Performance Tuning of MapReduce Jobs Using Surrogate-Based Modeling

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- ☐ 100
- ■ **Hundreds**

Hadoop's configuration file has more than 220 parameters.

A Sampling of Hadoop Configuration Parameters

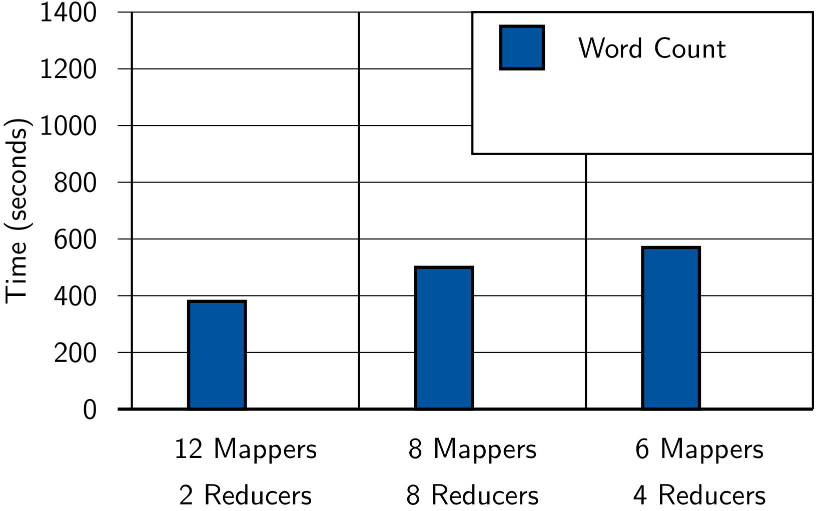
mapreduce.job.maps
mapreduce.job.reduces
mapreduce.map.memory.mb
mapreduce.map.cpu.vcores
mapreduce.reduce.memory.mb
mapreduce.reduce.cpu.vcores
mapreduce.job.userhistorylocation
mapreduce.task.io.sort.factor
mapreduce.task.io.sort.mb
mapreduce.map.sort.spill.percent
mapreduce.jobtracker.address
mapreduce.jobtracker.http.address
mapreduce.jobtracker.handler.count
mapreduce.tasktracker.report.address
mapreduce.cluster.local.dir
mapreduce.jobtracker.system.dir
mapreduce.jobtracker.staging.root.dir
mapreduce.cluster.temp.dir
mapreduce.tasktracker.instrumentation
mapreduce.jobtracker.restart.recover
mapreduce.jobtracker.taskscheduler
mapreduce.job.running.map.limit
mapreduce.job.running.reduce.limit
mapreduce.job.max.split.locations
mapreduce.job.split.metainfo.maxsize
mapreduce.map.maxattempts
mapreduce.reduce.maxattempts
mapreduce.reduce.shuffle.read.timeout
mapreduce.task.timeout
mapreduce.jobtracker.instrumentation
mapred.child.java.opts
mapreduce.map.java.opts

mapreduce.admin.user.env
mapreduce.map.log.level
mapreduce.reduce.log.level
mapreduce.reduce.merge.inmem.threshold
mapreduce.reduce.shuffle.merge.percent
mapreduce.reduce.input.buffer.percent
mapreduce.shuffle.ssl.enabled
mapreduce.shuffle.ssl.file.buffer.size
mapreduce.shuffle.max.connections
mapreduce.shuffle.max.threads
mapreduce.shuffle.transferTo.allowed
mapreduce.shuffle.transfer.buffer.size
mapreduce.map.speculative
mapreduce.reduce.speculative
mapreduce.job.jvm.numtasks
mapreduce.job.ubertask.enable
mapreduce.job.ubertask.maxmaps
mapreduce.job.ubertask.maxreduces
mapreduce.job.ubertask.maxbytes
mapreduce.job.emit-timeline-data
mapreduce.jobtracker.maxtasks.perjob
mapreduce.tasktracker.dns.interface
mapreduce.tasktracker.dns.nameserver
mapreduce.tasktracker.http.threads
mapreduce.tasktracker.http.address
mapreduce.map.output.compress
mapreduce.map.output.compress.codec
map.sort.class
mapreduce.task.userlog.limit.kb
yarn.app.mapreduce.shuffle.log.backups
mapreduce.job.userlog.retain.hours
mapreduce.jobtracker.hosts.filename

mapreduce.task.profile.params
mapreduce.task.profile.map.params
mapreduce.task.profile.reduce.params
mapreduce.task.skip.start.attempts
mapreduce.map.skip.proc.count.autoincr
mapreduce.job.skip.outdir
mapreduce.map.skip.maxrecords
mapreduce.reduce.skip.maxgroups
mapreduce.ifile.readahead
mapreduce.ifile.readahead.bytes
mapreduce.jobtracker.taskcache.levels
mapreduce.job.queuename
mapreduce.job.tags
mapreduce.cluster.acls.enabled
mapreduce.job.acl-modify-job
mapreduce.job.acl-view-job
mapreduce.tasktracker.indexcache.mb
mapreduce.job.token.tracking.ids
mapreduce.task.merge.progress.records
mapreduce.tasktracker.taskcontroller
mapreduce.tasktracker.group
mapreduce.shuffle.port
mapreduce.job.counters.limit
mapreduce.framework.name
yarn.app.mapreduce.am.staging-dir
mapreduce.am.max-attempts
mapreduce.job.end-notification.url
mapreduce.job.log4j-properties-file
yarn.app.mapreduce.am.env
yarn.app.mapreduce.am.admin.user.env
yarn.app.mapreduce.am.command-opts
yarn.app.mapreduce.client.max-retries

How Much Does the Configuration Matter?

Two benchmarks: Word Count and PageRank



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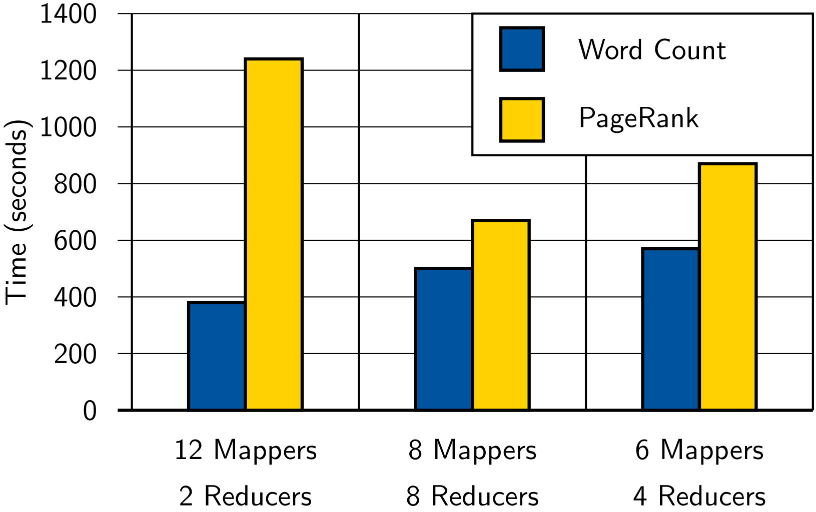

