



UNIVERSITY
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Predicting WCET Trends in Long-lived Real-time Applications

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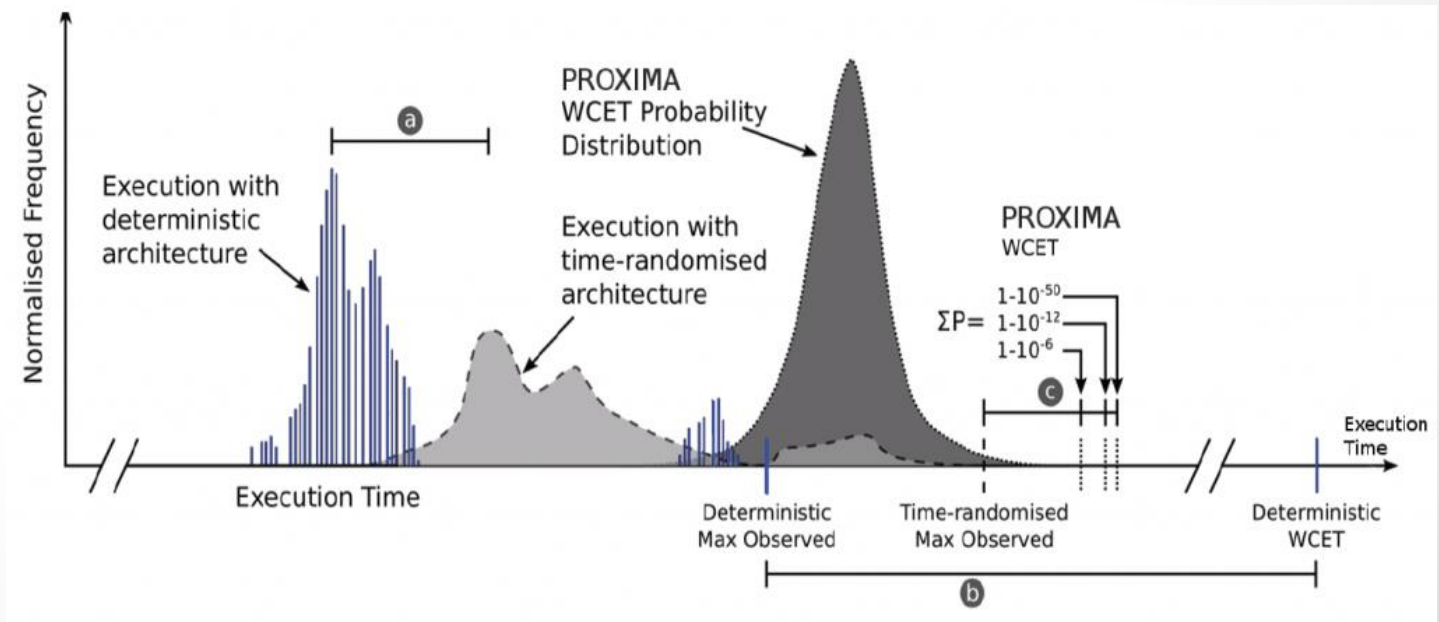
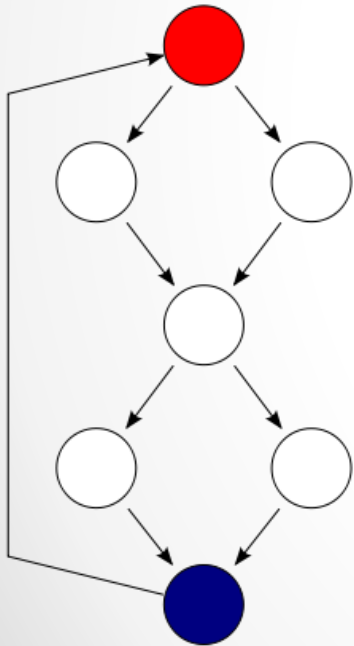


Contents

- I. Motivation
- II. Adaptive Scheduling Framework
- III. Trend Identification Methods
- VI. Evaluation
- V. Conclusion

Background | Motivation

- Worst-case execution time (WCET)
 - is important in timing analysis (DO-178 and ISO26262)
 - static and measurement-based
 - pWCET



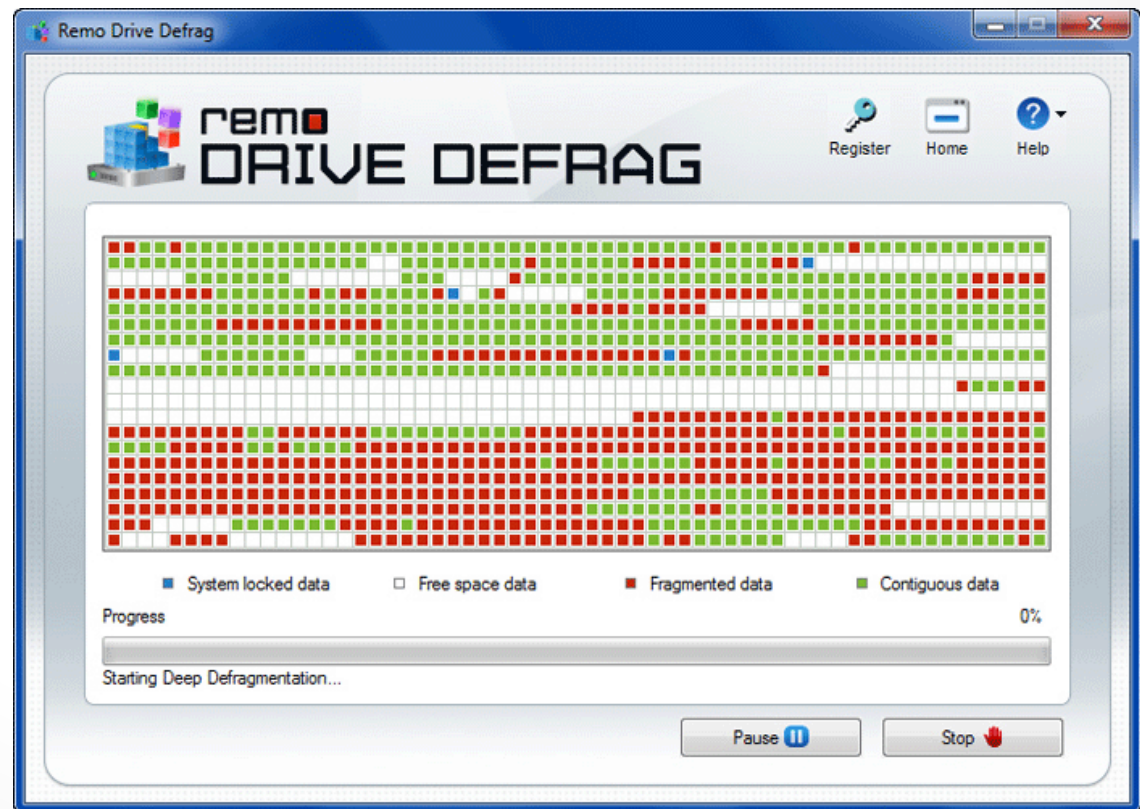
Background | Motivation

- Current understanding of WCETs:
 - A theoretical boundary exists, if designed and programmed with constrained models.
 - Known as a static, upper-bound value of execution times



