IRIS: Iterative and Intelligent Experiment Selection

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OUTLINE

- Motivation
- Related work
- IRIS method
- Evaluation
- Tuning guideline
- Conclusions



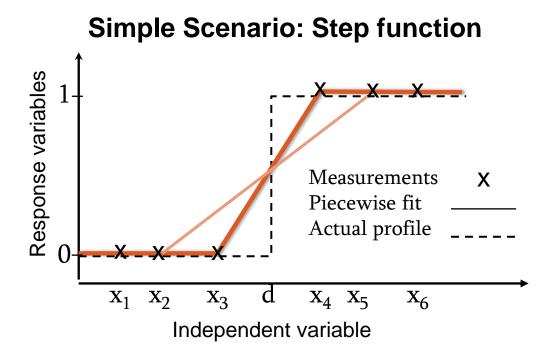




MOTIVATION

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Benchmarking is not always cheap: time, resource limits

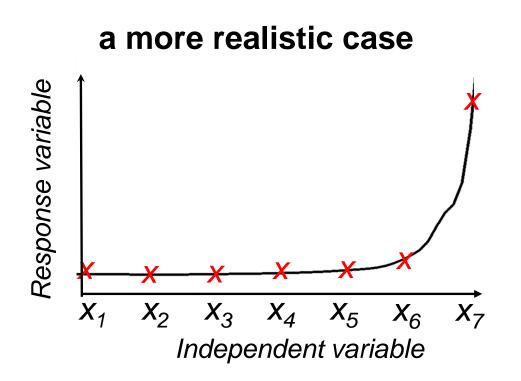


- Not all measurement points have the same value
- The position of points affect the accuracy of the fit
- Selecting points closer to step → more accurate fit with less budget





MOTIVATION



- Experiment results from a real server
- Removing points X₂ to X₅ has little effect on prediction accuracy





RELATED WORK

Response Surface Methodology

- Select most effective parameters
- Find optimum point of the system function
- e.g. Box–Behnken, fractional factorial
- Regression based, iterative function prediction techniques
 - Build model in each iteration
 - 1. More costly due to model validation techniques
 - 2. Model error can propagate into future iterations



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RELATED WORK

The problem scope

• Given the previously identified independent variables of interest, how to select the placement of experiment points?

Criteria

- Should consider both independent and response variables when deciding about the next experiment point
- Scalability for scenarios with many independent variables







Two steps algorithm:

1) Initial Point Selection

- Select a set of initial points to run the experiment based on:
 - An educated guess (e.g. a queueing model, ...)
 - Or a linear assumption

2) Iterative Point Selection

- Assumption: The experiment budget is limited
 - IRIS iteratively selects the next point to run the experiment, until it runs out of budget
 - Each point is selected based on the results of all previous experiments

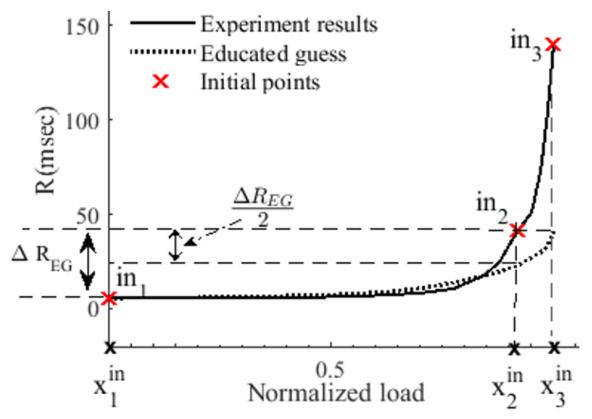






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A multi-core web server (load vs. response time)