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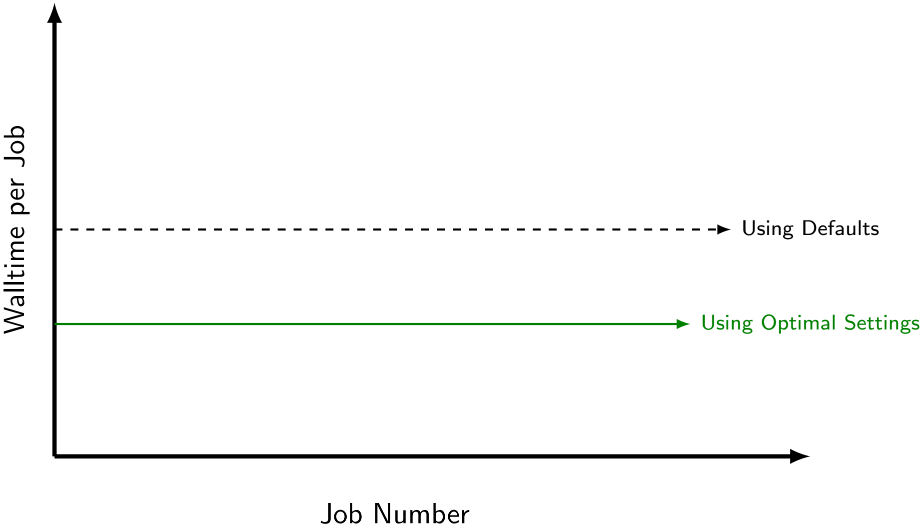
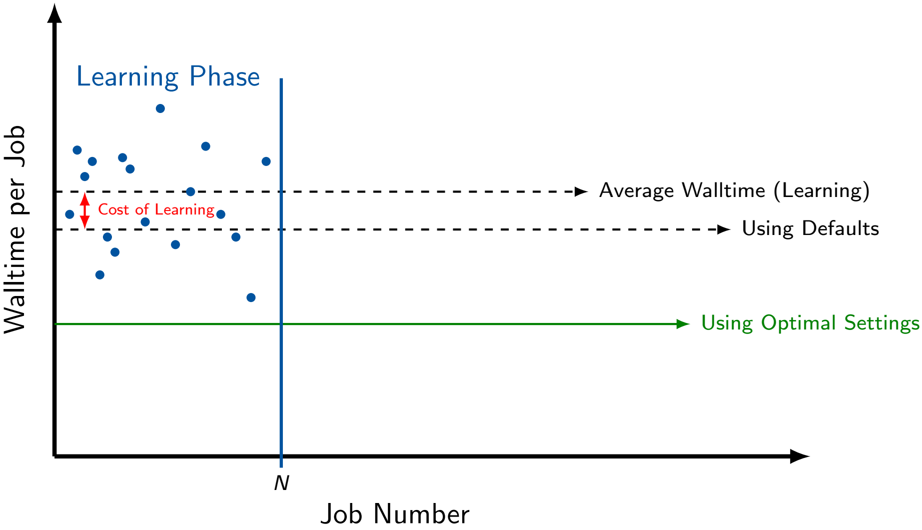
- Amortize the cost of sampling with future gains in performance.

Amortizing the Cost of Sampling



Amortizing the Cost of Sampling



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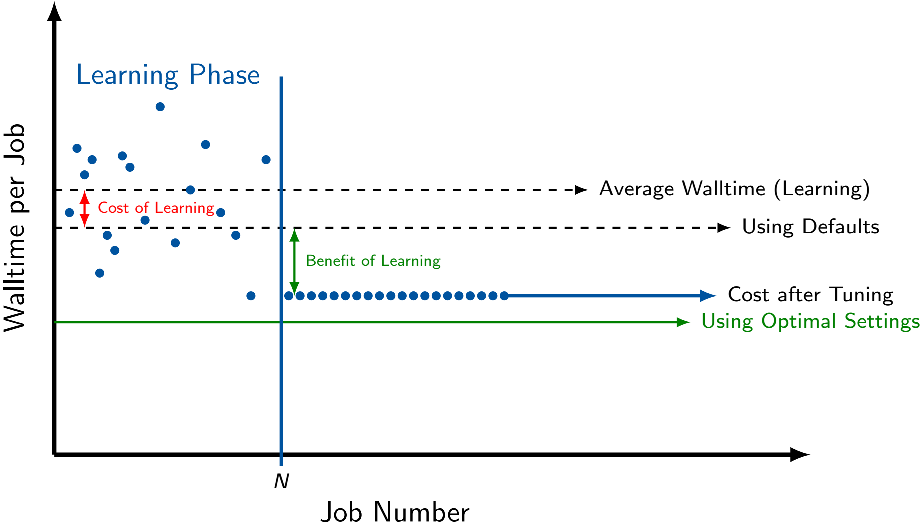

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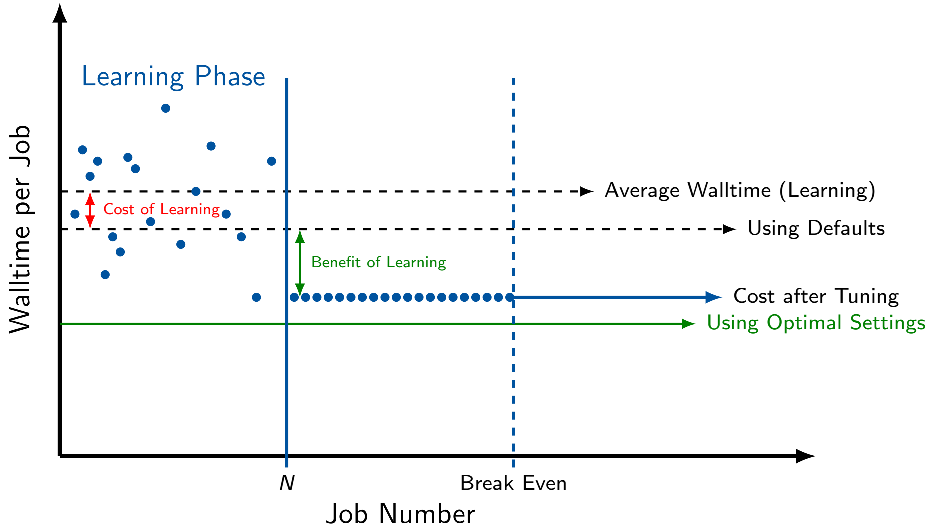
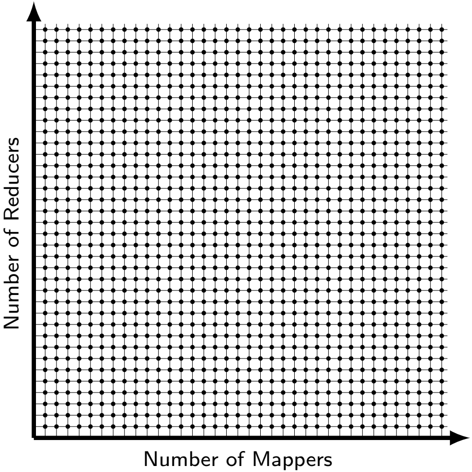


Question:

How do we focus the learning phase to **maximize** the return on our investment?

