Input Responsiveness: Using Canary Inputs to Dynamically Steer Approximation

Michael A. Laurenzano, Parker Hill, Mehrzad Samadi, Scott Mahlke, Jason Mars, Lingjia Tang

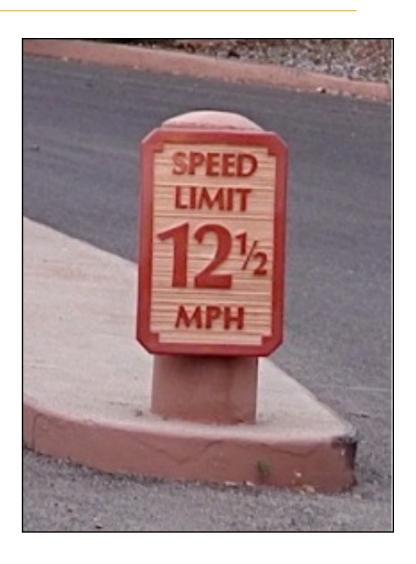
ACM SIGPLAN Conference on Programming Language Design and Implementation (PLDI) June 15, 2016















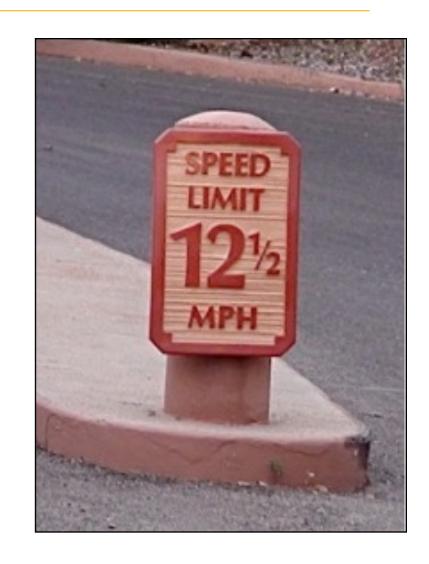
 Trade small losses in accuracy for big gains in performance/energy







- Trade small losses in accuracy for big gains in performance/energy
- Why approximation?
 - Machine learning, data mining, image, video and sound processing, statistics, graphics
 - Loose constraints on output quality, growing computational demands











Central question — how to approximate?





- Central question how to approximate?
 - How to parameterize approximation





- Central question how to approximate?
 - How to parameterize approximation
 - Where in the application to approximate









 Insight — input is a key component in answering this question





- Insight input is a key component in answering this question
- Example gamma correction





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Example — gamma correction





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- Example gamma correction

input





exact output









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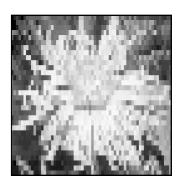
exact output





approximate output (8x8 tiling)











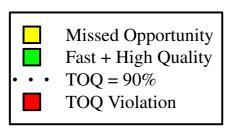


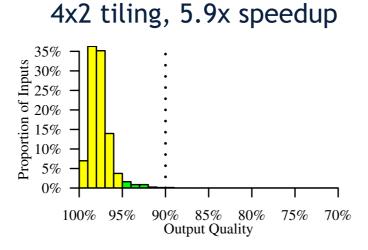
• Example: gamma correction, 2 tiling approximations, 800 inputs

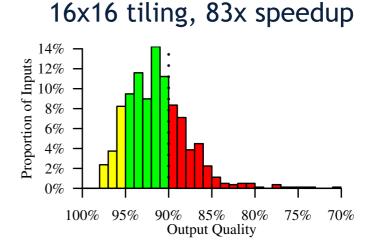




Example: gamma correction, 2 tiling approximations, 800 inputs

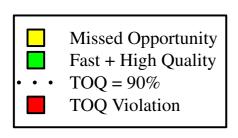


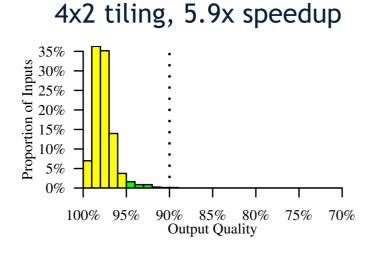


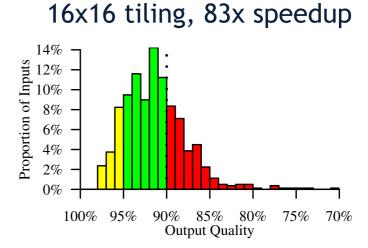




Example: gamma correction, 2 tiling approximations, 800 inputs





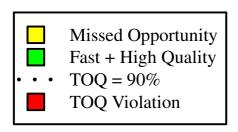


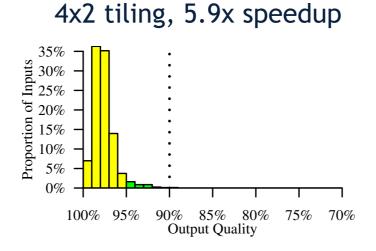
What if we take full advantage of the differences among inputs?

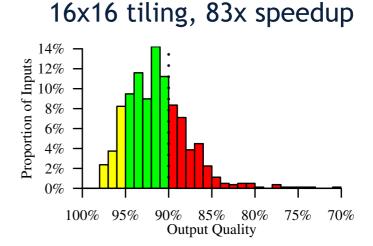




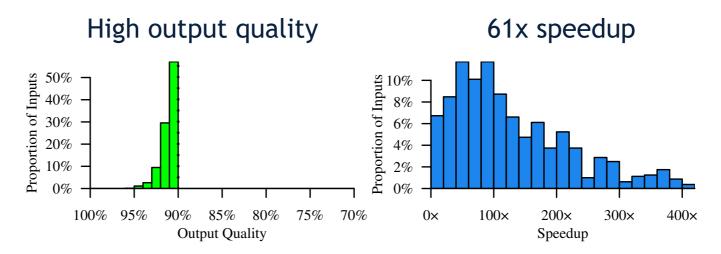
Example: gamma correction, 2 tiling approximations, 800 inputs







· What if we take full advantage of the differences among inputs?







Achieving Input Responsiveness





Achieving Input Responsiveness

- Goal end-to-end runtime system to choose how to approximate, customized for each input
 - Maximize performance given an accuracy target





Achieving Input Responsiveness

- Goal end-to-end runtime system to choose how to approximate, customized for each input
 - Maximize performance given an accuracy target
- Challenges
 - Choose highly effective approximation per input
 - Choose it quickly!







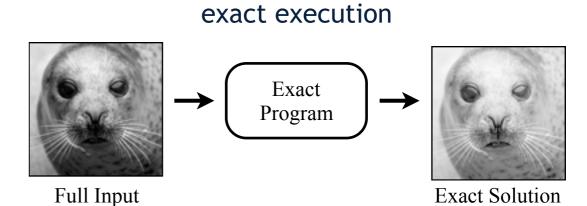


$\begin{array}{c} \text{exact execution} \\ \hline \\ \hline \\ \text{Full Input} \end{array} \begin{array}{c} \text{Exact} \\ \text{Program} \end{array} \begin{array}{c} \\ \\ \end{array} \begin{array}{c} \\ \\ \end{array} \begin{array}{c} \text{Exact Solution} \end{array}$





 Create a small canary input from full input

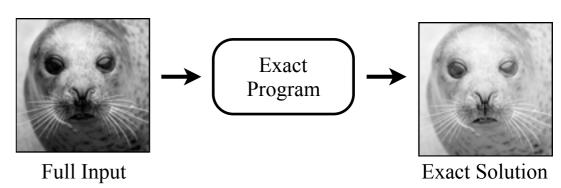


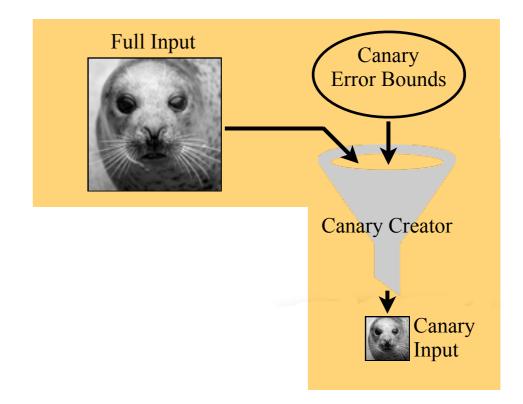




 Create a small canary input from full input

exact execution



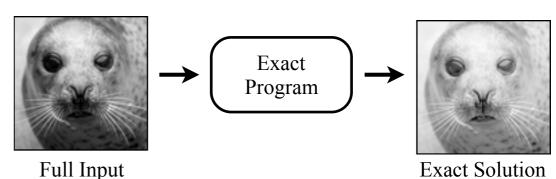


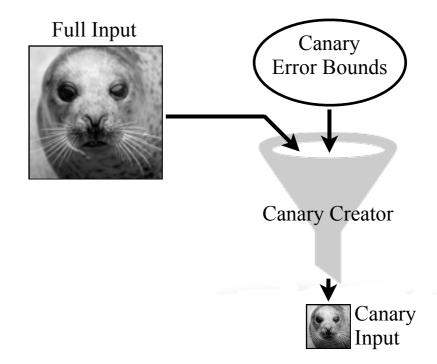




- Create a small canary input from full input
- Choose an approximation using canary

exact execution



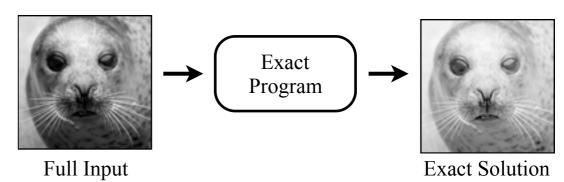


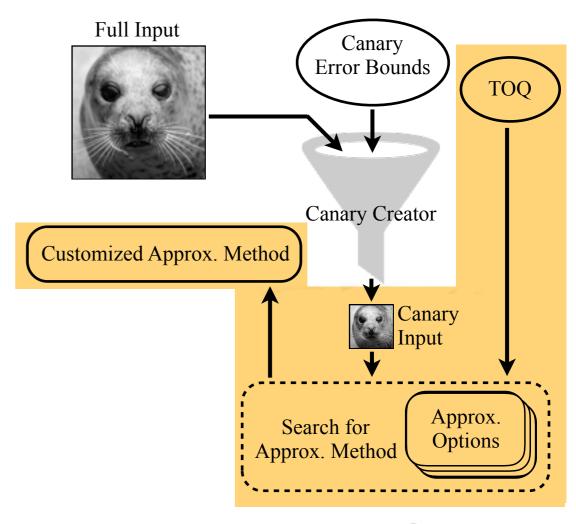




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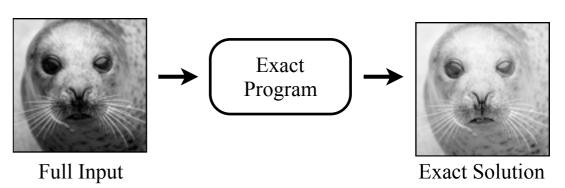


