



Firas Ben Jedidia



Benjamin Doerr

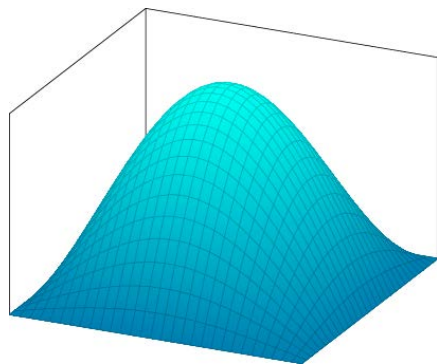


Martin S. Krejca

Estimation-of-Distribution Algorithms for Multi-Valued Decision Variables

Background

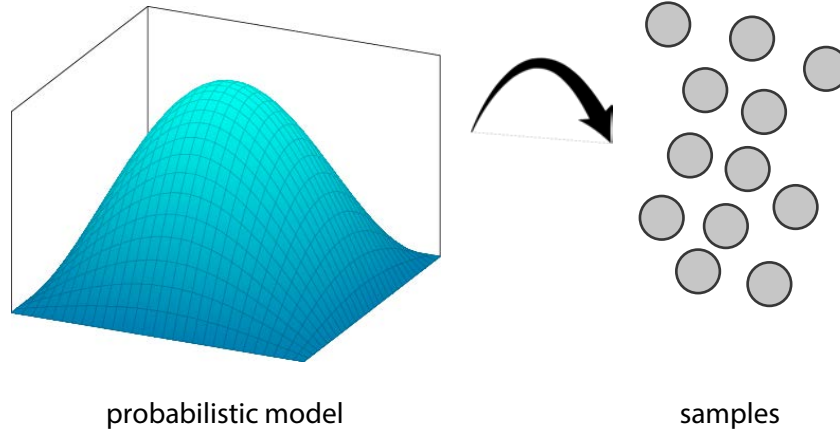
Estimation-of-Distribution Algorithms



probabilistic model

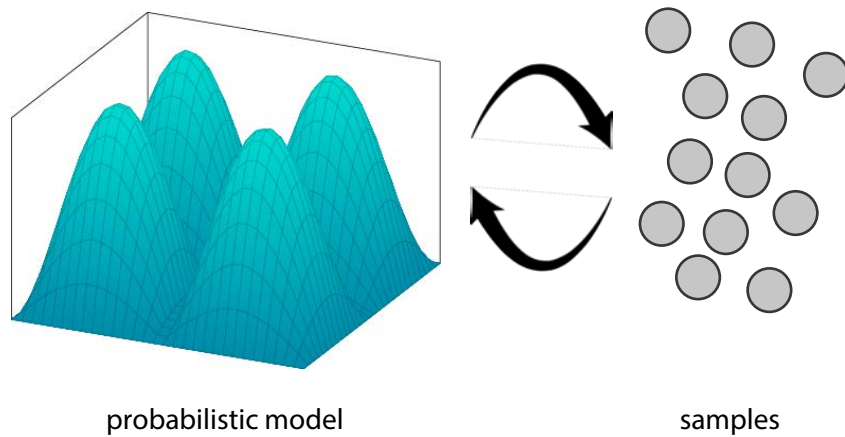
Background

Estimation-of-Distribution Algorithms



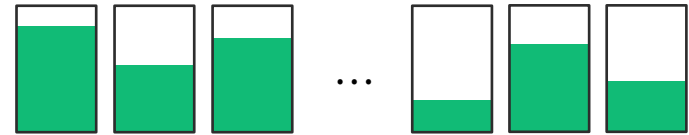
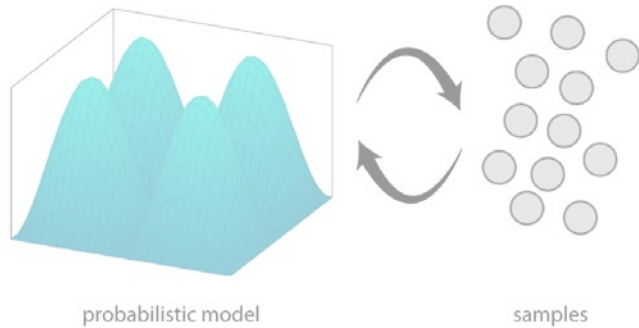
Background