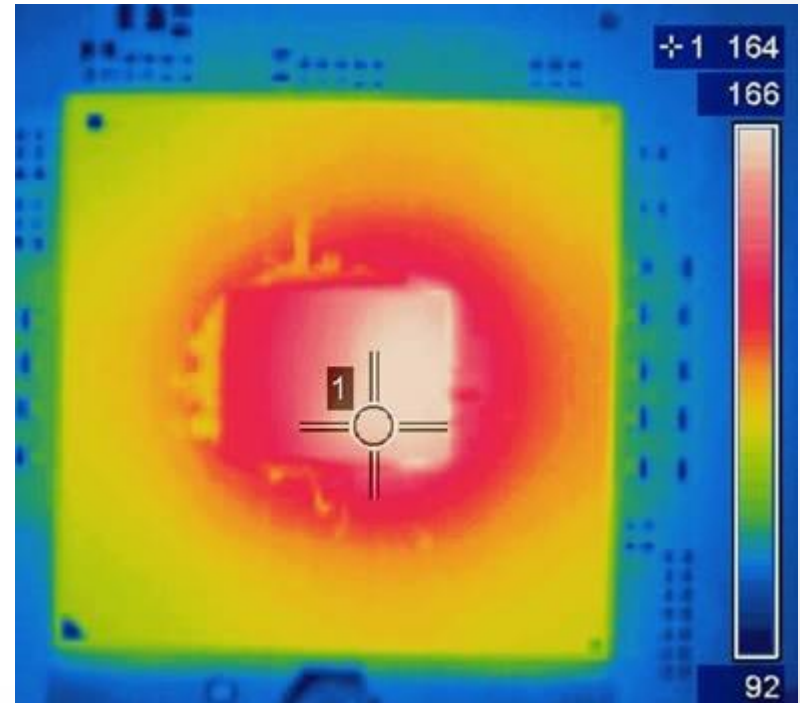
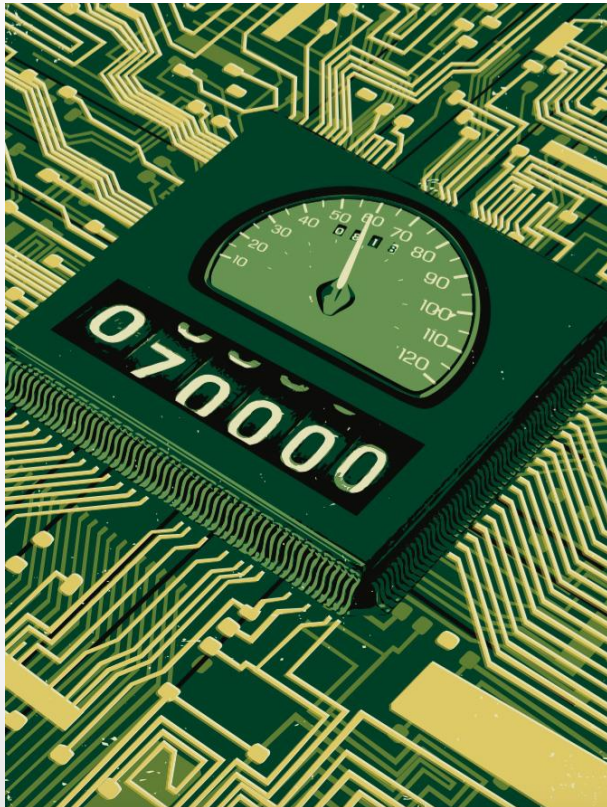
Issues | Motivation

- Data accessing time \uparrow
 - relevant data growth
 - hard disk fault/fragmented



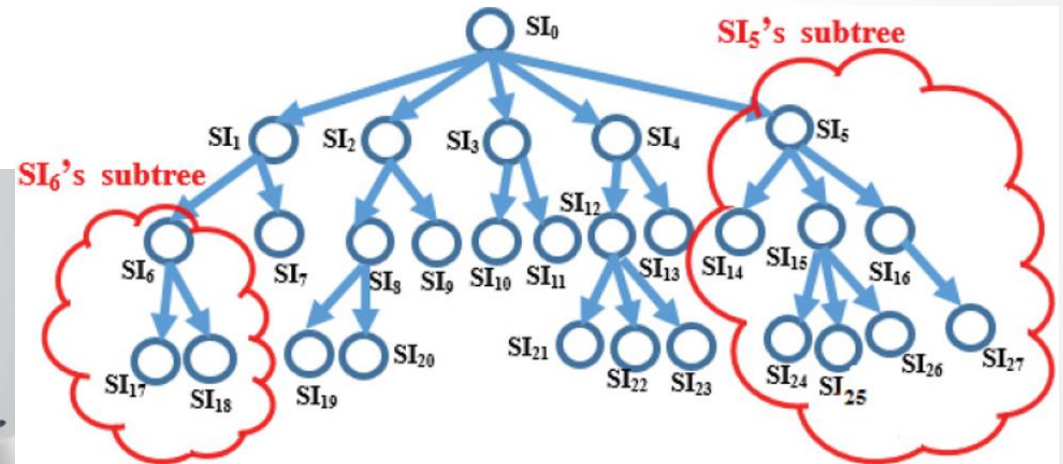
Issues | Motivation

- Hardware ageing: computer systems age just like humans
 - CPU transistor ageing: fundamental speed \downarrow
 - Thermal performance decreased: lacking maintenance



Issues | Motivation

- Emerging systems
 - Self-adaptive systems: increased software complexity
 - Machine that learns and evolves, e.g., autonomous robots



Issues (continue) | Motivation

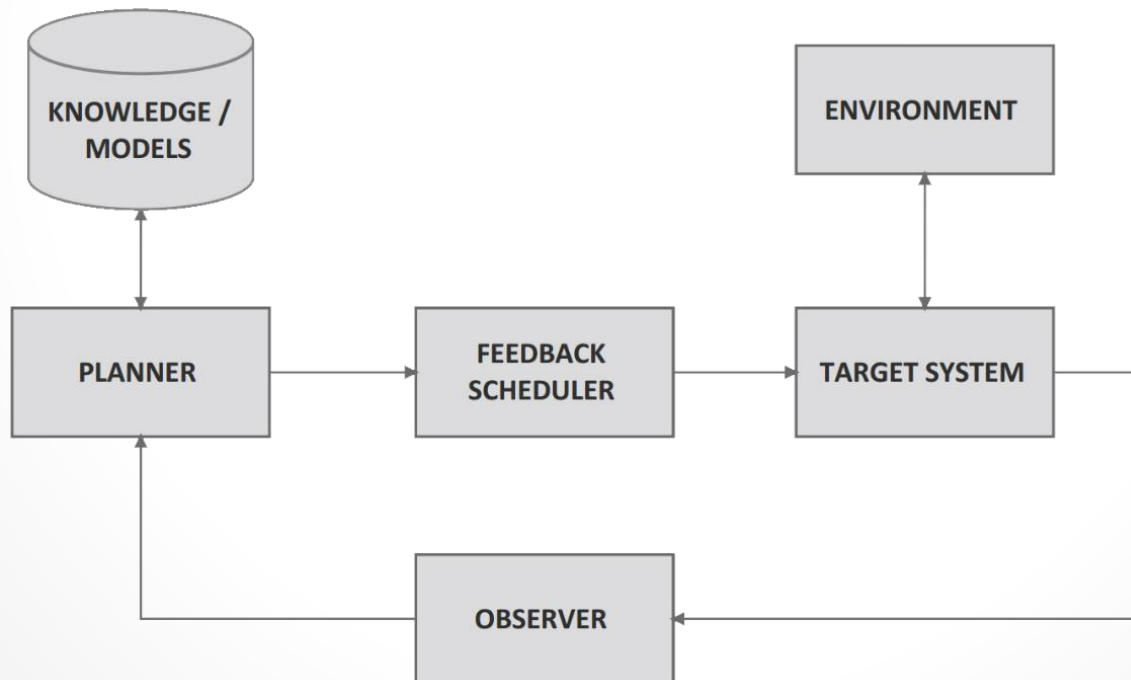
- Contribute **negative** and **non-deterministic** effects on WCETs.
- Subtle in a short period, but noticeable in long-term.
- Traditional WCET analysis could solve this by giving a very **pessimistic** boundary.
- A new perspective on WCET:
a dynamic view of WCET (dWCET), as an extension of traditional WCET analysis.

dWCET | Motivation

- Run-time modelling of WCET.
- Enhanced Parametric WCET:
 $WCET = f(t, \text{system changes}[, \text{mode, state, input, ...}])$.
- Pro 1: Early detection of potential timing errors, and achieve graceful degradation.
- Pro 2: Utilize resources better (with feedback scheduling) .

