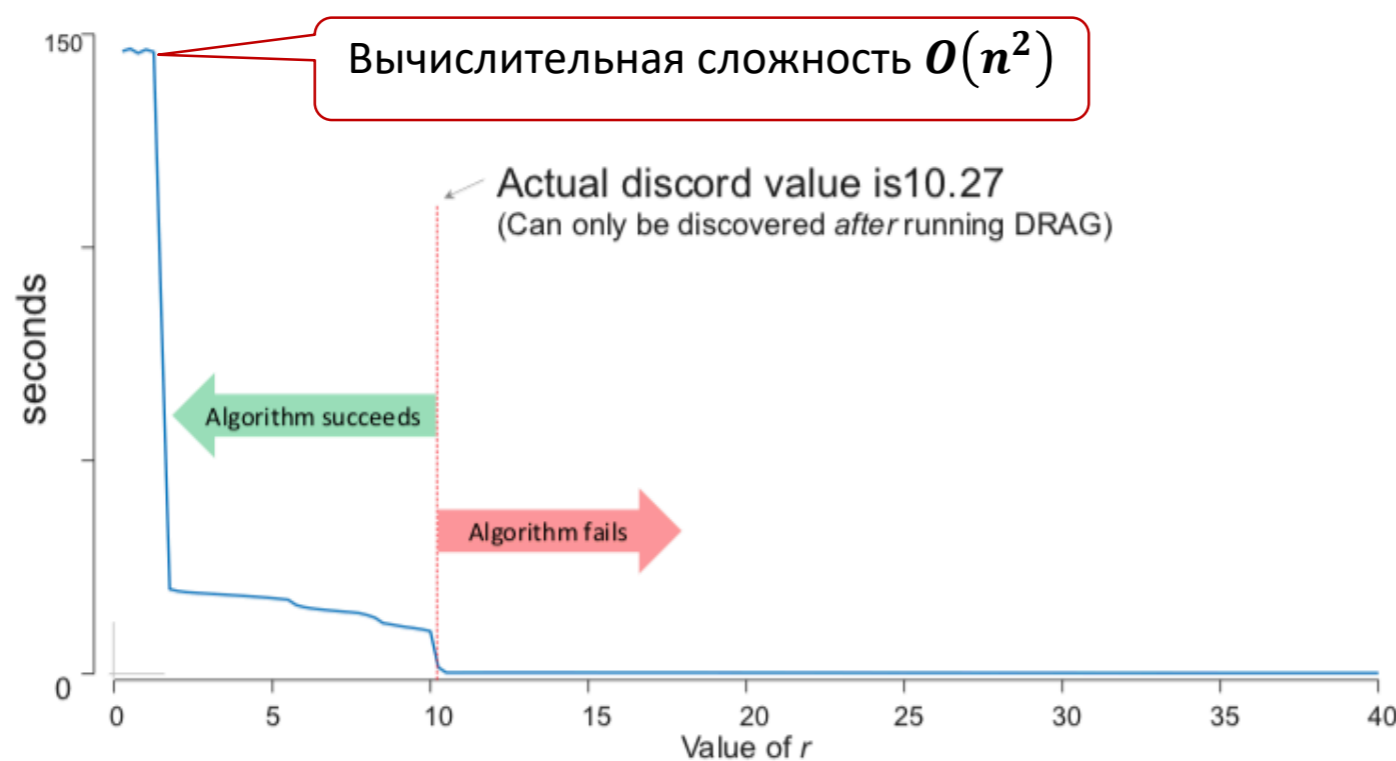


Накладные расходы на подбор параметров m и r

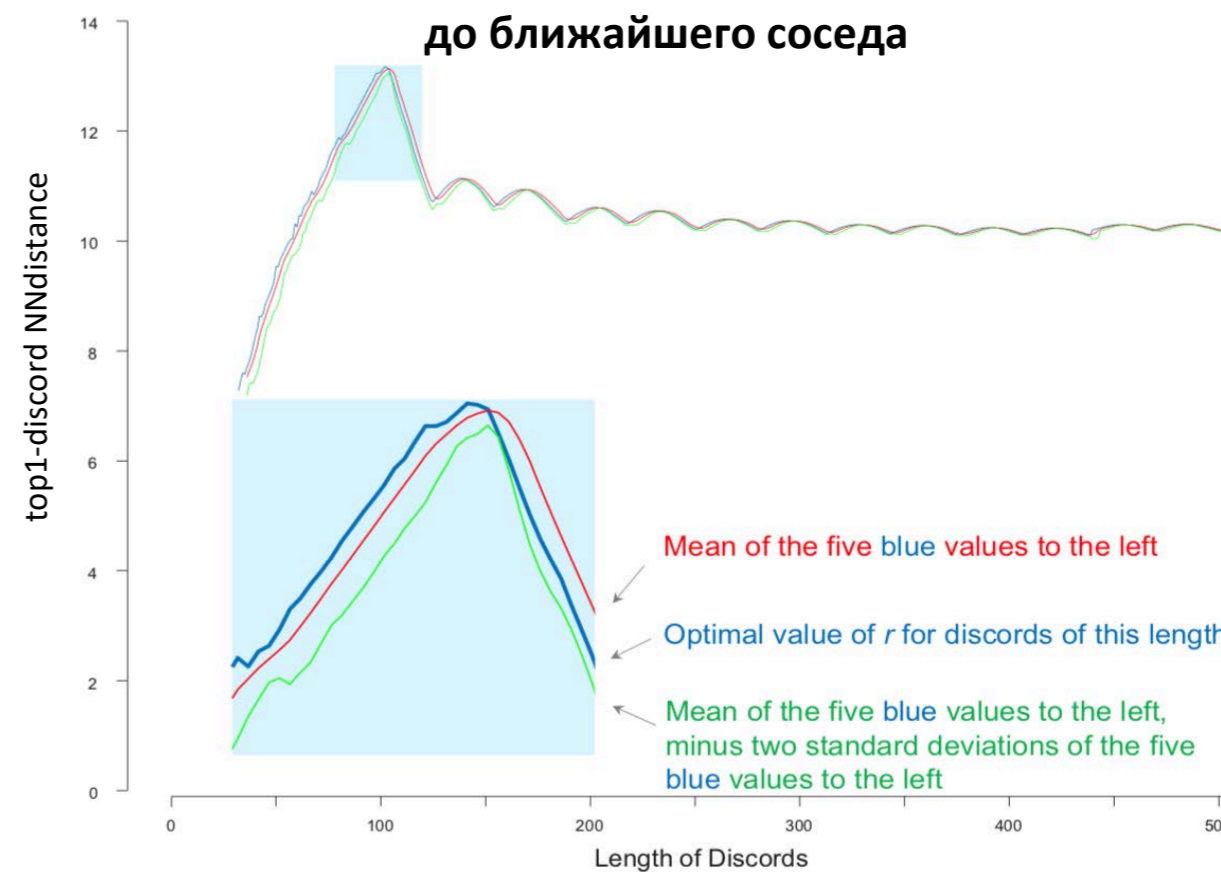
Подбор порога r



Влияние величины порога r на время выполнения DRAG



Влияние длины диссонанса на расстояние диссонанса до ближайшего соседа



Длина диссонанса, m	Порог, r
$\min L$	$r = 2\sqrt{\min L}$
$\min L + 1, \dots, \min L + 4$	$r = 0.99 * \text{nndist}(m - 1)$
$\min L + 5, \dots, \max L$	$r = \mu - 2\sigma$

PALMAD: Parallel Arbitrary Length MERLIN-based Anomaly Discovery

1. Применение ED_{norm}^2 в качестве функции расстояния¹⁾

$$ED_{\text{norm}}^2(T_{i,m}, T_{j,m}) = 2m \left(1 - \frac{T_{i,m} \cdot T_{j,m} - m\mu_i\mu_j}{m\sigma_i\sigma_j} \right)$$

2. Сокращение избыточных вычислений μ и σ при вычислении ED_{norm}^2

Лемма. Пусть даны ряд T , $|T| = n$ и подпоследовательности $T_{i,m}$ и $T_{i,m+1}$. Тогда

$$\mu_{T_{i,m+1}} = \frac{1}{m+1} (m\mu_{T_{i,m}} + t_{i+m}), \quad \sigma_{T_{i,m+1}}^2 = \frac{m}{m+1} \left(\sigma_{T_{i,m}}^2 + \frac{1}{m+1} (\mu_{T_{i,m}} - t_{i+m})^2 \right).$$

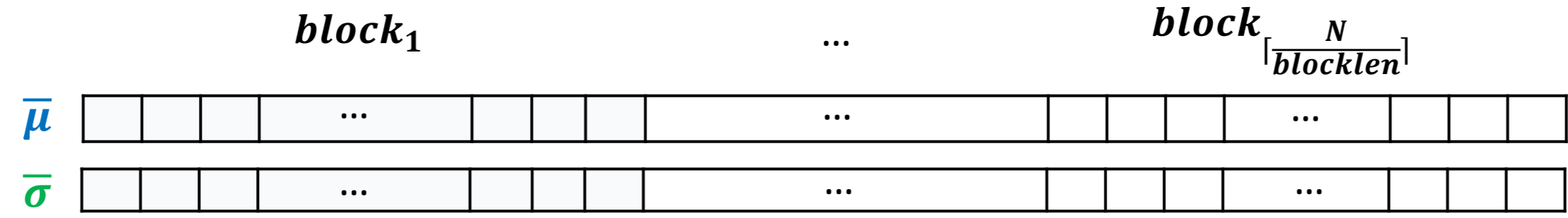
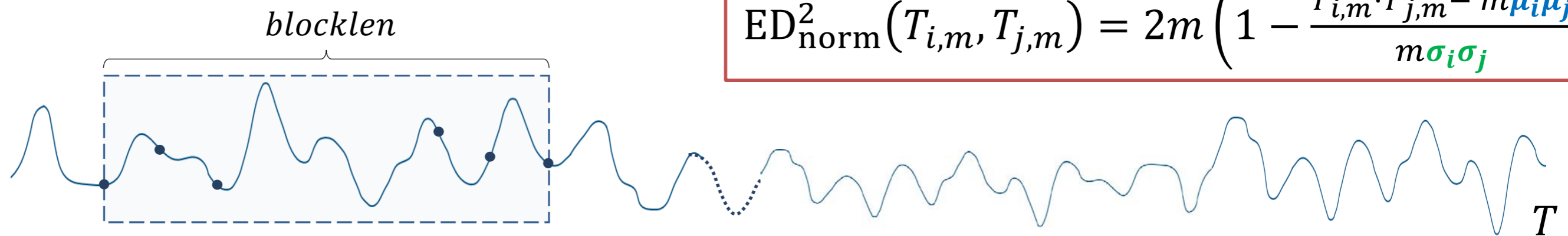
3. Автоматизированный подбор порога r
4. Тепловая карта диссонансов

¹⁾ Mueen A. et al. Fast approximate correlation for massive time-series data. SIGMOD 2010. pp. 171-182. ACM (2010). <https://doi.org/10.1145/1807167.1807188>

Сокращение избыточных вычислений $\bar{\mu}$ и $\bar{\sigma}$

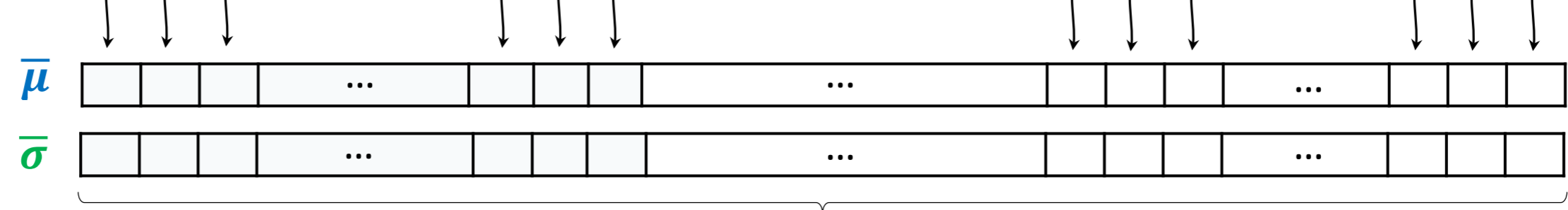
Вычисленные $\bar{\mu}$ и $\bar{\sigma}$ для под-ей ряда длины, меньшей на 1

$$ED_{\text{norm}}^2(T_{i,m}, T_{j,m}) = 2m \left(1 - \frac{T_{i,m} \cdot T_{j,m} - m\mu_i\mu_j}{m\sigma_i\sigma_j} \right)$$



Лемма

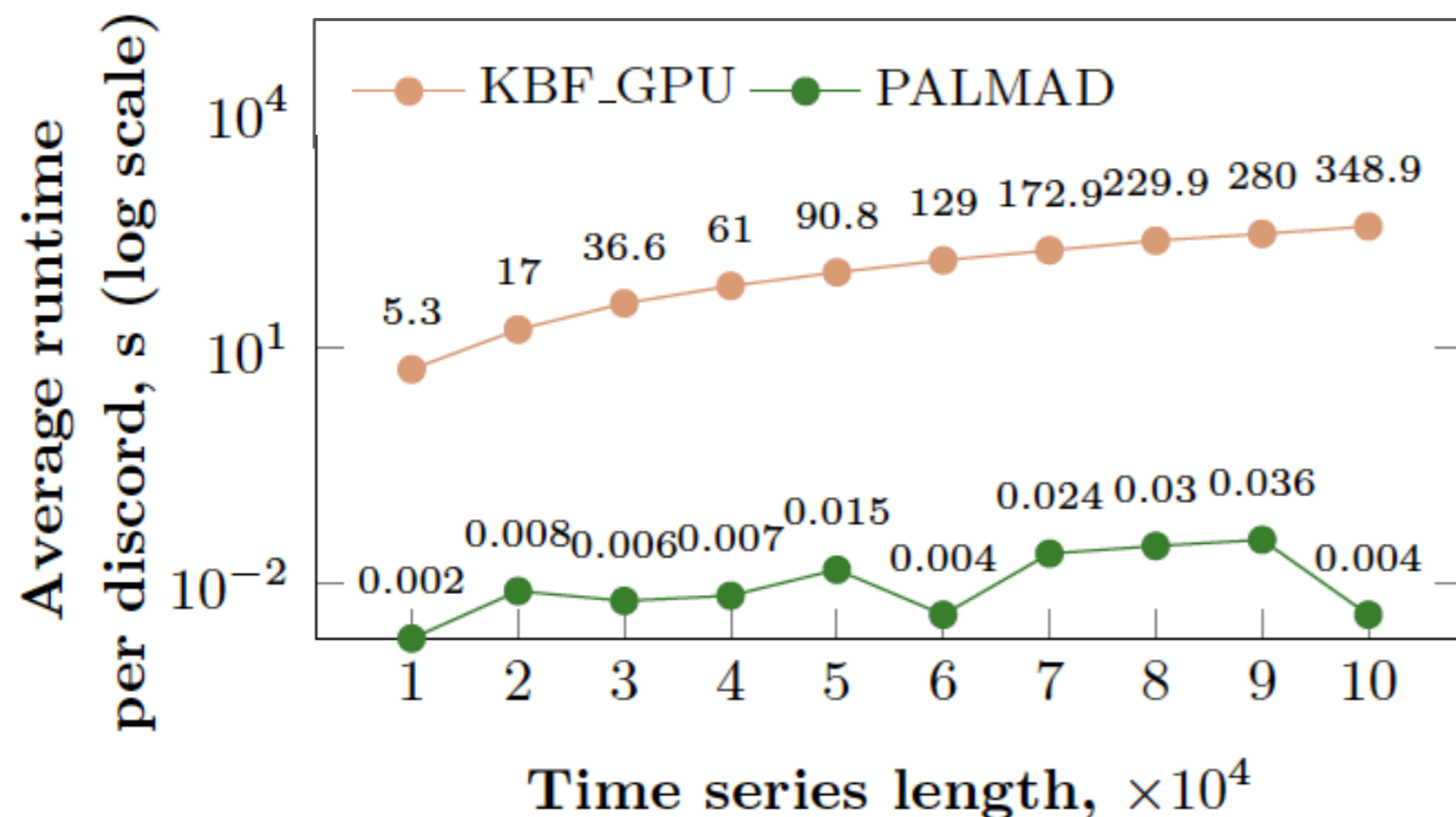
$$\mu_{T_{i,m+1}} = \frac{1}{m+1} (m\mu_{T_{i,m}} + t_{i+m}), \quad \sigma_{T_{i,m+1}}^2 = \frac{m}{m+1} \left(\sigma_{T_{i,m}}^2 + \frac{1}{m+1} (\mu_{T_{i,m}} - t_{i+m})^2 \right)$$