Estimation-of-Distribution Algorithms



Background

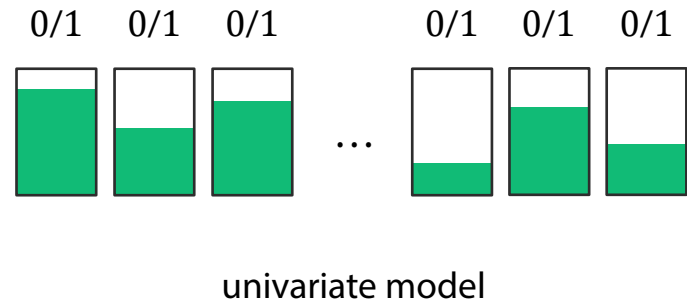
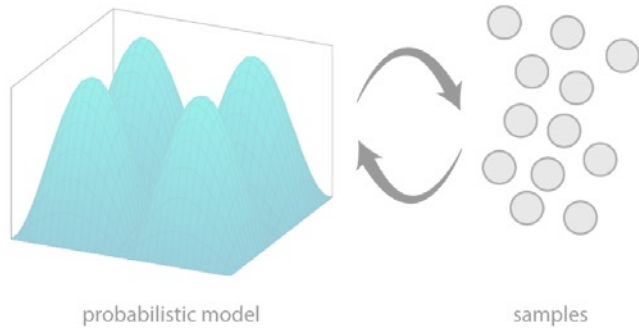
Estimation-of-Distribution Algorithms



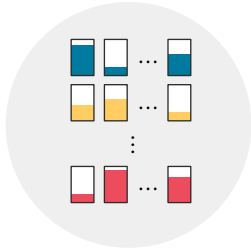
univariate model

Background

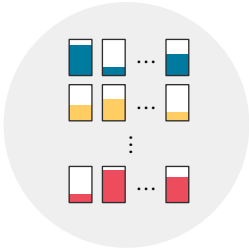
Estimation-of-Distribution Algorithms



Our Contribution



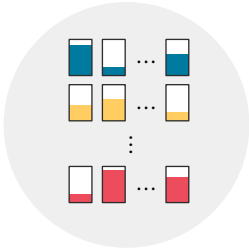
Our Contribution



1. Our Model



Our Contribution



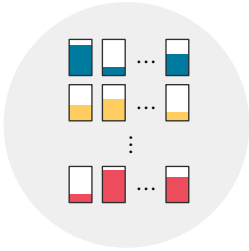
1. Our Model



2. Properties



Our Contribution



1. Our Model



2. Properties



3. Run Time Analysis

Our Model

(Univariate) Multi-Valued EDAs



$$[0..r-1]^n$$

Our Model

(Univariate) Multi-Valued EDAs



$$[0..r-1]^n$$



$$\mathbf{p} \in [0,1]^{n \times r}$$

(frequency matrix)

Our Model

(Univariate) Multi-Valued EDAs

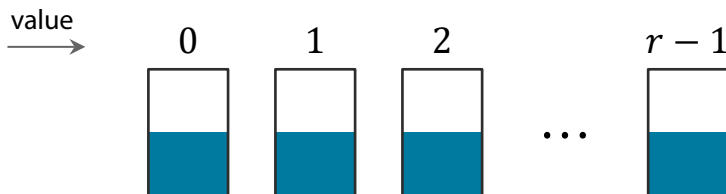


$$[0..r-1]^n$$



$$\mathbf{p} \in [0,1]^{n \times r}$$

(frequency matrix)



Our Model

(Univariate) Multi-Valued EDAs



$$[0..r-1]^n$$



$$\mathbf{p} \in [0,1]^{n \times r} \quad (\text{frequency matrix})$$

value
→



...



$$\sum \text{[bar icon]} = 1$$

Our Model

(Univariate) Multi-Valued EDAs



$$[0..r-1]^n$$



$$\mathbf{p} \in [0,1]^{n \times r}$$

(frequency matrix)

value
→



...



