



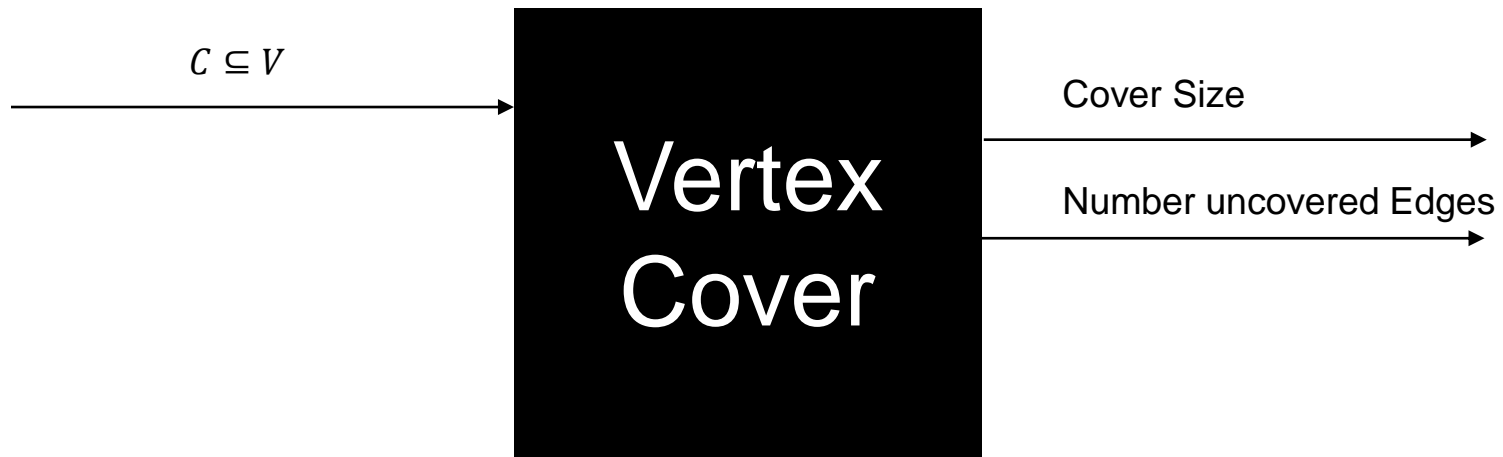
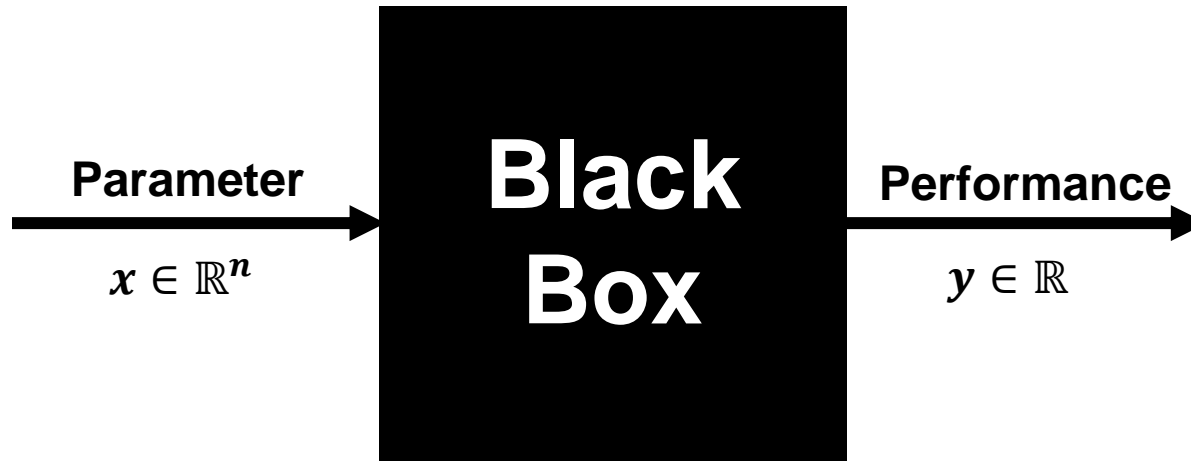
Drift Theory and its use for the Analysis of Evolutionary Algorithms

