Denoising Application Performance Models with Noise-Resilient Priors

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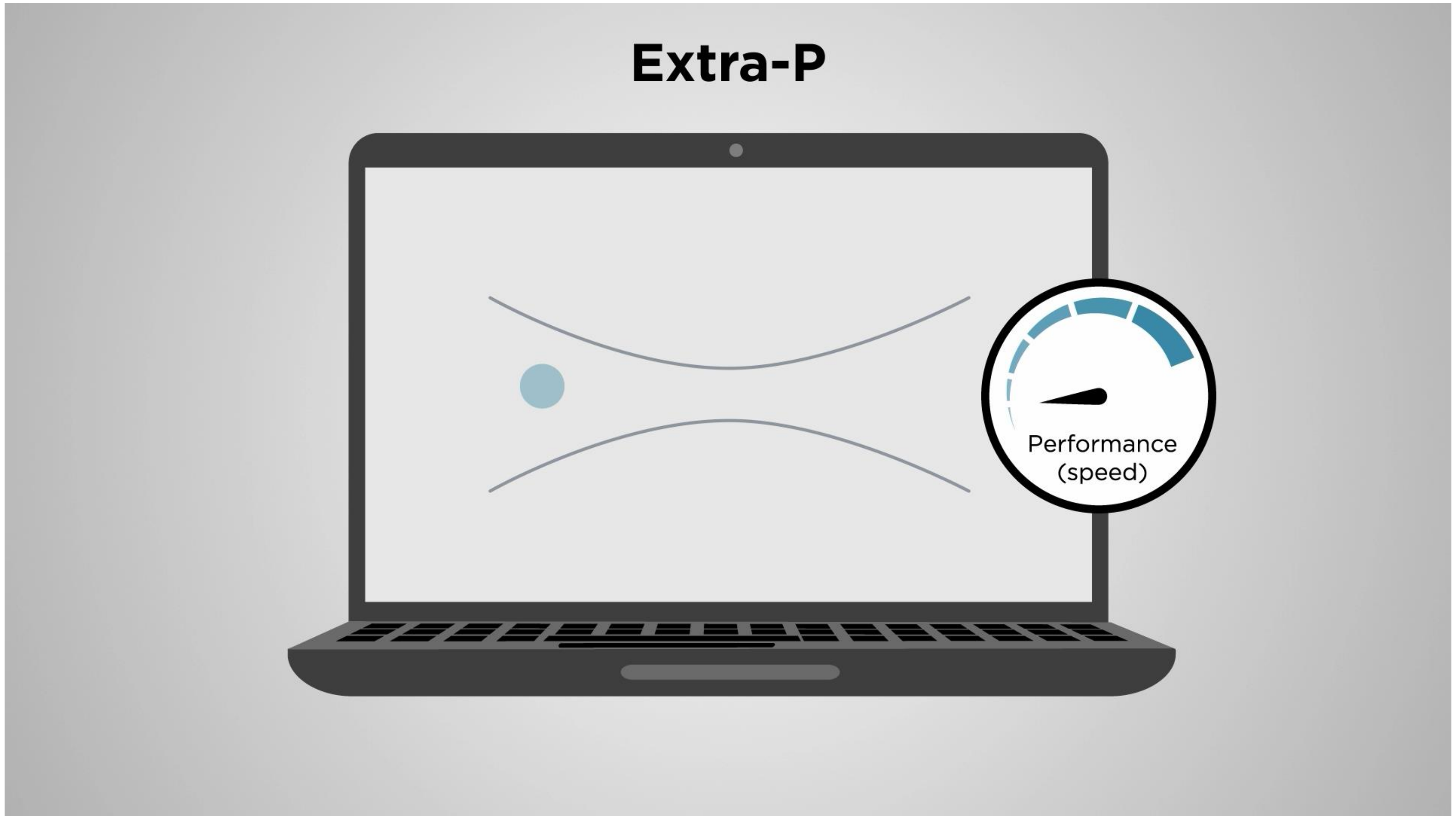
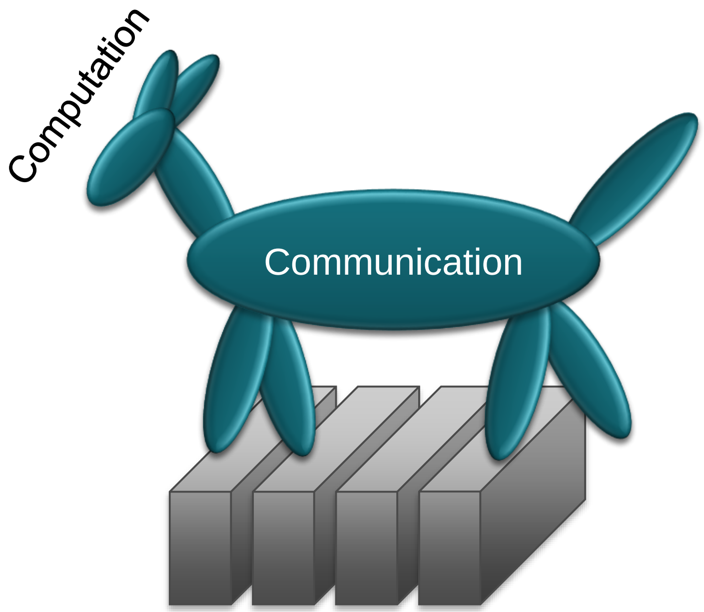
Motivation