• An educated guess: a layered queueing model (LQM) for the

system with estimated resource demands



IRIS ITERATIVE POINT SELECTION

Inputs

- a list of already measured $(x_i; y_i)$ points where $1 \le i \le N_i$
- N_t: total experiment budget
- α : gain trade-off factor

output

• List of all experimented points (x_j ; y_j) where $1 \le j \le N_t$



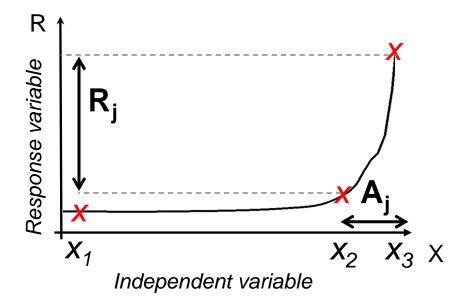


IRIS GAIN FORMULA

Gain for each interval

$$G_j = A_j^{\alpha} * R_j^{1-\alpha}$$

- $A_j = Size \ of \ interval$
- $R_j = |R(x_{j+1}) R(x_j)|$
- Trade-off factor: α







IRIS – ITERATIVE PHASE

algorithm

- 1. $n=N_i$, $P = \{p_i | 1 < i < N_i\}$
- 2. For each of thr n-1 intervals $[x_j : x_{j+1}]$ where $1 \le j < n$, calculate Gj
- 3. Find the interval $[x_{k}, x_{k+1}]$, where $G_k = \max\{G_j\}$

4.
$$p_n = \frac{(x_k + x_{k+1})}{2}, P = P \cap \{P_n\}, n = n+1$$

5. If $(n \le N_t)$ then goto 2, else END

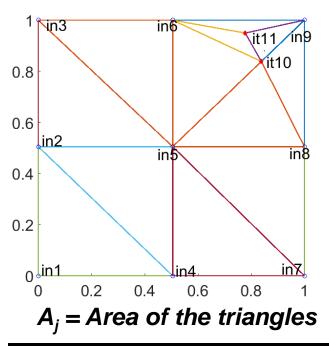


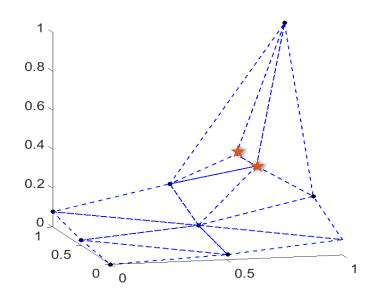


IRIS MULTI-DIMENSIONAL SCENARIO

Delaunay triangulation to calculate *Aj*

- A unique planar triangulation of the independent variable space
- The resulting triangles consist of points with high proximity
- Easy to calculate
- Generalizes to multiple dimensions





R_j = *Maximum* difference in response variables of the 3 nodes in each triangle

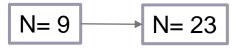


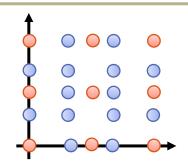


EVALUATION BASE-LINE: EQUAL DISTANCE POINT SELECTION

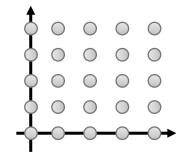
- Equal Distance Point Selection (EQD)
 - Possible range of each independent variable is divided into N -1 equally sized intervals.

Multi-stage EQD: available point budget is spent in multiple stages of EQD





Single-stage EQD: all the budget is spent in a single round (penalty free)