$$\sum \text{bin} = 1 \quad \mathbf{p}_{i,j}^{(0)} = \frac{1}{r}$$

Our Model

(Univariate) Multi-Valued EDAs

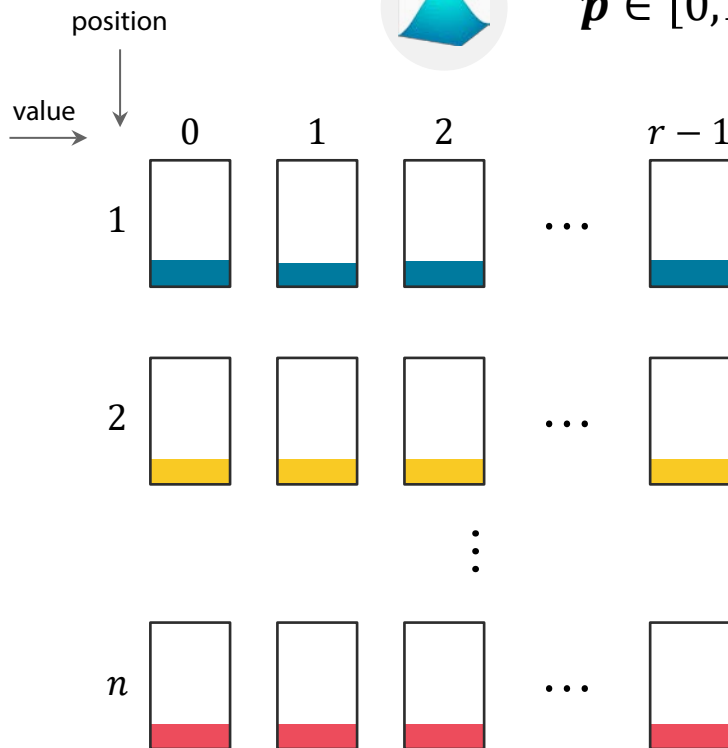


$$[0..r-1]^n$$



$$\mathbf{p} \in [0,1]^{n \times r}$$

(frequency matrix)