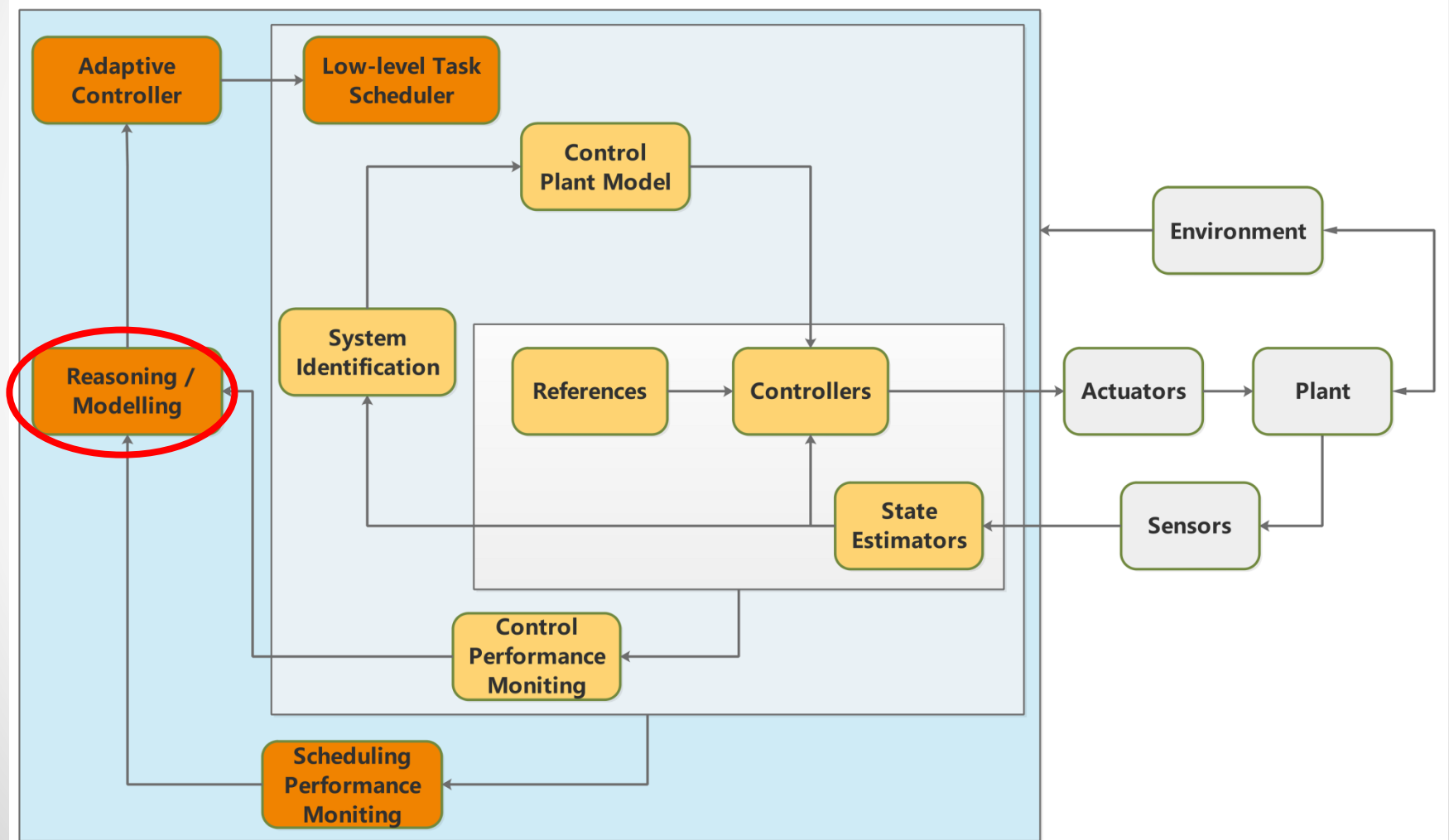
Adaptive Feedback Scheduling

- A variation of Feedback Control Scheduling (FBS)
- Adaptive
 - ability to handle unexpected events
 - understanding of the system increases



In Practice | A-FBS

- A-FBS uses with an adaptive control system:



Advantages | A-FBS

- Explicitly monitoring and modelling the system.
- Handling uncertainties in run-time executions.
- Increase system resilience: automated the process of (proactive) fault tolerance.
- Dynamic resource allocation: run-time optimization of scheduling.

What's Next?

- The activation of system changes/degrades will be propagated in the system and reflects on WCETs.
- There are many ways we can model dynamics in WCETs.
- In this initial study, we consider one of these: trends in WCET.
- Use a linear model to describe trend.

Trend Identification

- Many techniques in the literature:
 - AR / ARMAX
 - Regression Analysis
 - Non-parametric
 - EVT
 - Neural Network
 - Decision Tree Regression
 - ...
- but not all of them fit our case:
 - data points are execution times
 - distribution is not known
 - few prior knowledge
 - need a long-term prediction

Methods | Trend Identification

- Non-parametric Methods
 - TSE: Theil-Sen Estimator
- Regression Analysis
 - OLS: Ordinary least-squares regression (OLS-regression)
- Extreme-value Theory
 - EVD: Generalized Extreme-value distribution
- Machine Learning Methods
 - SVR: Support Vector Regression
- These methods have never been used to analysis trends in WCETs. How to evaluate?

[1] Sen, P.K., "Estimates of the regression coefficient based on Kendall's tau" (1968).

[2] Basak, Debasish et al. "Support Vector Regression." (2008).

[3] Kotz, S.. "Extreme Value Distributions: Theory and Applications." (2016).

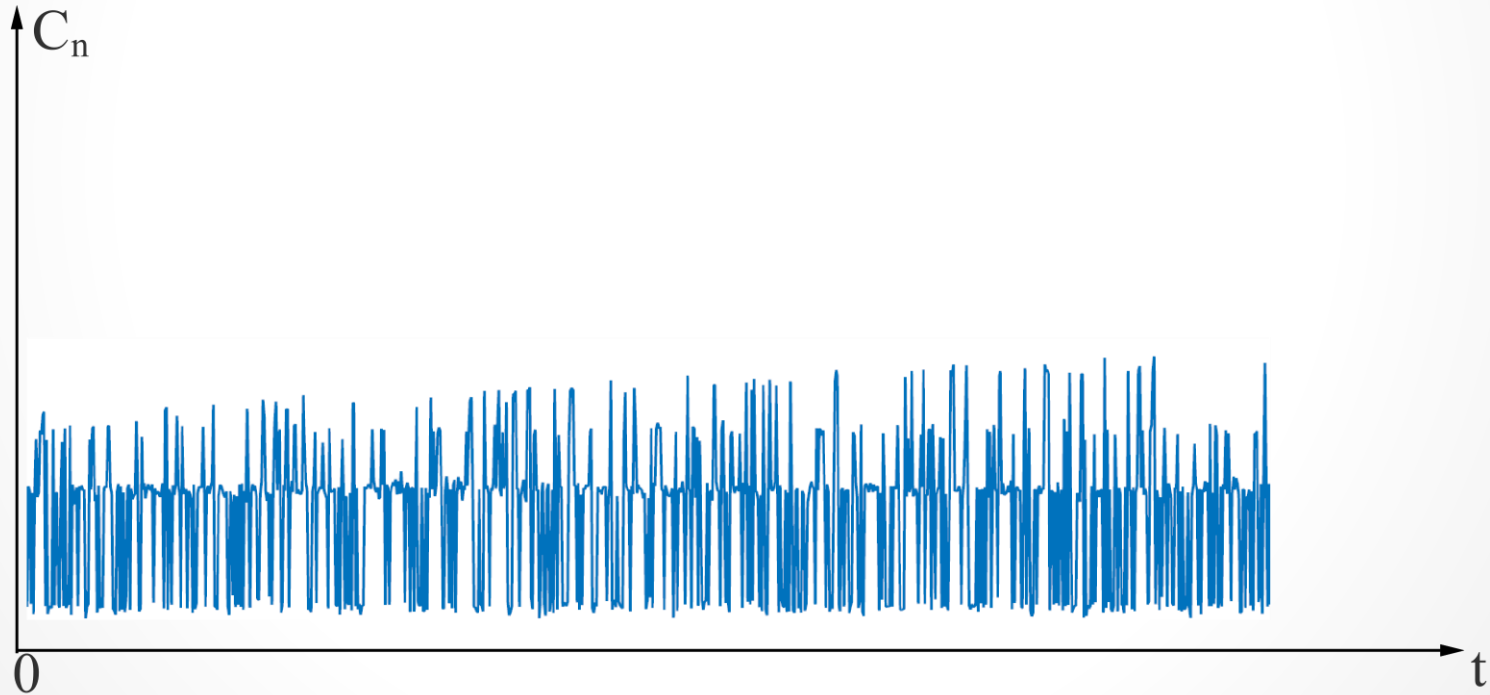
Dataset | Evaluation

- Use synthetic data to make it evaluable.
- One observation represents a high watermark of run-time executions.
- Markov model with multiple dominated paths.
- An increasing trend only in the worst-case path.