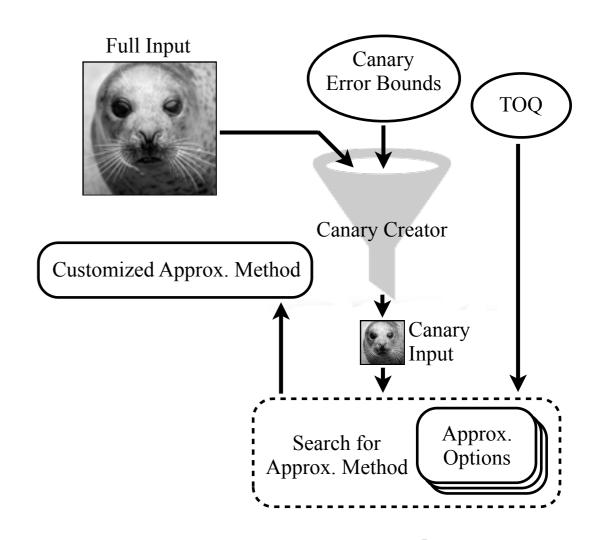




- Create a small canary input from full input
- Choose an approximation using canary
- Compute approximate solution on full input

exact execution



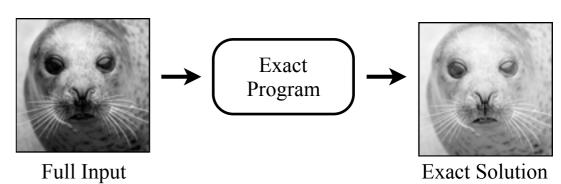


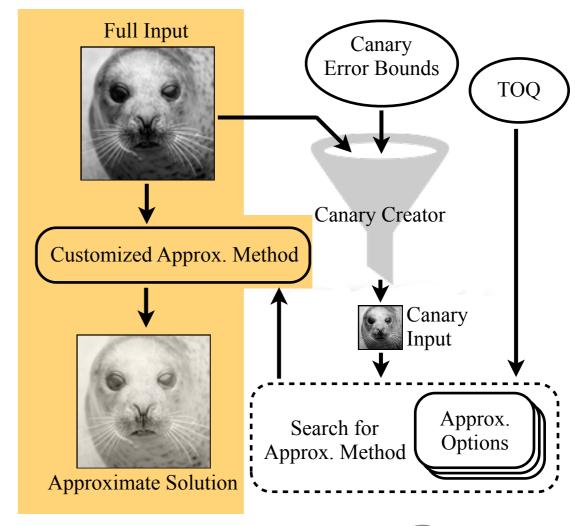




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exact execution













Similarity — sufficient similarity to full input





- Similarity sufficient similarity to full input
- Inexpensive Computation create it quickly





- Similarity sufficient similarity to full input
- Inexpensive Computation create it quickly
- Size Reduction
 - Computational complexity often depends on input size
 - · Canary should be as small as possible

