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Memetic Multilevel Hypergraph Partitioning

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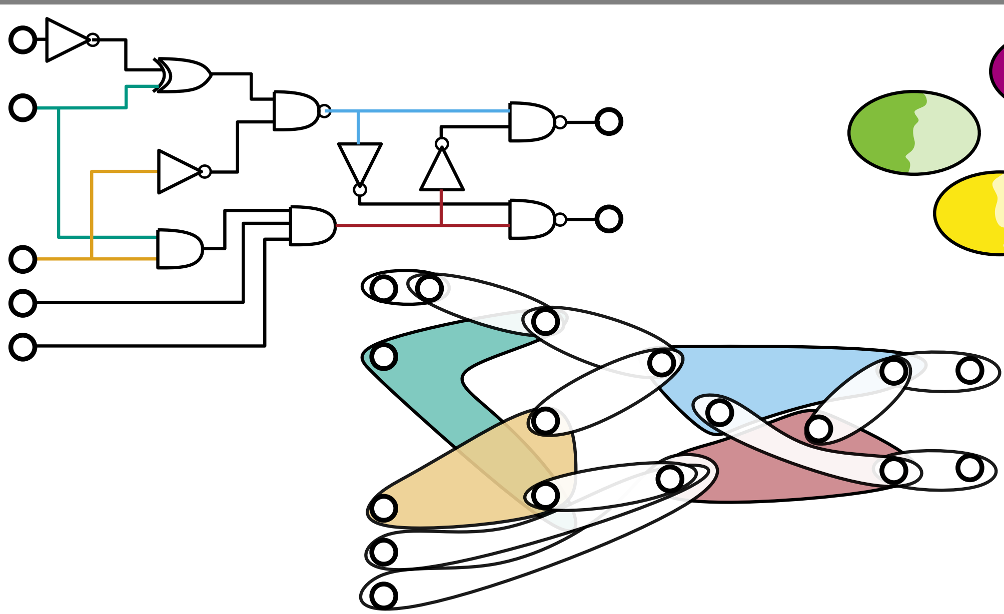
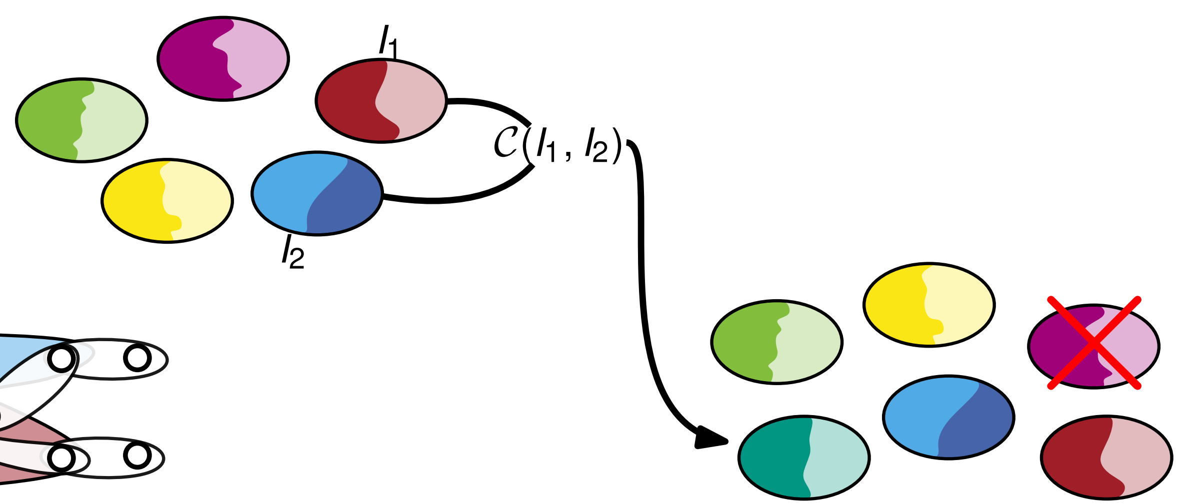
Institute of Theoretical Informatics ·



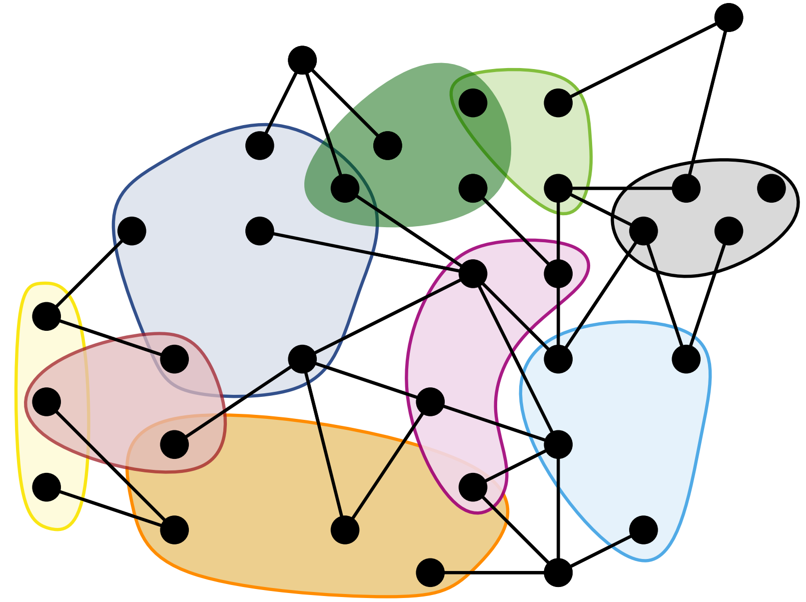


Hypergraphs

- generalization of graphs
  $\Rightarrow$ hyperedges connect ≥ 2 nodes

- graphs $\Rightarrow$ dyadic ($\mathbf{2}$**-ary**) relationships
- hypergraphs $\Rightarrow$ ($\mathbf{d}$**-ary**) relationships

- hypergraph $H = (V, E, c, \omega)$
  - vertex set $V = \{1, ..., n\}$
  - edge set $E \subseteq \mathcal{P}(V) \setminus \emptyset$
  - node weights $c : V \to \mathbb{R}_{\geq 1}$
  - edge weights $\omega : E \to \mathbb{R}_{\geq 1}$



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- hypergraphs $\Rightarrow$ (**d-ary**) relationships

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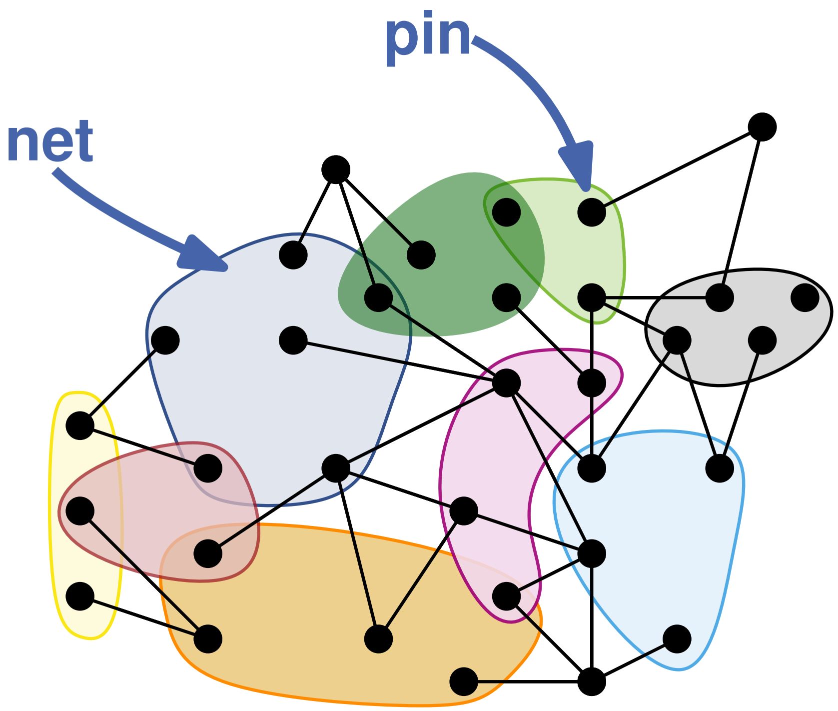
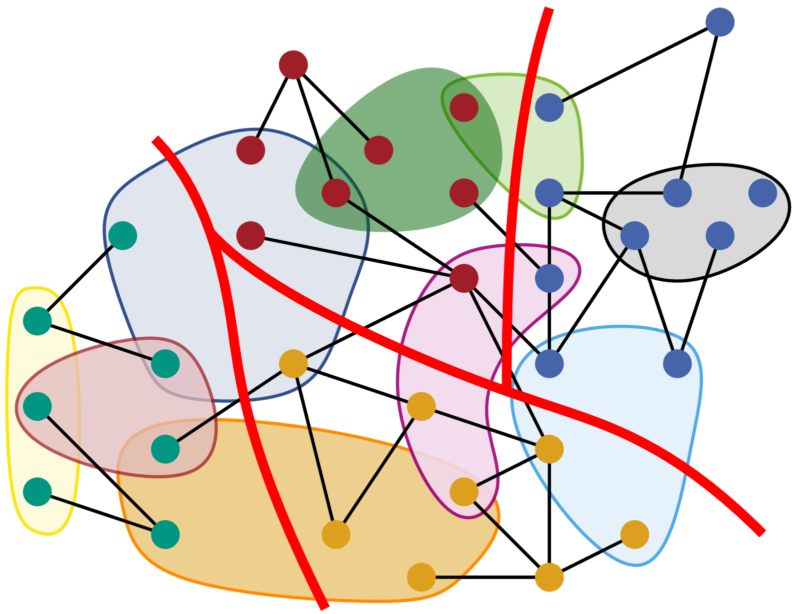


ε-Balanced Hypergraph Partitioning Problem

Partition hypergraph $H = (V, E, c, \omega)$ into $\mathbf{k}$ disjoint blocks $\Pi = \{V_1, \ldots, V_k\}$ such that:

- blocks V_i are **roughly equal-sized**:

$$c(V_i) \leq (1 + \varepsilon) \left\lceil \frac{c(V)}{k} \right\rceil$$



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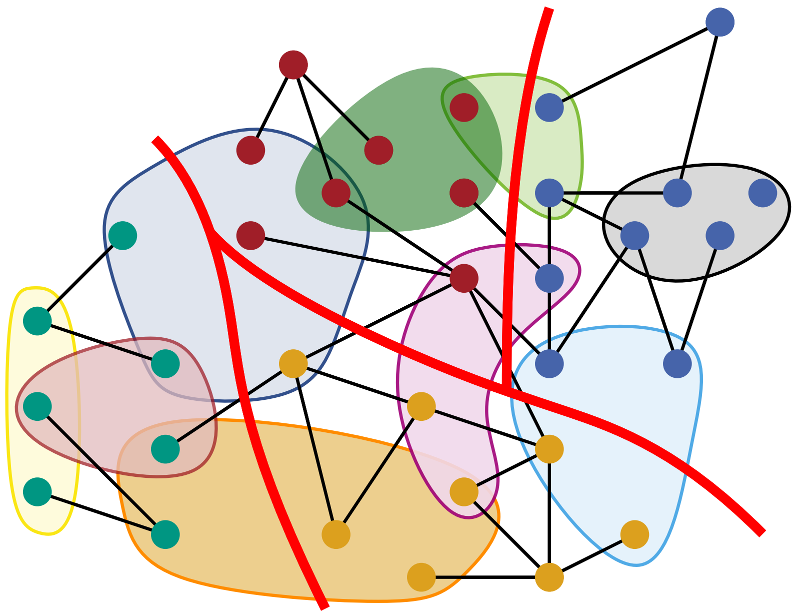
imbalance parameter



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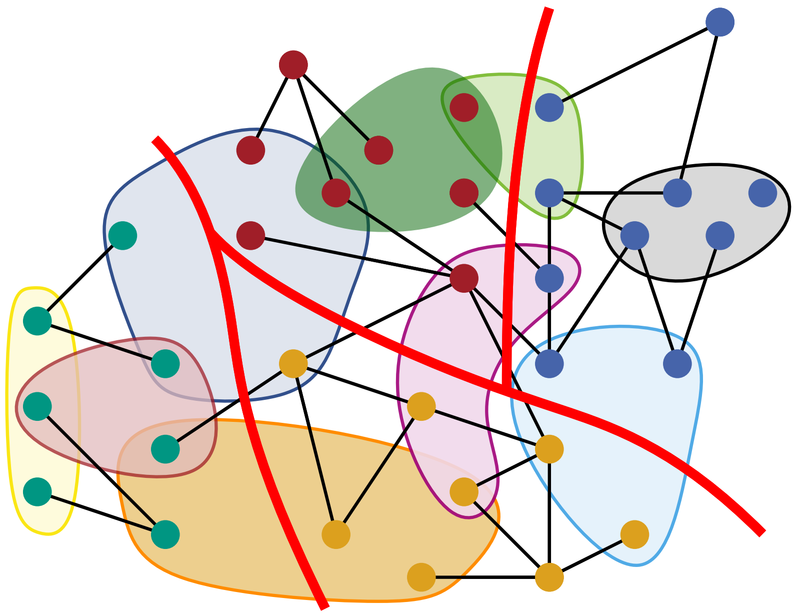

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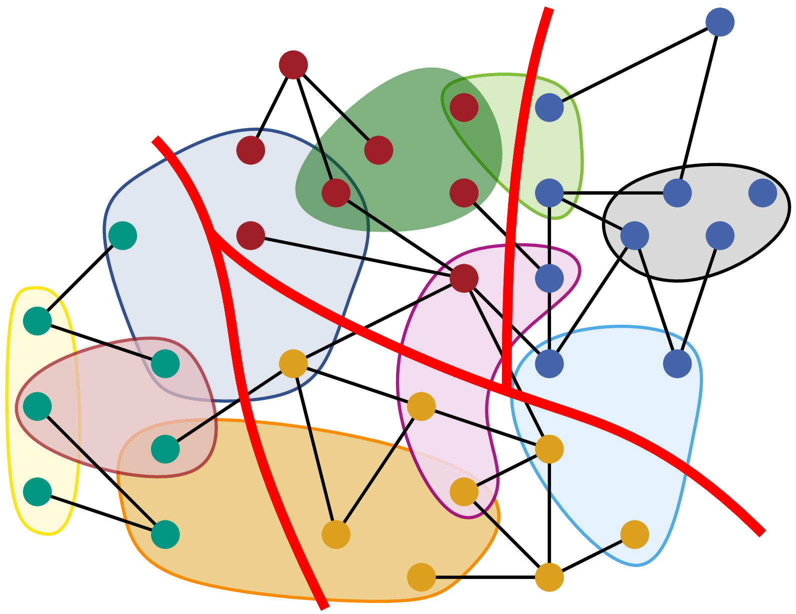
$$\sum_{e \in \text{cut}} (\lambda - 1)\, \omega(e)$$

connectivity:
 # blocks connected by net e



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$$\sum_{e \in \text{cut}} (\lambda - 1)\, \omega(e) = 12$$

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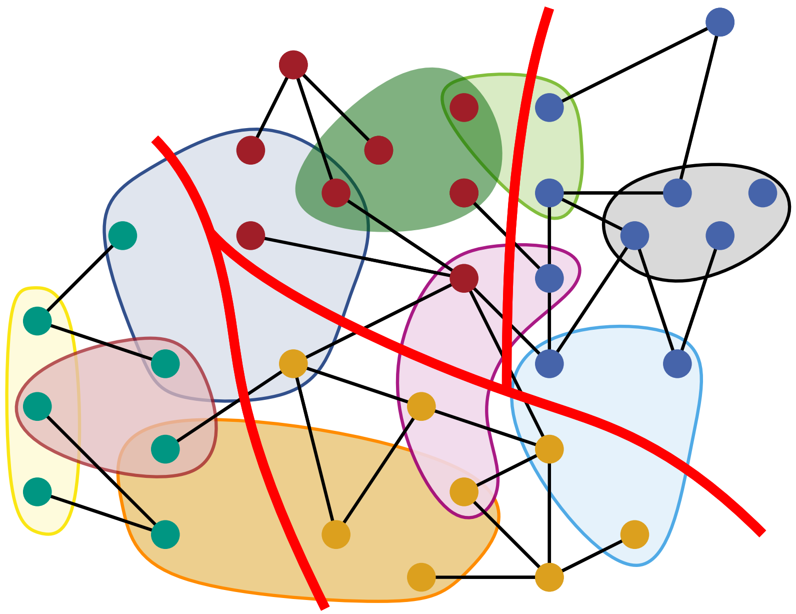
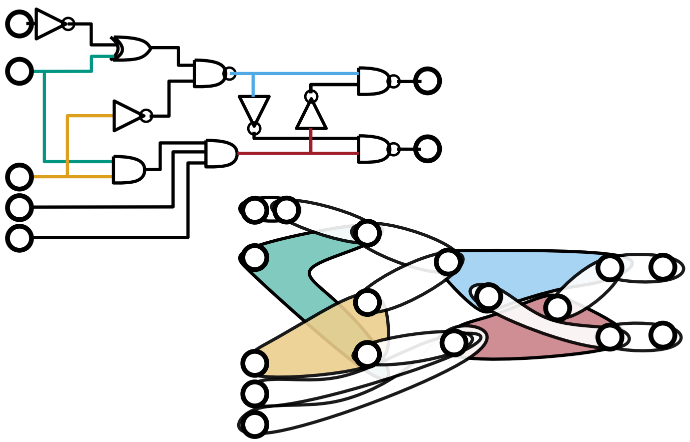


Applications

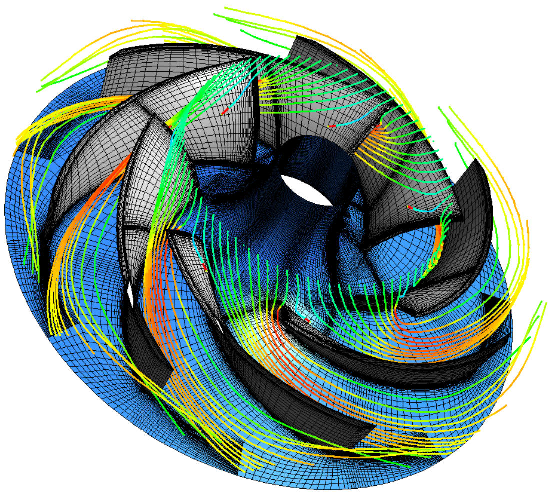


VLSI Design

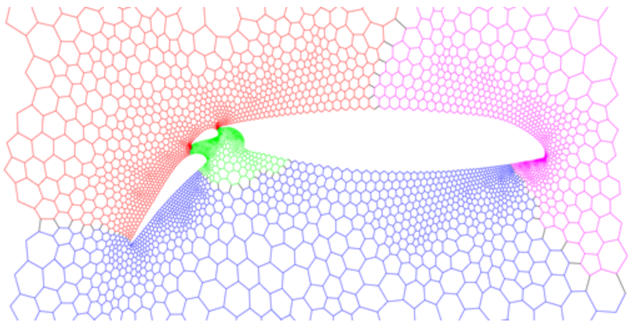
Warehouse Optimization

Complex Networks

Route Planning



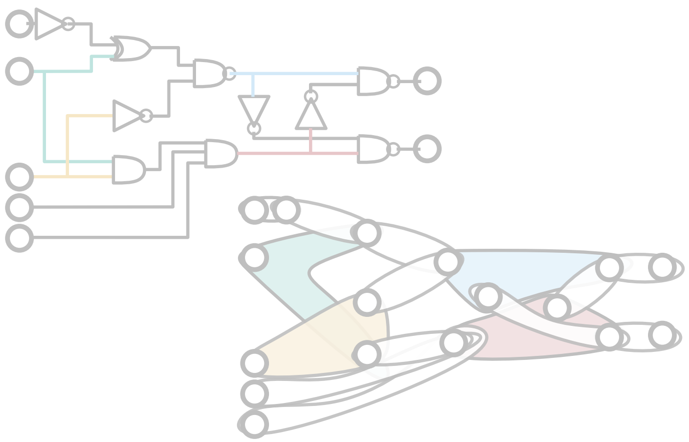
Simulation

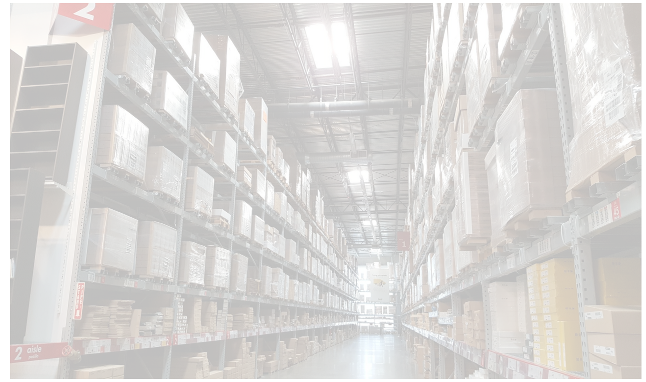


$$\mathbf{R}^{n \times n} \ni Ax = b \in \mathbf{R}^n$$

Scientific Computing

Applications

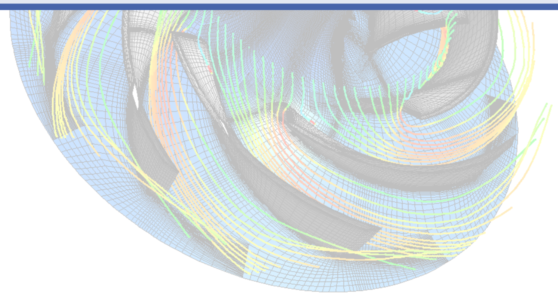




- hypergraph partitioning is **NP-hard**
- even finding **good approximate** solutions for graphs is NP-hard

