Empirical performance modeling of GPU kernels using active learning

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Joint work with

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Motivation

GPU computing

- performance gains for algorithms exposing fine grained parallelism
- improvements of about an order of magnitude over CPUs

Autotuning in GPU getting more difficult

- mapping even simple linear algebra operations to the underlying hardware can be difficult
- high cardinality of the set of kernel instantiations (block sizes for better cache reuse and the number of concurrent threads)
- long execution times to find high performing variant

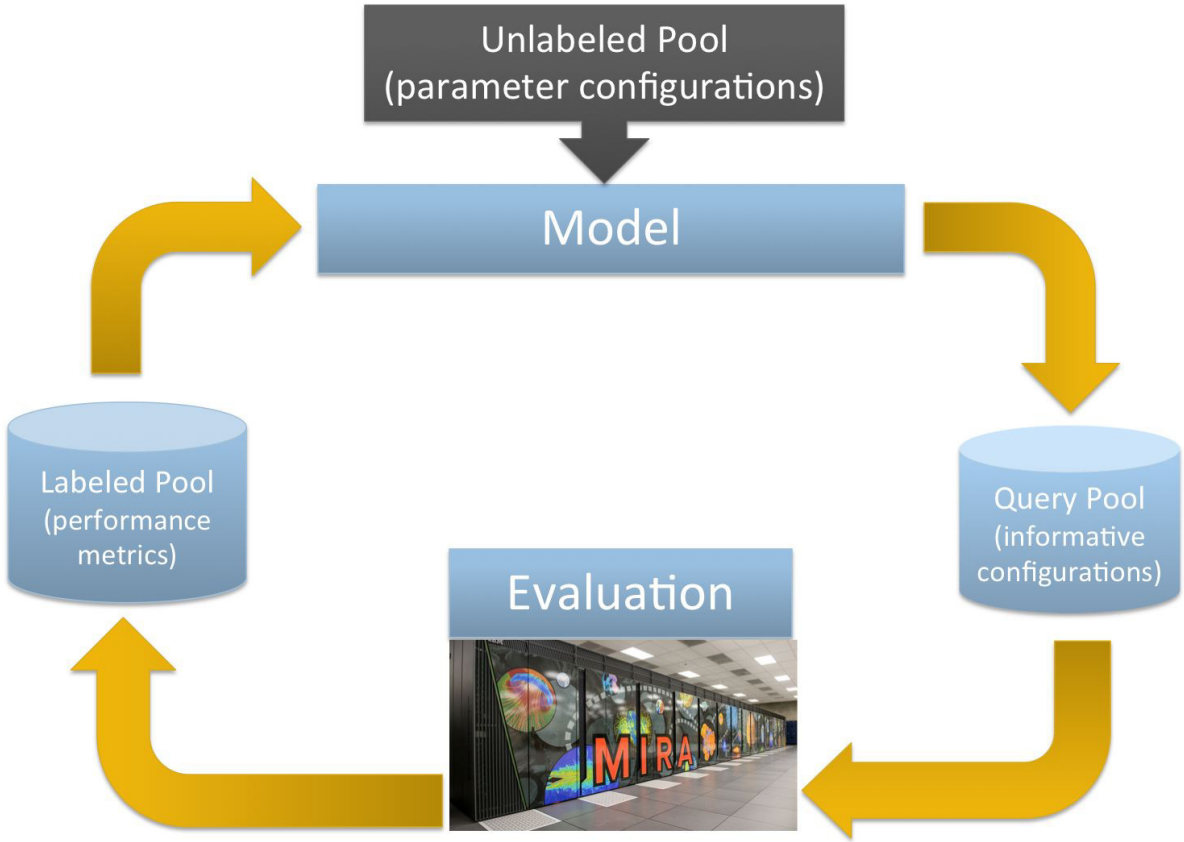
Performance portability

- GPU computing presents a significant burden for application developers

Machine learning for performance modeling

- performance modeling may provide a much more efficient methodology for coping with high-dimensional search spaces in auto tuning
- algebraic performance models increasingly challenging
- statistical performance models: an effective alternative
- small number of input-output points obtained from empirical evaluation
- deployed to test and/or aid search, compiler, and auto tuning

