

Solving Portfolio Optimization Problems Using MOEA/D and Lévy Flight

Knowledge System Lab

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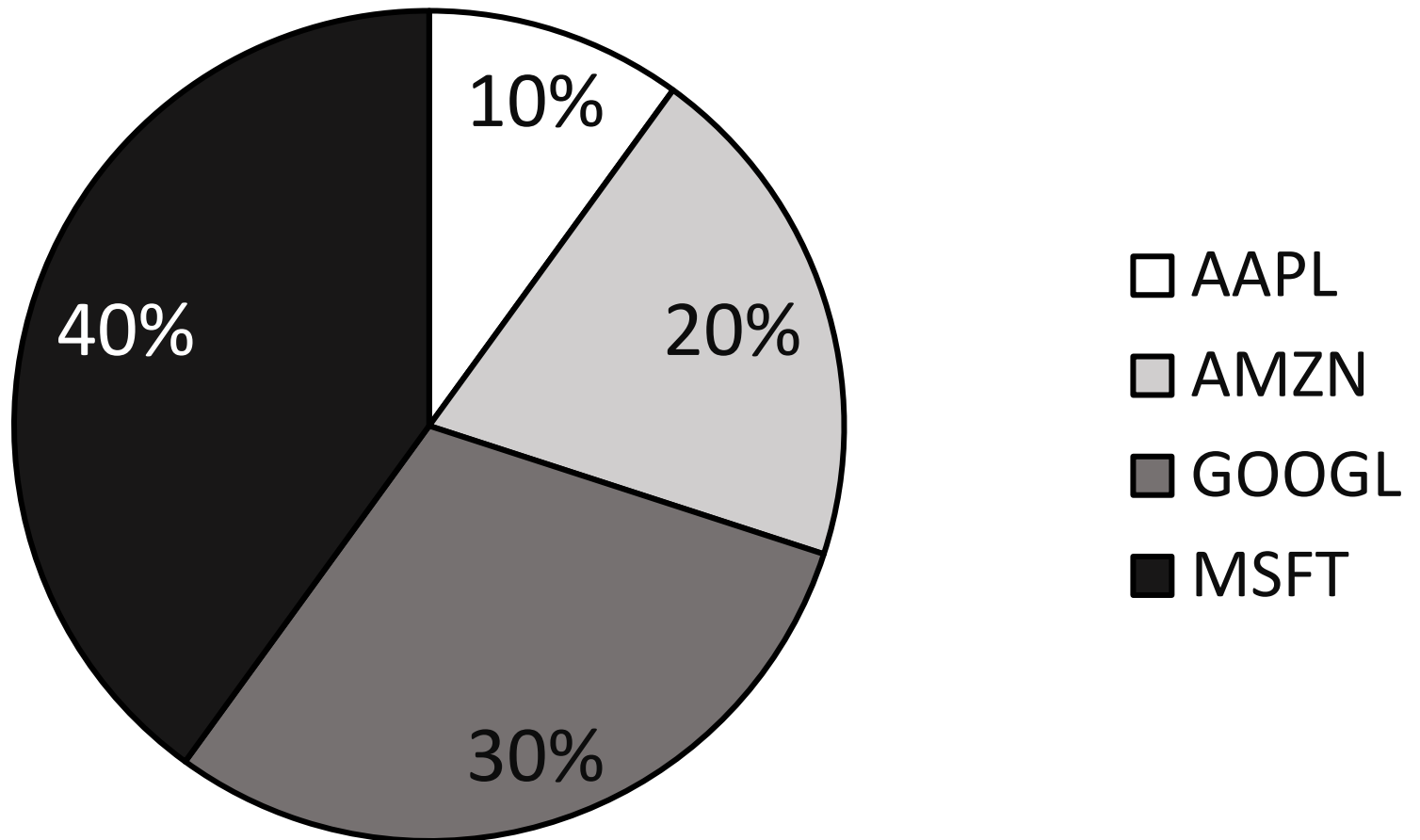
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Outline

*Lévy Flight keeps a good **balance between local and global** search. Furthermore, it utilizes structural **information of the problem** when solving portfolio optimization.*