$\Rightarrow$ our focus: **solution quality**

Route Planning



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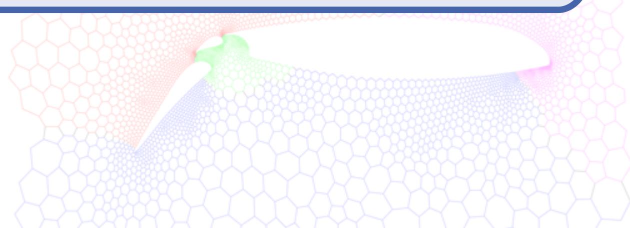

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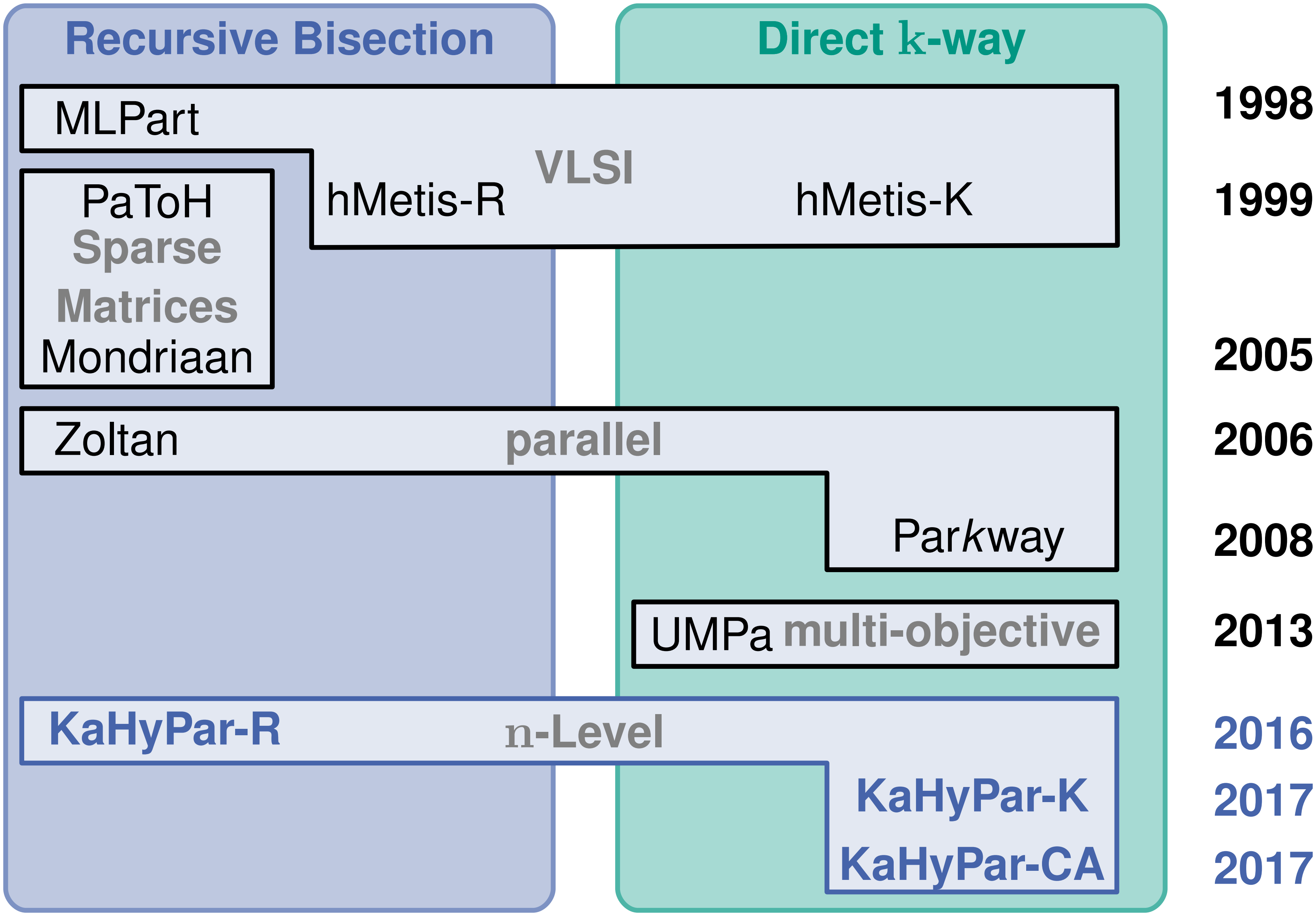
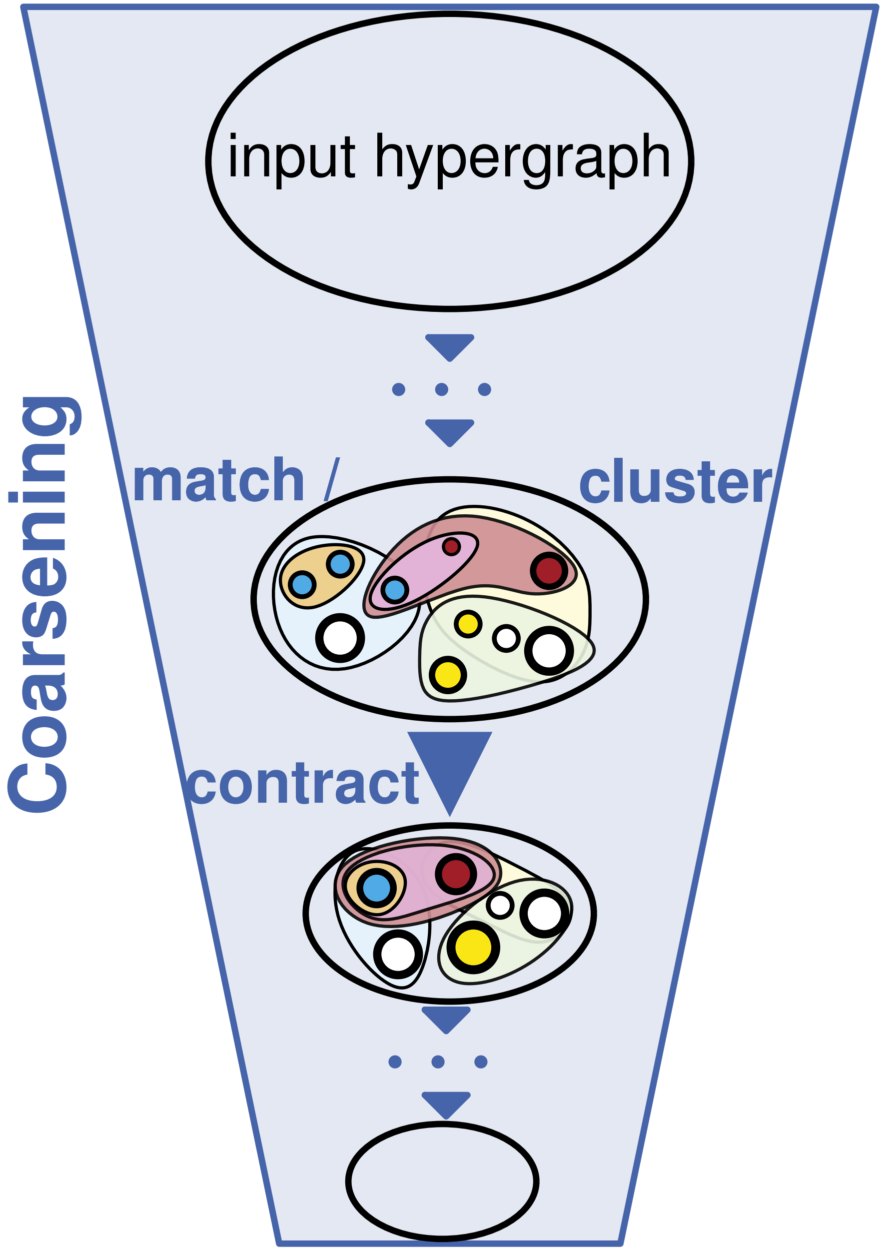
Scientific Computing

Taxonomy of Hypergraph Partitioning Tools



The Multilevel (ML) Framework



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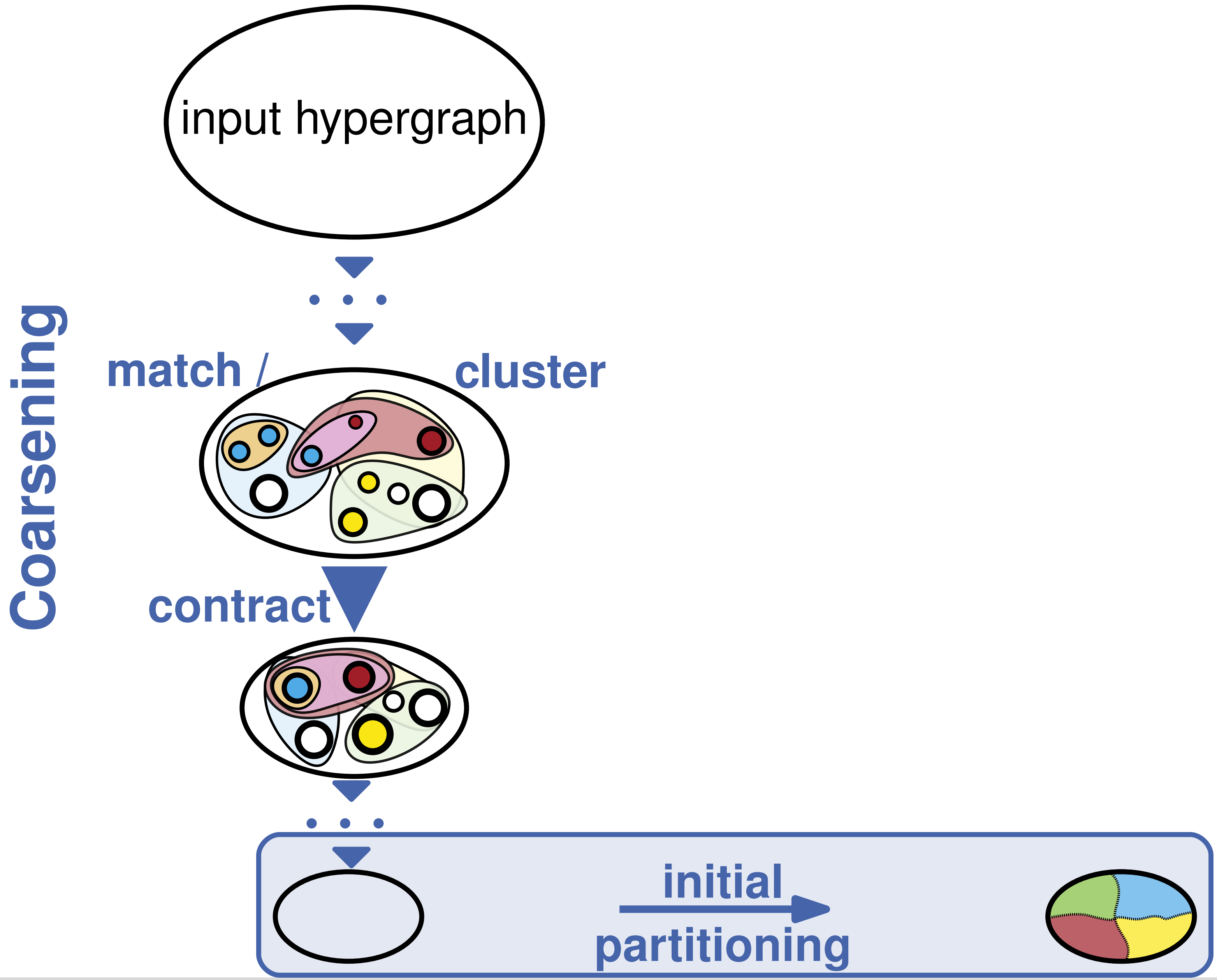

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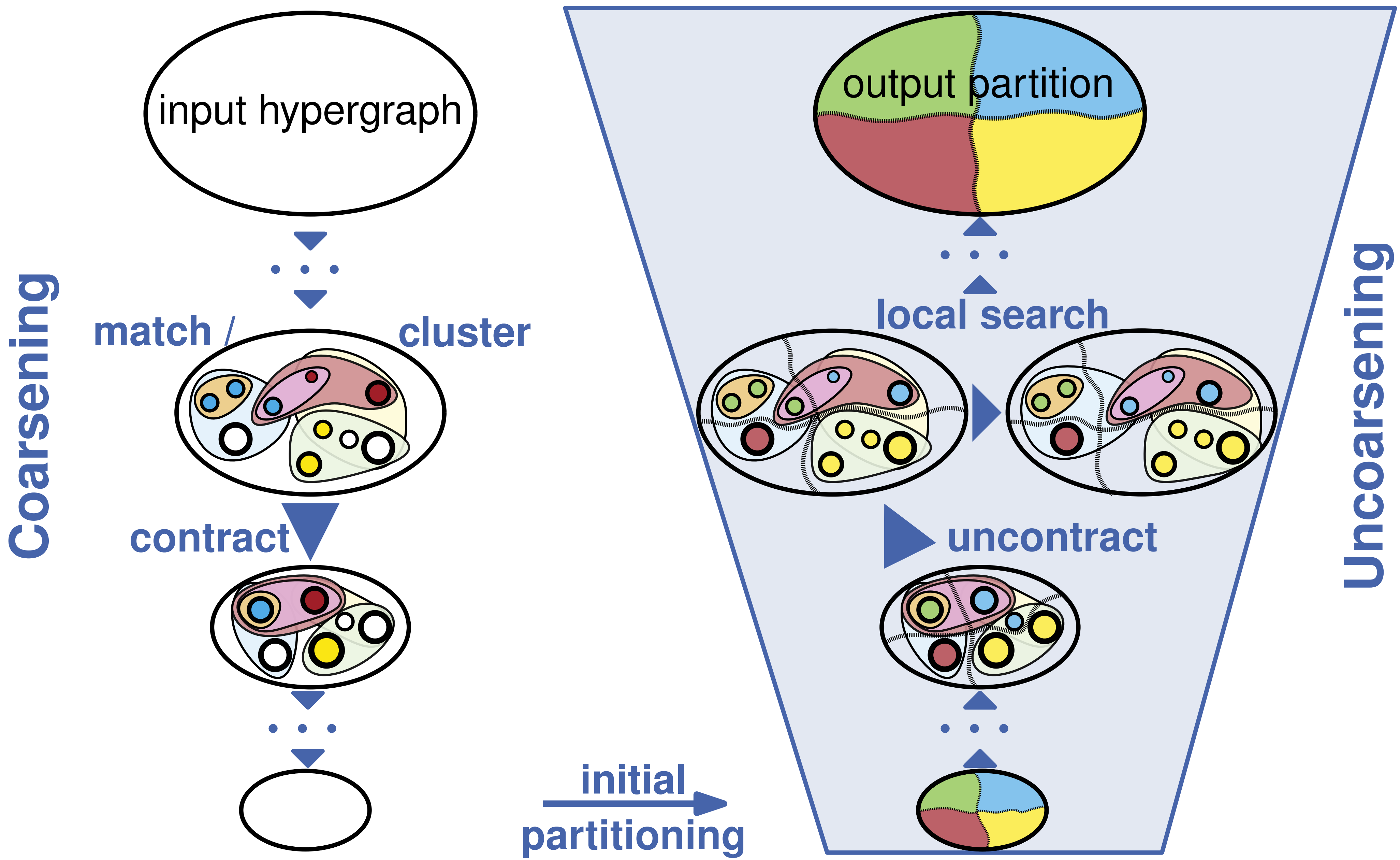

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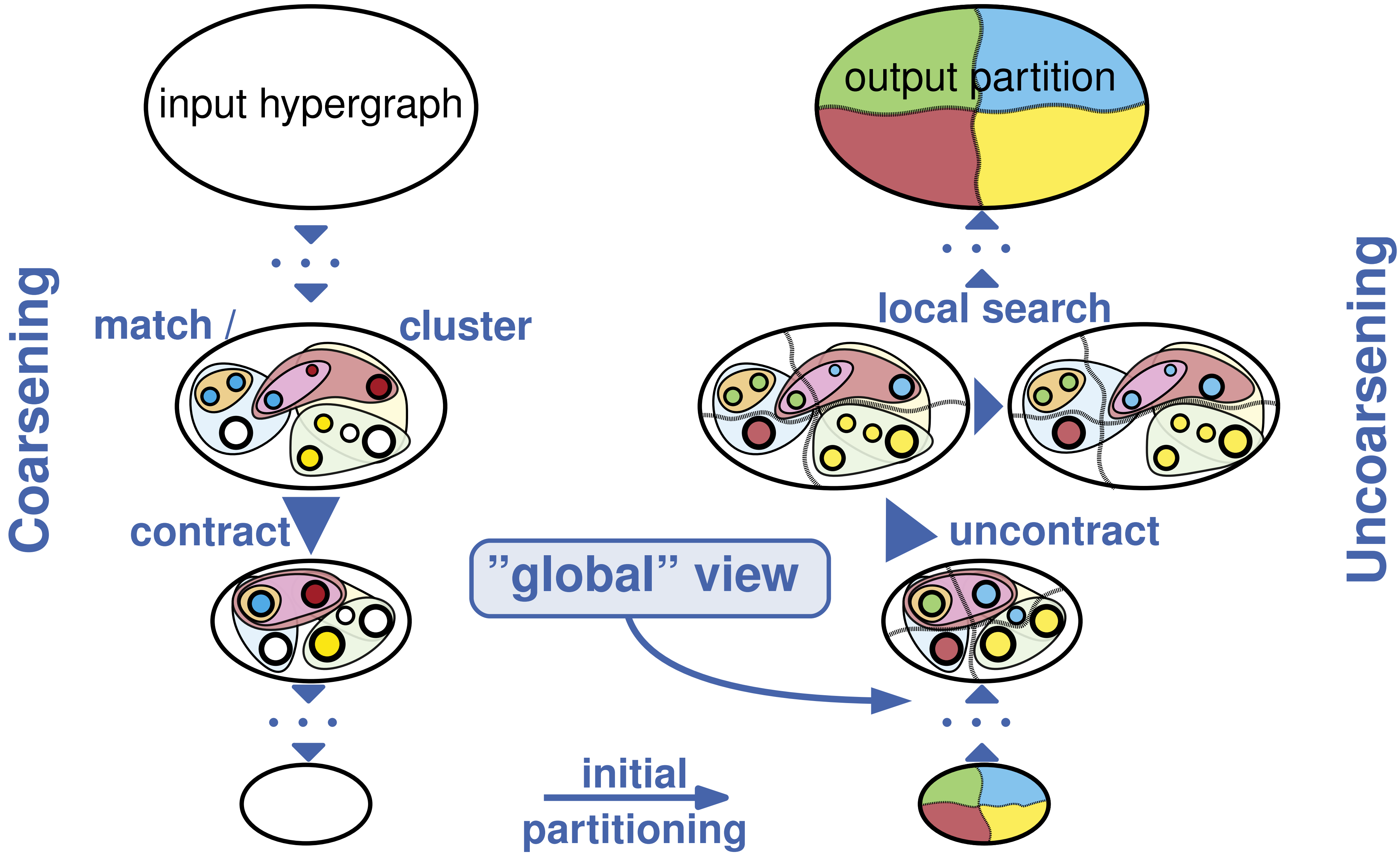

