Some Theory Behind Algorithms for Stochastic Optimization

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Overview

- Problem formulation
- Theoretical performance of stochastic adaptive search methods
- Algorithms based on Hit-and-Run to approximate theoretical performance
- Incorporate random sampling and noisy objective functions

What is Stochastic Optimization?

- Randomness in algorithm AND/OR in function evaluation

- Related terms:
  - Simulation optimization
  - Optimization via simulation
  - Random search methods
  - Stochastic approximation
  - Stochastic programming
  - Design of experiments
  - Response surface optimization

Problem Formulation

- Minimize $f(x)$ subject to x in S
- x: n variables, continuous and/or discrete
- $f(x)$: objective function, could be black-box, ill-structured, noisy
- S: feasible set, nonlinear constraints, or membership oracle
- Assume an optimum x^* exists, with $y^*=f(x^*)$

Example Problem Formulations

- Maximize expected value
  subject to standard deviation < b
- Minimize standard deviation
  subject to expected value > t
- Minimize CVaR (conditional value at risk)

- Minimize sum of least squares from data
- Maximize probability of satisfying noisy constraints

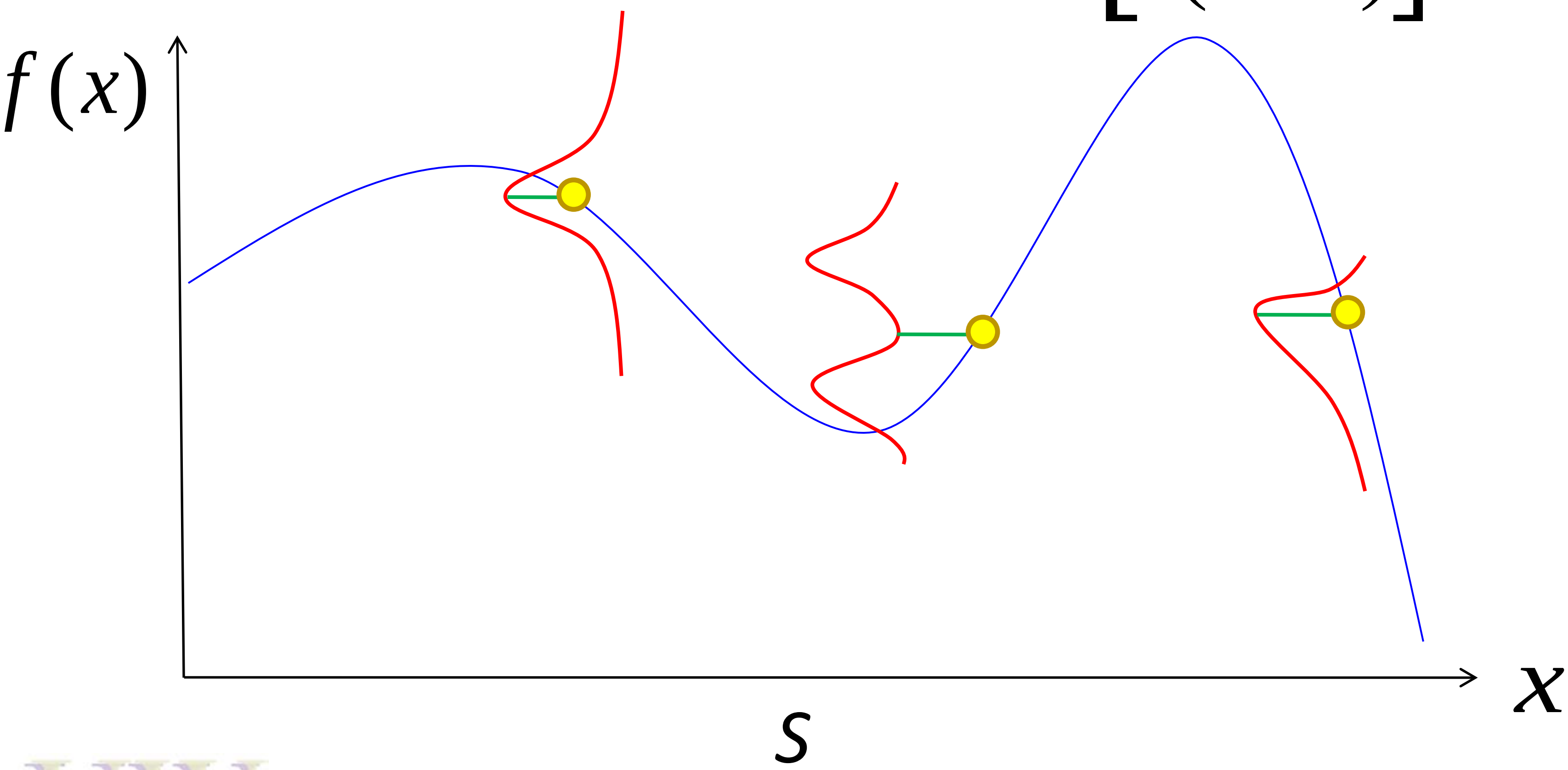
Approximate or Estimate $f(x)$?

- Approximate a complicated function:
  - Taylor series expansion
  - Finite element analysis
  - Computational fluid dynamics

- Estimate a noisy function with:
  - Replications
  - Length of discrete-event simulation run

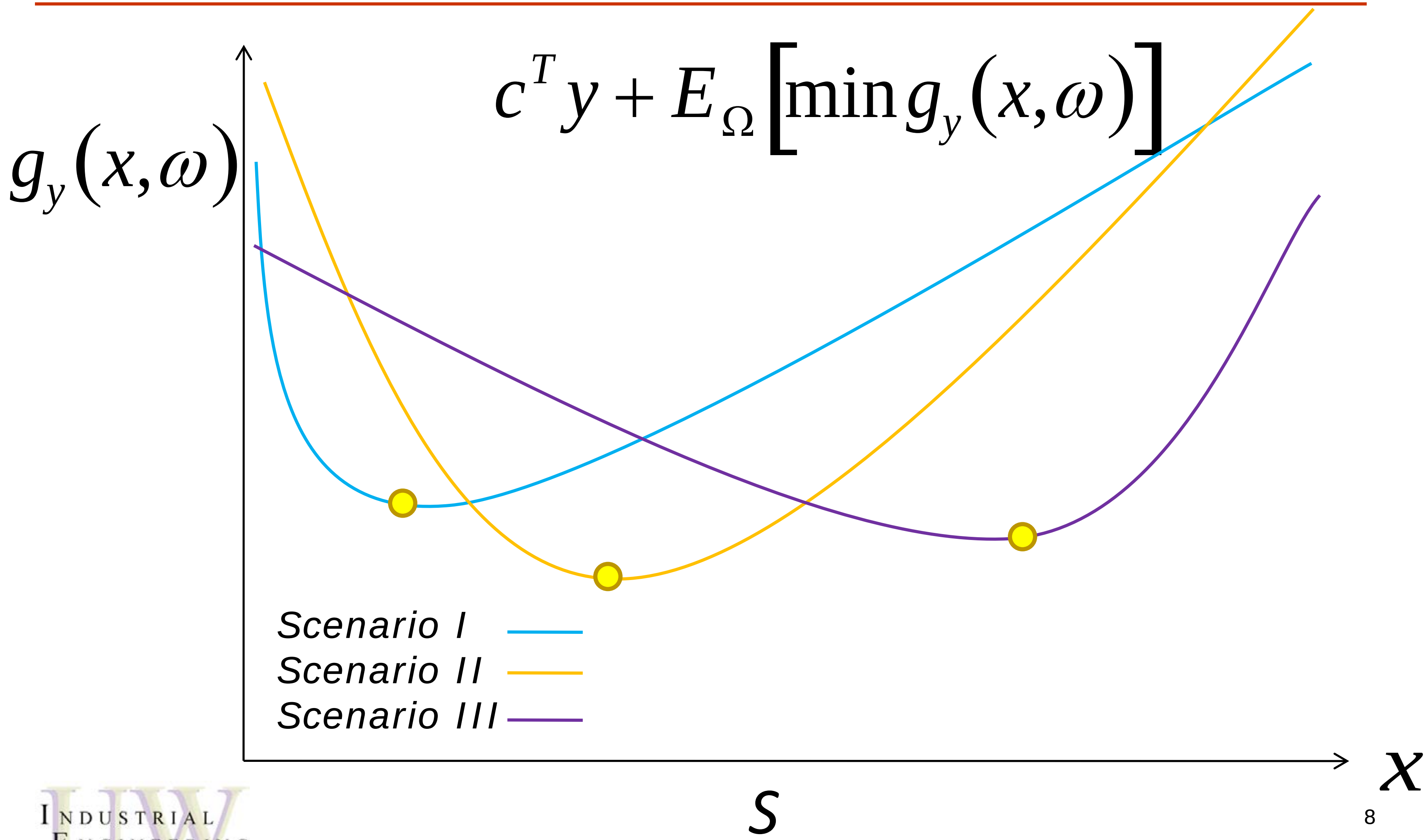
Noisy Objective Function

$$f(x) = E_{\Omega}\left[g\left(x, \omega_x\right)\right]$$



Scenario-based Recourse Function

$$c^T y + E_\Omega\left[\min g_y(x,\omega)\right]$$



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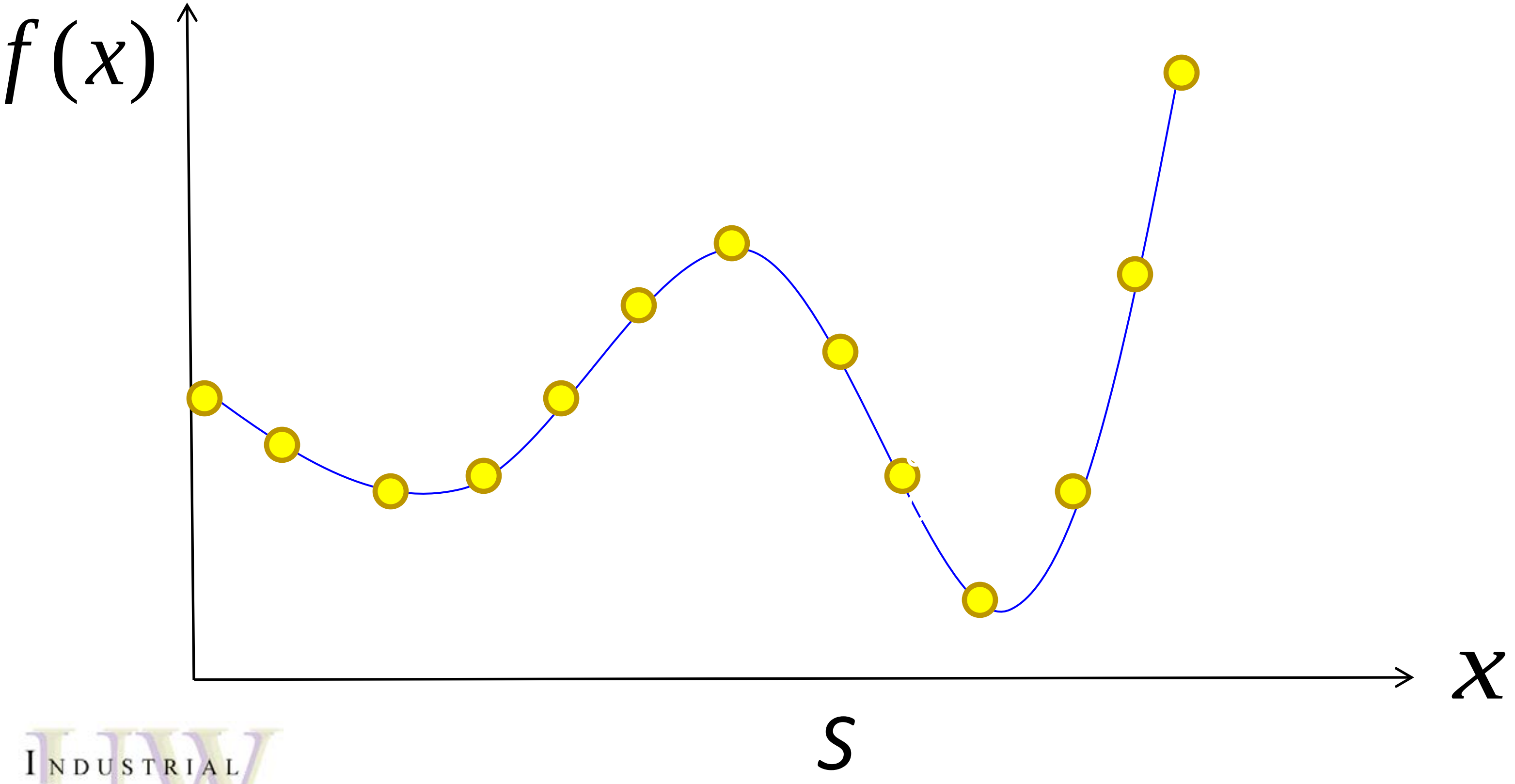
Local versus Global Optima