Exhaustive Searching [1]



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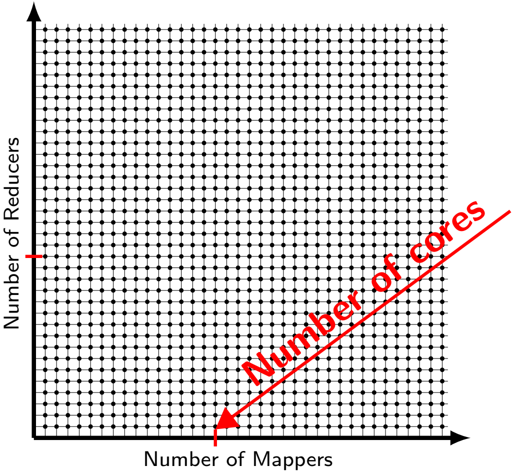

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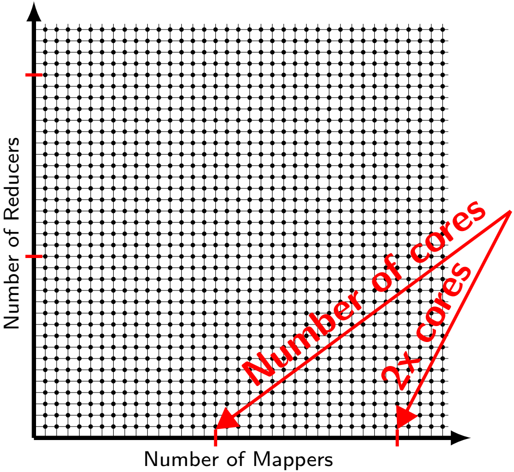

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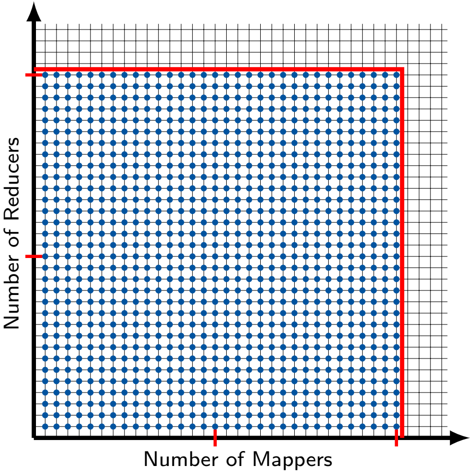

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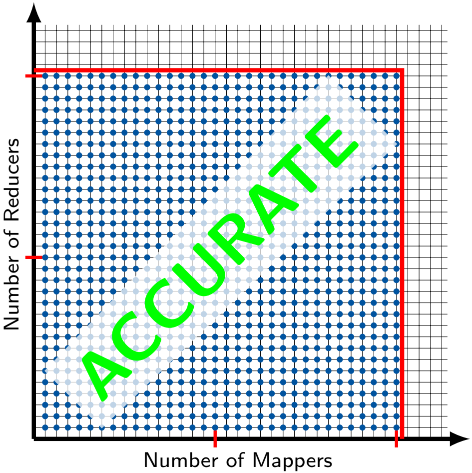

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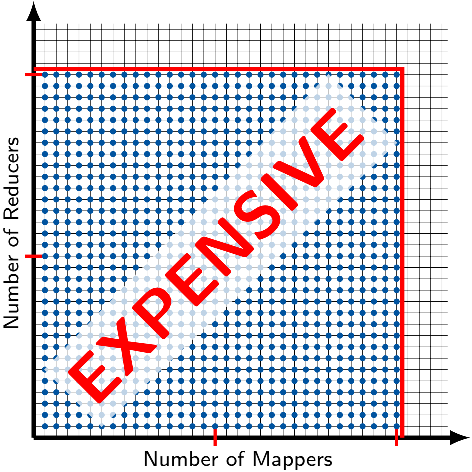

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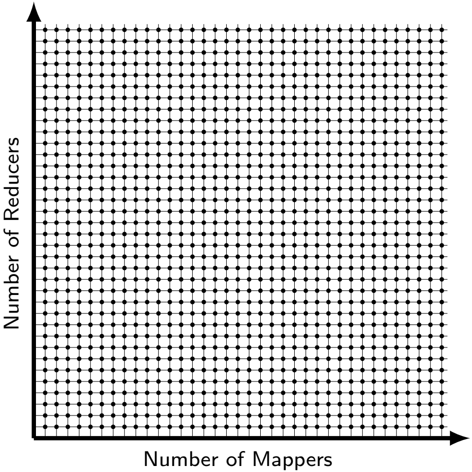
Local Searching Algorithms

Grid Hill [2] and Simulated Annealing [3]



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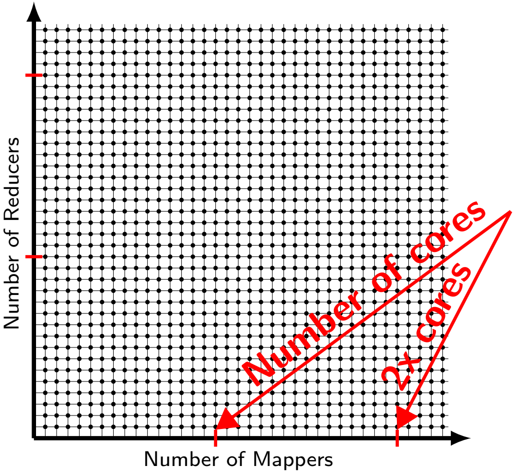

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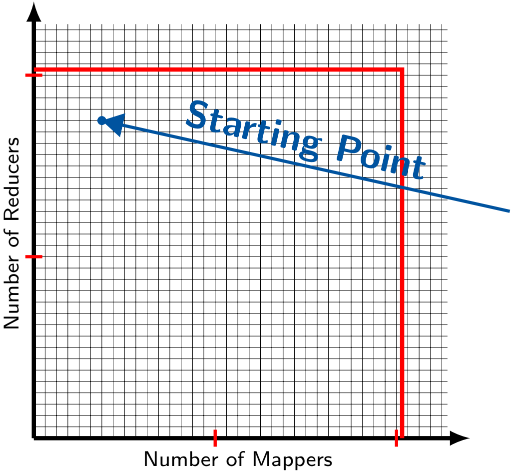

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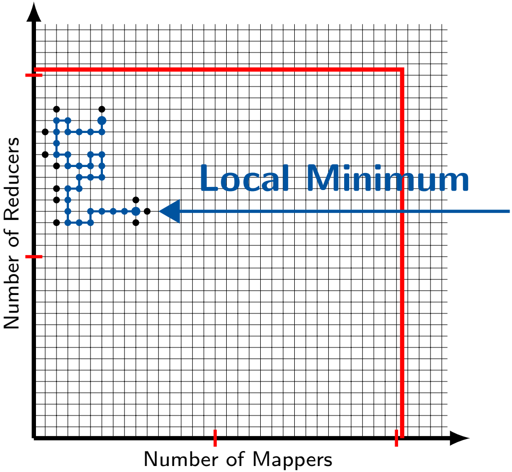

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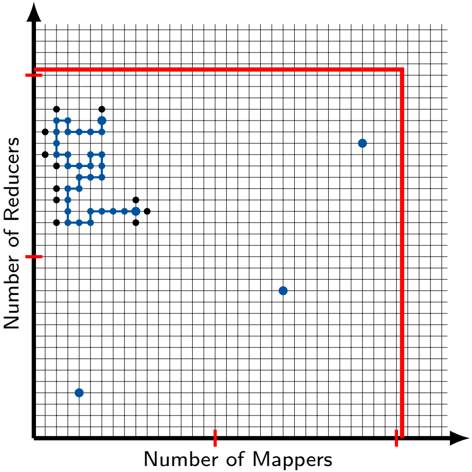

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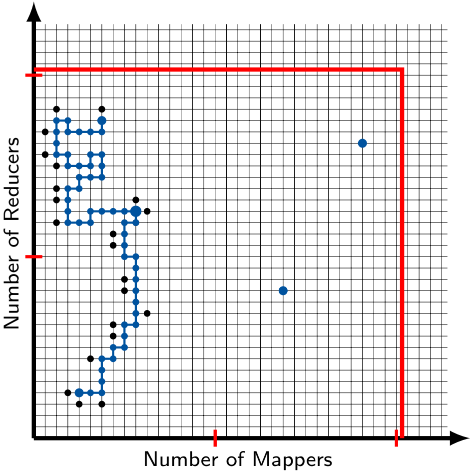