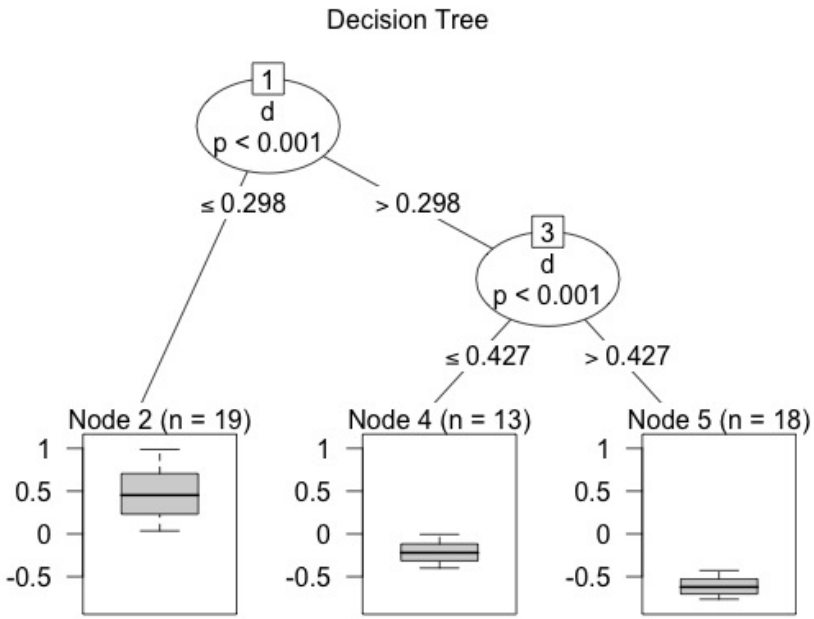
Active learning for performance modeling



- key idea: greater accuracy with fewer training points when allowed to choose the training data
- actively query the model to assess predictive variance

Active learning using dynaTrees

- Based on a classical nonparametric (do not rely on data belonging to any particular distribution) modeling technique [M. Taddy et al. 2011]



Algorithm

- trees to represent input-output relationships using binary recursive partitioning

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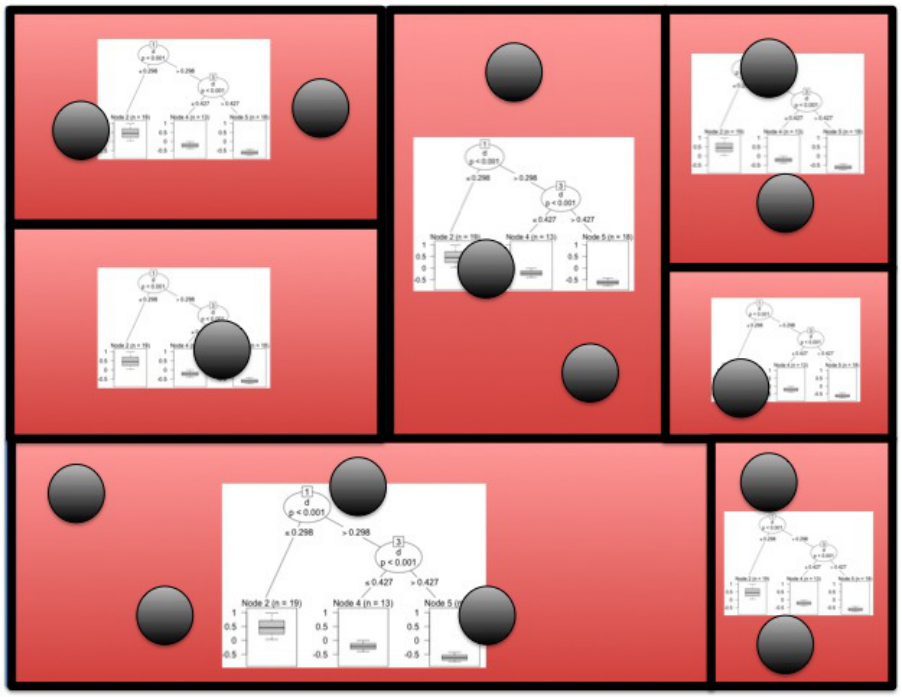