- “Local” optima are relative to the neighborhood and algorithm



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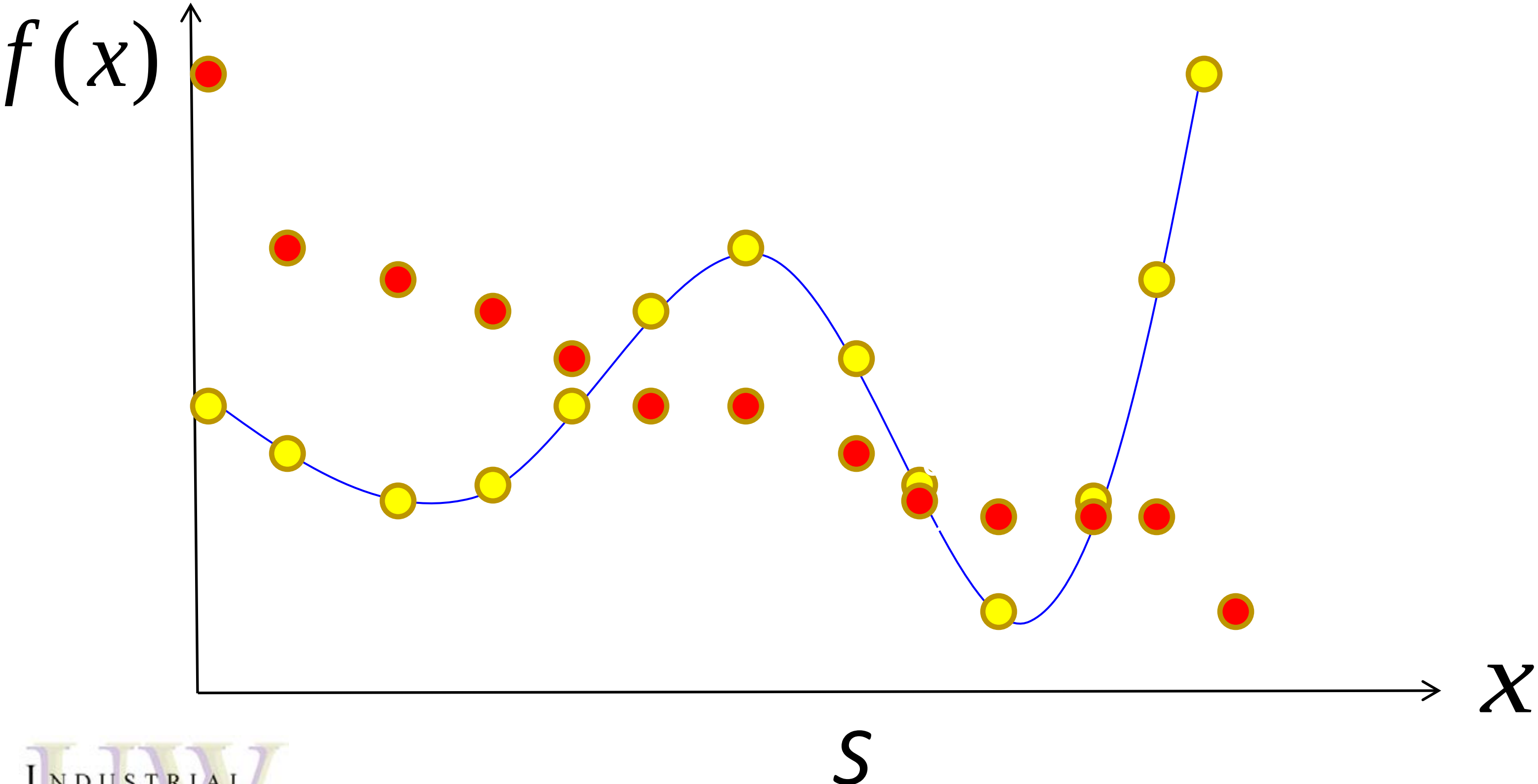


Research Question: What Do We Really Want?

- Do we really just want the optimum?
- What about sensitivity?
- Do we want to approximate the entire surface?
- Multi-criteria?
- Role of objective function and constraints?
- Where does randomness appear?

How can we solve…?

IDEAL Algorithm:

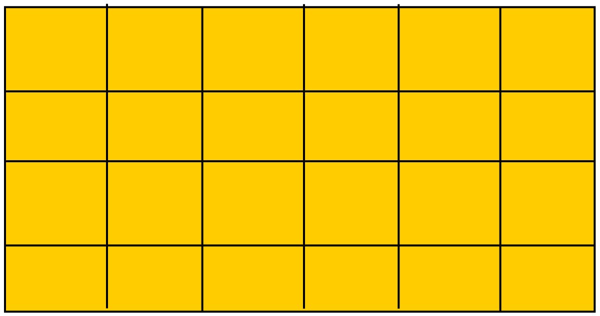
- Optimizes any function quickly and accurately
- Provides information on how "good" the solution is
- Handles black-box and/or noisy functions, with continuous and/or discrete variables
- Is easy to implement and use

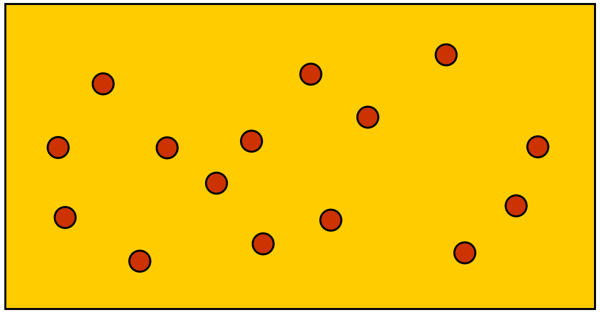
Theoretical Performance of Stochastic Adaptive Search

- What kind of performance can we hope for?
- Global optimization problems are NP-hard
- Tradeoff between accuracy and computation
- Sacrifice guarantee of optimality for speed in finding a “good” solution
- Three theoretical constructs:
  - Pure adaptive search (PAS)
  - Hesitant adaptive search (HAS)
  - Annealing adaptive search (AAS)

Performance of Two Simple Methods

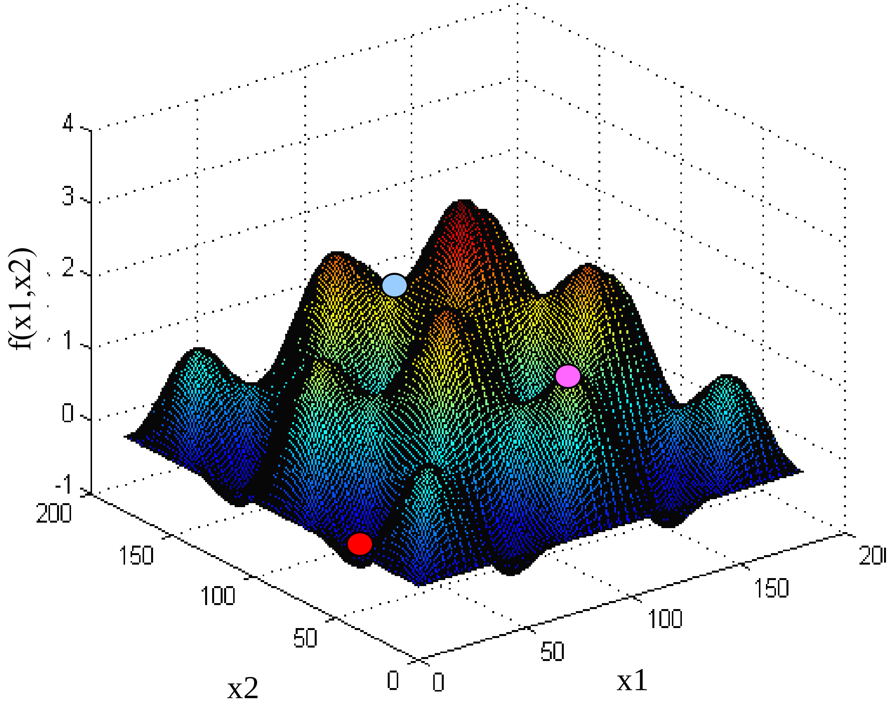
- **Grid Search**: Number of grid points is $O((L/\varepsilon)^n)$, where L is the Lipschitz constant, n is the dimension, and ε is distance to the optimum
- **Pure Random Search**: Expected number of points is $O(1/p(y^*+\varepsilon))$, where $p(y^*+\varepsilon)$ is the probability of sampling within ε of the optimum y^*
- Complexity of both is exponential in dimension

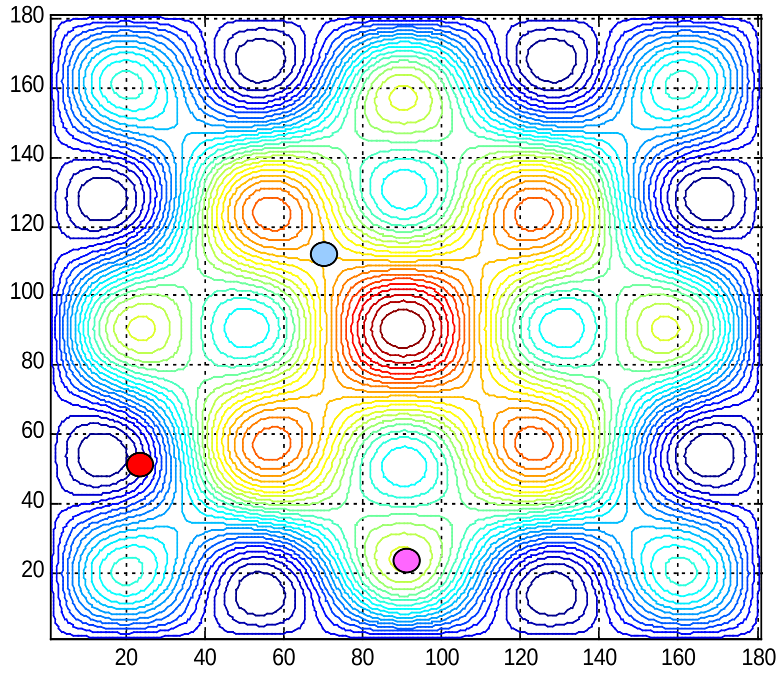




Pure Adaptive Search (PAS)

- PAS: chooses points uniformly distributed in improving level sets





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Bounds on Expected Number of Iterations

- PAS (continuous):

$$E[N(y^*+\varepsilon)] \leq 1 + \ln\left(1/p(y^*+\varepsilon)\right)$$

where $p(y^*+\varepsilon)$ is the probability of PRS sampling within ε of the global optimum y^*

- PAS (finite):

$$E[N(y^*)] \leq 1 + \ln\left(1/p_1\right)$$

where p_1 is the probability of PRS sampling the global optimum

[Zabinsky and Smith, 1992]
[Zabinsky, Wood, Steel and Baritompa, 1995]

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Pure Adaptive Search

- Theoretically, PAS is LINEAR in dimension
- Theorem:

For any global optimization problem in *n* dimensions, with Lipschitz constant at most *L*, and convex feasible region with diameter at most *D*, the expected number of PAS points to get within ε of the global optimum is:

$$E[N(y^*+\varepsilon)] \leq 1 + n \ln(LD / \varepsilon)$$

[Zabinsky and Smith, 1992]

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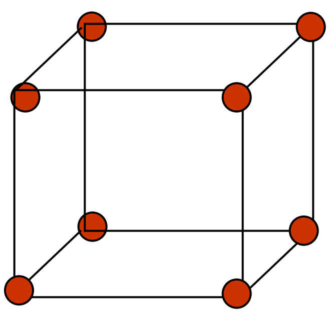
Finite PAS

- Analogous LINEARITY result
- Theorem:

For an n dimensional lattice $\{1,\ldots,k\}^n$, with distinct objective function values, the expected number of points for PAS, sampling uniformly, to first reach the global optimum is:

$$E[N(y^*)] < 2 + n \ln(k)$$



[Zabinsky, Wood, Steel and Baritompa, 1995]

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Hesitant Adaptive Search (HAS)

- What if we sample improving level sets with "bettering" probability *b(y)* and "hesitate" with probability *1-b(y)* ?

$$E[N(y^*+\varepsilon)] = \int_{y^*+\varepsilon}^{\infty} \frac{d\rho(t)}{b(t)\,p(t)}$$

where $\rho(t)$ is the underlying sampling distribution and $p(t)$ is the probability of sampling t or better

[Bulger and Wood, 1998]

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General HAS

- For a mixed discrete and continuous global optimization problem, the expected value of $N(y^*+\varepsilon)$, the variance, and the complete distribution can be expressed using the sampling distribution $\rho(t)$ and bettering probabilities $b(y)$

[Wood, Zabinsky and Kristinsdottir, 2001]

Annealing Adaptive Search (AAS)

- What if we sample from the original feasible region each iteration, but change distributions?