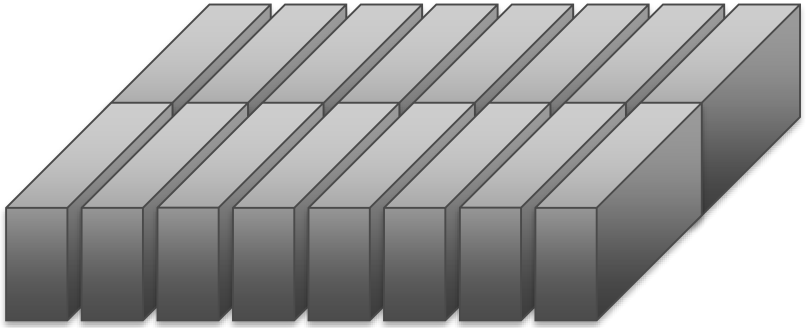


Watch Extra-P overview video

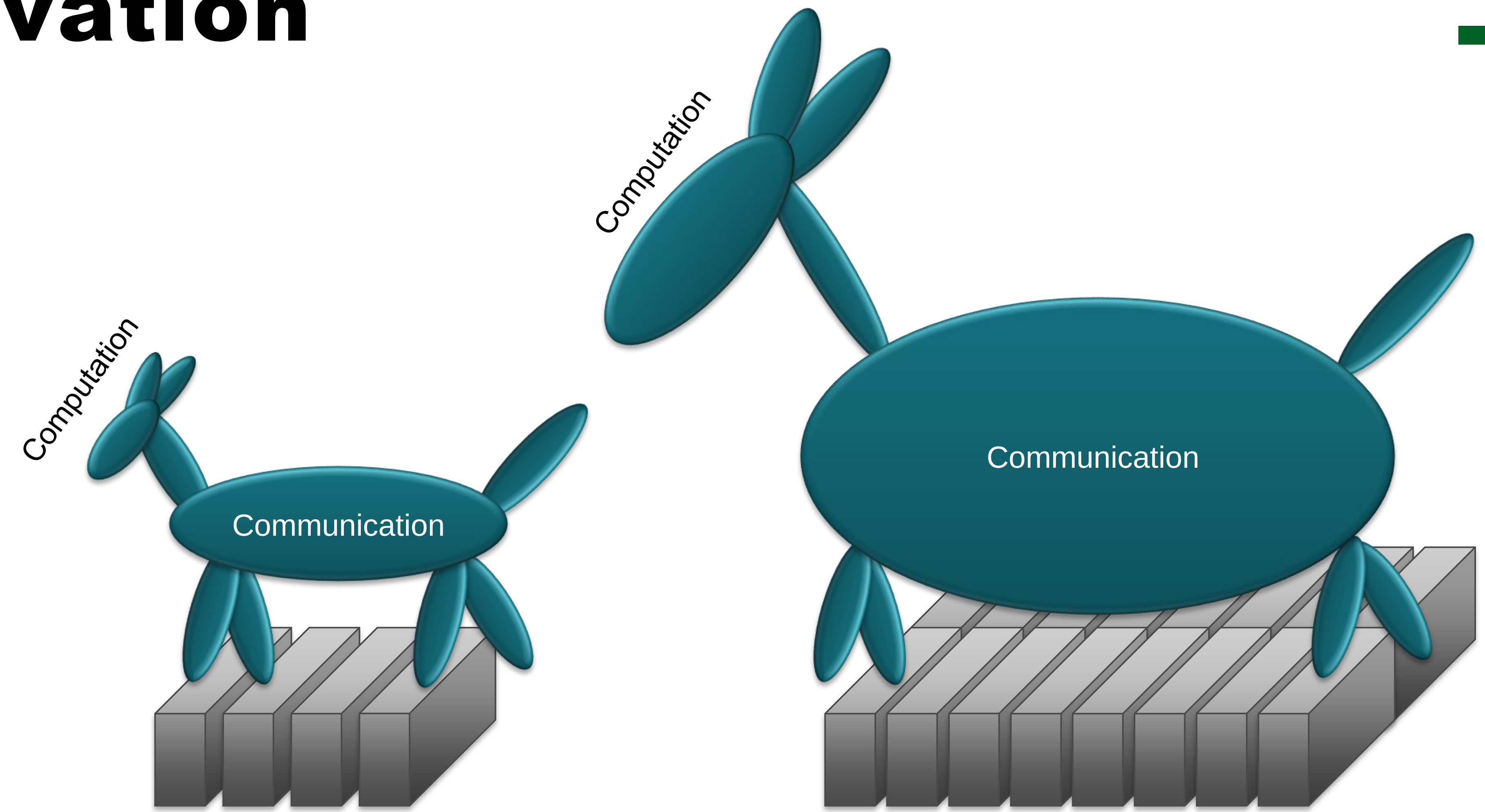
https://www.youtube.com/watch?v=Cv2YRCMWqBM

