

Predicting WCET Trends in Long-lived Real-time Applications

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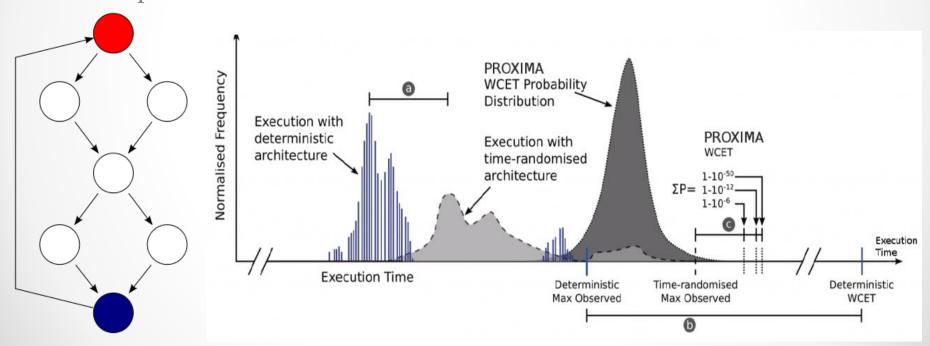


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Background | Motivation

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



Background | Motivation

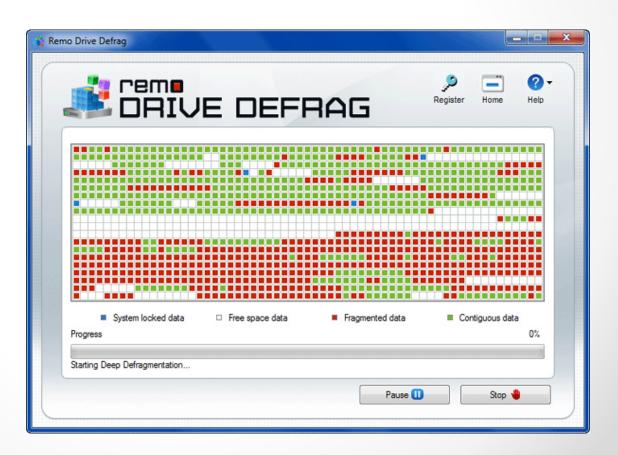
- Current understanding of WCETs:
 - A theoretical boundary exists, if designed and programmed with constrained models.
 - Known as a static, upper-bound value of execution times



Issues | Motivation

- Data accessing time ↑
 - o relevant data growth
 - hard disk fault/fragmented

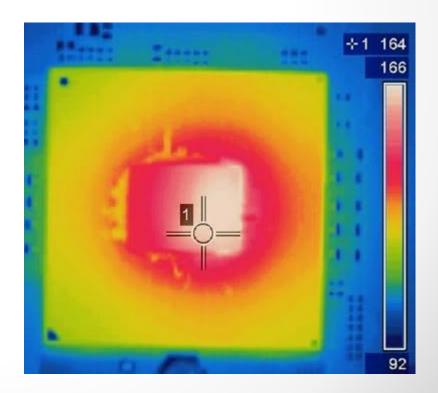




Issues | Motivation

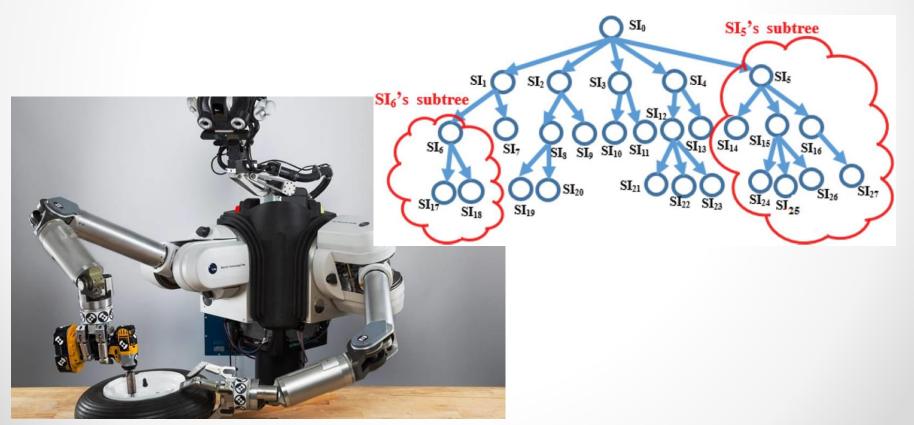
- Hardware ageing: computer systems age just like humans
 - CPU transistor ageing: fundamental speed ↓
 - o Thermal performance decreased: lacking maintenance