- Generate points over the whole domain using a Boltzmann distribution parameterized by temperature T
  - Boltzmann distribution becomes more concentrated around the global optima as the temperature decreases
  - Temperature is determined by a cooling schedule

- The *record values* of AAS are dominated by PAS and thus LINEAR in dimension

[Romeijn and Smith, 1994]

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Performance of Annealing Adaptive Search

- The expected number of *sample points* of AAS is bounded by HAS with a specific *b(y)*

- Select the next temperature so that the probability of generating an improvement under that Boltzmann distribution is at least 1-α , i.e.,

$$P\left(Y_{R(k)+1}^{AAS} < y \mid Y_{R(k)}^{AAS} = y\right) \geq 1 - \alpha$$

- Then the *expected number of AAS sample points* is LINEAR in dimension

[Shen, Kiatsupaibul, Zabinsky and Smith, 2007]

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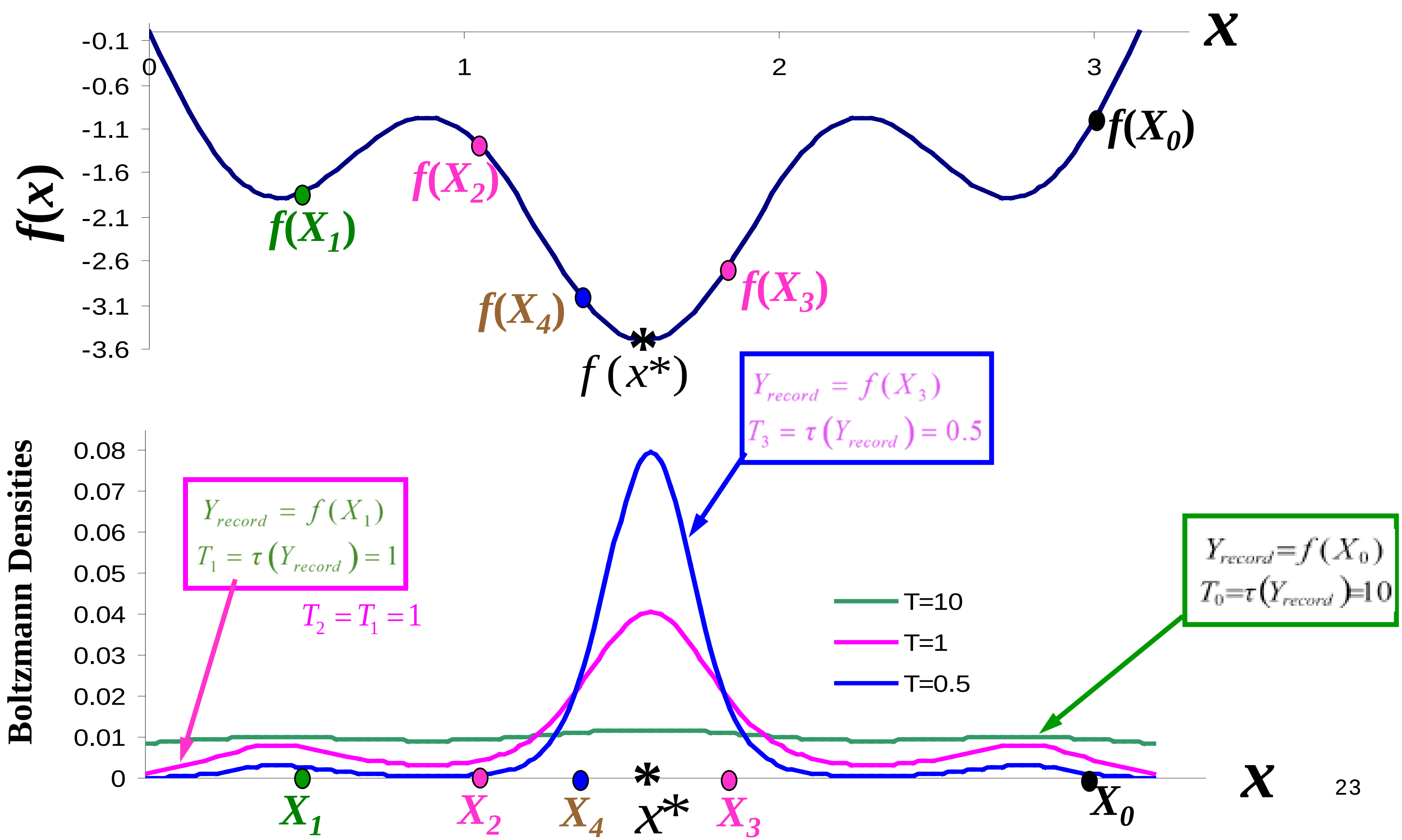
AAS with Adaptive Cooling Schedule



Research Areas

- Develop theoretical analysis of PAS, HAS, AAS for noisy or approximate functions
  - Model approximation or estimation error
  - Characterize impact of error on performance

- Use theory to develop algorithms
  - Approximate sampling from improving sets (as PAS) or Boltzmann distributions (as AAS)
  - Use HAS, with $\rho(t)$ and $b(y)$, to quantify and balance accuracy and efficiency

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Random Search Algorithms

- Instance-based methods
  - Sequential random search
  - Multi-start and population-based algorithms

- Model-based methods
  - Importance sampling
  - Cross-entropy [Rubinstein and Kroese, 2004]
  - Model reference adaptive search [Hu, Fu and Marcus, 2007]

[Zlochin, Birattari, Meuleau and Dorigo, 2004]

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Sequential Random Search

- Stochastic approximation [Robbins and Monro, 1951]
- Step-size algorithms [Rastrigin, 1960] [Solis and Wets, 1981]
- Simulated annealing
  [Romeijn and Smith, 1994], [Alrafaei and Andradottir, 1999]
- Tabu search [Glover and Kochenberger, 2003]
- Nested partition [Shi and Olafsson, 2000]
- COMPASS [Hong and Nelson, 2006]

- View these algorithms as Markov chains with
  - Candidate point generators
  - Update procedures

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Use Hit-and-Run to Approximate AAS

- Hit-and-Run is a Markov chain Monte Carlo (MCMC) sampler
  - converges to a uniform distribution

    [Smith, 1984]
  - in polynomial time $O(n^3)$

    [Lovász, 1999]
  - can approximate any arbitrary distribution by using a filter

- The difficulty of implementing AAS is to generate points directly from a family of Boltzmann distributions

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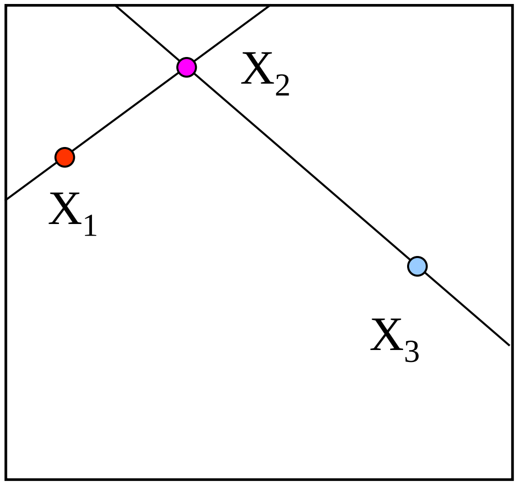
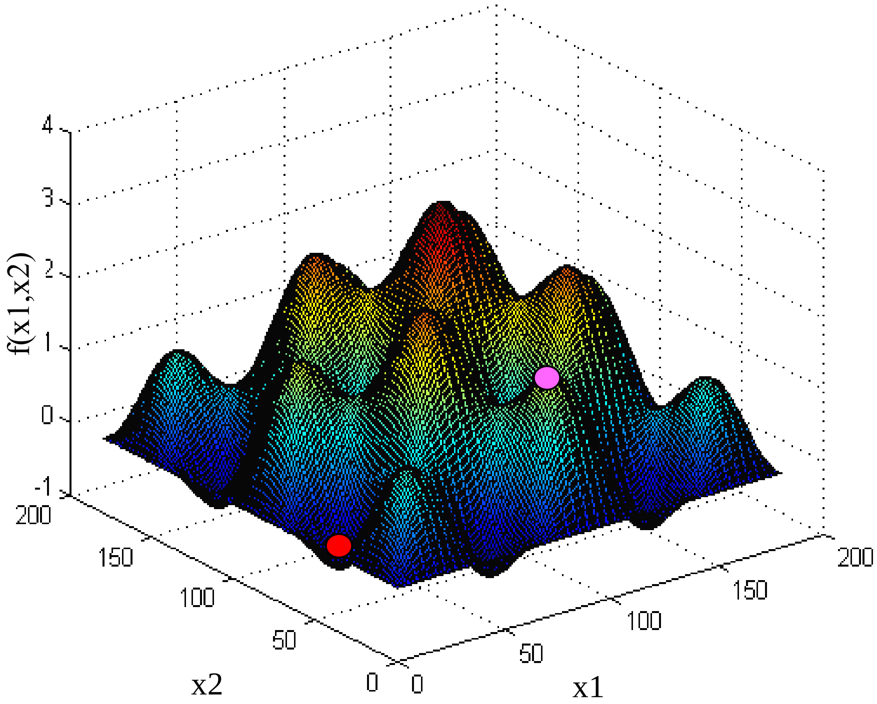
Hit-and-Run

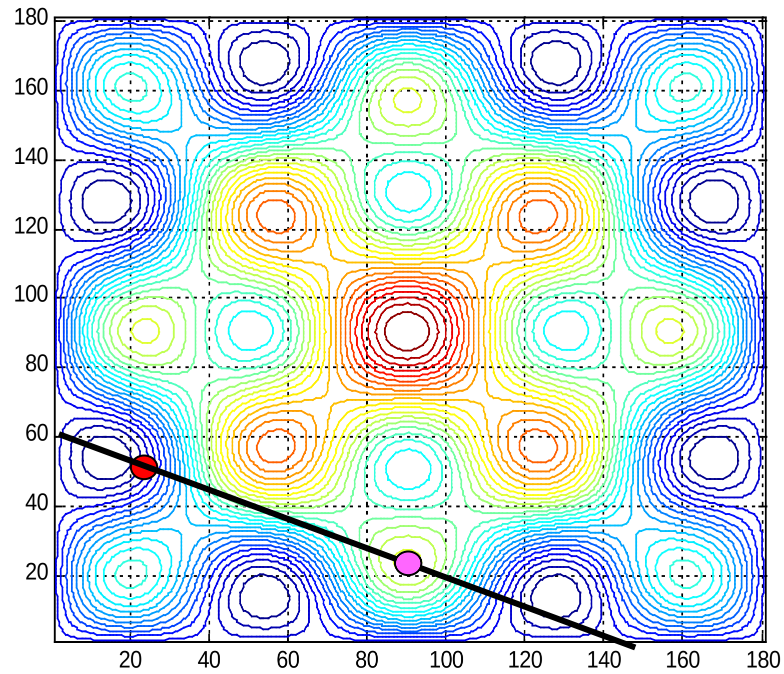
- Hit-and-Run generates a random direction (uniformly distributed on a hypersphere) and a random point (uniformly distributed on the line)



Improving Hit-and-Run

- IHR: choose a random direction and a random point, accept only improving points





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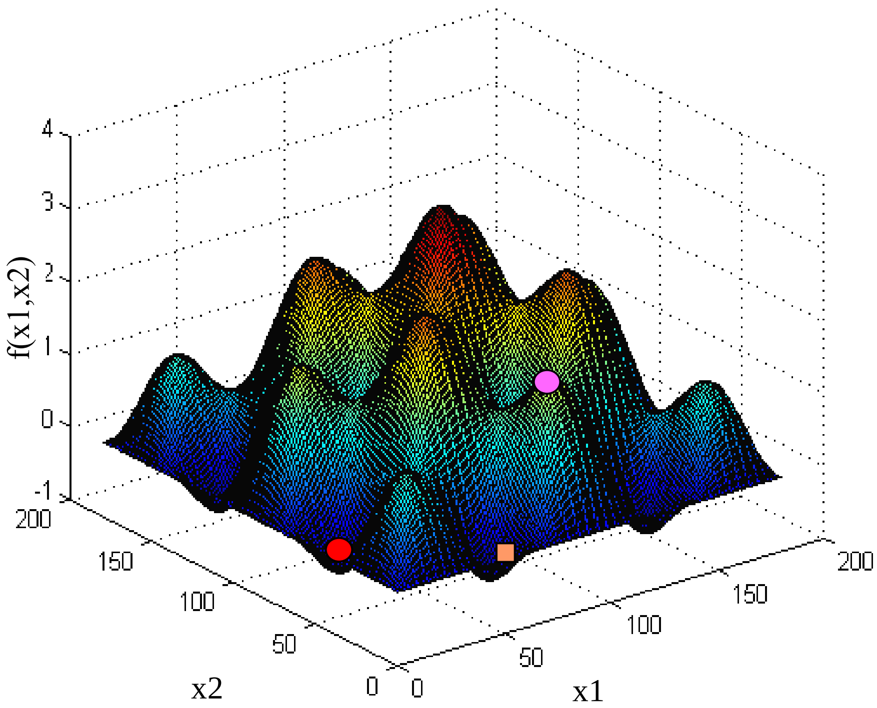