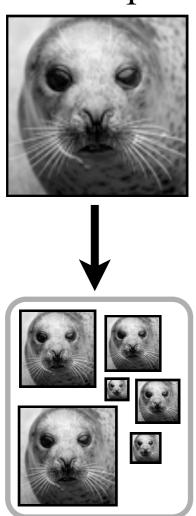




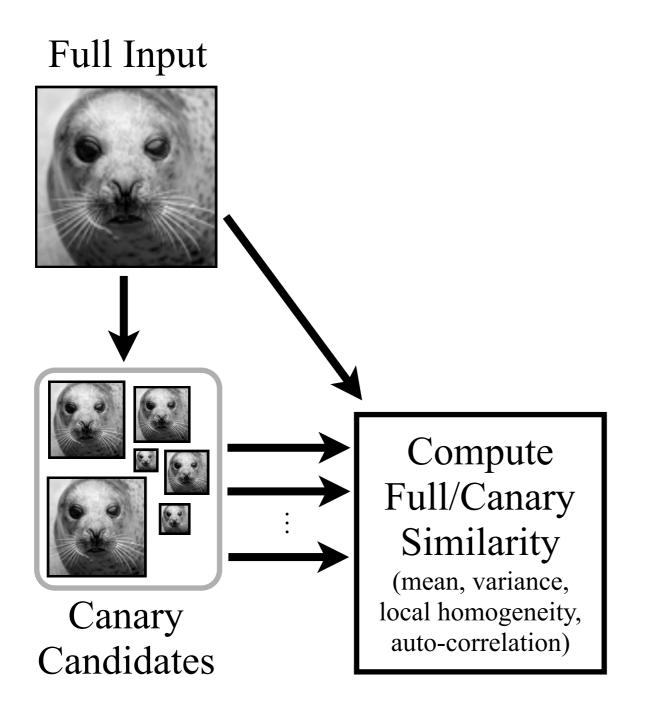
Full Input

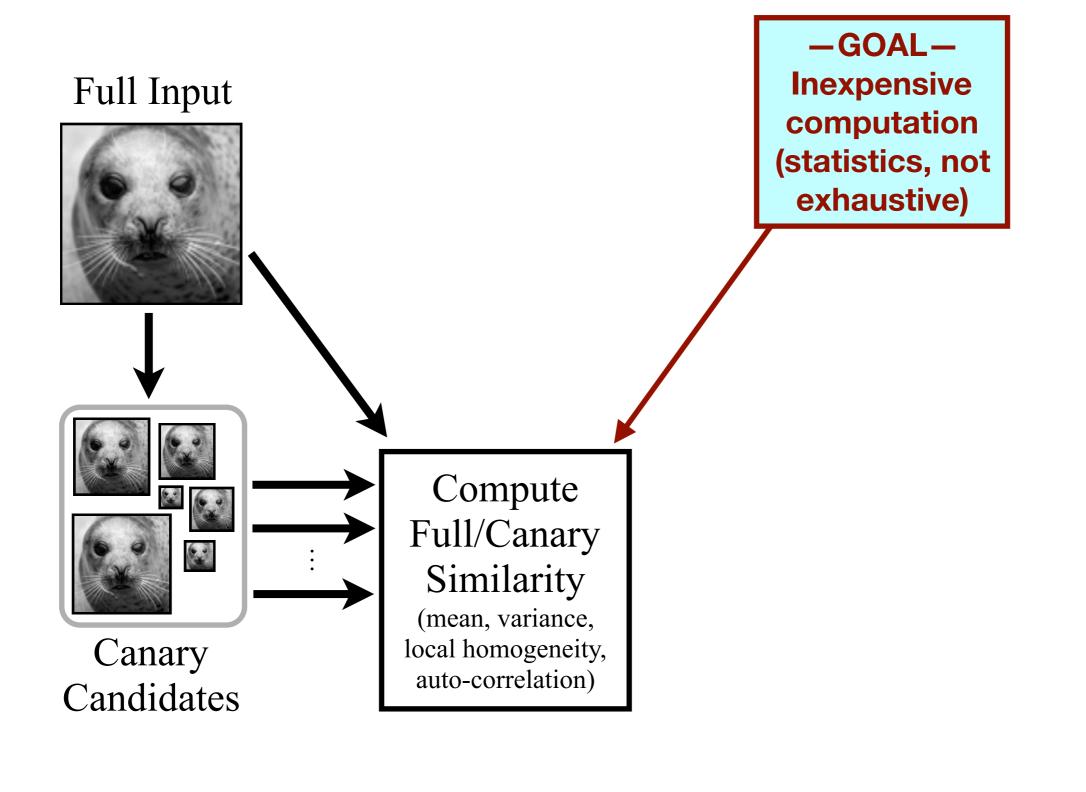


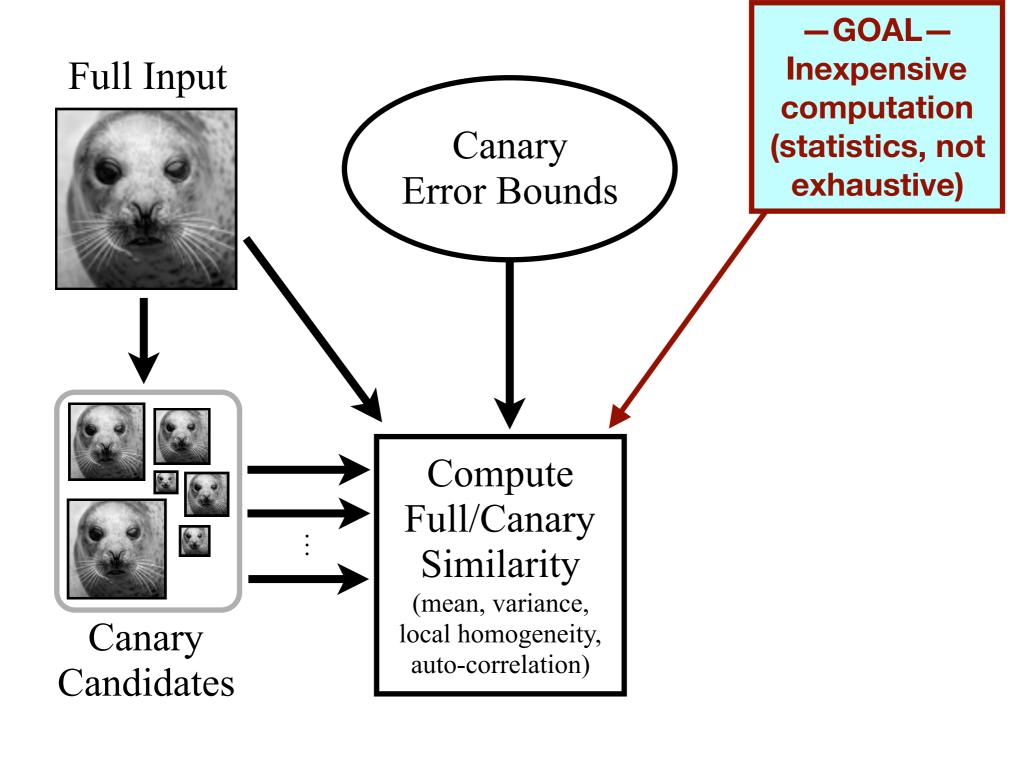
Full Input



Canary Candidates





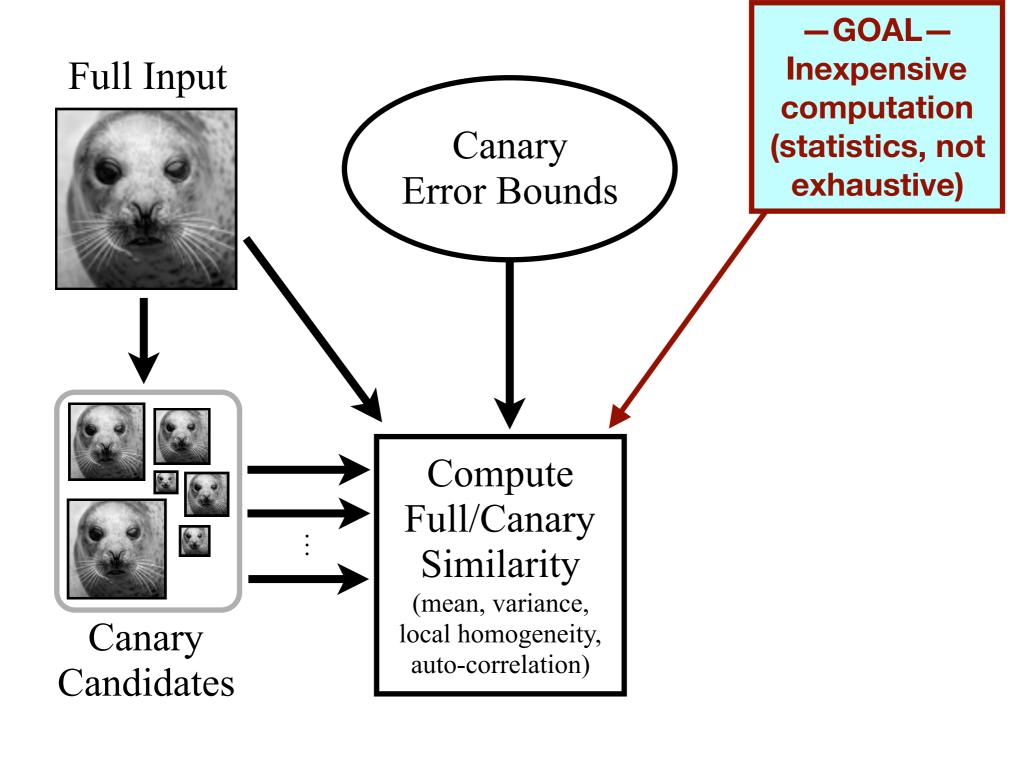


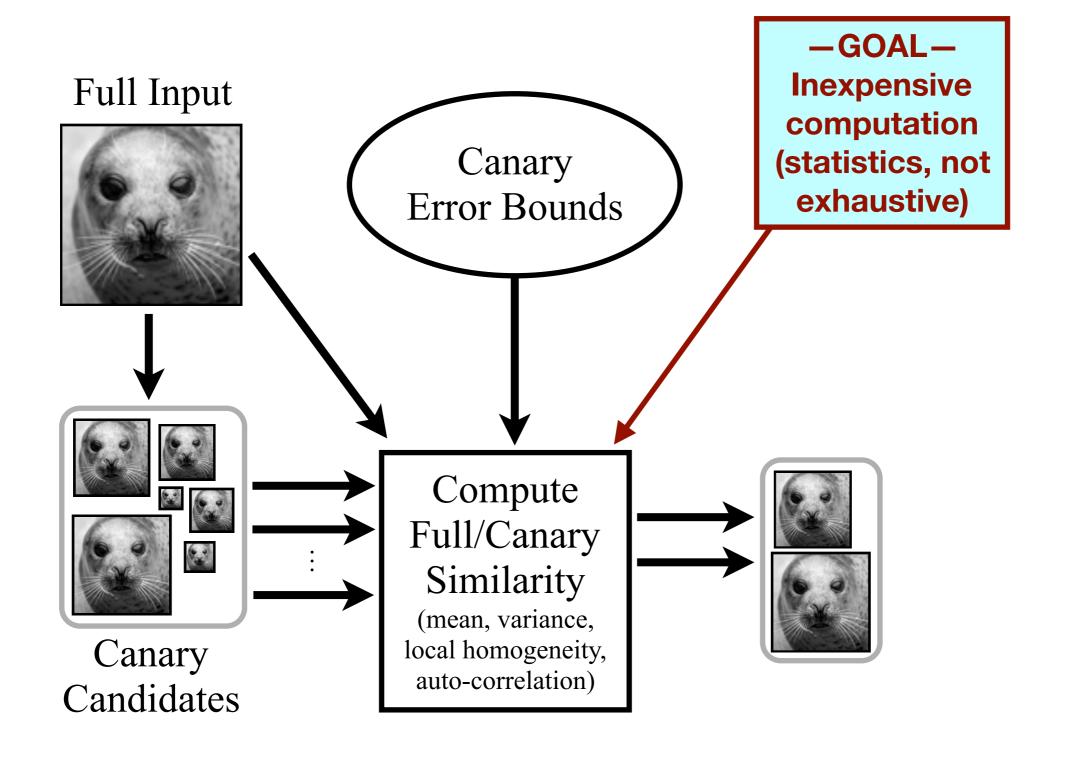
Full Input

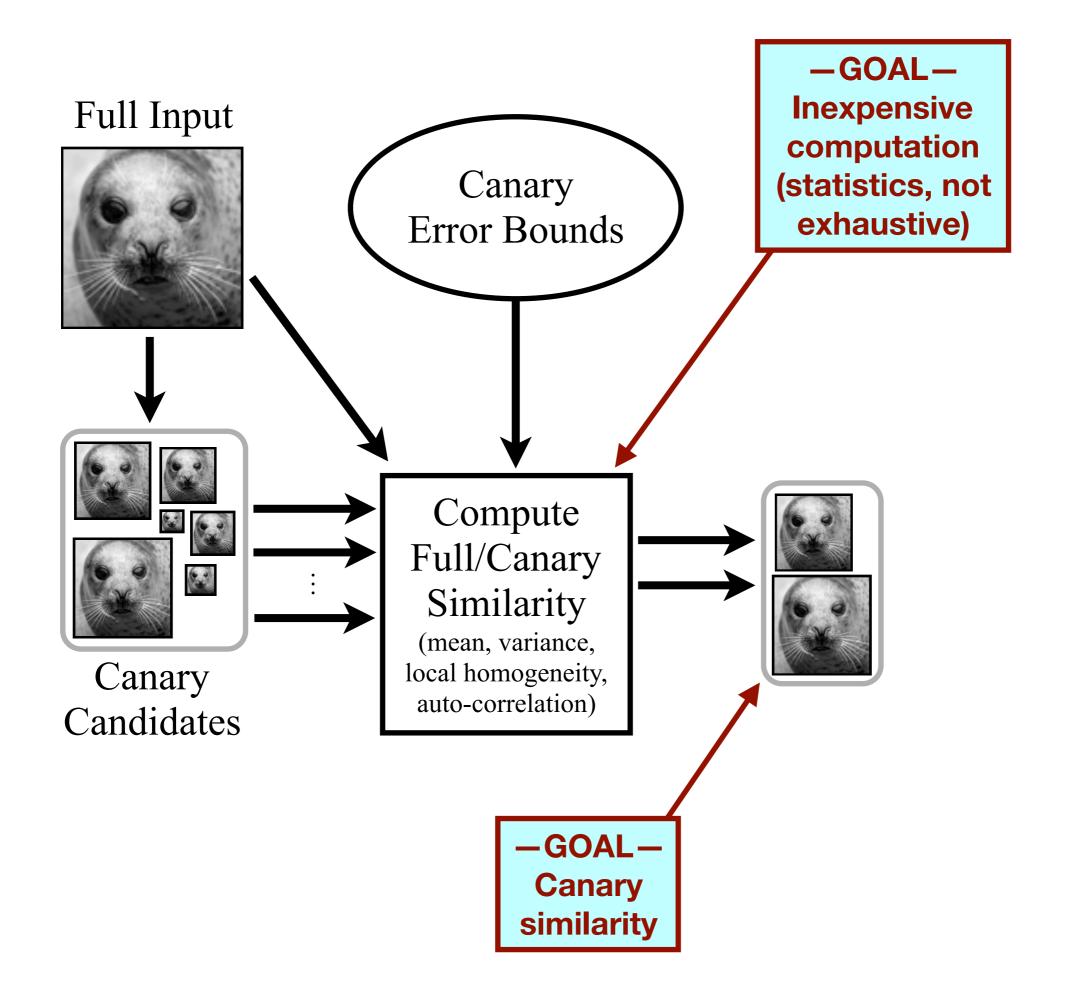


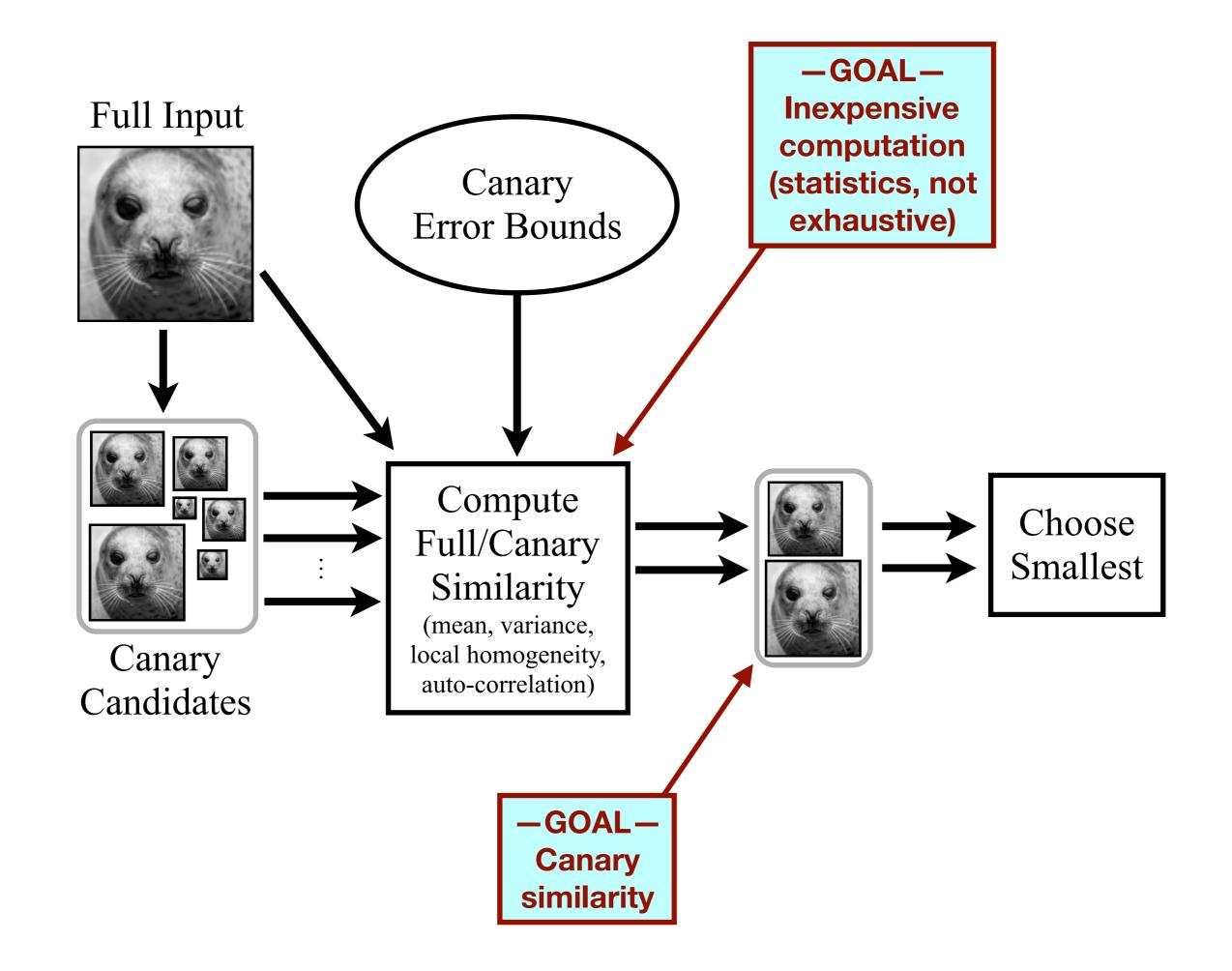
-GOALInexpensive
computation
(statistics, not
exhaustive)