- Background
- Related Work
- Proposed Method
- Experiments

An example of portfolio on four stocks



Description of Portfolio

- One single stock

Get many money
Get little money
Lose little money
Lose many money

} Return as a
random variable
 R_i

- With normal assumption,

$E(R_i)$

$V(R_i)$

Average
return

Chance of a low return
= Risk

Description of Portfolio

- Portfolio: weighted sum of stocks

$$R = \sum_{i=1}^n w_i \cdot R_i$$

w_i : i -th invest weight R_i : i -th asset return

- Portfolio return: expectation value of a sum

$$E(R) = \sum_{i=1}^n w_i \cdot E(R_i)$$

- Portfolio risk: variance of a sum

$$V(R) = \sum_{i=1}^n \sum_{j=1}^n w_i \cdot w_j \cdot Cov(R_i, R_j)$$

Unconstrained PO Problem

- Given n stocks holding returns $\{R_1, \dots, R_n\}$
- Find a portfolio weight $\{w_1, \dots, w_n\}$

- Maximize portfolio return

$$\sum_{i=1}^n w_i \cdot E(R_i)$$

- Minimize portfolio risk

$$\sum_{i=1}^n \sum_{j=1}^n w_i \cdot w_j \cdot Cov(R_i, R_j)$$

- Subject to,

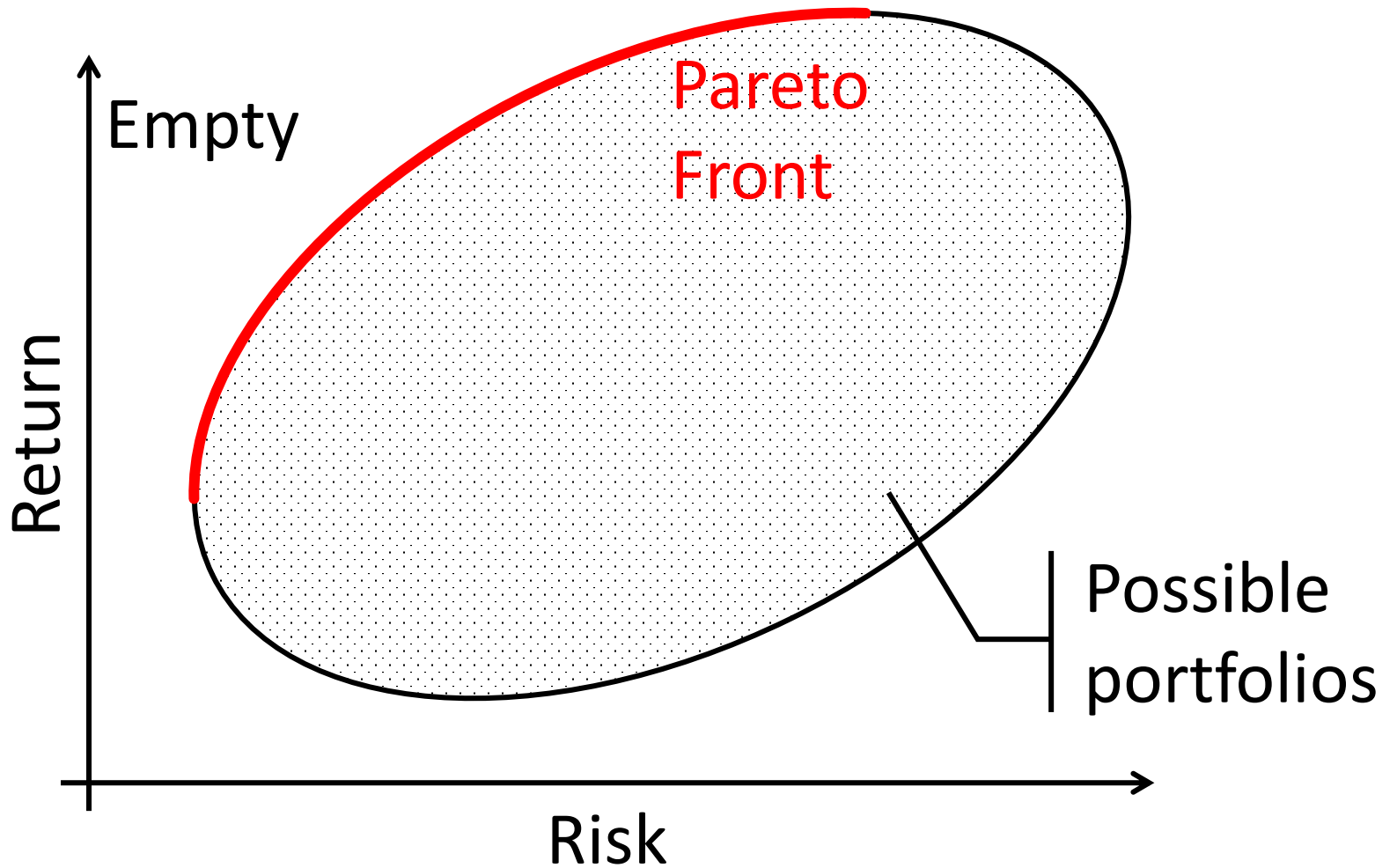
- Unit constraint $\sum_{i=1}^n w_i = 1$