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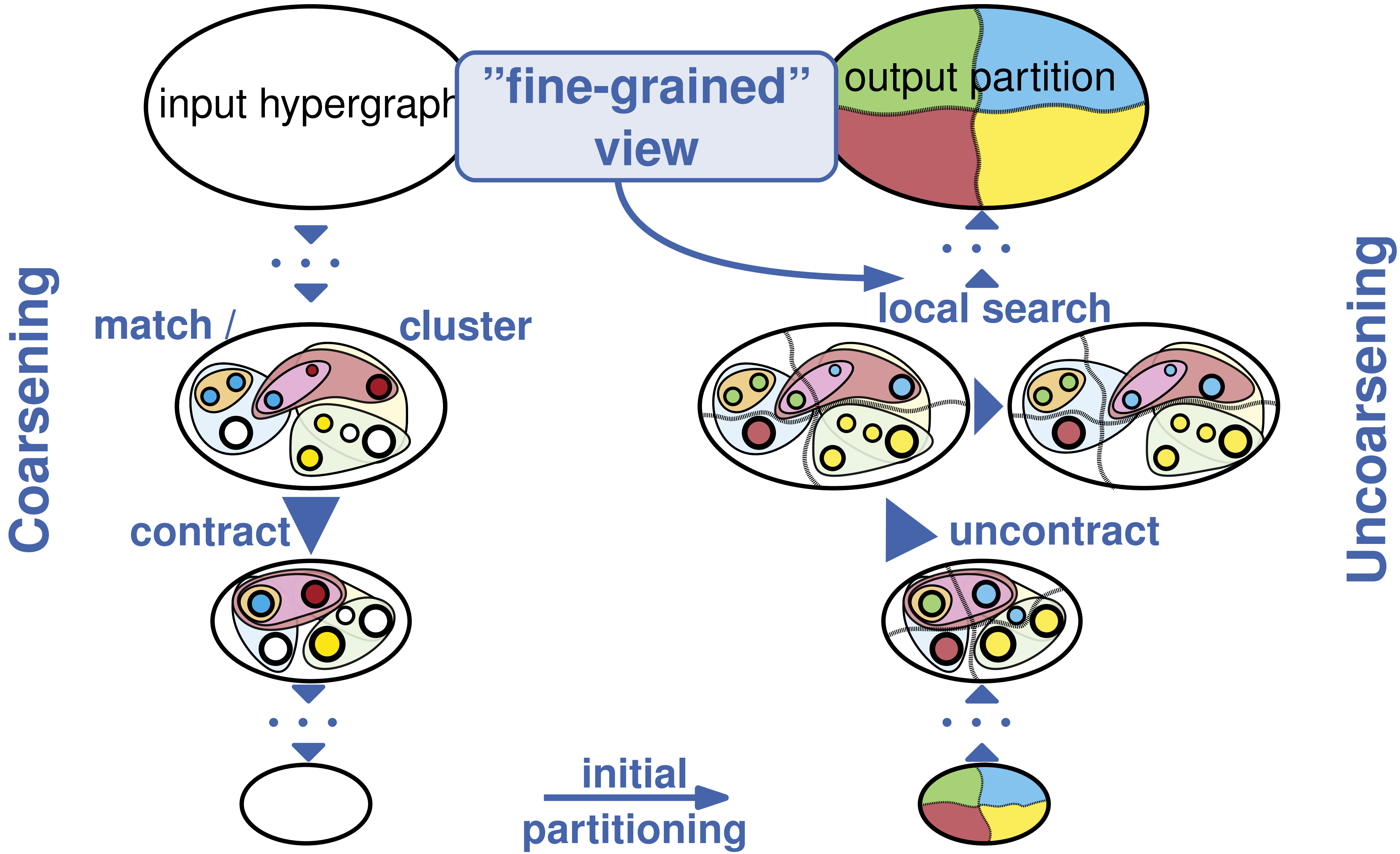

Evolutionary Algorithm – Outline

Algorithm 1: Steady-State EA

```
create initial population 𝒫
while stopping criterion not fulfilled do
    select parents I1, I2 from 𝒫
    recombine I1 with I2 to offspring o
    mutate offspring o
    evict individual from 𝒫 using o
return fittest individual
```

Evolutionary Algorithm – Outline

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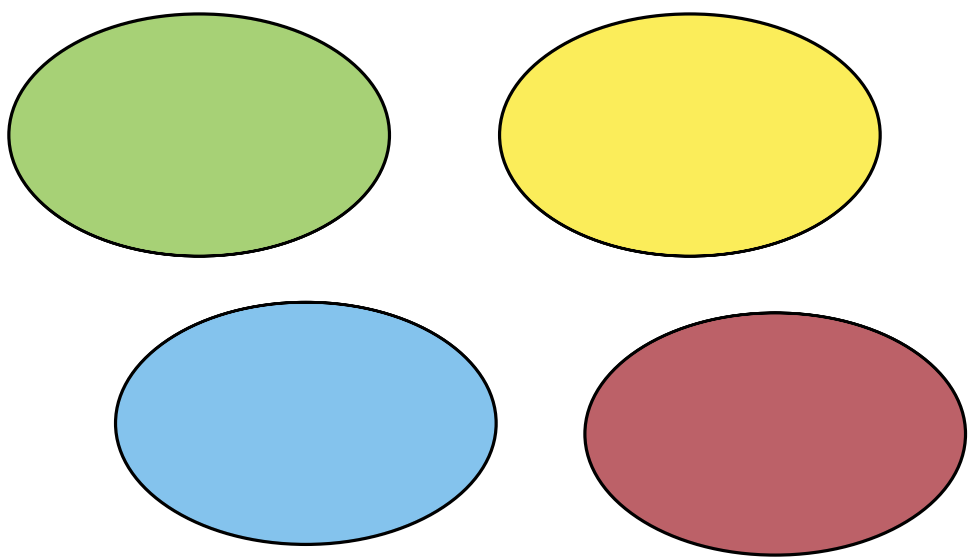

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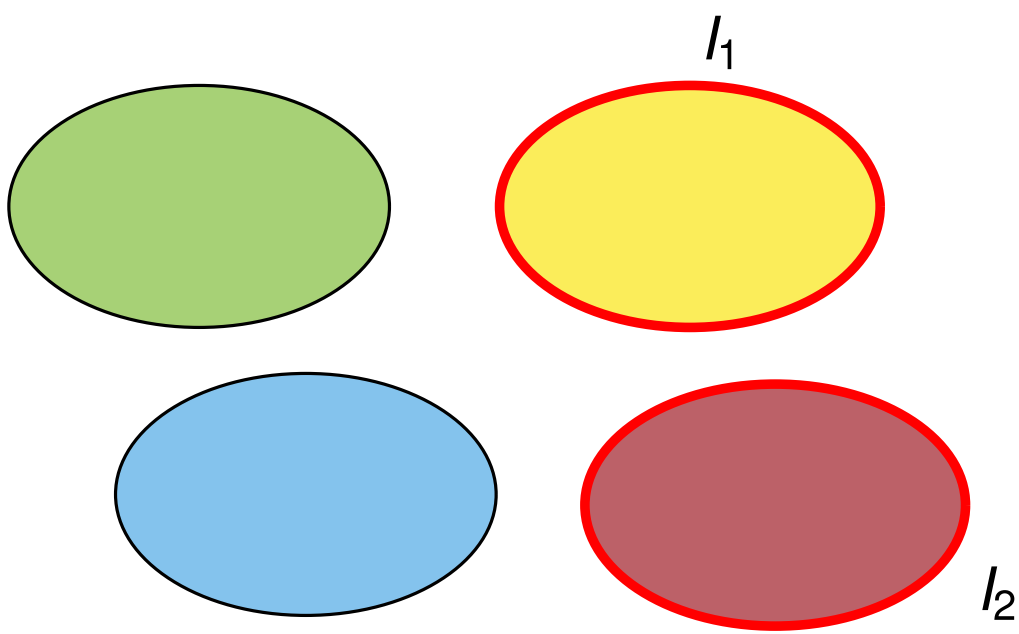

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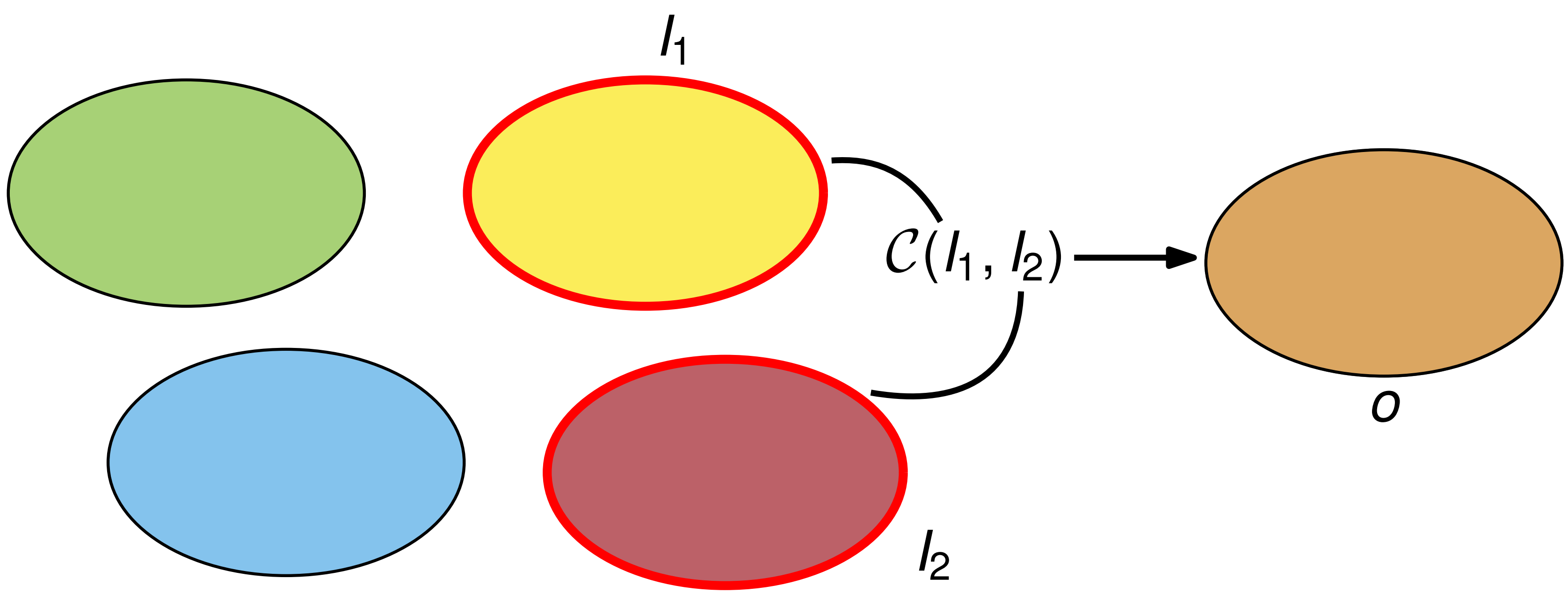

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Karlsruhe Institute of Technology

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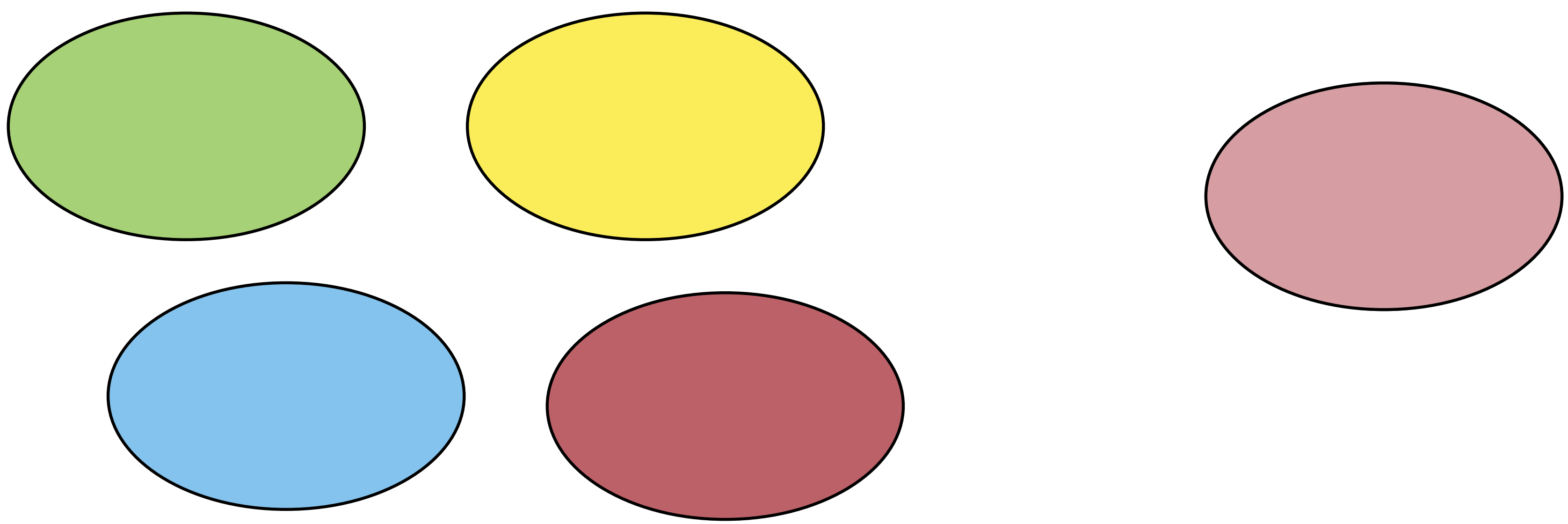

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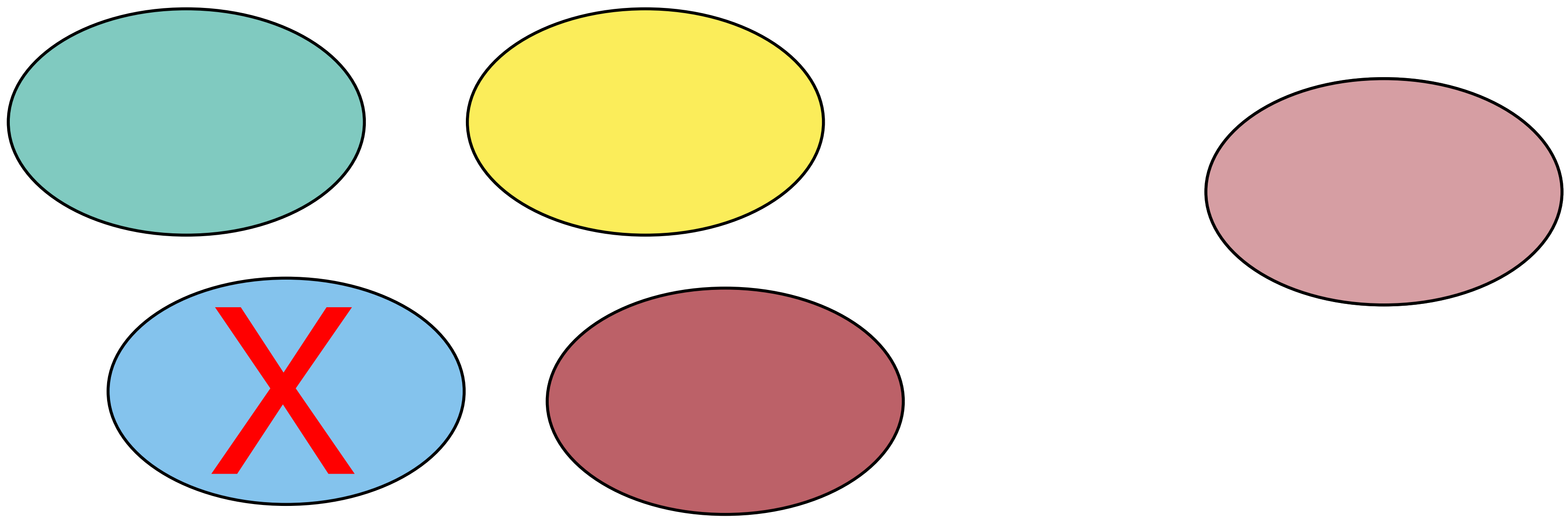

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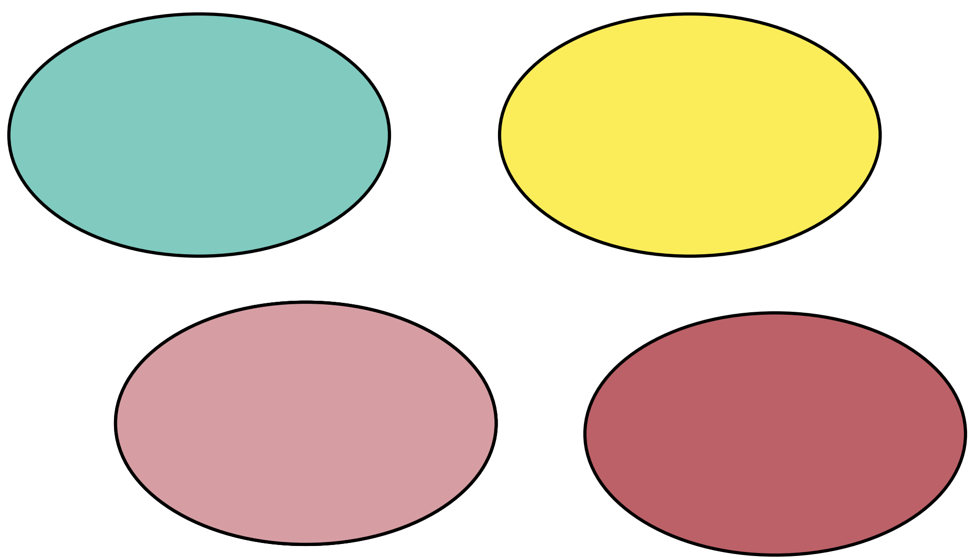

Evolutionary Algorithm – Outline

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Algorithm 1: Steady-State MA