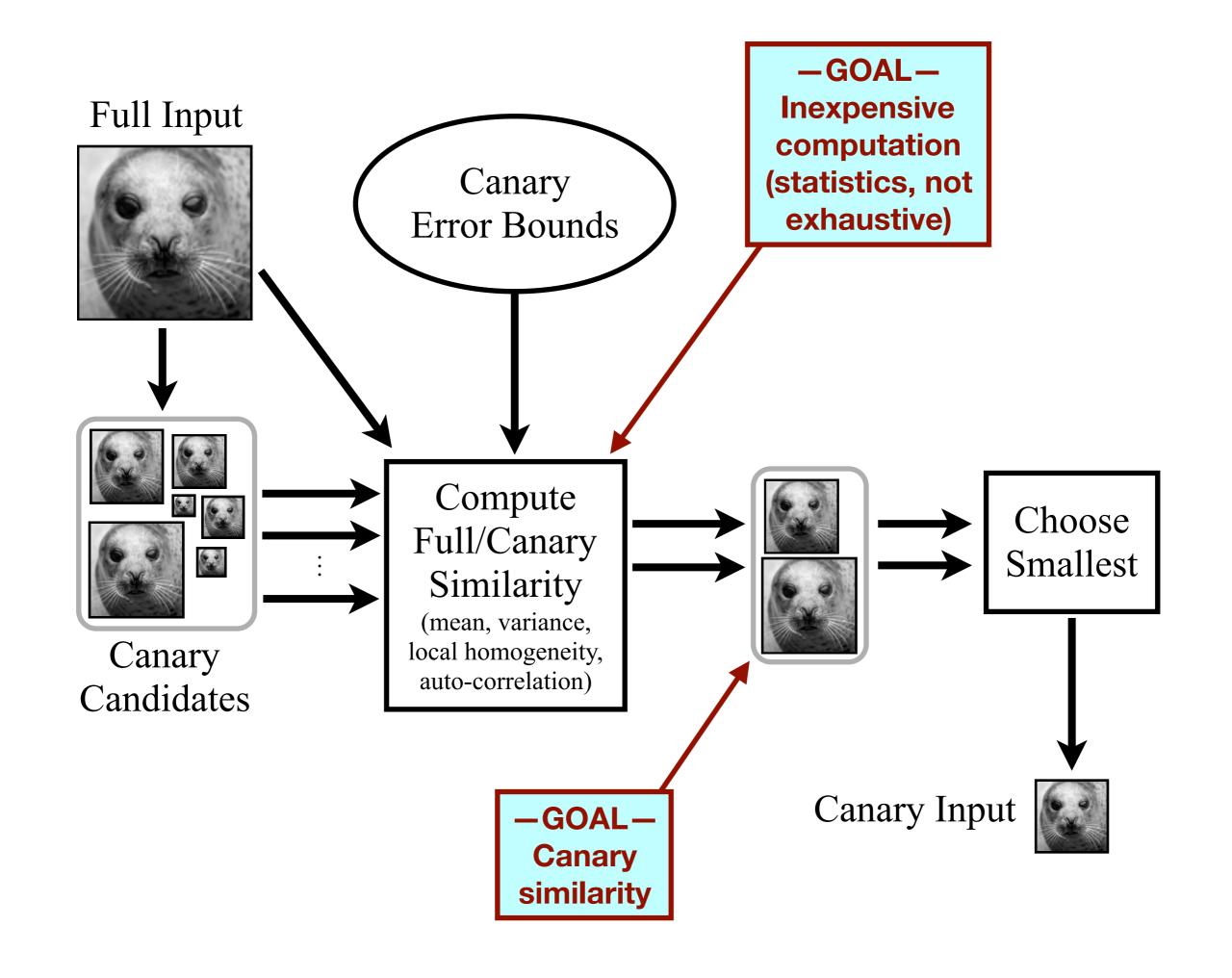
	Mean	Variance	Local Homogeneity	Autocorrelation
Description	Mean μ of input elements	Variance σ^2 of input elements	Proportion Λ of elements represented by λ in canary $\notin [\lambda - \sigma z_{1-\alpha/2}, \lambda + \sigma z_{1-\alpha/2}]$	Correlation ρ among pairs of input elements (y_j, y_{j+1})
Null Hypothesis (H_0) Alt. Hypothesis (H_A)	$H_0: \overline{\mu_i} = \mu_0$ $H_A: \overline{\mu_i} \neq \mu_0$	$H_0: \overline{\sigma_i}^2 = \sigma_0^2$ $H_A: \overline{\sigma_i}^2 \neq \sigma_0^2$	$H_0: \overline{\Lambda_i} \le 0.1$ $H_A: \overline{\Lambda_i} > 0.1$	$H_0: \overline{\rho_i} = \rho_0 H_A: \overline{\rho_i} \neq \rho_0$
Test Statistic (t_i)	$t_i = \frac{\mu_0 - \overline{\mu_i}}{\overline{\sigma_i}\sqrt{n}}$	$t_i = \frac{\overline{\sigma_i}^2}{\sigma_0^2}$	$t_i = \frac{\sqrt{n} \overline{\Lambda_i} - 0.1 }{\sqrt{0.1(1 - 0.1)}}$	$t_i = \frac{\ln\left(\frac{(1+\rho_0)(1-\overline{\rho_i})}{(1-\rho_0)(1+\overline{\rho_i})}\right)}{2\sqrt{n-3}}$
p -value (p_i)	$p_i = 2P(Z > t_i)$	$p_i = 2P(F_{n-1,n-1} > t_i)$	$p_i = 2P(Z > t_i)$	$p_i = 2P(Z > t_i)$
Sample Size (n)	$n = 2(z_{1-\alpha/2k} + z_{1-\beta/k})^2$	Formula yields no simple form; see Cohen [14] for details.	$g(x) = \sqrt{x(1-x)}$ $n = 0.1^{-2} (g(0.1)z_{1-\alpha/2k} + g(\overline{\Lambda_i})z_{1-\beta/k})^2$	$n = \frac{4(z_{1-\alpha/2k} + z_{1-\beta/k})^{2}}{\ln((1+\rho_{0})/(1-\rho_{0}))^{2}}$
Acceptability Test	Holm-Bonferroni method: sort p-values $p_1, p_2, \dots p_k$ to obtain sorted p-values $p_{(1)}, p_{(2)}, \dots p_{(k)}$. Find the minimum index m such that $p_{(m)} > \frac{\alpha}{k+1-m}$, then reject all canaries $C_{(i)}$ where $i \geq m$.			
Definitions	α : the desired bound on the probability of committing any Type I errors (false negative), β : the desired bound on Type II errors (false positive) k : the number of canary candidates, C_i : the i th canary candidate, $\overline{x_i}$: the sample statistic x for canary C_i , x_0 : the sample statistic x for the full input x_i : the standard normal distribution, x_i : the quantile function at x_i of x_i : the F-distribution with degrees of freedom x_i and x_i :			

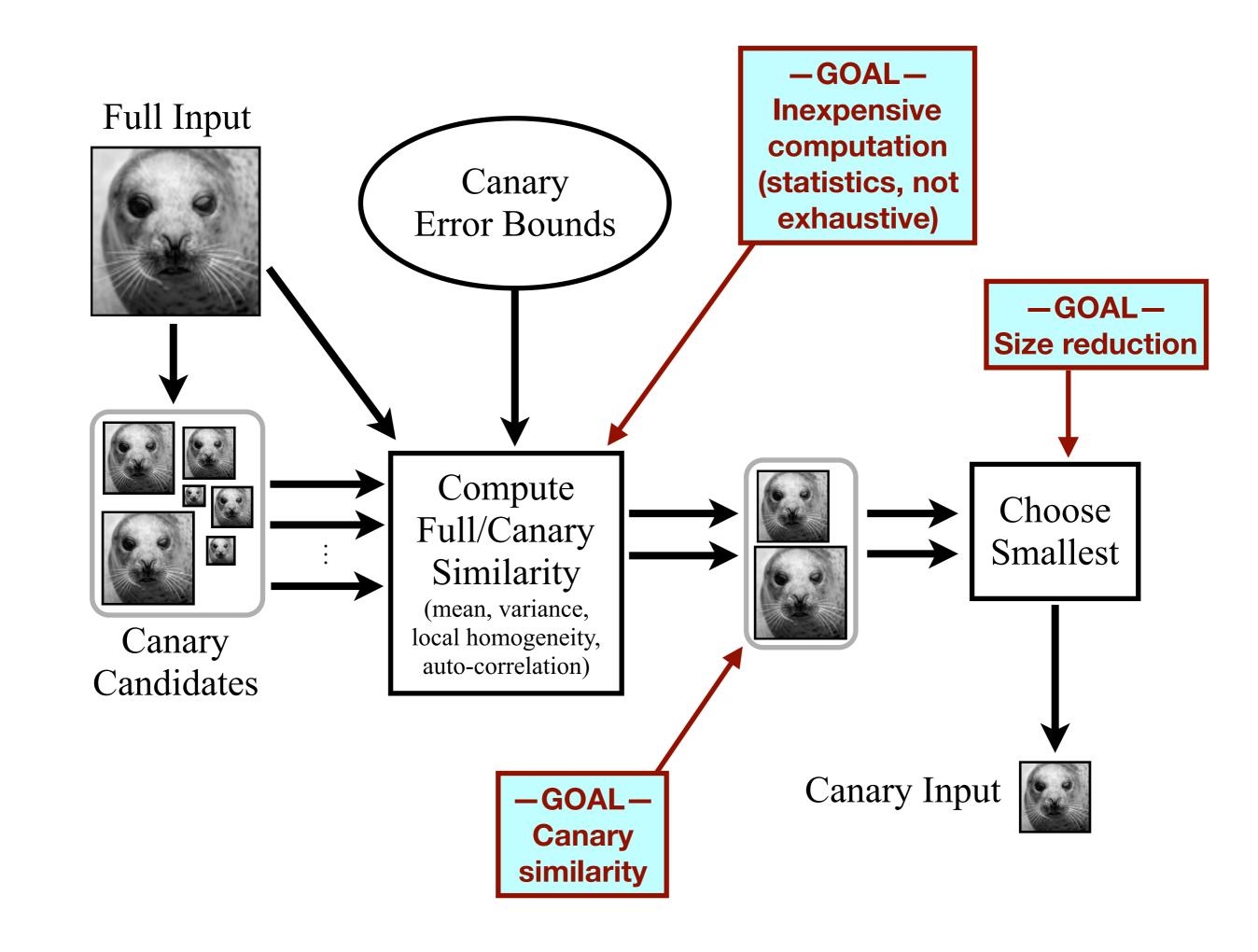
















 Tune approx. parameters within all code regions



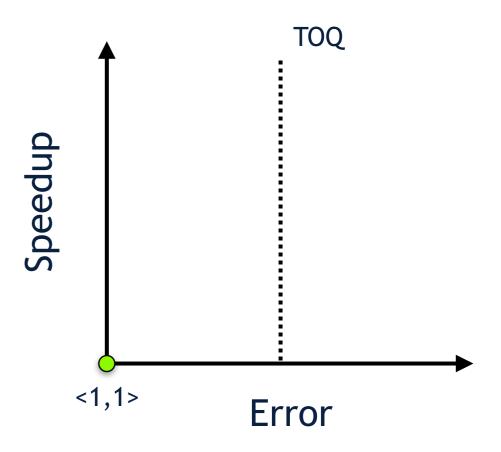


- Tune approx. parameters within all code regions
- Search (greedy) with steepest ascent hill climbing





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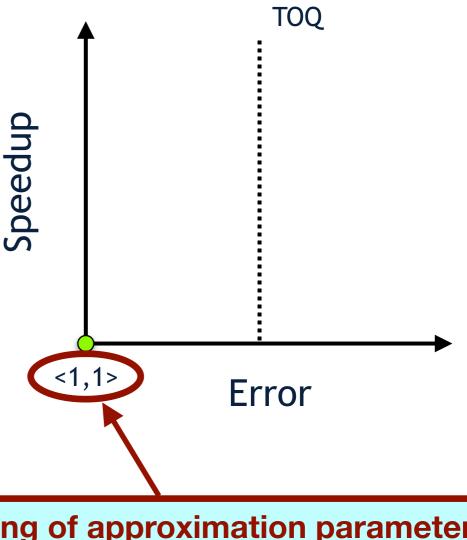






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Canary-driven Search

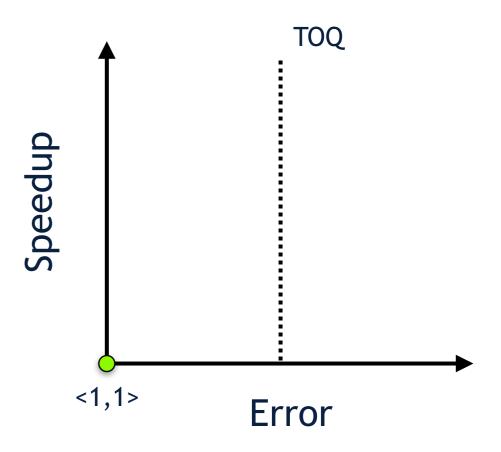


Encoding of approximation parameters (2 code regions)





