

# Sequential Bayes-Optimal Policies for Multiple Comparisons with a Control

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## Introduction

### Multiple Comparisons with a Control (MCC)

- ▶ determines which alternative systems under consideration have mean performance exceeding a known threshold;
- ▶ explores the unknown objective set  $\mathbb{B} = \{x : \theta_x \geq d_x\}$ .

### Bayes-Optimal Fully Sequential Policies for Allocating Simulation Effort

- ▶ can be characterized and computed efficiently, using techniques from **multi-armed bandits** and **optimal stopping**.
- ▶ are **flexible** in the sense that they
  - ▷ allow limitations on the ability to sample to be modeled with either a *random stopping time* or *sampling costs* or both;
  - ▷ allow sampling distributions from any *exponential family*.

## Problem Formulation

- ▶ Prior distributions from the *conjugate* exponential family are placed on the parameters of the sampling distributions. Parameters of these priors / posteriors form a stochastic process  $(S_n)_{n \geq 0}$ .
- ▶ Suppose there is some random time horizon  $T$  beyond which we will be unable to sample.  $T$  is geometrically distributed with parameter  $1 - \alpha$ ; allow  $T = +\infty$  a.s., in which case  $\alpha = 1$ .
- ▶ Our estimate of  $\mathbb{B}$  given the available information after  $n$  samples, i.e.,  $\mathcal{F}_n$ , is  $B_n = \{x : \mathbb{P}\{\theta_x \geq d_x \mid \mathcal{F}_n\} \geq 1/2\}$ . When sampling stops, we receive a *reward* equal to the total number of alternatives correctly classified by this estimate.
- ▶ A **policy**  $\pi$  is composed of a **sampling rule** for choosing an adapted sequence of sampling decisions  $(x_n)_{n \geq 1}$ , and a **stopping rule** for choosing an adapted stopping time  $\tau$ .
- ▶ Our goal is to find a policy that maximizes the **expected total reward**, i.e., ( $c_x$  is the sampling cost for alternative  $x$ )

$$\sup_{\pi} \mathbb{E}^{\pi} \left[ \sum_{x \in B_{\tau \wedge T}} \mathbf{1}_{\{x \in \mathbb{B}\}} + \sum_{x \notin B_{\tau \wedge T}} \mathbf{1}_{\{x \notin \mathbb{B}\}} - \sum_{n=1}^{\tau \wedge T} c_{x_n} \right].$$

## The Optimal Solution

We solve this sequential Bayesian MCC problem using **dynamic programming (DP)**. The **value function** is