`create` initial population $\mathcal{P}$ **+ local search**

while *stopping criterion not fulfilled* **do**

  `select` parents I_1, I_2 from $\mathcal{P}$

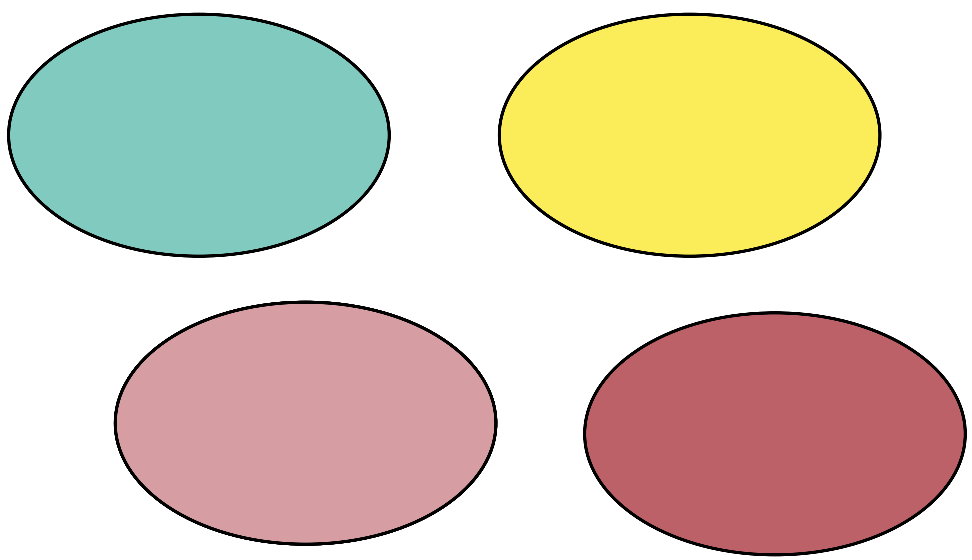
  `recombine` I_1 with I_2 to offspring o

  `mutate` offspring o **+ local search**

  `evict` individual from $\mathcal{P}$ using o

return *fittest individual*

memetic algorithm



Evolutionary Algorithms for HGP

	#	Population	Recombination	Mutation	LS	ML
Saab & Rao '89	k	bin packing	–	rand. greedy	–	–
Hulin '91	2	rand.	2-point	rand.	–	–
Bui & Moon '94	2	rand.	5-point	rand.	FM	–
Areibi '00	k	rand.	3/4-point	rand.	kFM	–
Areibi & Yang '04	k	rand./GRASP	3/4-point	rand.	kFM	–
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Individuals/Population

Partition 01011101010101101

$|V|$

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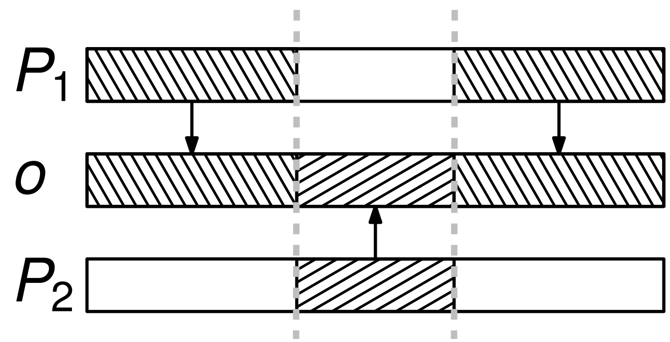
2-point crossover



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random mutation

010111010101010110 1

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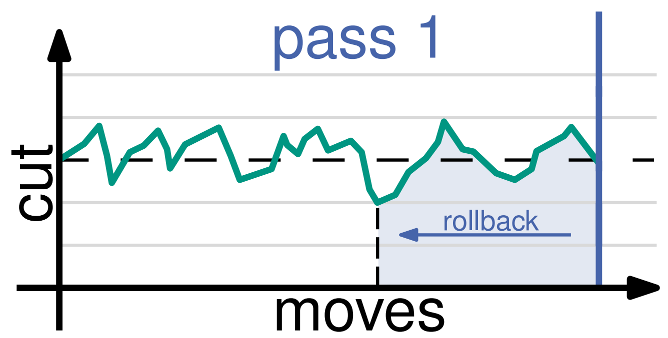
Algorithm 2: FM Local Search

while *improvement found* **do**
  while ¬ *done* **do**
    `find` best move
    `perform` best move
  `rollback` to best solution

pass

can worsen solution



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- **no** usage of multilevel paradigm
- considered **not** competitive with state-of-the-art tools [Cohoon et al. '03]
- benchmarked on **small** & **outdated** hypergraphs

Evolutionary Algorithms for HGP & Contributions

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Kim et al.					FM	–
Armstrong					kFM	–

Our Contribution:

first **memetic multilevel** HGP algorithm

⇒ problem-**specific** recombine & mutation operators

⇒ **extensive** experiments on **large** benchmark set

- **no** usage of multilevel paradigm
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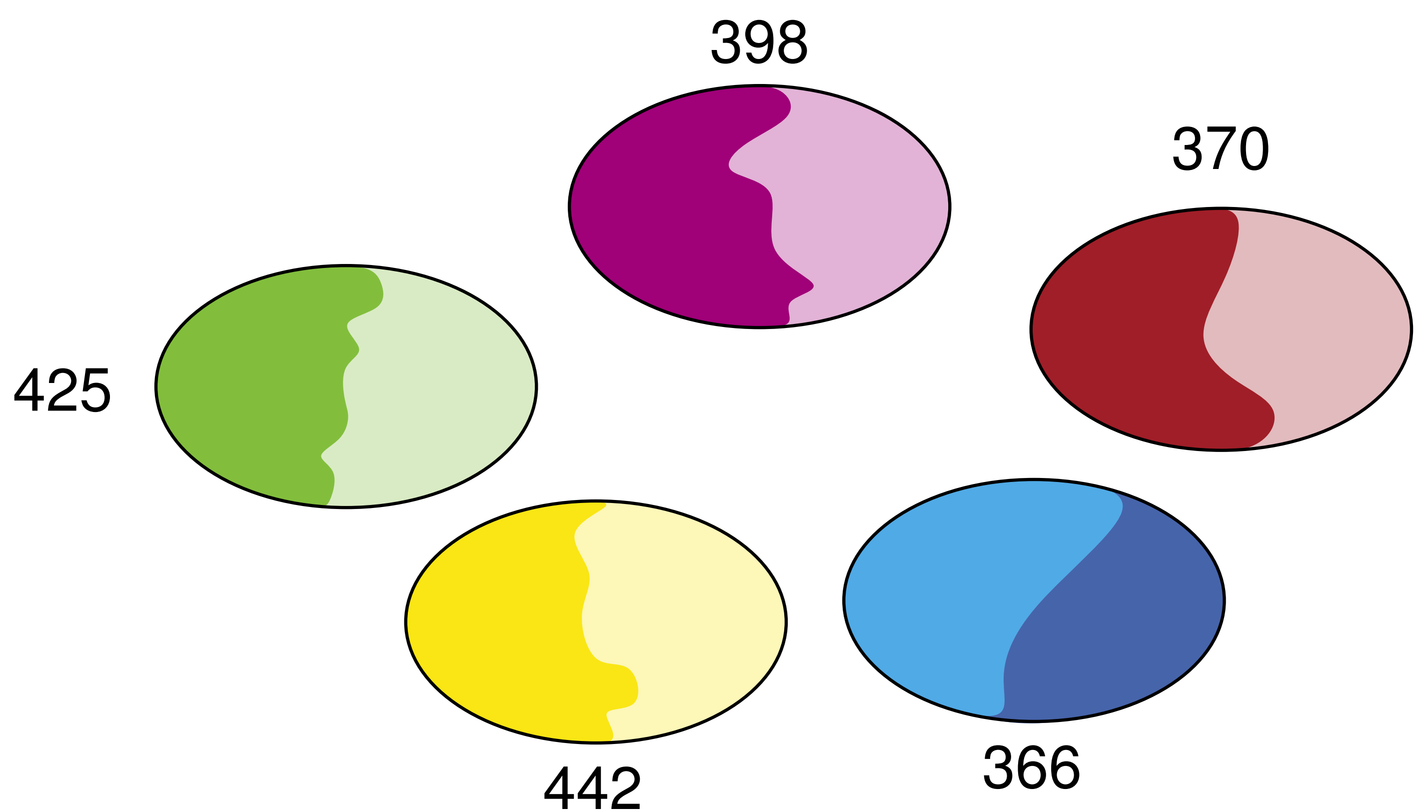
Memetic Multilevel HGP – Initial Population

generate initial population $\mathcal{P}$

- individuals $\rightsquigarrow$ **high-quality** partitions of KaHyPar-CA
- **dynamic** population size $|\mathcal{P}| := \max(3, \min(50, \delta \cdot \frac{t}{t_I}))$
- **fitness**: $(\lambda - 1)$ objective

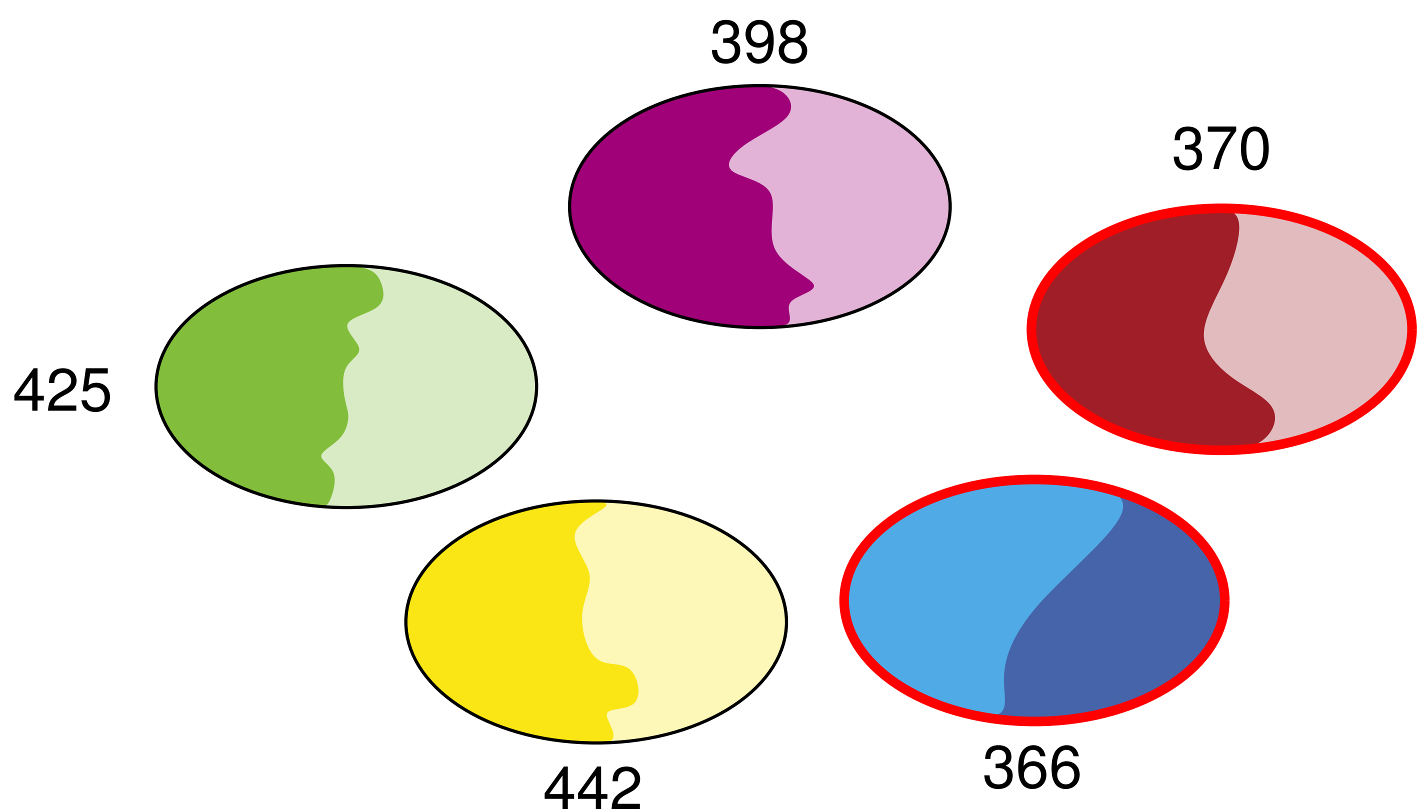
total time
tuning param.
time for 1 partition



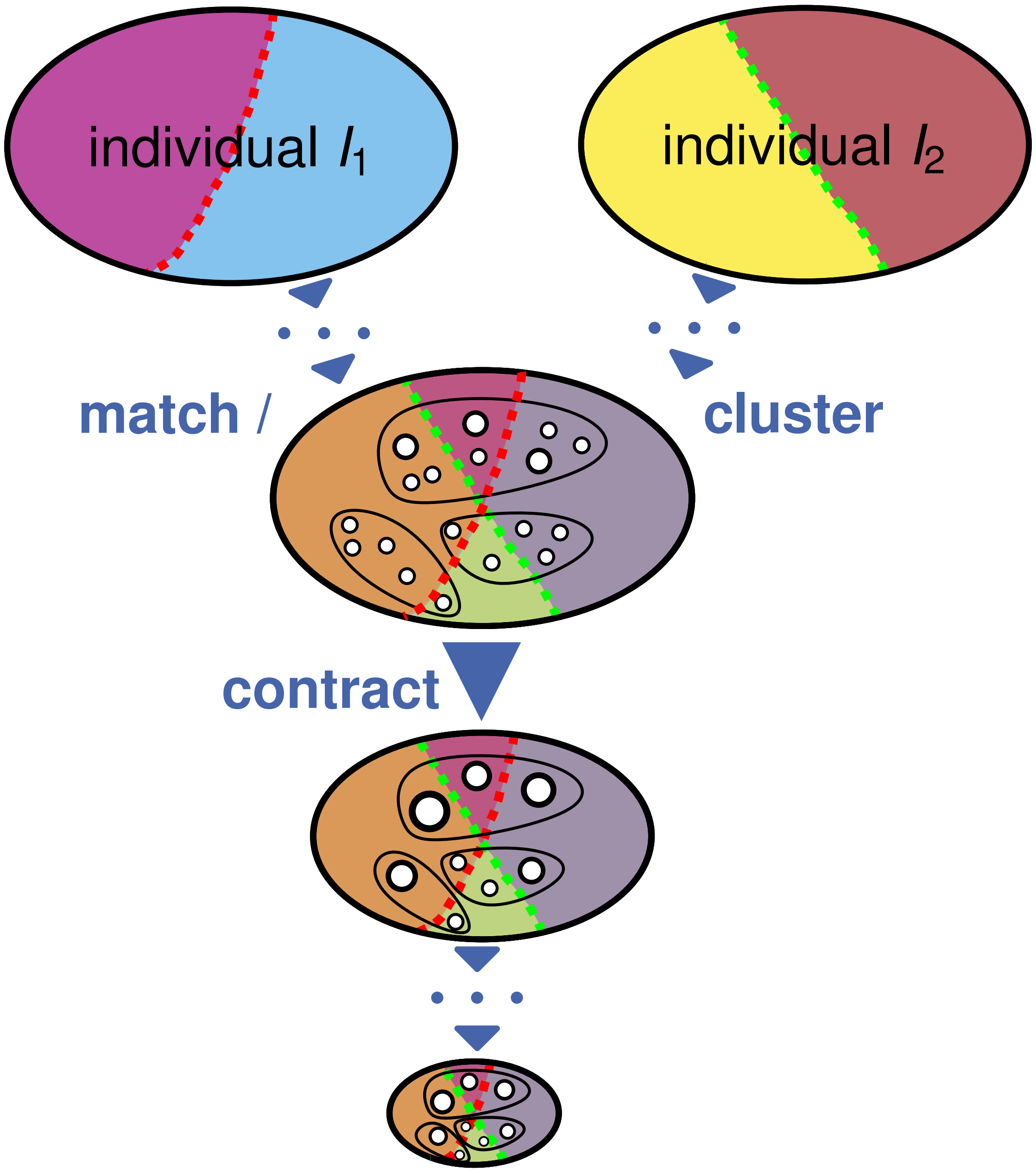
Memetic Multilevel HGP – Parent Selection

select individuals for recombination

- **Two**-Point Recombine ⇒ **binary** tournament selection
- Edge-Frequency **Multi**-Recombine ⇒ use $\lceil \sqrt{|\mathcal{P}|} \rceil$ **best**



Memetic Multilevel HGP – 2-Point Recombine (+C)



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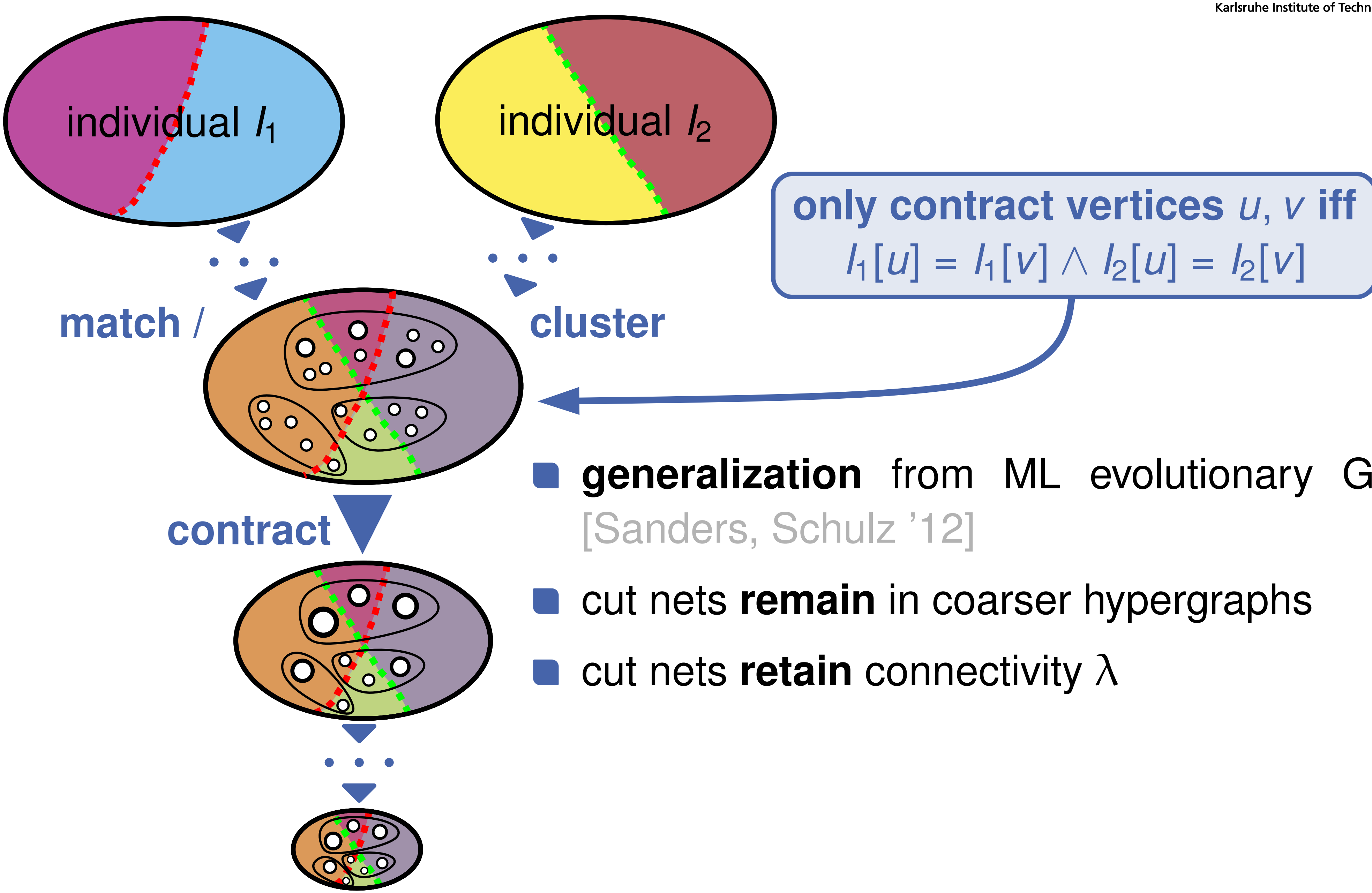

- **generalization** from ML evolutionary GP [Sanders, Schulz '12]
- cut nets **remain** in coarser hypergraphs
- cut nets **retain** connectivity λ

