

LLM-ASSISTED CROSSOVER

IN GENETIC IMPROVEMENT OF SOFTWARE



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MOTIVATION

End of Moore's Law?

**Hardware improvement has slowed down,
we need to focus on software**

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Traditional crossover in GL

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MOTIVATION

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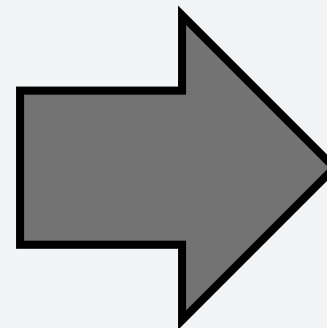
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Why LLMs?

**Need for an intelligent crossover operator
with contextual awareness:**

- Produce more offsprings that survive
- Produce fitter offsprings
- Guide the search more efficiently.

BACKGROUND

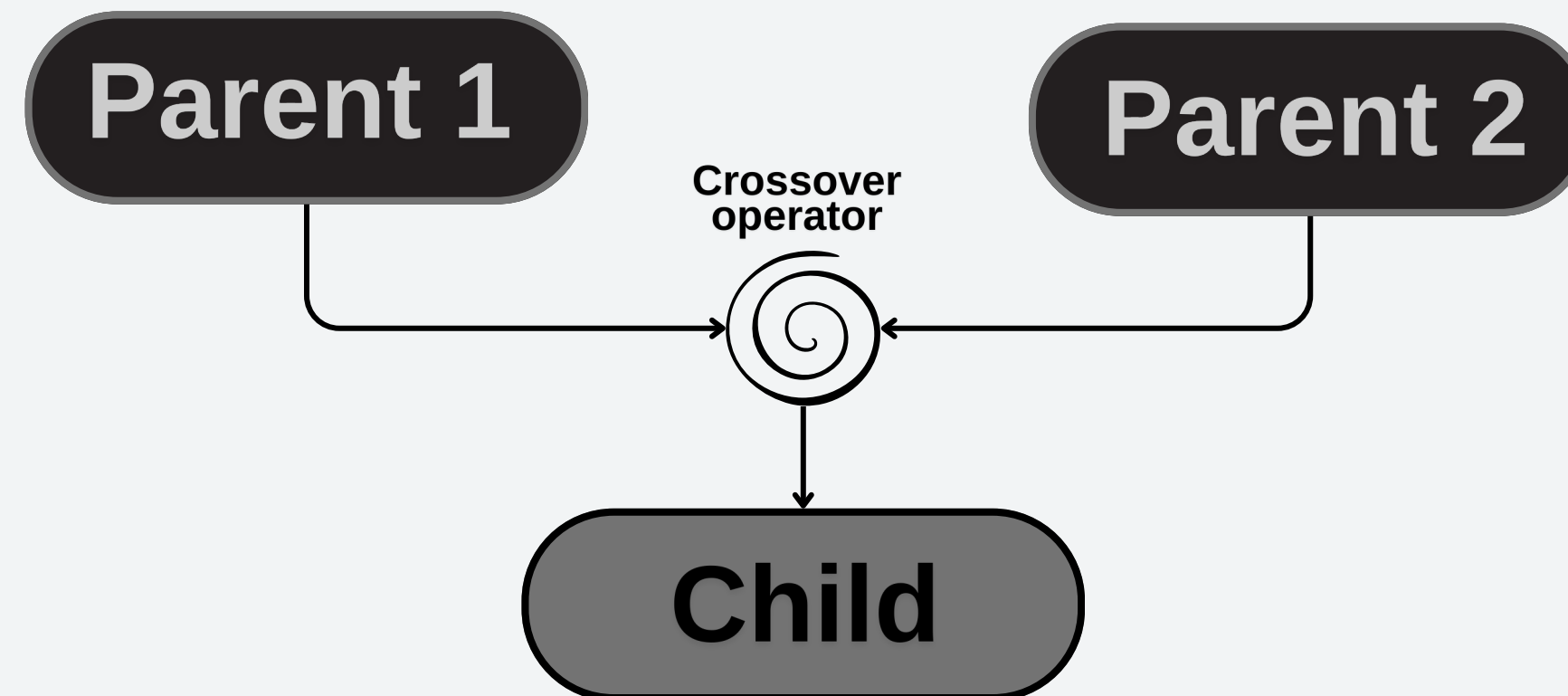
GI AND CROSSOVER

GI

Automated technique that applies evolutionary algorithms to improve software performance by modifying code or parameters, inspired by natural selection