- Tune approx. parameters within all code regions
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- Tune approx. parameters within all code regions
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Canary-driven Search

Steepest

TOQ

<1,2>
<1,1>
Error





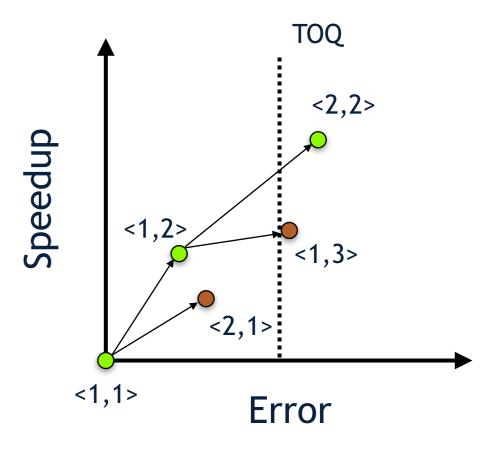
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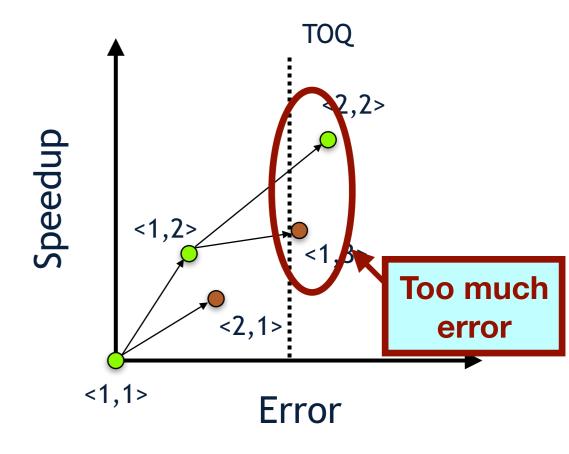
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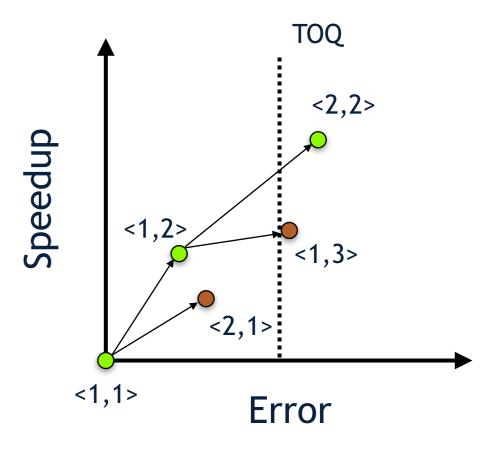
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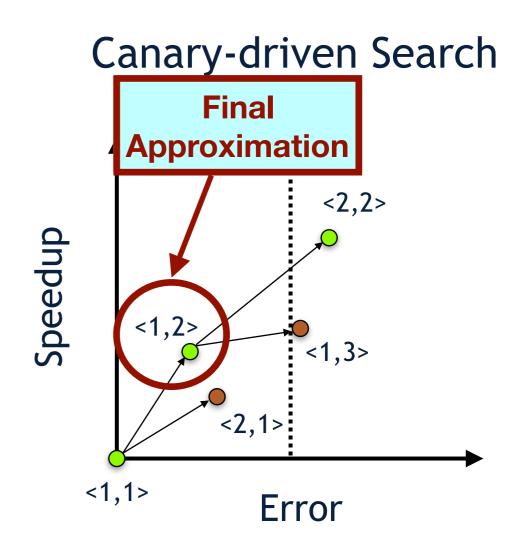
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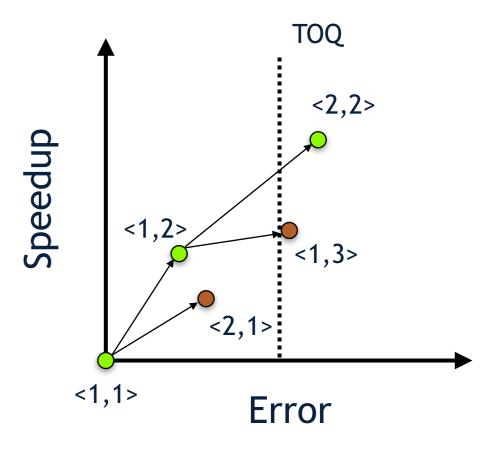
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- Tune approx. parameters within all code regions
- Search (greedy) with steepest ascent hill climbing
- Use the resulting approximation on full input







Evaluation









- 13 applications
 - Approximation opportunities per application 1-5
 - Inputs per application 2-800





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- Approximation classes
 - Loop perforation, tiling, algorithm choice, numerical approximation





- 13 applications
 - Approximation opportunities per application 1-5
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 - Loop perforation, tiling, algorithm choice, numerical approximation
- Canary similarity metric variance





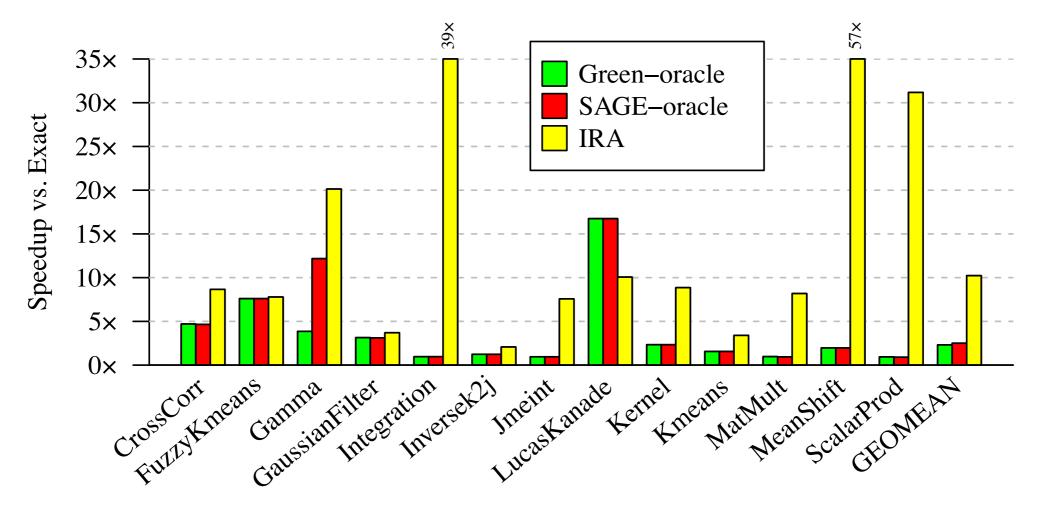
- 13 applications
 - Approximation opportunities per application 1-5
 - Inputs per application 2-800
- Approximation classes
 - Loop perforation, tiling, algorithm choice, numerical approximation
- Canary similarity metric variance
- Target output quality (TOQ) 90%





Speedup — IRA vs. Prior Work

- Calibration compare exact result to approximate result every so often
 - Oracle versions of SAGE [MICRO'13] and Green [PLDI'10]

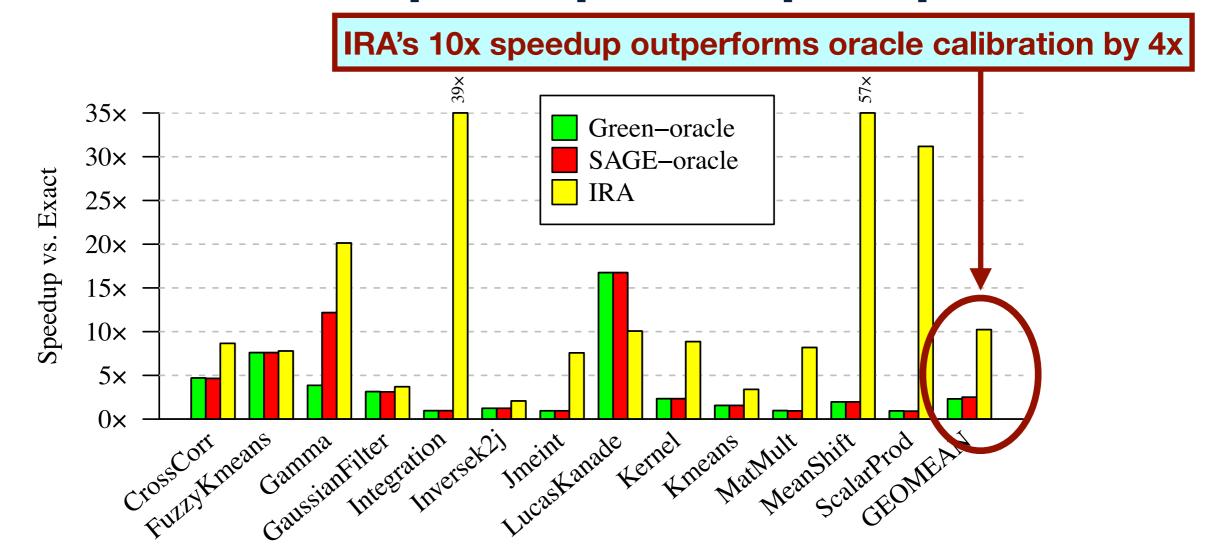






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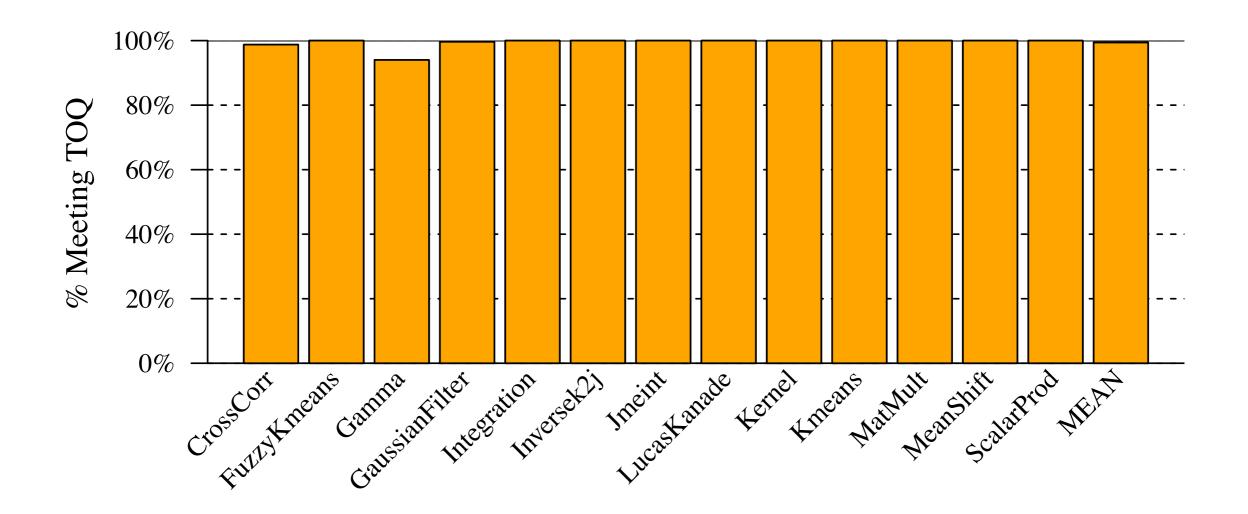






Accuracy of IRA

% of outputs meeting TOQ (TOQ=90%)