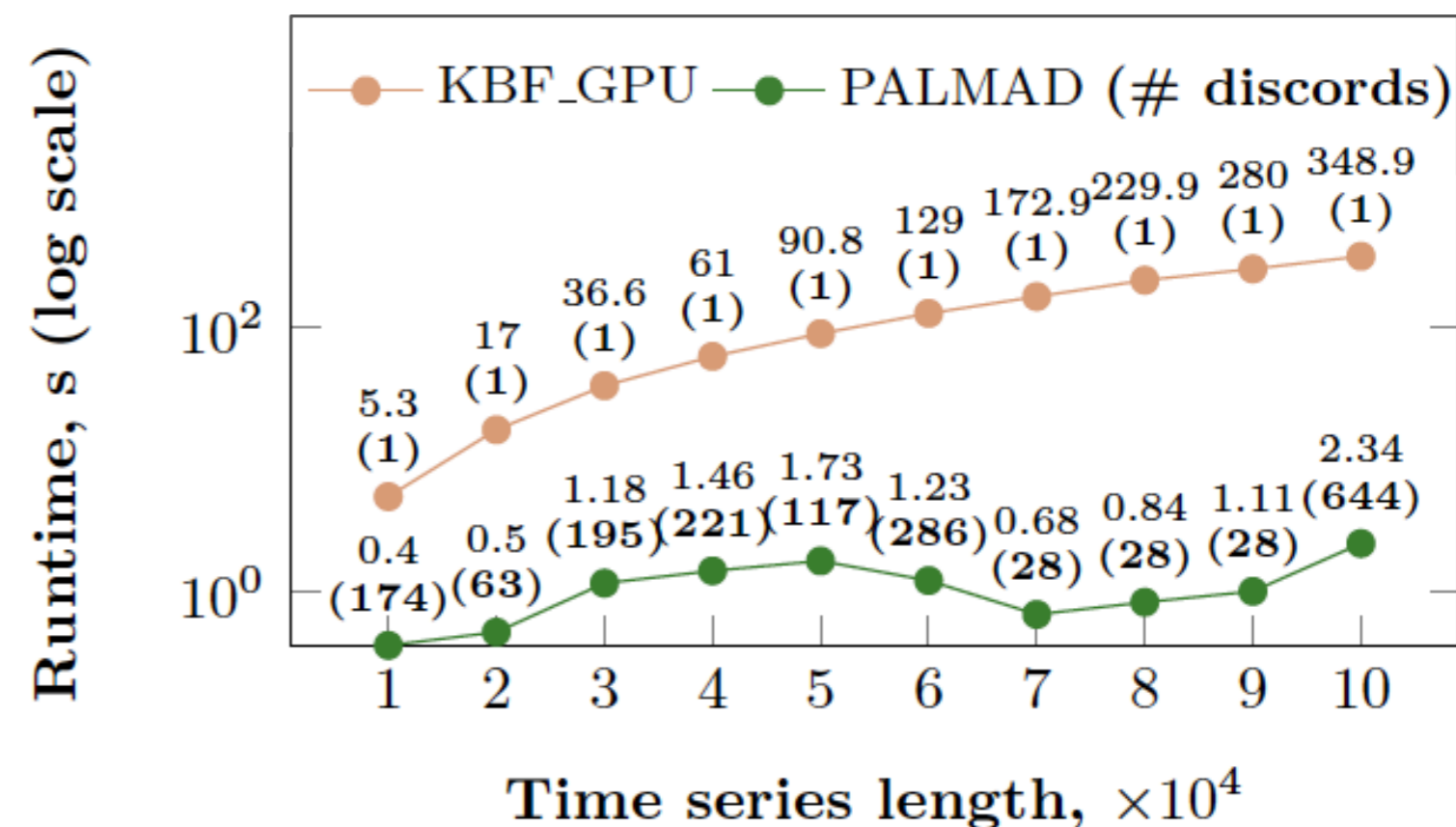
$$N = n - \text{min}L + 1$$

Производительность: сравнение с KBF_GPU¹⁾

Среднее время на поиск **одного** диссонанса



Время на поиск **всех** диссонансов



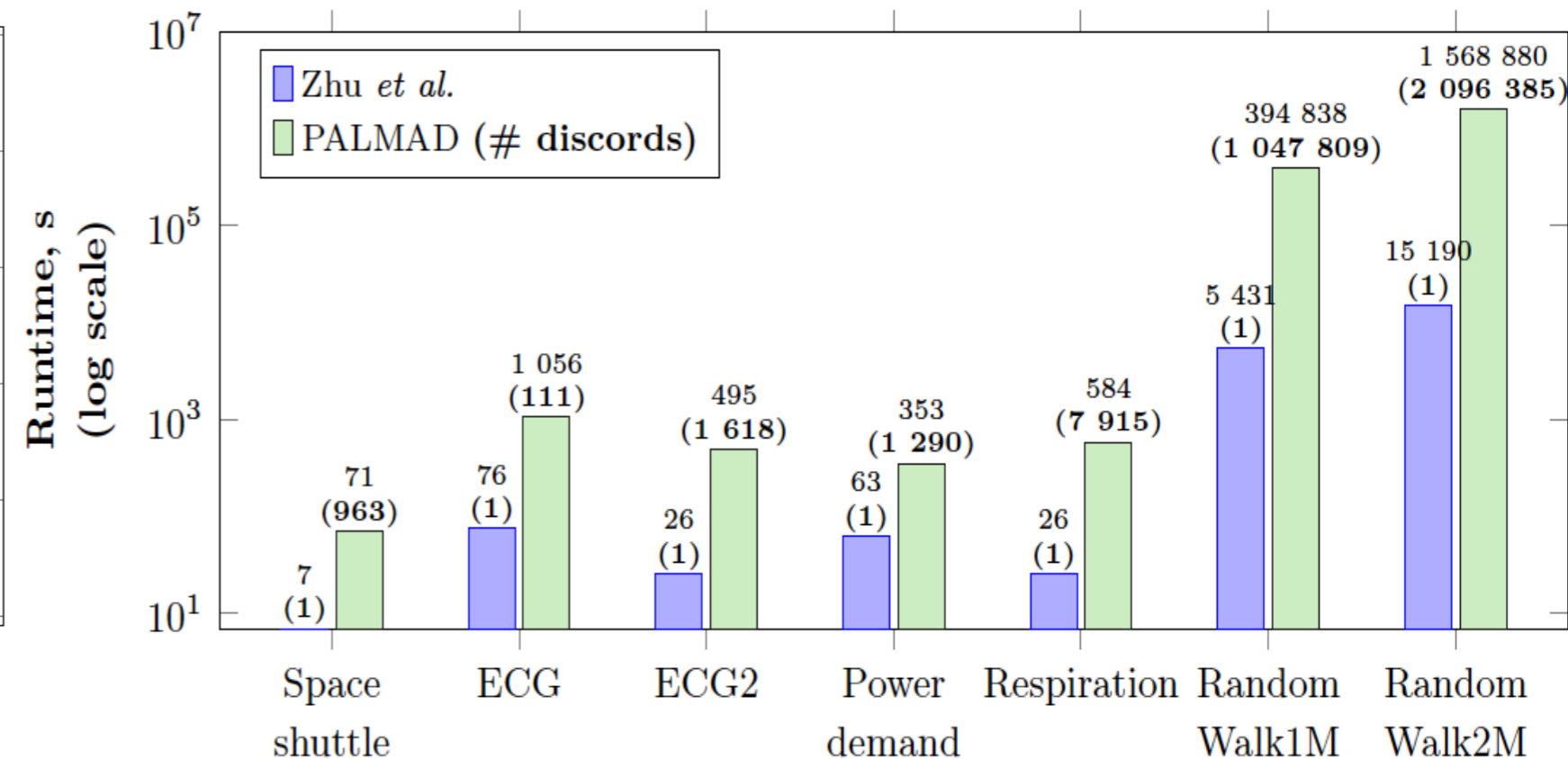
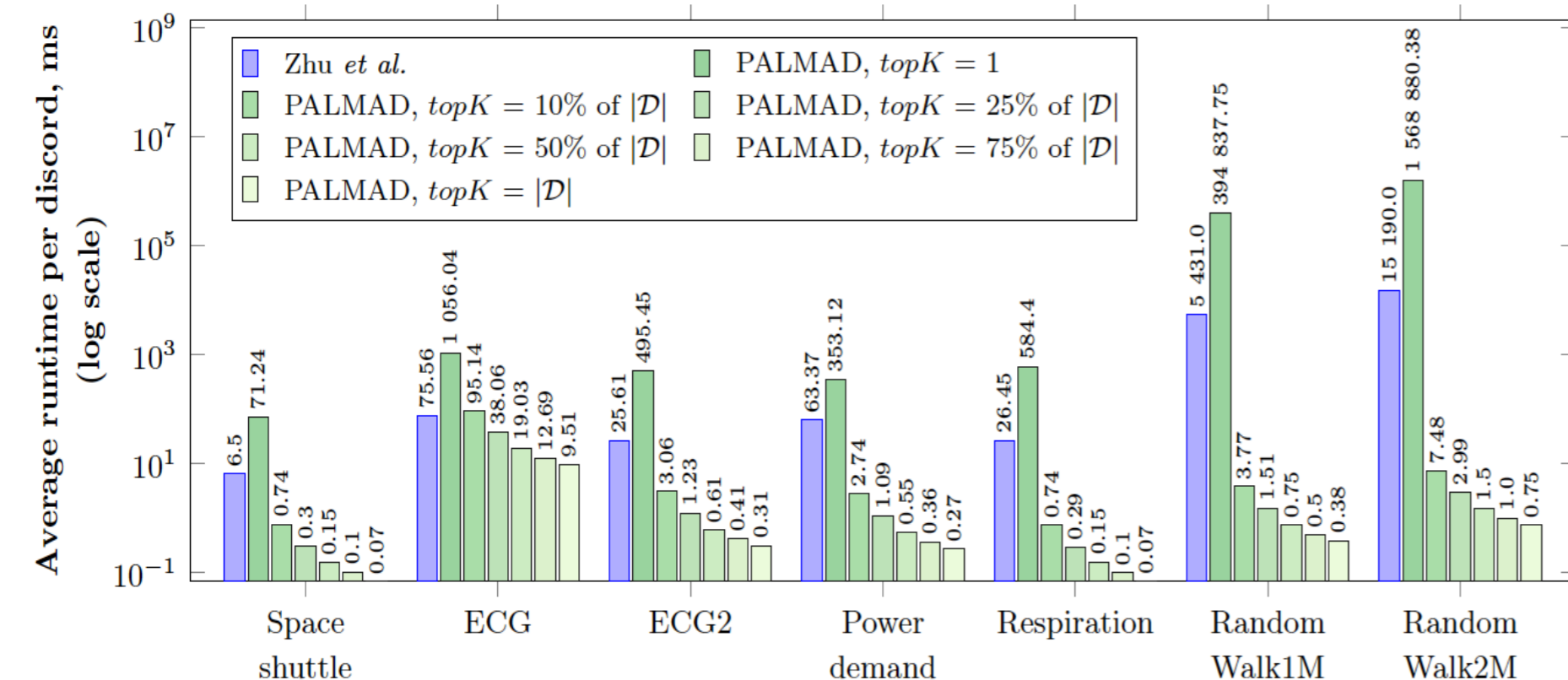
PALMAD опережает KBF_GPU как по общему времени работы, так и по среднему времени на поиск одного диссонанса

¹⁾ Thuy T.T.H. et al. A new discord definition and an efficient time series discord detection method using GPUs. ICSED 2021. pp. 63–70. <https://doi.org/10.1145/3507473.3507483>.

Производительность: сравнение с Zhu et al.¹⁾

Среднее время на поиск **одного** диссонанса

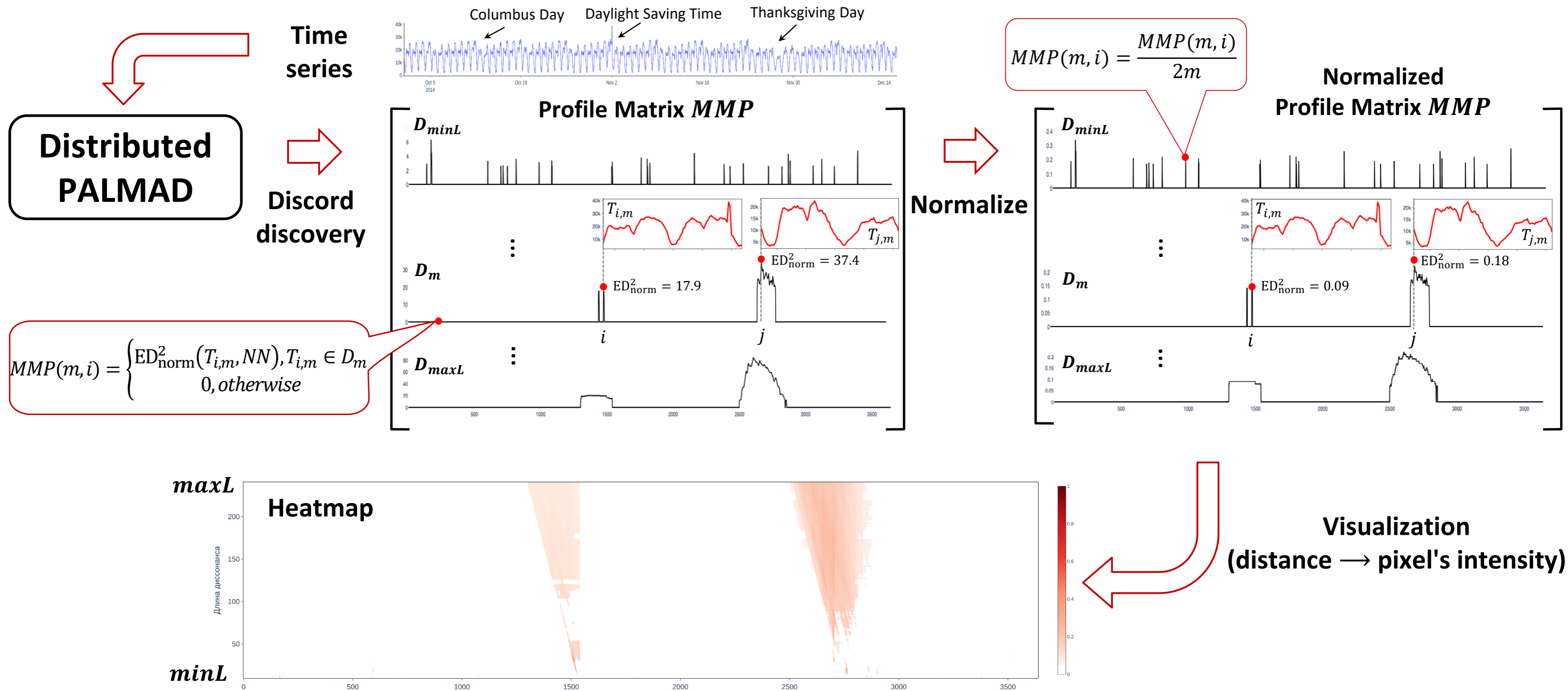
Время на поиск **всех** диссонансов



PALMAD значительно опережает алгоритм Zhu et al. по среднему времени на поиск одного диссонанса, начиная с поиска топ-k диссонансов, где k=10% от фактического числа диссонансов

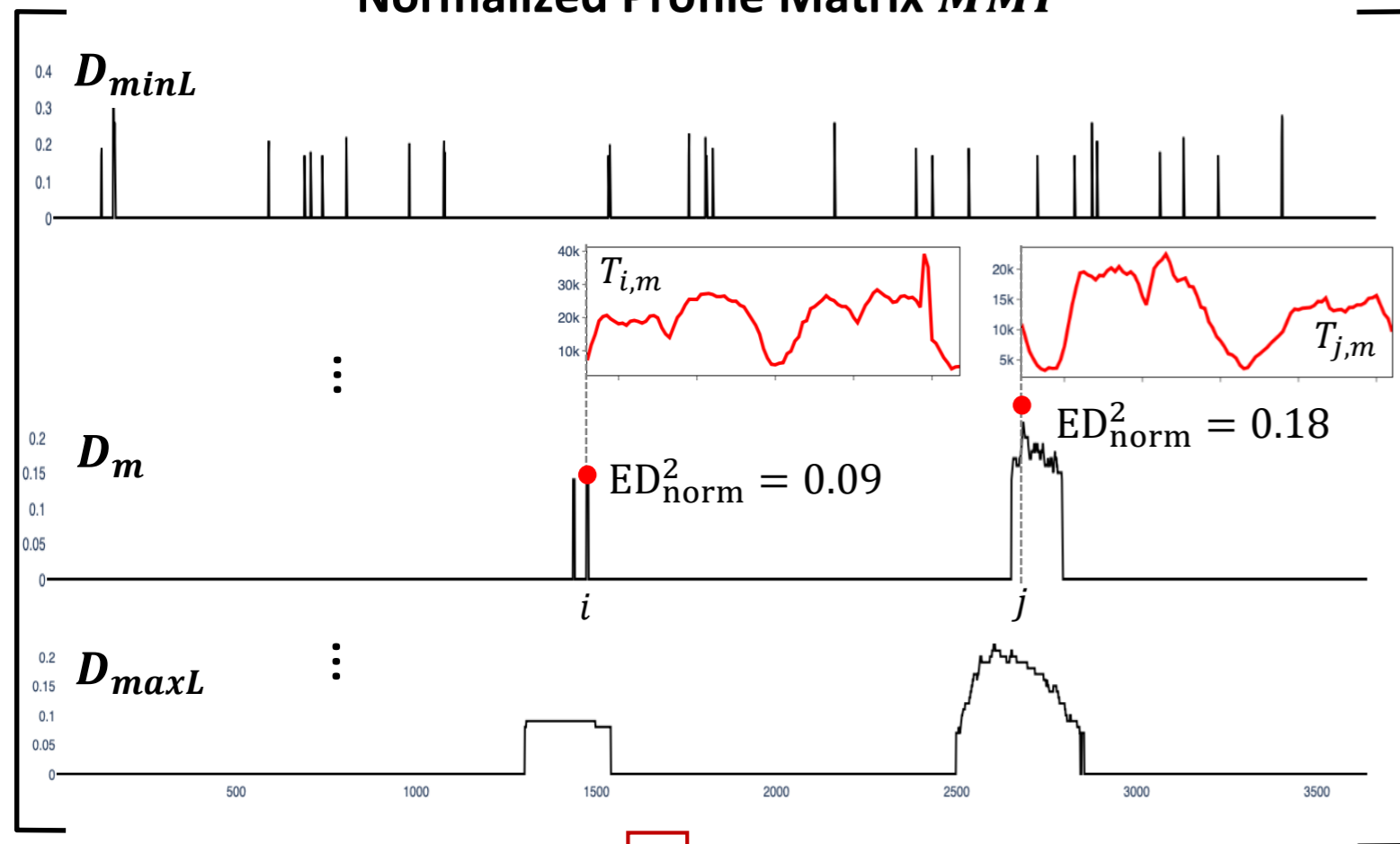
¹⁾ Zhu B. et al. A GPU Acceleration framework for motif and discord based pattern mining. IEEE Transactions on Parallel and Distributed Systems 32(8): 1987-2004. 2021. <https://doi.org/10.1109/TPDS.2021.3055765>.