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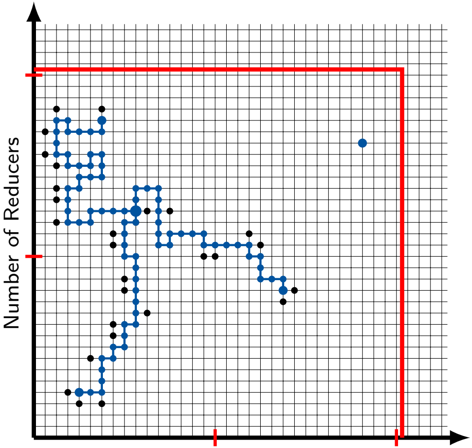

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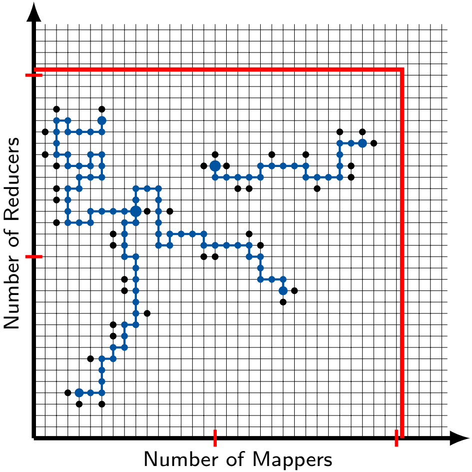

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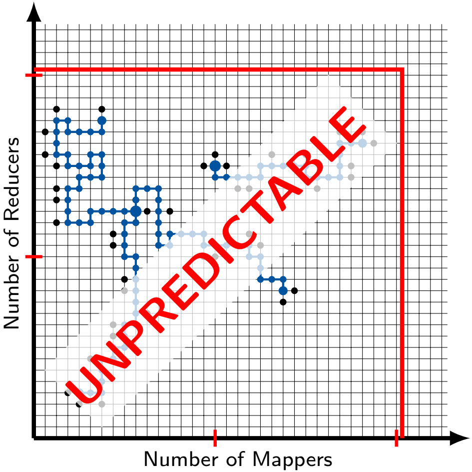

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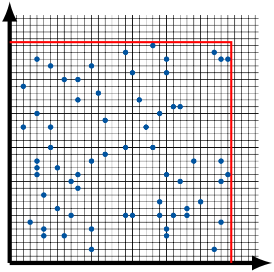
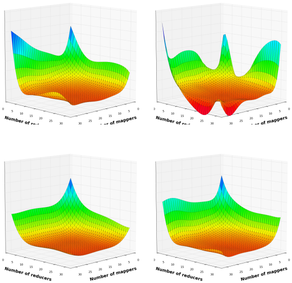
- Surrogate-based modeling can achieve near optimal results sampling 67% fewer points than LSAs!
- We can explicitly determine the number of points required to build a surrogate model!
- The surrogate model may predict optimal configurations that were **never sampled** in the learning phase!

Overview of Surrogate-Based Modeling



Step 1: Sample parameter space



Step 2: Build candidate surfaces

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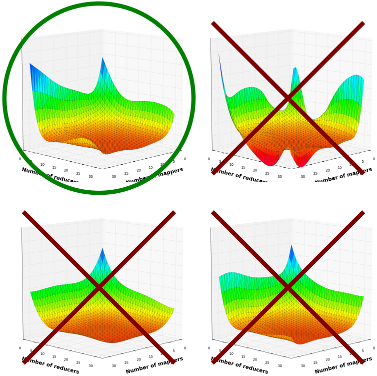
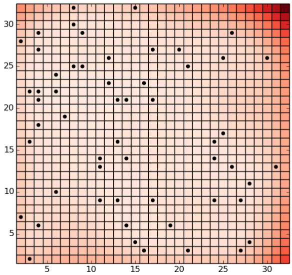


Step 3: Select the best surface



Step 4: Apply confidence interval

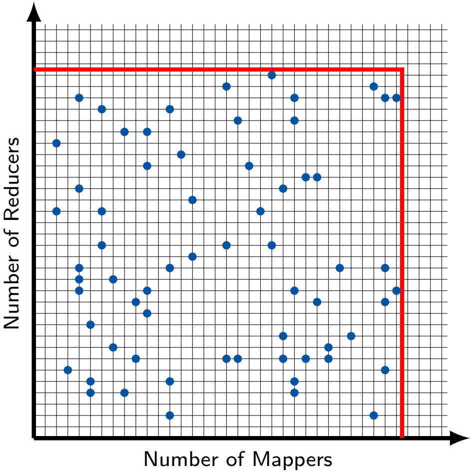
Case Study: Optimizing PageRank

Experimental Setup

- Use Hadoop and PageRank from the HiBench benchmarking suite
- Select two parameters to tune:
  - the number of mappers, x, and
  - the number of reducers, y.
- Input file is 1GB in size consisting of 5M inter-linked web pages.
- Computations are done on a single large memory node of Stampede with
  - 32 CPU cores, and
  - 1 TB memory.
- To enable validation of our method, we initially sample all points $2 \leq x, y \leq 32$: 961 total points.

Surrogate-Based Modeling

Step 1: Sampling the parameter space ($N = 64$ samples)



Random Sampling

Surrogate-Based Modeling

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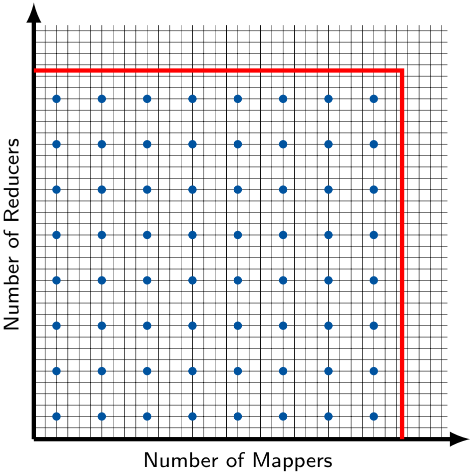

Grid-based Sampling

Surrogate-Based Modeling

Step 2: Building candidate surfaces

What kind of surfaces do we build?

We represent our surface by a multivariate polynomial.

The candidate surfaces become:

- $z_1(x, y) = \beta_1 + \beta_2 x + \beta_3 y$ Degree 1
- $z_2(x, y) = \beta_1 + \beta_2 x + \beta_3 y + \beta_4 x^2 + \beta_5 xy + \beta_6 y^2$ Degree 2
- $z_3(x, y) = z_2(x, y) + \beta_7 x^3 + \beta_8 x^2 y + \beta_9 xy^2 + \beta_{10} y^3$ Degree 3
- And so forth ...

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Why build a polynomial surface?

- Polynomials are easy to describe and represent in memory.
- Although the description is simple, polynomials can generate quite complex surfaces.
- Polynomials easily generalize to any number of variables.

How many points do we need to sample?

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Theoretical Minimum Number of Points

- To build the surface, we solve the matrix equation:

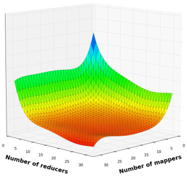
$$X^T X\beta = X^T Z$$

  to determine the coefficients β.
- If $X^T X$ is not invertible, then there is not a unique solution for β.
- If the number of samples taken is smaller than the number of terms in our polynomial, then $X^T X$ is not invertible.
- To build a surface of degree d with v variables we need at least $\binom{d+v}{v}$ samples.