Group	Subgroup	Dataset Index	Data Size	Increasing Trend
A	A1	1 - 10	5,000	0%
B	B1	11 - 20	5,000	1%
	B2	21 - 30	2,500	2%
	B3	31 - 40	1,667	3%
	B4	41 - 50	1,250	4%

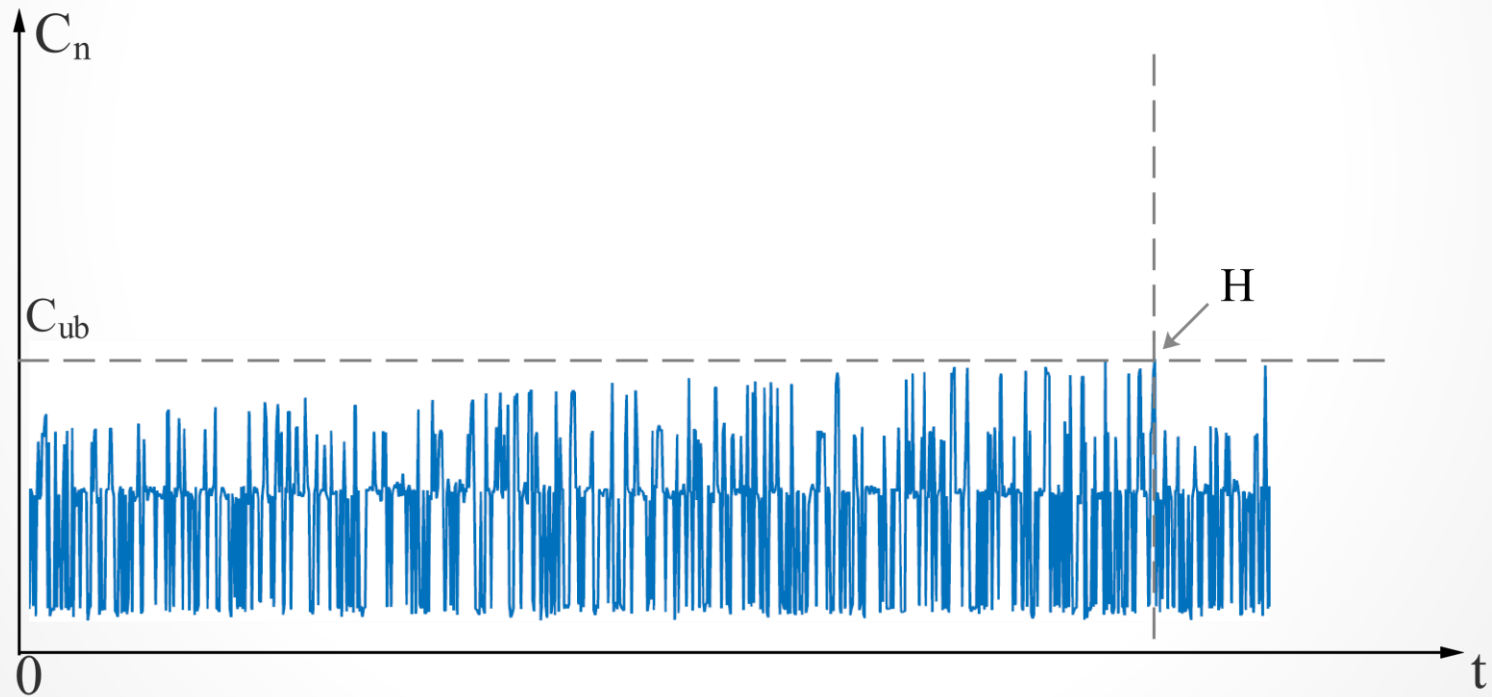
Evaluation

- The Evaluation Framework



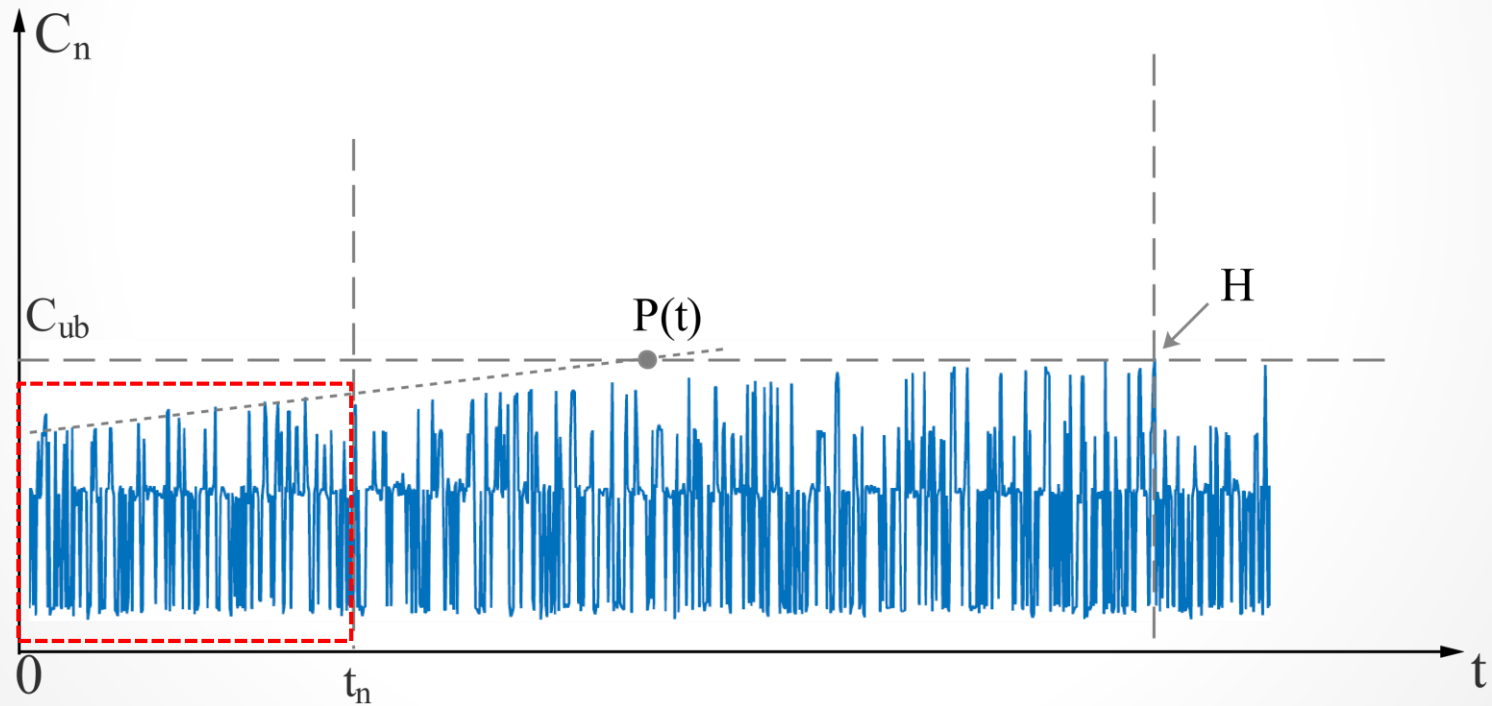