Discord Heatmap

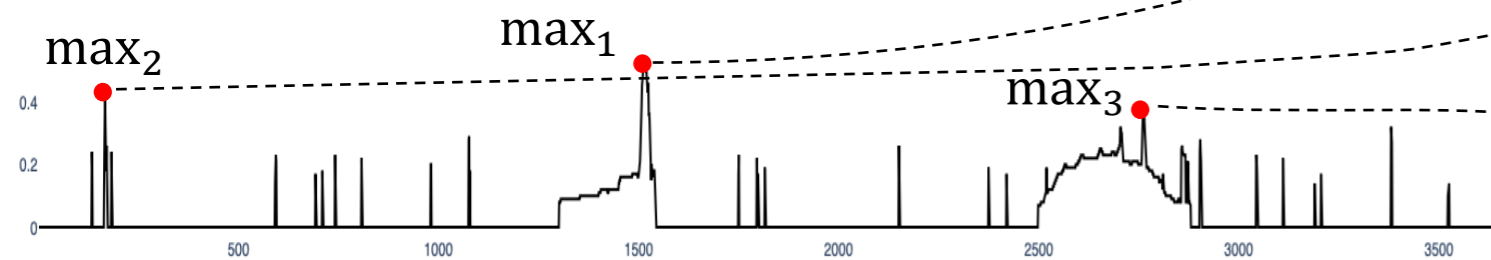


Discord ranking

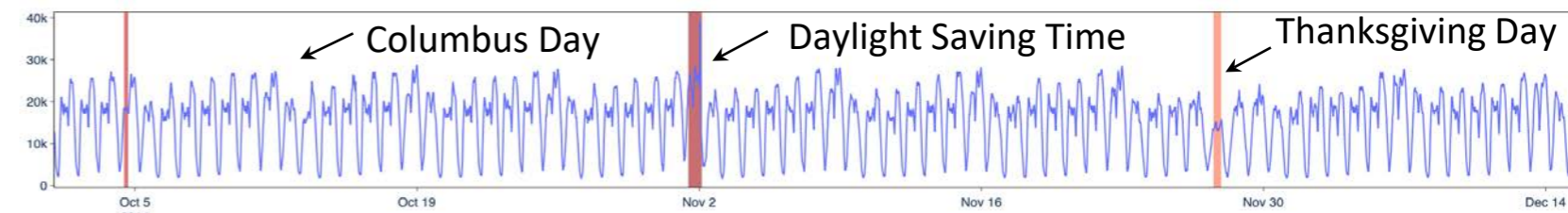
Normalized Profile Matrix MMP



max

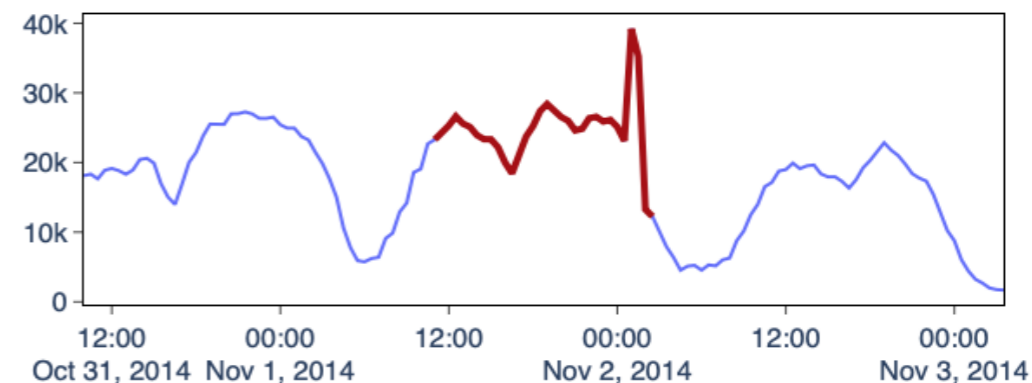


Time series



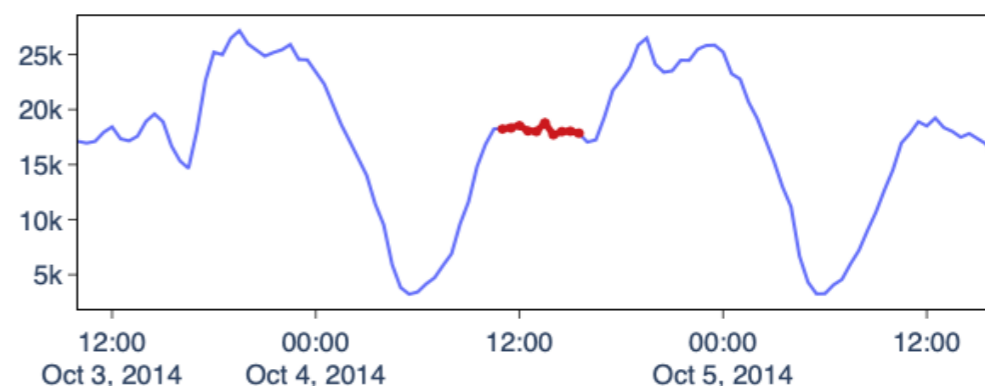
$ED_{norm}^2 = 0.52$

Top-1 discord, $m = 32$



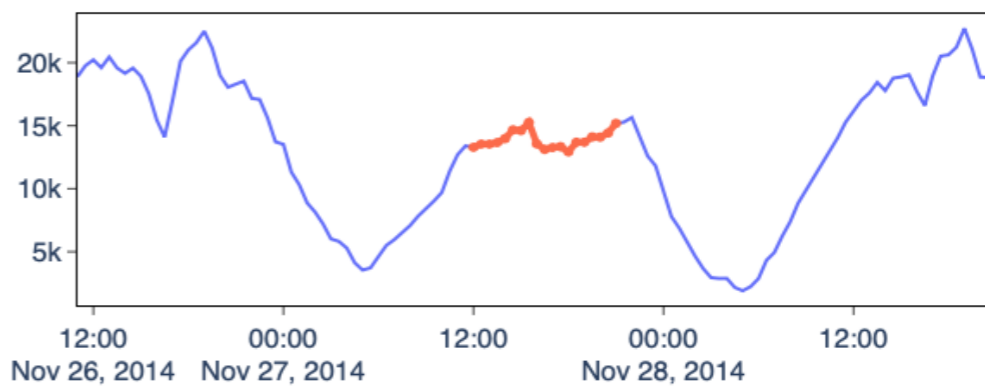
$ED_{norm}^2 = 0.43$

Top-2 discord, $m = 10$



$ED_{norm}^2 = 0.37$

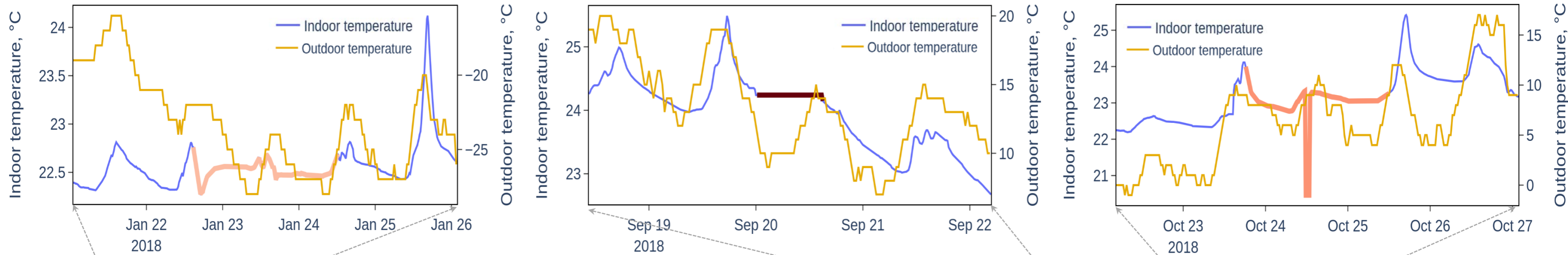
Top-3 discord, $m = 19$



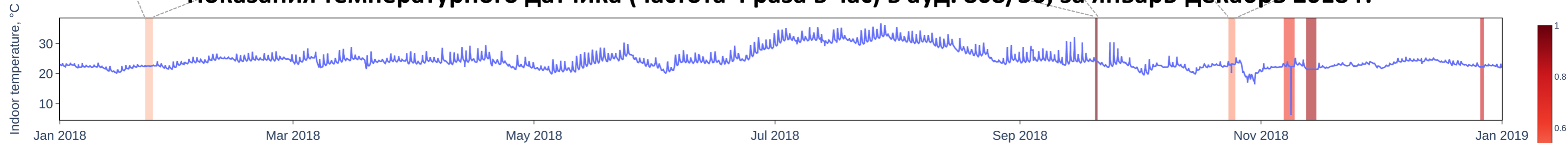
Выявление аномалий в системе отопления ЮУрГУ



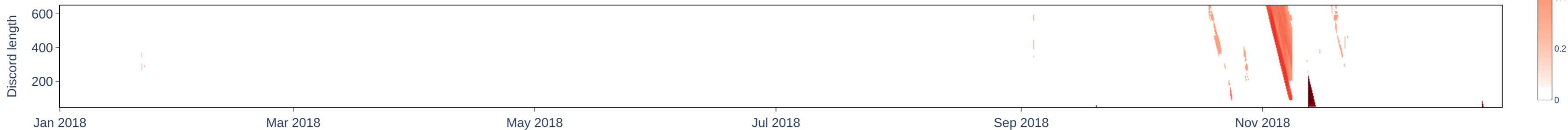
Примеры найденных аномалий длительностью 0.5-2 суток



Показания температурного датчика (частота 4 раза в час) в ауд. 808/36, за январь-декабрь 2018 г.



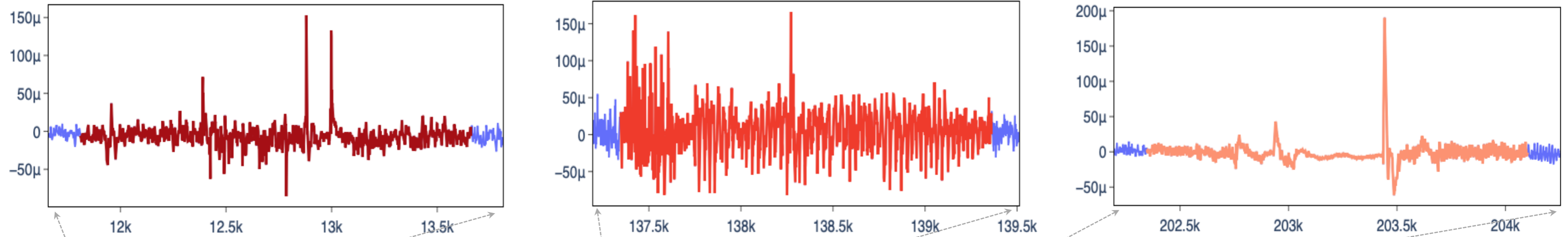
Тепловая карта найденных аномалий длительностью 0.5-2 суток



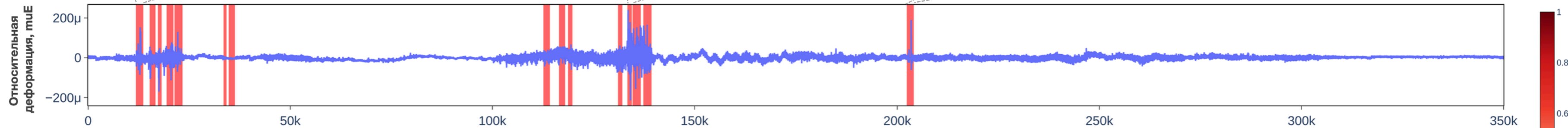
Выявление аномалий в машиностроении



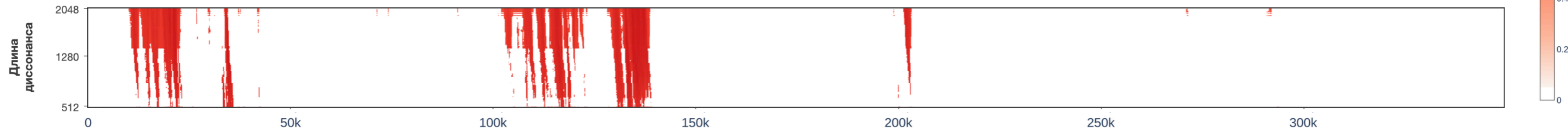
Примеры найденных аномалий длительностью 0.25-0.5 секунд



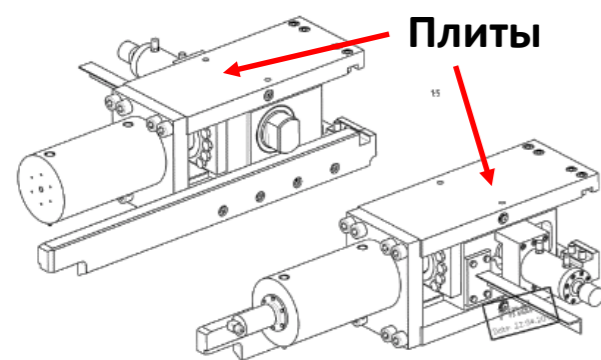
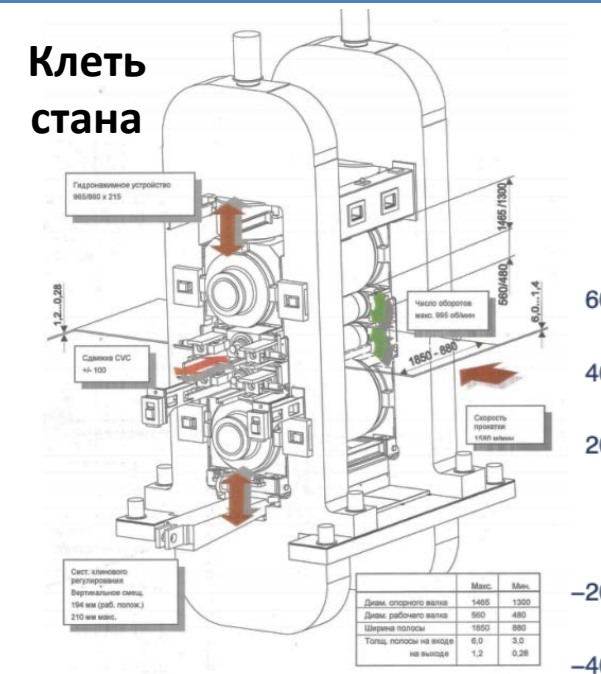
Относительные деформации механизма стыковки вагонов трамвая (частота 4 096 раз в сек) за 1.5 минуты



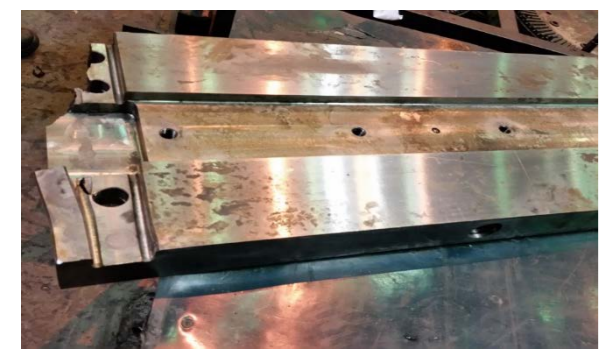
Тепловая карта найденных аномалий длительностью 0.25-0.5 секунд