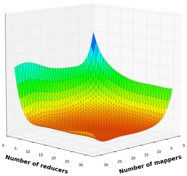
Surrogate-Based Modeling

Step 2: Building candidate surfaces

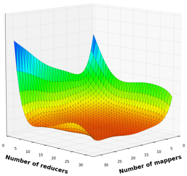
Degree 5



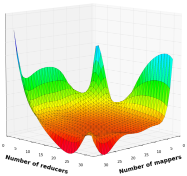
Degree 6

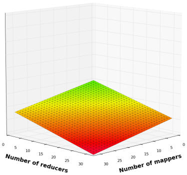


Degree 7



Degree 8





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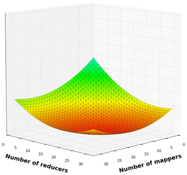
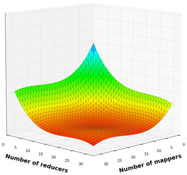
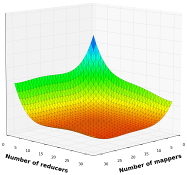


Degree 2



Degree 3

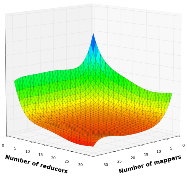


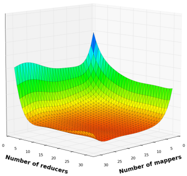
Degree 4

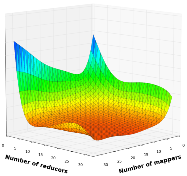
Surrogate-Based Modeling

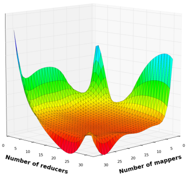
Step 2: Building candidate surfaces

Degree 5 | Degree 6 | Degree 7 | Degree 8

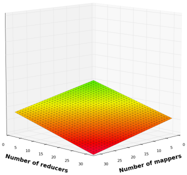


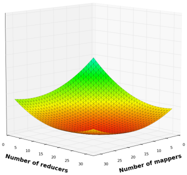


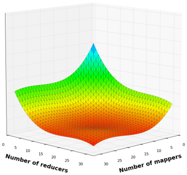


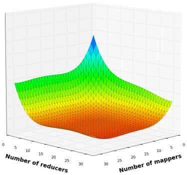


Which Model is Best?







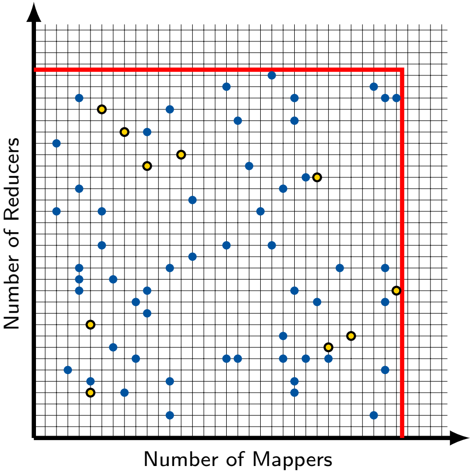


Degree 1 | Degree 2 | Degree 3 | Degree 4

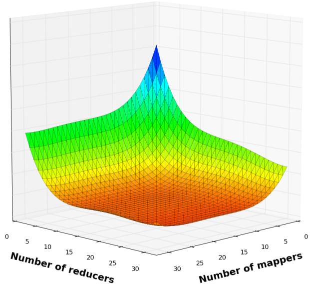
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



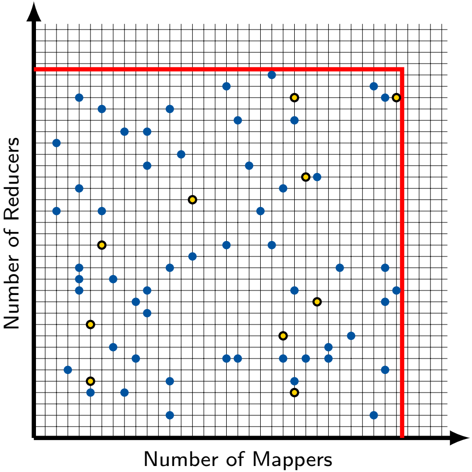
Degree 4 Surface

Surrogate-Based Modeling

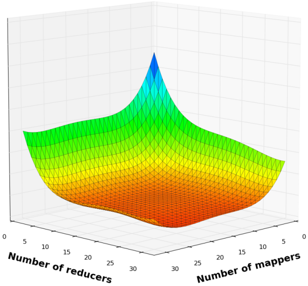
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



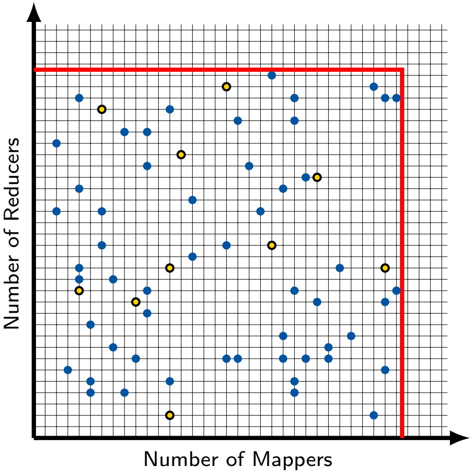
Degree 4 Surface

Surrogate-Based Modeling

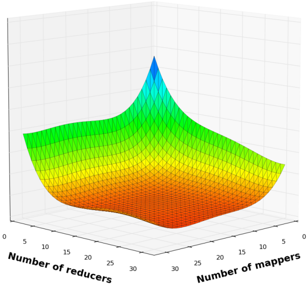
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



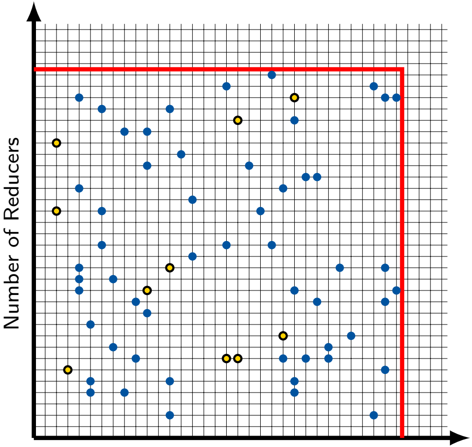
Degree 4 Surface

Surrogate-Based Modeling

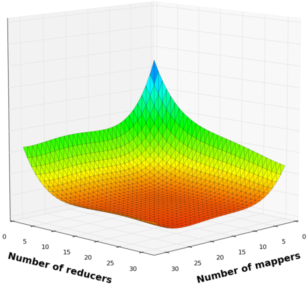
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



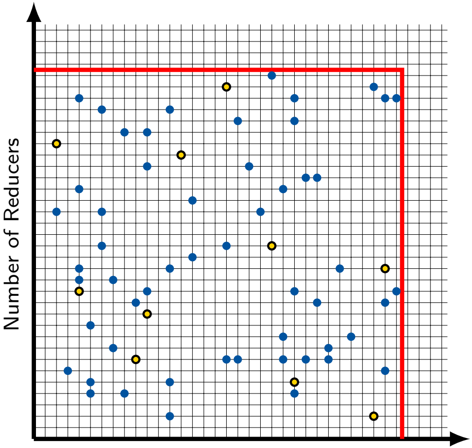
Degree 4 Surface

Surrogate-Based Modeling

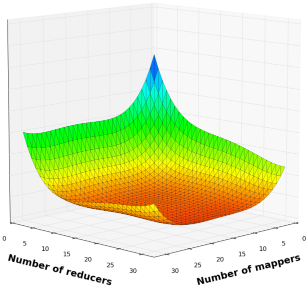
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