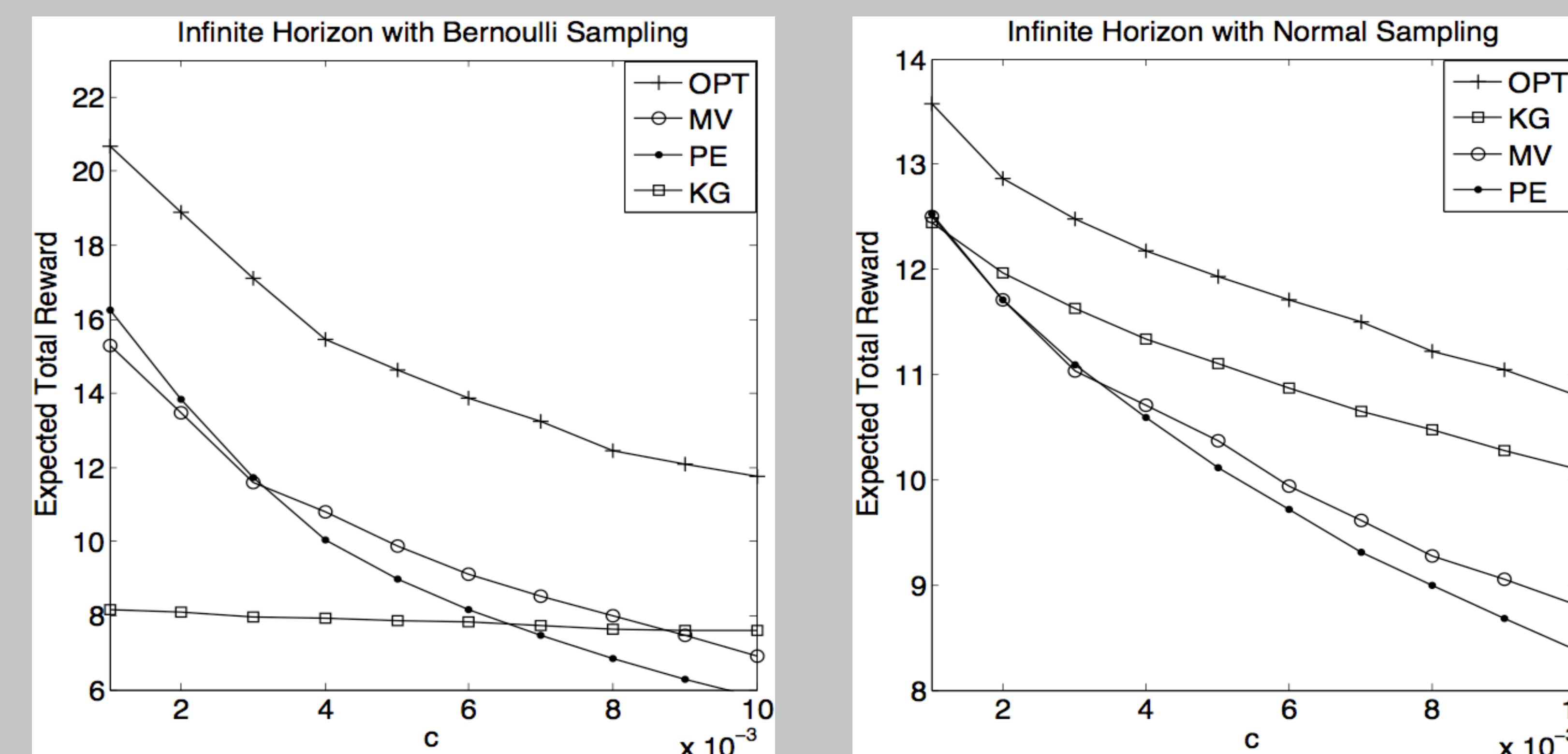
$$V(s) = \sup_{\pi} \mathbb{E}^{\pi} \left[ \sum_{n=1}^{\tau} \alpha^{n-1} \mathcal{R}_{x_n}(S_{n-1}, x_n) \mid S_0 = s \right],$$

where  $\mathcal{R}(\cdot)$  are single-period reward functions.