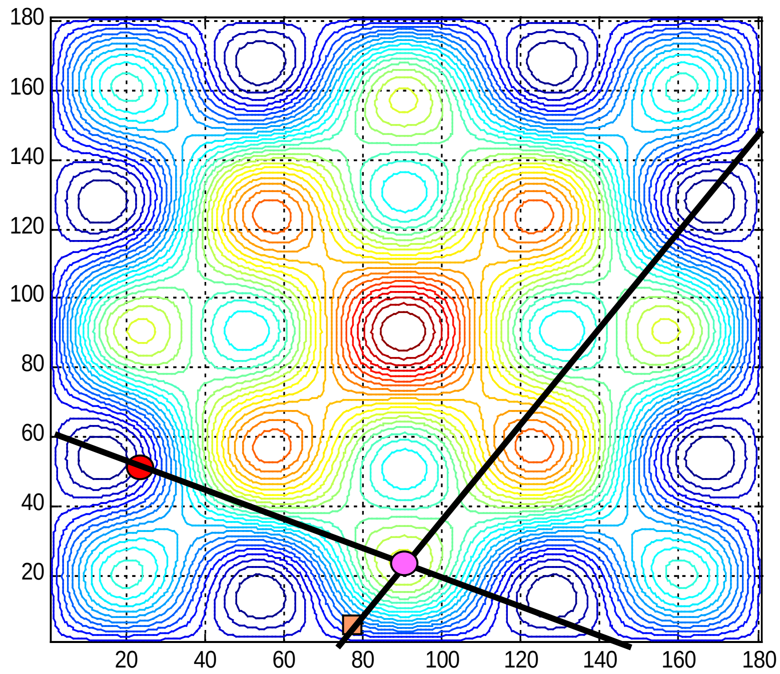

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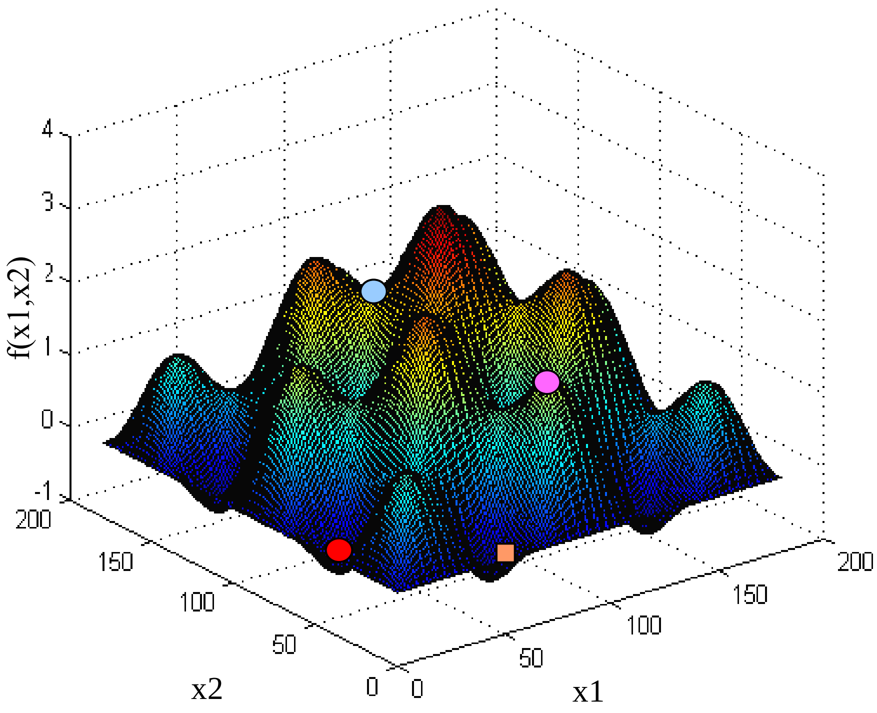
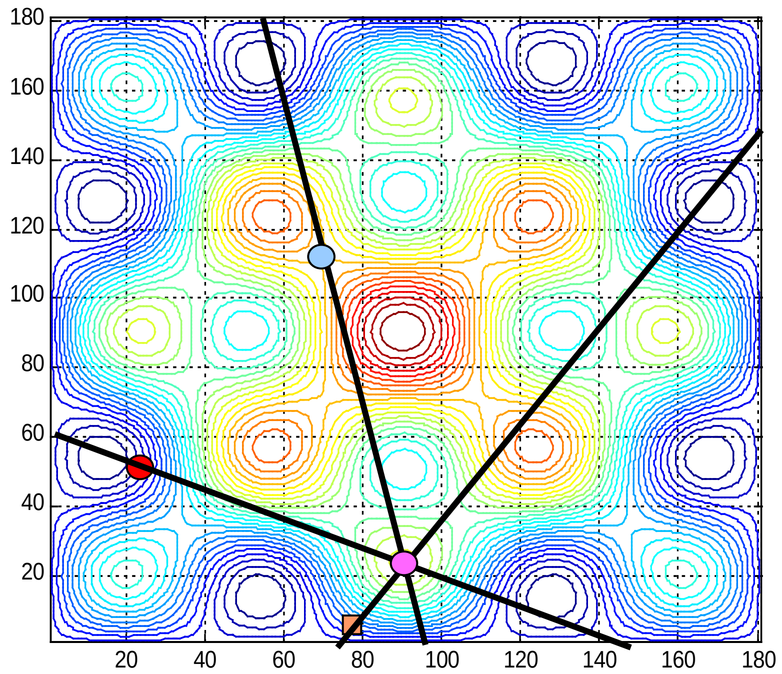
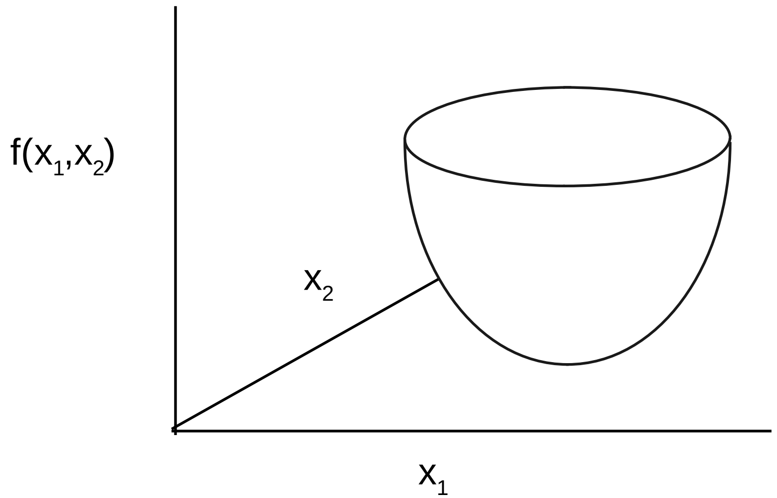




Is IHR Efficient in Dimension?

- Theorem:
  For any elliptical program in *n* dimensions, the expected number of function evaluations for IHR is: $O(n^{5/2})$

  [Zabinsky, Smith, McDonald, Romeijn and Kaufman, 1993]



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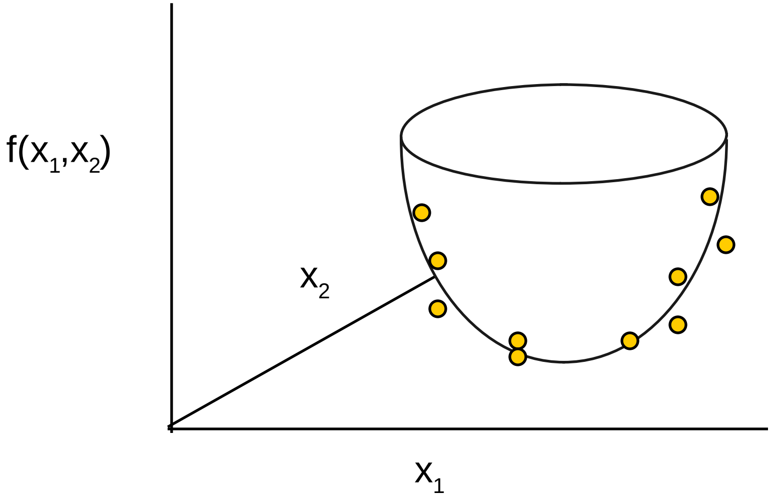

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Use Hit-and-Run to Approximate Annealing Adaptive Search

- Hide-and-Seek: add a probabilistic Metropolis acceptance-rejection criterion to Hit-and-Run to approximate the Boltzmann distribution
  [Romeijn and Smith, 1994]

- Converges in probability with almost any cooling schedule driving temperature to zero

- AAS Adaptive Cooling Schedule:
  - Temperature values according to AAS to maintain $1-\alpha$ probability of improvement
  - Update temperature when record values are obtained [Shen, Kiatsupaibul, Zabinsky and Smith, 2007]

Research Possibilities:

- How long should we execute Hit-and-Run at a fixed temperature?
- What is the benefit of sequential temperatures (warm starts) on convergence rate?
- Hit-and-Run has fast convergence on "well-rounded" sets; how can we modify transition kernel in general?
- Incorporate new Hit-and-Run on mixed integer/continuous sets
  - Discrete hit-and-run
    [Baumert, Ghate, Kiatsupaibul, Shen, Smith and Zabinsky, 2009]
  - Pattern hit-and-run
    [Mete, Shen, Zabinsky, Kiatsupaibul and Smith, 2010]

Simulated Annealing with Multi-start: When to Stop or Restart a Run?

- Use HAS to model progress of a heuristic random search algorithm and estimate associated parameters

- Dynamic Multi-start Sequential Search
  - If current run appears "stuck" according to HAS analysis, stop and restart
  - Estimate probability of achieving $y^* + \varepsilon$ based on observed values and estimated parameters
  - If probability is high enough, terminate

[Zabinsky, Bulger and Khompatraporn, 2010]

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Meta-control of Interacting-Particle Algorithm

- Interacting-Particle Algorithm
  - Combines simulated annealing and population based algorithms
  - Uses statistical physics and Feynman-Kac formulas to develop selection probabilities

[Del Moral, *Feynman-Kac Formulae: Genealogical and Interacting Particle Systems with Applications*, 2004]

- Meta-control approach to dynamically heat and cool temperature

[Kohn, Zabinsky and Brayman, 2006]
[Molvalioglu, Zabinsky and Kohn, 2009]

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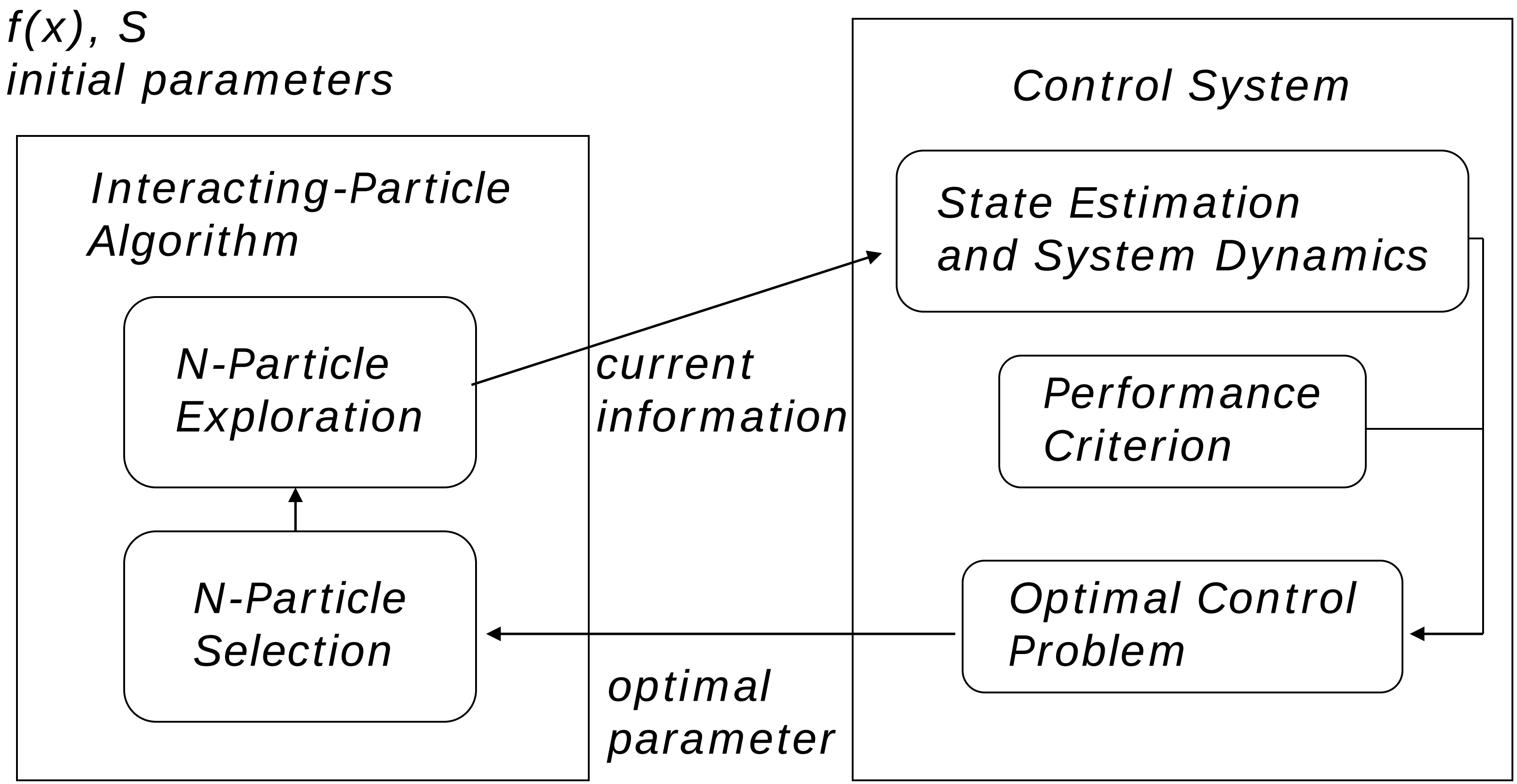
Meta-control Approach



Research Possibilities

- Combine theoretical analyses with MCMC and meta-control to:
  - Control the exploration transition probabilities
  - Obtain stopping criterion and quality of solution
  - Relate interacting particles to cloning/splitting

- Combine theoretical analyses and meta-control with model-based approach

Another Research Area: Quantum Global Optimization

- Grover's Adaptive Search can implement PAS on a quantum computer
  [Baritompa, Bulger and Wood, 2005]

- Apply research on quantum control theory to global optimization
  - [Gardiner, *Handbook of Stochastic Methods for Physics, Chemistry and the Natural Sciences*, 2004]
  - [Del Moral, *Feynman-Kac Formulae: Genealogical and Interacting Particle Systems with Applications*, 2004]

Optimization of Noisy Functions

- Use random sampling to explore the feasible region and estimate the objective function with replications
- Recognize two sources of noise:
  - Randomness in the sampling distribution
  - Randomness in the objective function
- Adaptively adjust the number of samples and the number of replications