Motivation



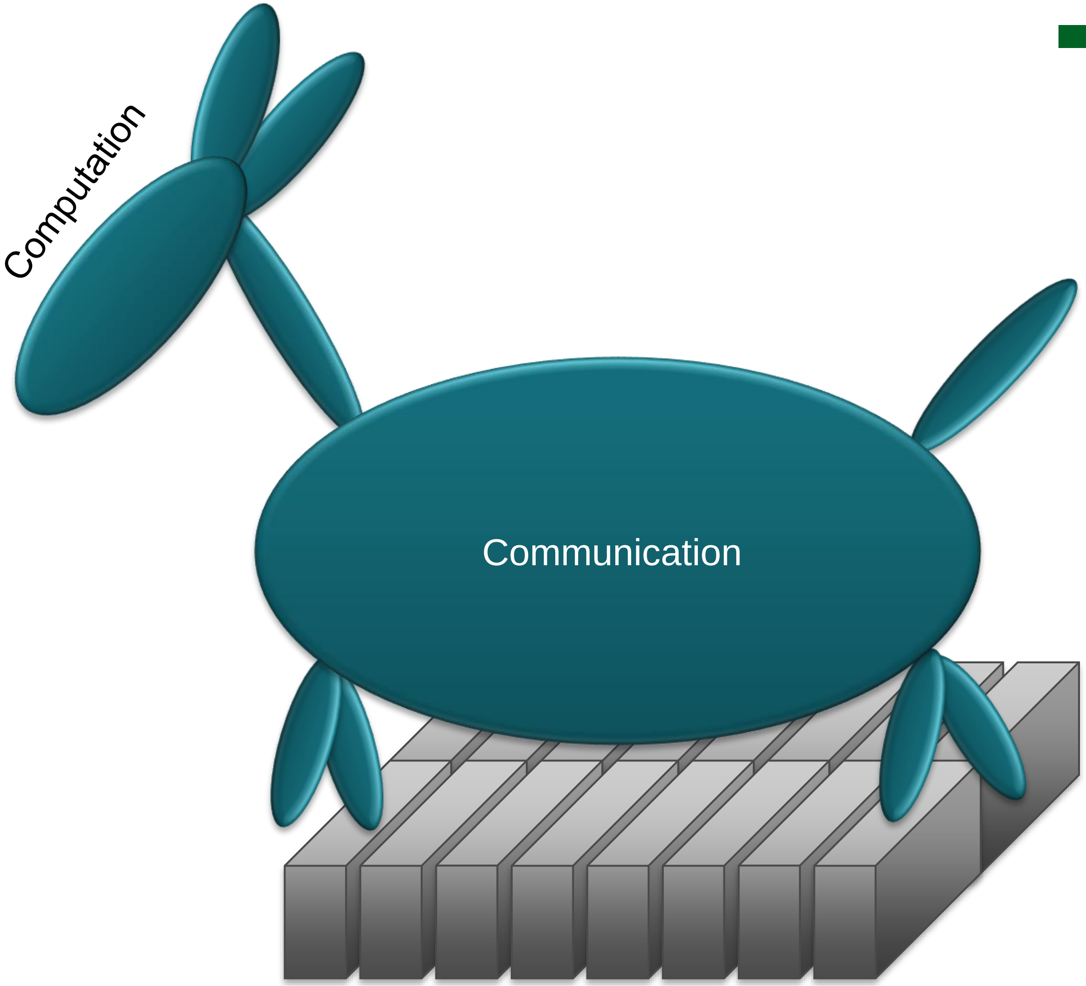


Motivation



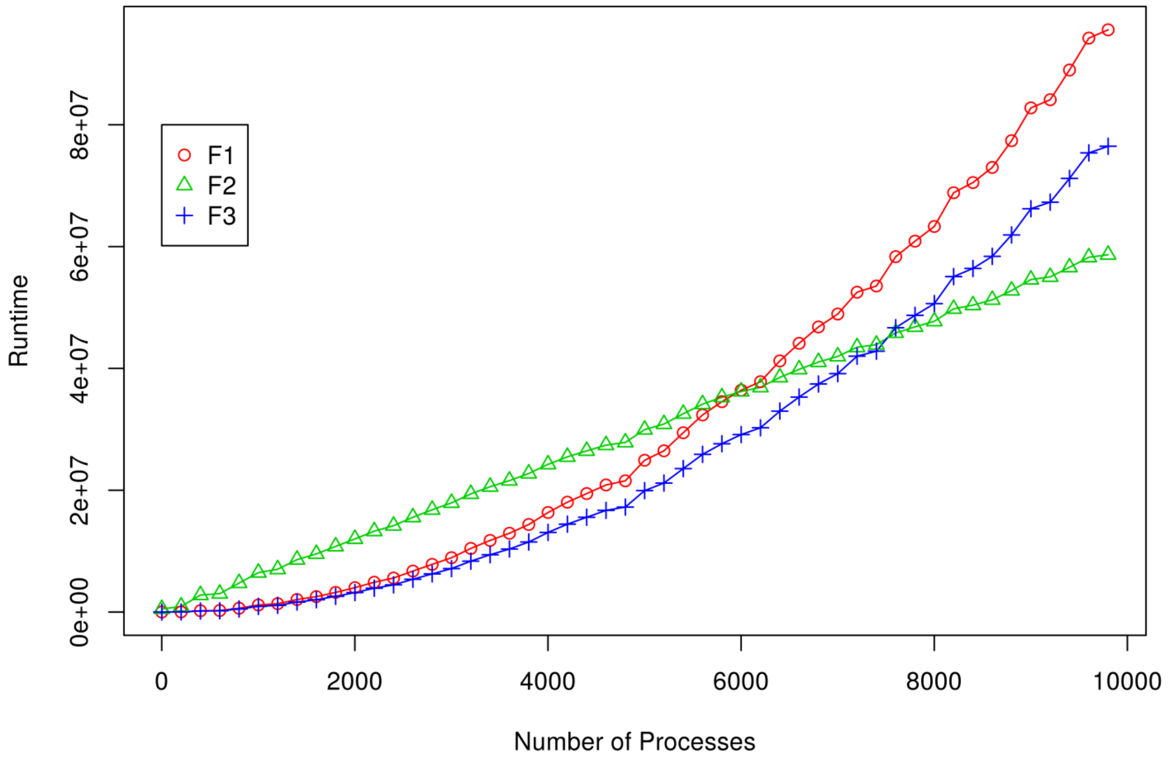
Motivation

We need to find scaling issues before they occur

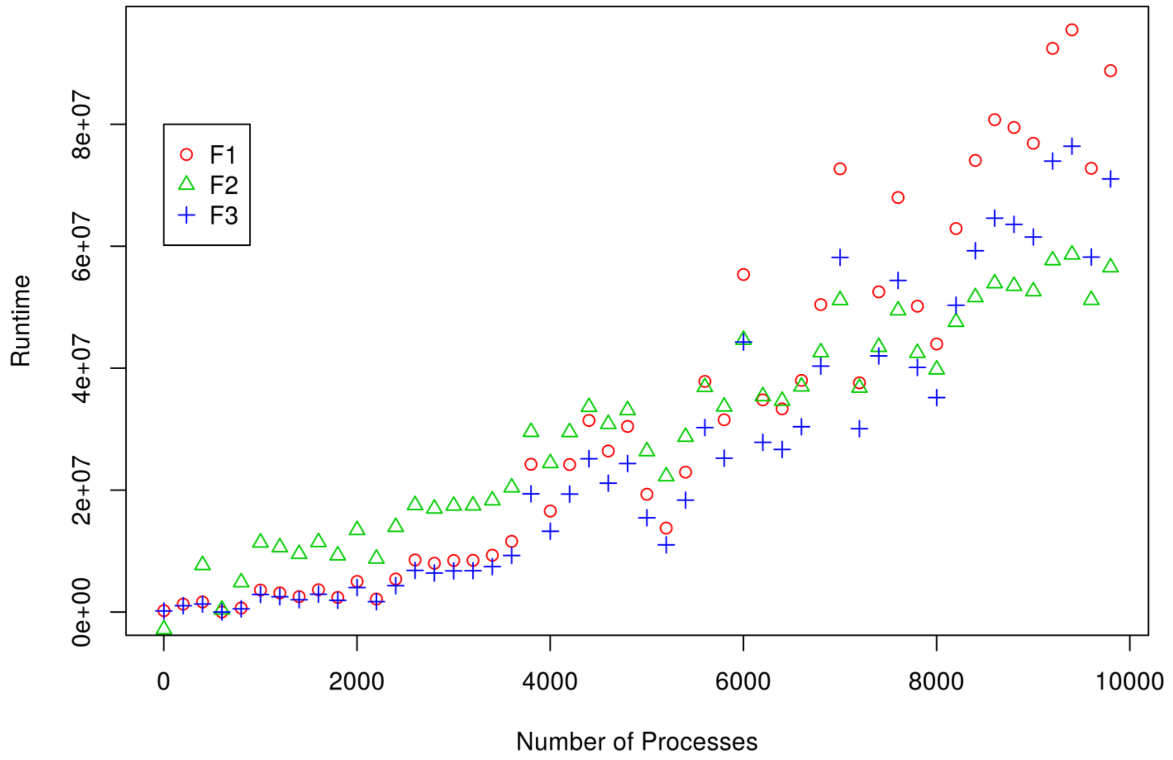


Motivation

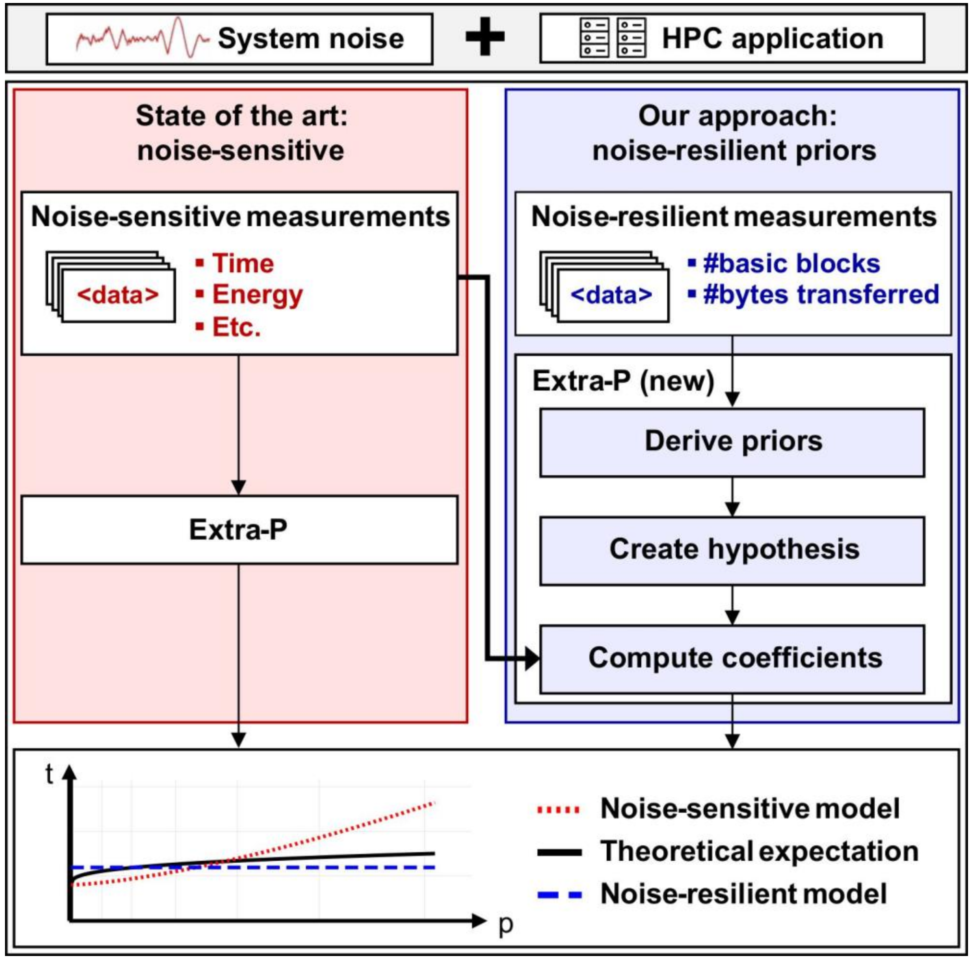
Common performance analysis chart in a paper



Production reality



Motivation



The noise-resilient model aligns with the theoretical expectation more closely

Noise-resilient measurements

- LLVM-IR [2] plug-in into Score-P [3] framework

Score-P
Scalable performance measurement infrastructure for parallel codes

Computation

```
int foo(int a, int b)
{
    Basic block 1
    @Score-P counter
    ...
    Basic block n
    @Score-P counter
}
```

Communication

```
MPI_Bcast(A, n, MPI_INT,
          0, MPI_COMM_WORLD);
```

- $n \times p \times 4$ bytes sent from the root
- $n \times 4$ bytes received at each process

Multi-parameter performance modeling

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Parallel Programming

- Performance Model Normal Format (PMNF) [1]

$$f(x_1, \dots, x_m) = \sum_{k=1}^{n} c_k \prod_{l=1}^{m} x_l^{i_{kl}} \cdot log_2^{j_{kl}}(x_l)$$

$$m, n \in \mathbb{N}$$
$$i_k \in I$$
$$j_k \in J$$
$$I, J \subset \mathbb{Q}$$

Model candidates

- Constant c_1
- Single parameter $c_1 + c_2 \cdot x_1$
- Multiple parameters
  - Additive $c_1 + c_2 \cdot x_1 + c_3 \cdot x_2$
  - Multiplicative $c_1 + c_2 \cdot x_1 \cdot x_2$
  - Complex $c_1 + c_2 \cdot x_1 \cdot x_2 + c_3 \cdot \log x_2 \cdot x_2^3$

...

Creating models from priors

Process count (x_1)

Problem size (x_2)

Order of a solver (x_3)

Result precision (x_4)

…

Independent or compounded effect?

