# The Parallel Knowledge Gradient Method for Batch Bayesian Optimization

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[The Parallel Knowledge Gradient Method for Batch Bayesian Optimization, NIPS 2016.]

## We would like to optimize expensive-to-evaluate functions.

- We would like to optimize a function  $f : \mathbb{A} \to \mathbb{R}$ .
- The feasible set  $\mathbb{A}$  is either a box or polyhedron, and compact.
- The unknown function f is smooth.
- We have no information about the derivative of f.
- f is typically expensive to evaluate.
  - Training and testing machine learning algorithms
  - Calibrating parameters of some complex simulators
  - Labor intensive experimental design



## **Application: tuning machine learning algorithms**



- Number of hidden units each layer
- Learning rate in SGD
- Number of iterations in training
- .....

### **Batch Bayesian Optimization**

• Common BayesOpt algorithms look like:



- We typically use a Gaussian Process prior.
  - Posterior after evaluating n points:

$$f(\mathbf{x}) \sim \mathcal{N}(\mu^{(n)}(\mathbf{x}), K^{(n)}(\mathbf{x}))$$

# The Parallel Knowledge Gradient (qKG)

• If we were to stop after n points,  $\min_{x \in \mathbb{A}} \mu^{(n)}(x)$  is the minimum of the mean function.

• If we take one additional iteration (q more points),  $\min_{x \in \mathbb{A}} \mu^{(n+q)}(x)$  is the minimum of the mean. It depends on where these q points are and their function values.

• The quality of the q points selected is quantified by

$$\min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n)}(x) - \mathbb{E}_n \left[ \min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n+q)}(x) | \boldsymbol{y}(\boldsymbol{z}^{(1:q)}) \right]$$

## The Parallel Knowledge Gradient (qKG)

• The q-KG criterion is defined as:

$$q - KG(\boldsymbol{z}^{(1:q)}, \mathbb{A}) = \min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n)}(x) - \mathbb{E}_n \left[ \min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n+q)}(x) | \boldsymbol{y}(\boldsymbol{z}^{(1:q)}) \right]$$

• The q-KG algorithm is to try maximize the criterion above.

$$\max_{\boldsymbol{z}^{(1:q)}\subset\mathbb{A}}q\text{-}KG(\boldsymbol{z}^{(1:q)},\mathbb{A})$$

















### Maximization of q-KG

$$q\text{-}KG(\boldsymbol{z}^{(1:q)}, \mathbb{A}) = \min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n)}(x) - \mathbb{E}_n \left[ \min_{x \in \mathbb{A}} \boldsymbol{\mu}^{(n+q)}(x) | \boldsymbol{y}(\boldsymbol{z}^{(1:q)}) \right]$$

Estimate  $\nabla q$ -*KG*( $\boldsymbol{z}^{(1:q)}, \mathbb{A}$ )



#### **Multi-start Stochastic Gradient Ascent**

### **Estimate the Derivative of q-KG when A is finite**

• By Gaussian process properties

$$\boldsymbol{\mu}^{(n+q)}(\mathbb{A}) = \boldsymbol{\mu}^{(n)}(\mathbb{A}) + C^{(n)}(\mathbb{A}, \boldsymbol{z}^{(1:q)})Z_q$$

where  $C^{(n)}$  is some function related to posterior covariance function. Z is q-dimensional standard normal.

• q-KG can be rewritten as

$$q\text{-}KG(\boldsymbol{z}^{(1:q)},\mathbb{A}) = \mathbb{E}_{Z_q}\left[\min \boldsymbol{\mu}^{(n)}(\mathbb{A}) - \min\left(\boldsymbol{\mu}^{(n)}(\mathbb{A}) + C^{(n)}(\mathbb{A}, \boldsymbol{z}^{(1:q)})Z_q\right)\right]$$

• When the prior mean and kernel function is continuously differentiable and A is bounded

$$\nabla q \cdot KG(\boldsymbol{z}^{(1:q)}, \mathbb{A}) = \mathbb{E}_{Z_q} \left[ \nabla \left( \min \boldsymbol{\mu}^{(n)}(\mathbb{A}) - \min \left( \boldsymbol{\mu}^{(n)}(\mathbb{A}) + C^{(n)}(\mathbb{A}, \boldsymbol{z}^{(1:q)}) Z_q \right) \right) \right]$$

#### We discretize A when A is a continuous domain

• We approximate A as

$$\mathbb{A}_n = \mathbb{A}_n^M \cup \boldsymbol{x}^{(1:n)} \cup \boldsymbol{z}^{(1:q)}$$

• The  $\mathbb{A}_n^M$  is the samples of the global optima based on the current posterior surface: random feature approximation.

• We then can use the multi-start gradient based optimizer.

#### q-KG Outperforms Other Algorithms on Noisy Synthetic Functions



## q-KG Outperforms State-of-Art when Tuning Logistic Regression



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MNIST Dataset, http://yann.lecun.com/exdb/mnist/

### q-KG Outperforms State-of-Art when Tuning CNN



## The code is made public, you can use it

- The paper is published at NIPS 2016 with the same title as this talk.
- We build the algorithm into the open-source package: MOE.
- The code is completely in C++, with a Python interface.
- It is available at <a href="https://github.com/wujian16/gKG">https://github.com/wujian16/gKG</a>

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Branch: master - New pull	request	Create new file Upload fi	les Find file Clone or download -
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conda-recipe	pre-tagging version bumping		2 years ago
docs	Update install.rst		10 months ago
im moe	Merge pull request #1 from wujian16/jianwu_8_c	cpp_KG_test	3 months ago
moe_examples	-fixing scoping issues in fixtures: previously T.c	class_setup style se	2 years ago
.gitignore	cpp codes compiled		11 months ago
.mailmap	Added .mailmap to clean up authors		3 years ago
.travis.yml	fixing cmake bug (EXISTS vs DFEINED), fixing to	ravis to use virtualenv	3 years ago
AUTHORS.md	Update AUTHORS.md		3 years ago
CHANGELOG.md	Fixing UCB1 and UCB1-tuned algorithm calculat	tion of upper confidence	2 years ago
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**Thanks! Any Question?**