Variant

A version of the software being improved, with some modification made on it



Mutation

Introduces new changes to a variant to explore new areas of the search space

Crossover

Combines 2 parent variants together to create a new variant: the child

BACKGROUND

TRADITIONAL CROSSOVER OPERATORS

1point

Choose 1 crossover point in both parents and swap edits at this point

2point

Choose 2 crossover points at both parents for more flexibility

Concat

Append the edits of the 2 parents

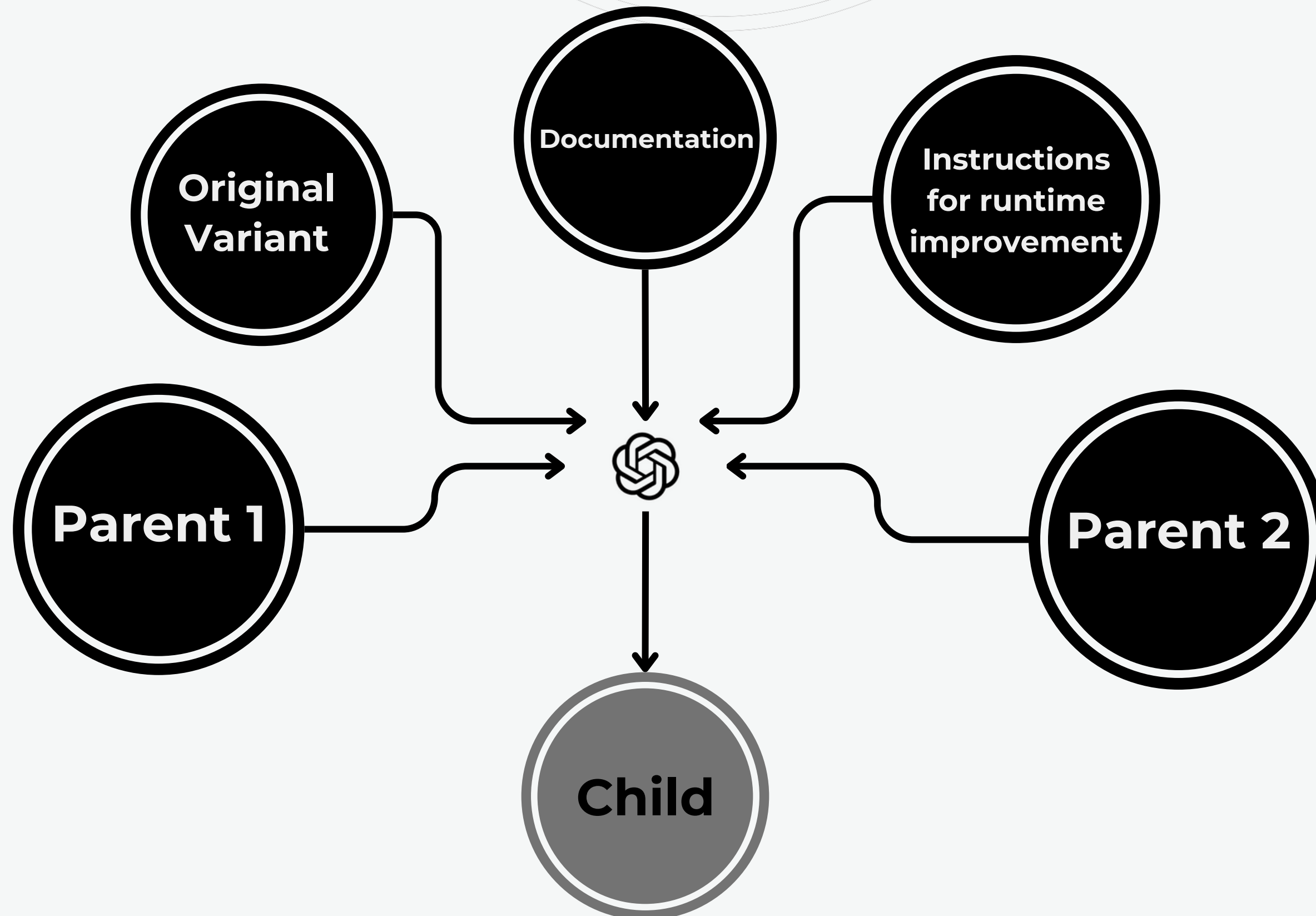
Uniform Concat