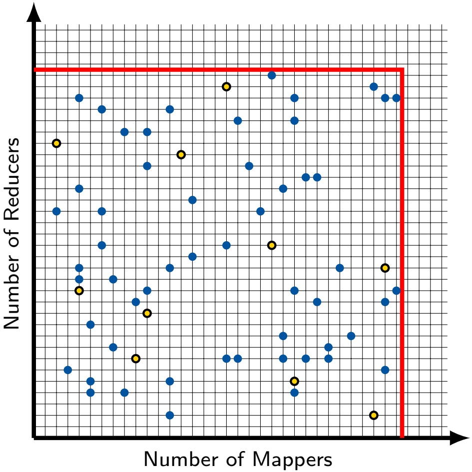
- **Learning Sets**
- **Testing Set**



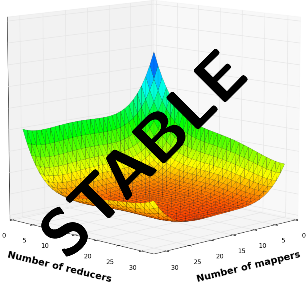
Degree 4 Surface

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k - 1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



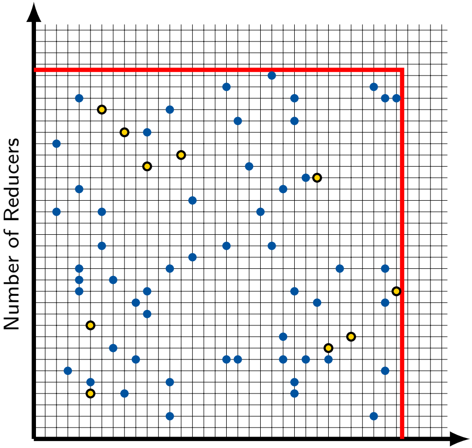
Degree 4 Surface

Surrogate-Based Modeling

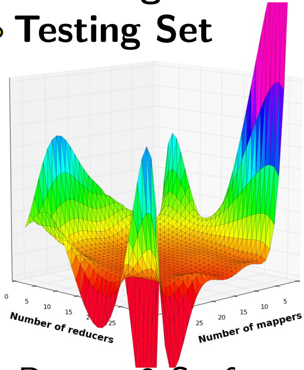
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



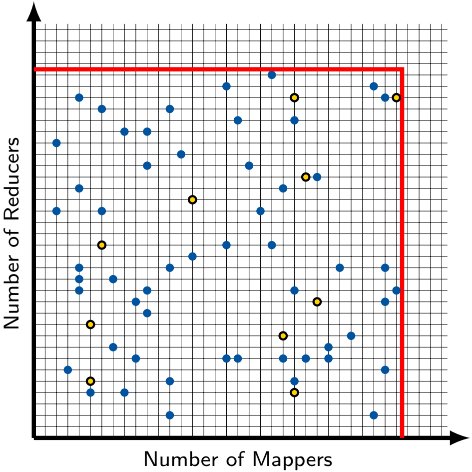
- **Learning Sets**
- **Testing Set**



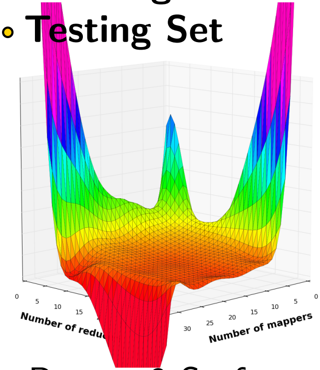
Degree 8 Surface

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



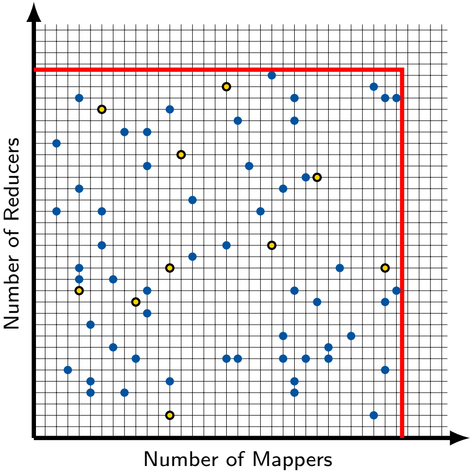
Degree 8 Surface

Surrogate-Based Modeling

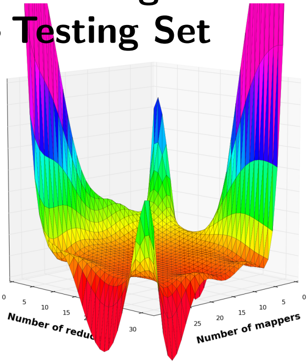
Step 3: Selecting the best surface using k-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k - 1$ sets are used for learning.



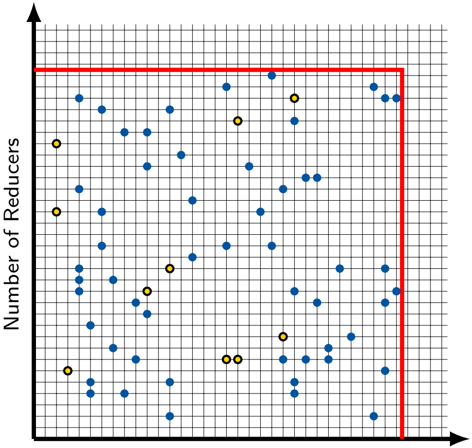
- **Learning Sets**
- **Testing Set**



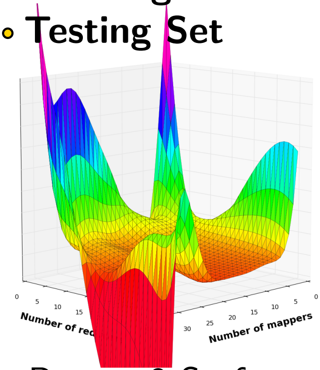
Degree 8 Surface

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



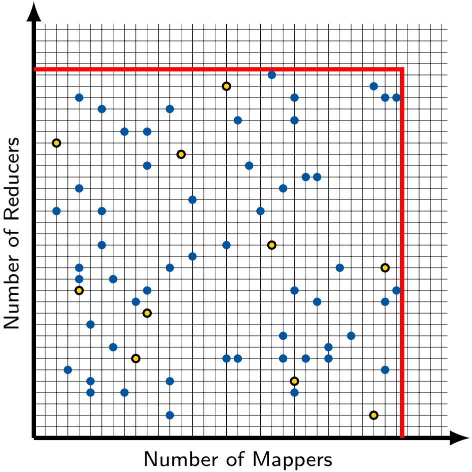
Degree 8 Surface

Surrogate-Based Modeling

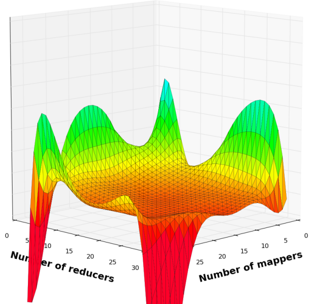
Step 3: Selecting the best surface using *k*-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.



- **Learning Sets**
- **Testing Set**



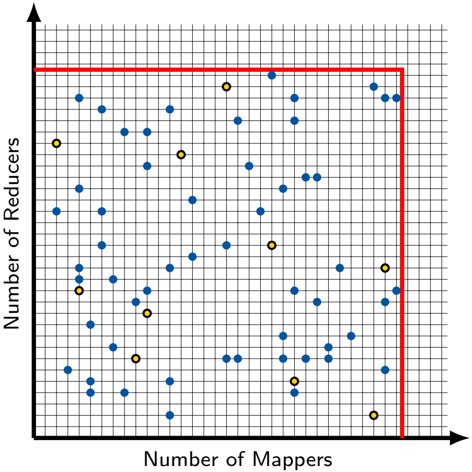
Degree 8 Surface

Surrogate-Based Modeling

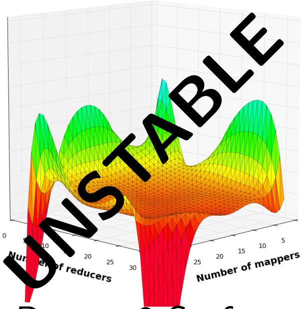
Step 3: Selecting the best surface using *k*-fold cross validation

Partition the samples into k sets of (nearly) equal size.