Evaluation

- The Evaluation Framework



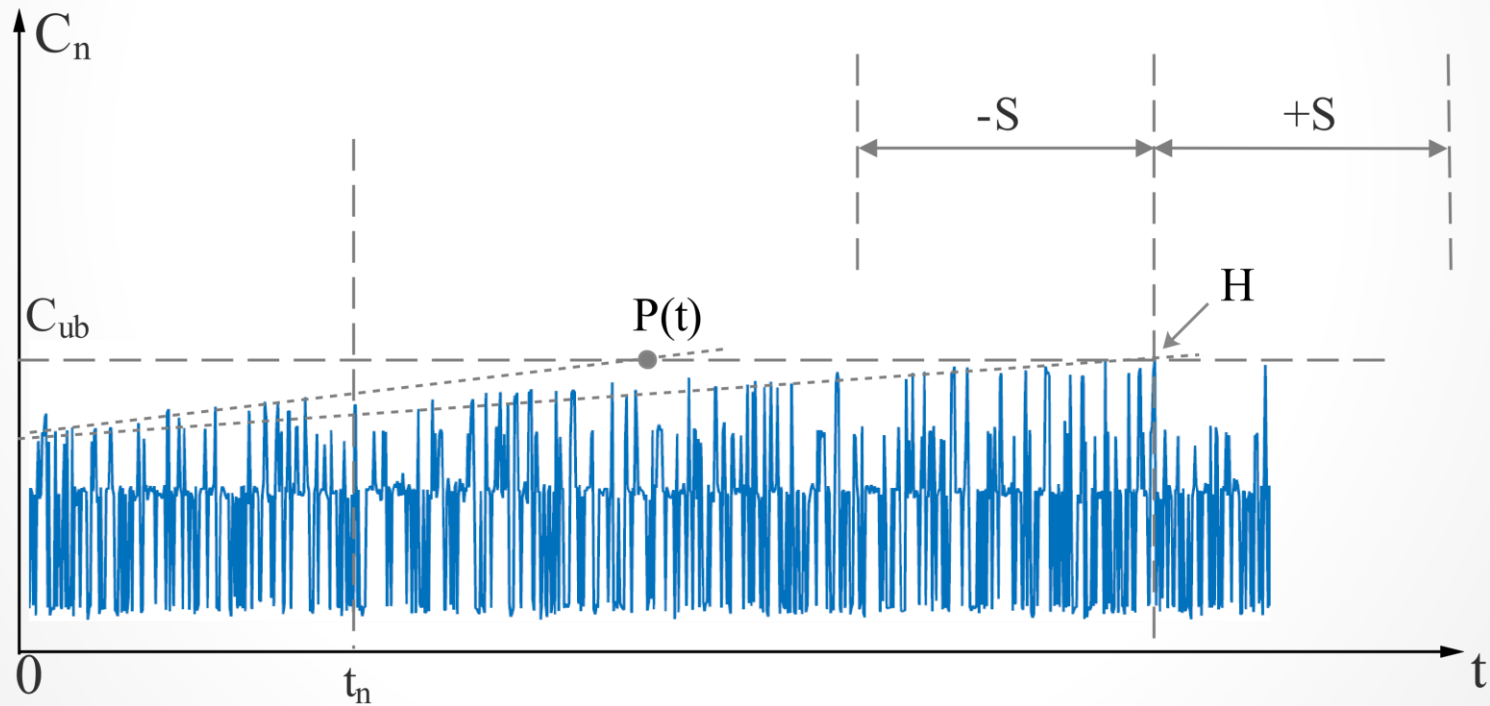
Evaluation

- The Evaluation Framework



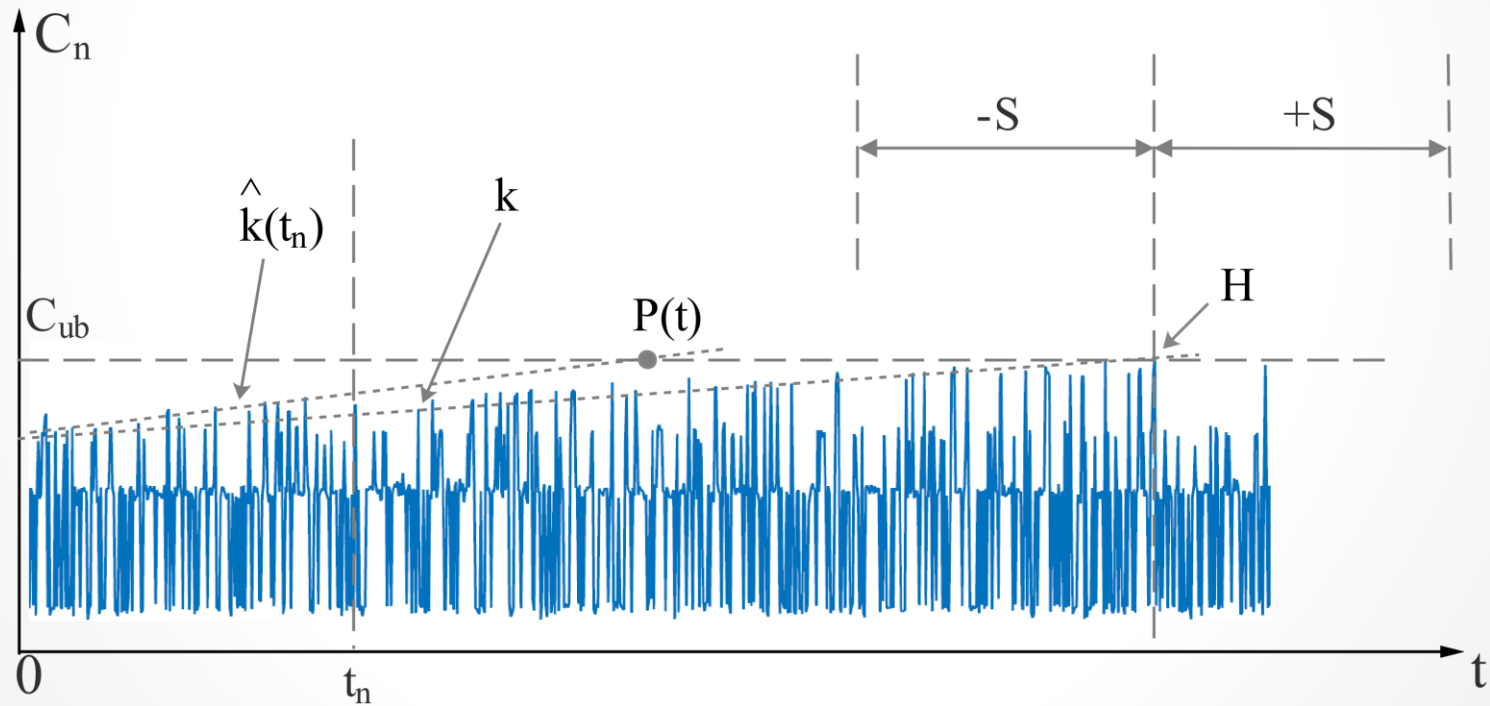
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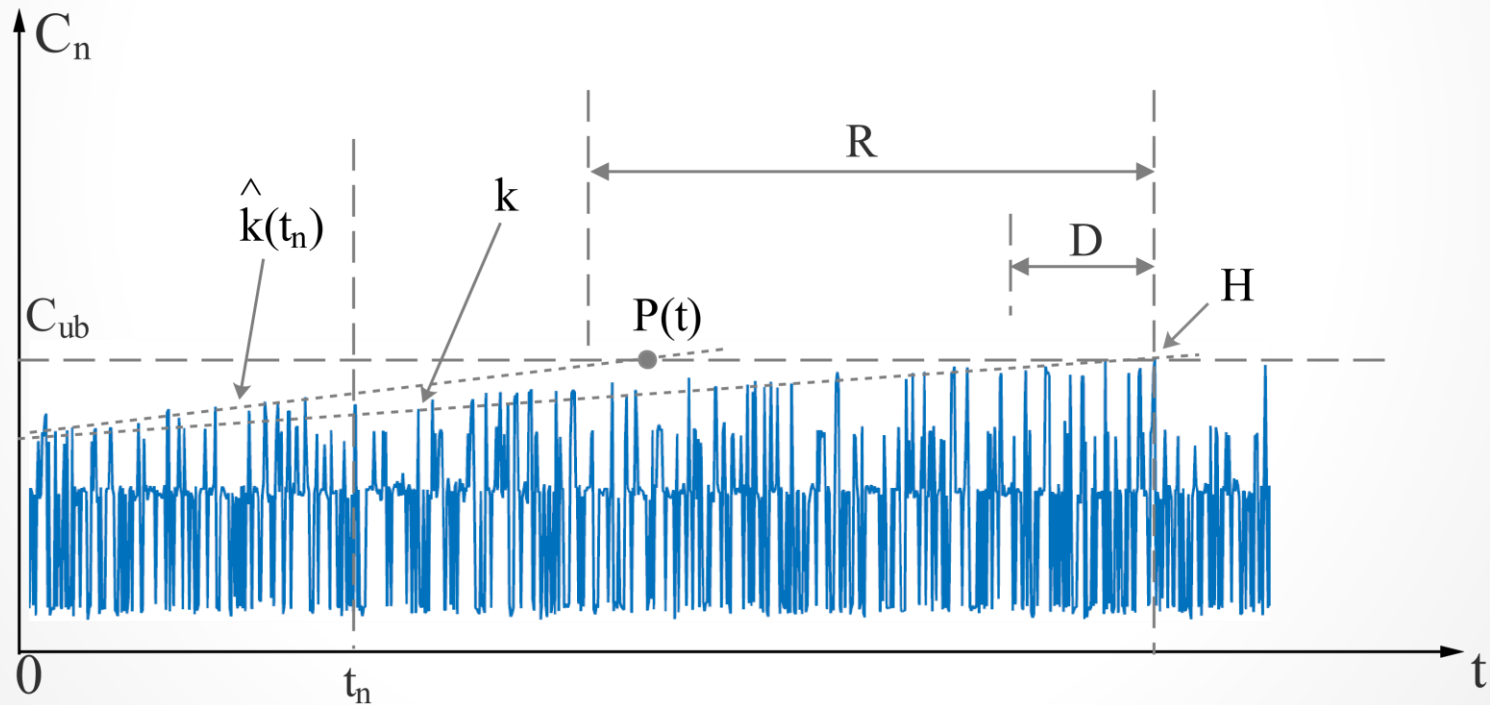
Evaluation