Issues | Motivation

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



Issues (continue) | Motivation

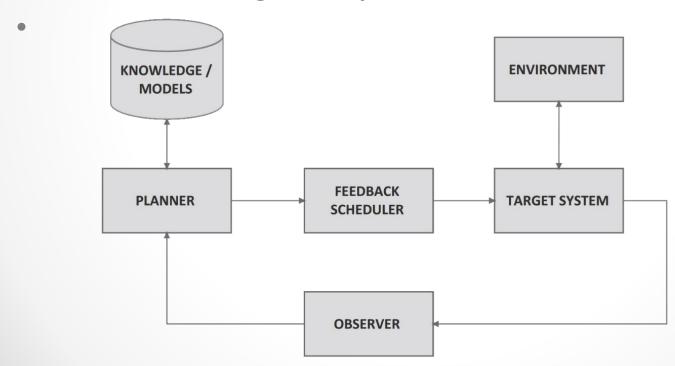
- Contribute negative and non-deterministic effects on WCETs.
- Subtle in a short period, but noticeable in long-term.
- Traditional WCET analysis could solve this by giving a very pessimistic boundary.
- A new perspective on WCET:
 <u>a dynamic view</u> of WCET (dWCET), as an extension of traditional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

dWCET | Motivation

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

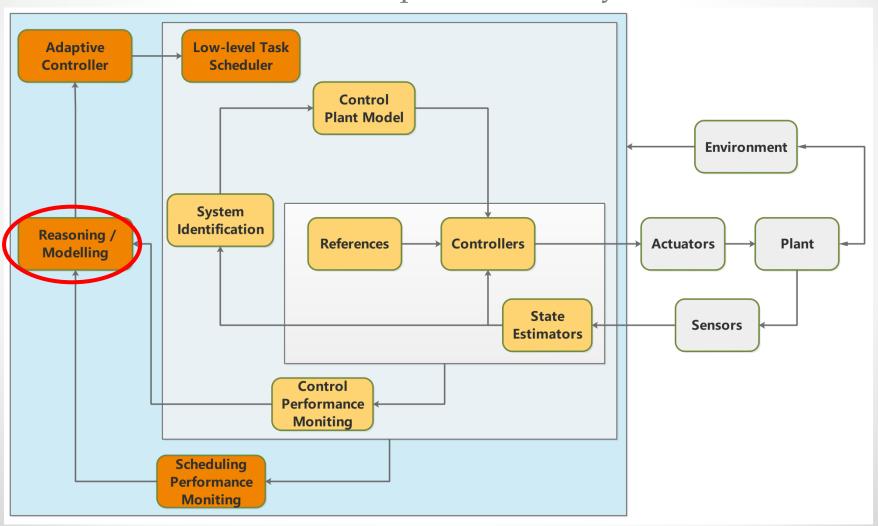
Adaptive Feedback Scheduling

- A variation of Feedback Control Scheduling (FBS)
- Adaptive
 - o 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:
 - o AR/ARMAX
 - Regression Analysis
 - o Non-parametric
 - o EVT
 - Neural Network
 - Decision Tree Regression
 - 0 ...
- but not all of them fit our case:
 - data points are execution times
 - distribution is not known
 - o few prior knowledge
 - o need a long-term prediction

Methods | Trend Identification

- Non-parametric Methods
 - o TSE: Theil-Sen Estimator
- Regression Analysis
 - OLS: Ordinary least-squares regression (OLS-regression)
- Extreme-value Theory
 - o 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).