One set is reserved for testing; $k-1$ sets are used for learning.

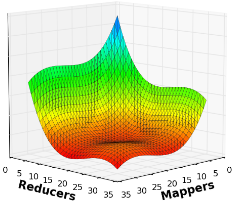


- **Learning Sets**
- **Testing Set**

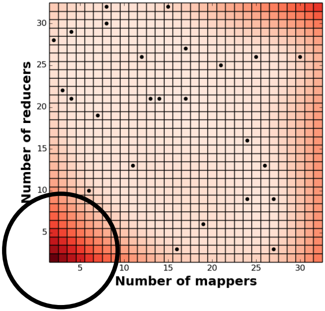


Degree 8 Surface

The Model



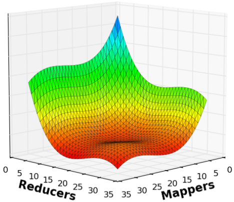
Width of Confidence Interval



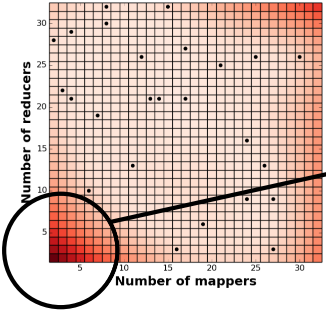
Surrogate-Based Modeling

Step 4: Applying a confidence interval

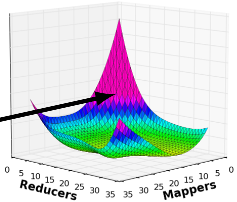
The Model



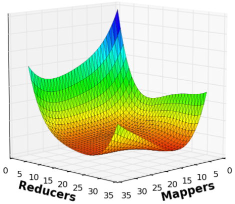
Width of Confidence Interval



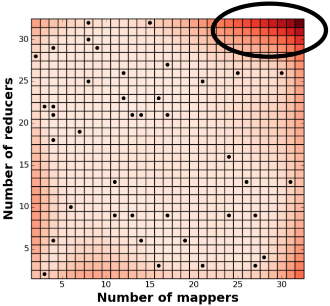
Model + Confidence Interval



The Model



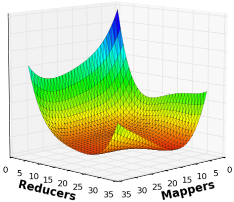
Width of Confidence Interval



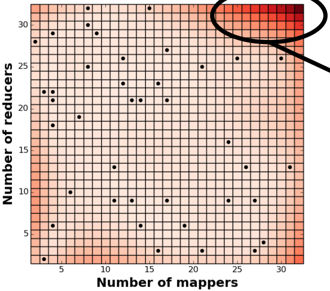
Surrogate-Based Modeling

Step 4: Applying a confidence interval

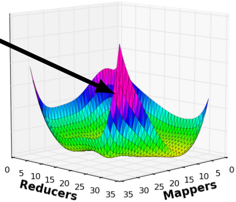
The Model



Width of Confidence Interval



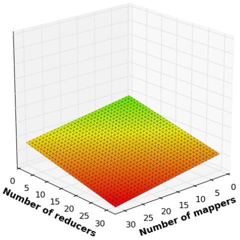
Model + Confidence Interval



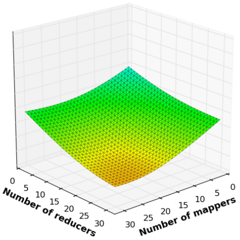
Case Study: Optimizing PageRank

Random sampling: 10 points, degree 1 surface

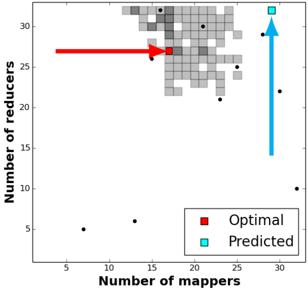
Constructed Model



Model + Conf. Interval



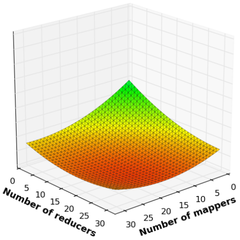
Sampling and Prediction



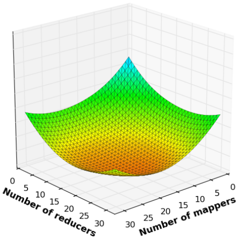
Case Study: Optimizing PageRank

Random sampling: 20 points, degree 2 surface

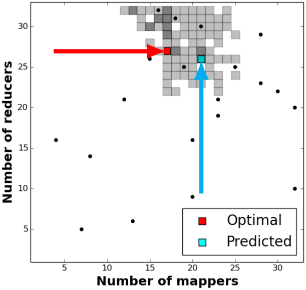
Constructed Model



Model
+
Conf. Interval



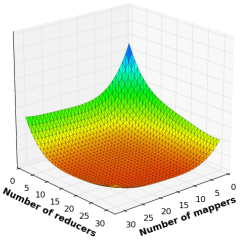
Sampling and Prediction



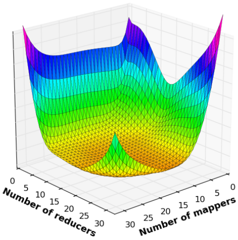
Case Study: Optimizing PageRank

Random sampling: 30 points, degree 4 surface

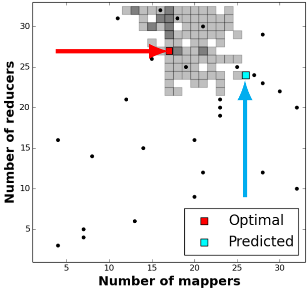
Constructed Model



Model + Conf. Interval

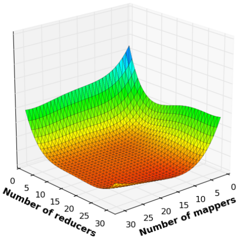


Sampling and Prediction

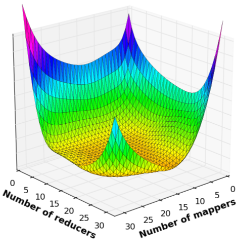


Random sampling: 40 points, degree 4 surface

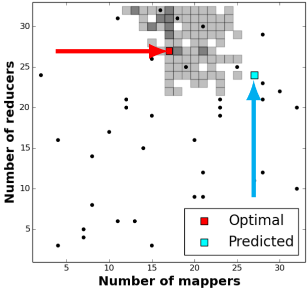
Constructed Model



Model + Conf. Interval



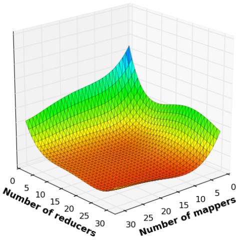
Sampling and Prediction



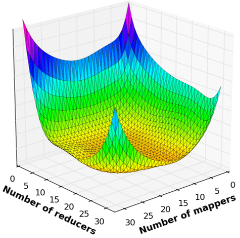
Case Study: Optimizing PageRank

Random sampling: 50 points, degree 4 surface