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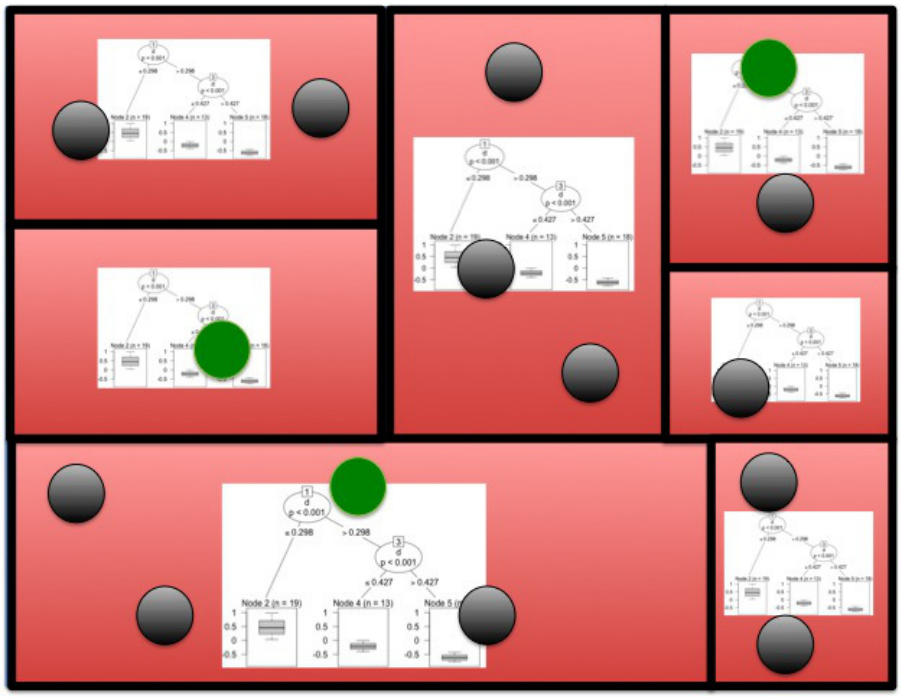

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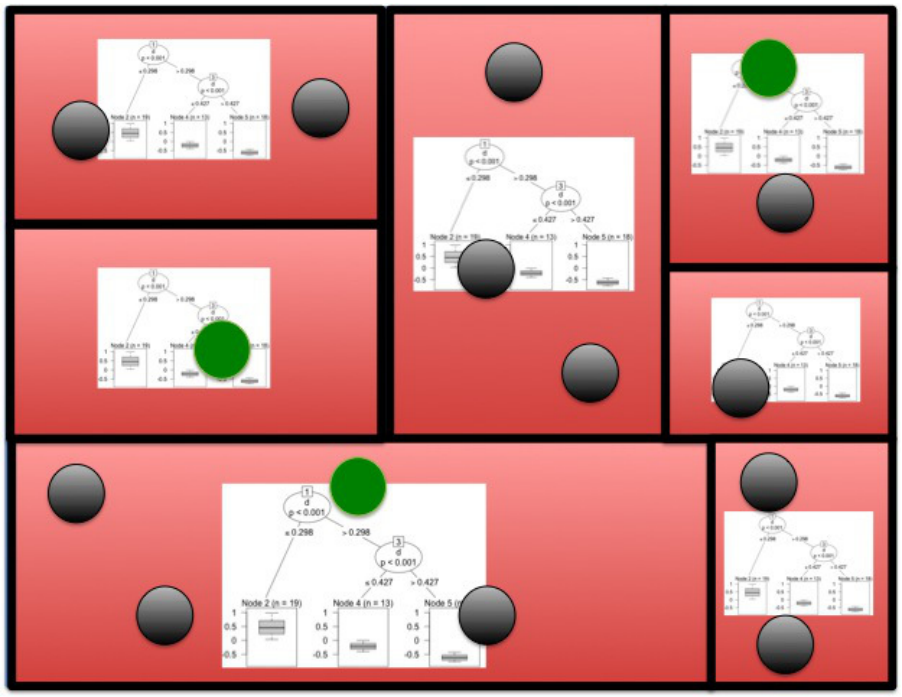

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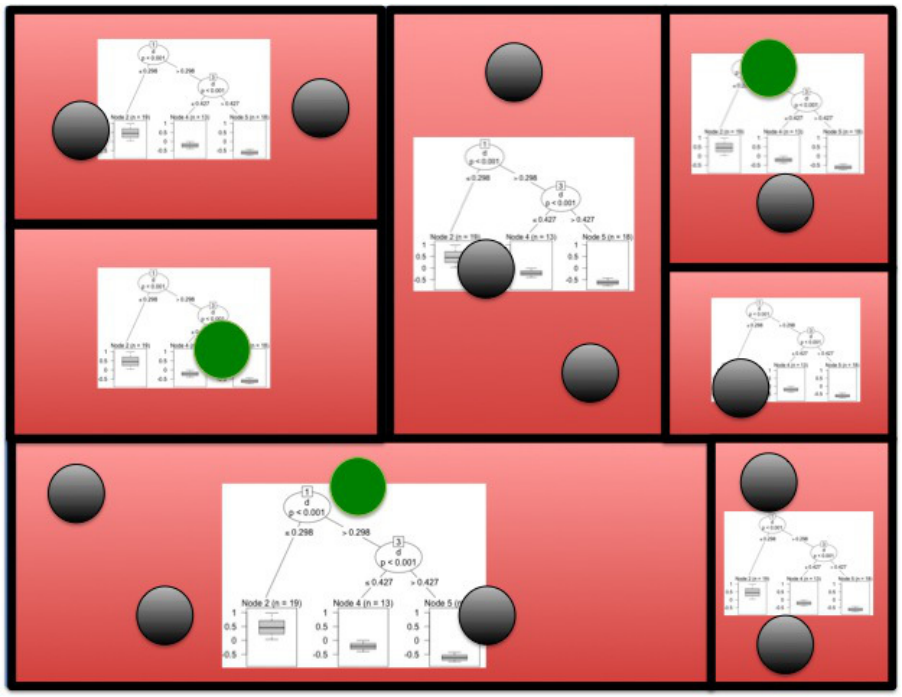