Multi-parameter Performance models

Performance models:

$\boldsymbol{x} = \{x_1, \dots, x_m\}$

Basic-blocks → $f(\boldsymbol{x}, p) = c_1 + c_2\sqrt{p} + c_3 \cdot x_1 + {x_2}^2$

Bytes → $B(\boldsymbol{x}, p) = c_1 + c_2 \cdot x_1 \cdot x_2$

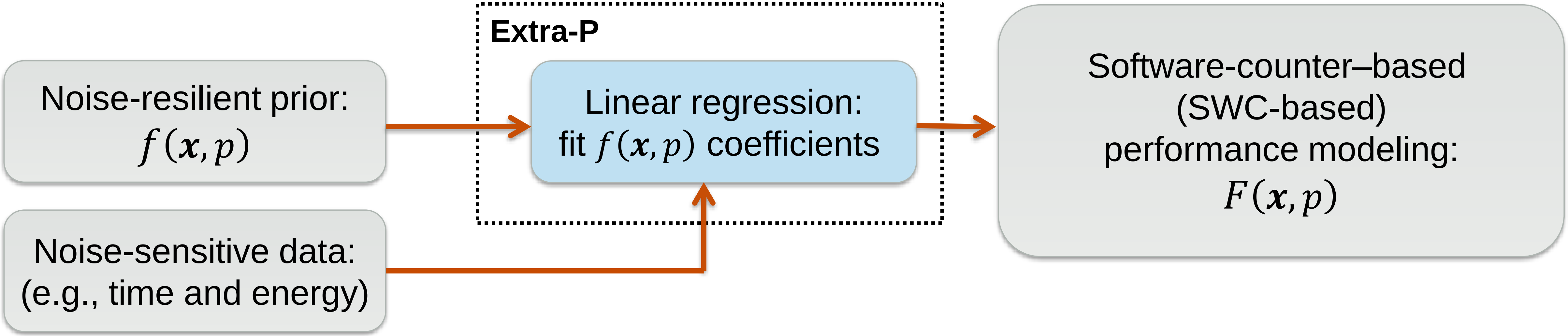
Creating models from priors

- Communication

MPI function	Expected runtime	Ref.
Send	$f(\boldsymbol{x},p) = \alpha + B(\boldsymbol{x},p) \cdot \beta$	[5]
Receive		
Broadcast	$f(\boldsymbol{x},p) = \log_2(p) \cdot \alpha + B(\boldsymbol{x},p) \cdot \beta$	[6]
Scatter	$f(\boldsymbol{x},p) = \log_2(p) \cdot \alpha + B(\boldsymbol{x},p) \cdot \frac{p-1}{p} \cdot \beta$	[6]
Gather		
Allgather		
Reduce	$f(\boldsymbol{x},p) = \log_2(p) \cdot \alpha + \left(\beta + \frac{p-1}{p} \cdot \gamma\right) \cdot B(\boldsymbol{x},p)$	[6]
Allreduce		

	Summary
$f(\boldsymbol{x},p)$	Prior model
$B(\boldsymbol{x},p)$	Bytes model
$\boldsymbol{x}$	Input parameters
p	MPI ranks
α	Latency
β	Bandwidth
γ	Computation cost

Creating models from priors



Creating models from priors

- Example

```
void F0 (int* V, int n, int p) {
  // int V[n*p];
  MPI_Bcast(V, n*p, ...);
  for(int i = 0; i < n/100; i++) {
    // calculate something
    for(int j = 0; j < p; j++) {
      // calculate something
}}}
```

Communication

Computation

Communication

Time: $13.0 \cdot 10^3 + 0.506n + 0.185np$

Bytes transferred: $0.1 \cdot 10^{-3} + 4.0np$

Theoretical model: $\log_2(p)\,\alpha + B(p,n)\beta$

Prior: $c_0 + c_1 \log_2(p) + c_2 np$

Noise-resilient: $7366 + 0 \log_2(p) + 0.189np$

Determine prior

Create model

Computation

Time: $-7782 + 0.755n + 0.002\, np^{\frac{3}{4}} \log_2^2(p)$

Basic blocks: $275 + 1.6n + 0.48np$

Prior: $c_0 + c_1 n + c_2 np$

Noise-resilient: $-7071 + 0.142n + 0.037np$

Determine prior

Create model

Benefits

Accuracy

Robustness to noise

Experimental cost

Evaluation

Test systems	Comparison baseline	Accuracy metrics
Lichtenberg II Cluster	SWC-based	Exponent deviation (ED) $ED(f_1(x_i), f_2(x_i)) = \lvert n_1 - n_2 \rvert$
Jureca-DC Cluster	Classic	Relative error (RE) $RE\left(f_1(x_i)\right) = \frac{\lvert y_i - f_1(x_i) \rvert}{y} \cdot 100\%$
	DNN-based [6]	

Evaluation with synthetic benchmarks

- Benchmark Generator for parallel codes
  - Allows flexibility on the performance behavior
  - Functions with known theoretical analytical complexity

C++ kernels

for (int $i = 0; i < x^y; i++)$ {
$sum = v_1[i] + v_2[i]$}

$O(x^y)$

for (int $i = 0; i < x; i++)$ {
for (int j $= 0; j < x; j++)$ {
$mul = v_1[i] * v_2[j]$}}

$O(x^2)$

for (int $i = 0; i < x^y; i++)$ {
$a = std :: \max(a, v_1[i]);$
$v_2[i] = a;$ }

$O(x^y)$

Evaluation with synthetic benchmarks

- Benchmark Generator

User definition

- Input parameter (e.g., n)
- Individual kernel complexity
- Multiple kernel composition

C++ code

- Kernel 1: MPI Bcast $\mathrm{V}[n]$
- Kernel 2: O($n^{\frac{1}{2}}$)
- Kernel 3: O(n^1)
  Kernel 4: O(n^1)
- Kernel 5: O(n^0)

Resulting complexity

Communication:
O($\log_2(\mathrm{p}) + n$)

Computation:
O(n^2)