$$\sum \text{box} = 1 \quad \mathbf{p}_{i,j}^{(0)} = \frac{1}{r}$$

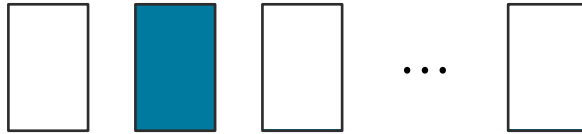
Our Model

Rounding Frequencies



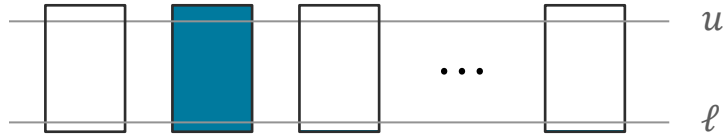
Our Model

Rounding Frequencies



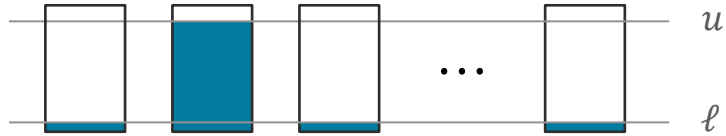
Our Model

Rounding Frequencies



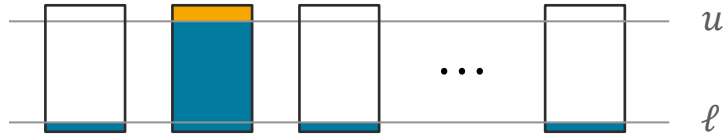
Our Model

Rounding Frequencies



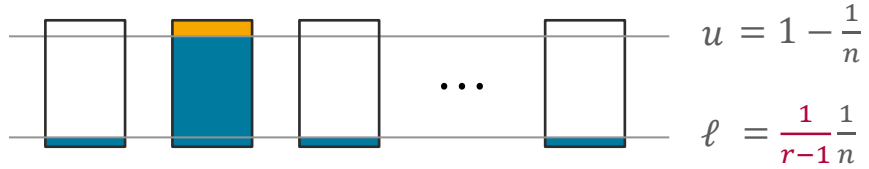
Our Model

Rounding Frequencies



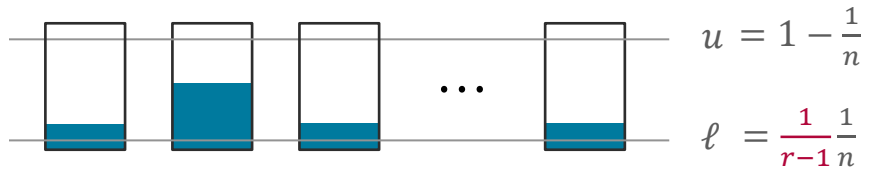
Our Model

Rounding Frequencies



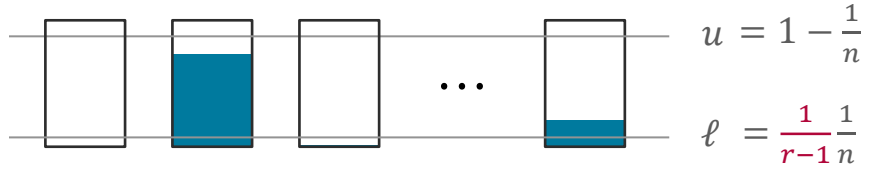
Our Model

Rounding Frequencies



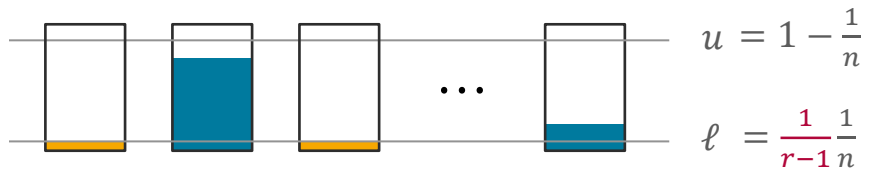
Our Model

Rounding Frequencies



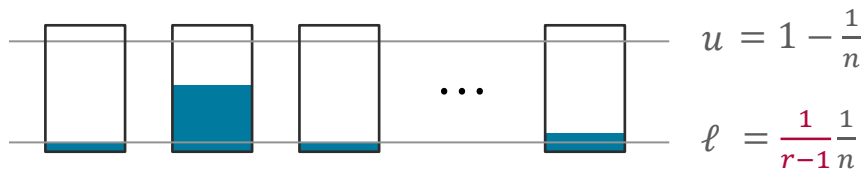
Our Model

Rounding Frequencies



Our Model

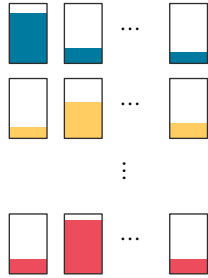
Rounding Frequencies



$$p_{i,j}^{\text{new}} = \left(p_{i,j}^{\text{after rounding}} - \ell \right) \frac{1 - r\ell}{1 - r\ell + \text{bin}} + \ell$$