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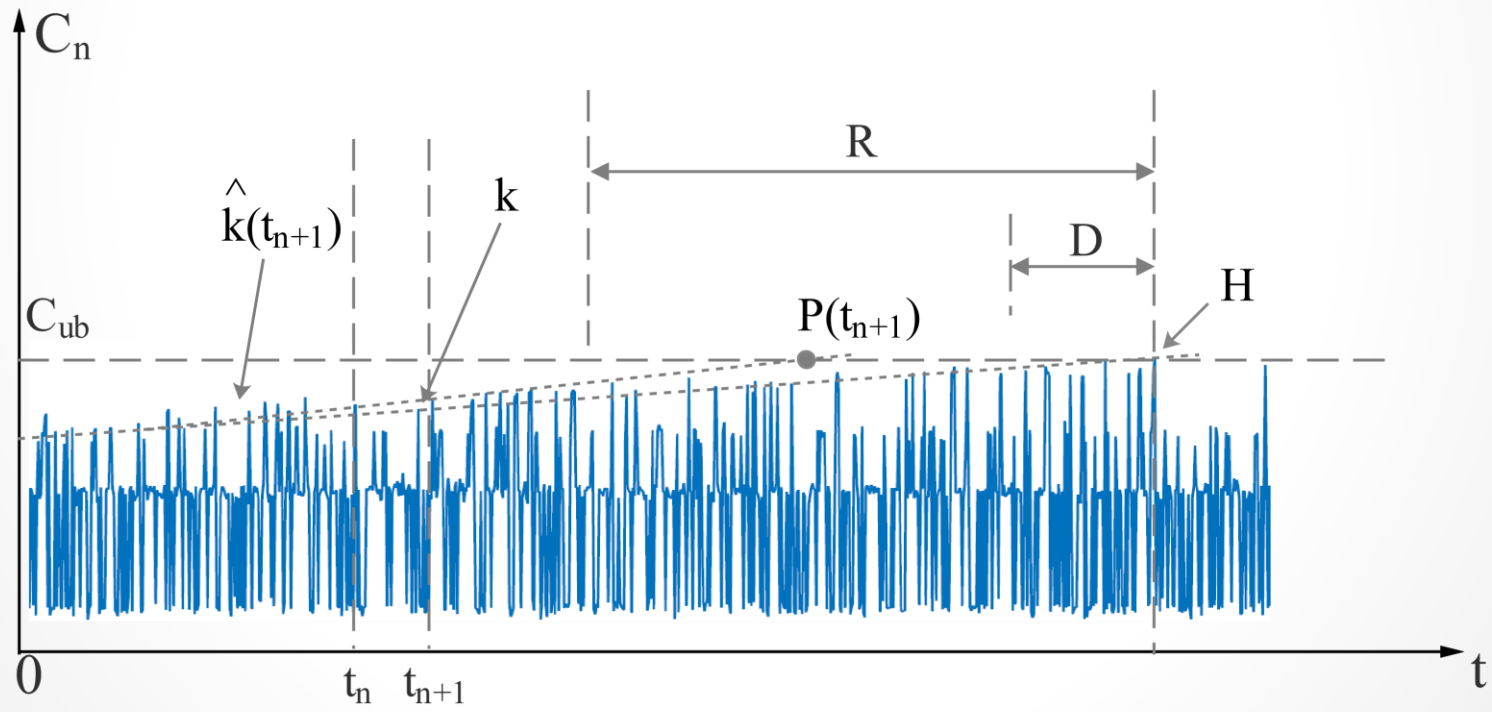
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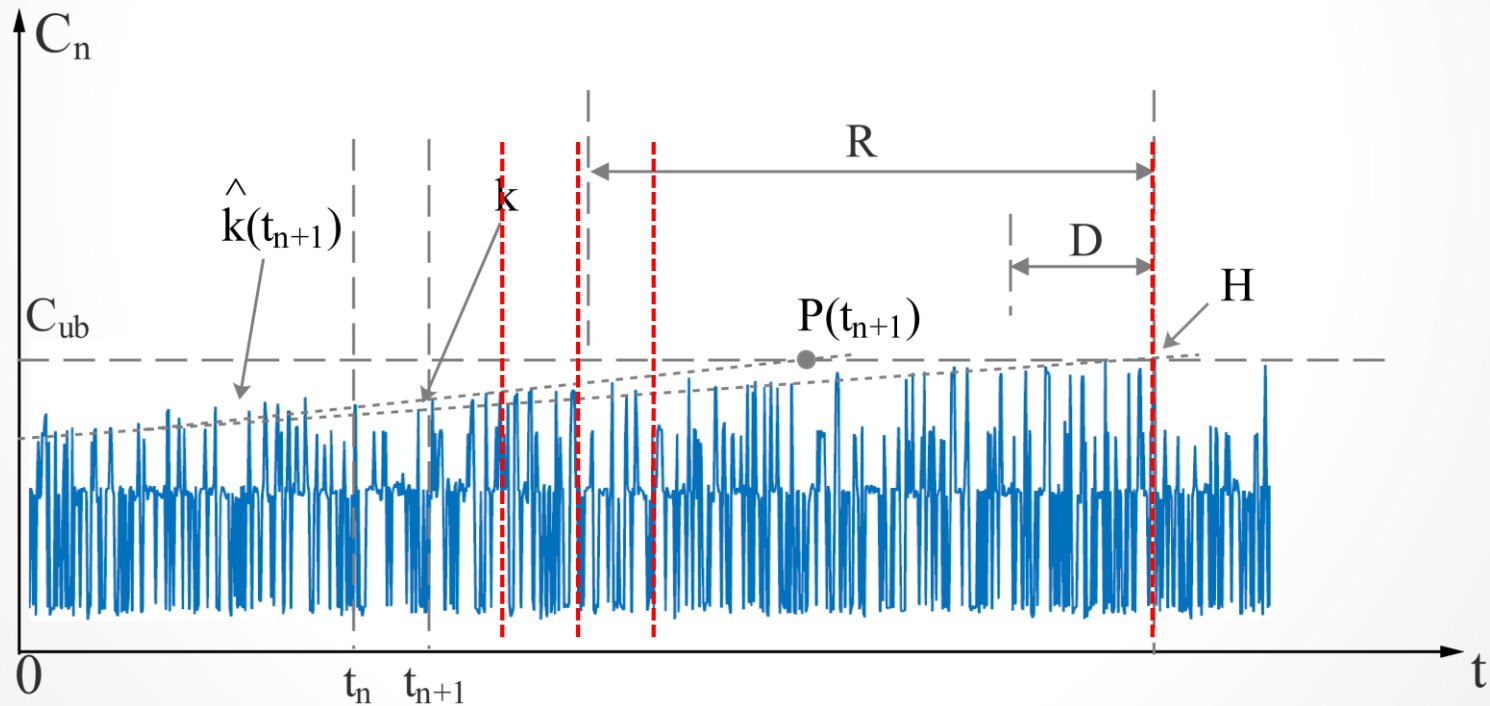
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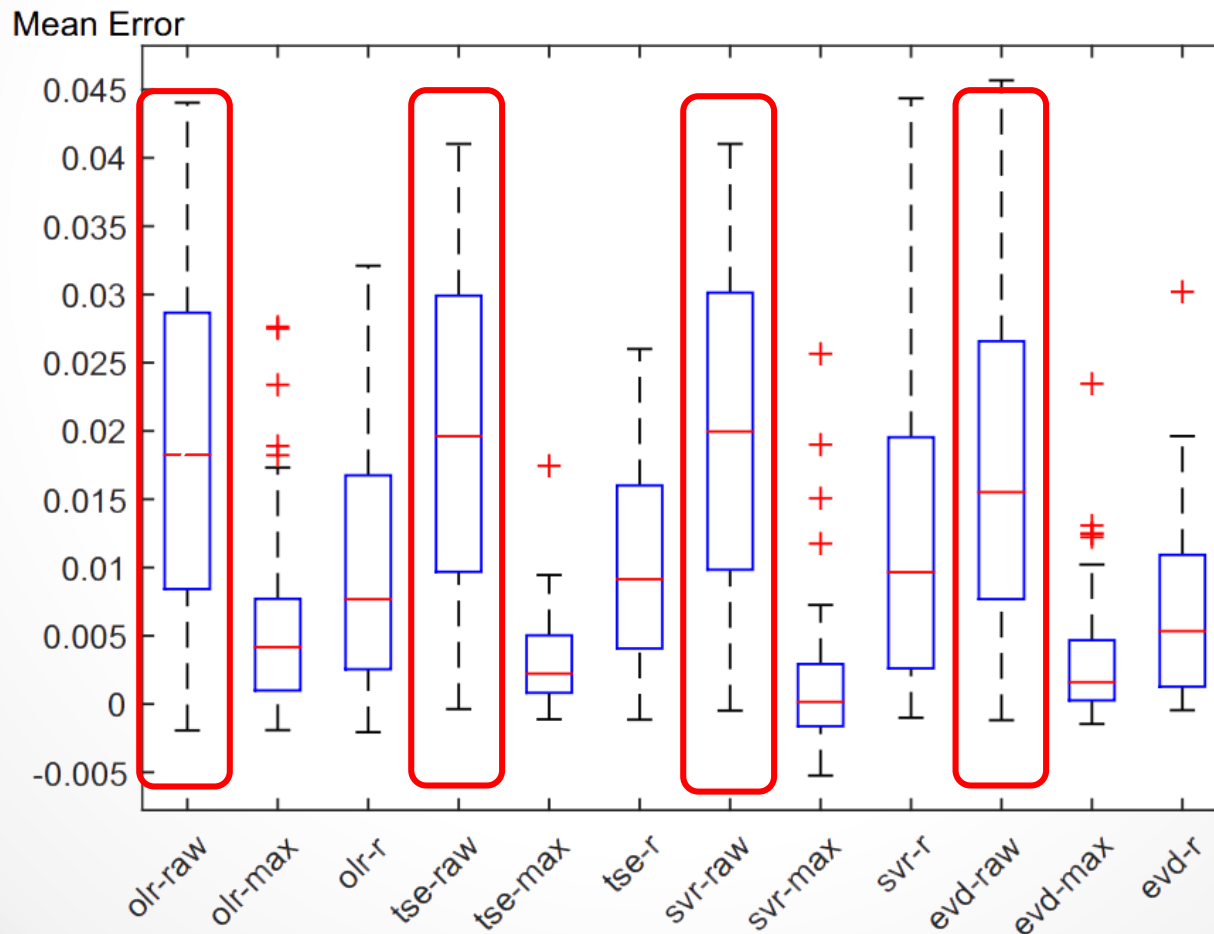
Evaluation