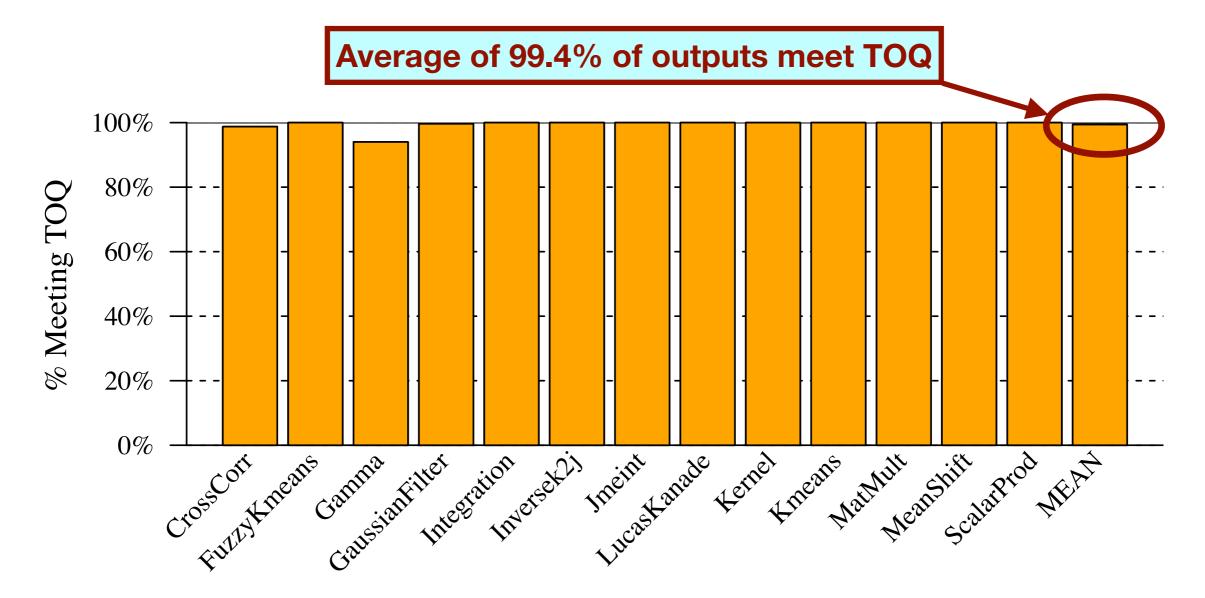






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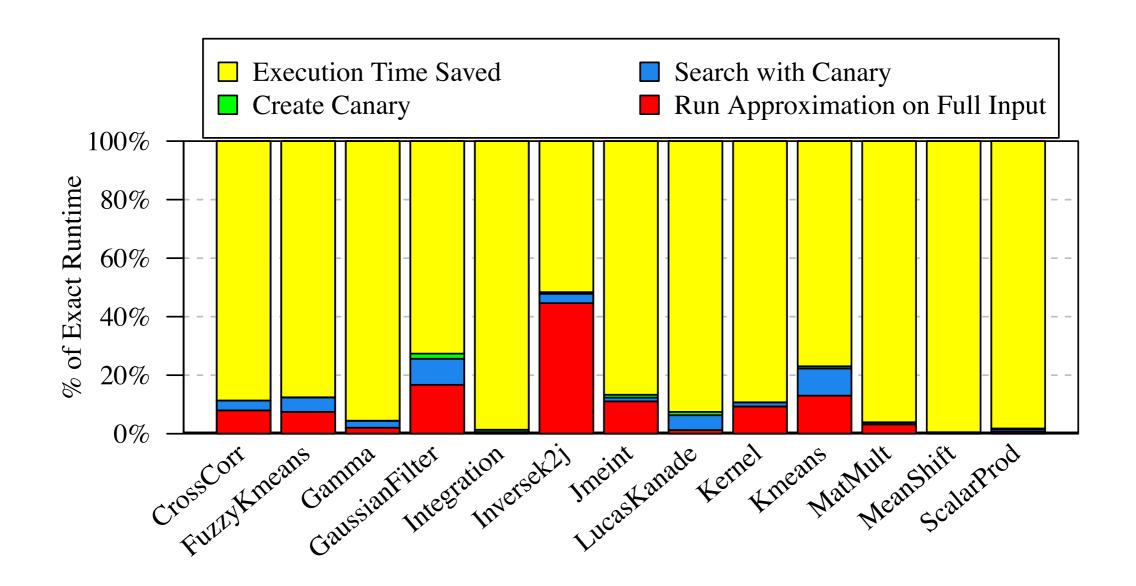






Where is the Time Spent?

End-to-end execution time broken down

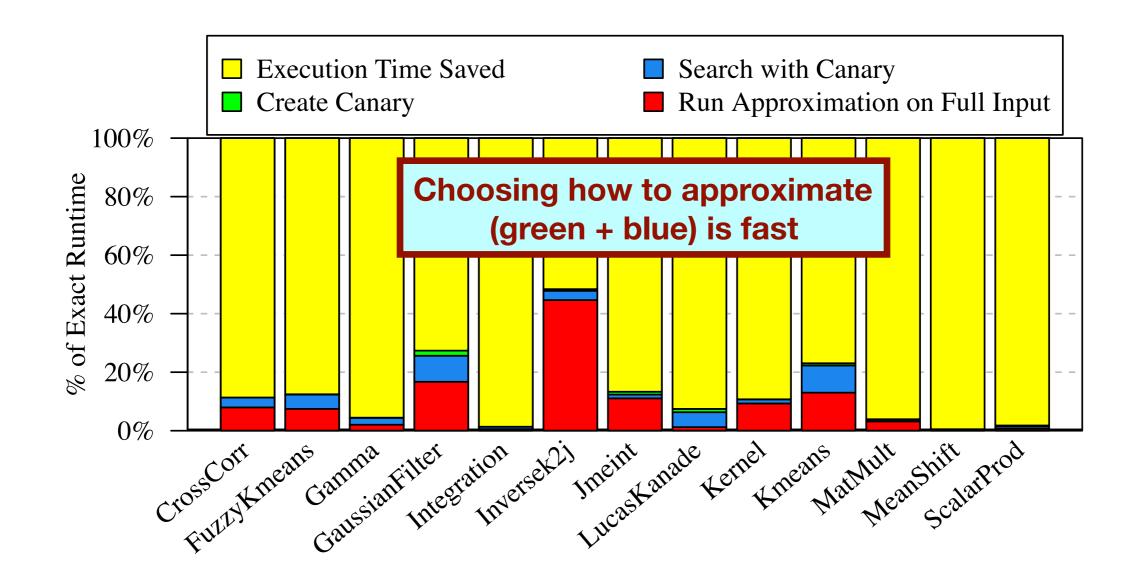






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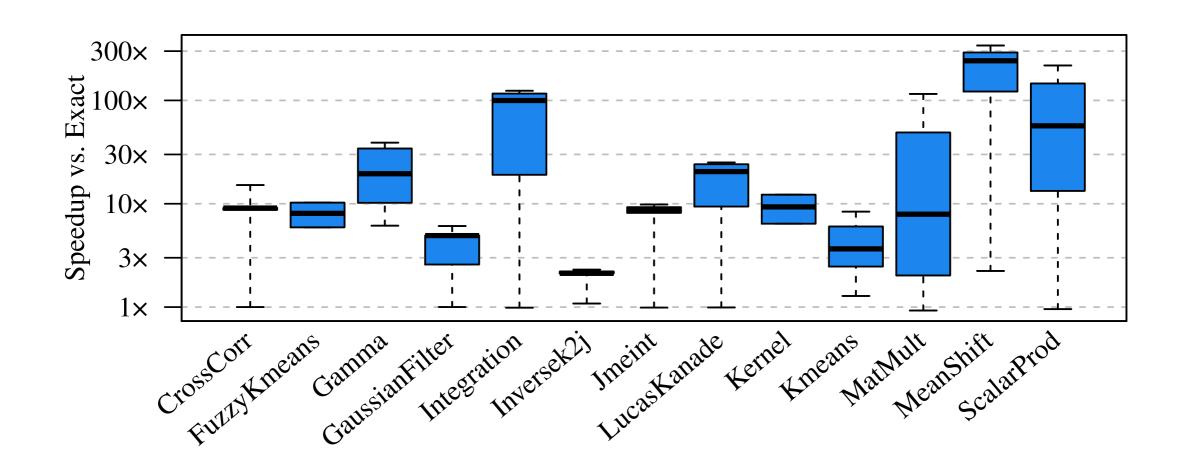






Input Responsiveness

 Wide range of speedups (and approximations) used across different inputs

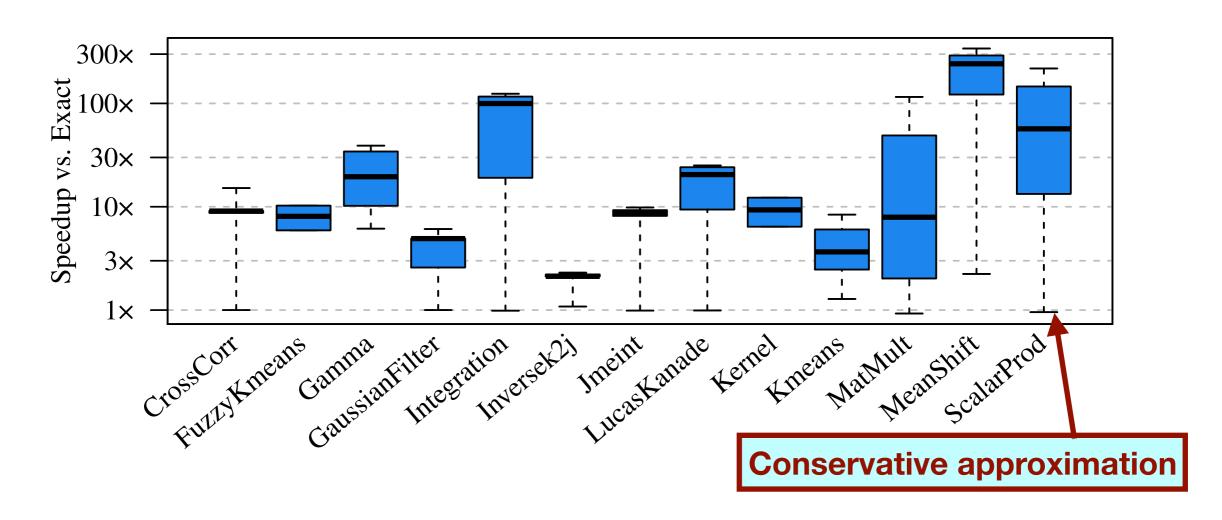






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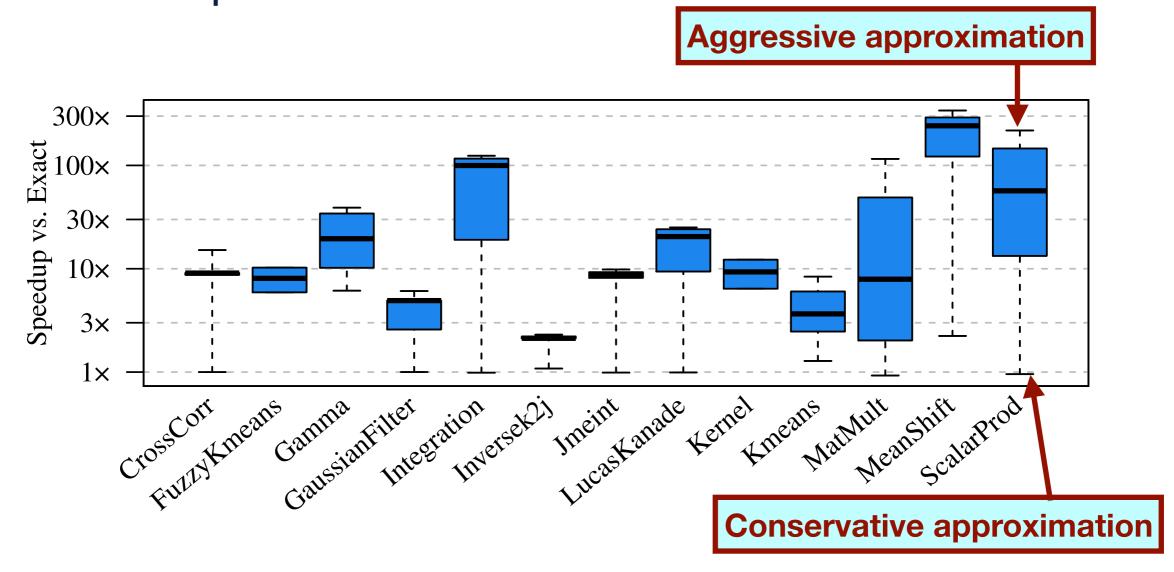






Input Responsiveness

 Wide range of speedups (and approximations) used across different inputs







Conclusion





Conclusion

- Input is a key component in approximation
- IRA end-to-end system for input responsive approximation
 - Driven by canaries smaller representations of full input
 - Chooses code regions to approximate and how to parameterize approximation
 - 10x speedup across applications (90% TOQ)
 - Outperforms oracle calibration by ~4x











Backup Slides









 Canary — a smaller program input to model full input behavior





- Canary a smaller program input to model full input behavior
- Why is a canary useful?