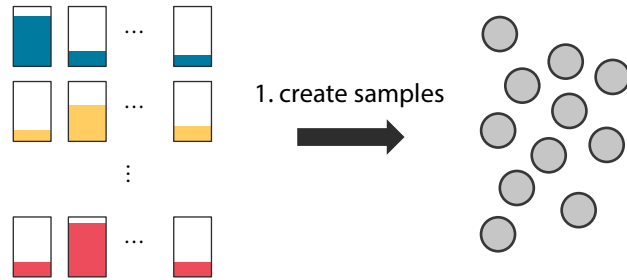
Our Model

r -UMDA



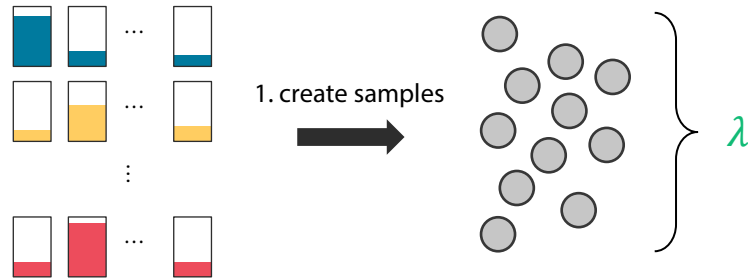
Our Model

r -UMDA



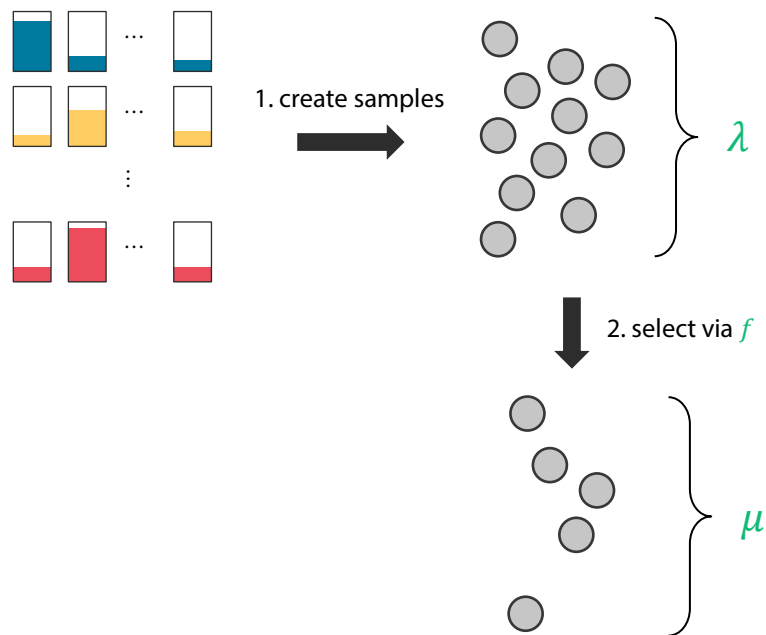
Our Model

r -UMDA



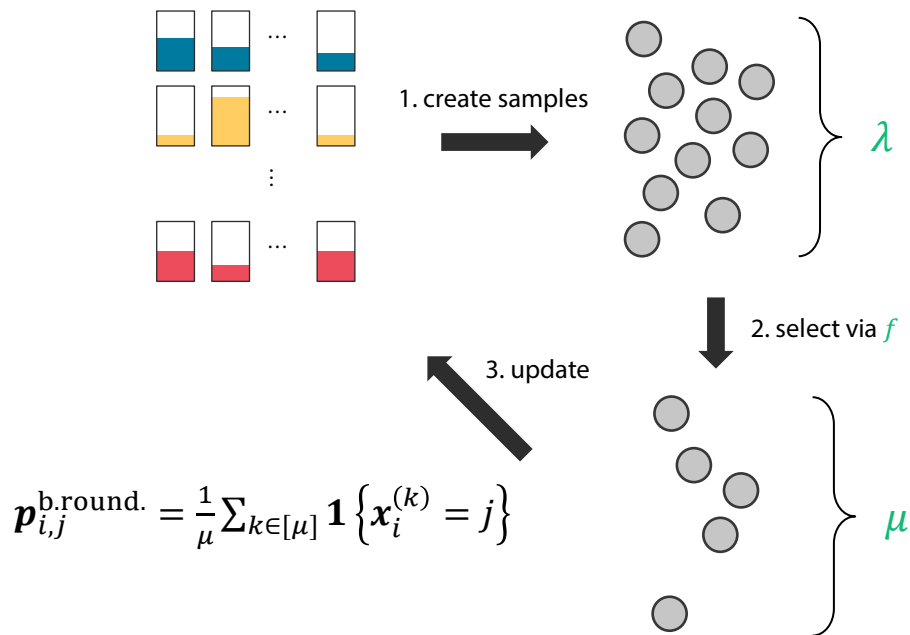
Our Model

r -UMDA



Our Model

r -UMDA



Balanced Frequencies

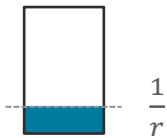


$$\mathbb{E} \left[\mathbf{p}_{i,j}^{(t+1)} \mid \mathbf{p}_{i,j}^{(t)} \right] = \mathbf{p}_{i,j}^{(t)} \quad (\text{balanced frequency})$$

Balanced Frequencies



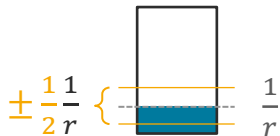
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Balanced Frequencies



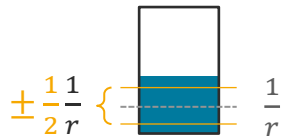
$$\mathbb{E} \left[\mathbf{p}_{i,j}^{(t+1)} \mid \mathbf{p}_{i,j}^{(t)} \right] = \mathbf{p}_{i,j}^{(t)} \quad (\text{balanced frequency})$$