EVALUATION COMPARISON METRICS

Average Absolute Error

$$AAE = \frac{\sum_{j=1}^{n} |R_{PRD}(X_j) - R(X_j)|}{\sum_{j=1}^{n} R(X_j)}$$

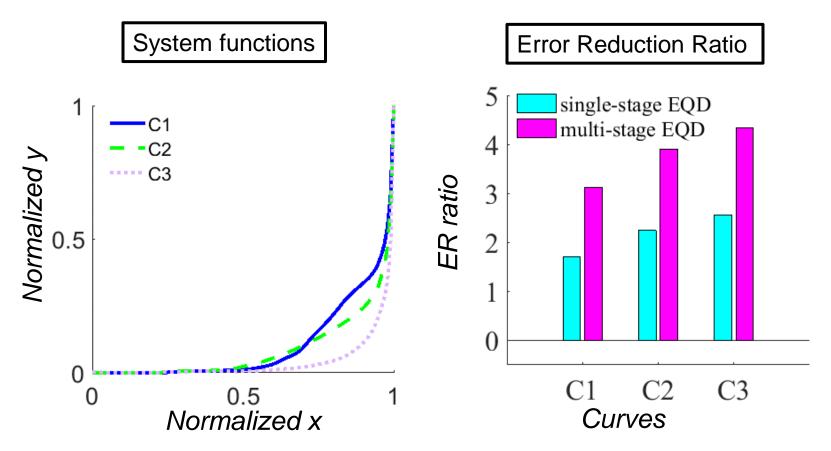
Error Reduction Ratio

$$ER = \frac{(\overline{AAE}_{baseline} - \overline{AAE}_{IRIS})}{\overline{AAE}_{IRIS}}$$

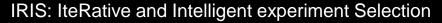




EVALUATION SINGLE INDEPENDENT VARIABLE

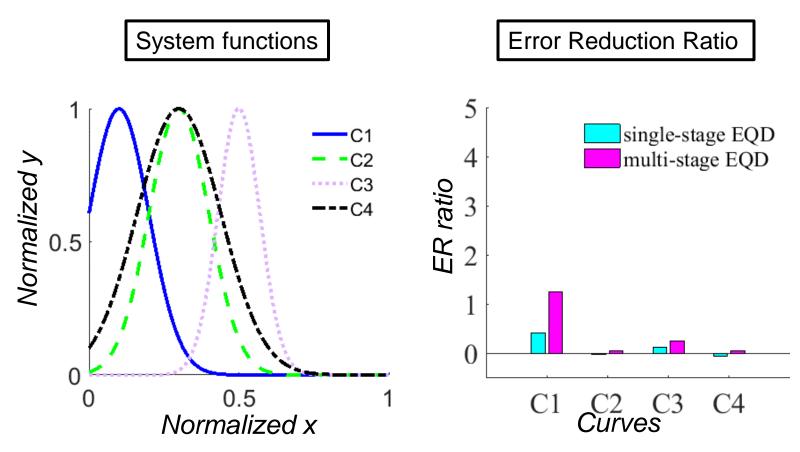


- An experimental system with web workload on a multi-core server
- **Result:** Higher ER ratio in the graph with larger flat region





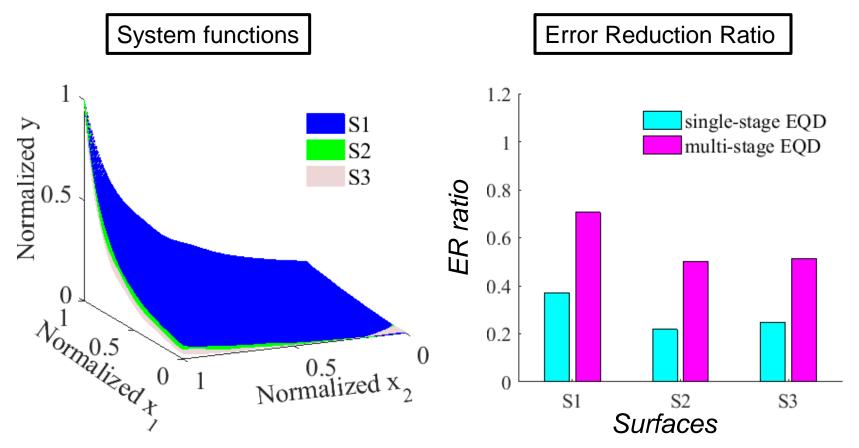
EVALUATION SINGLE INDEPENDENT VARIABLE



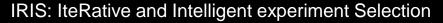
- A group of bell-shaped synthetic functions representing normal distributions
- **Result:** IRIS more effective for non-symmetric curves



