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Deriving tight and safe task execution time bounds in a flexible and easy way independently of the system complexity...

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Although still far away of that dream, let's be a step closer to it!

What is this talk about?

- Deriving execution time bounds is challenging
  - Precise models may not be possible for complex systems
  - Measurement-based approaches are appealing
  - Applying Extreme Value Theory (EVT) is tempting
    - EVT is a branch of Statistics to model the maximum (*i.e.*, extreme) of a stochastic process

What is this talk about?

- Deriving execution time bounds is challenging
  - Precise models may not be possible for complex systems
  - Measurement-based approaches are appealing
  - Applying Extreme Value Theory (EVT) is tempting
    - EVT is a branch of Statistics to model the maximum (*i.e.*, extreme) of a stochastic process
- But a valid application of EVT requires EVT-compliant data
  - Execution time data is not always good for EVT
  - Hardware randomisation has been called for *e.g.*, Kosmidis *et al.*, 2014; Mezzetti *et al.*, 2015.
  - Although random hardware helps, it may not be effective, Lima *et al.*, 2016.

What is this talk about?

We offer a way of ensuring EVT-compliant data without relying on randomisation at hardware or system levels

Valid Application of EVT in Timing Analysis by Randomising Execution Time Measurements

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RTAS, 2017

Our contribution into context

Timing analysis aims at deriving models that represent the execution timing behavior of system tasks, and, based on these models, determining upper bounds on task execution times

- Traditionally... models are analytical and bounds are deterministic

Our contribution into context

Timing analysis aims at deriving models that represent the execution timing behavior of system tasks, and, based on these models, determining upper bounds on task execution times

- Recently... probabilistic models and bounds are called for
  - Task execution time seen as a random variable
  - Intrinsic uncertainties due to sw/hw complexity to be captured

Our contribution into context

Timing analysis aims at deriving models that represent the execution timing behavior of system tasks, and, based on these models, determining upper bounds on task execution times

- We add... randomness to measurements, inducing pessimism into probabilistic models (only when necessary) so that probabilistic bounds can be indirectly derived via EVT

Our contribution into context

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- We add... randomness to measurements, inducing pessimism into probabilistic models (only when necessary) so that probabilistic bounds can be indirectly derived via EVT

– IESTA –

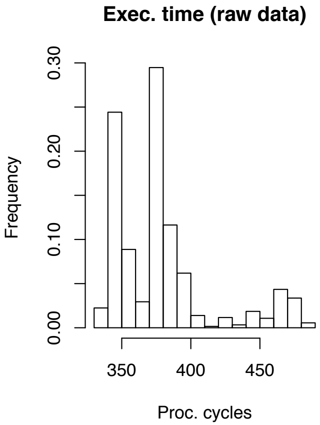
Indirect Estimation in Statistical Timing Analysis

EVT applied to timing analysis

- Measure the execution time of a task thousands of times
- Get a representative sample of maxima
- Apply suitable procedures (offered by EVT)
  - to estimate the maximum associated with a low exceedance probability, *i.e.*, a high quantile of a distribution
  - ...which is usually named pWCET

EVT-based time analysis – a motivation example

Data from Law and Bate, ECRTS 2016
A Rolls-Royce engine control task:



Almost $300K$ measurements

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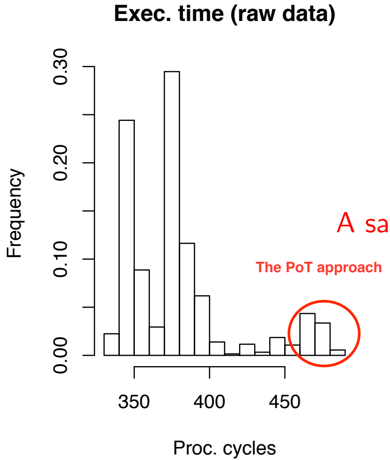

A sample of maxima is selected

EVT-based time analysis – a motivation example

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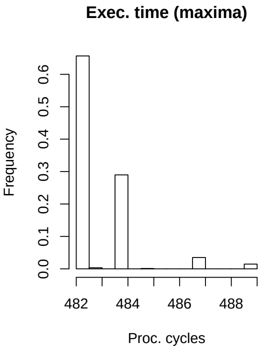

Data is not good for EVT: distribution of maxima is discrete!
(other aspects may prevent the use of EVT)

EVT-based time analysis – a motivation example

What if we randomise our measurements X by adding a known random variable Z to it, *i.e.*,

$$Y = X + Z$$

so that pWCET for X can be indirectly estimated via Y?