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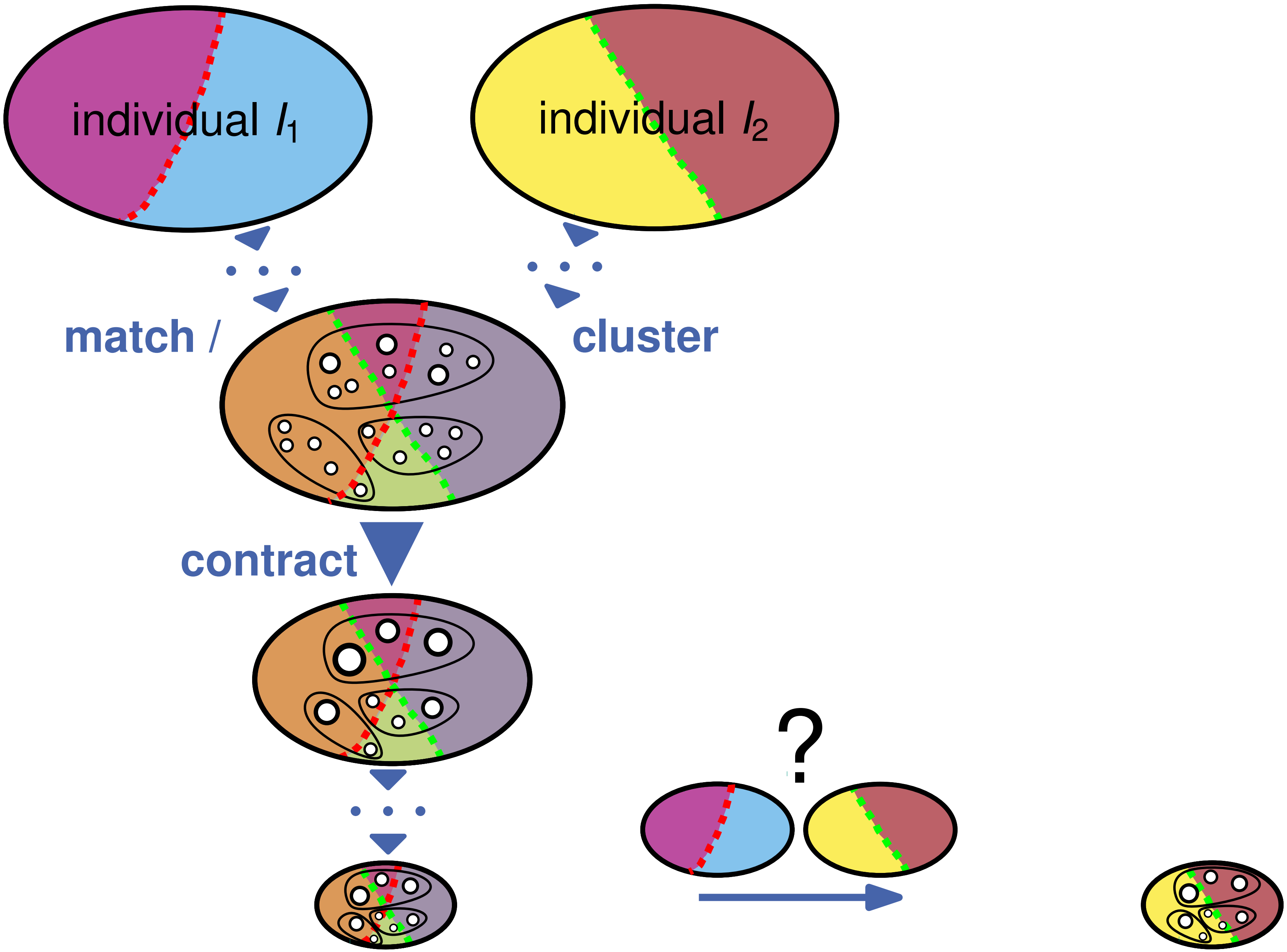
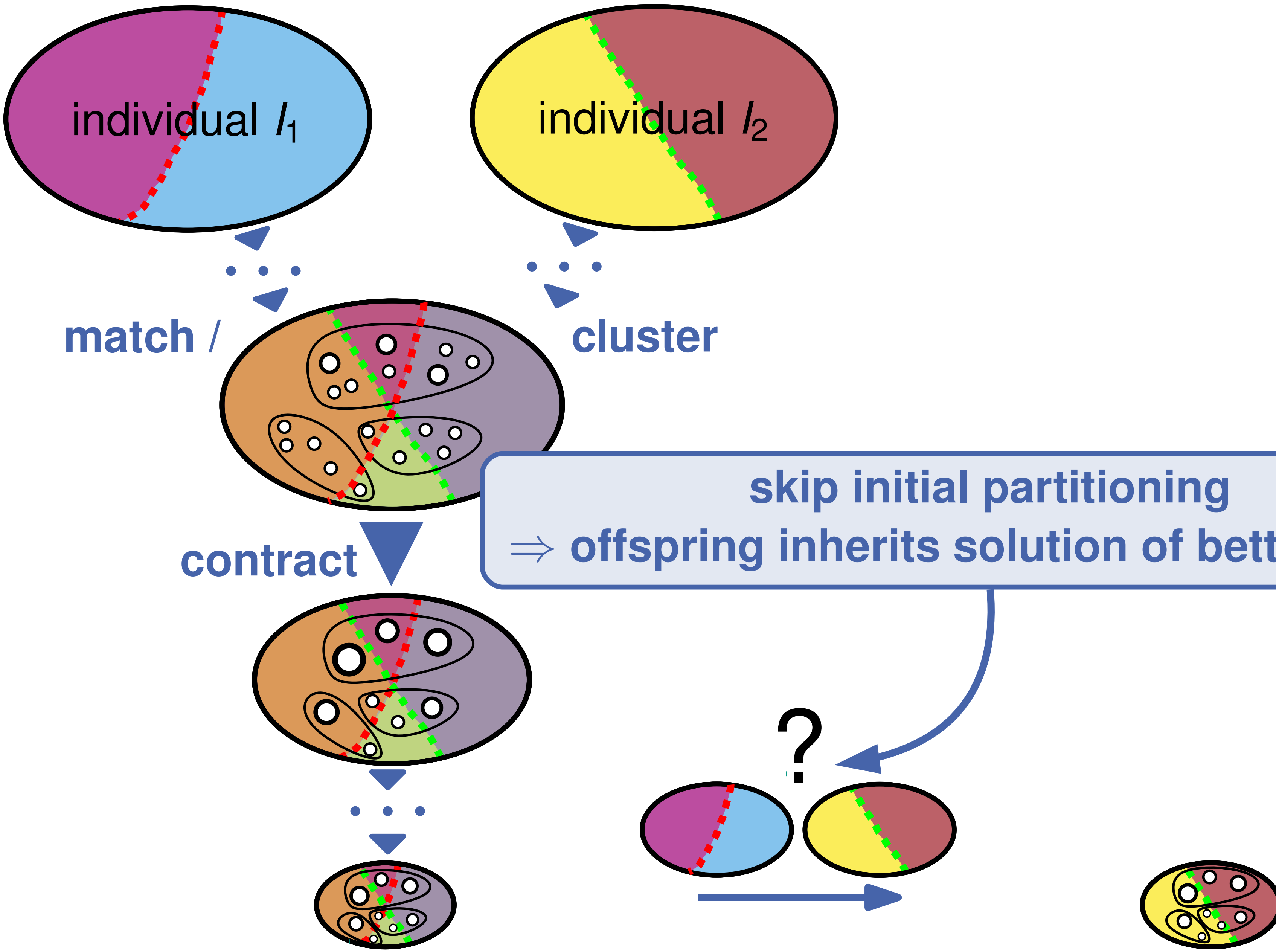


Memetic Multilevel HGP – 2-Point Recombine (+C)



skip initial partitioning
⇒ offspring inherits solution of better parent

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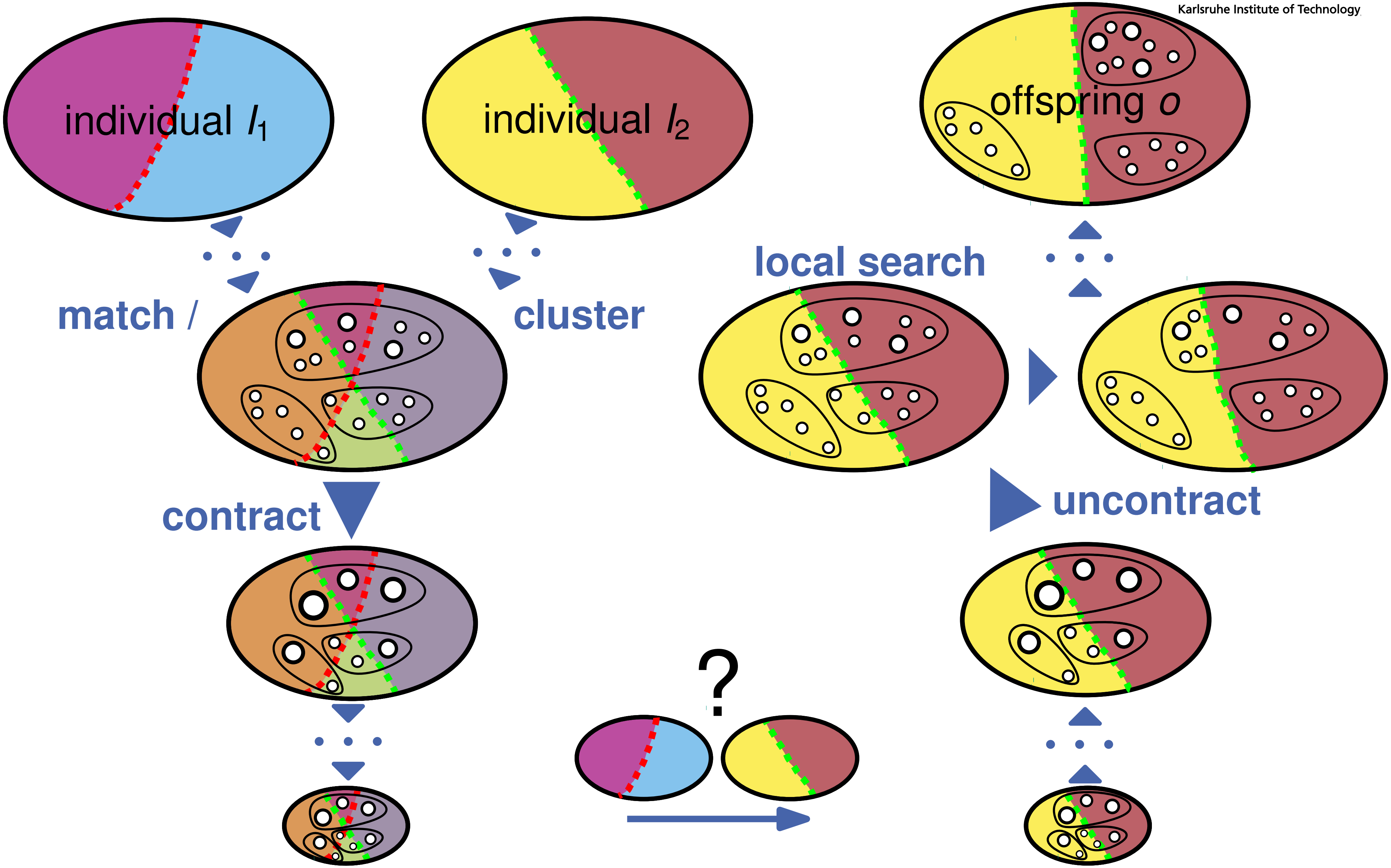
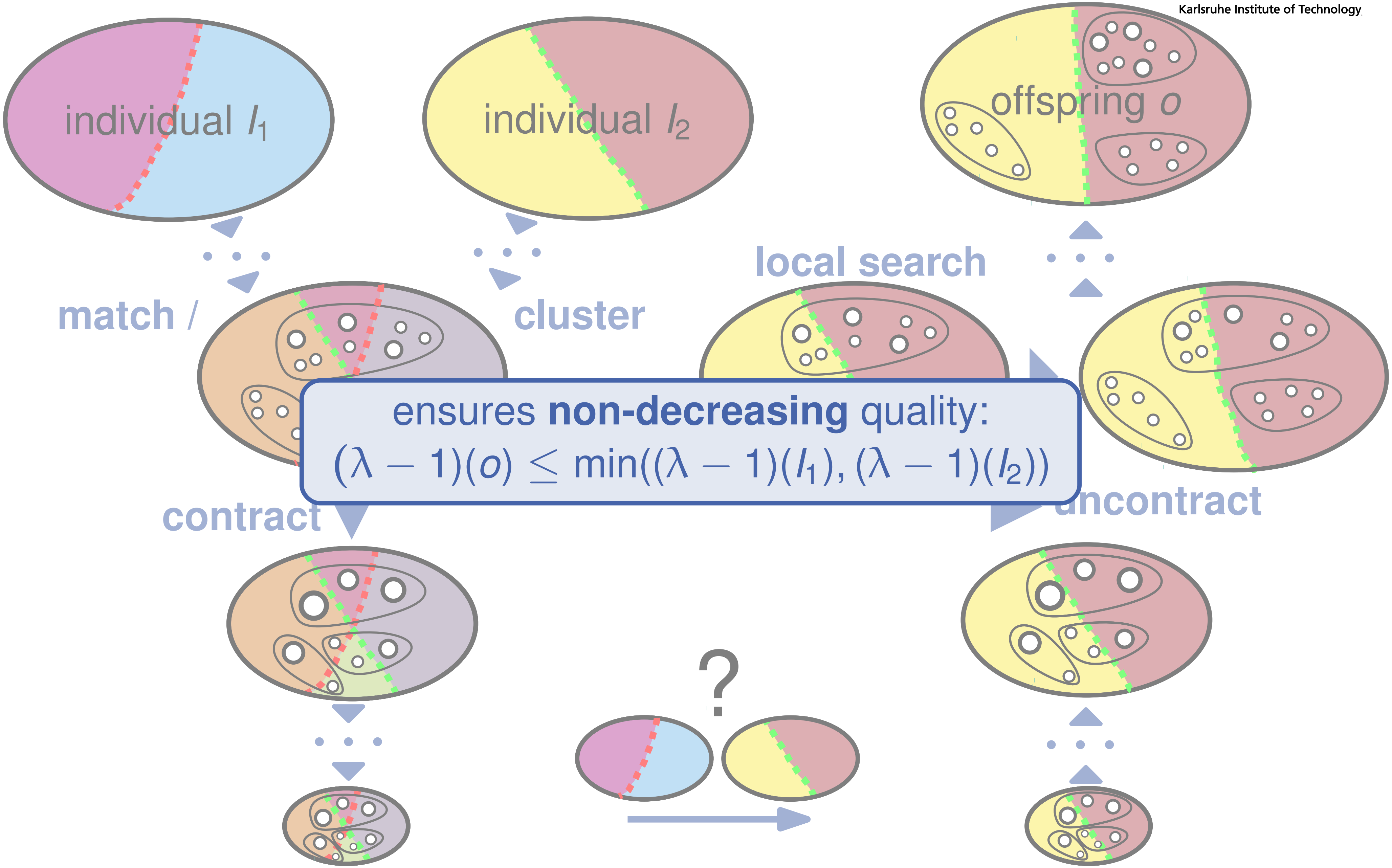


Memetic Multilevel HGP – 2-Point Recombine $(+C)$



ensures **non-decreasing** quality:
$(\lambda - 1)(o) \leq \min((\lambda - 1)(I_1), (\lambda - 1)(I_2))$

Memetic Multilevel HGP – Multi-Recombine ($+ER$)

Idea: frequently occurring cut nets likely part of high quality solutions

- look at $t = \lceil \sqrt{|\mathcal{P}|} \rceil$ **best** individuals
- compute **edge frequency** $f(e) := \left|\left\{I \in t \middle| \lambda(e) > 1\right\}\right|$
- prefer contractions of vertices incident to **low frequency** nets:

$$r(u, v) := \frac{1}{c(v) \cdot c(u)} \sum_{e \in \{\mathrm{I}(v) \cap \mathrm{I}(u)\}} \frac{\exp(-\gamma f(e))}{|e|}$$ [Wichlund, Aas '98]

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prefer light vertices

large number ...

... of **low-frequency** nets ...

... with small size

[Wichlund, Aas '98]

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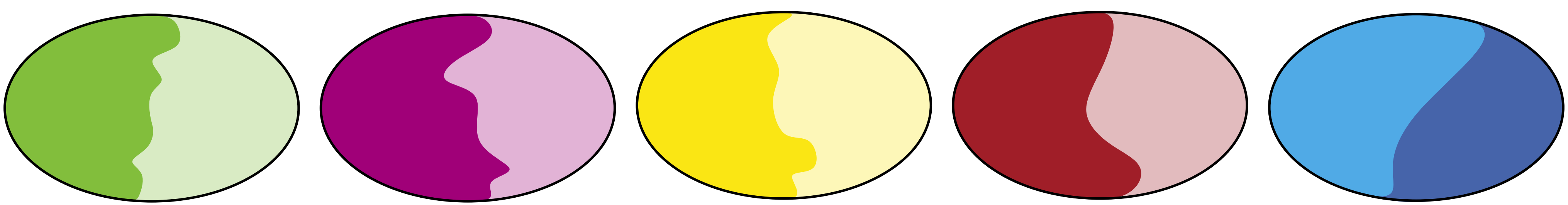

425 398 442 370 366

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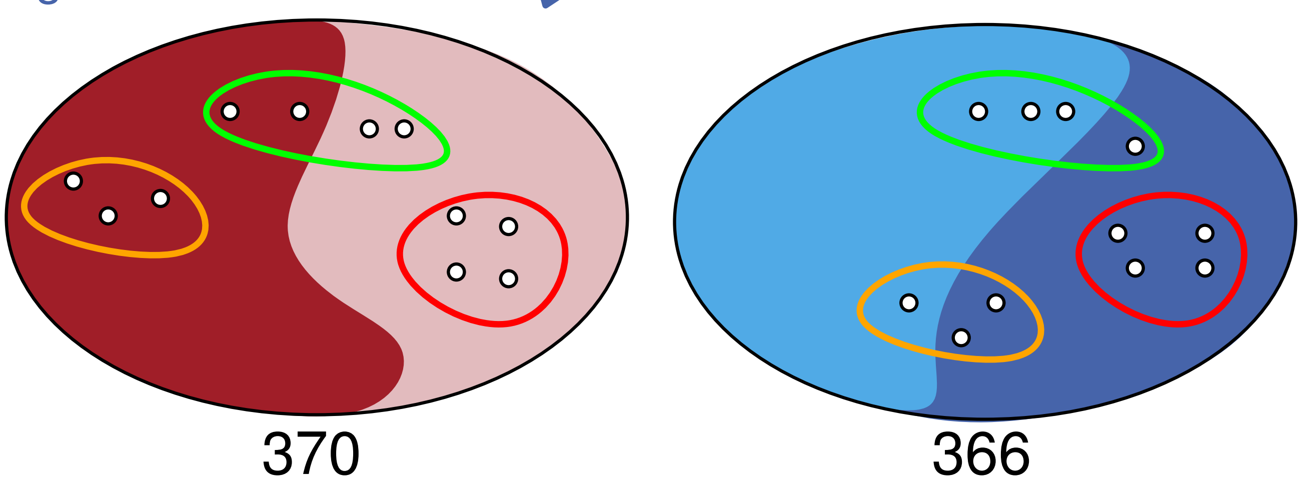