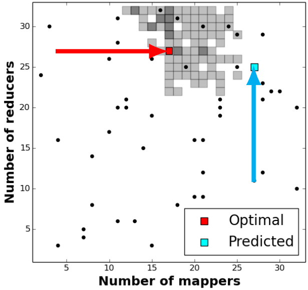
Constructed Model



Model + Conf. Interval



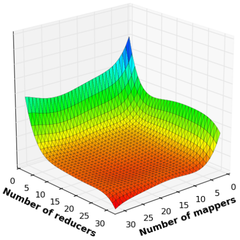
Sampling and Prediction



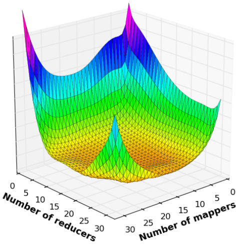
Case Study: Optimizing PageRank

Random sampling: 60 points, degree 5 surface

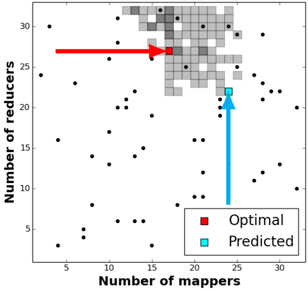
Constructed Model



Model + Conf. Interval



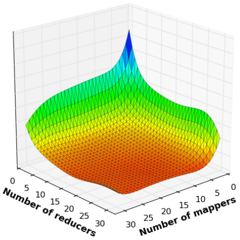
Sampling and Prediction



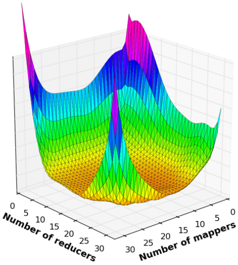
Case Study: Optimizing PageRank

Random sampling: 70 points, degree 6 surface

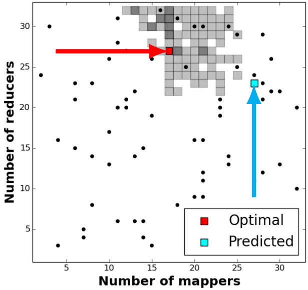
Constructed Model



Model + Conf. Interval



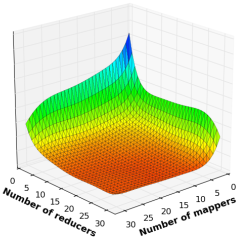
Sampling and Prediction



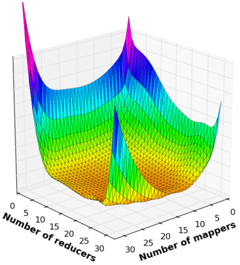
Case Study: Optimizing PageRank

Random sampling: 80 points, degree 6 surface

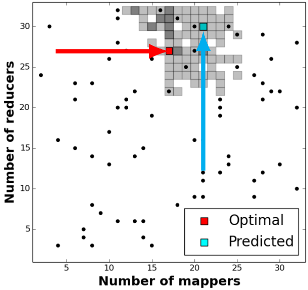
Constructed Model



Model
+
Conf. Interval



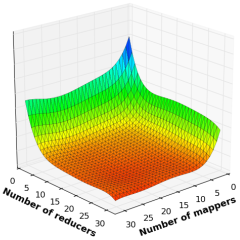
Sampling and Prediction



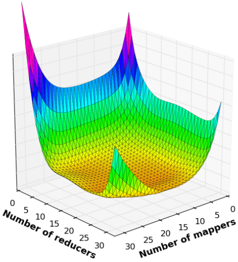
Case Study: Optimizing PageRank

Random sampling: 90 points, degree 5 surface

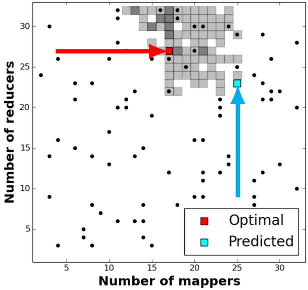
Constructed Model



Model
+
Conf. Interval



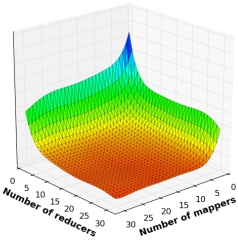
Sampling
and
Prediction



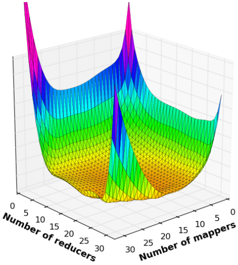
Case Study: Optimizing PageRank

Random sampling: 100 points, degree 6 surface

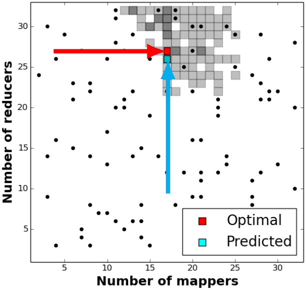
Constructed Model



Model + Conf. Interval

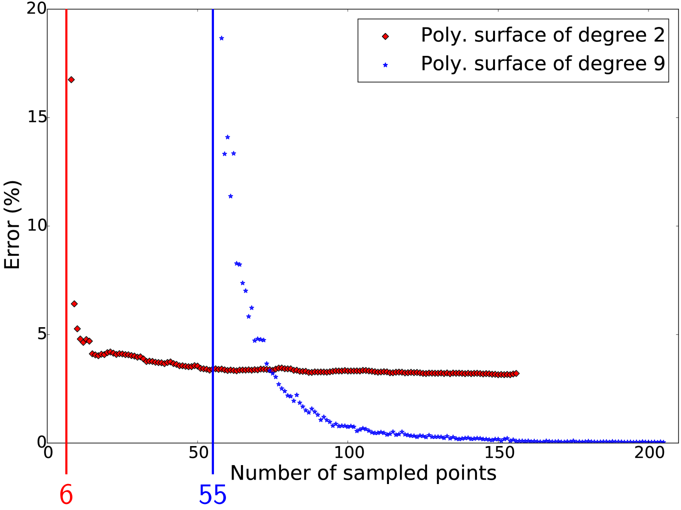


Sampling and Prediction



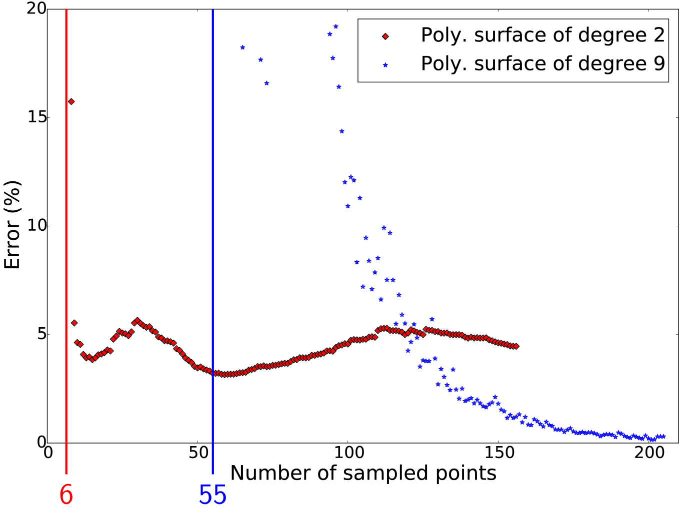
Case Study: Optimizing PageRank

Accuracy by random sampling



Case Study: Optimizing PageRank

Accuracy by grid sampling



Conclusion

- The surrogate model predicted configurations within 1% of optimal sampling only 90 configurations.
  - 90% reduction in sampling from exhuastive search
  - 67% reduction in (expected) sampling compared to grid hill
- The reduction in sampling makes it feasible to
  - tune more parameters
  - explore a wider range of possible parameter values

Thank You

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