- No short selling $w_i \geq 0$

Importance of PO Problem

- Practical meaning (it makes money)
- Theoretical meaning (it is hard)
 - High dimension
 - NP-hard with proper constraints
[Bienstock 1996]

Optimal Portfolios



MOEA based on Decomposition (MOEA/D) [Zhang 2007]

- E.g. PO: $\{\max E, \min V\} \Rightarrow \min\{-E, V\}$

- $s_1 = -0.0E + 1.0V$

- $s_2 = -0.2E + 0.8V$

- $s_3 = -0.4E + 0.6V$

- $s_4 = -0.6E + 0.4V$

- $s_5 = -0.8E + 0.2V$

- $s_6 = -1.0E + 0.0V$

Sub-problems

$x^{(i)}$: solution of s_i

Borrow from neighbors

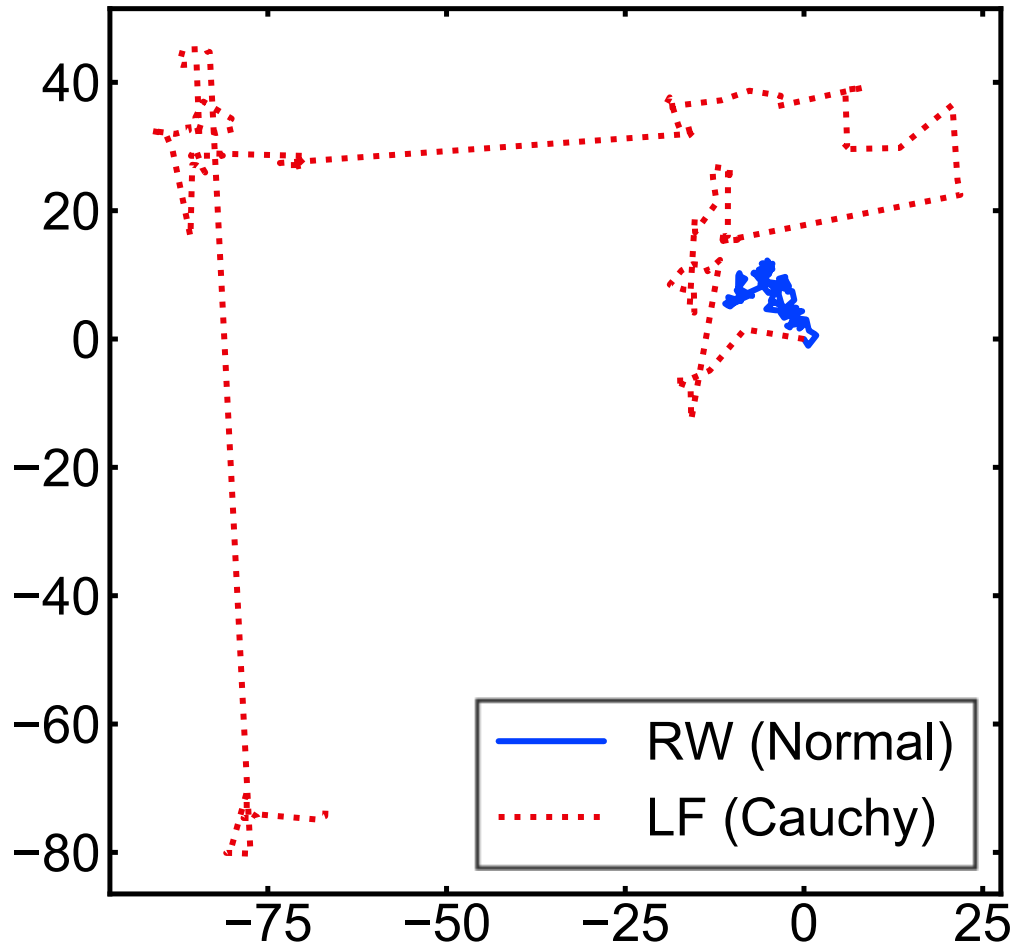
- Before reproduction:
Select from neighbors
- After reproduction:
Update neighbors by
offspring