Поиск аномалий во временных рядах из цифровой индустрии

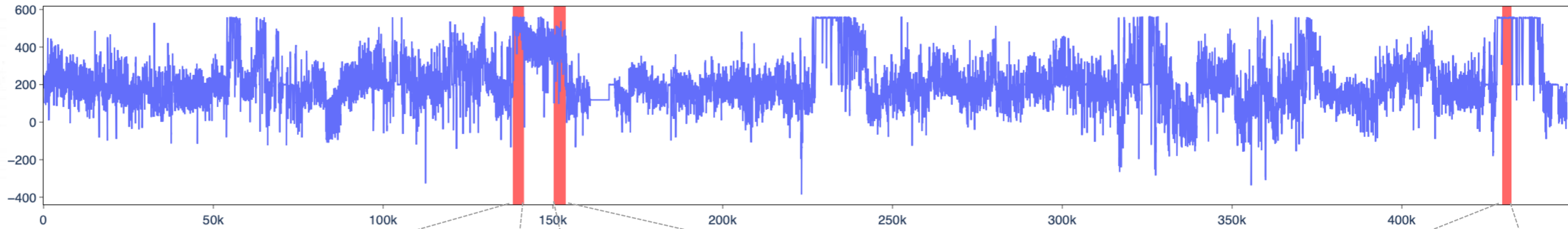


Система валков с непрерывно изменяемой кривизной

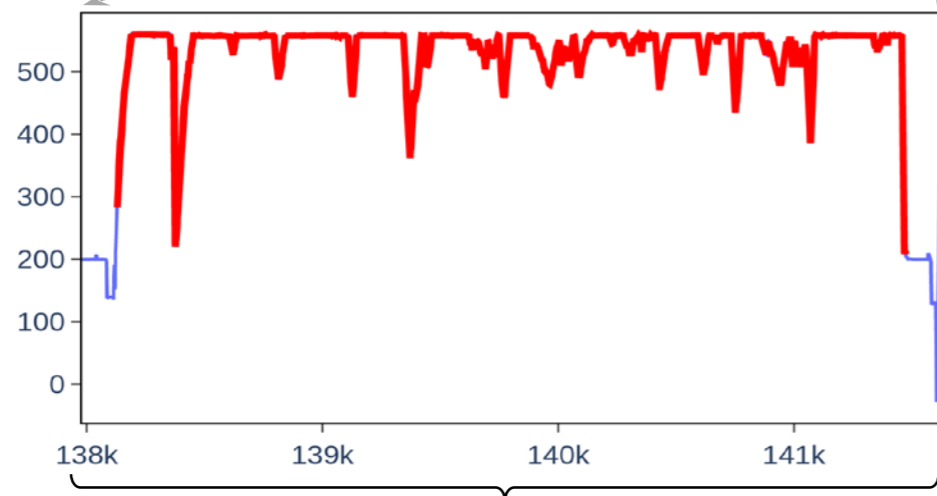


Разрушение плит

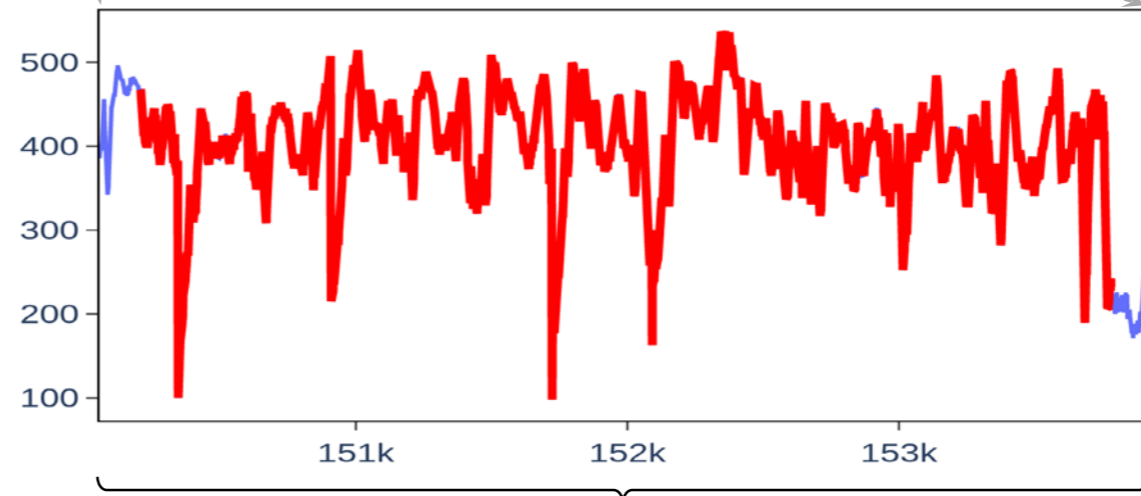
Фактическое изгибающее усилие прокатки



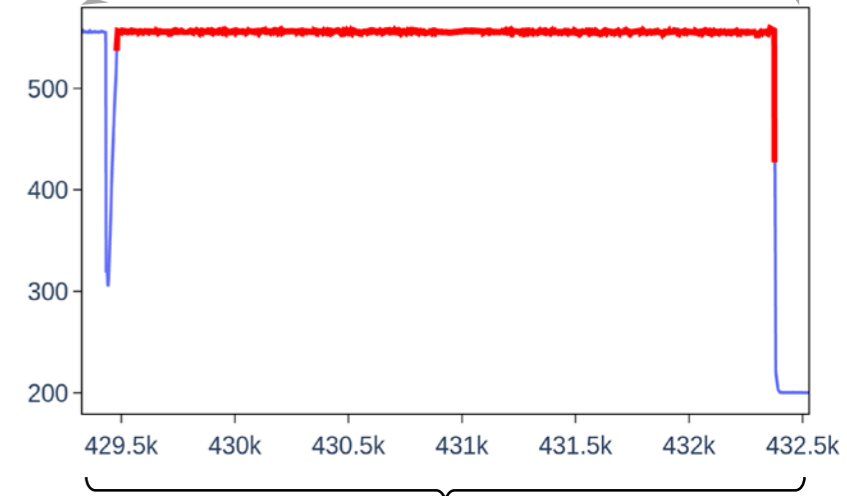
Аномальные напряжения плит



55 минут

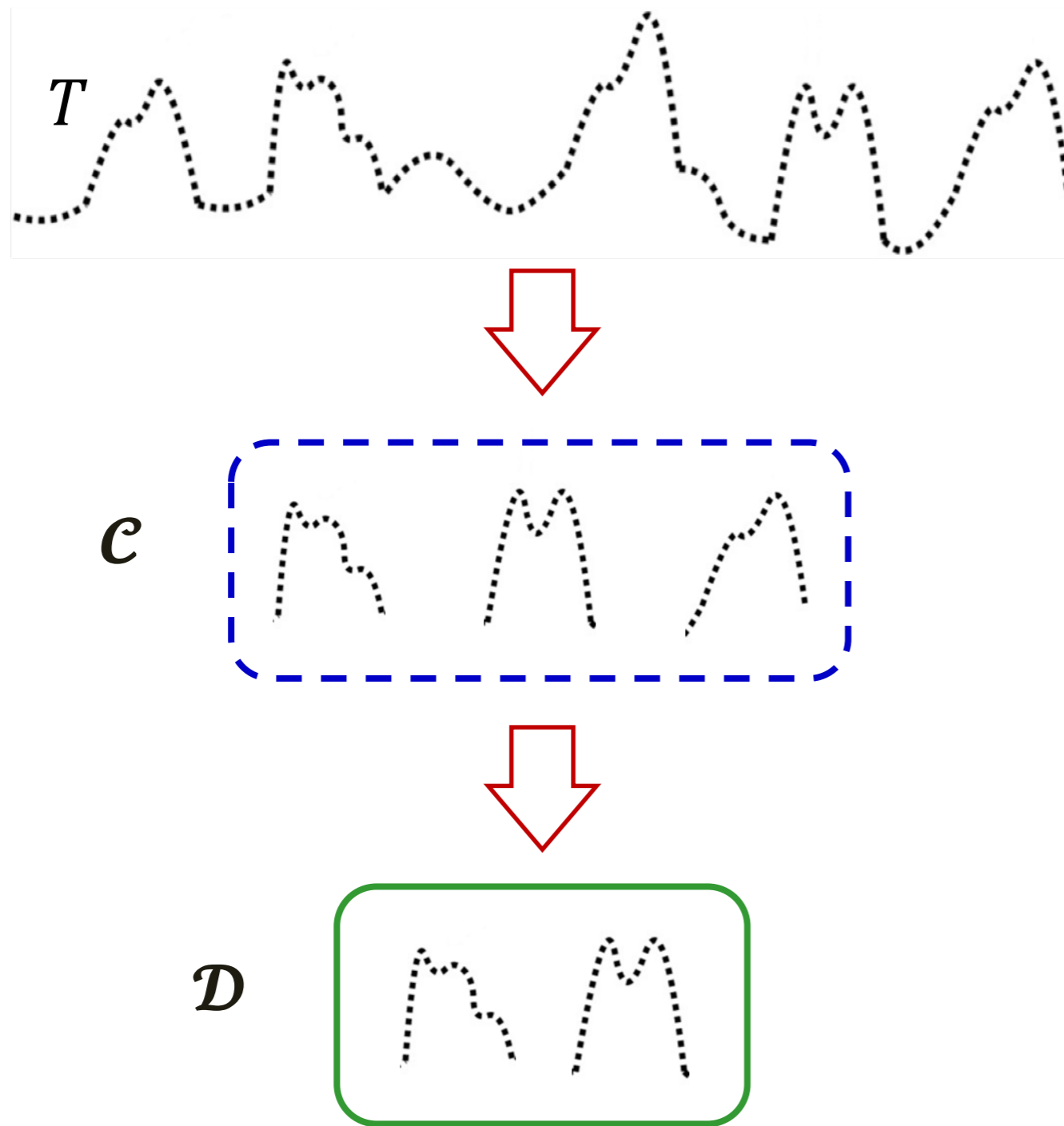


1 час



48 минут

PD3: Parallel DRAG-based Discord Discovery



1. Отбор

За одно сканирование ряда сформировать **множество кандидатов** в диссонансы

2. Очистка

За одно сканирование ряда **отбросить ложноположительных кандидатов**

Отбор кандидатов

пока не конец ряда T :

текущая подпоследовательность s

Кандидат := TRUE

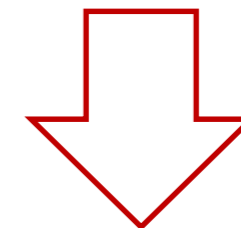
для всех $c_i \in \mathcal{C}$ и $s \cap c_i = \emptyset$

если $\text{dist}(s, c_i) < r$ то

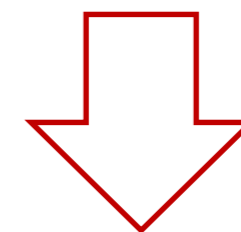
$\mathcal{C} := \mathcal{C} \setminus c_i$; Кандидат := FALSE

если Кандидат = TRUE то $\mathcal{C} := \mathcal{C} \cup s$

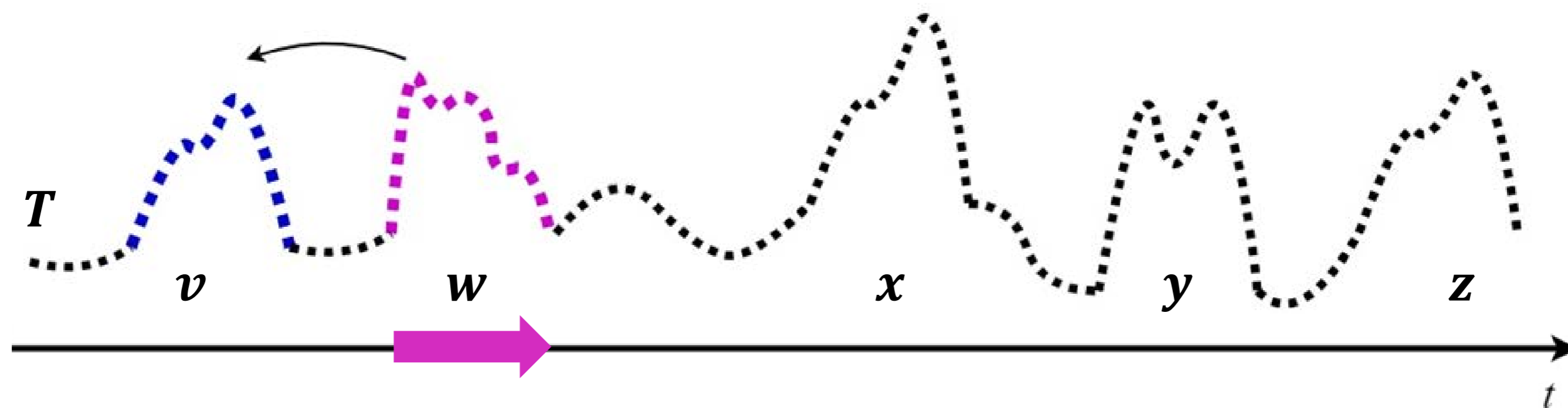
$$\mathcal{C} = \{v\}$$



$$\text{dist}(w, v) \geq r$$



$$\mathcal{C} = \{v, w\}$$



Отбор кандидатов

пока не конец ряда T :

текущая подпоследовательность s

Кандидат := TRUE

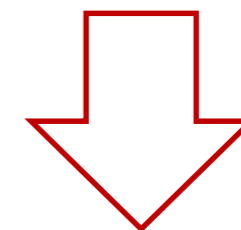
для всех $c_i \in \mathcal{C}$ и $s \cap c_i = \emptyset$

если $\text{dist}(s, c_i) < r$ то

$\mathcal{C} := \mathcal{C} \setminus c_i$; Кандидат := FALSE

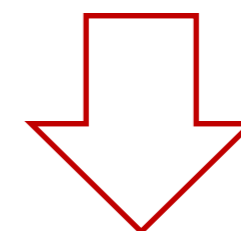
если Кандидат = TRUE то $\mathcal{C} := \mathcal{C} \cup s$

$$\mathcal{C} = \{v, w\}$$

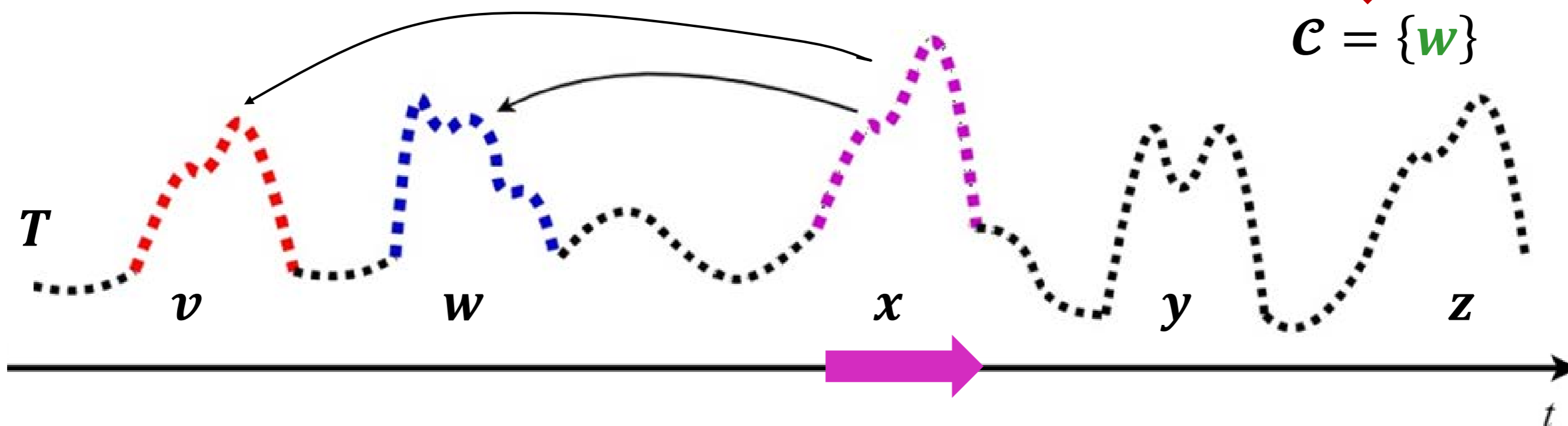


$$\text{dist}(x, v) < r$$

$$\text{dist}(x, w) \geq r$$



$$\mathcal{C} = \{w\}$$



Отбор кандидатов

пока не конец ряда T :

текущая подпоследовательность s

Кандидат := TRUE

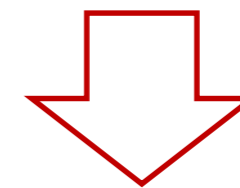
для всех $c_i \in \mathcal{C}$ и $s \cap c_i = \emptyset$

если $\text{dist}(s, c_i) < r$ то

$\mathcal{C} := \mathcal{C} \setminus c_i$; Кандидат := FALSE

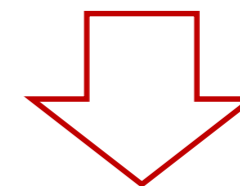
если Кандидат = TRUE то $\mathcal{C} := \mathcal{C} \cup s$

$$\mathcal{C} = \{w, y\}$$

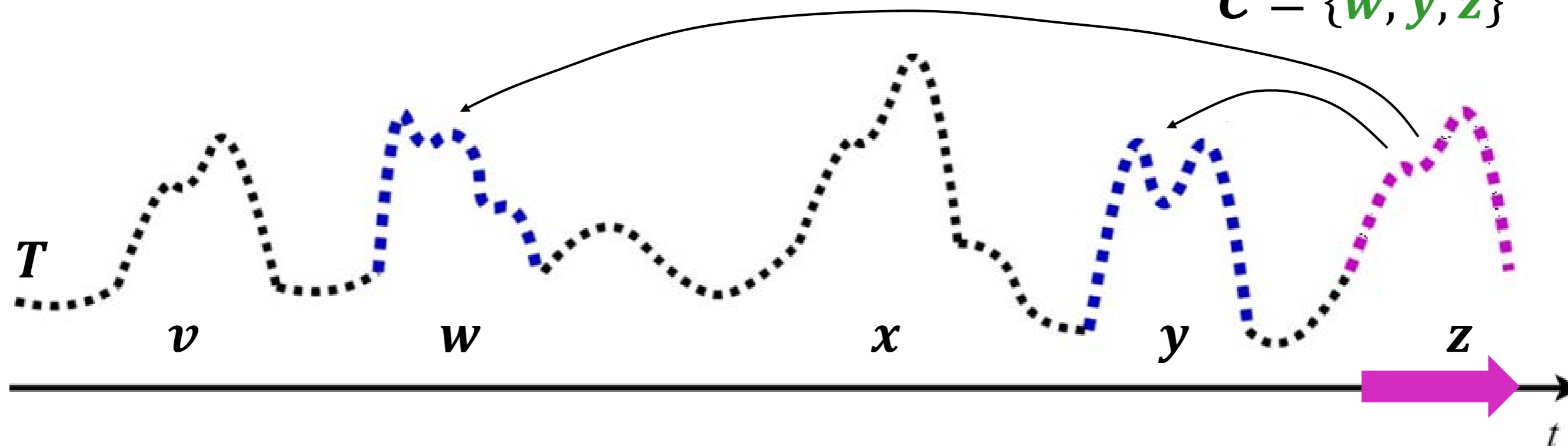


$$\text{dist}(z, w) \geq r$$

$$\text{dist}(z, y) \geq r$$



$$\mathcal{C} = \{w, y, z\}$$



Очистка кандидатов

$$\mathcal{D} := \mathcal{C}$$

пока не конец ряда T :

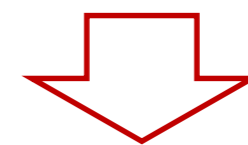
текущая подпоследовательность s

для всех $d_i \in \mathcal{D}$ и $s \cap d_i = \emptyset$

если $\text{dist}(s, d_i) < r$ то

$$\mathcal{D} := \mathcal{D} \setminus d_i$$

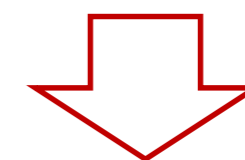
$$\mathcal{D} = \{w, y, z\}$$



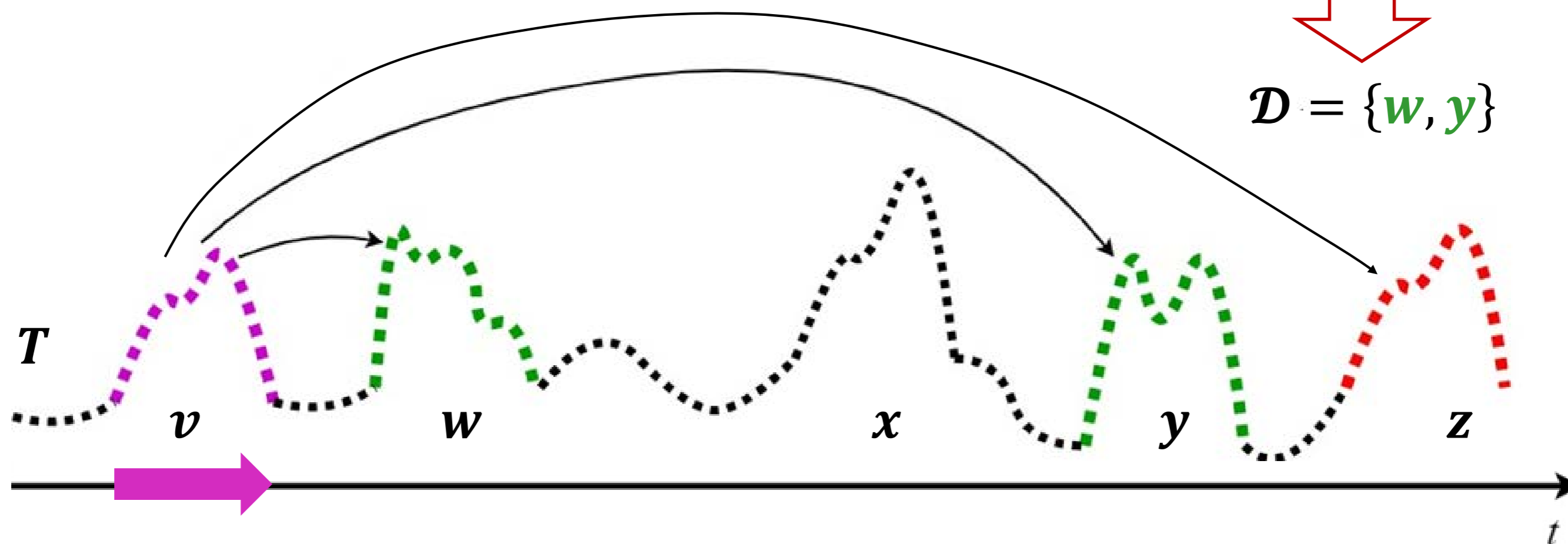
$$\text{dist}(v, w) \geq r$$

$$\text{dist}(v, y) \geq r$$

$$\text{dist}(v, z) < r$$



$$\mathcal{D} = \{w, y\}$$



Очистка кандидатов

$$\mathcal{D} := \mathcal{C}$$

пока не конец ряда T :