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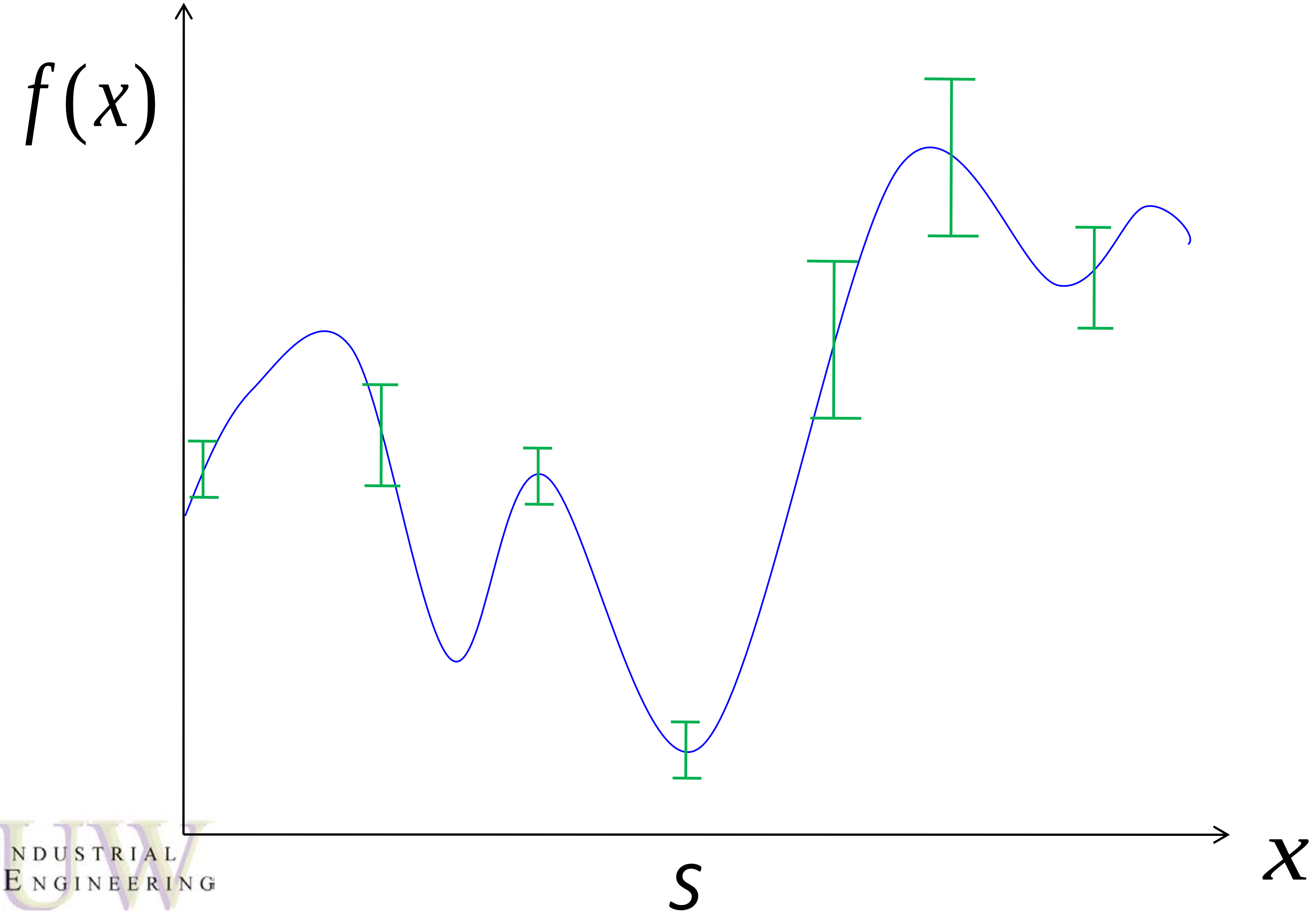
Noisy Objective Function



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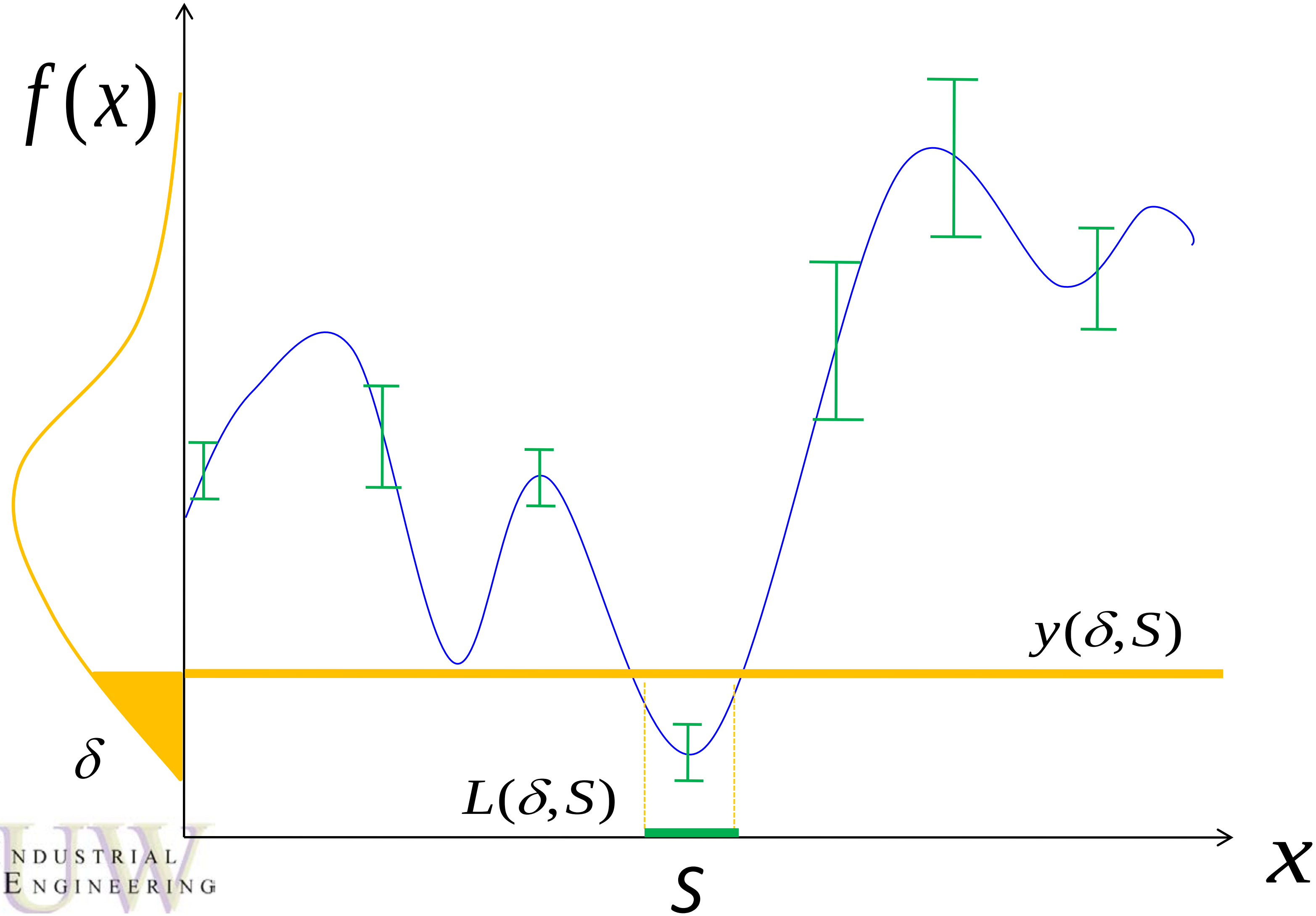
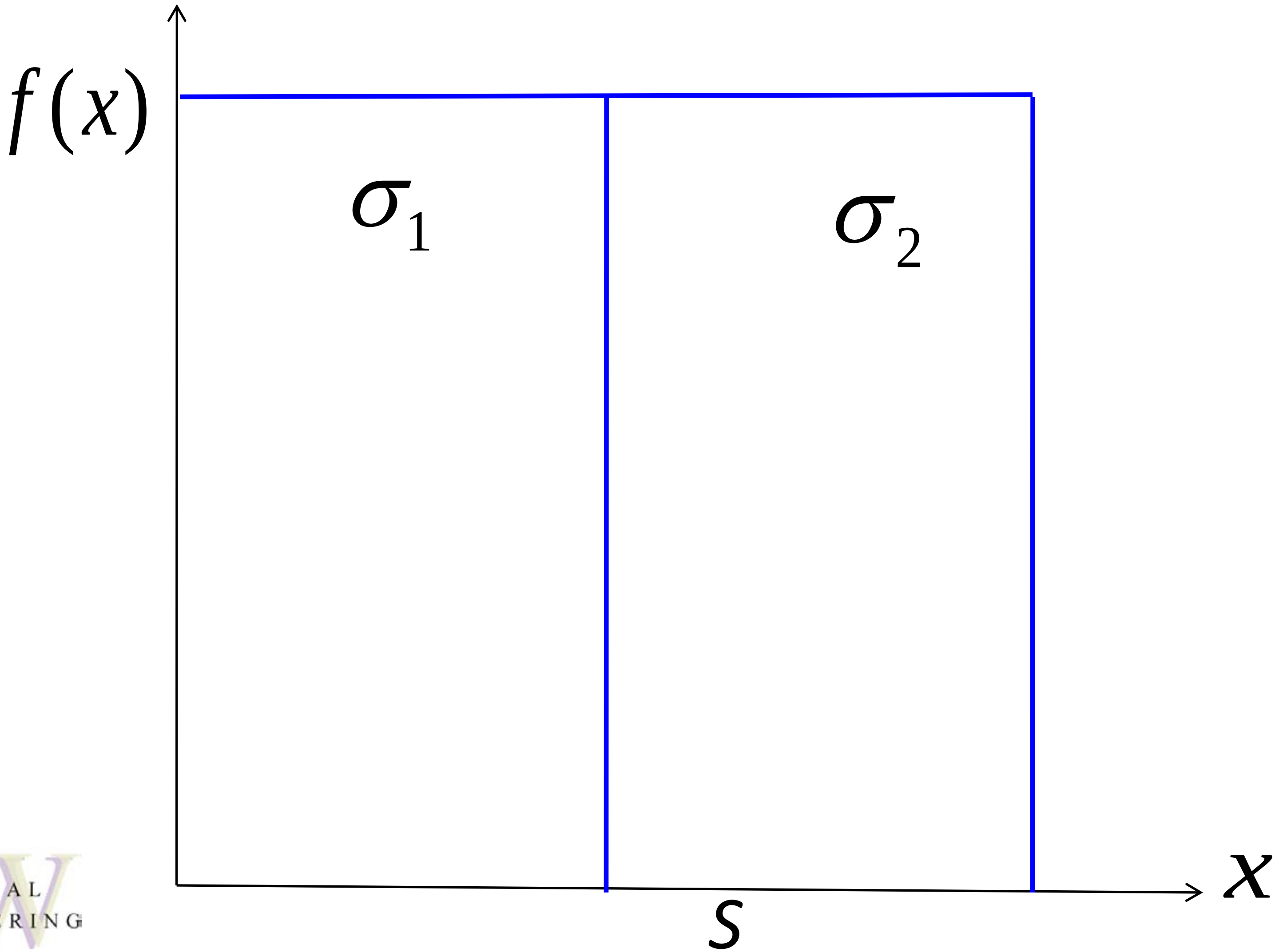
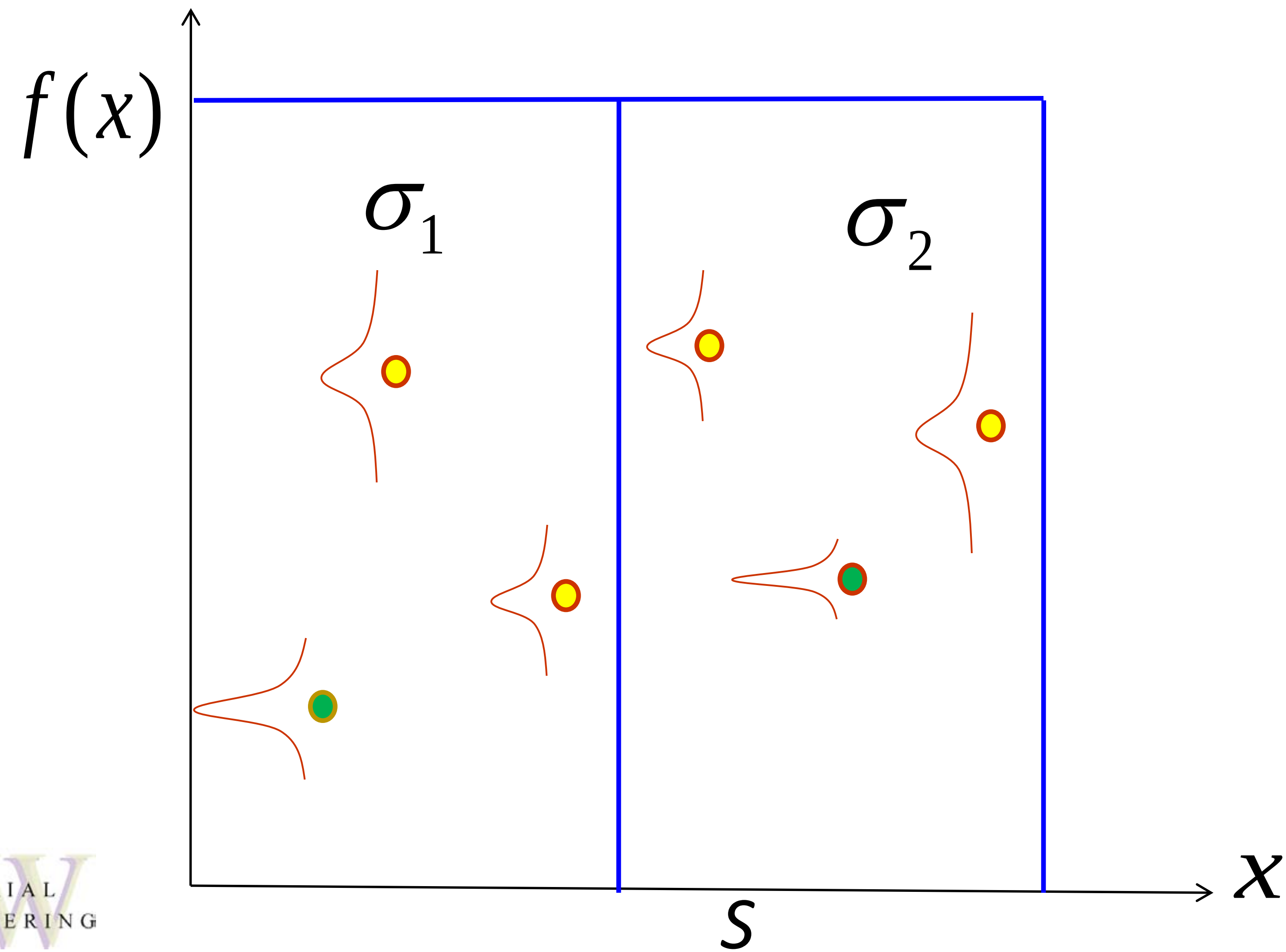
Noisy Objective Function