Evaluation with synthetic benchmarks

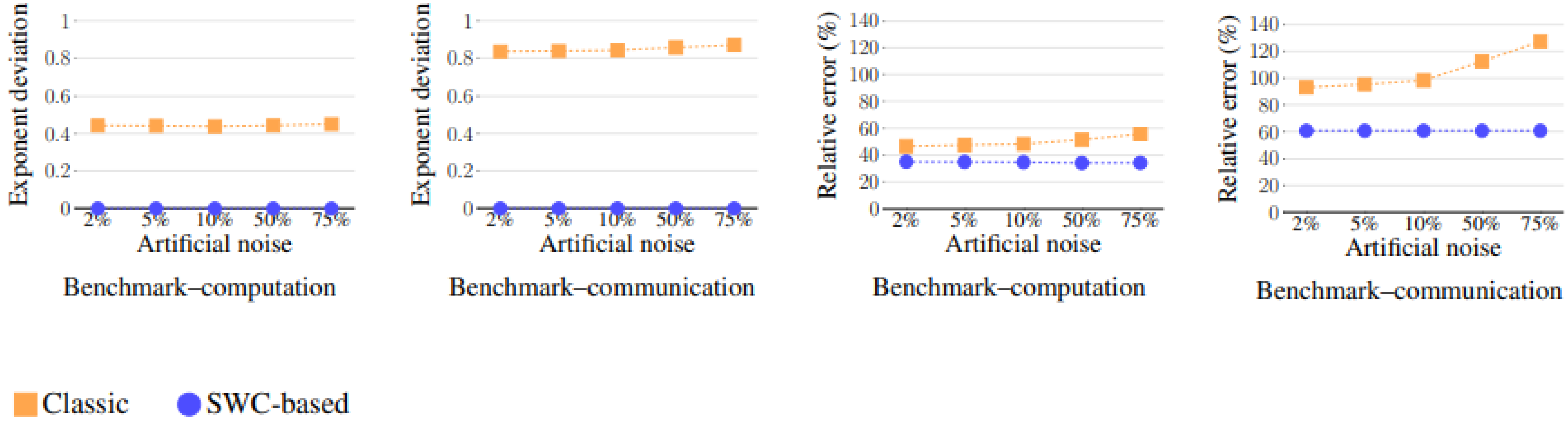
- 200 synthetic functions
- Accuracy
  - Exponent deviation: comparing performance models with their theoretical expectation

Models	Computation	Communication	
		MPI ranks	Message size
SWC-based	0	0	0
Classic	0.44	1.14	0.57

  - Relative error
    - SWC-based: 35% (computation) and 60% (communication)
    - Classic: 45% (computation) and 91% (communication)

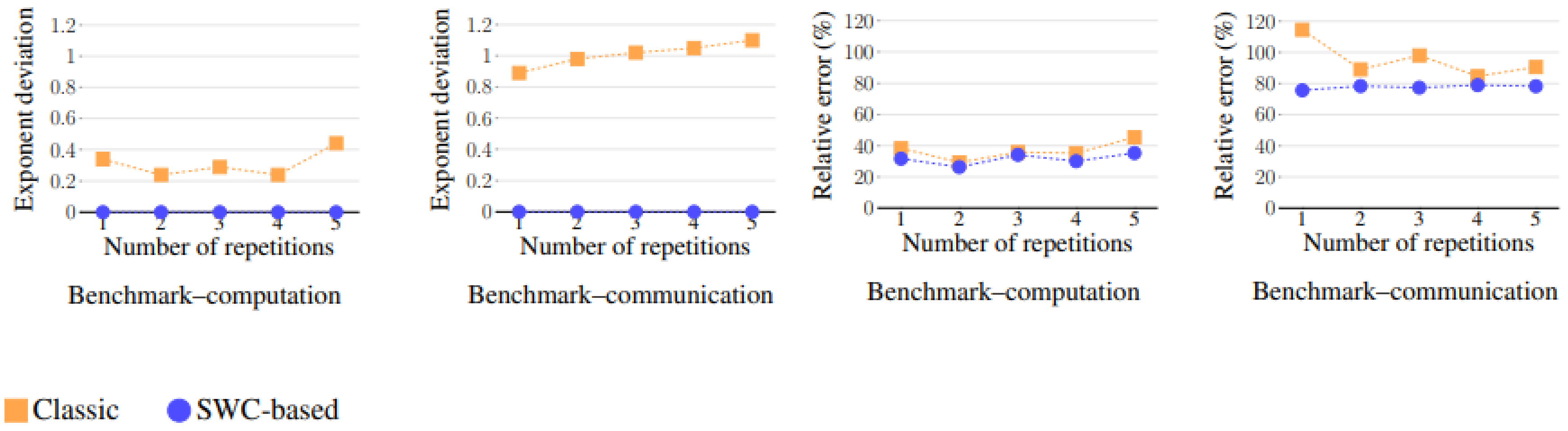
Evaluation with synthetic benchmarks

- Robustness to noise



Evaluation with synthetic benchmarks

- Experimental costs



Application case studies

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Parallel Programming

- Kripke [7]
- Relearn [8]

Known theoretical performance

App/System	Training configurations	Test points
Kripke Lichtenberg II	$p \in \{512, 1000, 1728, 2744, 4096\}$ $G \in \{32, 64, 96, 128, 160\}$ $Z \in \{4^3, 8^3, 12^3, 16^3, 20^3\}$	$(p, G, Z) = (5832, 160, 20^3)$ $(p, G, Z) = (4096, 192, 20^3)$ $(p, G, Z) = (4096, 160, 24^3)$
RELeARN Jureca-DC	$p \in \{32, 64, 128, 256, 512\}$ $n \in \{250, 300, 350, 400, 450\}$	$(p, n) = (1024, 450)$ $(p, n) = (512, 500)$