Mutation Methods in MOEA/D

Algorithm	Mutation	Publication
MOEA/D-	PSO	Particle Swarm Optimization [Peng 2008]
	DE	Differential Evolution [Li 2009]
	ACO	Ant Colony Optimization [Ke 2013]

- MOEA/D-DE [Li 2009]
 - DE mutation: $\mathbf{y} = \mathbf{x}^{(i)} + F \cdot (\mathbf{x}^{(j)} - \mathbf{x}^{(k)})$
 - Polynomial mutation

Lévy Flight (LF): A Comparison with Random Walk



- Random walk (RW) whose step length follows stable distribution (heavy-tailed)

100 Steps of RW
and LF from (0,0) in
2D Space

Related Work: Solving PO with MOEAs

- Non-MOEA/D methods
 - SPEA2, NSGA-II [Mishra 2011]
 - NS-MOPSO [Mishra 2014], MOBFO [Mishra 2014], M-CABC [Kumar 2017]
- MOEA/D-based methods
 - Mutation: MOEA/D-DE [Zhang 2010] (with DE mutation only in reproduction)
 - Weight vector: MOEA/D-CP [Zhang 2018]
 - Initialization: DEA-MOEA/D [Zhou 2019]

Proposed Method: MOEA/D-Lévy

- Inject LF mutation into MOEA/D:
 - $\mathbf{y} = \mathbf{x}^{(i)} + \alpha_0 \cdot (\mathbf{x}^{(i)} - \mathbf{x}^{(j)}) \oplus \text{Levy}(\beta)$
 - \oplus : entry-wise multiplication
 - α_0 : scaling factor
 - $\beta \in [0.3, 1.99]$: shape parameter
 - Polynomial mutation
- Repair steps
 - Set negative variables to 0
 - Scale to satisfy unit constraint

Experimental Settings

- Data: PO benchmark in OR library (Nikkei, size=225) [[Chang 2000](#)]
- Parameters, convergence settings are fine-tuned or set according to prior studies
- Evaluation Metrics (totally six)
 - Inverted Generation Distance (IGD)
 - Hypervolume (HV)

Comparison with Literature Methods

Method	Mutation	Publication
MOEA/D-	Lévy Polynomial mutation	Proposed method
	DEM DE mutation + Polynomial mutation	[Li 2009]
	DE DE mutation only	[Zhang 2010]
	GA GA reproduction	[Zhang 2007]
NSGA-II		[Deb 2002]

Experimental Results on Nikkei

Metric	MOEA/D -Lévy	MOEA/D -DEM	MOEA/D -DE	MOEA/D -GA	NSGA-II
IGD					
Best	1.77e-05	1.90e-05	7.90e-05	1.77e-04	4.64e-05
Median	2.39e-05	2.73e-05	2.23e-04	2.41e-04	9.69e-05
Std.	1.15e-05	4.09e-04	6.95e-05	5.29e-04	3.67e-05
HV					
Best	8.31e-06	8.29e-06	7.96e-06	7.87e-06	8.19e-06
Median	<u>8.29e-06</u>	8.26e-06	7.23e-06	7.54e-06	7.94e-06
Std.	1.59e-08	9.52e-07	3.43e-07	1.20e-06	1.08e-07