Probabilistic Branch-and-Bound (PBnB)



Sample N^* Uniform Random Points with R^* Replications



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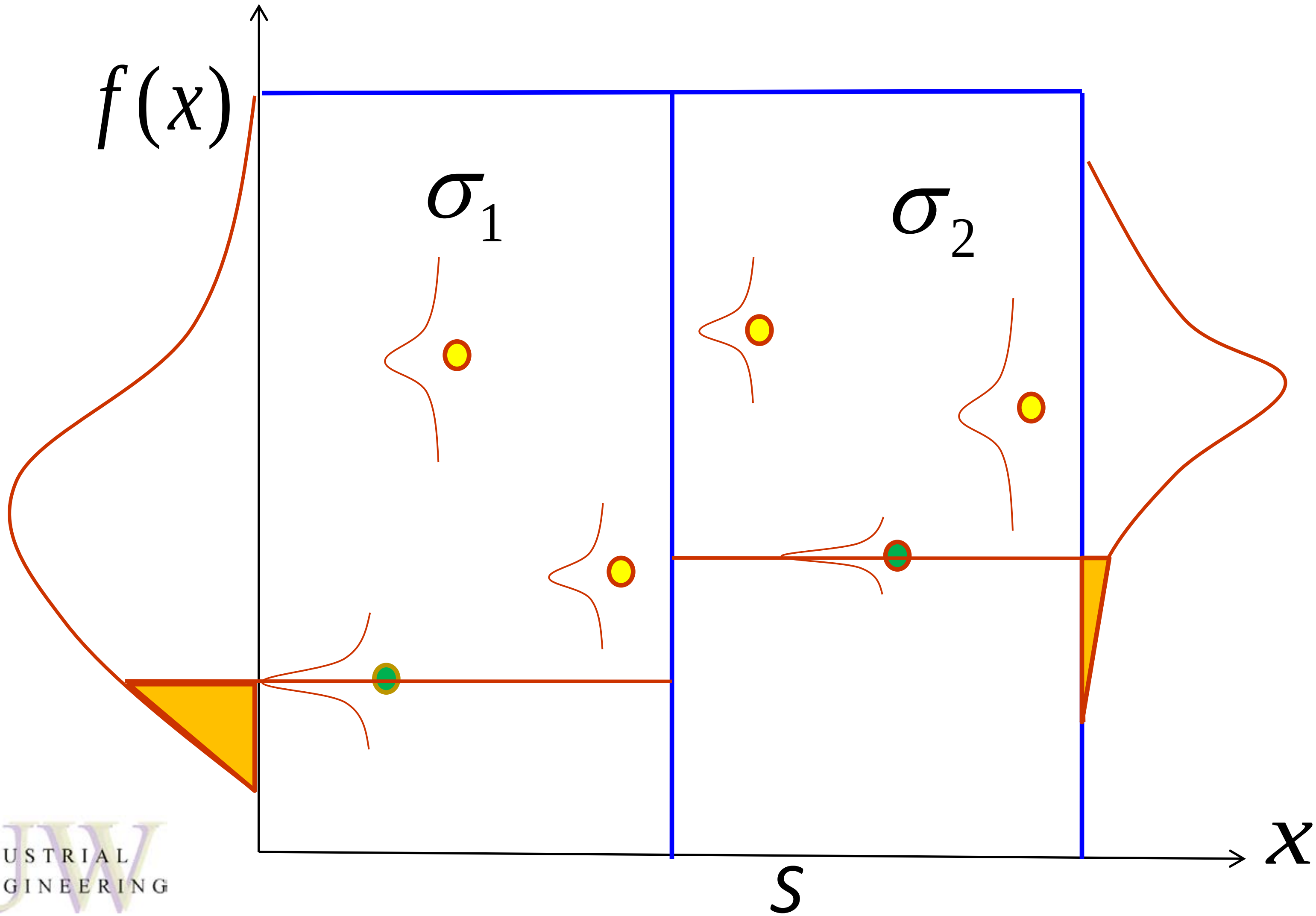
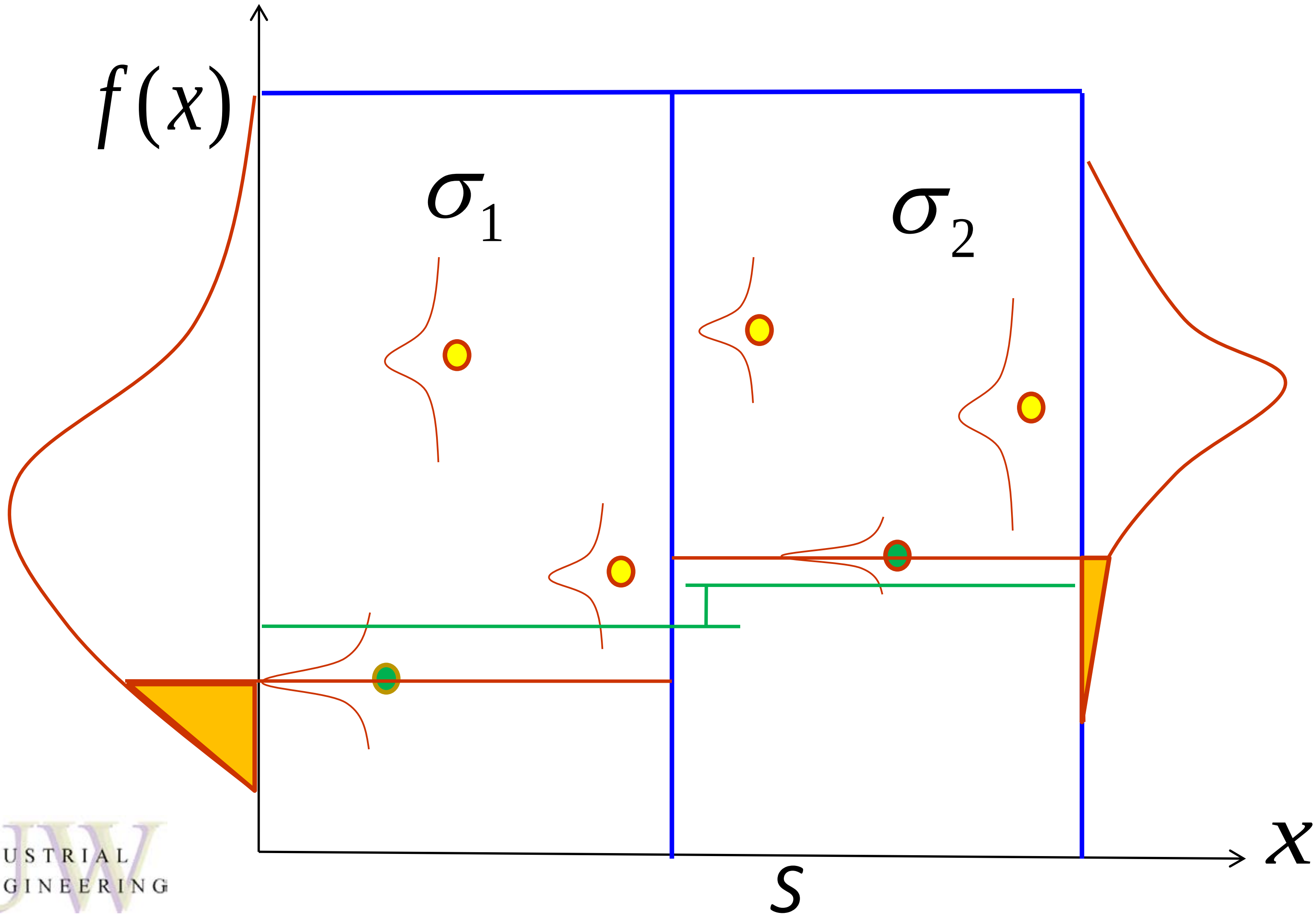
Use Order Statistics to Assess Range Distribution