EVALUATION MULTIPLE INDEPENDENT VARIABLES

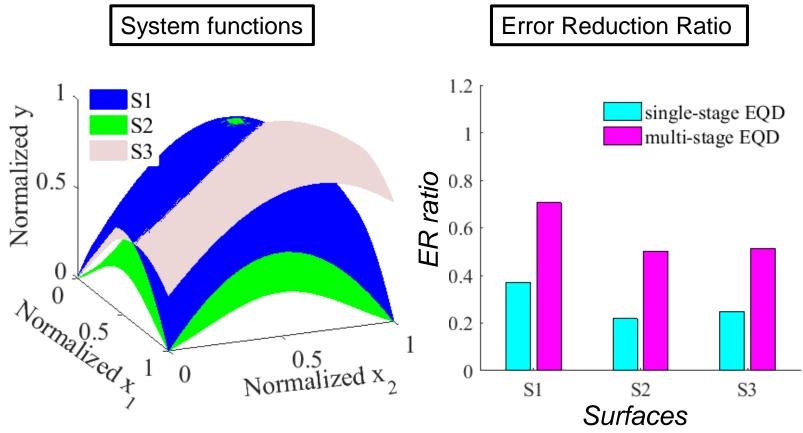


- Load-response time dataset with two load parameters as independent variables
- **Result:** Lower ER due to large flat surface

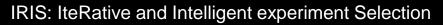




EVALUATION MULTIPLE INDEPENDENT VARIABLES

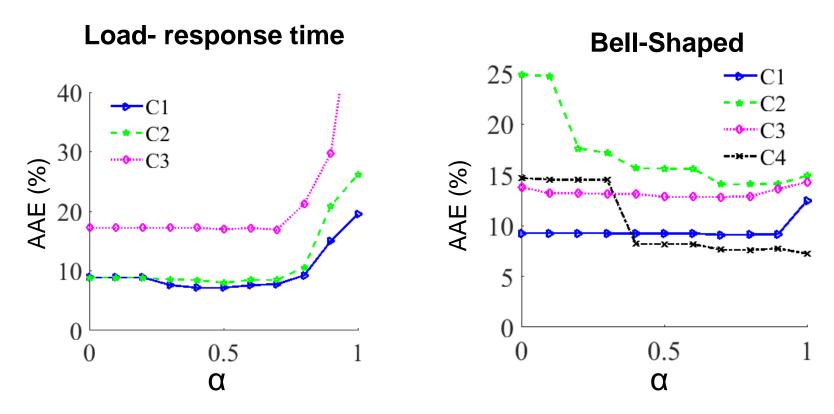


- A group of three synthetic Gaussian surfaces with different means and standard deviations
- **Result:** higher ER in surfaces with larger slope









- A convex sharp knee in the system function \rightarrow Smaller α values
- A concave and symmetric maximum point \rightarrow Larger α values





TUNING GUIDELINE ERROR DISTRIBUTION

- IRIS can improve prediction in the *Region of Interest* in the parameter space
- **Trade-off**: Slightly lower prediction accuracy for the rest of the parameter space

Normalized x₂

0

0

IRIS

Error colormap

Obtained Contour lines

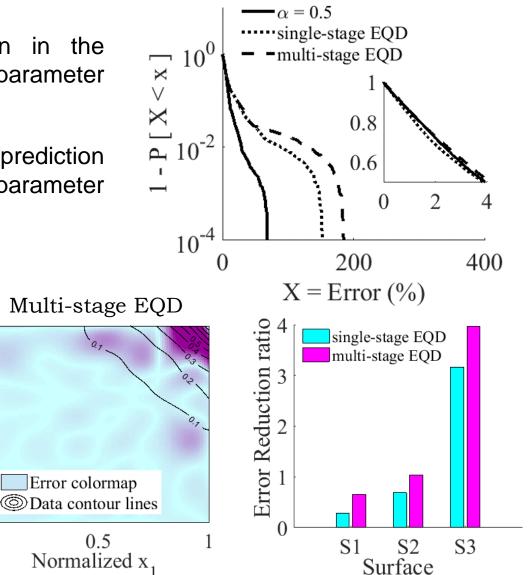
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0.5

Normalized x

Normalized x₂

0



ICPE17

CONCLUSIONS

- IRIS outperforms equal distance for the majority of the evaluated systems
- Trade-off factor is tuned through initial system knowledge
- More reduction in Region of Interest
- In future, we are going to examine systems with higher dimensionality





Thank you!

Questions?

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