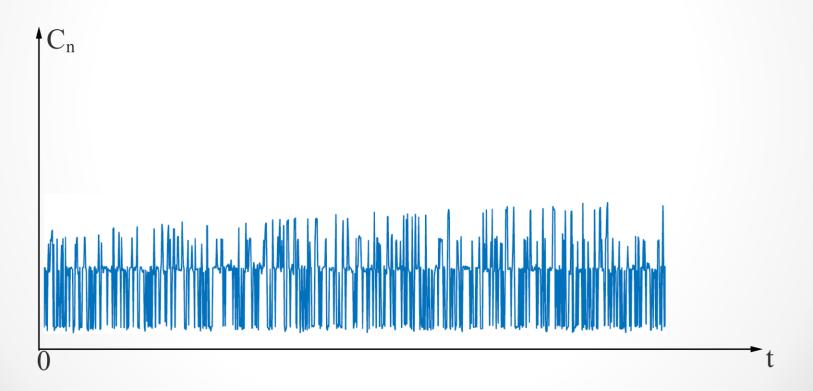
^[2] Basak, Debasish et al. "Support Vector Regression." (2008).

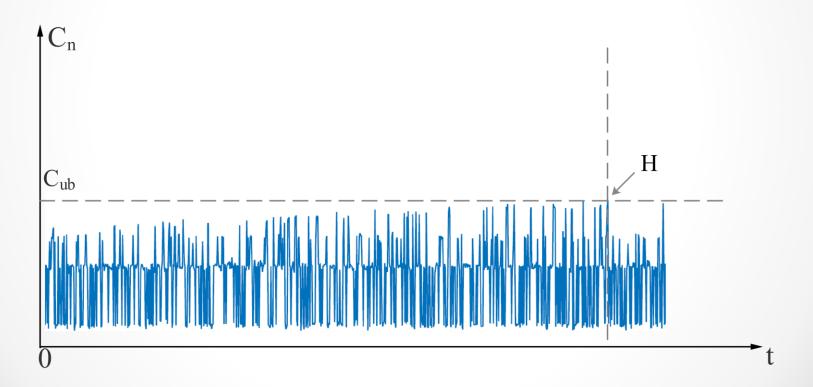
^[3] Kotz, S.. "Extreme Value Distributions: Theory and Applications." (2016).

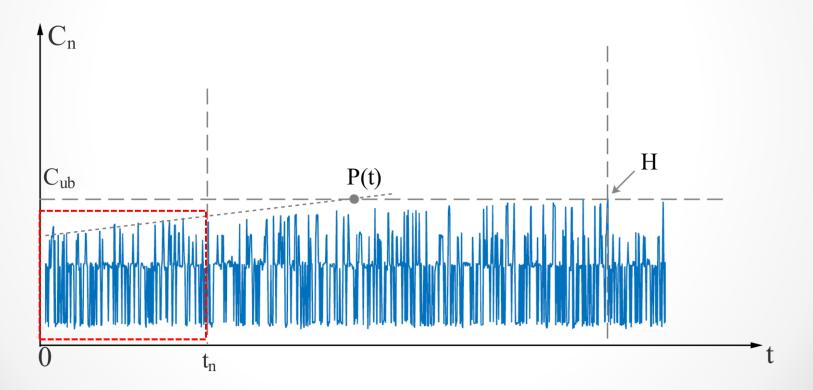
Dataset | Evaluation

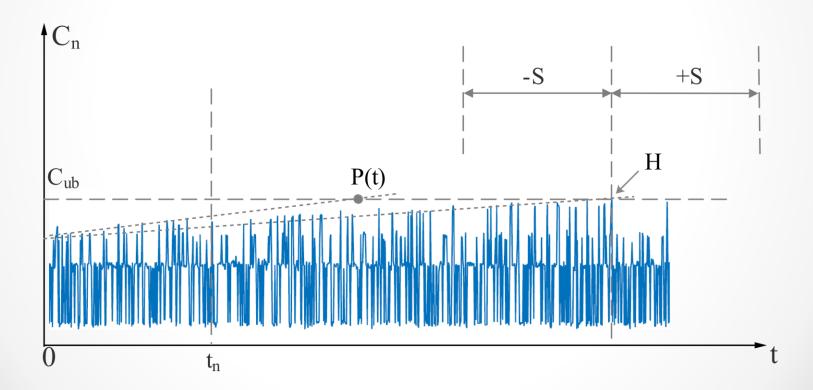
- Use synthetic data to make it evaluable.
- One observation represents a high watermark of run-time executions.
- Markov model with multiple dominated paths.
- An increasing trend only in the worst-case path.