Prune, if Statistically Confident



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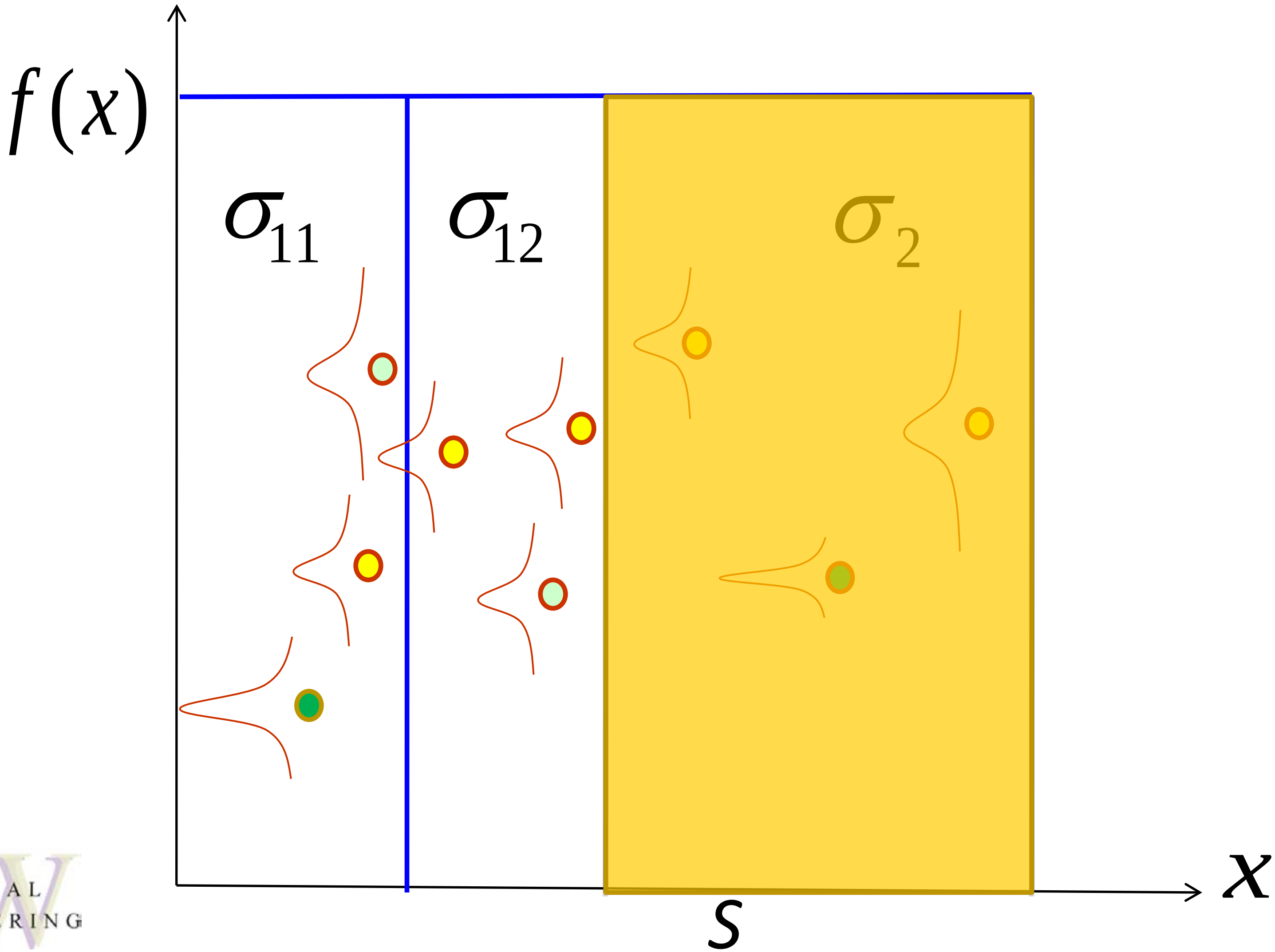
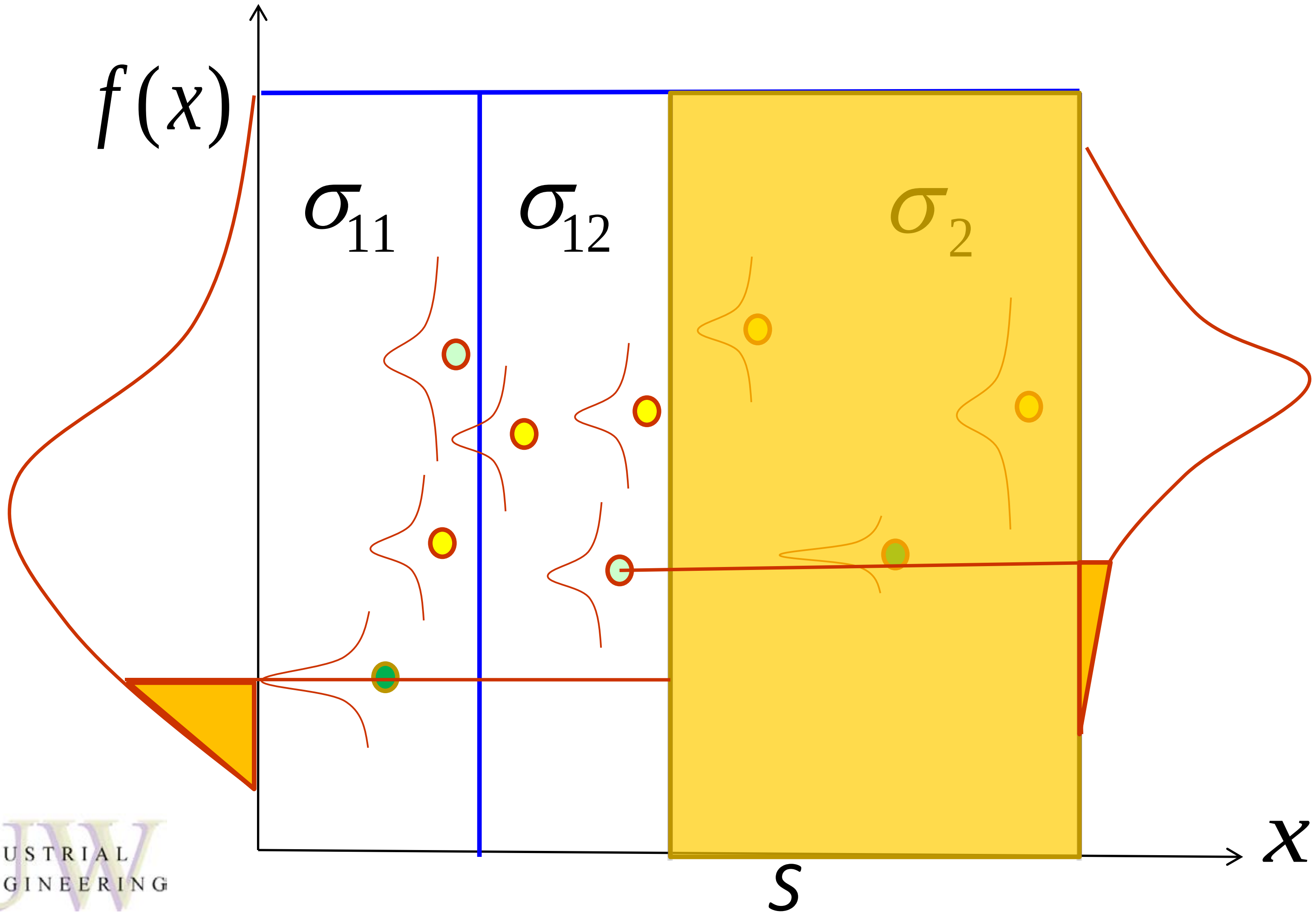
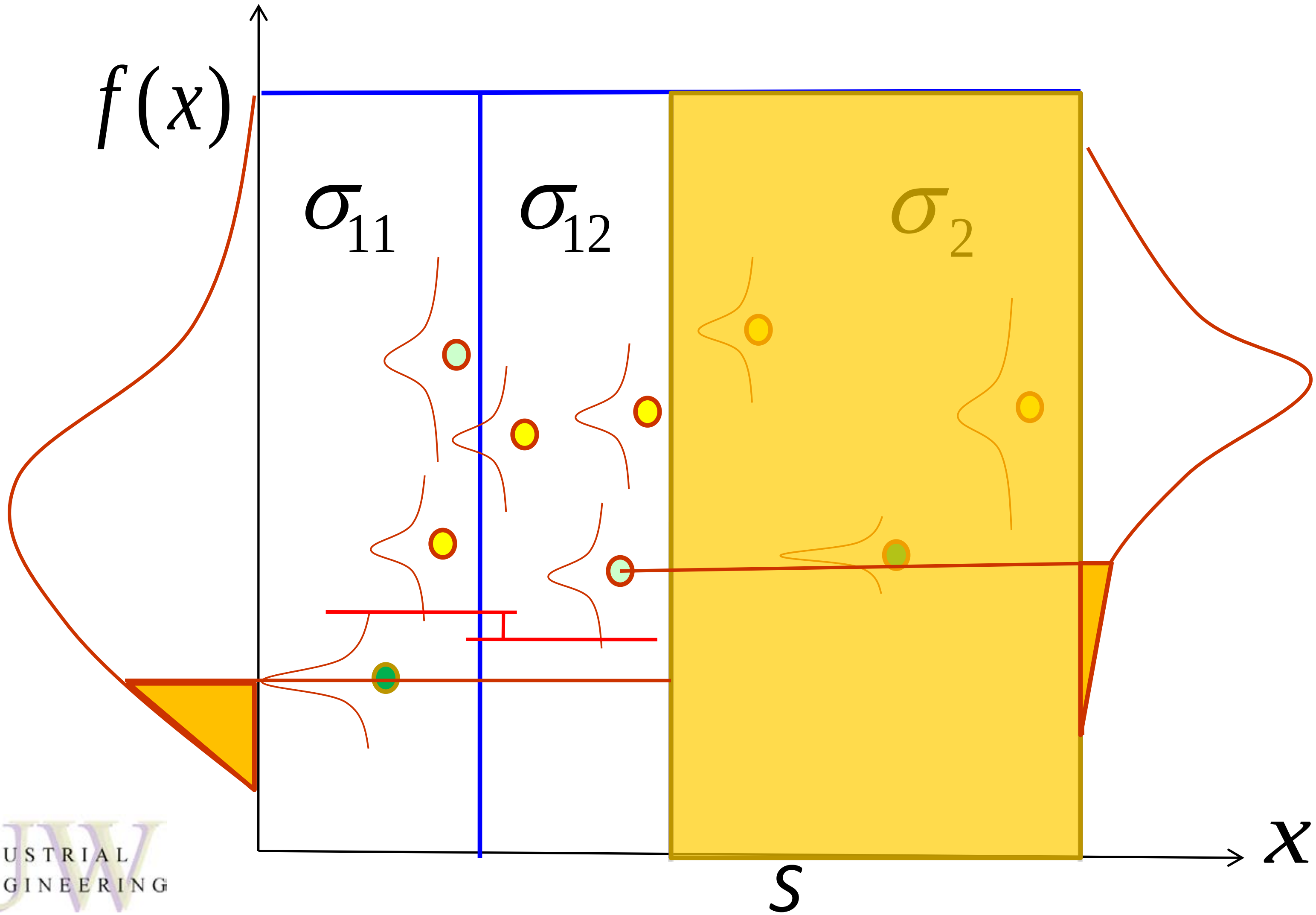
Subdivide & Sample Additional Points



Reassess Range Distribution



If No Pruning, Then Continue …



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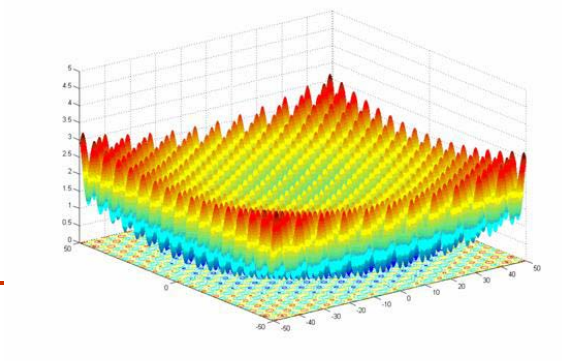
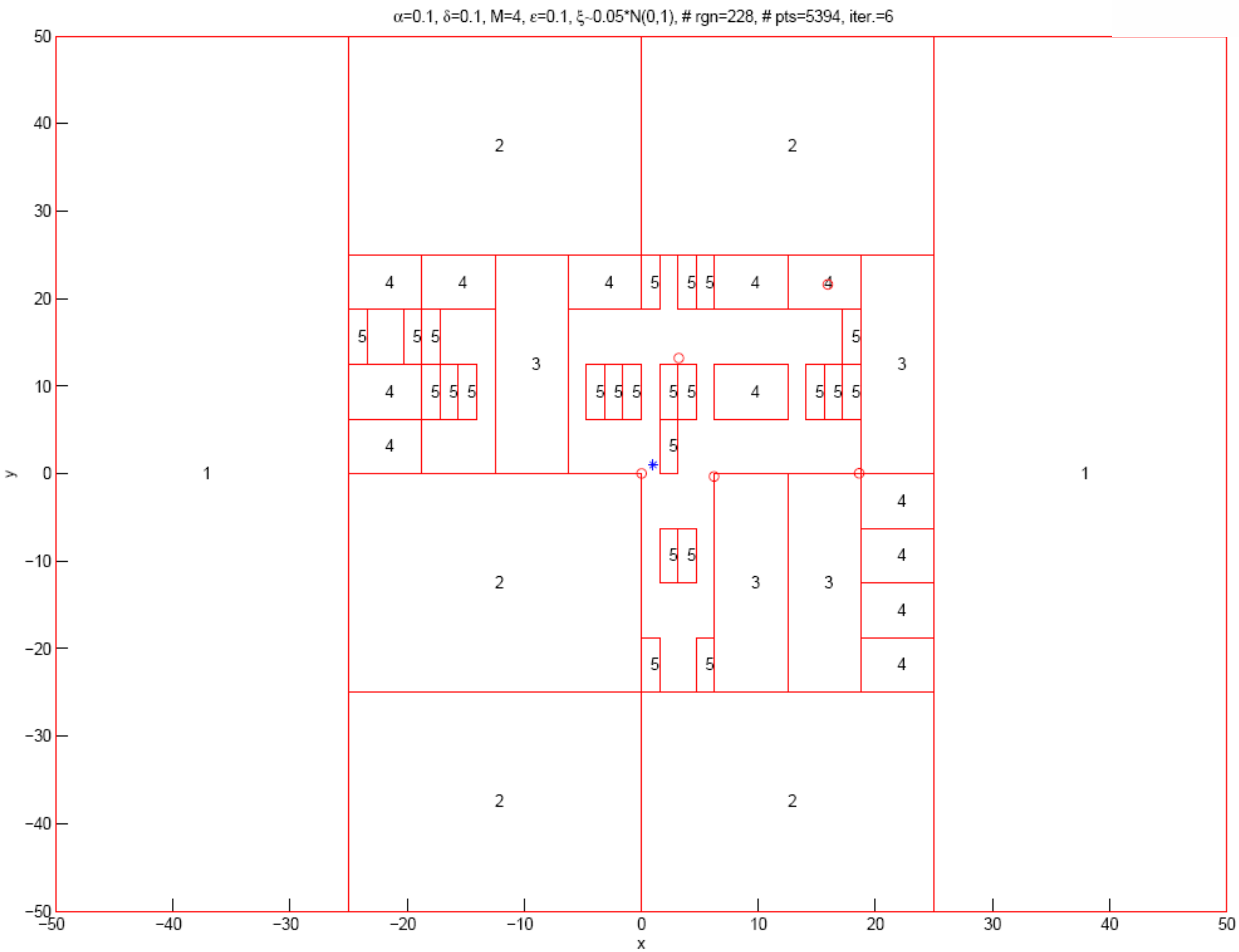
PBnB: Numerical Example





Research Areas

- Develop theory to tradeoff accuracy with computational effort
- Use theory to develop algorithms that give insight into original problem
  - Global optima and sensitivity
  - Shape of the function or range distribution
- Use interdisciplinary approaches to incorporate feedback

Summary

- Theoretical analysis of PAS, HAS, AAS motivates random search algorithms
- Hit-and-Run is a MCMC method to approximate theoretical performance
- Meta-control theory allows adaptation based on observations
- Probabilistic Branch-and-Bound incorporates noisy function evaluations and sampling noise into analysis

Additional Slides for Details on Interacting Particle Algorithm

Interacting-Particle Algorithm

- Simulated Annealing: Markov chain Monte Carlo method for approximating a sequence of Boltzmann distributions

$$\eta_t(dx) = \frac{e^{-f(x)/T_t}}{\int_S e^{-f(y)/T_t} dy} dx$$

- Population-based Algorithms: simulate a distribution (e.g. Feynman-Kac annealing model)such that

$$E_{\eta_t}(f) \to y^* \quad \text{as} \quad t \to \infty$$

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Interacting-Particle Algorithm