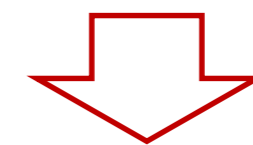
текущая подпоследовательность s

для всех $d_i \in \mathcal{D}$ и $s \cap d_i = \emptyset$

если $\text{dist}(s, d_i) < r$ то

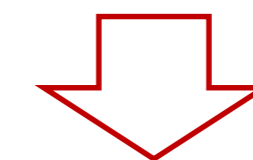
$$\mathcal{D} := \mathcal{D} \setminus d_i$$

$$\mathcal{D} = \{w, y\}$$

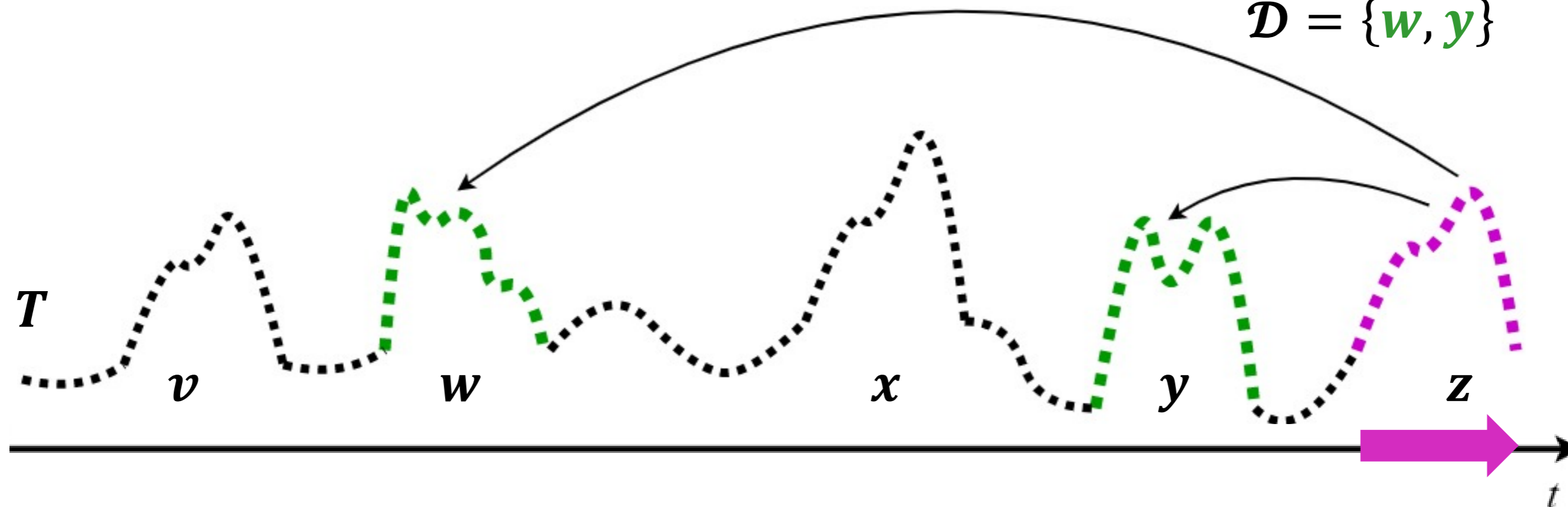


$$\text{dist}(z, w) \geq r$$

$$\text{dist}(z, y) \geq r$$



$$\mathcal{D} = \{w, y\}$$



PALMAD: автоматизированный подбор порога

Algorithm 3 PALMAD (IN T , $minL$, $maxL$, $topK$; OUT \mathcal{D})

```
1:  $\mathcal{D} \leftarrow \emptyset$ ;  $r \leftarrow 2\sqrt{minL}$ ;  $nnDist_{minL} \leftarrow -\infty$ 
2:  $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{CALCMEANSTD}(T, minL)$ 
3: while  $nnDist_{minL} < 0$  and  $|D_{minL}| < topK$  do
4:    $D_{minL} \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, minL, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_{minL}$ ;  $nnDist_{minL} \leftarrow \min_{d \in D_{minL}} d.nnDist$ 
5:    $r \leftarrow 0.5 \cdot r$ 
6: for  $i \leftarrow minL + 1$  to  $minL + 4$  do
7:    $nnDist_i \leftarrow -\infty$ 
8:    $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{UPDATEMEANSTD}(T, \bar{\mu}, \bar{\sigma}, i)$ 
9:   while  $nnDist_i < 0$  and  $|D_i| < topK$  do
10:     $r \leftarrow 0.99 \cdot nnDist_{i-1}$ 
11:     $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
12:     $r \leftarrow 0.99 \cdot r$ 
13: for  $i \leftarrow minL + 5$  to  $maxL$  do
14:    $\mu \leftarrow \text{Mean}(\{nnDist_k\}_{k=i-1}^{i-5})$ ;  $\sigma \leftarrow \text{Std}(\{nnDist_k\}_{k=i-1}^{i-5})$ ;  $r \leftarrow \mu - 2\sigma$ 
15:    $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{UPDATEMEANSTD}(T, \bar{\mu}, \bar{\sigma}, i)$ 
16:    $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
17:   while  $nnDist_i < 0$  and  $|D_i| < topK$  do
18:     $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
19:     $r \leftarrow r - \sigma$ 
20: return  $\mathcal{D}$ 
```

Шаг 1. Поиск диссонансов минимальной длины $minL$

$$r = 2\sqrt{minL}$$

Шаг 2. Поиск диссонансов следующих четырех длин

$$r = 0.99 \cdot nnDist_{m-1}$$

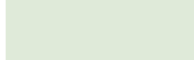
Шаг 3. Поиск диссонансов всех оставшихся длин

$$r = \mu - 2\sigma$$

Algorithm 3 PALMAD (IN T , $minL$, $maxL$, $topK$; OUT \mathcal{D})

```

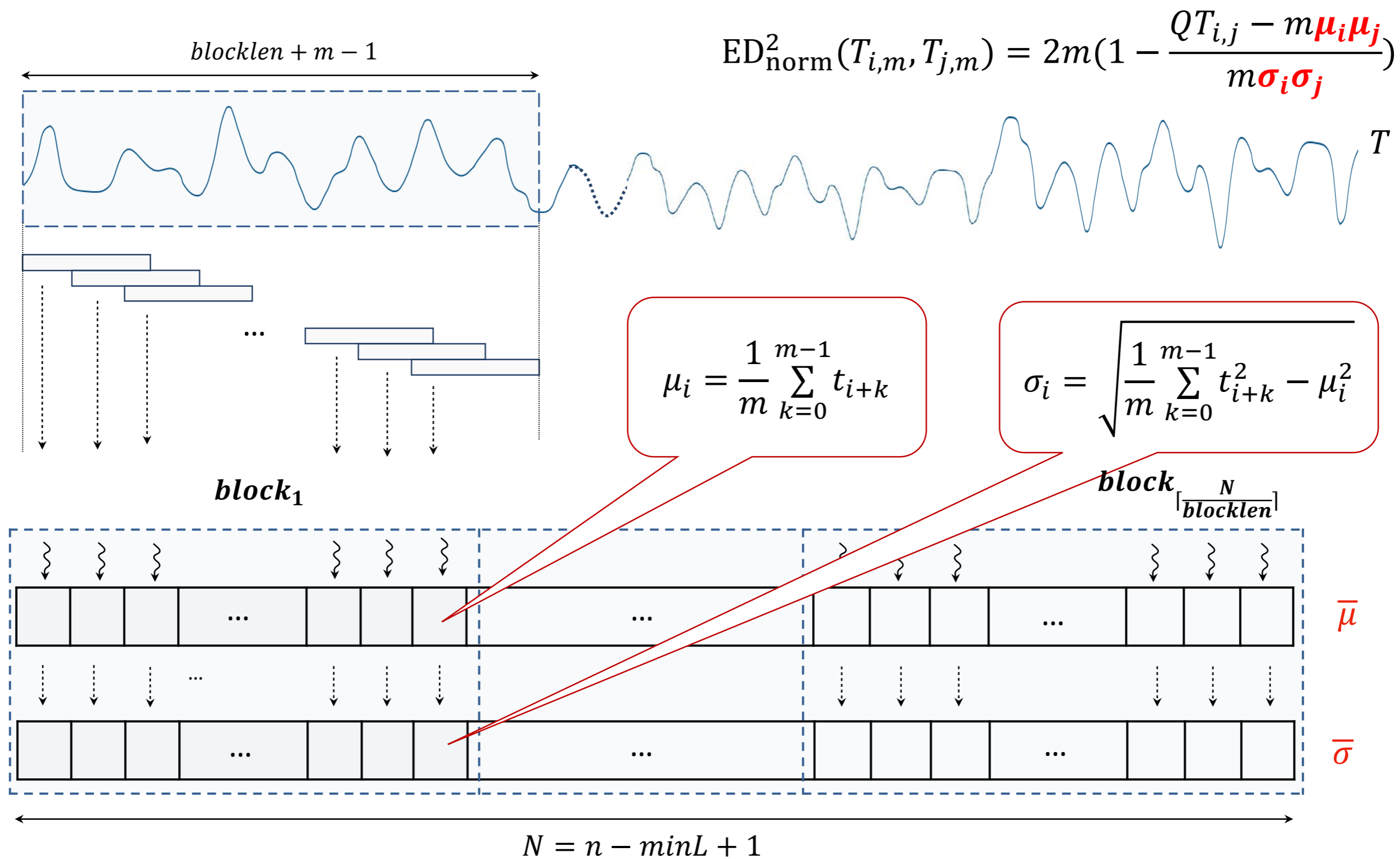
1:  $\mathcal{D} \leftarrow \emptyset$ ;  $r \leftarrow 2\sqrt{minL}$ ;  $nnDist_{minL} \leftarrow -\infty$ 
2:  $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{CALCMEANSTD}(T, minL)$ 
3: while  $nnDist_{minL} < 0$  and  $|D_{minL}| < topK$  do
4:    $D_{minL} \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, minL, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_{minL}$ ;  $nnDist_{minL} \leftarrow \min_{d \in D_{minL}} d.nnDist$ 
5:    $r \leftarrow 0.5 \cdot r$ 
6: for  $i \leftarrow minL + 1$  to  $minL + 4$  do
7:    $nnDist_i \leftarrow -\infty$ 
8:    $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{UPDATEMEANSTD}(T, \bar{\mu}, \bar{\sigma}, i)$ 
9:   while  $nnDist_i < 0$  and  $|D_i| < topK$  do
10:     $r \leftarrow 0.99 \cdot nnDist_{i-1}$ 
11:     $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
12:     $r \leftarrow 0.99 \cdot r$ 
13: for  $i \leftarrow minL + 5$  to  $maxL$  do
14:    $\mu \leftarrow \text{Mean}(\{nnDist_k\}_{k=i-1}^{i-5})$ ;  $\sigma \leftarrow \text{Std}(\{nnDist_k\}_{k=i-1}^{i-5})$ ;  $r \leftarrow \mu - 2\sigma$ 
15:    $\{\bar{\mu}, \bar{\sigma}\} \leftarrow \text{UPDATEMEANSTD}(T, \bar{\mu}, \bar{\sigma}, i)$ 
16:    $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
17:   while  $nnDist_i < 0$  and  $|D_i| < topK$  do
18:     $D_i \leftarrow \text{PD3}(T, \bar{\mu}, \bar{\sigma}, i, r^2)$ ;  $\mathcal{D} \leftarrow \mathcal{D} \cup D_i$ ;  $nnDist_i \leftarrow \min_{d \in D_i} d.nnDist$ 
19:     $r \leftarrow r - \sigma$ 
20: return  $\mathcal{D}$ 
  
```

 – сокращение избыточных вычислений

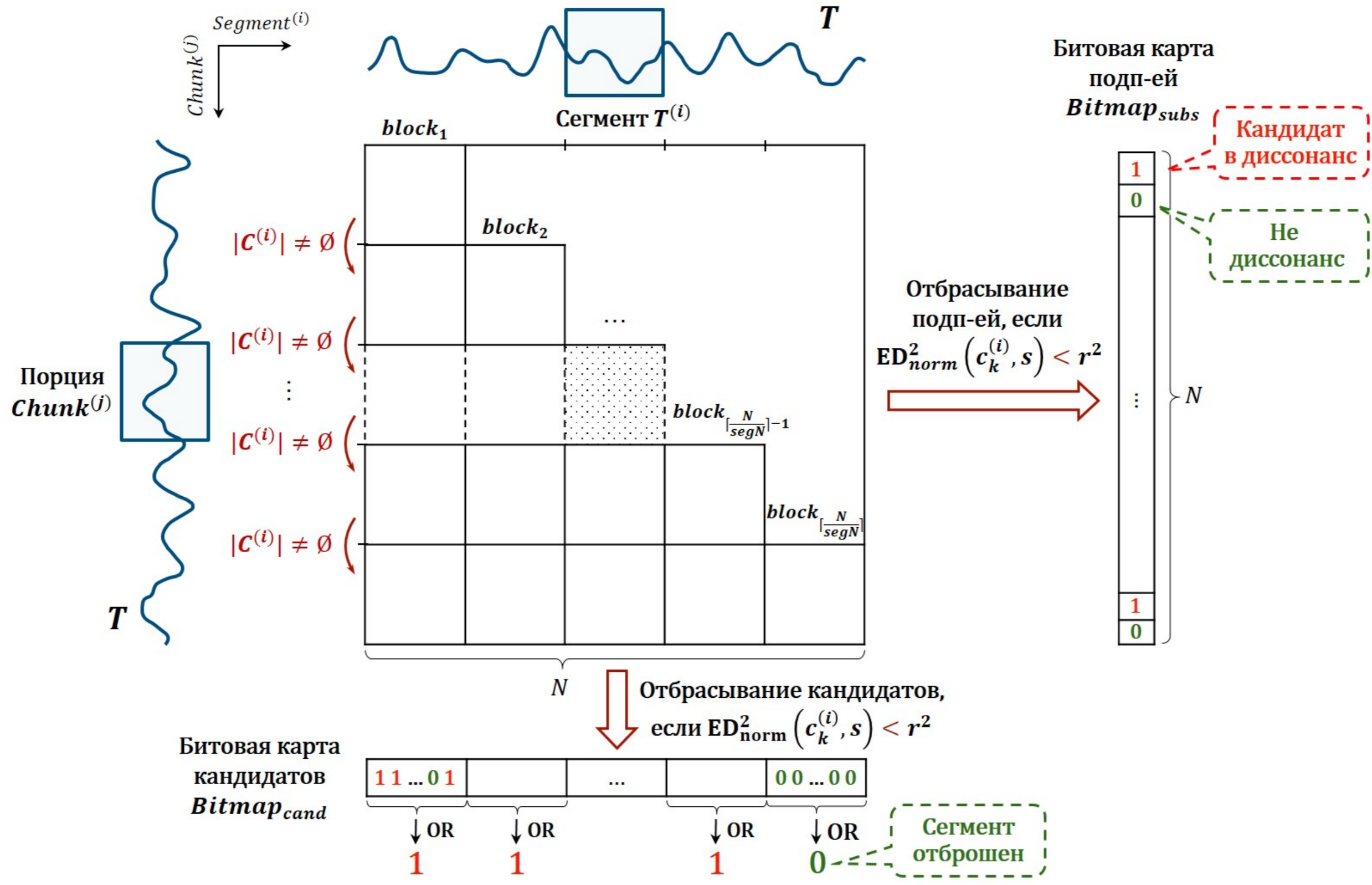
 – использование PD3

 – применение ED_{norm}^2

Предобработка: вычисление $\bar{\mu}$ и $\bar{\sigma}$



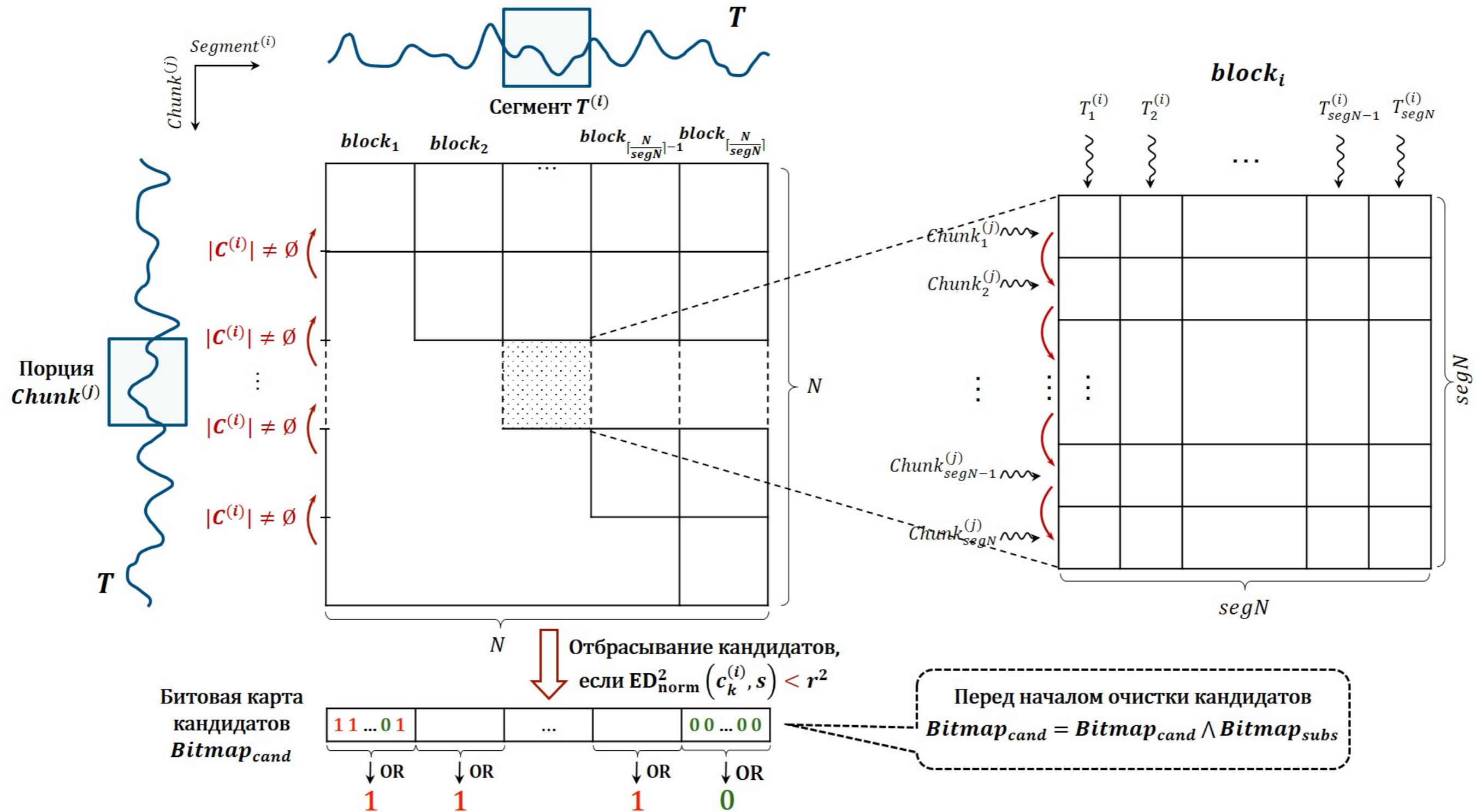
PD3: Отбор кандидатов, блочное распараллеливание



