

Are the artificially generated instances uniform in terms of difficulty?

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Outline

Introduction

Difficulty and parametric roughness

Experiments

Conclusions

Motivation

- ▶ Combinatorial optimization problems (**COP**):
instances \equiv parameters
- ▶ Artificially generated **benchmarks**
- ▶ Usually **parameters** are generated uniformly at random (**u.a.r**)
- ▶ How is the **distribution of the difficulty** of the generated instances?
- ▶ Goal: **empirically** analyze the distribution of the difficulty
- ▶ Difficulty is algorithm dependent: **local search**

Combinatorial optimization problems (COP)

Objective/fitness function

$$\begin{aligned} f &: \Omega \rightarrow \mathbb{R} \\ x &\mapsto f(x; \Theta) \end{aligned}$$

- ▶ In this work: linear ordering problem (**LOP**), flowshop scheduling problem (**FSP**) and quadratic assignment problem (**QAP**)
- ▶ Discrete search space, Ω : permutations of size n .
- ▶ Parameters, Θ : instance.

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Neighborhood

Progresses by moving from one solution to a better neighboring.

- ▶ First improvement
- ▶ Best improvement (**BI**)

Neighborhoods

$$\begin{aligned} N : \quad \Omega &\rightarrow 2^\Omega \\ x &\mapsto N(x) \end{aligned}$$

2^Ω represents the power set of the search space.

- ▶ **Swap**: Perform any exchange of two items in consecutive positions (Kendall's distance one).
- ▶ **Interchange**: Perform any exchange of the items in any two positions i and j (Cayley's distance one).
- ▶ **Insert**: Move any item from a position i to any position j (Ulam's distance one).

Difficulty of an instance

Difficulty

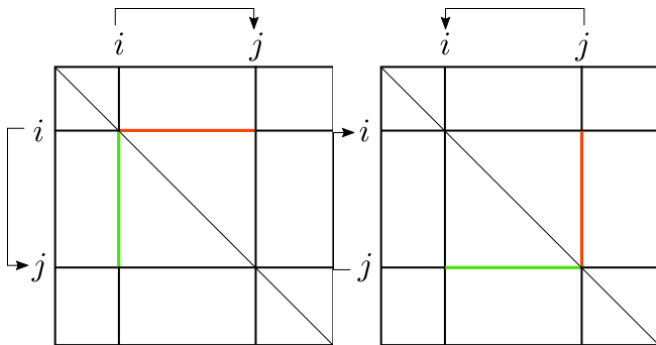
The **probability of not reaching the global optimum** when starting from a solution taken u.a.r.

- ▶ Inversely proportional to the size of the **basis of attraction of the global optimum**: number of solutions from which BI reaches the optimum
- ▶ Classify instances according to the difficulty: $\mathcal{O}(n!)$ equivalence classes.

Parametric roughness

The **number of parameters that differ** between a solution and its neighbors in the computation of their fitness functions.

- ▶ **LOP**: $f(\sigma; B = \{b_{i,j}\}_{n \times n}) = \sum_{i=1}^{n-1} \sum_{j=i+1}^n b_{\sigma_i, \sigma_j}$
- ▶ **Insert**



Parametric roughness

| | Swap | Interchange | Insert |
|-------------|------------------|---------------------|-------------------------------------|
| Size | $\mathcal{O}(n)$ | $\mathcal{O}(n^2)$ | $\mathcal{O}(n^2)$ |
| LOP | 1 | $2 i - j - 1$ | $ i - j $ |
| FSP | $m(n - i)$ | $m(n - \min(i, j))$ | $m(n - \min(i, j))$ |
| QAP | $4(n - 1)$ | $4(n - 1)$ | $2n(i - j + 1) - (i - j + 1)^2$ |

- ▶ Related to the **smoothness of the landscapes**.
- ▶ Roughness and the **Size** of a neighborhood: distribution of the difficulty.

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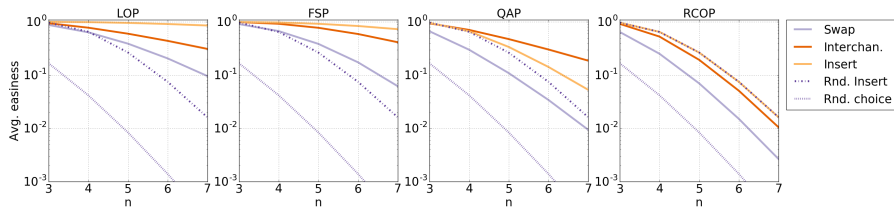
Difficulty and parametric roughness