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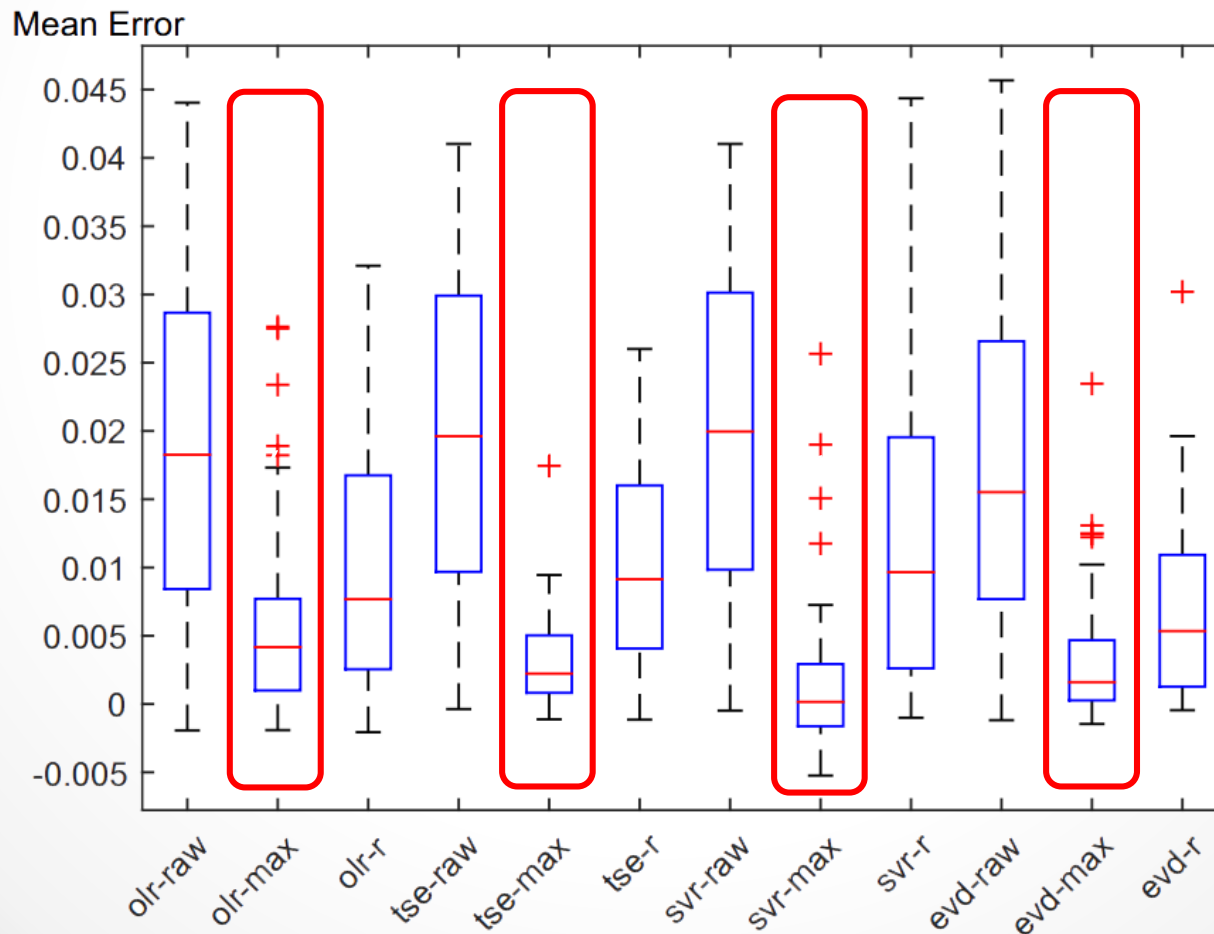
Pre-processing | Evaluation

- Evaluated with **raw**, block **maxima** and **r-largest**
- Mean (absolute) error of trend magnitude