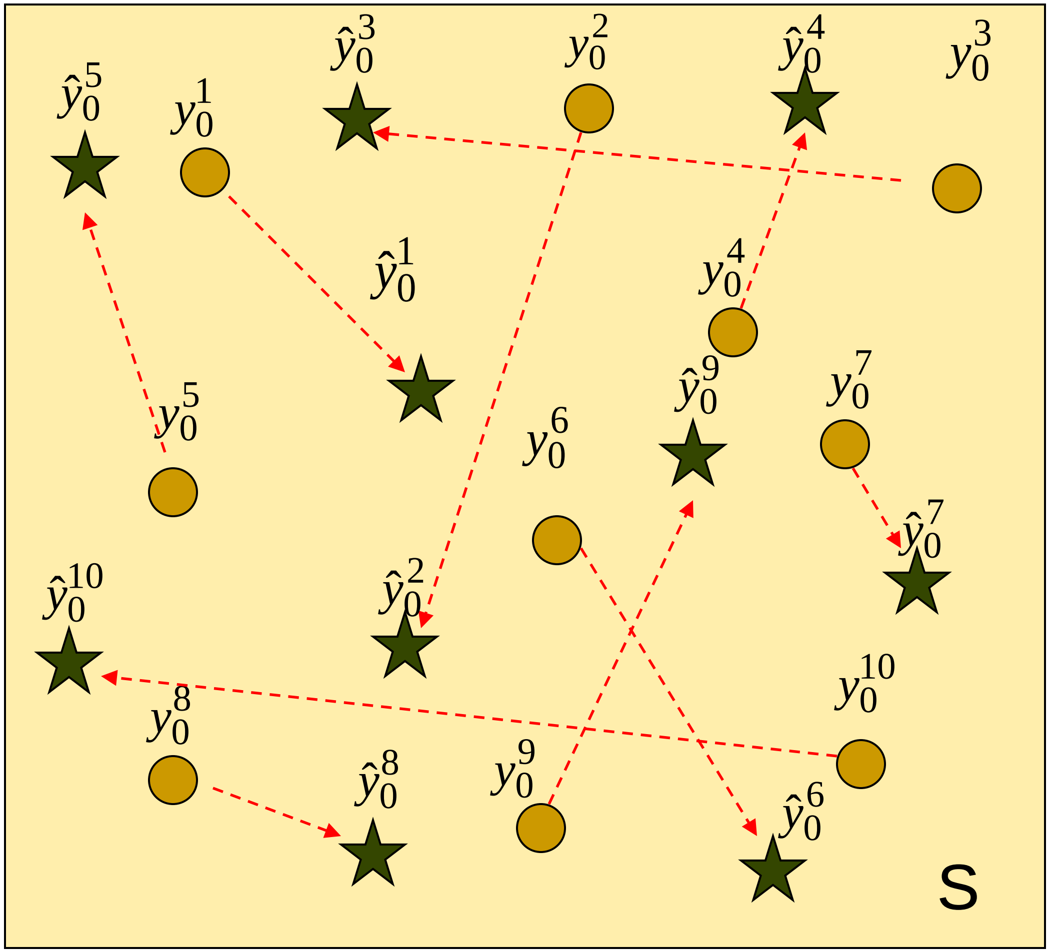
- **Initialization:** Sample the initial locations y_0^i for particle *i=1,…,N* from the distribution η_0

For $t=0,1,\ldots,$

- **N-particle exploration:** Move particle *i=1,…,N* to location $\hat{y}_t^i$ with probability distribution $E(y_t^i, d\hat{y}_t^i)$
- **Temperature Parameter Update:** $T_t = (1+\varepsilon_t)T_{t-1}, \quad \varepsilon_t \geq -1$
- **N-particle selection:** Set the particles' locations $y_{t+1}^k, i=1,\ldots,N$

$$y_{t+1}^k = \hat{y}_t^i \text{ with probability } \frac{e^{-f(\hat{y}_t^i)/T_t}}{\sum_{j=1}^{N} e^{-f(\hat{y}_t^j)/T_t}}$$

Illustration of Interacting-Particle Algorithm

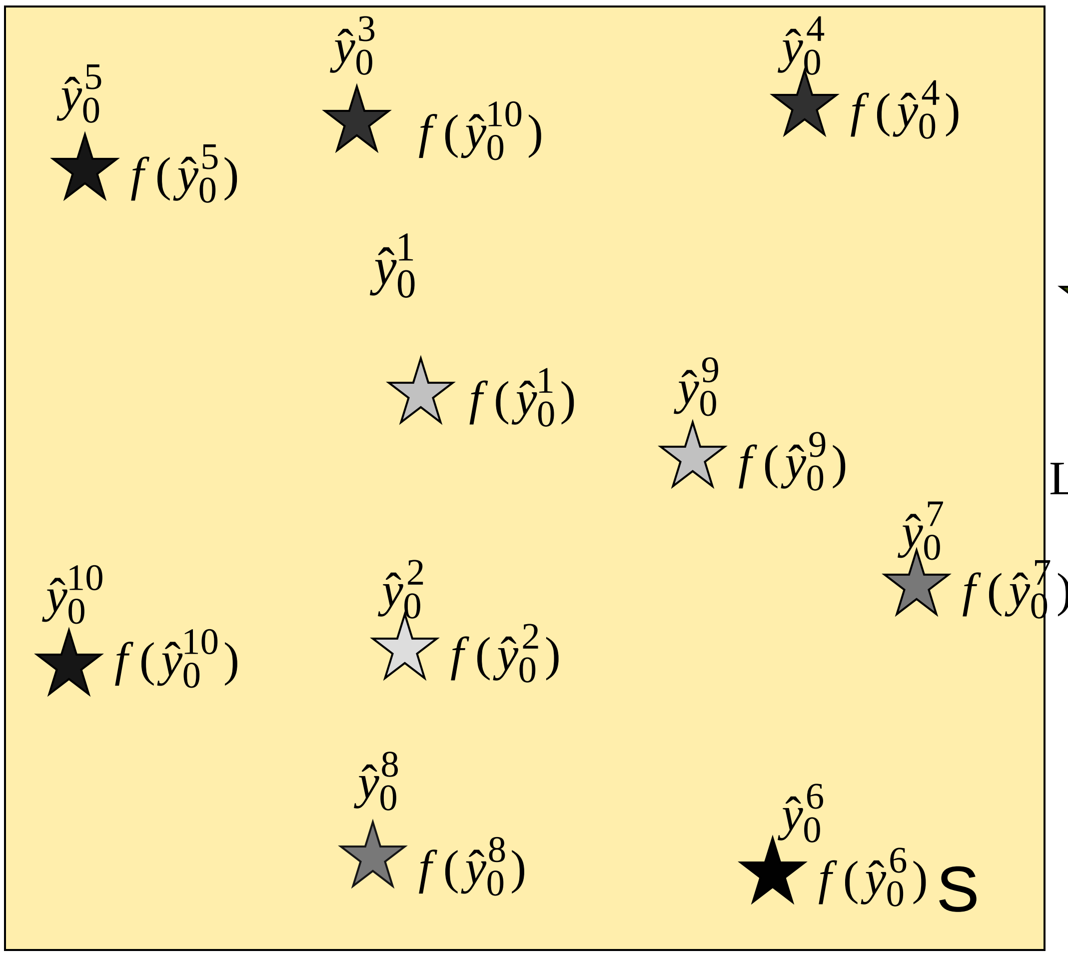


Initialization: Sample N=10 points uniformly on S

N-particle exploration:

Move particles from ● to ★ using Markov kernel E

Illustration of Interacting-Particle Algorithm



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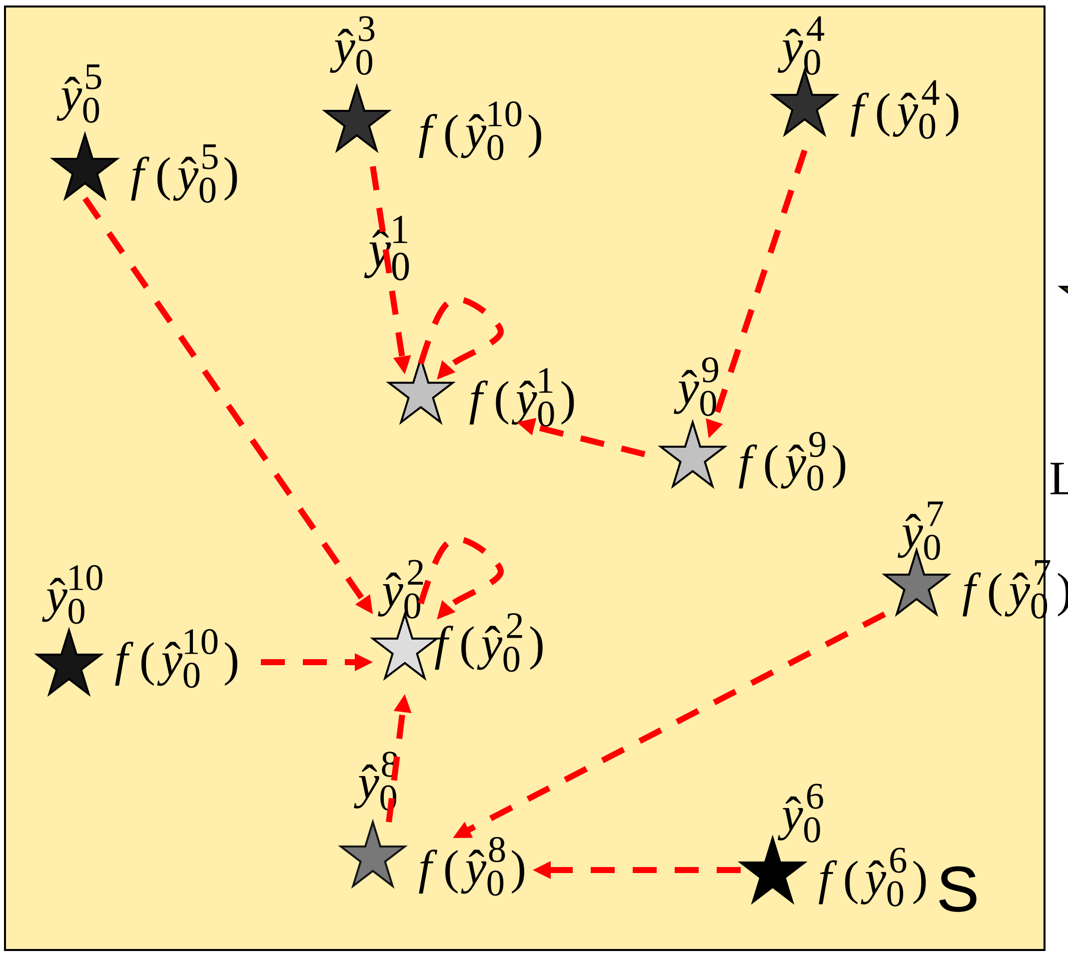
Evaluate $f(.)$

Illustration of Interacting-Particle Algorithm



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N-particle selection:

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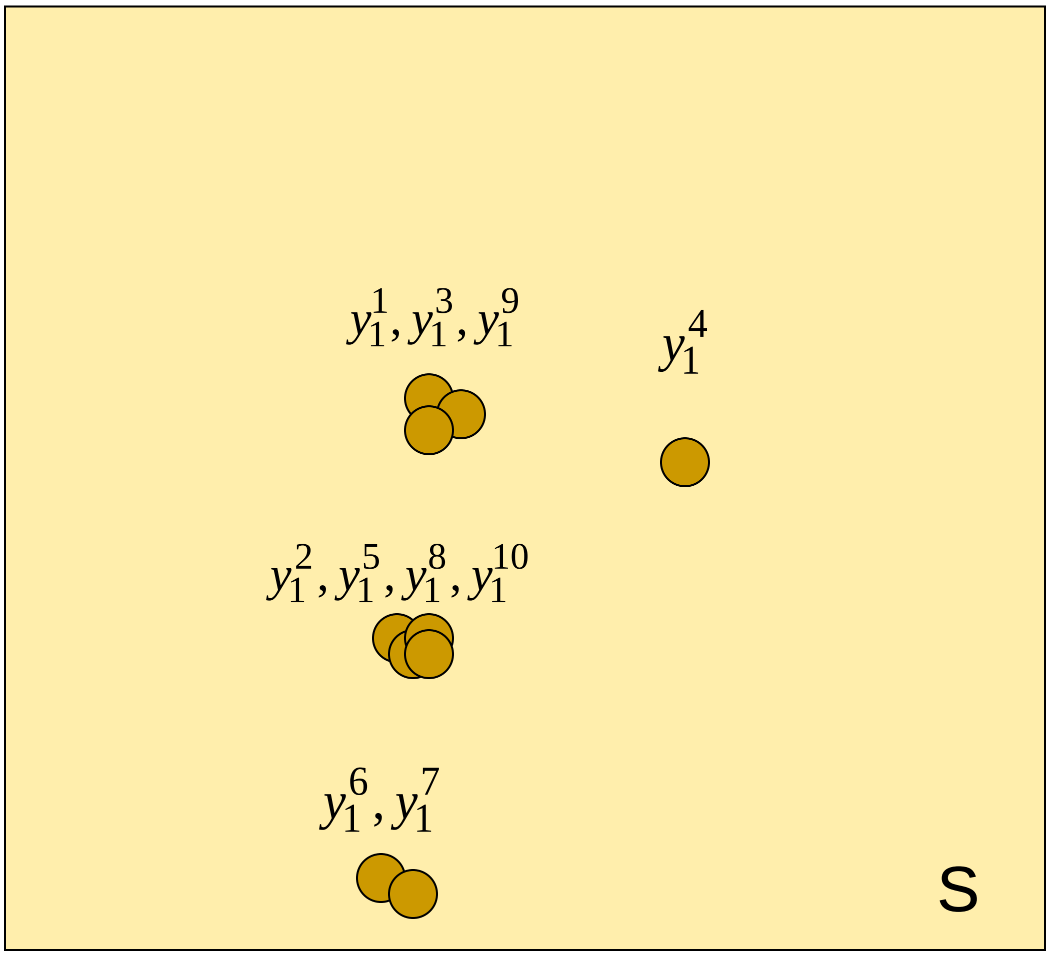
Illustration of Interacting-Particle Algorithm



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Multi-start or Population-based Algorithms

- Multi-start and clustering algorithms
  [Rinnooy Kan and Timmer, 1987] [Locatelli and Schoen, 1999]
- Genetic algorithms [Davis, 1991]
- Evolutionary programming [Bäck, Fogel and Michalewicz, 1997]
- Particle swarm optimization [Kennedy, Eberhart and Shi, 2001]
- Interacting particle algorithm [del Moral, 2004]

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