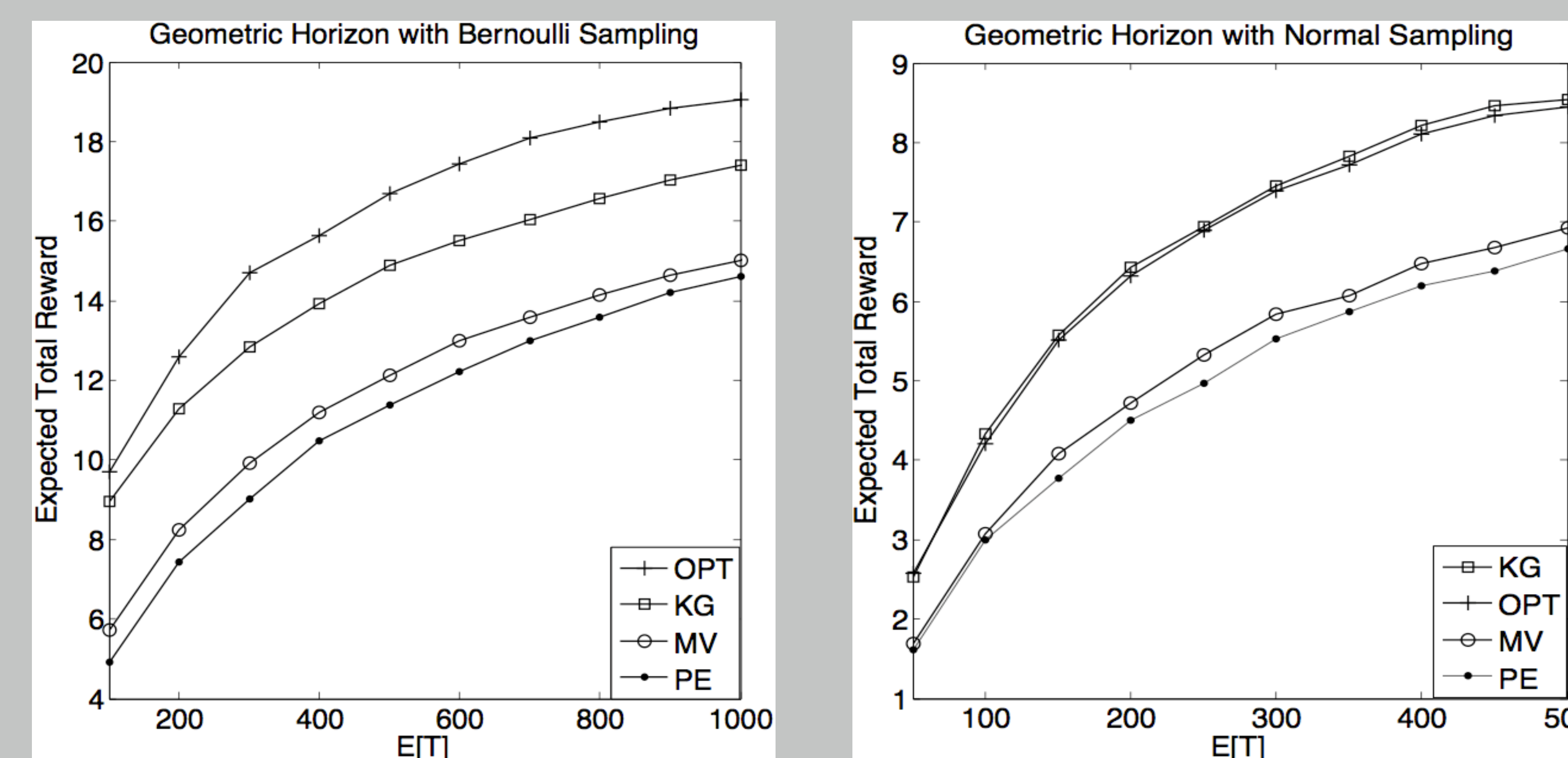
- ▶ Optimal policies  $(x_n^*)_{n \geq 1}$  and  $\tau^*$  are theoretically specified.
- ▶ Approximations are applied to the numerical implementations.