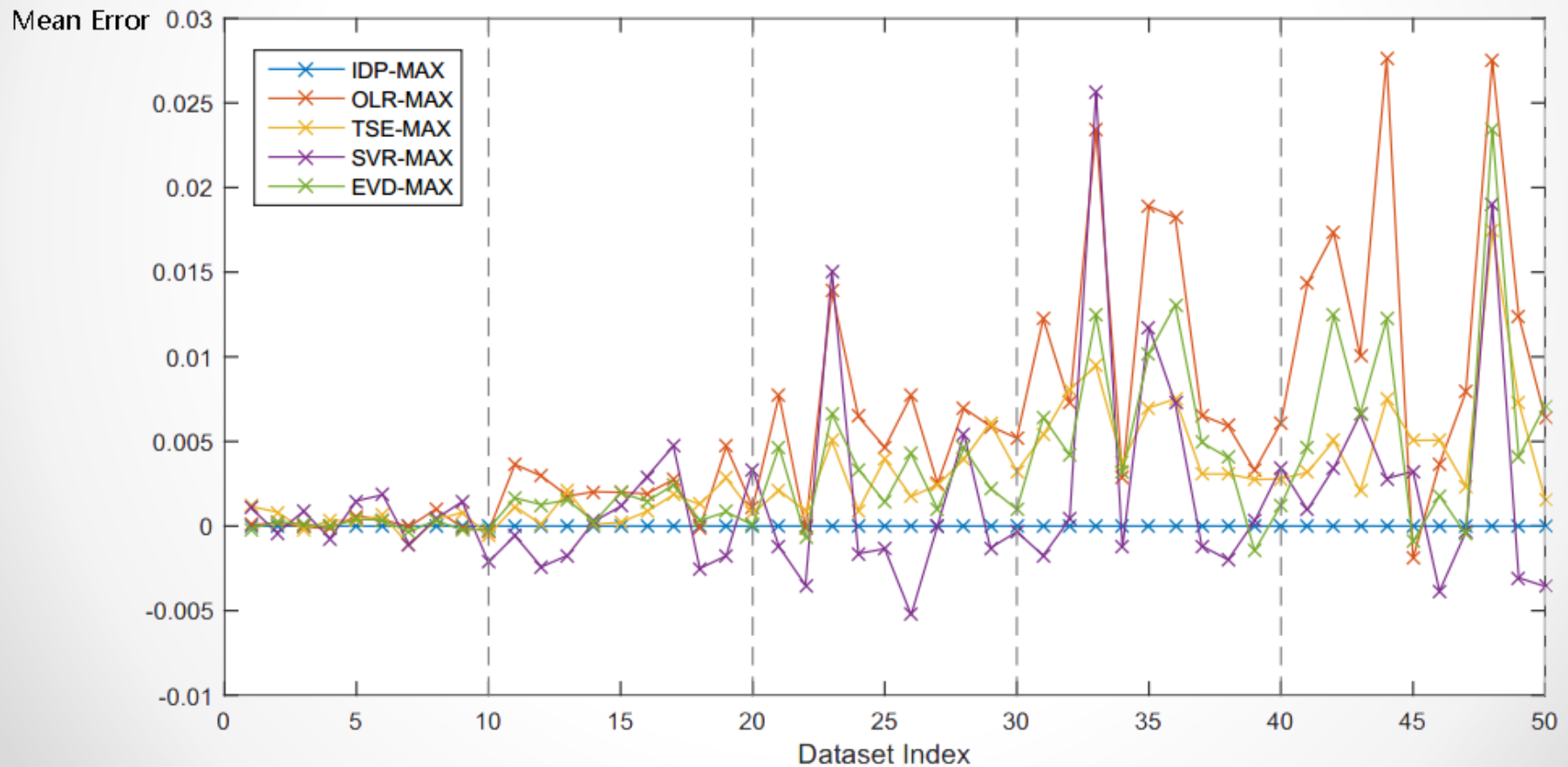
Pre-processing | Evaluation

- Evaluated with **raw**, block **maxima** and **r-largest**
- Mean (absolute) error of trend magnitude



Dataset Sensitivity | Evaluation

- All methods use block maxima
- Subgroups are separated by dashed lines



Trend Error | Evaluation

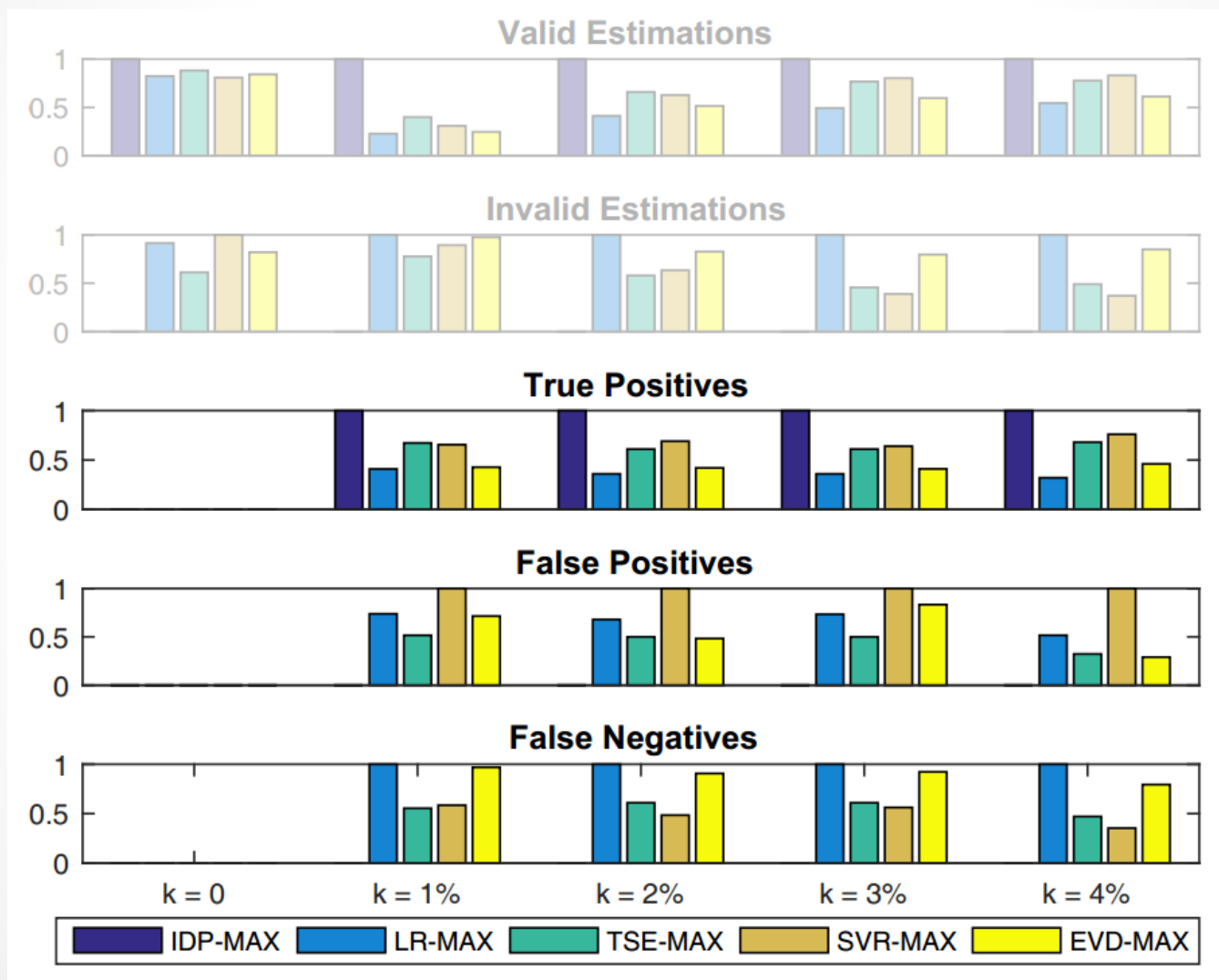
- Evaluate Trend error (= actual k - predicted k):

	Minimum	Median	Mean	Maximum	σ
olr-max	-1.91	4.16	6.31	27.64	7.21
olr-r	-2.07	7.68	10.59	32.10	9.31
tse-max	-1.12	2.23	3.07	17.45	3.27
tse-r	-1.15	9.14	9.91	26.00	7.72
svr-max	-5.24	0.15	1.60	25.65	5.71
svr-r	-1.00	9.65	12.72	44.36	12.74
evd-max	-1.46	1.60	3.40	23.47	4.75
evd-r	-0.45	5.34	6.86	30.20	6.77

Normalized Performance | Evaluation



Normalized Performance | Evaluation



Mean Penalties | Evaluation

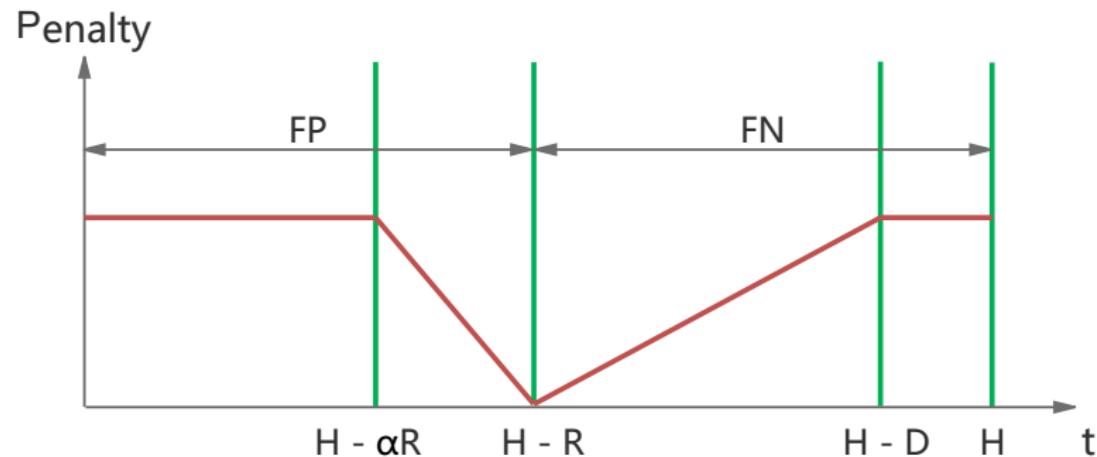


Table 4. Mean penalties over all datasets for each prediction method

	OLR	TSE	SVR	EVD
raw	62	62	62	62
maxima	58.28	29.02	42.26	49.68
r-largest	58.2	53.82	77.58	55.76

Conclusion

- Introduced dWCET and A-FBS
- Evaluated data pre-processing methods
- Result is sensitive to datasets
- Best two methods: svr-max and tse-max
- Future work
 - More dedicated dataset: e.g., with non-linear trend
 - Other analysis: anomaly detection, pattern recognition
 - Multiple variables + PCA
 - Evaluate with real-world data

Thank You for your attention!

Any Question/Comment?