22.11.2023

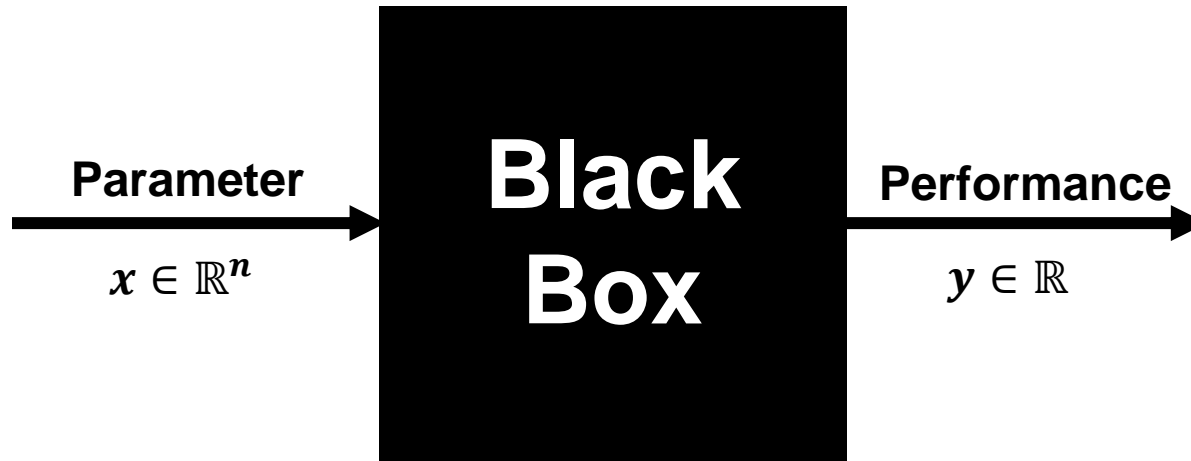
I have always had that **drift**, that's key for me.
- Yuzvendra Chahal

Dr. Timo Kötzing
Algorithm Engineering
Hasso-Plattner-Institut
Potsdam, Germany

What is black box optimization?



What is black box optimization?



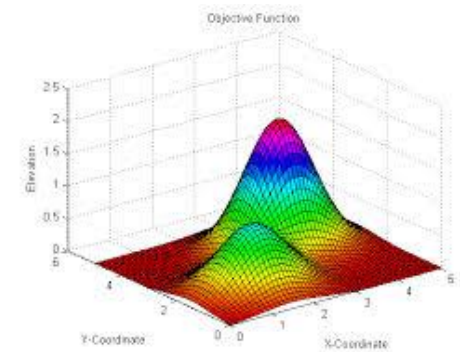
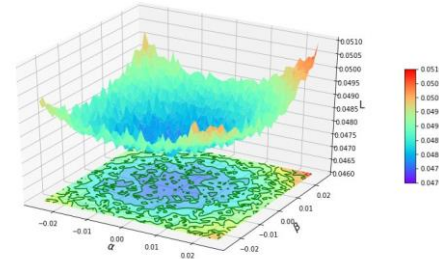
We **optimize** functions

$$f: \mathbb{R}^n \rightarrow \mathbb{R}.$$

Multi-Objective Optimization:

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^m.$$

- What hinders search?
 - ◆ Ruggedness
 - ◆ Local Optima
 - ◆ Noise
 - ◆ Dynamic Changes
 - ◆ Stagnation



Black-Box Algorithms for Theorists

Algorithm 1: Basic Search Algorithm

```
1  $x \leftarrow$  random individual;  
2 while true do  
3    $y \leftarrow$  mutate( $x$ );  
4   if  $f(y) \leq f(x)$  then  
5      $x \leftarrow y$ ;
```

- **Minimization**
- **Mutation** (for example $x \in \{0,1\}^n$)
 - ◆ Flip **one** bit u.a.r.
 - ◆ Flip **each bit independently** with prob. $1/n$
- Accept **equal**; reject **worse**