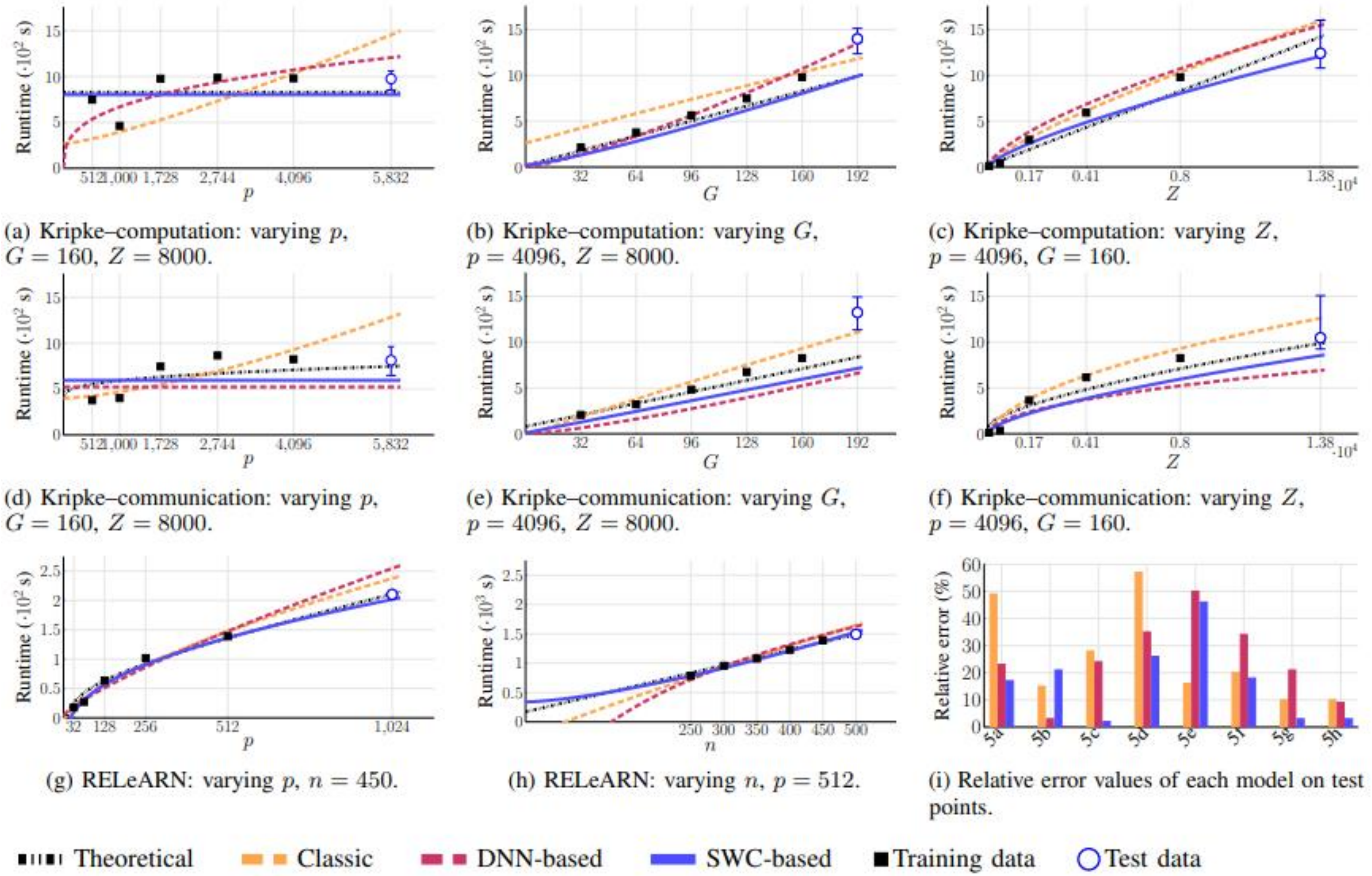
Evaluation

- Application case studies
  - Accuracy

Model	Asymptotic complexity	ED		
Kripke–computation		Δp	ΔG	ΔZ
Theoretical	$\mathcal{O}(G \cdot Z)$			
Classic	$\mathcal{O}(p \cdot \log_2^2(p) \cdot G^{\frac{3}{4}} \cdot \log_2(G) \cdot Z^{\frac{4}{5}})$	1	0.25	**0.20**
DNN-based	$\mathcal{O}(p \cdot G^{\frac{5}{4}} \cdot Z^{\frac{2}{3}})$	1	0.25	0.33
SWC-based	$\mathcal{O}(G \cdot \log_2(G) \cdot Z^{\frac{3}{4}})$	**0**	**0**	0.25
Kripke–communication		Δp	ΔG	ΔZ
Theoretical	$\mathcal{O}(p^{\frac{1}{3}} + G \cdot Z^{\frac{2}{3}})$			
Classic	$\mathcal{O}(p^{\frac{4}{3}} \cdot \log_2(p) \cdot G^{\frac{3}{4}} \cdot \log_2(G) \cdot Z^{\frac{1}{3}} \cdot \log_2^2(Z))$	1	0.25	0.33
DNN-based	$\mathcal{O}(G^{\frac{5}{4}} \cdot Z^{\frac{1}{2}})$	**0.33**	0.25	0.16
SWC-based	$\mathcal{O}(G \cdot Z^{\frac{2}{3}})$	**0.33**	**0**	**0**
RELeARN		Δp	Δn	
Theoretical	$\mathcal{O}(p + n \cdot \log_2(n \cdot p))$			
Classic	$\mathcal{O}(p^{\frac{2}{3}} \cdot n^{\frac{3}{4}} \cdot \log_2(n))$	0.33	**0.25**	
DNN-based	$\mathcal{O}(p^{\frac{2}{3}} \cdot \log_2(p) \cdot n^{\frac{1}{4}})$	0.33	0.75	
SWC-based	$\mathcal{O}(p + n^{\frac{5}{4}} \cdot \log_2(n) \cdot p^{\frac{1}{4}})$	**0**	**0.25**	