PD3: Очистка кандидатов

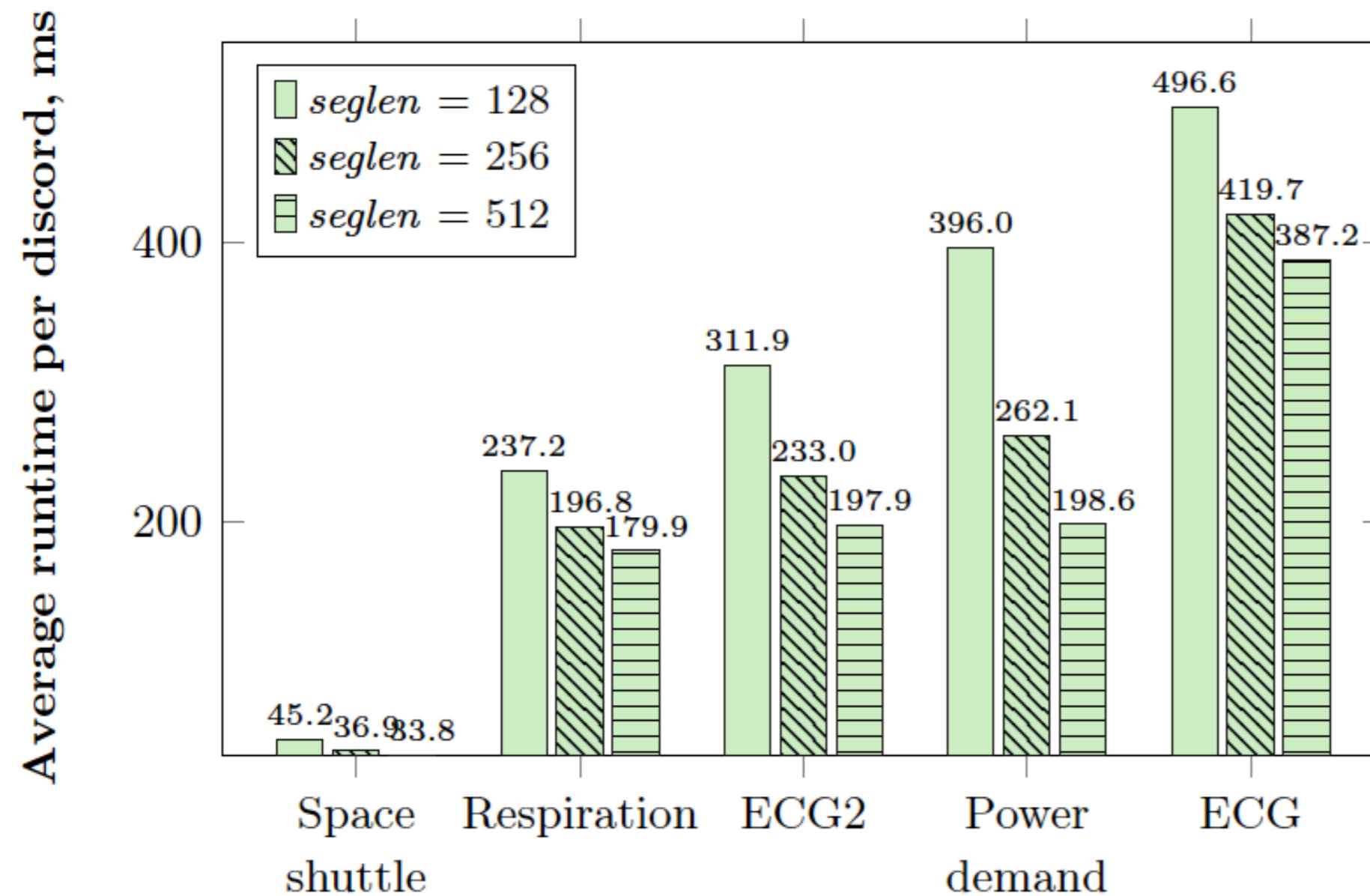
Блочное распараллеливание

Распараллеливание по нитям

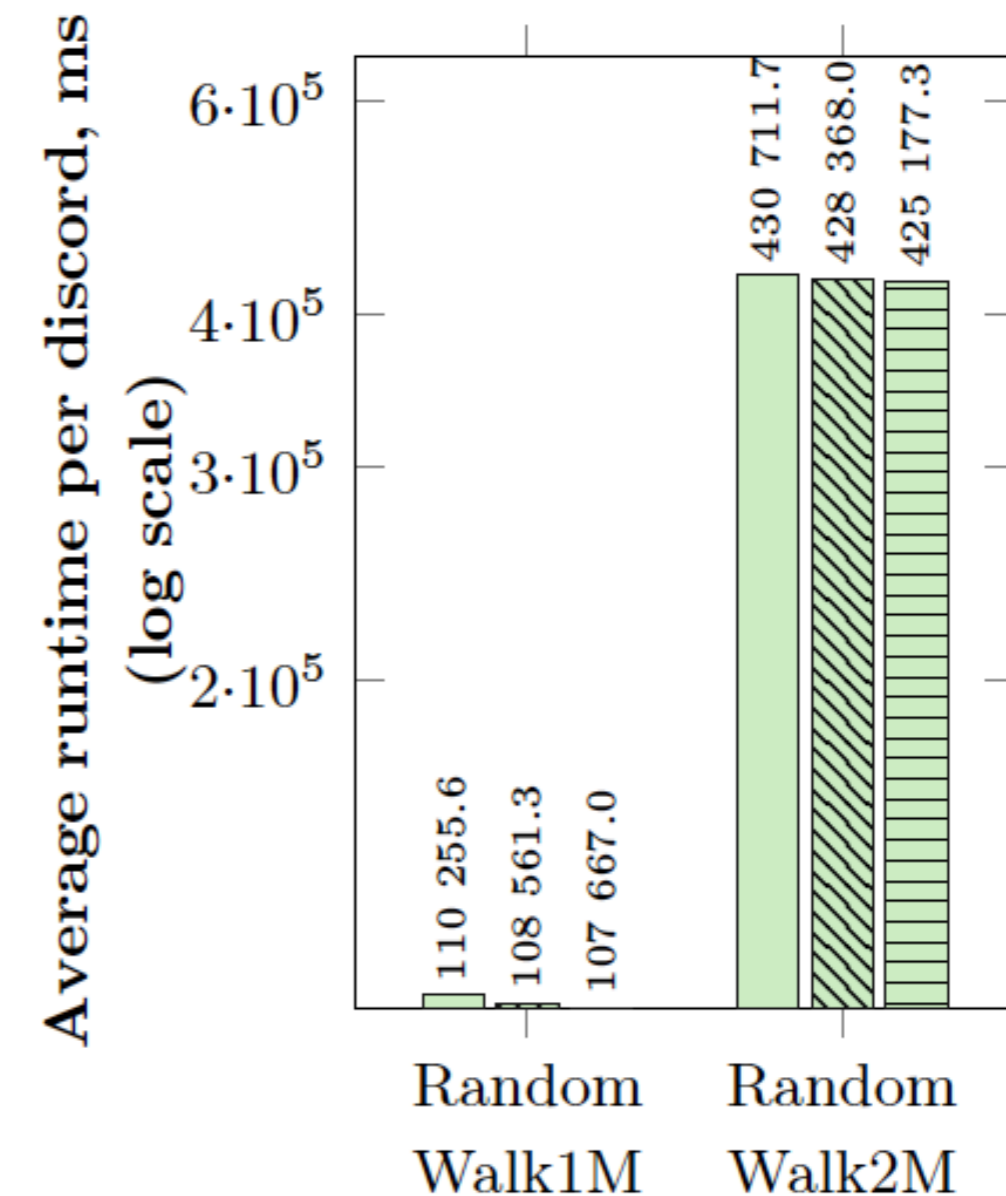


Производительность: влияние длины сегмента

Реальные временные ряды



Синтетические временные ряды



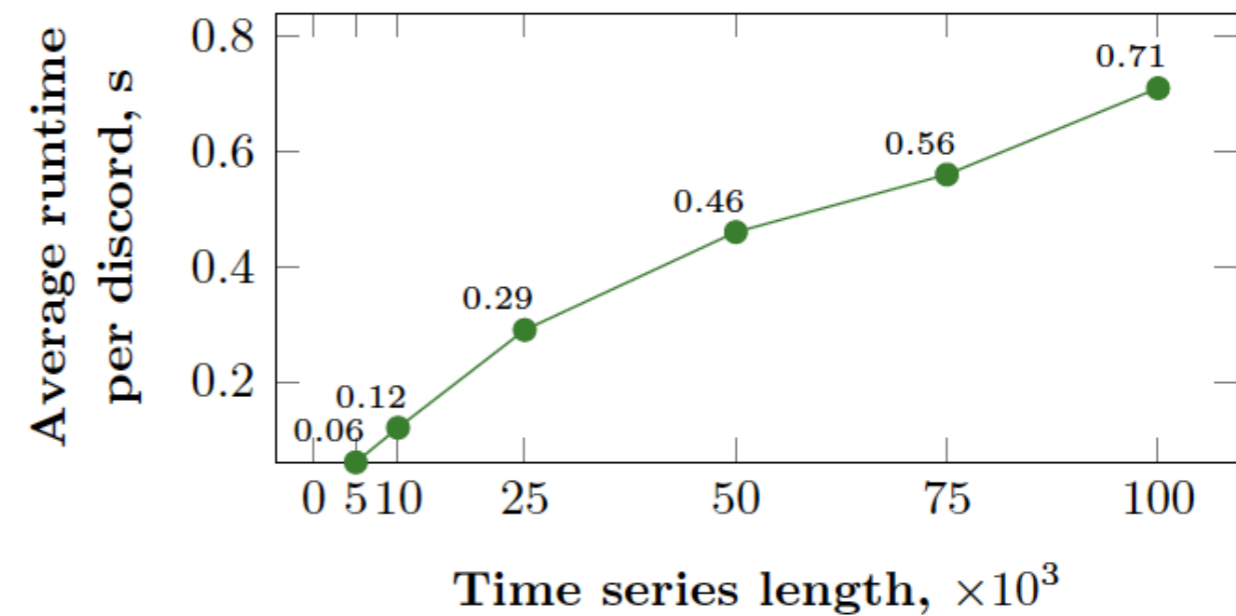
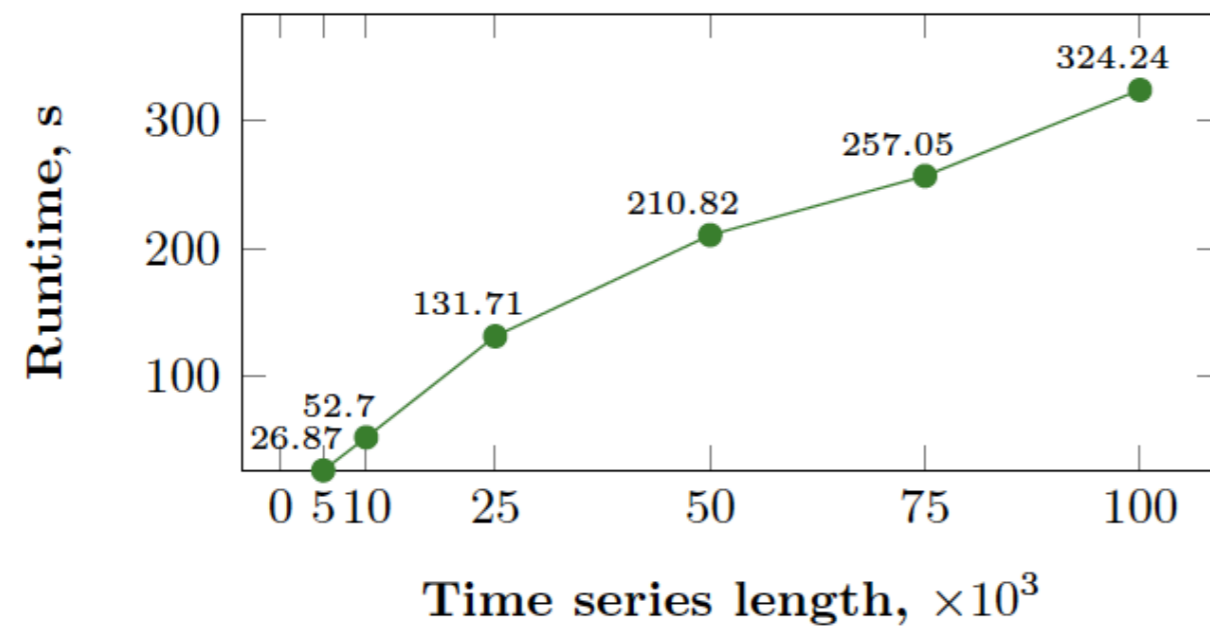
Производительность алгоритма пропорциональна длине сегмента

Масштабируемость: влияние длины ряда

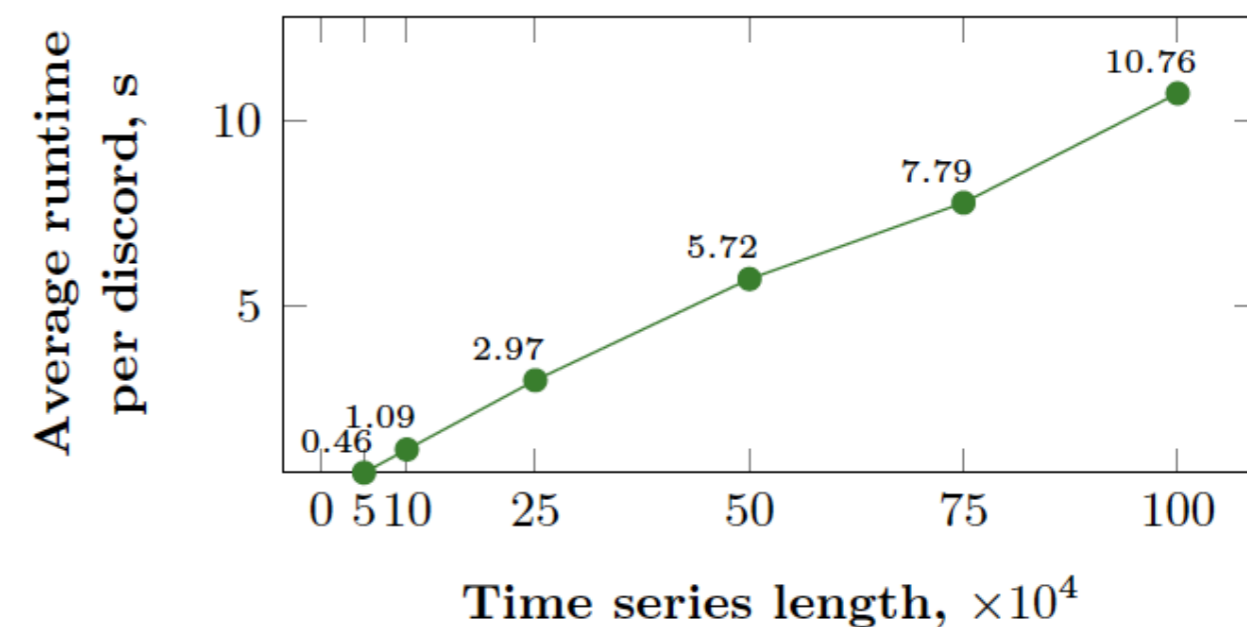
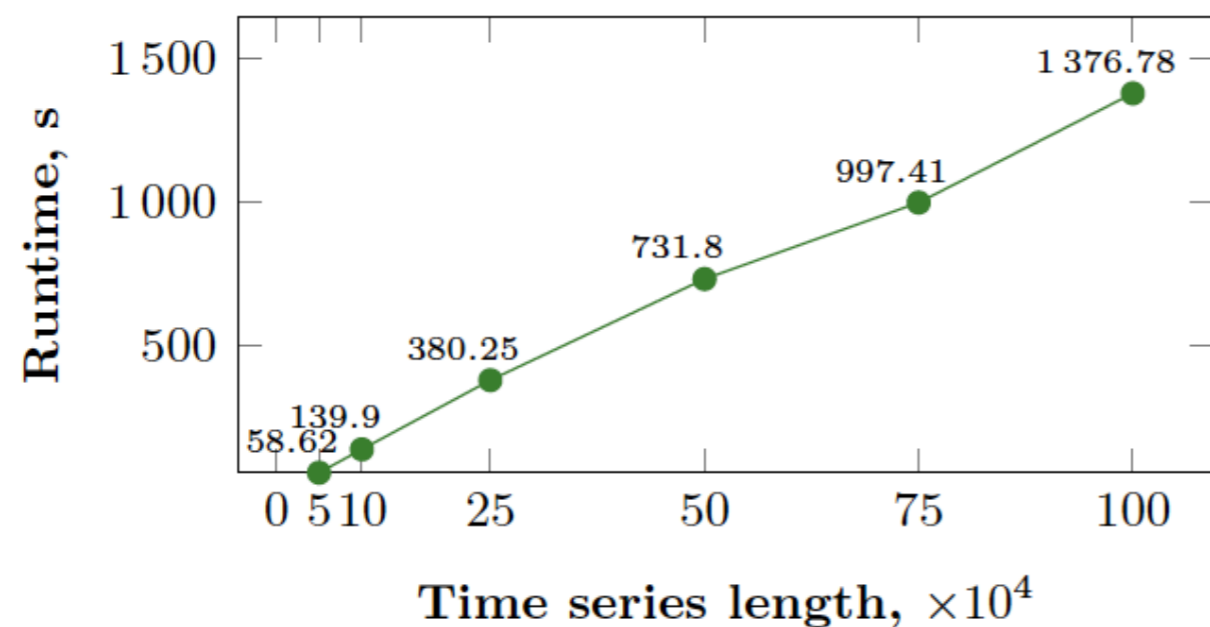
Время на поиск **всех** диссонансов