Balanced Frequencies



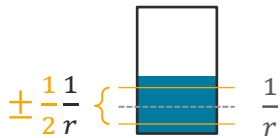
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Balanced Frequencies



$$\mathbb{E} \left[\mathbf{p}_{i,j}^{(t+1)} \mid \mathbf{p}_{i,j}^{(t)} \right] = \mathbf{p}_{i,j}^{(t)} \quad (\text{balanced frequency})$$

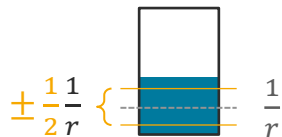


$$\Pr \left[\max_{s \in [0..T]} \left| \mathbf{p}_{i,j}^{(s)} - \frac{1}{r} \right| \geq \frac{1}{2r} \right] \approx \exp \left(-\frac{\mu}{Tr} \right) \quad (r\text{-UMDA})$$

Balanced Frequencies



$$\mathbb{E} \left[\mathbf{p}_{i,j}^{(t+1)} \mid \mathbf{p}_{i,j}^{(t)} \right] = \mathbf{p}_{i,j}^{(t)} \quad (\text{balanced frequency})$$



$$\Pr \left[\max_{s \in [0..T]} \left| \mathbf{p}_{i,j}^{(s)} - \frac{1}{r} \right| \geq \frac{1}{2r} \right] \approx \exp \left(-\frac{\mu}{Tr} \right) \quad (r\text{-UMDA})$$



Theoretician's Trick

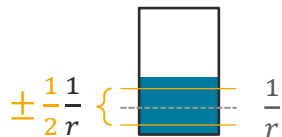
$T \dots$ intended run time ^(# iter.)

$$\mu = Tr \log(n)$$

Balanced Frequencies



$$\mathbb{E} \left[\mathbf{p}_{i,j}^{(t+1)} \mid \mathbf{p}_{i,j}^{(t)} \right] = \mathbf{p}_{i,j}^{(t)} \quad (\text{balanced frequency})$$



$$\Pr \left[\max_{s \in [0..T]} \left| \mathbf{p}_{i,j}^{(s)} - \frac{1}{r} \right| \geq \frac{1}{2} \frac{1}{r} \right] \lesssim \exp \left(-\frac{\mu}{Tr} \right) \quad (r\text{-UMDA})$$



Theoretician's Trick

$T \dots$ intended run time ^(# iter.)
 $\mu = Tr \log(n)$

$$\Rightarrow \Pr[\dots] \lesssim \frac{1}{n^{O(1)}}$$

Run Time Analysis



r-LeadingOnes

Run Time Analysis



r -LeadingOnes

$$(0, 15, 0, 0, 0, r - 1) \mapsto 1$$

$$\left(0, 0, 0, 1, 3, \frac{r}{2}\right) \mapsto 3$$

Run Time Analysis



r -LeadingOnes

$$(0, 15, 0, 0, 0, r - 1) \mapsto 1$$

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r -UMDA

Run Time Analysis



r -LeadingOnes

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r -UMDA



Our Result

Run Time Analysis



r -LeadingOnes

$$(0, 15, 0, 0, 0, r - 1) \mapsto 1$$

$$\left(0, 0, 0, 1, 3, \frac{r}{2}\right) \mapsto 3$$



r -UMDA



Our Result

$$T \lesssim n \log(r) \text{ w.h.p.}$$

if: $\mu \gtrsim n \log(r) \textcolor{teal}{r} \log(n)$

$$\lambda \gtrsim \mu$$

Run Time Analysis

Proof Sketch

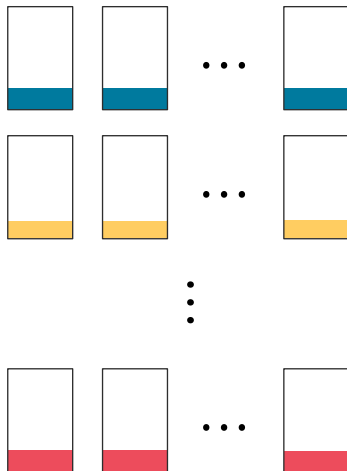


Our Result

$T \lesssim n \log(r)$ w.h.p.