(μ, λ) -EA

Algorithm 1: $(\mu + \lambda)$ -EA

```
1  $P \leftarrow \mu$  random individuals;
2 while true do
3    $P' \leftarrow \emptyset$ ;
4   for  $\lambda$  times do
5      $x \leftarrow \text{select}(P)$ ;
6      $y \leftarrow \text{mutate}(x)$ ;
7      $P' \leftarrow P' \uplus \{y\}$ ;
8    $P \leftarrow \text{pick}(\mu, P \cup P')$ ;
```

Algorithm 1: $(\mu + \lambda)$ -GA

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1  $P \leftarrow \mu$  random individuals;  
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5      $x \leftarrow \text{select}(P)$ ;  
6      $y \leftarrow \text{select}(P)$ ;  
7      $z \leftarrow \text{crossover}(x, y)$ ;  
8      $P' \leftarrow P' \uplus \{z\}$ ;  
9    $P \leftarrow \text{pick}(\mu, P \cup P')$ ;
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(μ, λ) -EA

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```

Algorithm 1: $(\mu + \lambda)$ -GA

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```

- EA \cong Mutation only
- GA \cong Crossover
- Plus-Selection \cong Keep the best
- Comma-Selection \cong Only new solutions

Mathematical Analysis

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Multiplicative Drift Theorem [DJW12]

If $E(Y_t - Y_{t+1} \mid X_t) \geq \delta Y_t$
Then, for $T = \min\{t \mid Y_t < 1\}$,
 $E(T) \leq \ln(Y_0)/\delta$

[DJW12] Doerr, Johannsen, Winzen:
Multiplicative Drift Analysis, 2012

- Suppose $f(x) = |x|_0$ (called **OneMax**)
- Defines **random process** $X_t \in \{0,1\}^n$
 - ◆ $E(f(X_0)) = n/2$
- $T =$ **random** time till optimum reached
- Know: **Step-wise** change
 - ◆ $E(f(X_t) - f(X_{t+1}) \mid X_t) \geq X_t/(en)$

$$E(T) \leq en \ln(n)$$

Multiplicative Drift Theorem
[DJW12]

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[DJW12] Doerr, Johannsen, Winzen:
Multiplicative Drift Analysis, 2012

- Prime example: **Coupon Collector**
- Multi-Drift \approx **Generalized Coupon Collector**
- Drift Theorem:
 - ◆ **Random** process \approx **deterministic** analogon

Algorithm 1: Basic Search Algorithm

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```

Additive Drift Theorem

[HY04]

If $E(Y_t - Y_{t+1} \mid X_t) \geq \delta$
Then, for $T = \min\{t \mid Y_t = 0\}$,
 $E(T) \leq Y_0/\delta$

[HY04] He, Yao: *A study of drift analysis for estimating computation time of evolutionary algorithms*, 2004

- $f(x) = \#$ of 1s before first 0 (called **LeadingOnes**)
 - ◆ $E(f(X_0)) \leq n$
- Know: **Step-wise** change
 - ◆ $E(f(X_t) - f(X_{t+1}) \mid X_t) \geq 1/(en)$
- $E(T) \leq en^2$

Additive Drift Theorem

[HY04]

If $E(Y_t - Y_{t+1} \mid X_t) \geq \delta$

Then, for $T = \min\{t \mid Y_t = 0\}$,

$$E(T) \leq Y_0 / \delta$$

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- **Random** process \approx **deterministic** analogon
- **Traps:**
 - ◆ **No overshooting** allowed!
 - ◆ **Unbounded** Search spaces?

- **Drift** theorems turn **step-wise** gains into expected **times**

Additive Drift Theorem

[HY04]

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Multiplicative Drift Theorem

[DJW12]

If $E(Y_t - Y_{t+1} \mid X_t) \geq \delta Y_t$

Then, for $T = \min\{t \mid Y_t < 1\}$,

$$E(T) \leq \ln(Y_0) / \delta$$

[DJW12] Doerr, Johannsen, Winzen: *Multiplicative Drift Analysis*, 2012

- **Main tool** of modern analyzes
- Many more **elaborate variants** exist
- **Approximations** also analyzable

Thank You!