## Bayes-Optimal (OPT) vs Other Policies

### Performance in Infinite Horizon with Sampling Costs



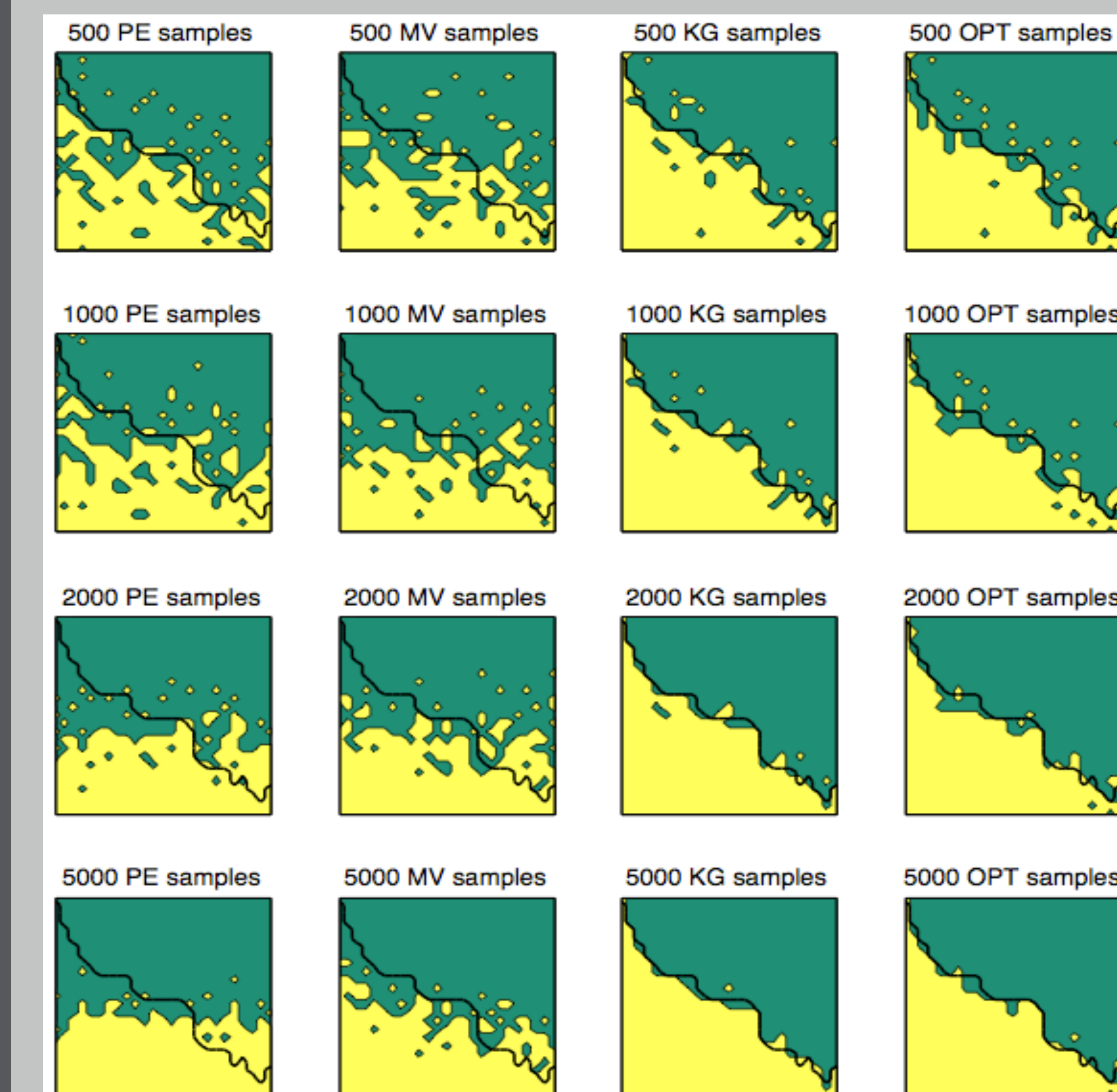
### Performance in Geometric Horizon without Costs



- ▶ Pure Exploration (PE):  $x_n \sim \text{Uniform}(1, \dots, k)$ .
- ▶ Max Variance (MV):  $x_{n+1} \in \text{argmax}_x \{\sigma_{nx}\}$ .
- ▶ Knowledge Gradient (KG):  $x_{n+1} \in \text{argmax}_x \{\mathcal{R}_x(S_{nx})\}$ .

## Ambulance Quality of Service Application

- ▶ Administrators of a city's emergency medical services would like to know which of several methods under consideration for positioning ambulances satisfy the minimum requirement of **70% of calls answered on time**.
- ▶ The **ambulance allocation plans** are distributed along the **x-axis** and the **call arrival rates** are distributed along the **y-axis**. A pair like this is considered an *alternative* and there are 625 alternatives. We assume a *normal sampling distribution* and a *geometric horizon with no sampling costs*.



The **black** curves are the boundary between  $\mathbb{B}$  (the set of qualified alternatives) and its complement.

The **yellow** regions are the estimates  $B_n$  under the corresponding sampling policy, given the stated number of samples.

## Conclusions

- ▶ We provide **new tools** for simulation analysts facing MCC problems. These new tools
  - ▷ dramatically improve **efficiency** over naive sampling methods;
  - ▷ make it possible to efficiently and accurately **solve** previously intractable MCC problems.
- ▶ **Other applications** include determining through simulation under which conditions the current policies of a logistics company are sufficient to maintain quality of service, and finding which projects have a positive net expected value.