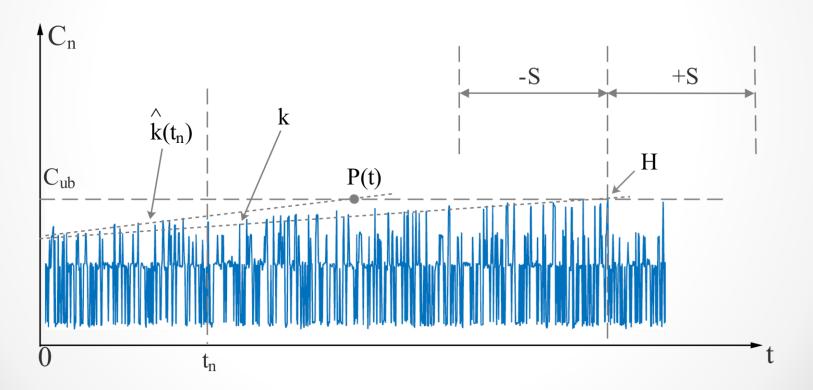
Group	Subgroup	Dataset Index	Data Size	Increasing Trend
A	A1	1 - 10	5,000	0%
В	B1	11 - 20	5,000	1%
	B2	21 - 30	2,500	2%
	B3	31 - 40	1,667	3%
	B4	41 - 50	1,250	4%