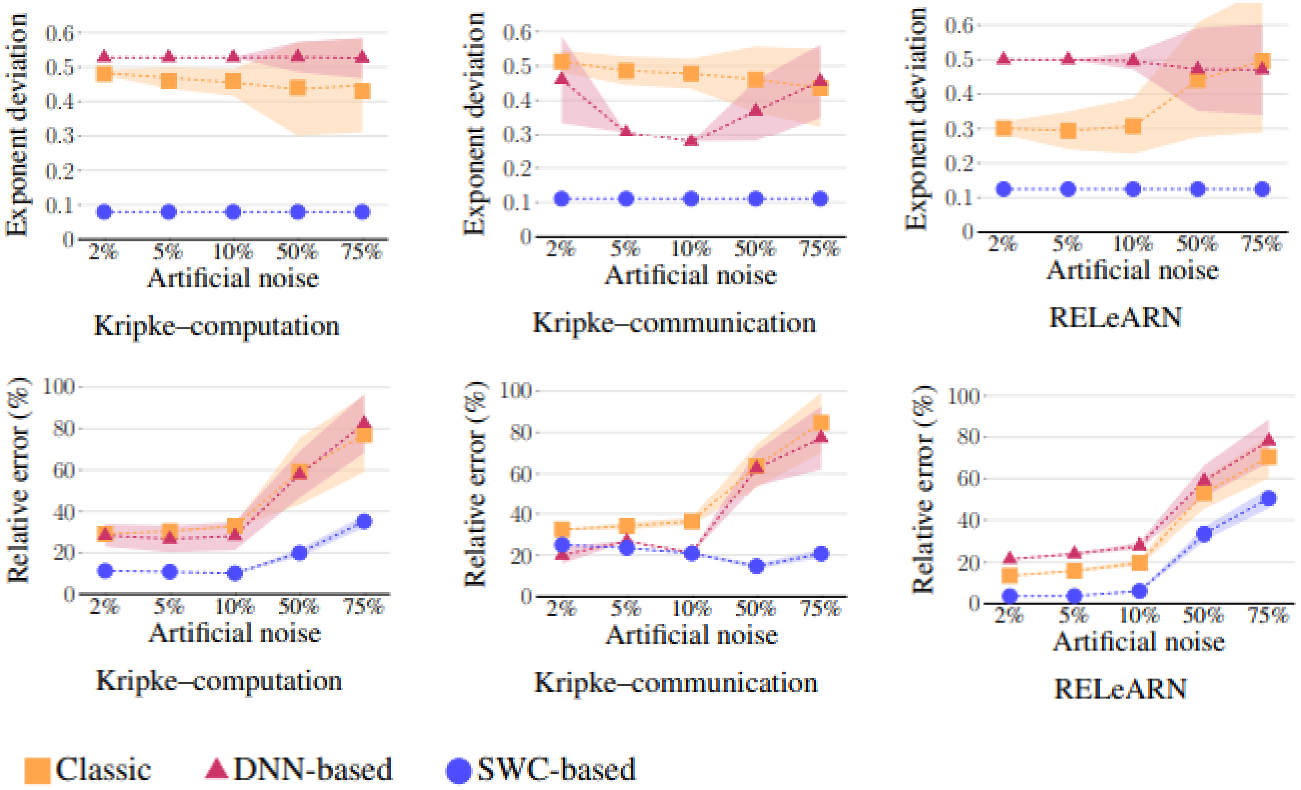
Evaluation

- Application case studies
  - Accuracy
  - Better in 6 out of 8 cases



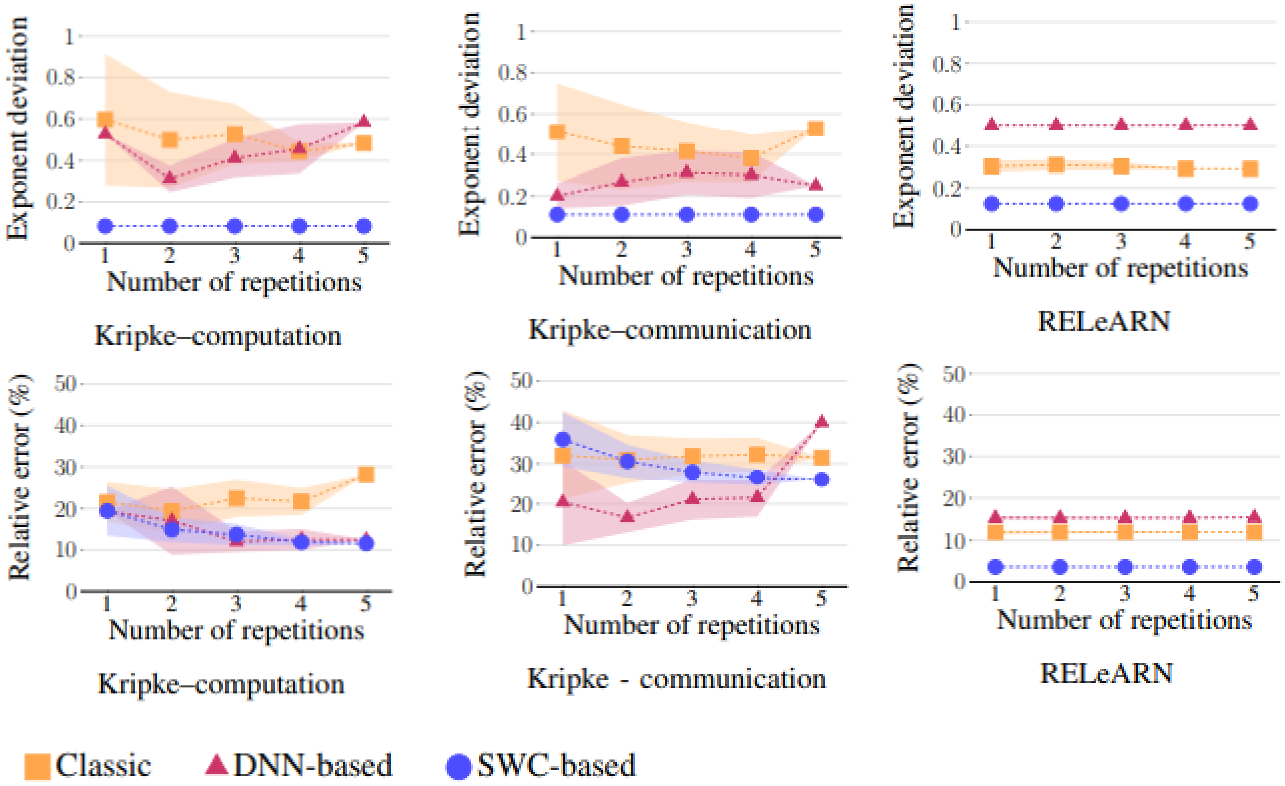
Application case studies

- Robustness to noise



Application case studies

- Experimental costs



Conclusion

- Our method accurately captures the computational effort of an application in close alignment with its theoretical performance model
- We reduce, if not eliminate, the need for multiple time measurements
- Under artificial noise, our models maintained stable error rates

- **Read the full paper at:** http://arxiv.org/abs/2504.10996
  - de Morais, G., Geiß, A., Calotoiu, A., Corbin, G., Tarraf, A., Hoefler, T., Mohr, B. and Wolf, F. Denoising Application Performance Models with Noise-Resilient Priors. *arXiv preprint arXiv:2504.10996, 2025*

References

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Parallel Programming

Thank you!

- You can contact us via email: extra-p-support@lists.parallel.informatik.tu-darmstadt.de
- Or on GitHub using the issues tool: https://github.com/extra-p/extrap