EVT-based time analysis – a motivation example

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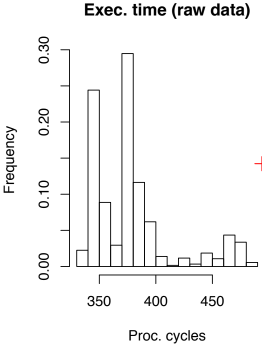
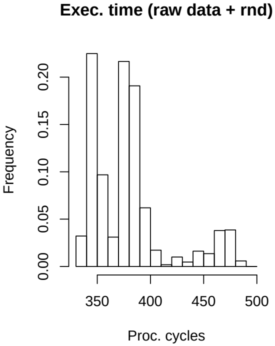
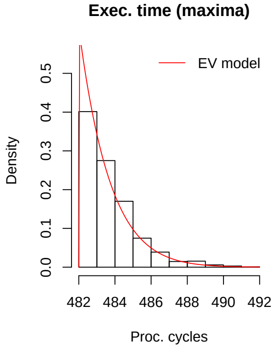


+randomisation
$\Longrightarrow$



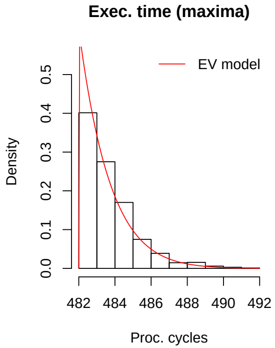
randomise data instead!!

EVT-based time analysis – a motivation example



Randomised data is now good for EVT!!!
(estimated EV model can be used to safely derive pWCET)

EVT-based time analysis – a motivation example



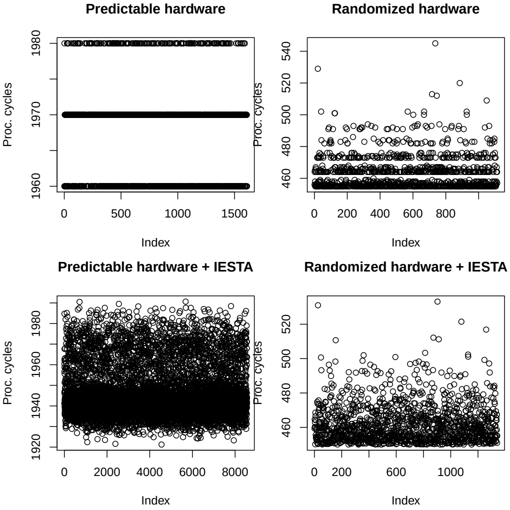
Randomised data is now good for EVT!!!

(estimated EV model can be used to safely derive pWCET)

– provided that data represents task behavior–

Data randomisation effects

data from Lima *et al.*, ECRTS 2016



Theoretical grounds of IESTA

- Let $X_1, \ldots, X_n$ be measured data
- Let $Z_1, \ldots, Z_n$ be a r.v. so that $a \leq Z_i \leq b$; $a < b$ constants
- Define $Y_i = X_i + Z_i$
- If $\Pr\{\max_1^n(Y_i) \leq v\}$ can be estimated via EVT, we are done:

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- If $\Pr\{\max_1^n(Y_i) \leq v\}$ can be estimated via EVT, we are done:

$$\underbrace{\Pr\{\max_1^n(X_i + b) \leq v\}}_{\text{since } Z_i \leq b} \leq \Pr\{\max_1^n(\overbrace{X_i + Z_i}^{Y_i}) \leq v\} \leq \underbrace{P\{\max_1^n(X_i + a) \leq v\}}_{\text{since } Z_i \geq a}$$