Interleave edits from both parents uniformly before appending them

Uniform Inter

Interleave the edits of the 2 parents together

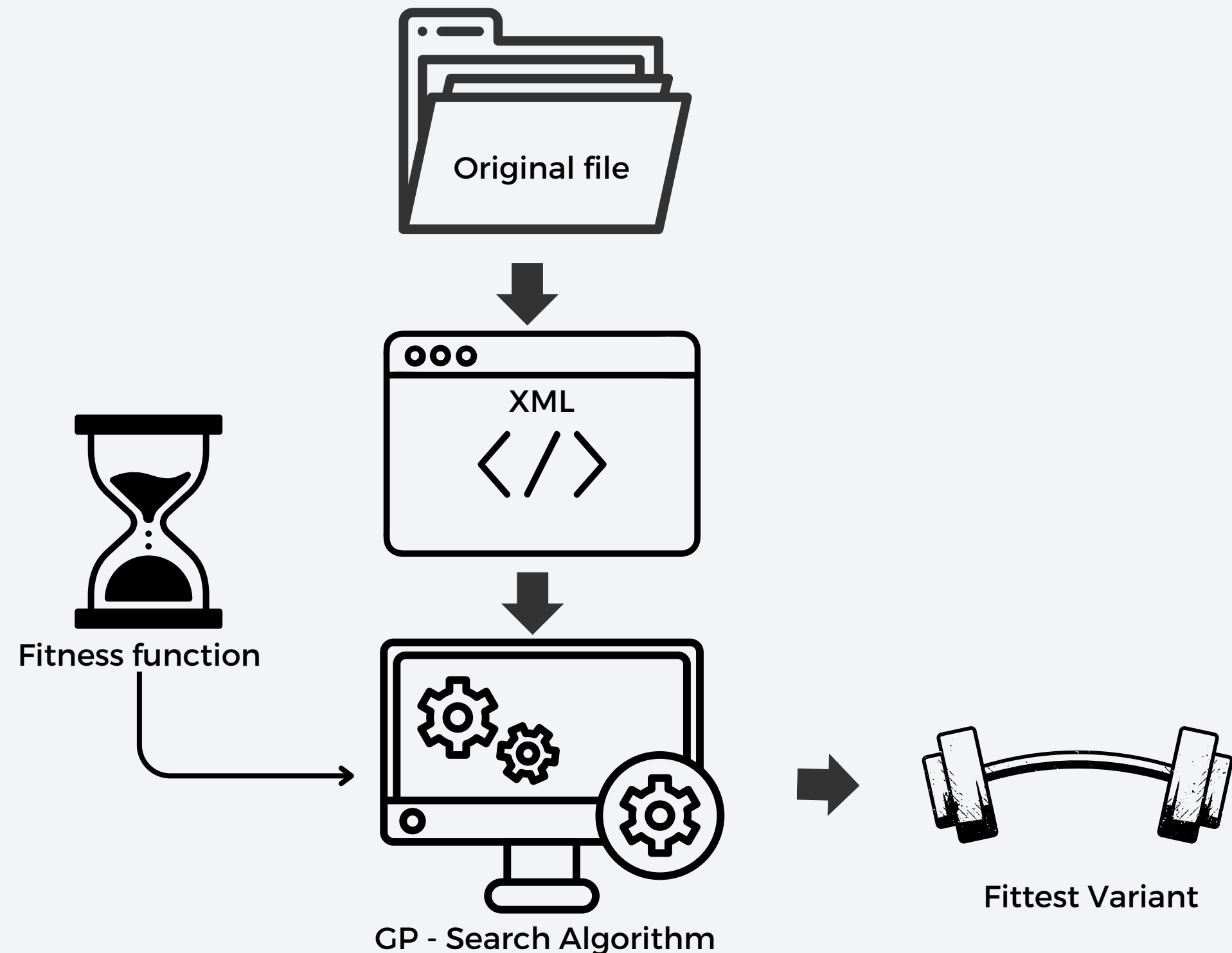
LLM ASSISTED CROSSOVER OPERATOR



MAGPIE FRAMEWORK

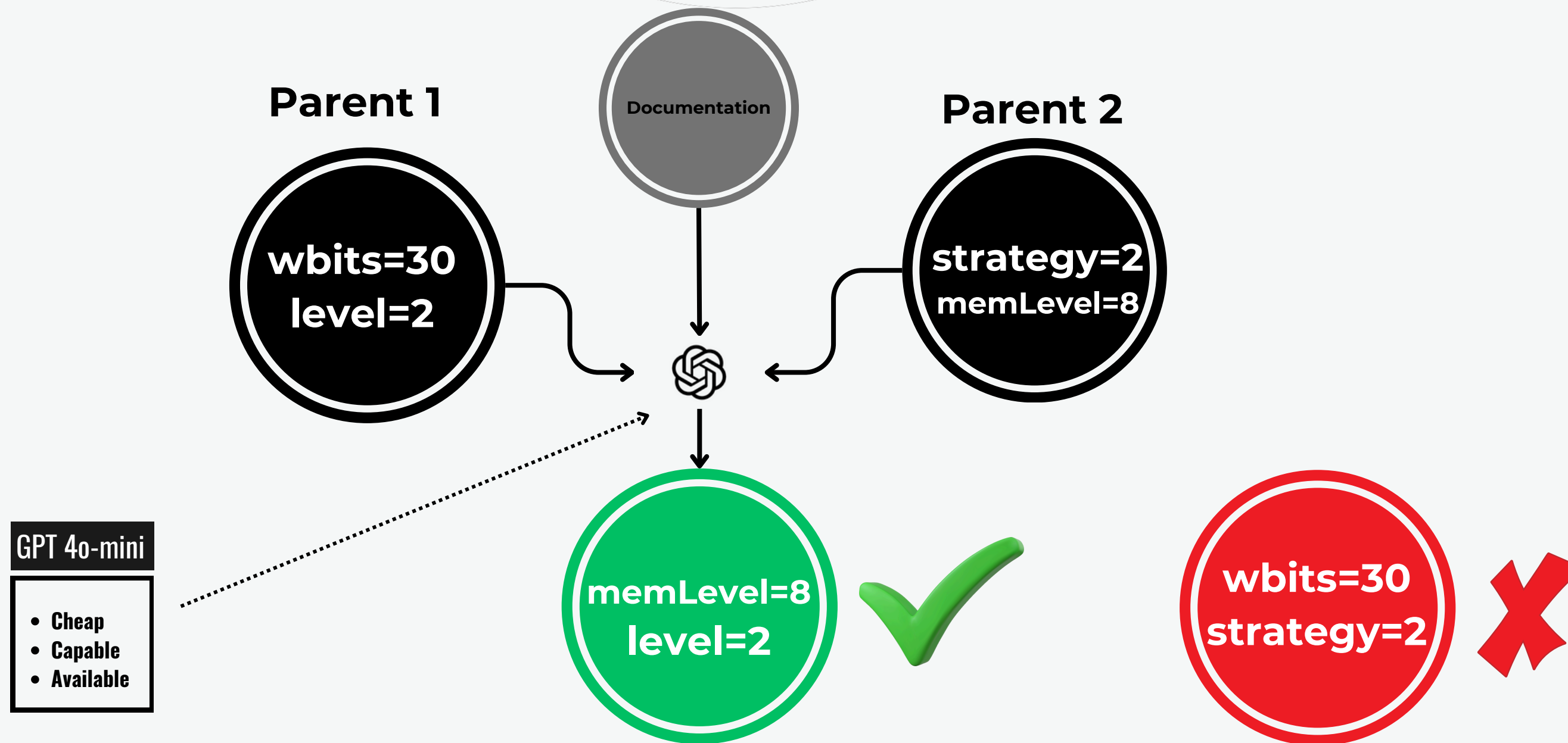
WHY MAGPIE?