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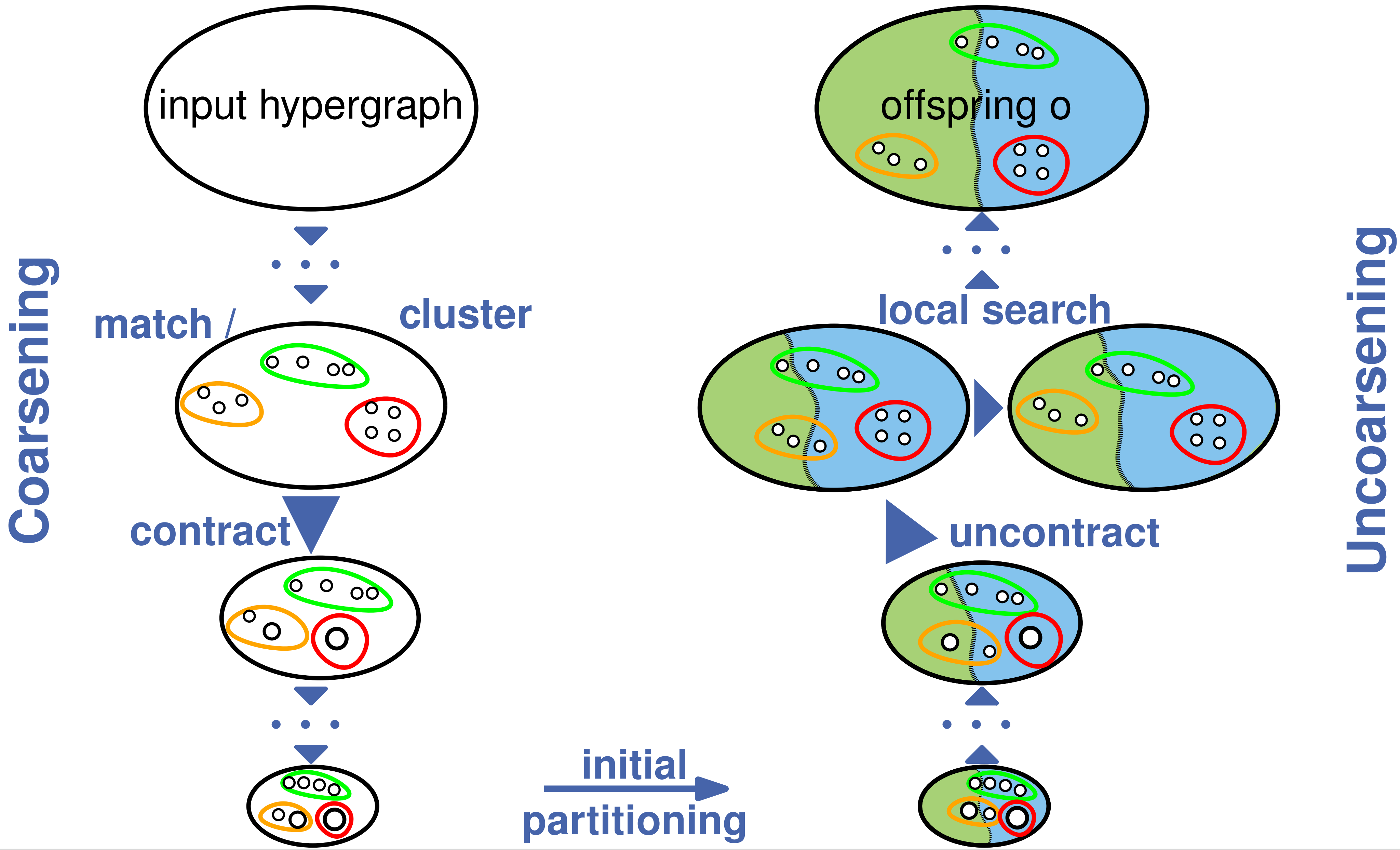

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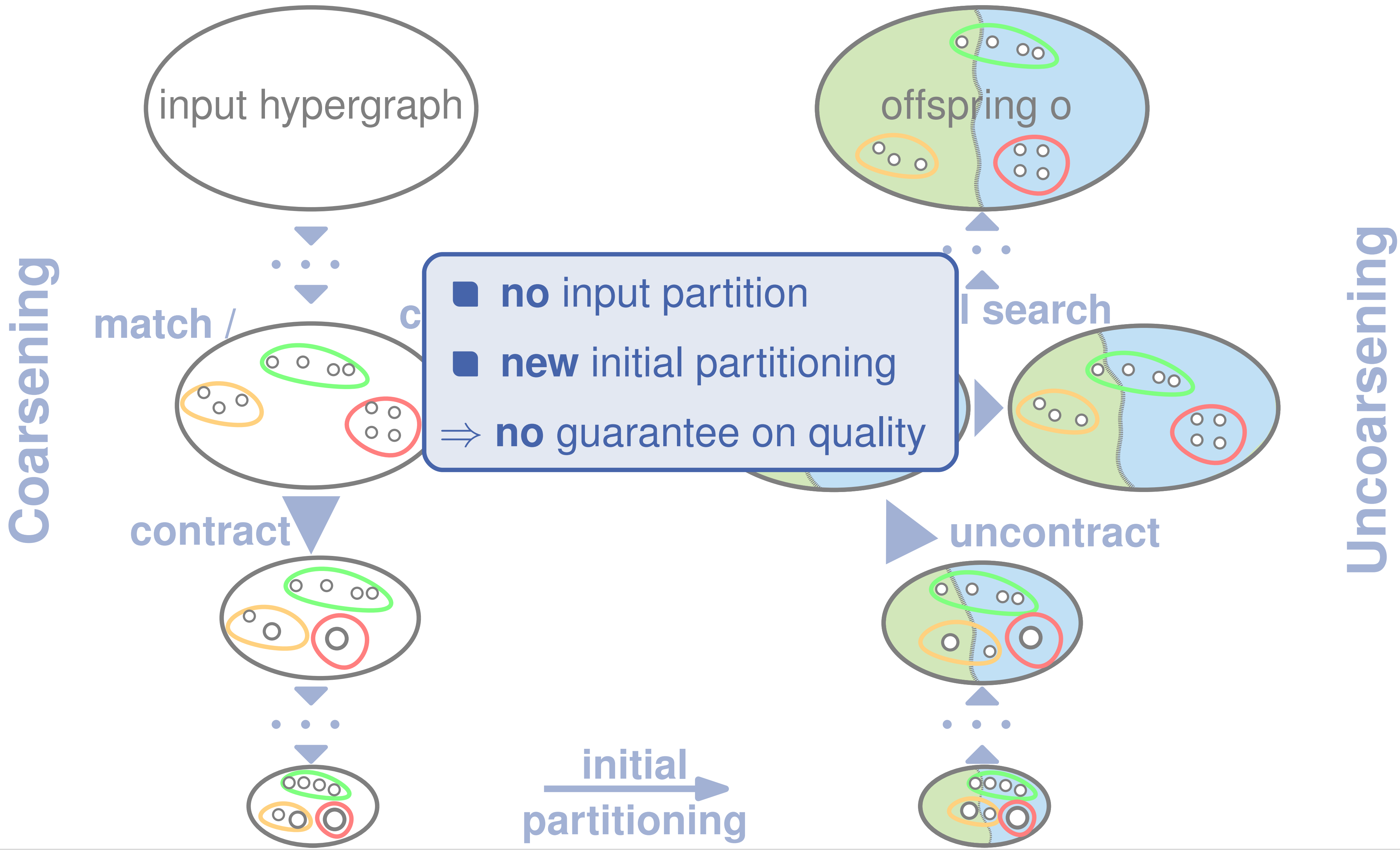
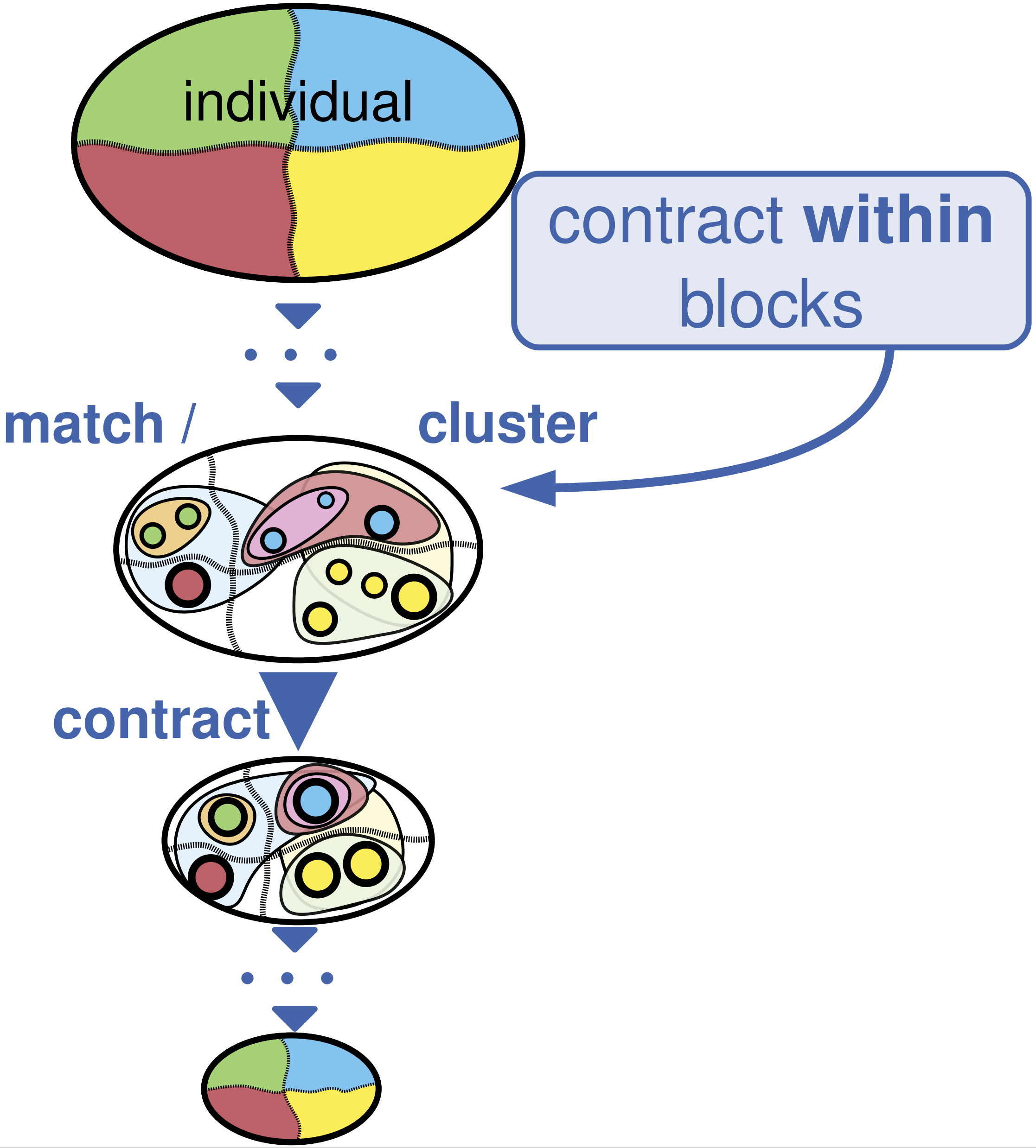


- **no** input partition
- **new** initial partitioning

$\Rightarrow$ **no** guarantee on quality

Memetic Multilevel HGP – V-Cycle Mutation (+M)

[Sanders, Schulz ’12]



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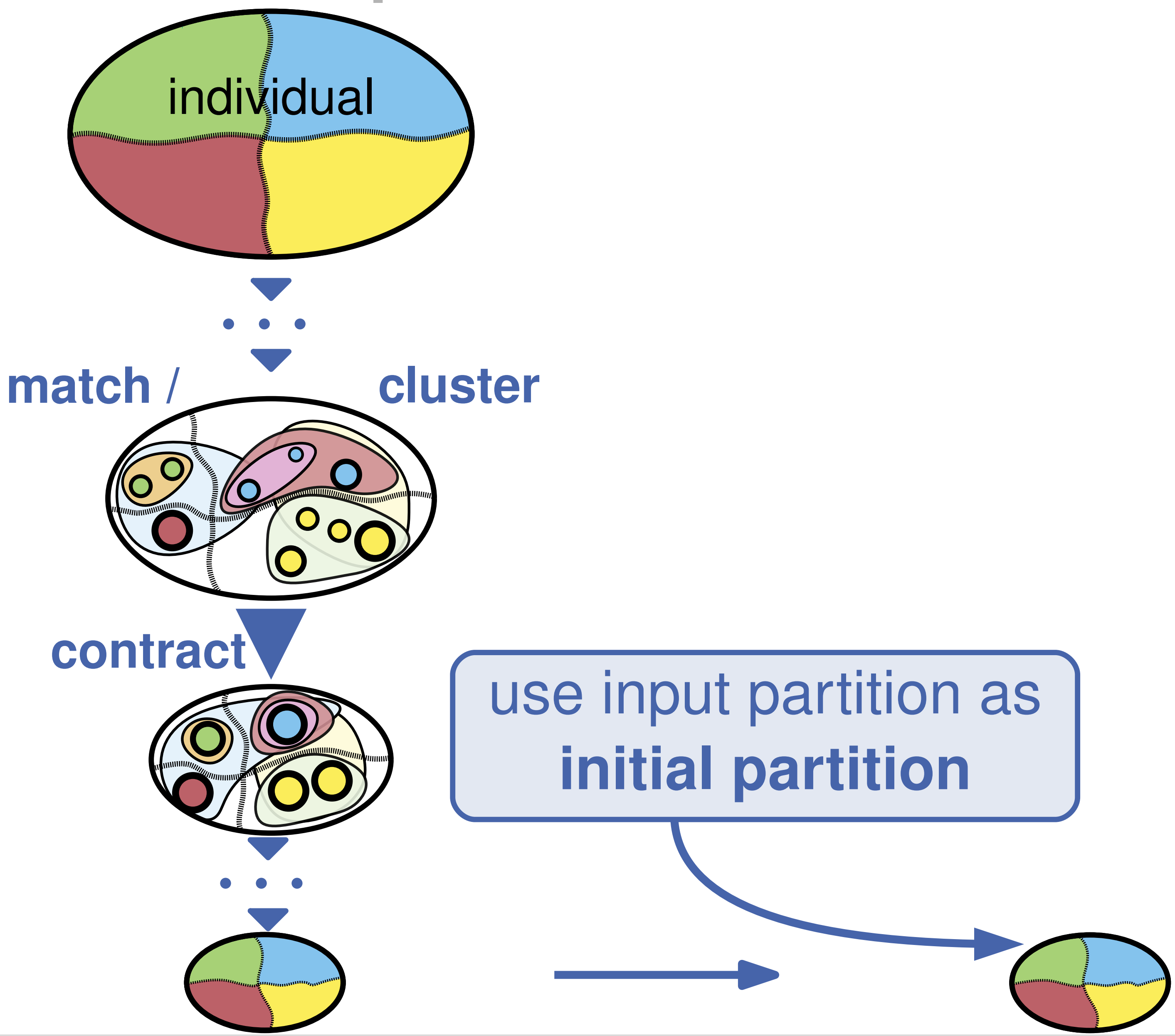
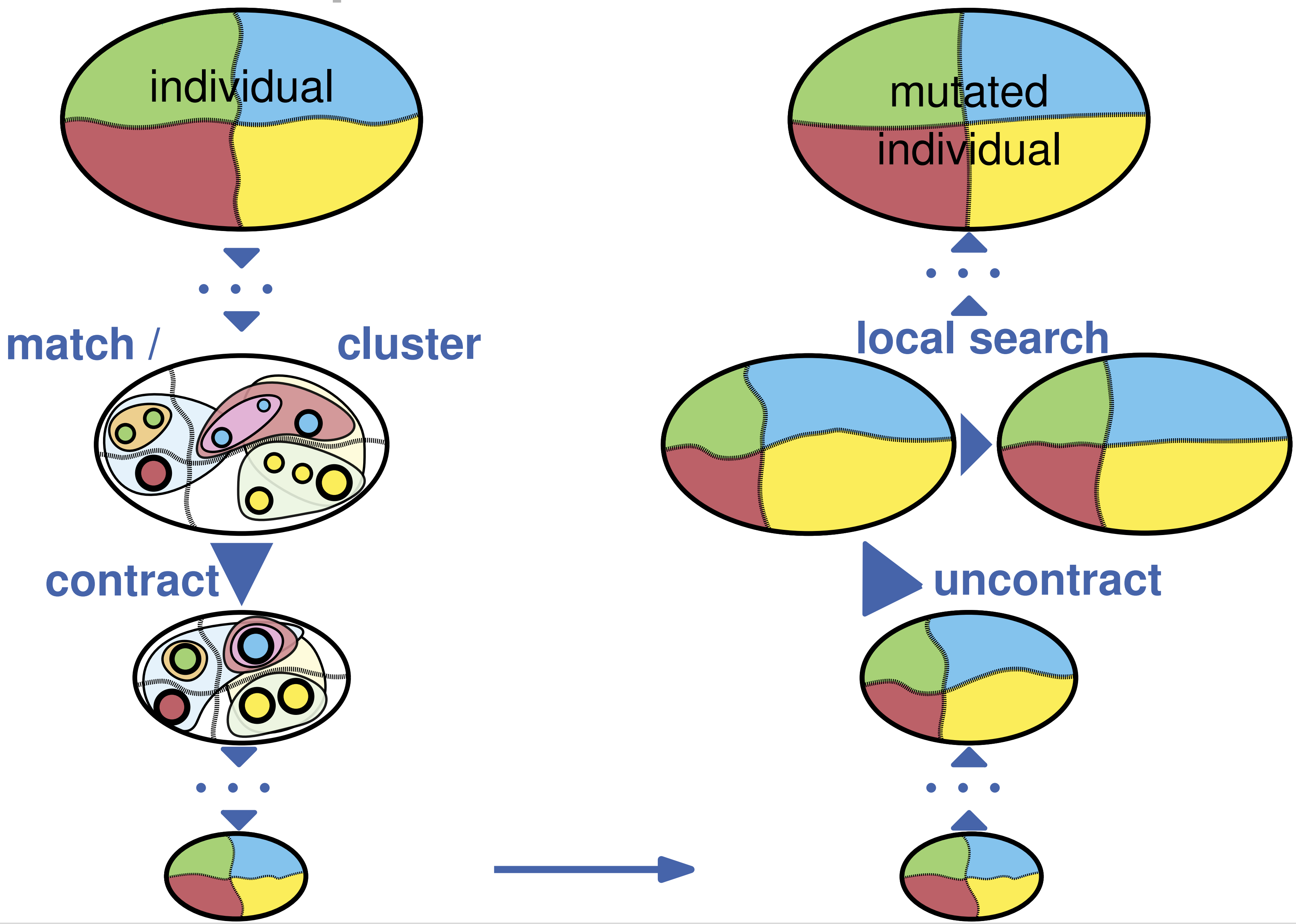


Memetic Multilevel HGP – V-Cycle Mutation (+*M*)

[Sanders, Schulz ’12]