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- If $\Pr\{\max_1^n(Y_i) \leq v\}$ can be estimated via EVT, we are done:

$$\Pr\{\max_1^n(X_i) \leq v - b\} \leq \Pr\{\max_1^n(Y_i) \leq v\} \leq P\{\max_1^n(X_i) \leq v - a\}$$

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This implies that

pWCET for $Y - b \leq$ pWCET for $X \leq$ pWCET for $Y - a$

"Details in the paper"

IESTA only when necessary (recap)

If EVT is not applicable for the measured data

- randomise data so as to make (a) EVT applicable and (b) estimations not optimistic
  (a) $\max(Y) \sim$ an EV distribution
  (b) $\mathrm{pWCET}(X) \leq \mathrm{pWCET}(Y) - a$

- That is, EVT is applied to randomised data Y, ensuring (approximate) pessimistic estimations

If EVT is applicable for the measured data

- apply EVT to the measured data X to estimate pWCET(X)

IESTA configuration

- Dispersion ratio factor:

$$\delta = \frac{b - a}{\max_1^n(X_i) - \min_1^n(X_i)}$$

- randomisation is via adding $Z_i \sim \mathcal{N}(0, \sigma^2)$ with

$$\sigma = \frac{[\max_1^n(X_i) - \min_1^n(X_i)]\,\delta}{10}$$

so that $\Pr(\underbrace{\alpha - 5\sigma}_{\approx a} < Z_i < \underbrace{\alpha + 5\sigma}_{\approx b}) = 0.9999994$

Experimental results

IESTA was applied to several data sets

⇒ Selected for this work

- Mälardalen benchmark – Binary search (BS)
  - The only issue with this data was a high degree of discreteness
  - Not EVT analyzable despite its simplicity, Lima *et al.*, 2016 (ECRTS)
- Rolls-Royce engine control (8 tasks)
  - Besides discreteness, a strong data dependency relations
  - Data by Law and Bate, 2016 (ECRTS)

⇒ Choosing dispersion ratio δ

- δ is increased until reaching an EVT-analyzable distribution
- The test by Dietritch *et al.*, 2002 has been used

Obtained results (summary)

IESTA pWCET estimation for exceedance probability $p = 10^{-4}$

Data set	δ	$\max(X)$	$\max(Y)$	pWCET	Pessimism
BS	3%	1 980	1 990.64	2 011	1.57%
F	66%	12 018	12 272.95	13 182	9.77%
ACDF	7%	308	310.73	316	2.60%
ACDN	6%	489	491.03	499	2.05%
ACDP	36%	1 229	1310.78	1 464	19.12%
ACDT	49%	985	985.79	1 036	5.18%
VCA	6%	2 799	2 805.42	2 898	3.54%
VCP	32%	2 533	5 922.13	6 520	157.40%
VCS	31%	1 712	2 450.84	2 576	50.47%

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Low increase in the maxima ($< 7\%$) is observed (thanks to Normal dist.)

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Low pessimism in the pWCET estimates

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Higher pessimism observed for high values δ and greater modifications in max(X)

Final comments

⇒ Be aware: EVT requires EV conditions to be satisfied

- underline distribution must belong to the max domain of attraction of an EV distribution

⇒ Good news: IESTA can ensure EVT-compliant data

- Evaluated on non-EVT-compliant real data from real applications
- Observed pessimism considered acceptable
- Agnostic w.r.t. system (hardware or software) randomisation

⇒ Recall: EVT-based analysis relies on data representativeness

- Mechanisms to check for and to sample data that represents the actual task execution behavior are needed
- An interesting (open) problem to be addressed in future research

Thanks!

Grants by Brazilian funding agencies CNPq and FAPESB and by UK EPSRC Project MCCps

The authors are grateful to Rolls-Royce Control Systems for making data available

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