Experiments

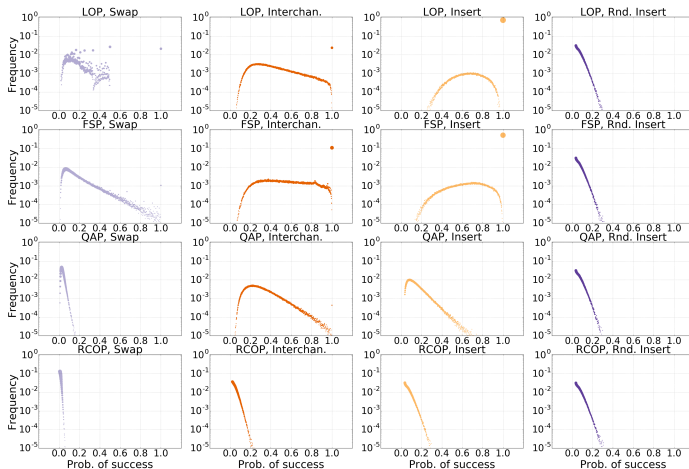
Conclusions

- ▶ COPS: LOP, FSP, QAP.
- ▶ Neighborhoods: Swap, Interchange, Insert.
- ▶ $5 \cdot 10^5$ instances for each COP.
- ▶ **RCOP**: random rankings of solutions.
- ▶ **Rand. insert**: relabeling of the insert neighborhood system.

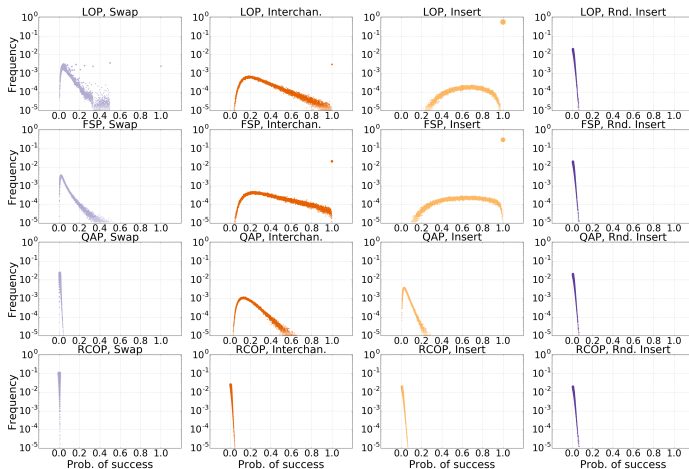
Evolution of the average easiness



Easiness, $n = 6$

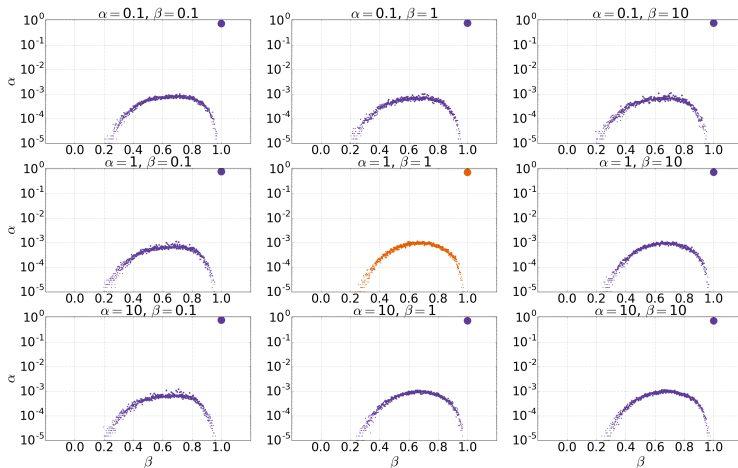


Easiness, $n = 7$



Alternative sampling: $Beta(\cdot; \alpha, \beta)$

- ▶ LOP + insert, $n = 6$.
- ▶ Distribution with many shapes, α and β .



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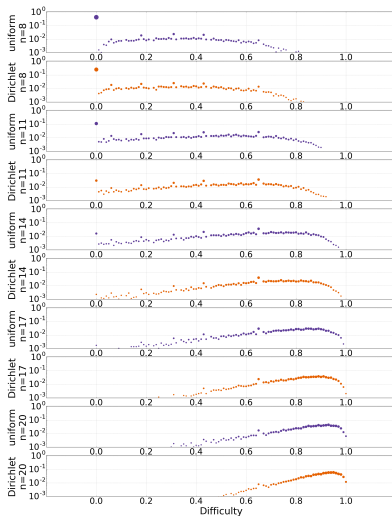
Conclusions

Conclusions

- ▶ Instances are **not uniformly** distributed in terms of difficulty.
- ▶ The distribution of the difficulty **depends on the problem and the neighborhood**.
- ▶ The distribution of the difficulty seems to be related with the **roughness** and the **size** of a neighborhood.
- ▶ A neighborhood with a **low roughness** is desirable

How can we control the difficulty of generated instances?

- LOP + insert: Dirichlet sampling, $n = 8, \dots, 20$.



Thanks for your attention!!!

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