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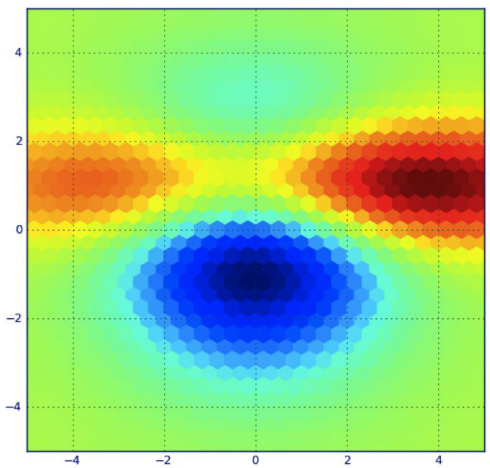
sequential!

Active learning with concurrent evaluations

- batch (n_b) of inputs, taken collectively, will lead to updates that are better than one-at-a-time schemes



The `ab-dynaTree` algorithm

- select points and evaluate concurrently

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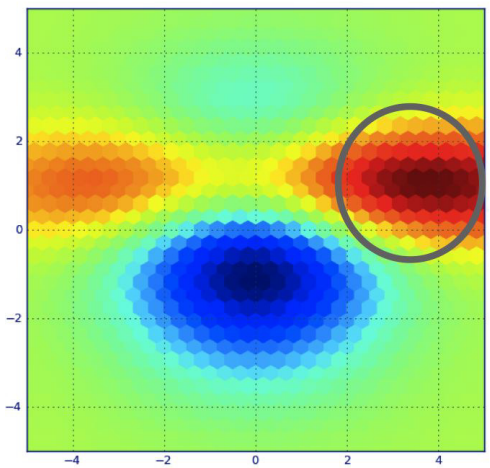

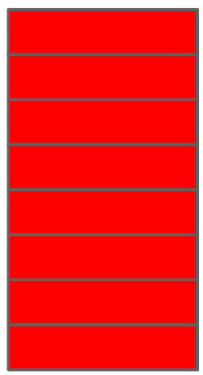

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- select points and evaluate concurrently
- issue: other configurations in the batch become less informative

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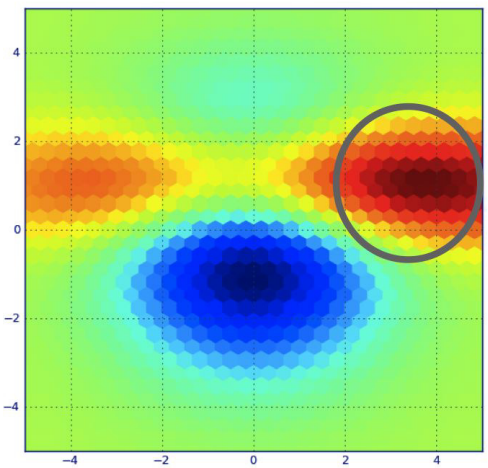

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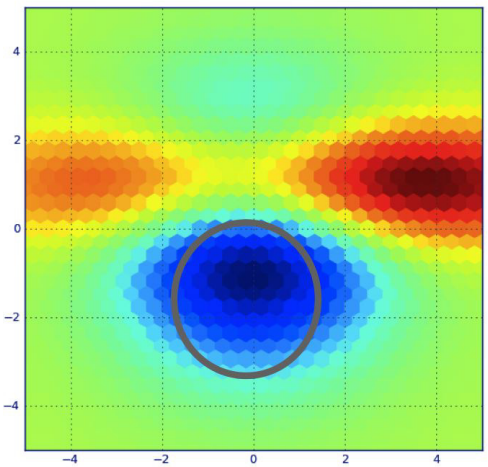