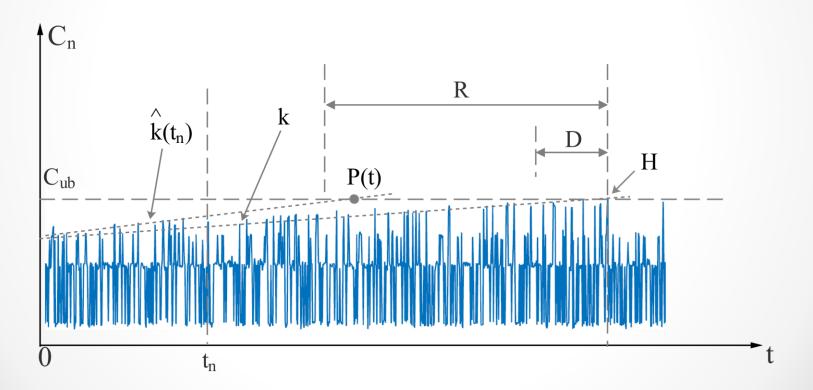


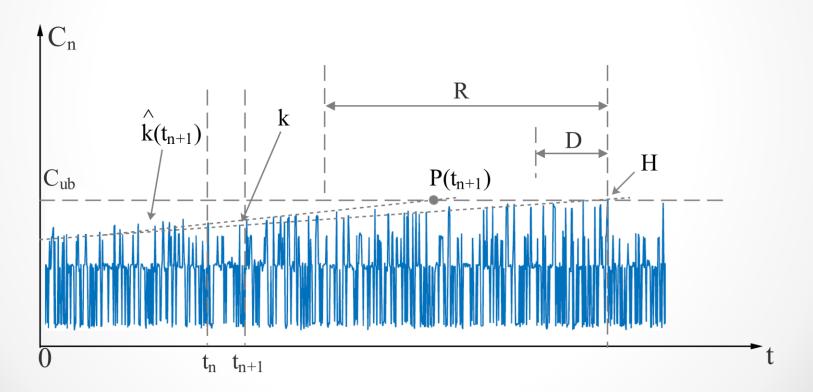


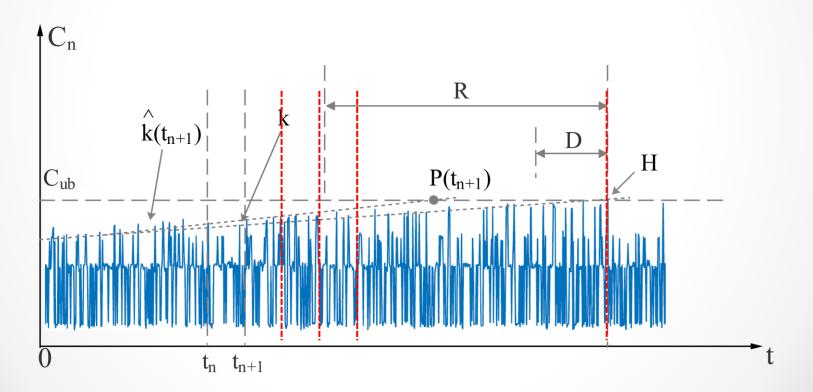






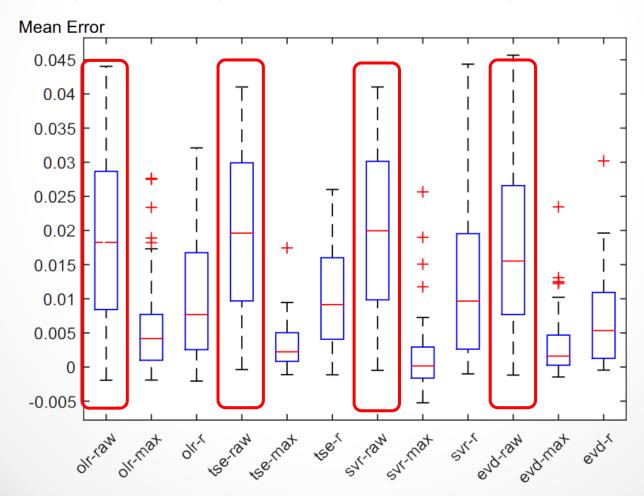






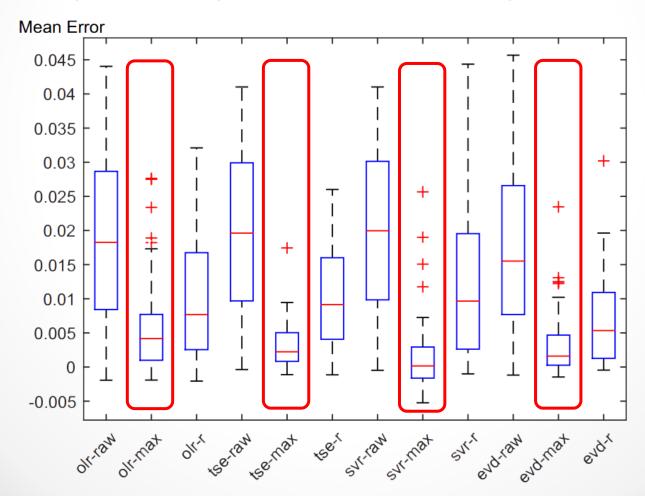
Pre-processing | Evaluation

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



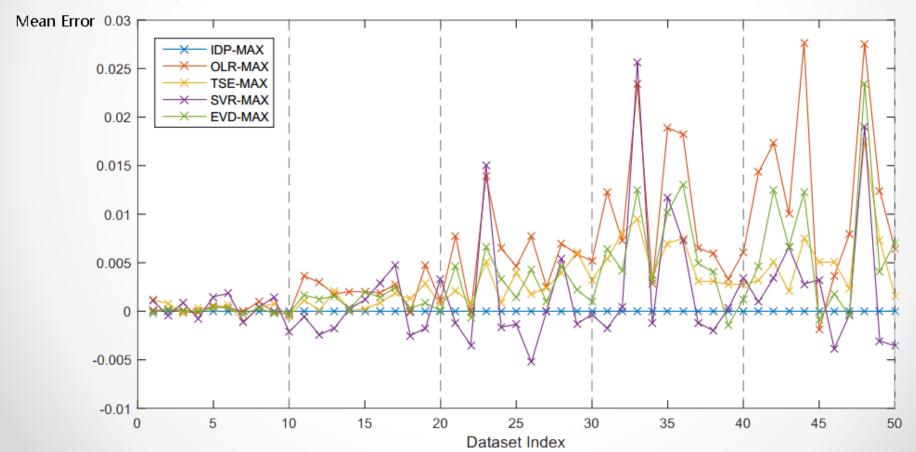
Pre-processing | Evaluation

- 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

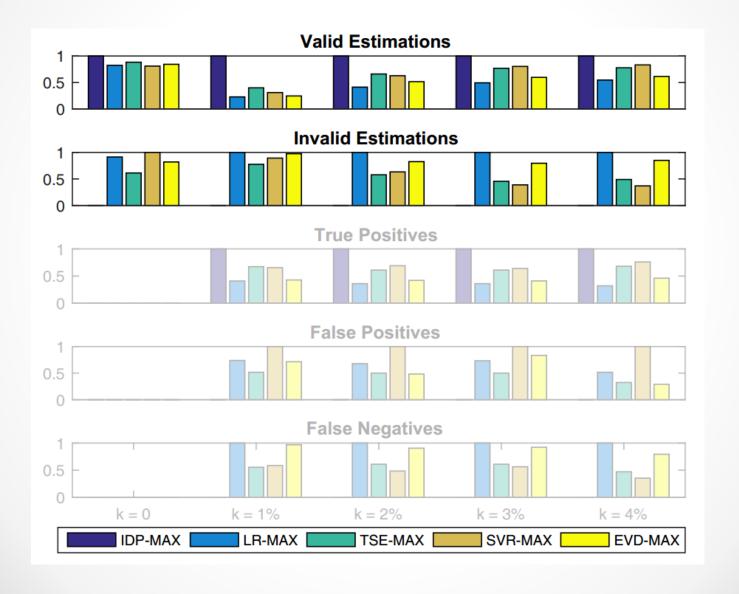


Trend Error | Evaluation

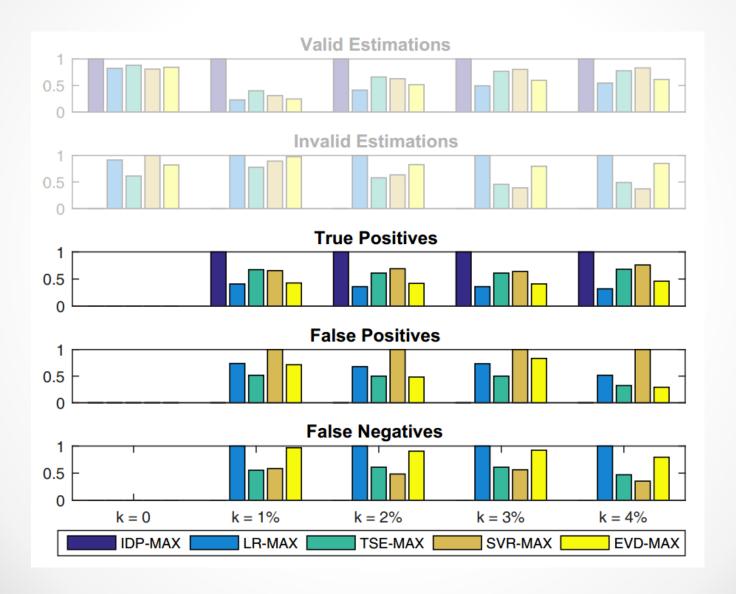
Evaluate Trend error (= actual k - predicted k):

	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

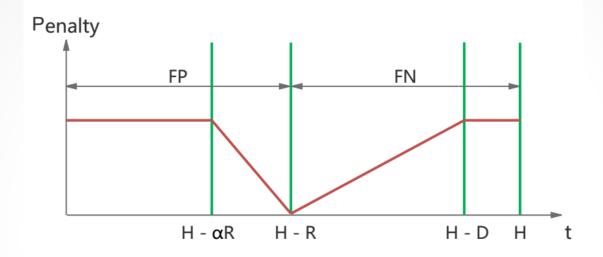


Table 4. Mean penalties over all datasets for each prediction method

	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
 - o More dedicated dataset: e.g., with non-linear trend
 - Other analysis: anomaly detection, pattern recognition
 - Multiple variables + PCA
 - o Evaluate with real-world data

Thank You for your attention!

Any Question/Comment?