- Canary a smaller program input to model full input behavior
- Why is a canary useful?
 - Characterize full input behavior without the computational expense





- Canary a smaller program input to model full input behavior
- Why is a canary useful?
 - Characterize full input behavior without the computational expense
 - Customize approximation for each input





Regularly-structured Computation

- Data-centric amount of computation depends on the size of the input
- Summarizable inputs redundancy, pattern, or marginal information in the input data
- E.g., image filters on the following











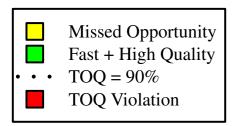


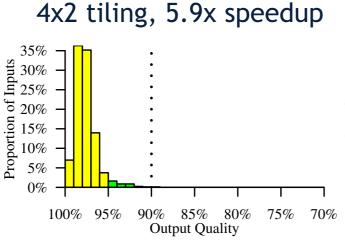
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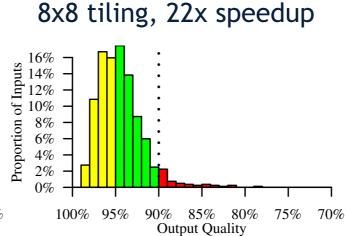


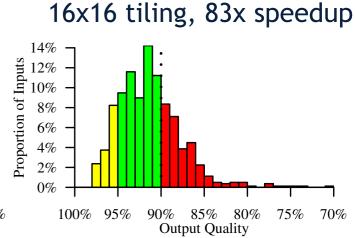


Example: gamma correction, 3 tiling approximations, 800 inputs



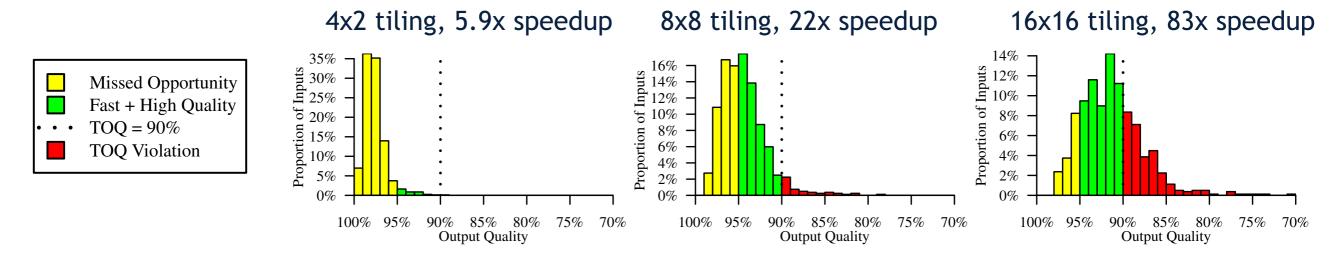








Example: gamma correction, 3 tiling approximations, 800 inputs

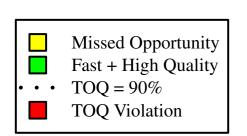


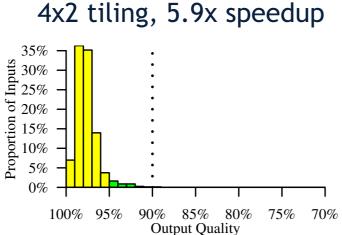
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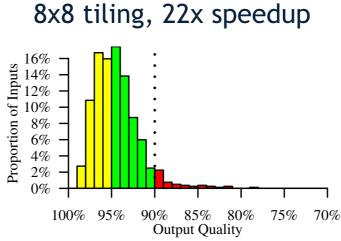


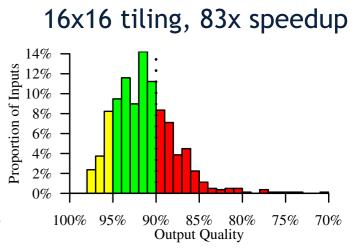


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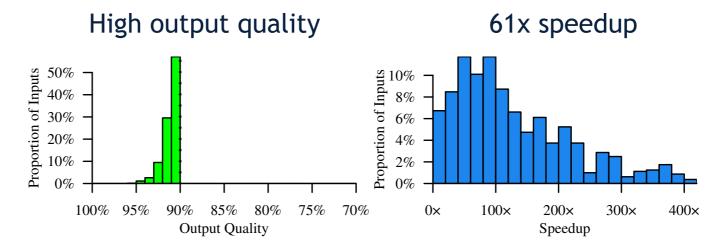








What if we take full advantage of the differences among inputs?







Sketch of Canary Creation Approach

- Create a batch of canary candidates subsets of full input
- Statistically measure similarity of candidates to full input
 - Hypothesis tests is canary candidate X similar to the full input?
 - · Metrics mean, variance, local homogeneity, auto-correlation
 - Multiple comparisons problem across all candidates, bound the probability of making a mistake
- Choose the smallest canary that is found to be similar





Addressing Challenges

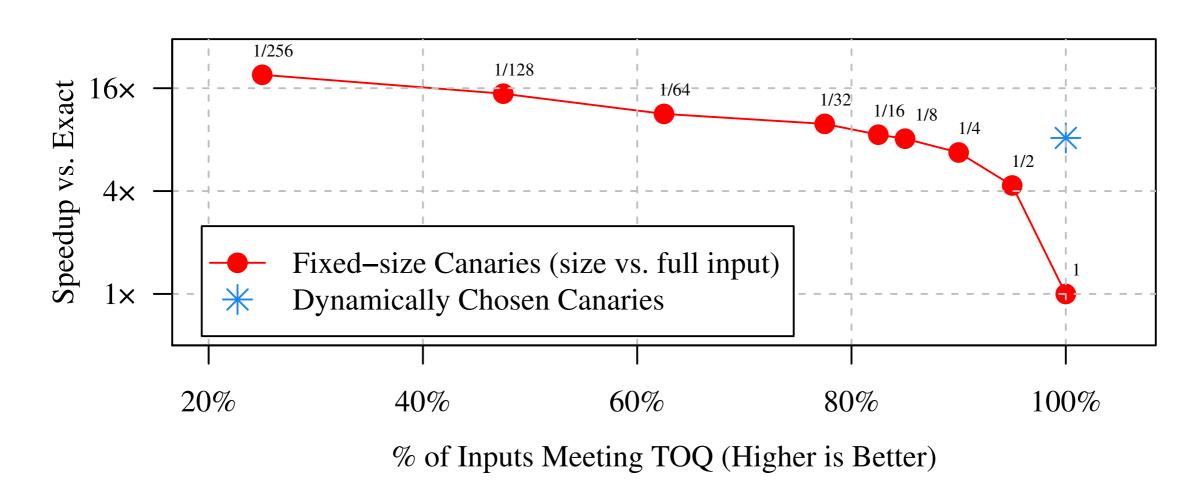
Challenge	Devised Solution
Similarity to Full Input	Explore 4 definitions of similarity ranging from simple to complex
Computational Expense	Use incomplete measures of similarity (i.e., use statistics)
Significant Size Reduction	Choose smallest from a set of acceptable canaries





Why Dynamically Chosen Canaries?

Matrix multiplication (40 inputs)

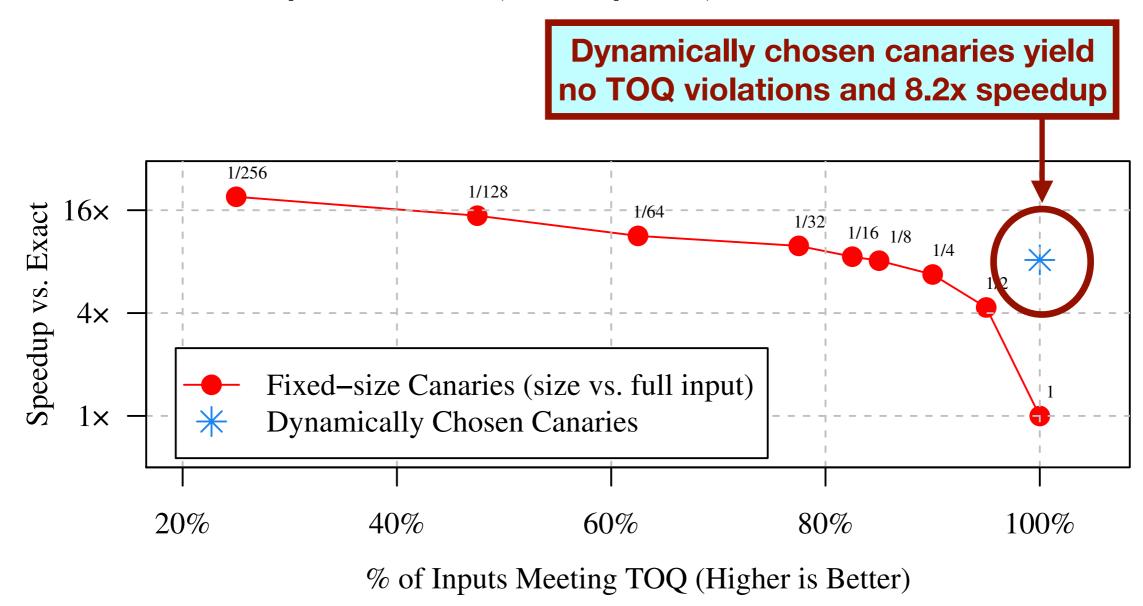






Why Dynamically Chosen Canaries?