Среднее время на поиск **одного** диссонанса

Ряд
Koski-ECG
 $m \in [458, 916]$



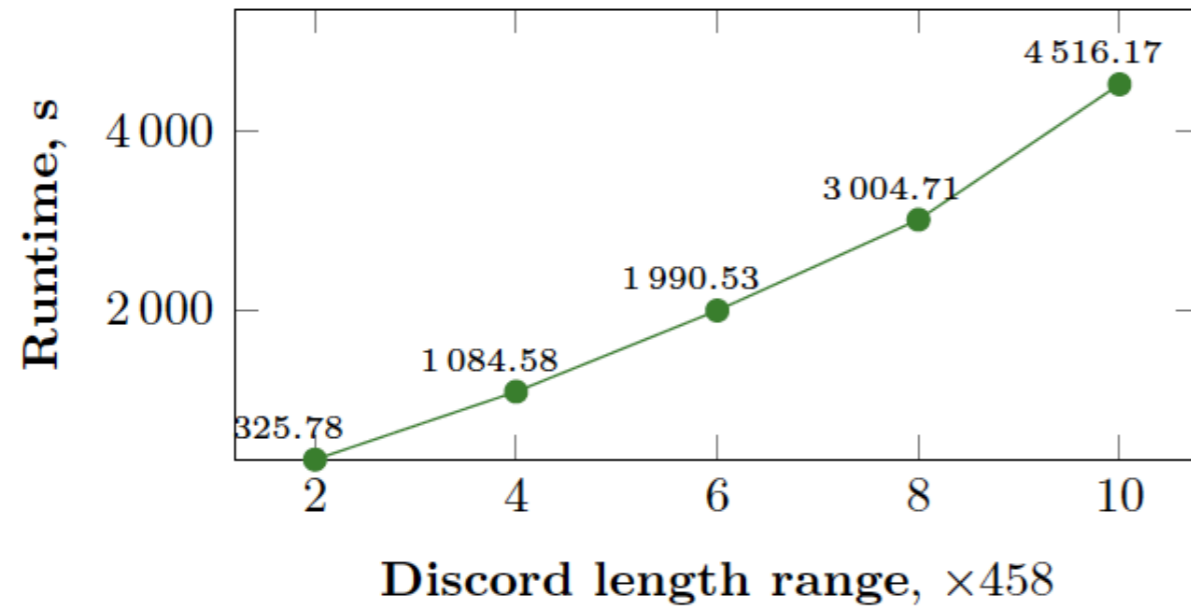
Ряд
RandomWalk1M
 $m \in [128, 256]$



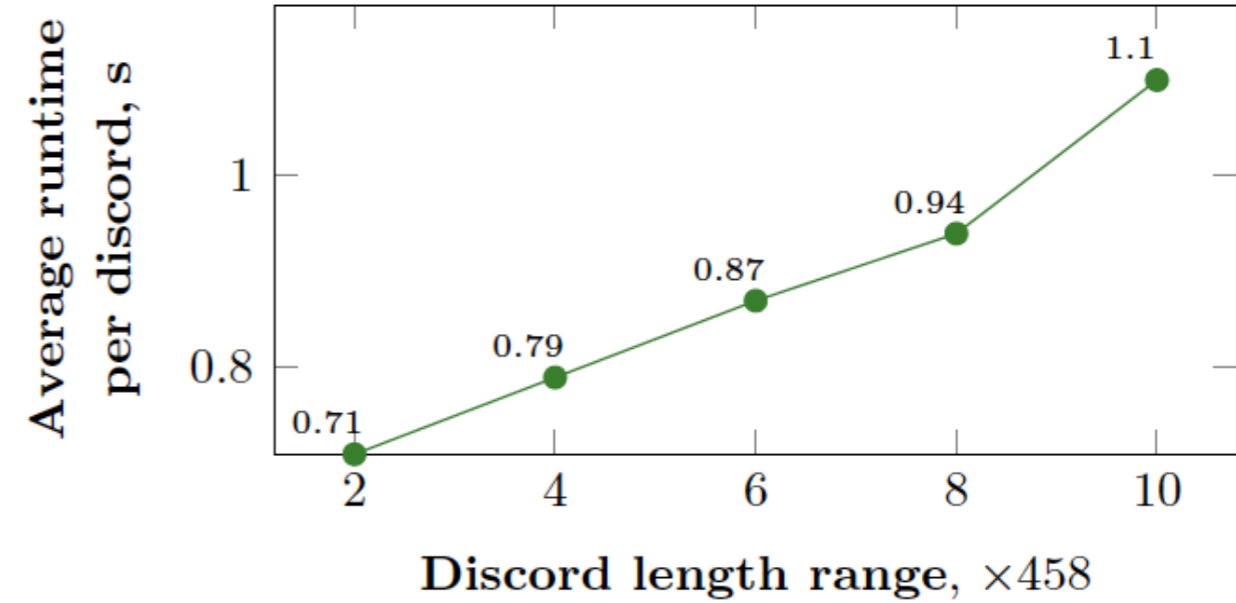
Масштабируемость: влияние диапазона длин диссонансов

Время на поиск **всех** диссонансов

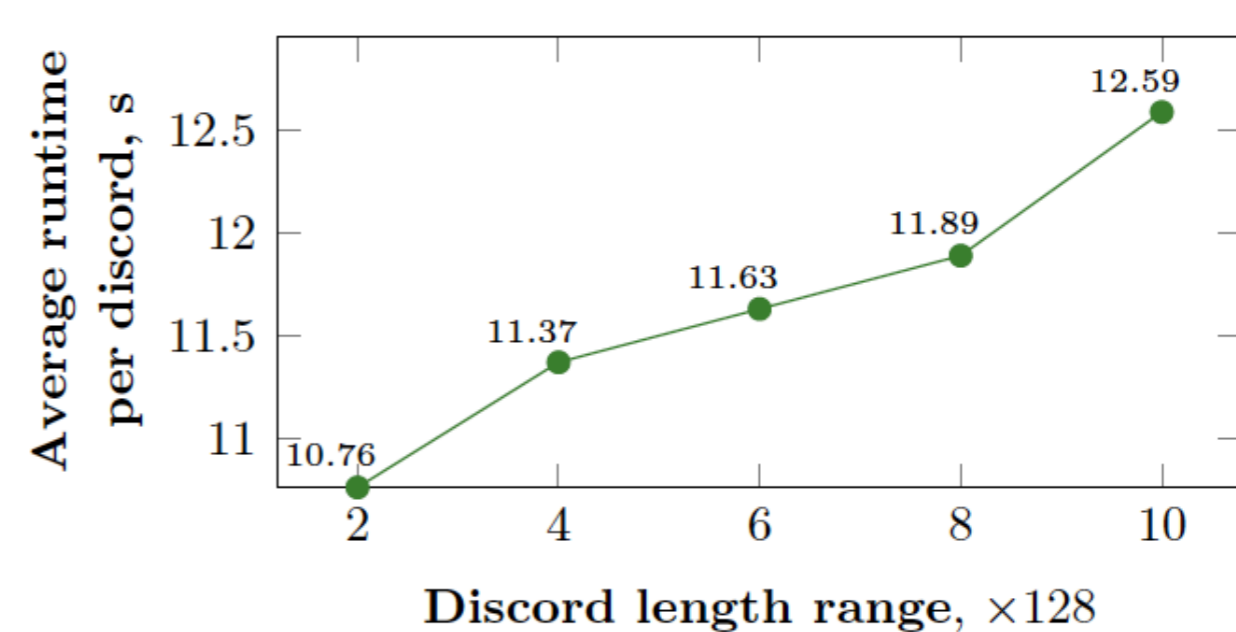
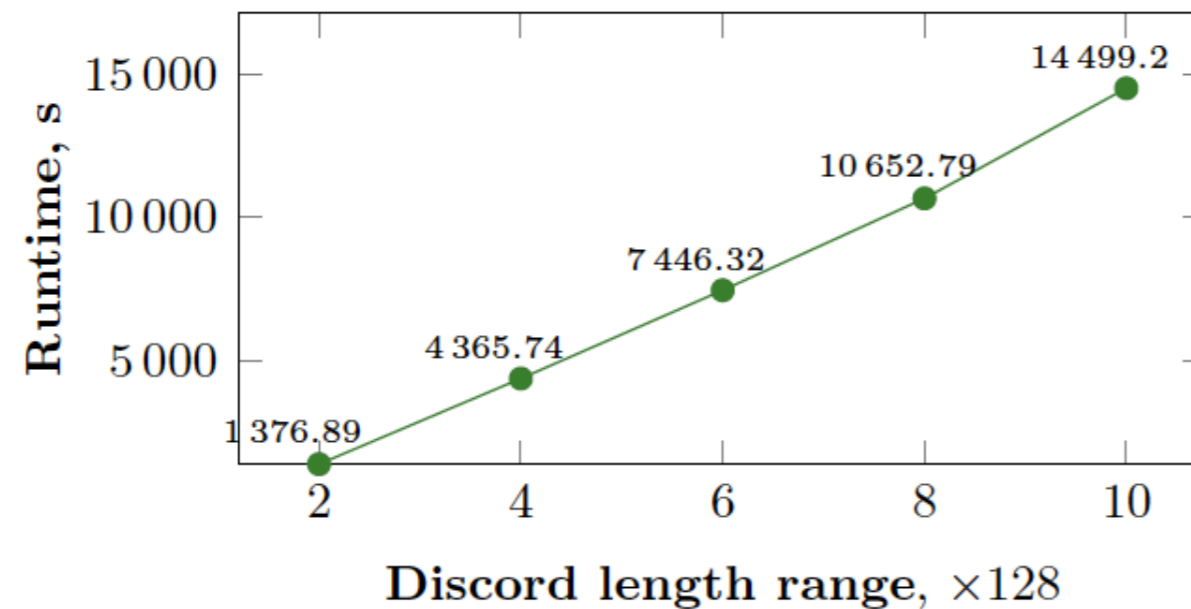
РЯД
Koski-ECG



Среднее время на поиск **одного** диссонанса



РЯД
RandomWalk1M

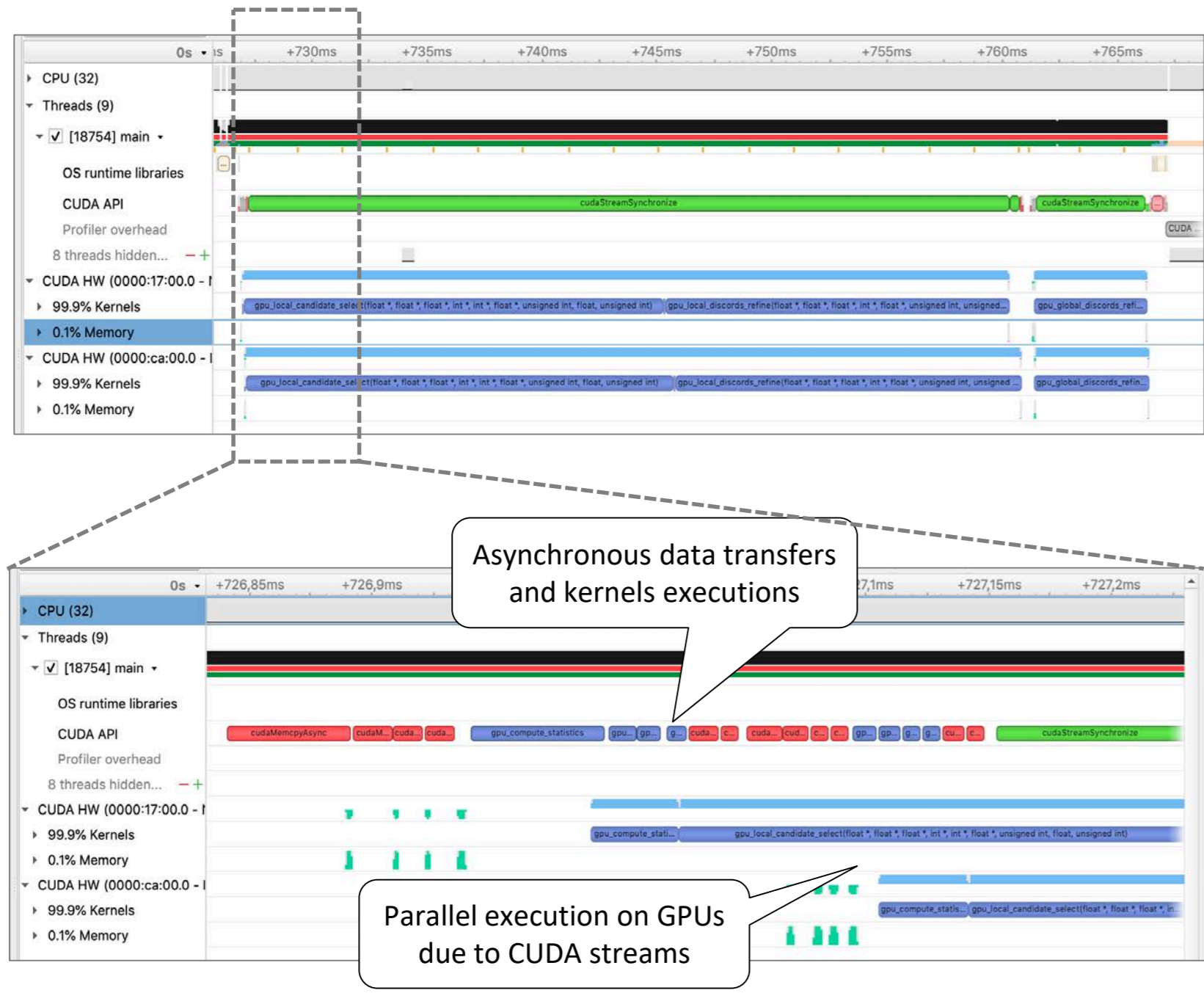


Efficient parallelization of PALMAD for a multi-GPU cluster node

- Non-swappable host memory for data from GPU
- CUDA stream for each GPU

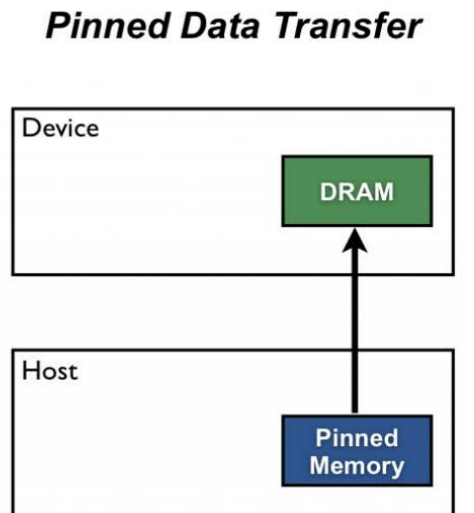
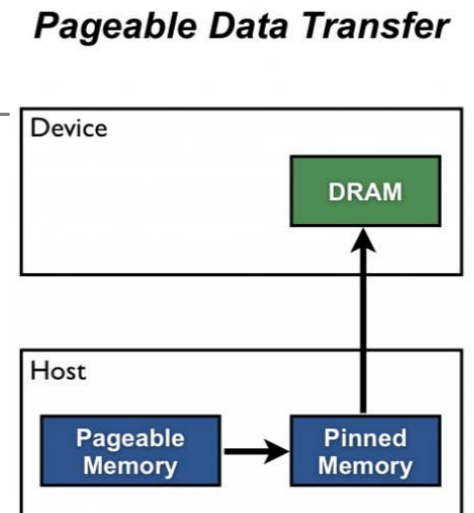
- Asynchronous CPU-GPU data transfers
- Asynchronous CUDA kernels

NVIDIA Nsight Systems



```

for (int i = 0; i < nGPUs; i++) {
    cudaSetDevice(i);
    cudaMalloc(...);
    cudaMallocHost(...);
    cudaStreamCreate(&streams[i]);
}
for (int i = 0; i < nGPUs; i++) {
    cudaSetDevice(i);
    cudaMemcpyAsync(..., cudaMemcpyHostToDevice, streams[i]);
    kernel<<<grid, block, 0, streams[i]>>>(...);
    cudaMemcpyAsync(..., cudaMemcpyDeviceToHost, streams[i]);
}
cudaDeviceSynchronize();
    
```



Experiments: Setup

- **Hardware:** Neurocomputer SUSU, NVIDIA Ampere A100 PCIe (6 912 CUDA-cores, 9.7 TFLOPS)
- **Data:** MIT-BIH Arrhythmia Database¹⁾
 - For generating the training dataset:

Time series	Training time series length, n_{train}	Test time series length, n_{test}	Snippet length, m	Subsequence length, l	Snippet number, K	Discord fraction, α
ECG_803_805	$5 \cdot 10^4$	$5 \cdot 10^4$	350	75	2	0.0002
ECG_803_806	$5 \cdot 10^4$	$5 \cdot 10^4$	350	75	2	0.0002

– For neural network learning: generate 170 000 pairs (2 positive + 2 negative pairs per 1 subsequence)

- **Measure:** $Precision = \frac{TP}{TP+FP}$, TP – true anomalies detected, FP – false positive anomalies detected
- **Neural Network Hyperparameters:**