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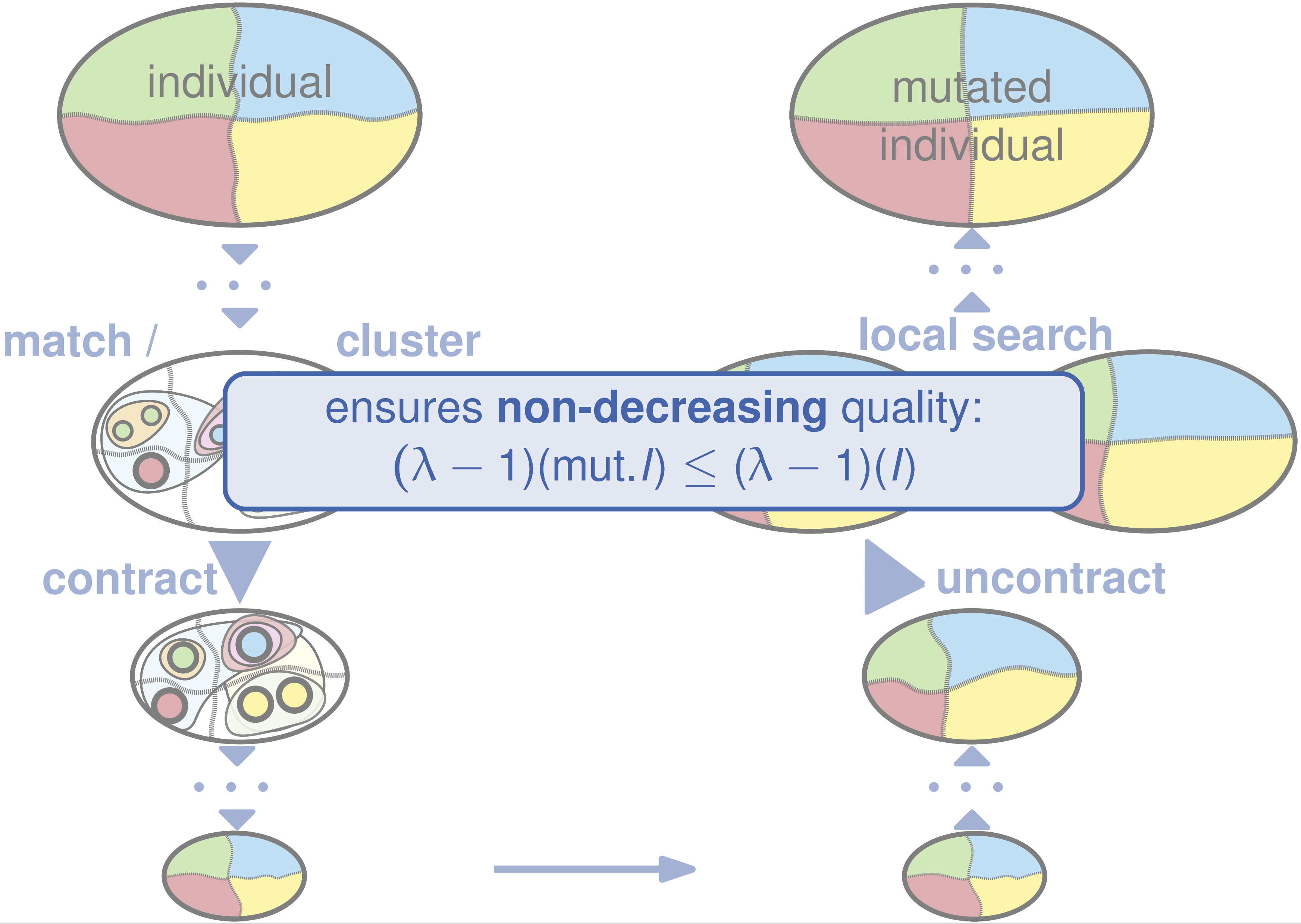

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Memetic Multilevel HGP – V-Cycle Mutation (+M)

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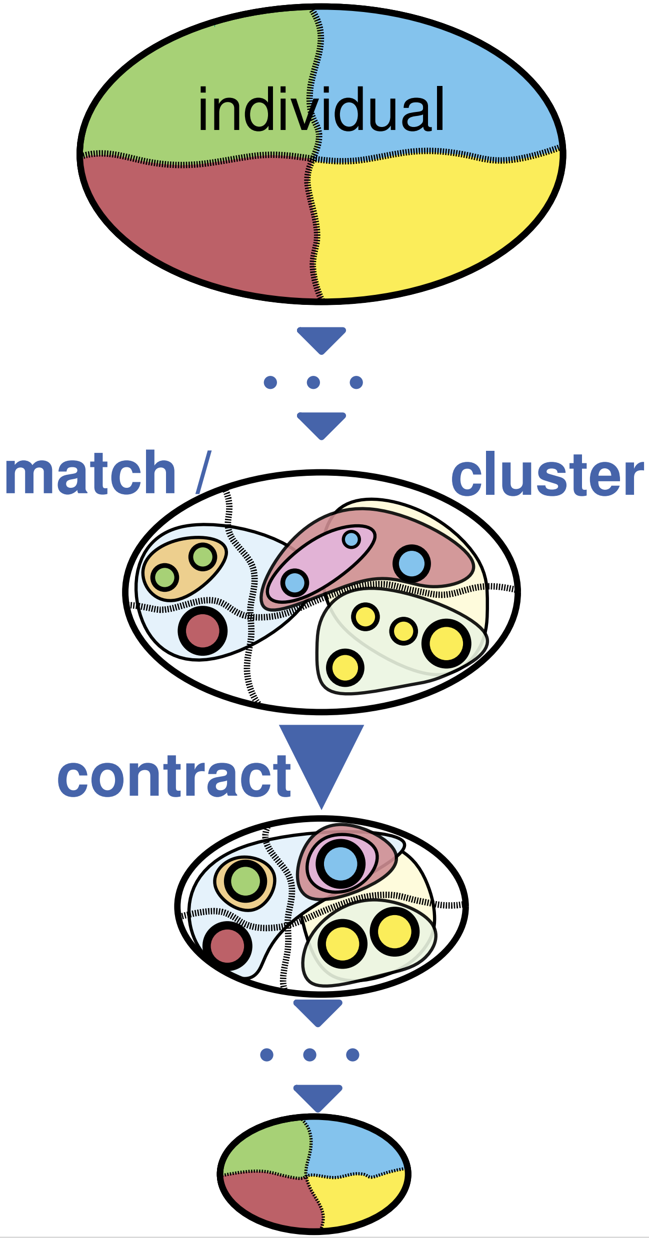
New Initial Partitioning



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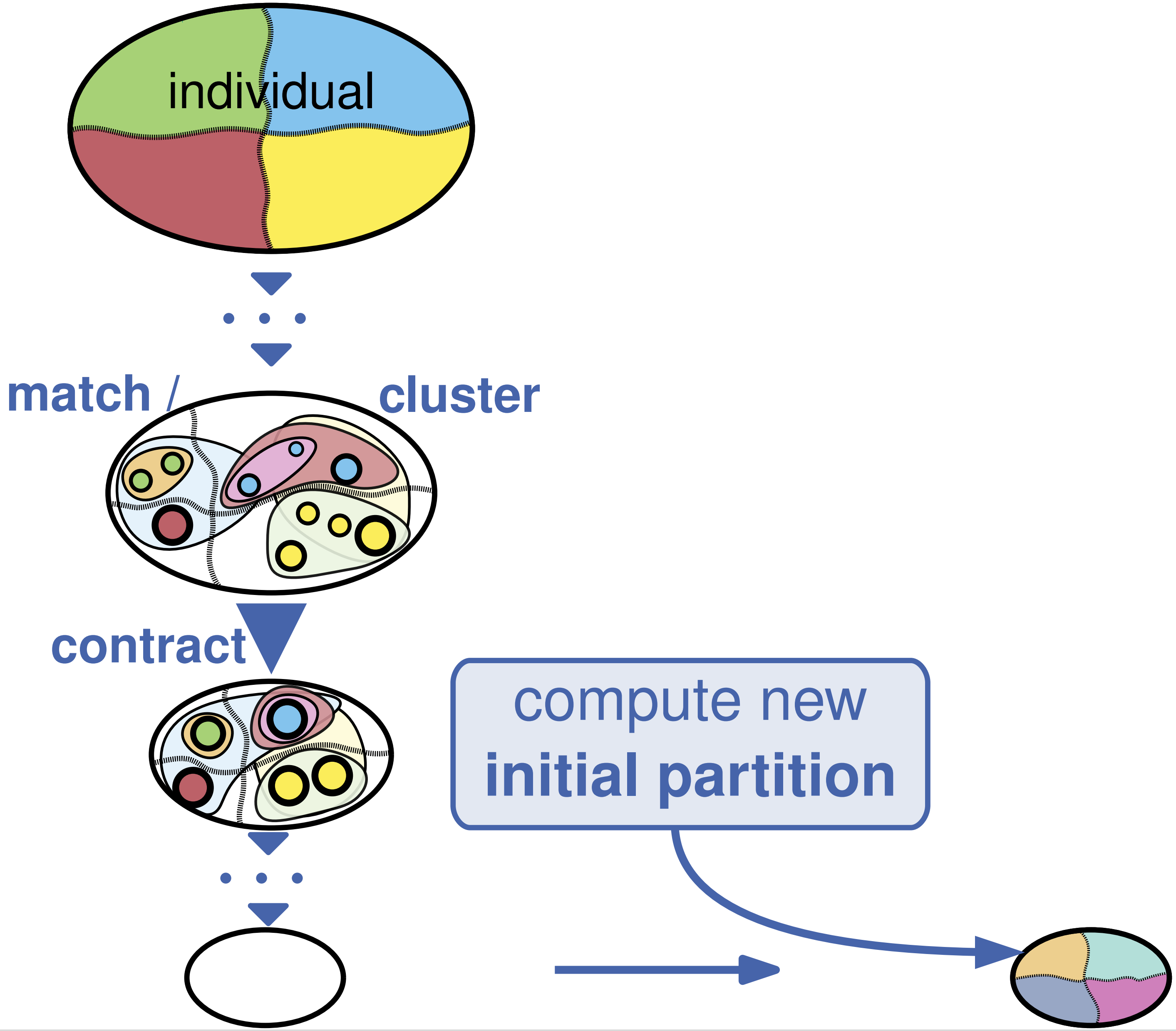

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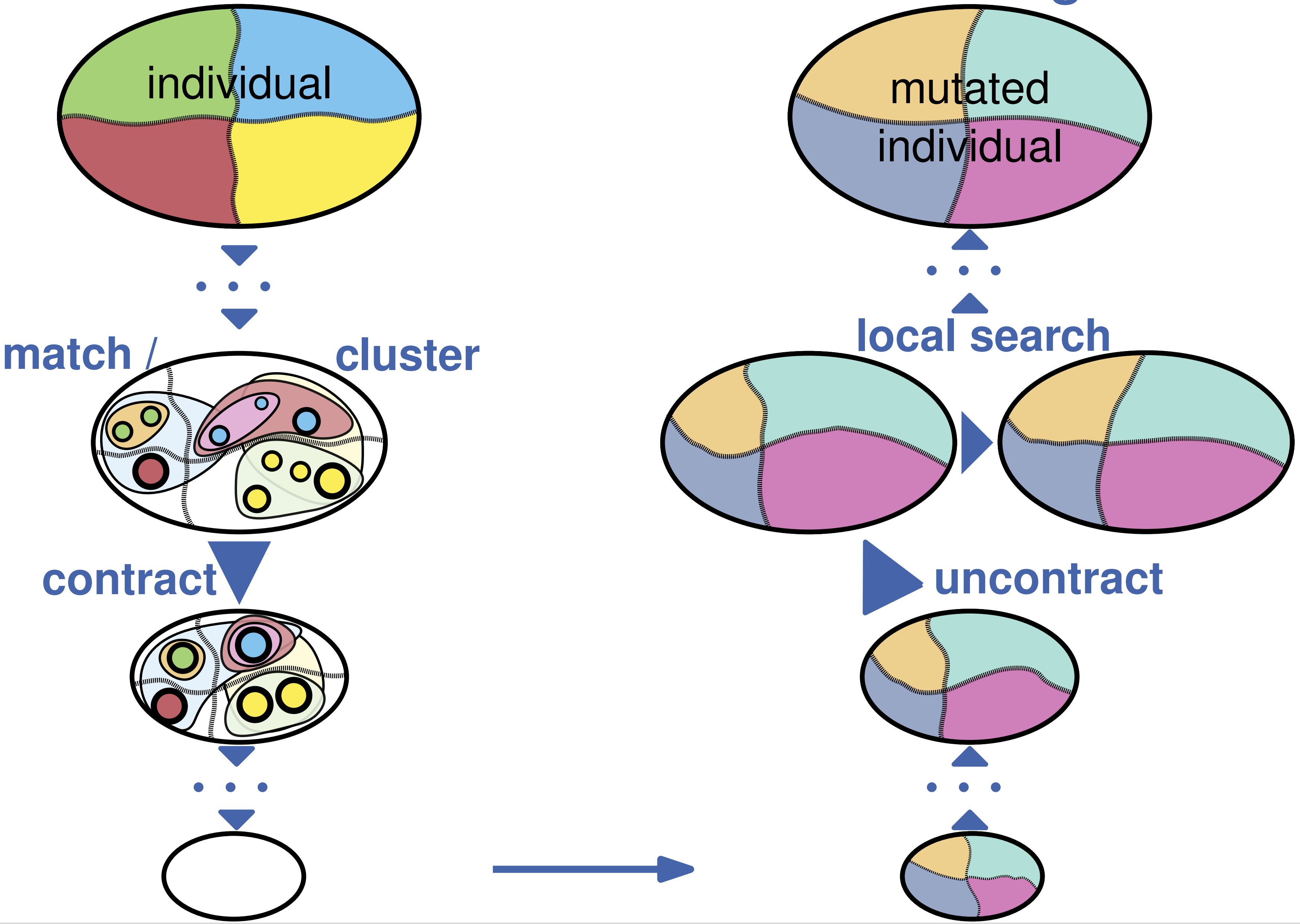

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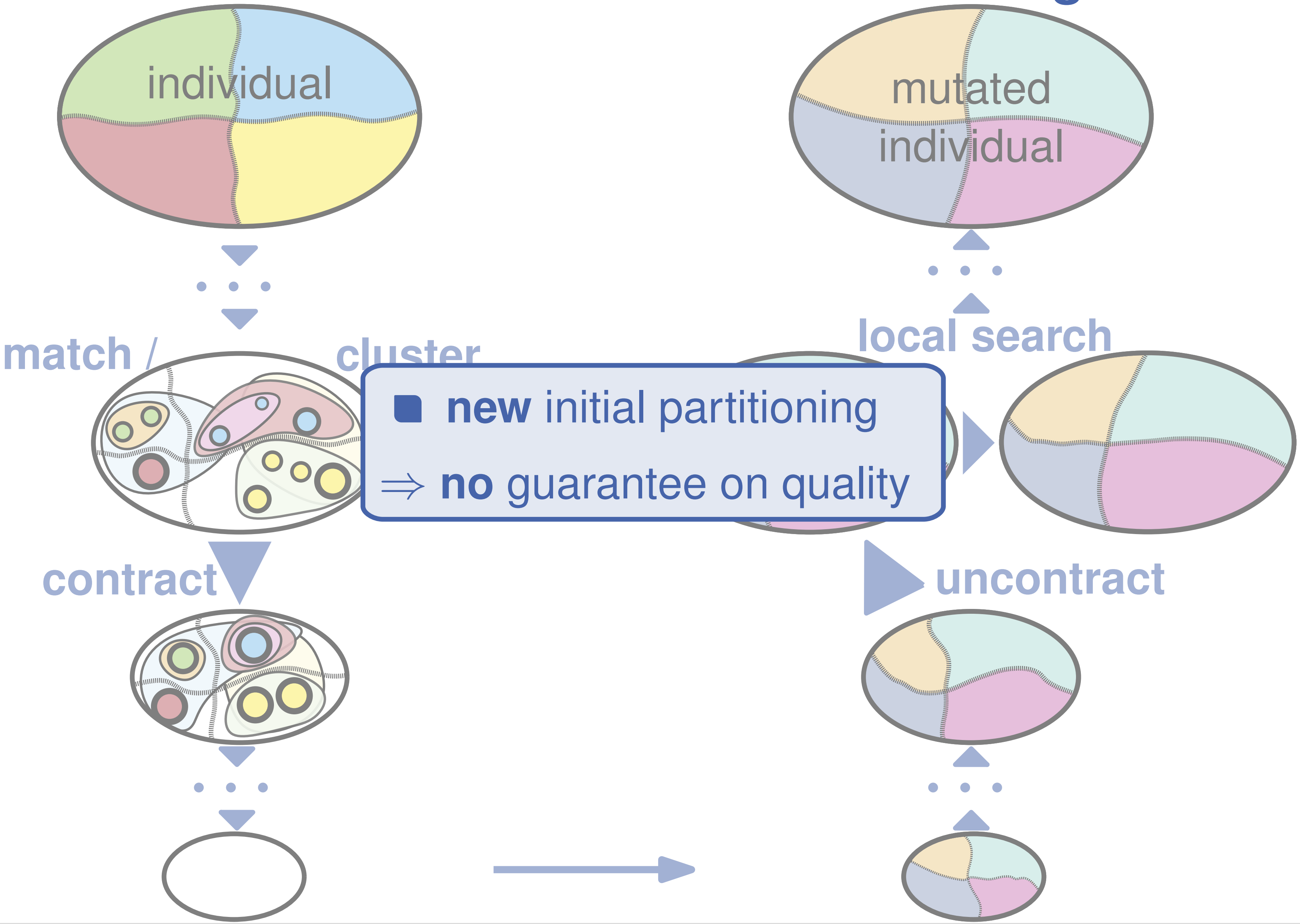

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Memetic Multilevel HGP – Replacement Rule

evict l most **similar** to offspring o with connectivity(l) $\geq$ connectivity(o)

Memetic Multilevel HGP – Replacement Rule

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similarity measure: $d(I, o) := \left|D_I \ominus D_o\right|$

$$D_x := \{(e, m(e)) : e \in E_x\}$$

$$m(e) := (\lambda(e) - 1)$$

symmetric difference

multiset of cut nets

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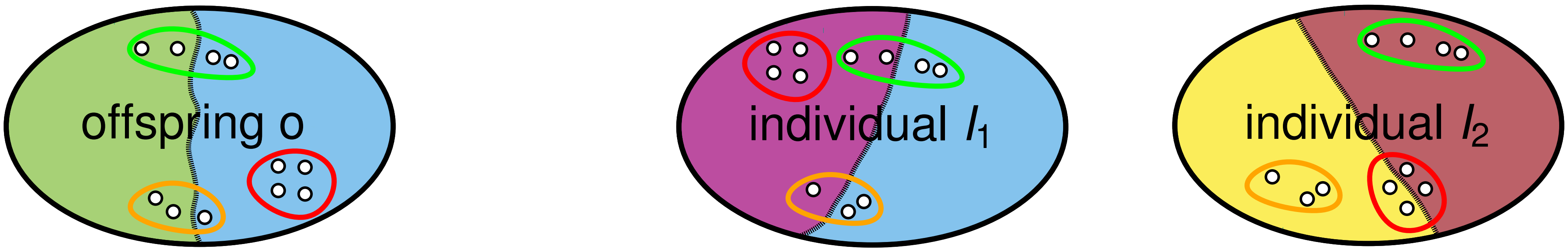

398 — $D_o = \{e, e\}$

398 — $D_{I_1} = \{e, e\}$

442 — $D_{I_2} = \{e\}$

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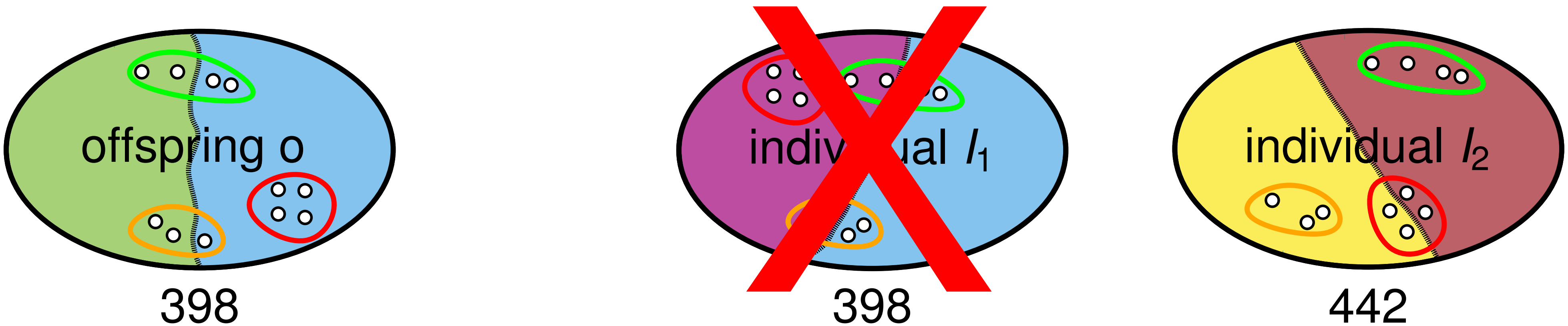

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Experiments – Benchmark Setup