*The special font shows **Best** and **Statistical significance**

Comparison with Other Distribution-based Mutation

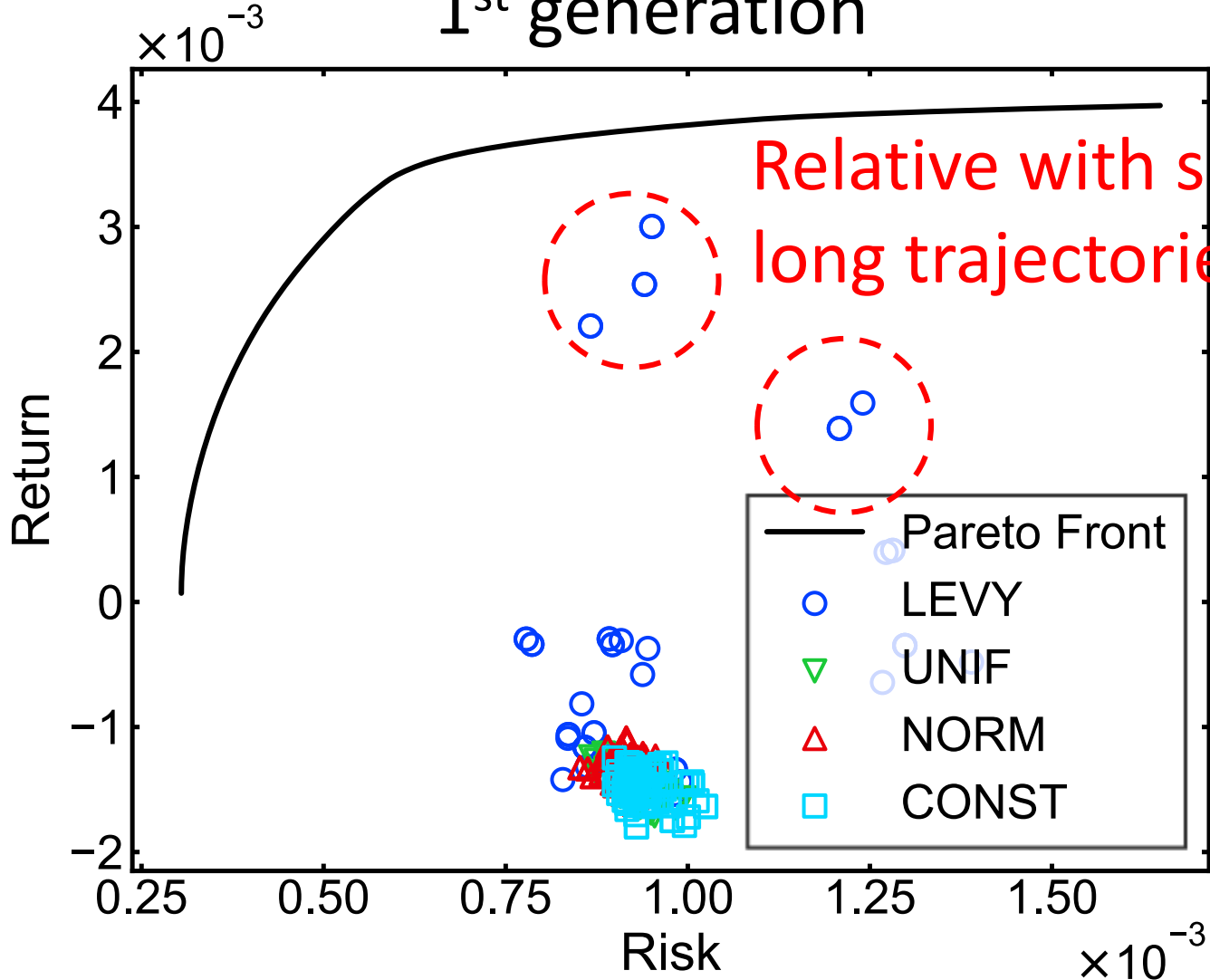
Method	Mutation
LEVY	$\mathbf{y} = \mathbf{x}^{(i)} + \alpha_0 \cdot (\mathbf{x}^{(i)} - \mathbf{x}^{(j)}) \oplus \text{Levy}(\beta)$
UNIF	$\mathbf{y} = \mathbf{x}^{(i)} + C \cdot (\mathbf{x}^{(j)} - \mathbf{x}^{(k)}) \oplus \text{Unif}(-1, 1)$
NORM	$\mathbf{y} = \mathbf{x}^{(i)} + C \cdot (\mathbf{x}^{(j)} - \mathbf{x}^{(k)}) \oplus \mathbf{N}(\mathbf{0}, \mathbf{1})$
CONST	$\mathbf{y} = \mathbf{x}^{(i)} + F \cdot (\mathbf{x}^{(j)} - \mathbf{x}^{(k)}) \oplus \mathbf{1}$

Tracking Successful Trajectories

1st generation

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Trajectories as Capital Re-allocation in PO

Strategy	Asset Type	Portfolio
Random	-	Low risk
Centralized	High return	High return

Heavy-tailed

- Many small values
- Few large values

Re-allocation by LF is
centralized!

Trajectories as Capital Re-allocation in PO

Parent

0.10	0.15	0.20	0.15	0.18	0.02	0.20
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Mutation (Re-allocation) Vector by LF

0.05	5.00	0.10	0.50	0.08	0.02	0.67
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Offspring before Repair

0.15	5.15	0.30	0.65	0.26	0.04	0.87
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Offspring after Repair

0.02	0.69	0.04	0.09	0.03	0.01	0.12
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Conclusions

- Summary of the Research
 - Inject LF into MOEA/D and assess on PO
 - Relation between long trajectories and moving solution to high return areas
 - Explain by considering property of PO
- Future Work
 - Adaptive strategy
 - Solve sub-problems with different mutation methods