– **Loss function:** contractive loss

$$L(x_i, x_j, \delta_{x_i x_j}) = \delta_{x_i x_j} ED^2(h_i, h_j) + (1 - \delta_{x_i x_j}) \max(0, \tau - ED(h_i, h_j))^2,$$

where τ – margin between samples of different classes

– **Optimizer:** Adam

– **# Epochs:** 40

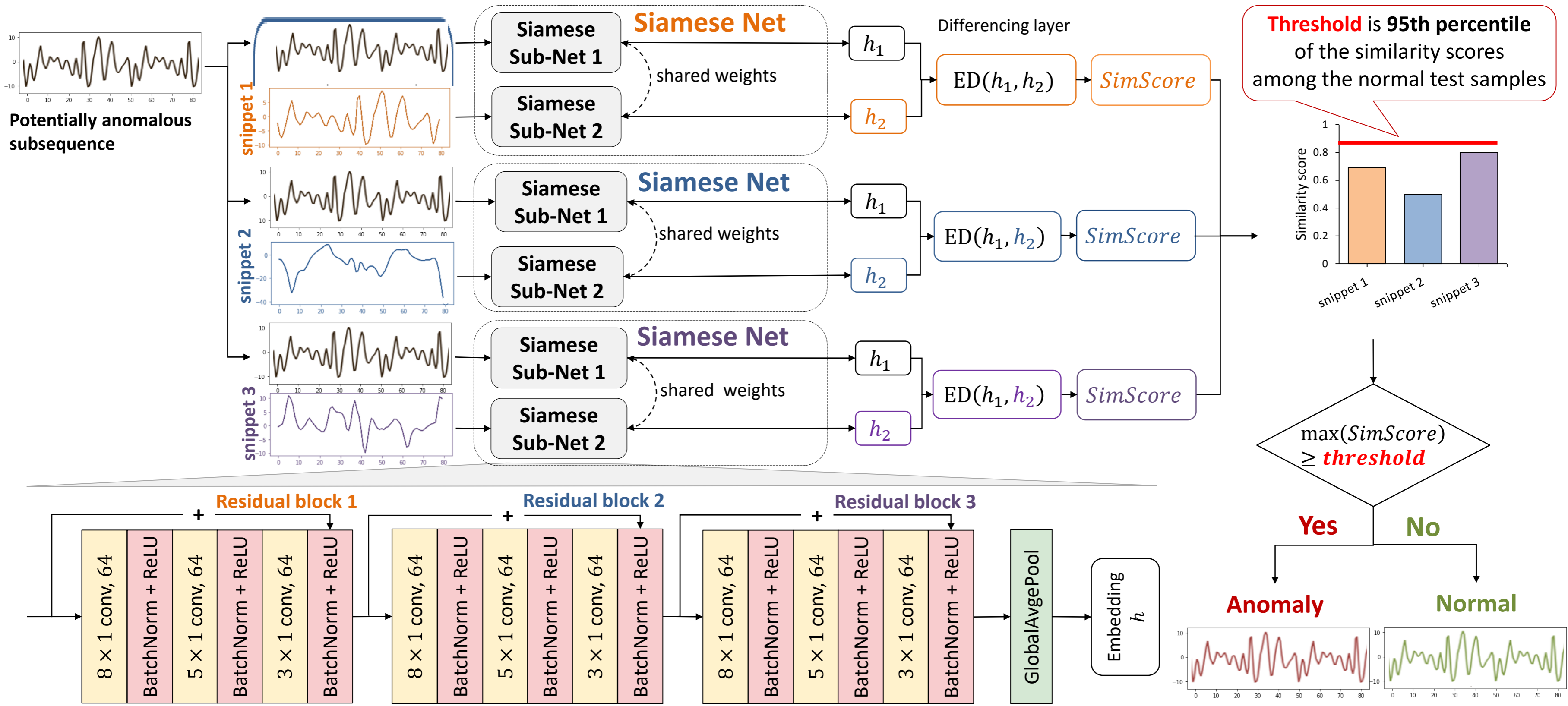
– **Batch size:** 128

– **Learning rate:** $1 \cdot 10^{-3}$

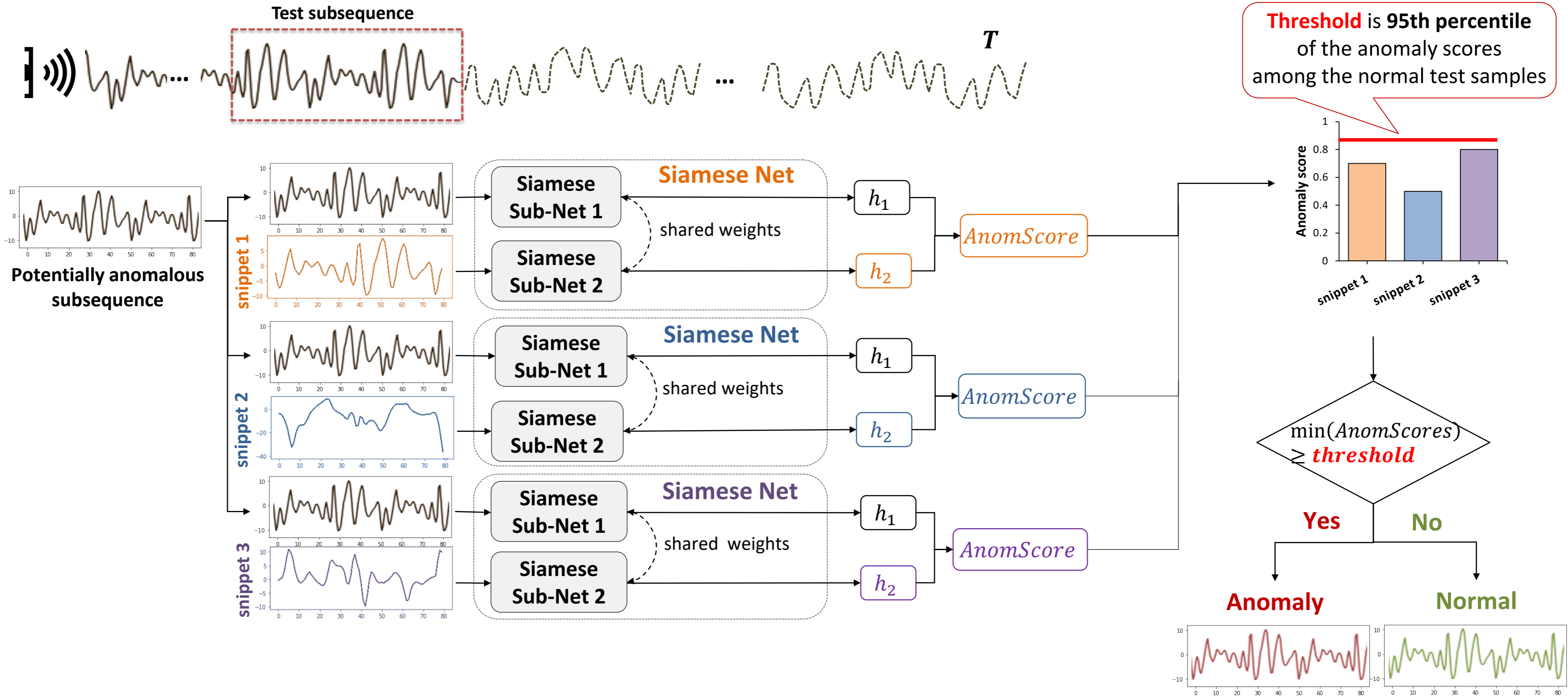
– **Embedding size:** 128

¹⁾ Goldberger A. L., et al. PhysioBank, PhysioToolkit, and PhysioNet components of a new research resource for complex physiologic signals. Circulation 101(23): 215-220. 2000.

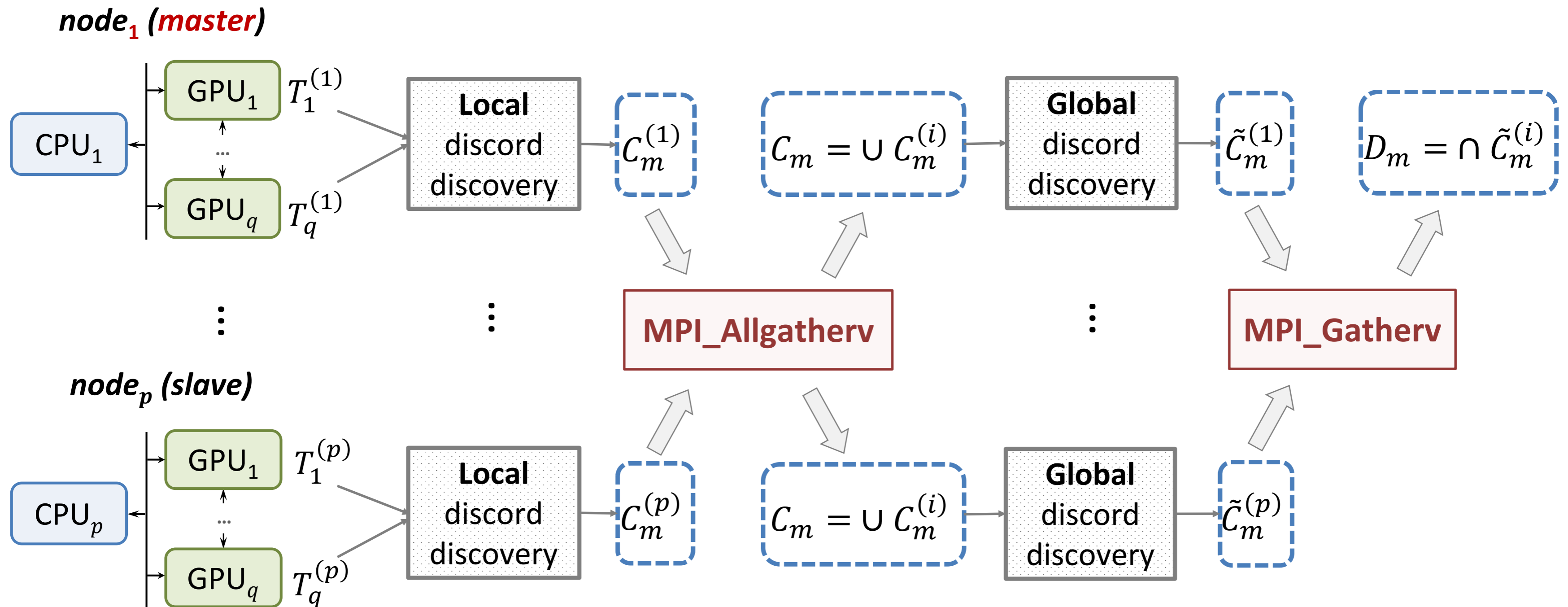
DiSSiD: Discord, Snippet, and Siamese Net-based Detector of anomalies



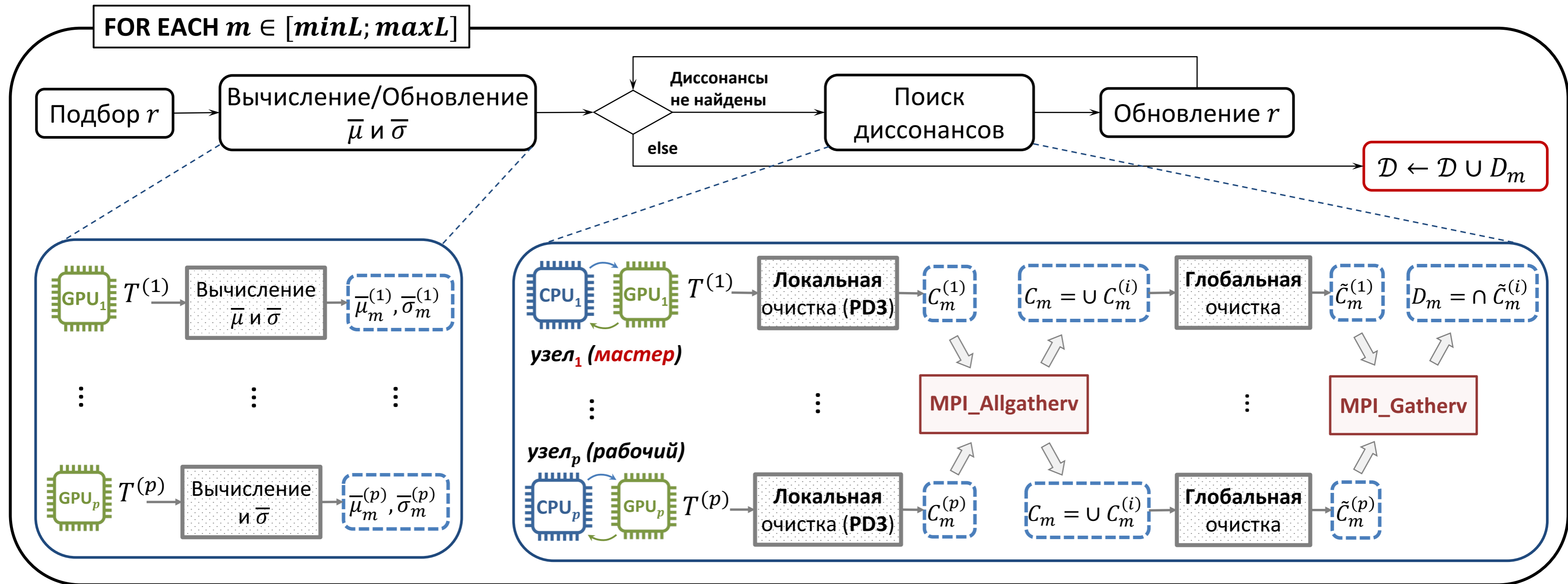
DiSSiD: Discord, Snippet, and Siamese Net-based Detector of anomalies



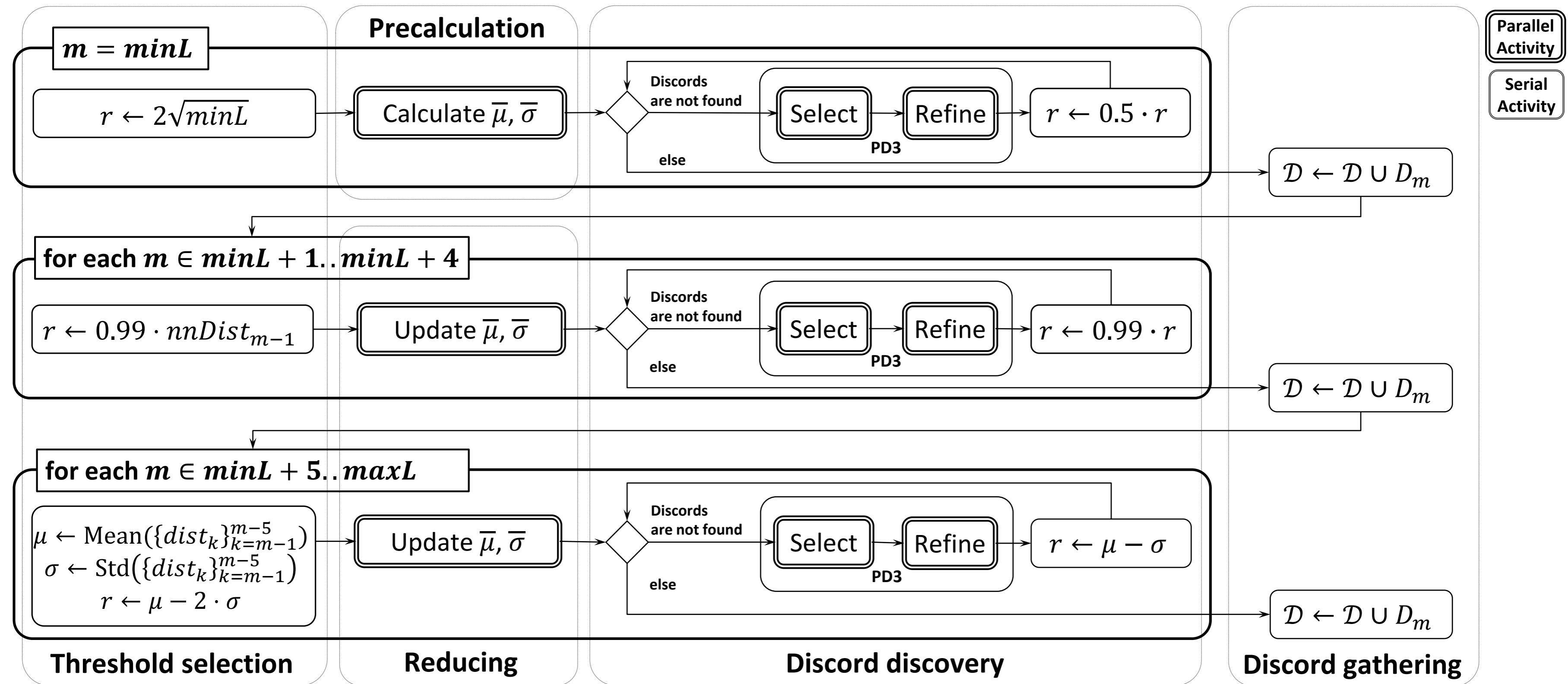
Distributed PALMAD: general scheme

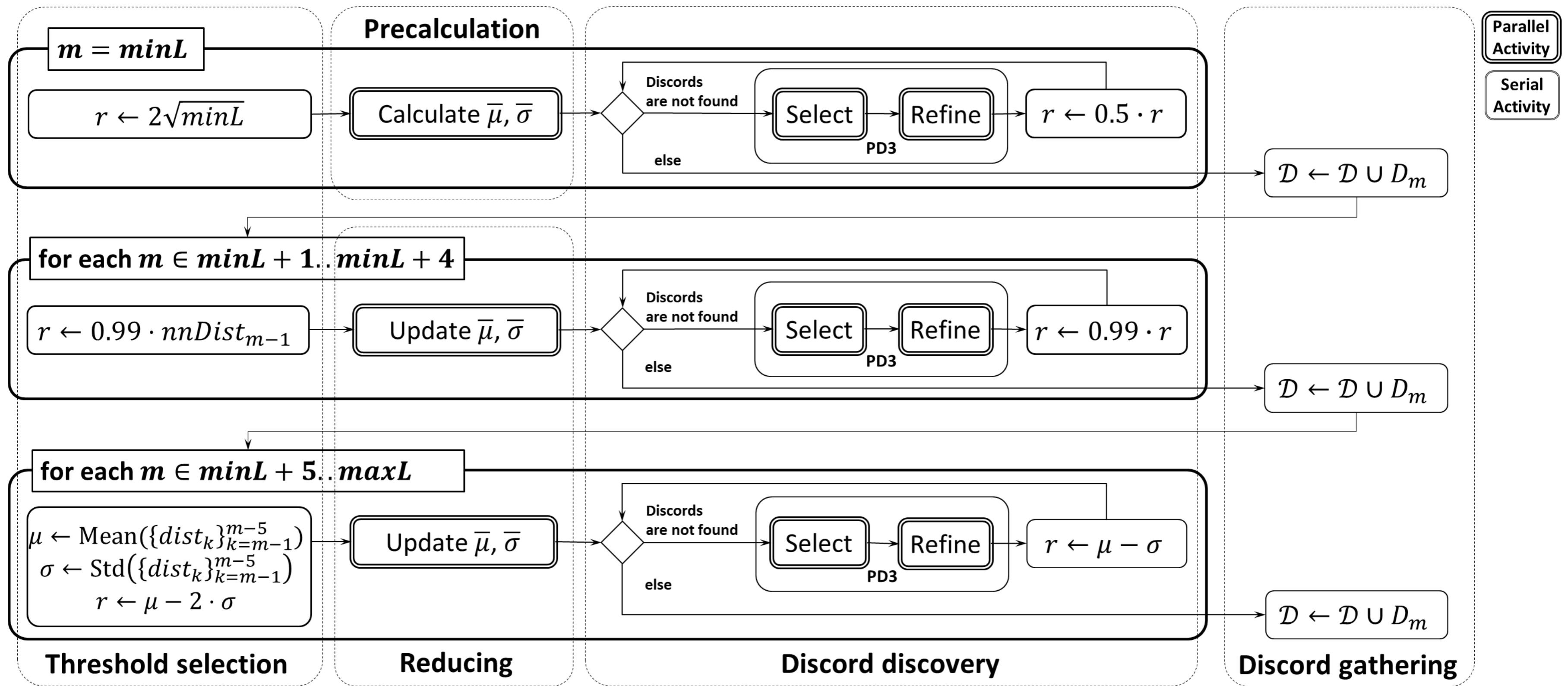


Distributed PALMAD: general scheme



PALMAD (Parallel Arbitrary Length MERLIN-based Anomaly Discovery)¹⁾





PD3: Parallel DRAG-based Discord Discovery