if: $\mu \gtrsim n \log(r)$ $r \log(n)$

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Run Time Analysis

Proof Sketch

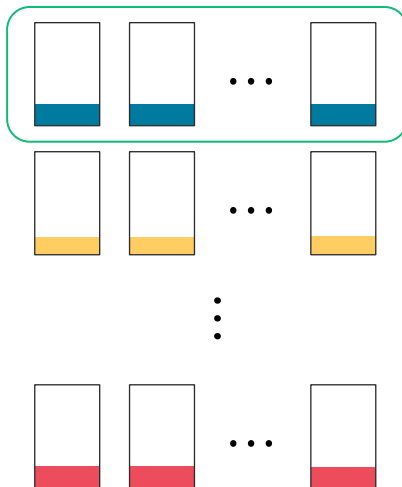


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Run Time Analysis

Proof Sketch

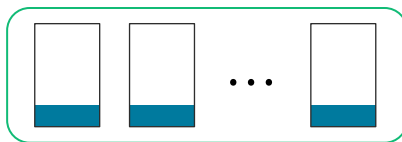


Our Result

$T \lesssim n \log(r)$ w.h.p.

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$\lambda \gtrsim \mu$



$(0, 15, 0, 0, 0, r-1)$ $(2, 1, 12, 3, r-5, 0)$

$(0, 0, 7, r-2, 4, 2)$ $(3, 0, 0, 7, 18, 23)$



$\vdots$



Run Time Analysis

Proof Sketch

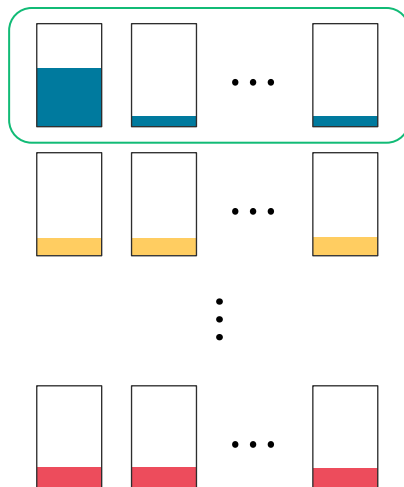


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Run Time Analysis

Proof Sketch

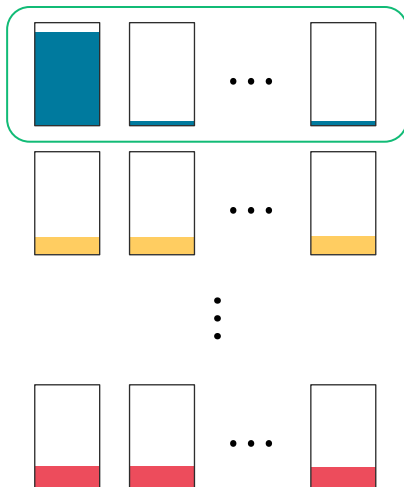


Our Result

$T \lesssim n \log(r)$ w.h.p.

if: $\mu \gtrsim n \log(r)$ $r \log(n)$

$\lambda \gtrsim \mu$



$\approx \log(r)$

Run Time Analysis

Proof Sketch



Our Result

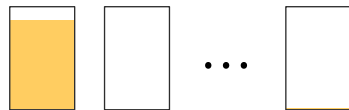
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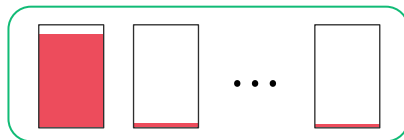


$\approx \log(r)$



$\approx \log(r)$

$\vdots$



$\approx \log(r)$

Run Time Analysis

Proof Sketch



Our Result

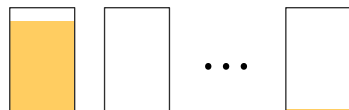
$T \lesssim n \log(r)$ w.h.p.

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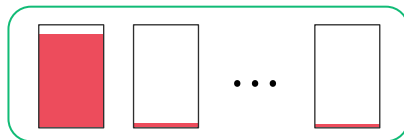


$\approx \log(r)$



$\approx \log(r)$

$\vdots$



$\approx \log(r)$

fin

» Runtime Analysis of a Multi-Valued Compact Genetic Algorithm on Generalized OneMax



[Adak, Witt'24]