Karlsruhe Institute of Technology

- system: Intel Xeon E5-2670 @ 2.6 Ghz, 64 GB RAM

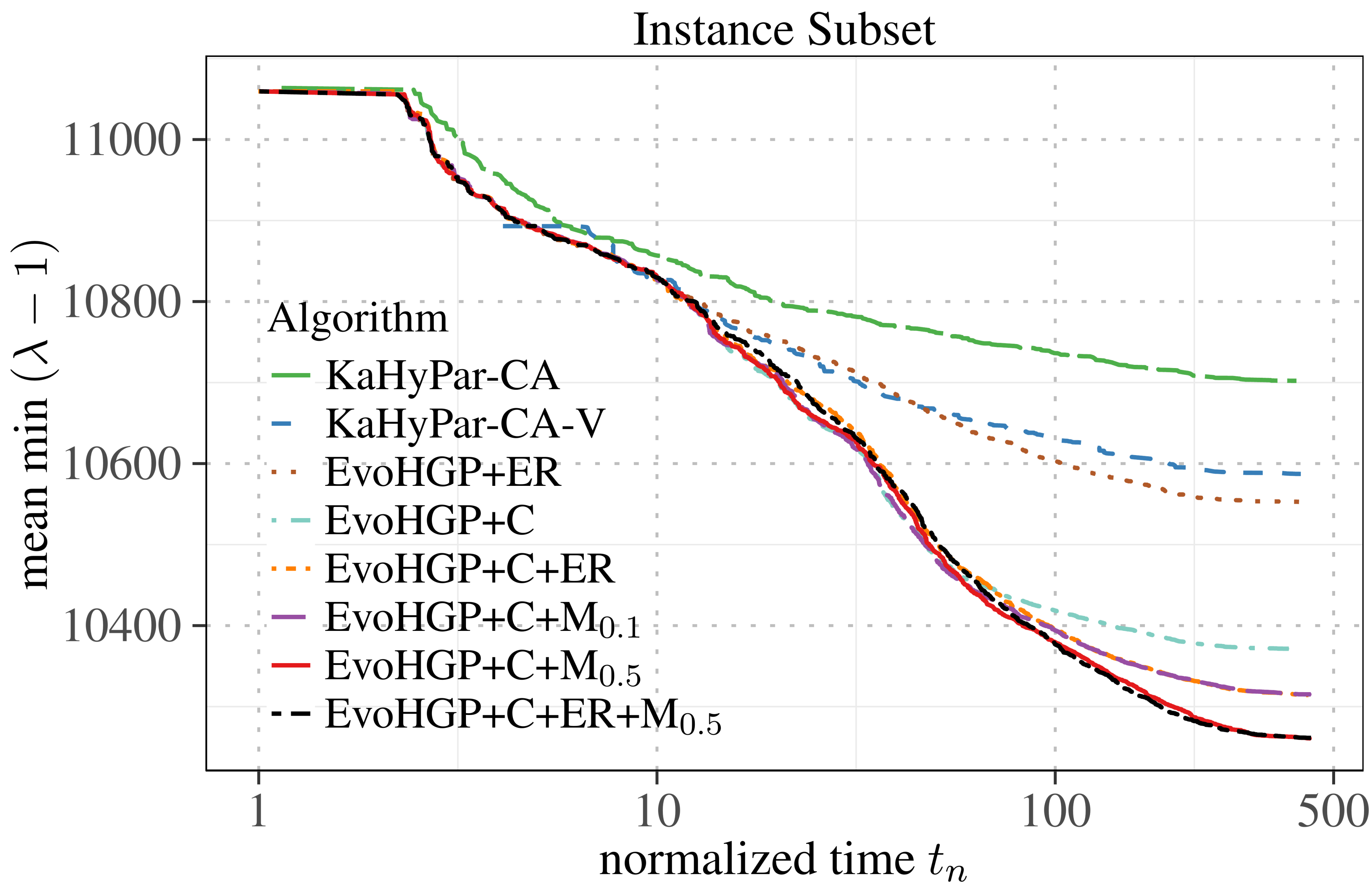
- # hypergraphs: [publicly available]

# hypergraphs: [publicly available]	total	subset
SuiteSparse Matrix Collection	32	5
SAT Competition 2014 (3 representations)	18·3	5·3
ISPD98 & DAC2012 VLSI Circuits	14	5

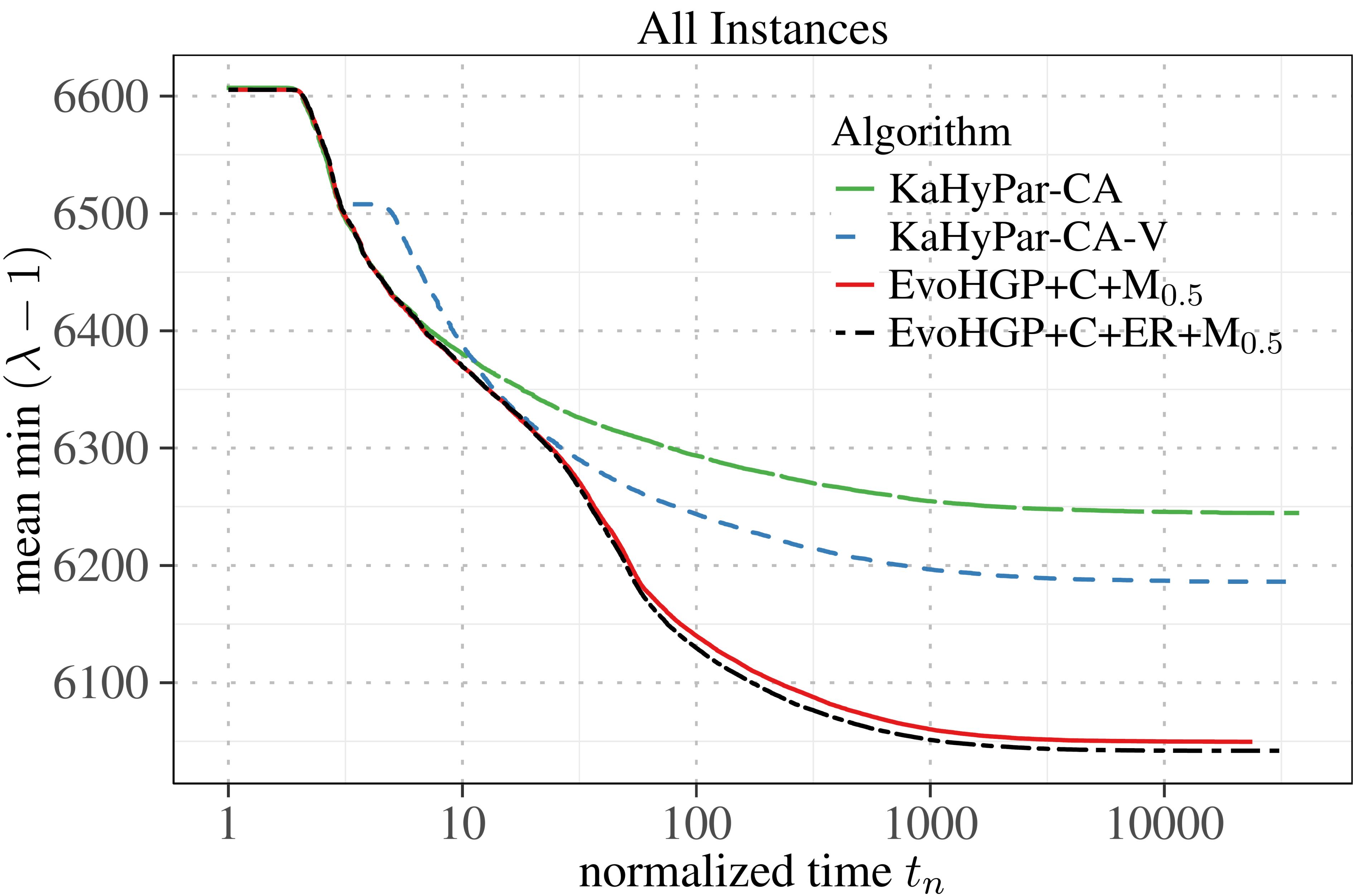
- $k \in \{2, 4, 8, 16, 32, 64, 128\}$ with imbalance: $\varepsilon = 3\%$
- timelimit: 8h / instance
- 5 repetitions / instance

- comparing **EvoHGP** (KaHyPar-E) with:
  - KaHyPar-CA
  - KaHyPar-CA + V-Cycles
  - hMetis-R & hMetis-K
  - PaToH-Default & PaToH-Quality

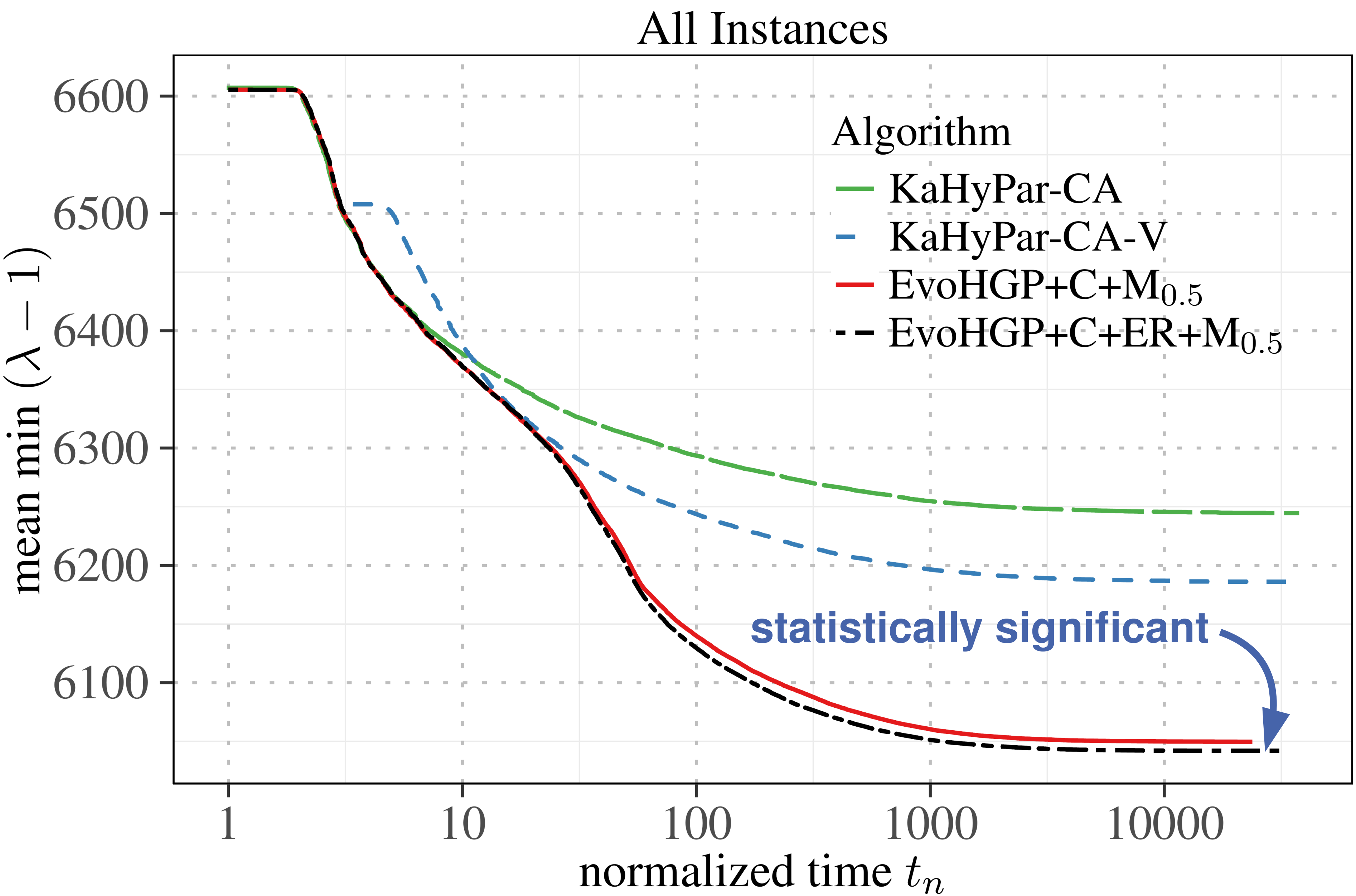
Influence of Algorithmic Components



EvoHGP vs. KaHyPar-CA & KaHyPar-CA-V



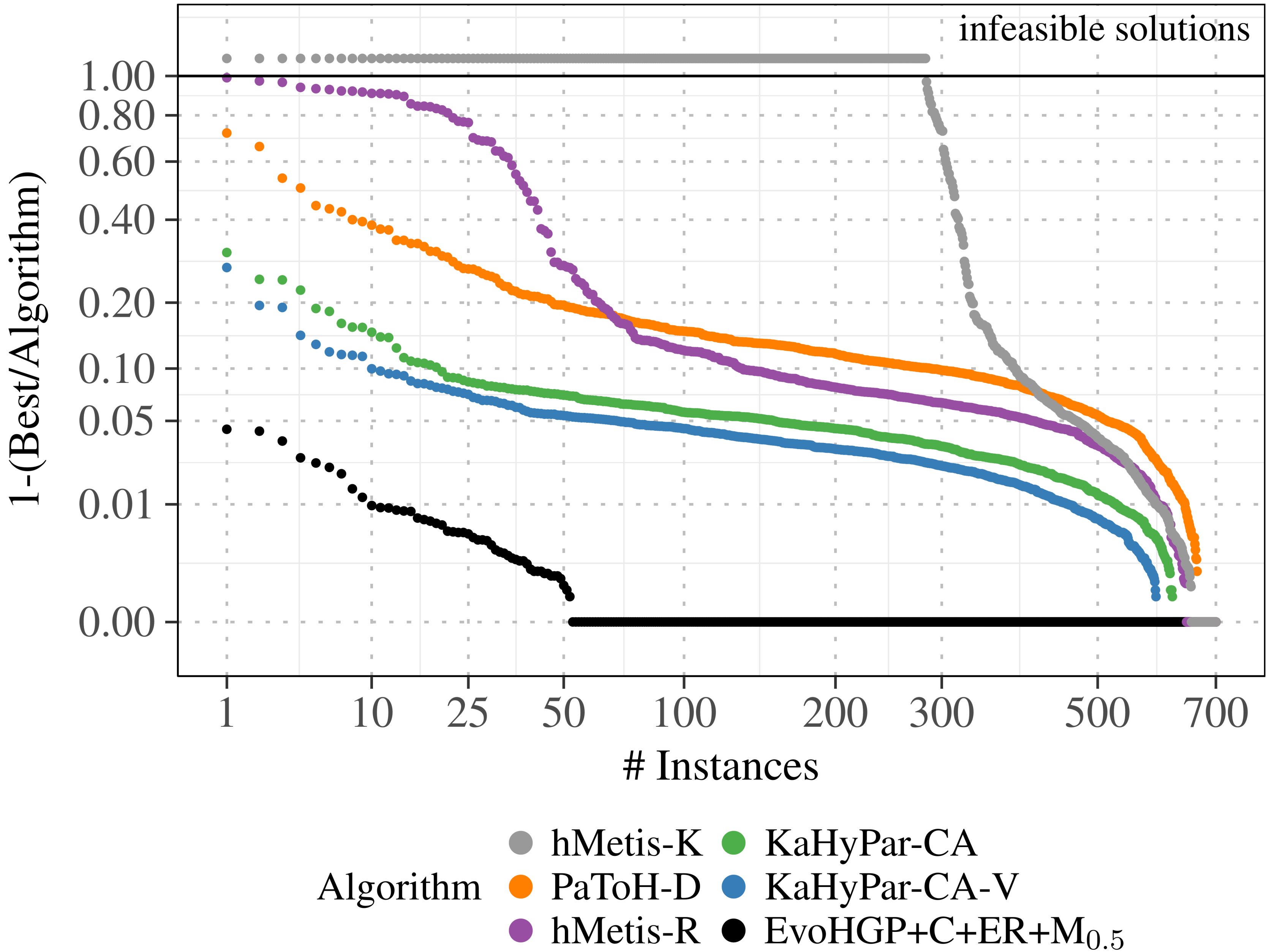
EvoHGP vs. KaHyPar-CA & KaHyPar-CA-V



EvoHGP Improvment over KaHyPar-CA & -CA-V

	KaHyPar-CA vs. EvoHGP		KaHyPar-CA-V vs. EvoHGP	
k	$+C+M_{0.5}$	$+C+ER+M_{0.5}$	$+C+M_{0.5}$	$+C+ER+M_{0.5}$
all	3.3%	3.4%	2.3%	2.4%
2	0.9%	0.9%	0.3%	0.4%
4	1.3%	1.4%	0.8%	1.0%
8	2.7%	2.9%	1.9%	2.0%
16	3.5%	3.6%	2.5%	2.6%
32	4.3%	4.6%	3.2%	3.5%
64	4.9%	5.0%	3.5%	3.6%
128	5.4%	5.4%	3.7%	3.7%

Comparison with Best Non-Evo Algorithms



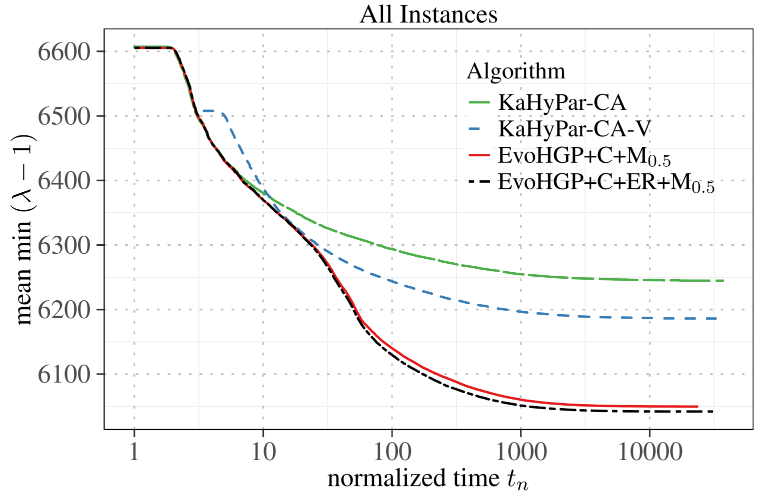
Conclusion & Discussion

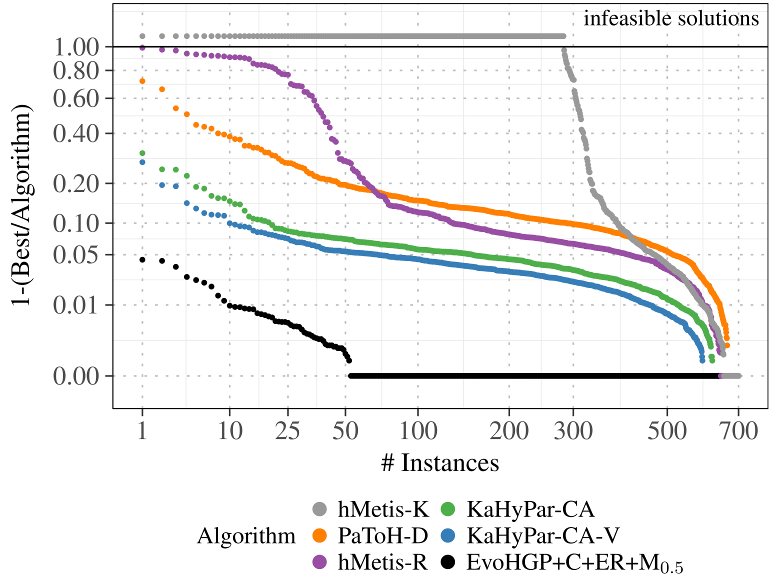
KaHyPar-E – memetic **multilevel** *k*-way HGP

- problem-**specific** recombination
- problem-**specific** mutation

Future Work:

- shared-memory parallelization
- distributed-memory parallelization





KaHyPar-Framework
Open-Source:
`http://kahypar.org`