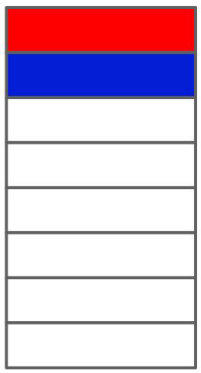

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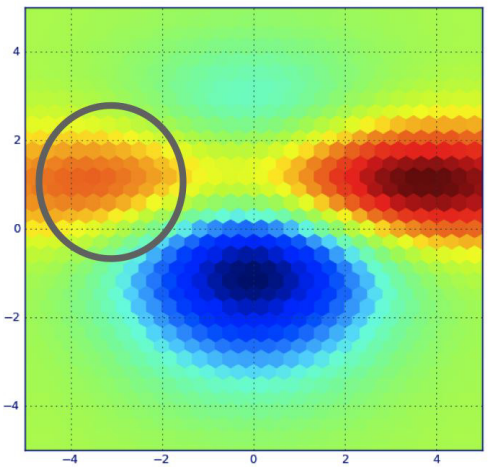

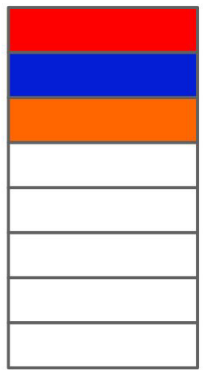

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- better exploration

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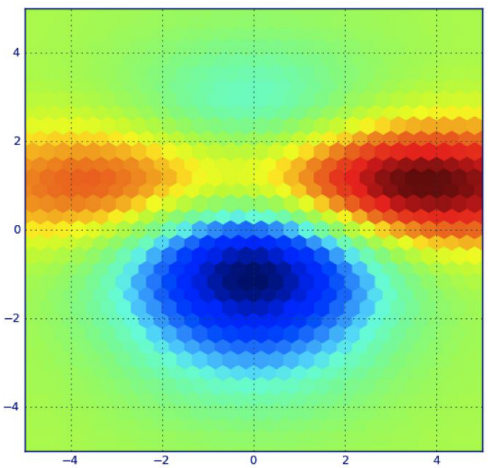

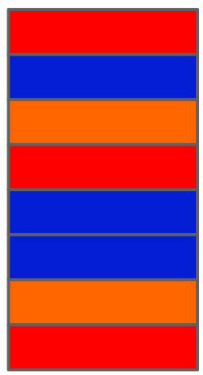

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- better exploration
- leads to better surrogates with minimum evaluations

See [Balaprakash et al., Cluster'13]

The ab-dynaTree algorithm for GPU kernels

- kernels executed in sequence on a single device (absence of a GPU cluster)
- $n_b = 1$: "serial version" of ab-dynaTree
- $n_b > 1$: model is updated only after these n_b serial evaluations

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Goal

does batching still provide significant benefits over the classical sequential strategy?