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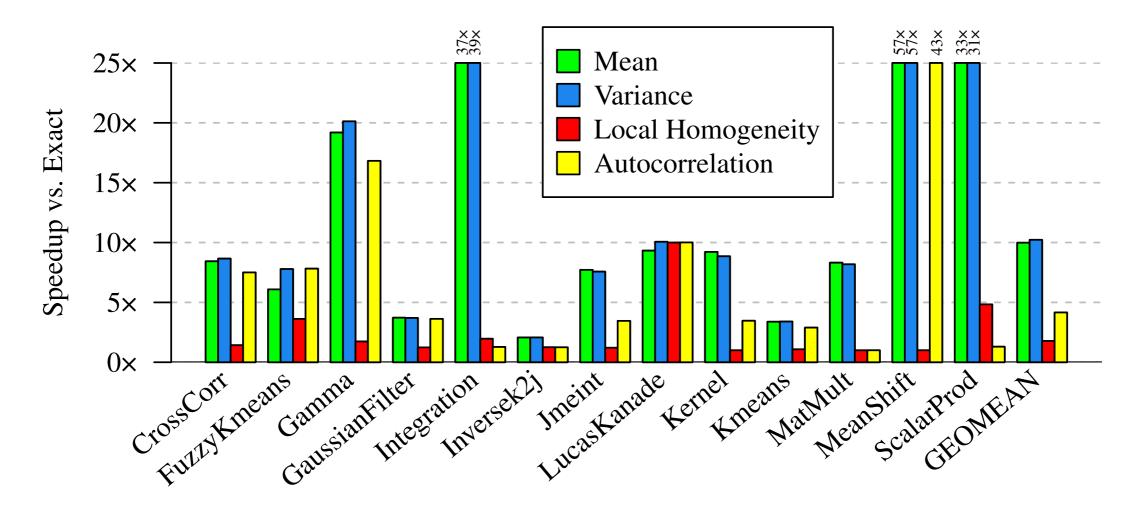






Canary Metrics Comparison

End-to-end IRA speedup across 4 similarity metrics

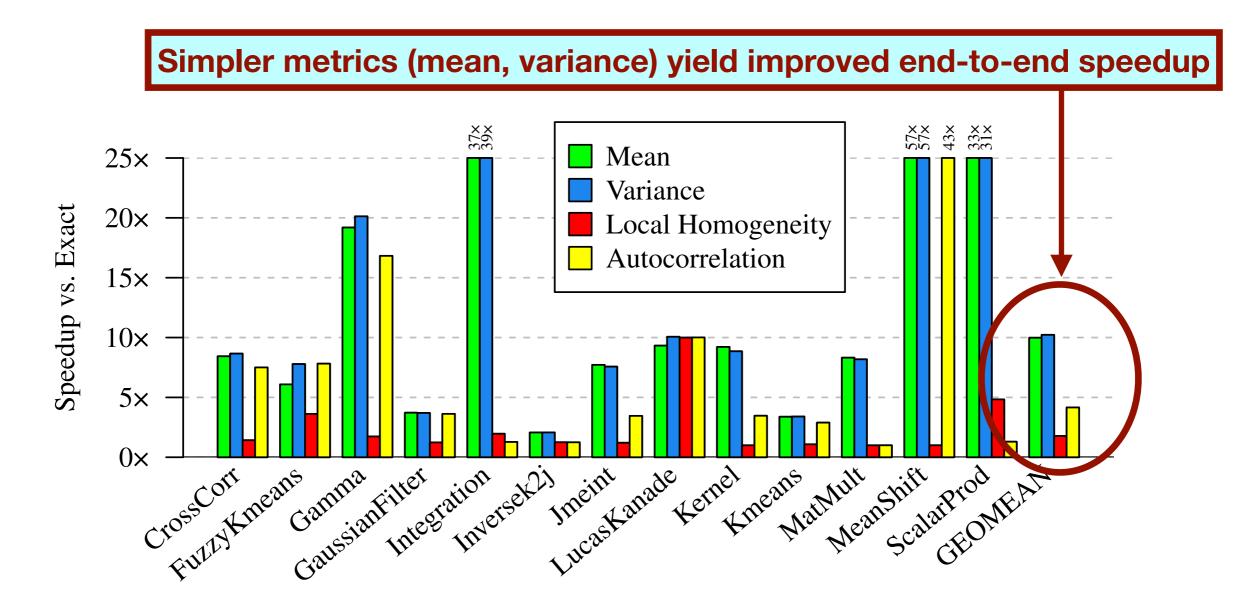






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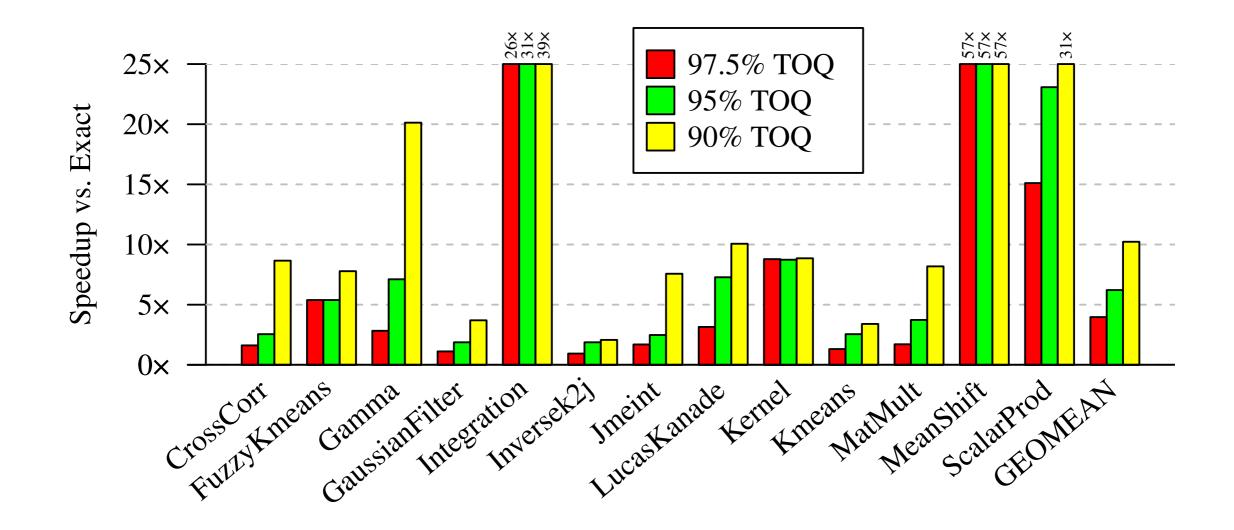






Differences in Output Quality

Higher output quality ~ lower speedup









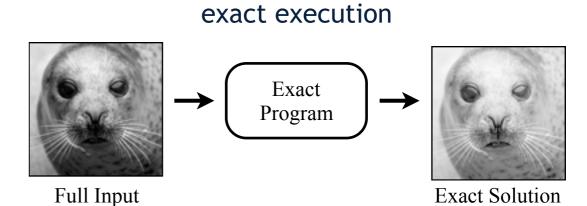


$\begin{array}{c} \text{exact execution} \\ \hline \\ \hline \\ \text{Full Input} \end{array} \begin{array}{c} \text{Exact} \\ \text{Program} \end{array} \begin{array}{c} \\ \\ \end{array} \begin{array}{c} \\ \\ \end{array} \begin{array}{c} \text{Exact Solution} \end{array}$





 Create a small canary input from full input

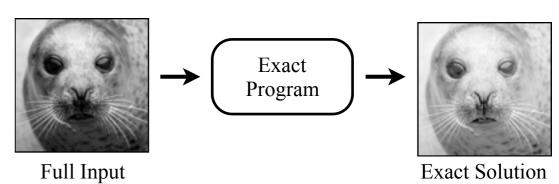


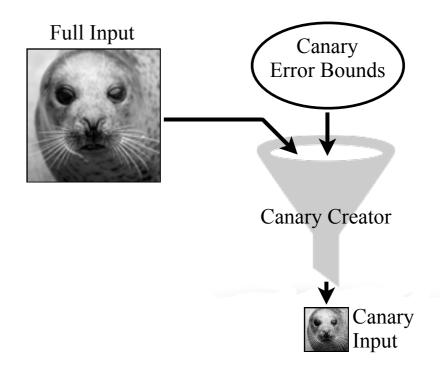




 Create a small canary input from full input

exact execution



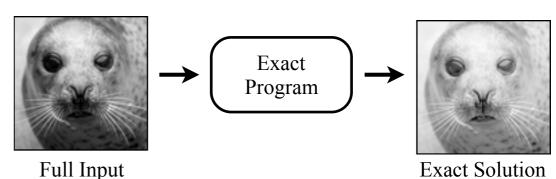


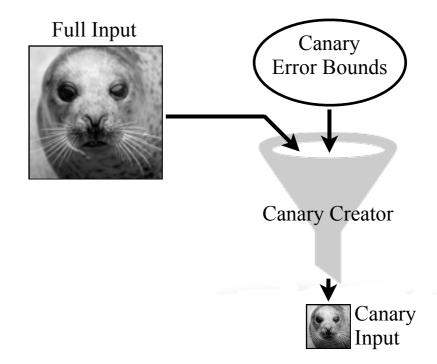




- Create a small canary input from full input
- Choose an approximation using canary

exact execution



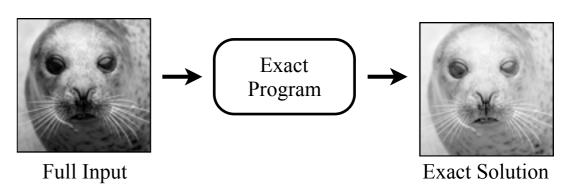


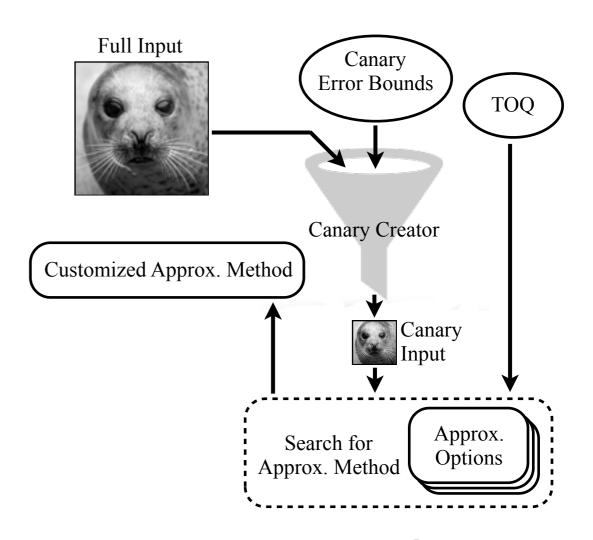




- Create a small canary input from full input
- Choose an approximation using canary

exact execution



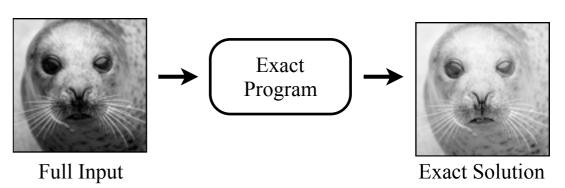


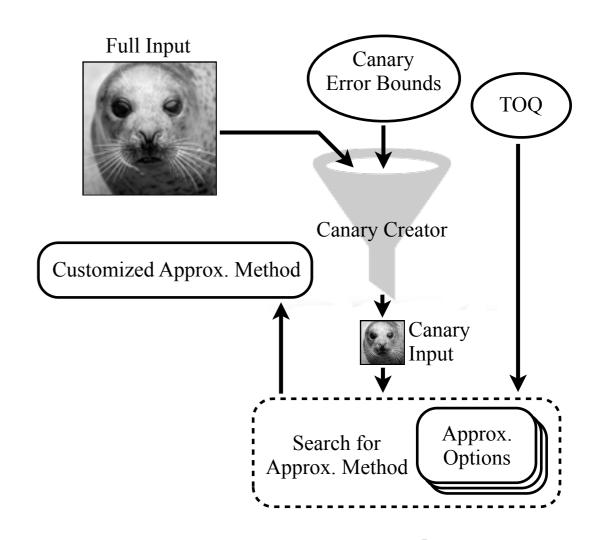




- Create a small canary input from full input
- Choose an approximation using canary
- Compute approximate solution on full input

exact execution









- Create a small canary input from full input
- Choose an approximation using canary
- Compute approximate solution on full input

exact execution