Experimental setup

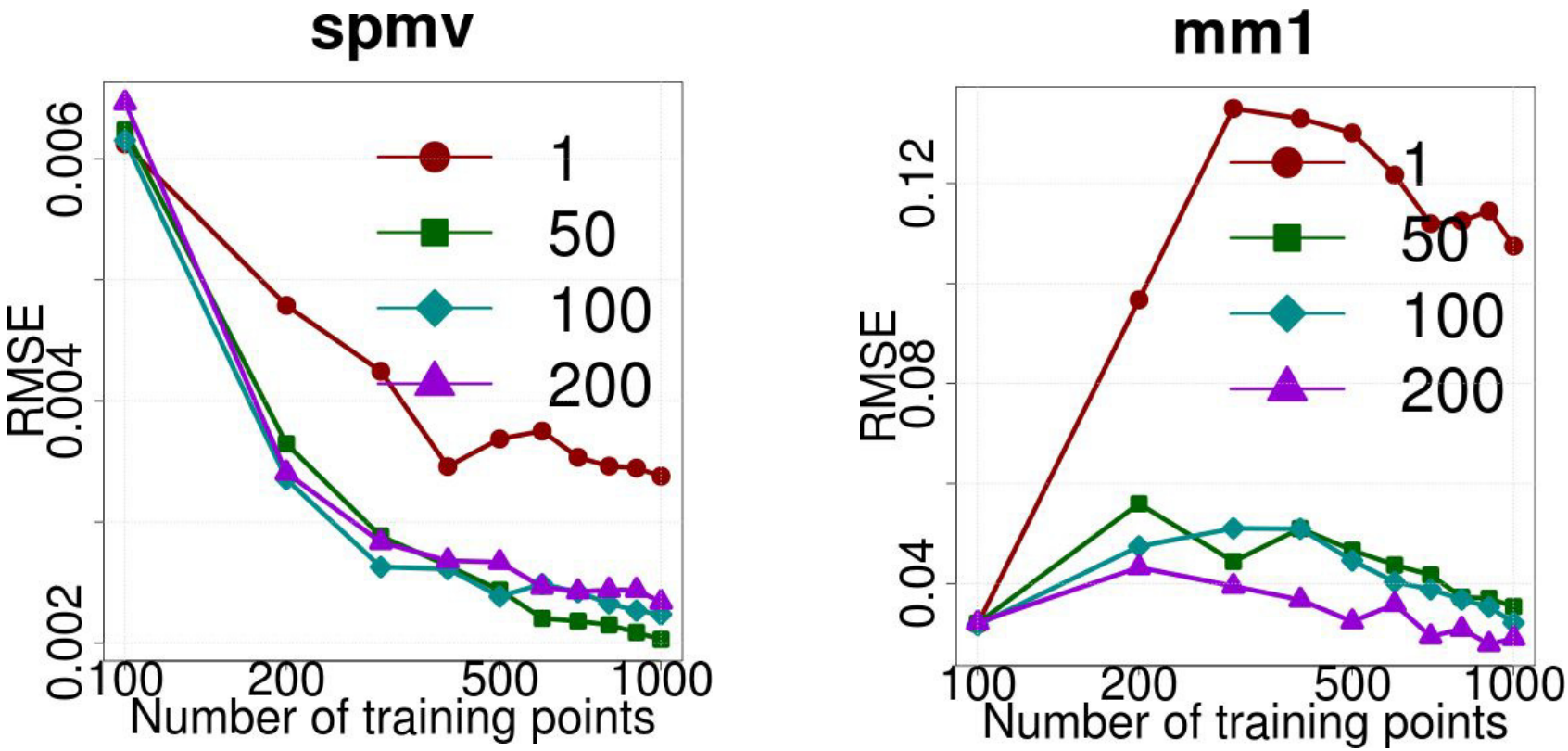
Problems	Operations	Graphic Card	# Param.	Valid Conf. $\lvert\mathcal{X}_p\rvert$
vc1	vector copy	Nvidia GeForce GTX 285	4	2,560
vc2	vector copy	Nvidia GeForce GTX 470	4	2,560
vc3	vector copy	Nvidia Tesla C2050	4	2,560
vc4	vector copy	AMD Radeon HD 7970	4	2,560
vdot	vector dot product	Nvidia Tesla C2050	6	6,144
axpy	vector-scalar product	Nvidia Tesla C2050	6	7,680
spmv	sparse matrix-vector	Nvidia Tesla K20X	4	10,752
mm1	matrix multiplication	Nvidia GeForce GTX 470	10	8,465
mm2	matrix multiplication	AMD Radeon HD 7970	10	3,568

- surrogate models to minimize execution times
- all valid configurations evaluated and stored in a lookup table

Experimental setup

- `ab-dynaTree` algorithm with a maximum budget of $1,000$ evaluations ($\mathcal{X}_{\text{out}}$, $\mathcal{Y}_{\text{out}}$)
- three non linear regression algorithms:
  - dynaTrees algorithm (dT)
  - random forest (rf)
  - neural networks (nn)
- active learning (al) variants: ($\mathcal{X}_{\text{out}}$,$\mathcal{Y}_{\text{out}}$) as the training set
- random sampling (rs) variants: 1,000 randomly chosen points
- test set $\mathcal{T}_{25\%}$: the subset of data points whose mean run times are within the lower 25% quartile of the empirical distribution for the run times
- root-mean-squared error (RMSE) as a measure of prediction accuracy

Impact of batch size (n_b) in `ab-dynaTree`



- $n_b > 1$: explore and identify multiple regions in the input space
- $n_b = 1$: high probability of sampling from only one promising region
- on **7 out of 9** problems, large batch size beneficial

Comparison between regression algorithms

Table : RMSE averaged over 10 replications on the $\mathcal{T}_{25\%}$ test set for 1,000 training points. The value is typeset in *italics* (**bold**) when a variant is significantly *worse* (**better**) than dT(al) according to a t-test with significance (alpha) level 0.05.

Problem	dT(al)	dT(rs)	nn(al)	nn(rs)	rf(al)	rf(rs)
vc1	0.035	*0.050*	0.036	*0.044*	*0.122*	*0.179*
vc2	0.041	*0.067*	0.039	*0.058*	*0.137*	*0.173*
vc3	0.124	*0.201*	0.131	*0.173*	*0.262*	*0.372*
vc4	0.026	*0.043*	*0.031*	*0.038*	*0.124*	*0.153*
vdot	0.009	*0.014*	0.010	*0.016*	*0.012*	*0.021*
axpy	0.014	*0.022*	0.012	*0.017*	*0.016*	*0.029*
spmv	0.002	*0.003*	0.002	*0.003*	*0.008*	*0.014*
mm1	0.029	*0.045*	0.027	*0.040*	0.028	*0.046*
mm2	0.036	*0.053*	**0.030**	*0.043*	**0.031**	*0.052*

- al variants of dT, rf, and nn obtain lower RMSE than rs variants
- dT(al) completely dominates the three random sampling variants
- dT(al) obtains lower average RMSE than does rf(al)
- dT(al) and nn(al) are similar due to expensive parameter tuning of nn

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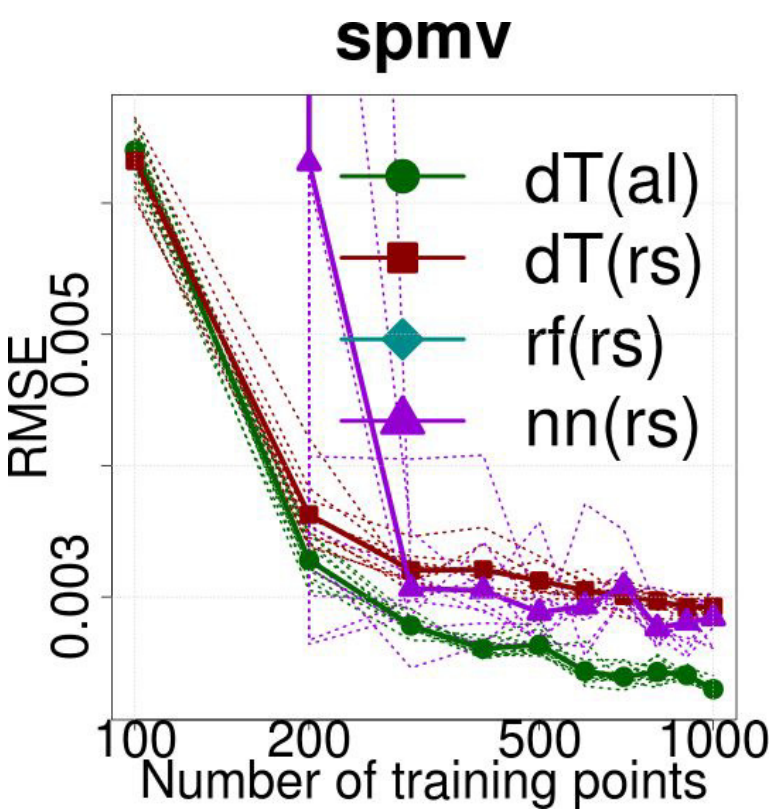
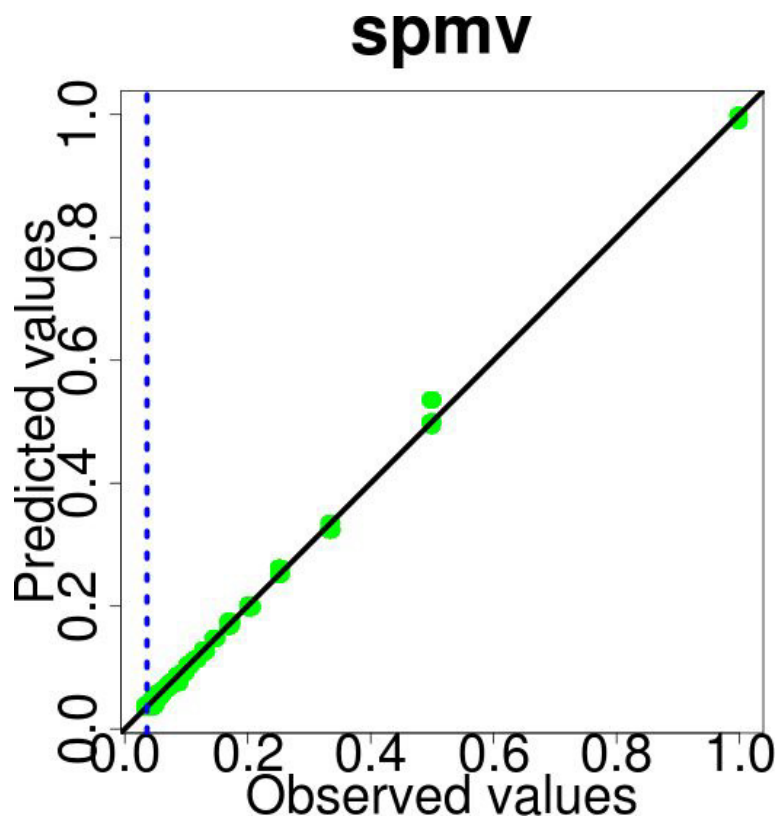
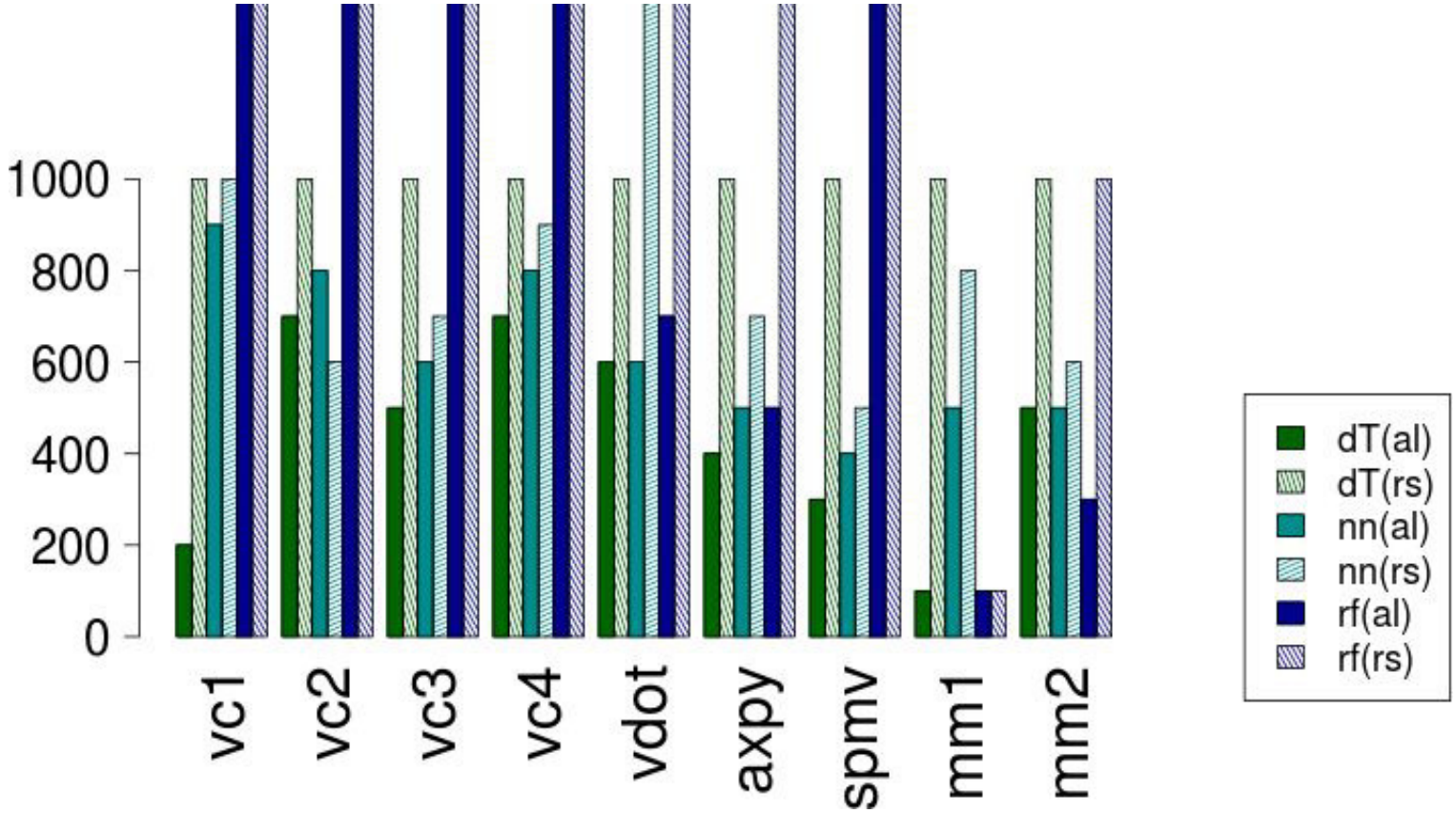




- **Double win: Better RMSE, less training points** (=time/evaluation)
- dT(al) requires relatively fewer evaluations to achieve a smaller RMSE

Comparison between regression algorithms

- number of evaluations required by the variants to reach the RMSE obtained by dT(rs) with 1,000 evaluations.



- on **7 out of 9** problems, dT(al) reaches the RMSE of dT(rs) within 300 to 700 training points; mm1 and mm2 rf(al) outperform dT(al)
- savings up to a factor of three

Summary

- `ab-dynaTree` for developing empirical performance models of GPU kernels
- active learning as an effective data acquisition strategy
- batch mode provides significant benefits over the classical, serial mode: high degree of exploration

Future work

- asynchronous model updates
- multiobjective surrogate modeling
- structure exploiting numerical optimization algorithms
- deployment of `ab-dynaTree` in autotuning search algorithms