- **Language Agnostic** : everything is translated to XML format
- **Multiple modification types**: source code and parameter configuration
- **Multiple search types**: GP, Local Search etc
- **Easy to modify** : Written in Python with documentation support



MOTIVATIONAL EXAMPLE

COMPRESSION LIBRARY



LLM
Response
Summary

To optimize runtime I will select the following edits: level =2, which lowers the compression level, resulting in faster compression and memLevel = 8 which increases the memory level, improving performance and lowering runtime

BENCHMARKS - EXPERIMENTS

Selected Benchmarks

Benchmark	Description	Parameter	Source Code	Language
MiniSAT Hack	SAT solver	✓	✓	C++
MiniSAT	SAT solver	✓	✓	C++
WEKA	Data mining tool	✓	✓	Java
zlib	Compression library	✓		Python
SciPy	Scientific computing	✓		Python
Sat4j	Boolean satisfiability	✓	✓	Java
LPG	AI planner	✓		C

Configs

- **Model : GPT 4o-mini**
- **pop_size = 20**
- **offspring_elitism = 0.2**
- **offspring_crossover = 0.6**
- **offspring_mutation = 0.2**
- **epochs = 11**

RESULTS

AVERAGE BEST RUNTIME

Comparison of Crossover methods based on average best fitness

Crossover Method	AOF(s)	AF(s)	Avg Ranking
UniformConcat	4.598	6.094	3.00
Concat	4.734	5.841	3.55
1Point	4.971	6.333	3.82
2Point	5.169	6.463	4.27
UniformInter	4.991	6.348	4.09
LLM-Assisted	4.477	5.834	2.27

AOF (s): Average Optimal Fitness in seconds.

AF (s): Average Fitness of all variants in seconds.

-8.5% AOF
-6.1% AF } **compared to the average of the 5 methods**

RESULTS

REACHING PERFORMANCE MILESTONES

Comparison of Crossover methods based on time needed to reach performance milestones

Crossover Method	25% Improvement	50% Improvement	75% Improvement	100% Improvement
UniformConcat	56.45 variants	68.55 variants	112.27 variants	227.27 variants
Concat	72.91 variants	105.82 variants	140.73 variants	228.73 variants
1Point	70.18 variants	78.55 variants	179.45 variants	242.27 variants
2Point	97.73 variants	129.64 variants	170.18 variants	230.73 variants
UniformInter	77.36 variants	130.27 variants	135.18 variants	244.91 variants
LLM-Assisted Crossover	39.82 variants	48.27 variants	119.00 variants	209.18 variants

Reached performance milestones with 25.6% fewer generated variants on average.

RESULTS

NUMBER OF VIABLE VARIANTS

Comparison of Crossover methods based on the number of viable variants produced

Crossover Method	Average Number of Viable Variants
UniformConcat	187.73
Concat	186.27
1Point	182.18
2Point	185.73
UniformInter	185.55
LLM-Assisted Crossover	194.45

On average of 4.8% more viable variants

RELATED WORK

Traditional Crossover

- **Easy , cheap**
 - **No context-awareness**
 - **Random selection of modifications**
-

- **LLM's contextual knowledge**
- **Documentation**

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Semantic & Context-Aware Crossover

- **Semantically Driven Crossover**
 - **Locally Geometric Semantic Crossover**
 - **Scalability Issues**
 - **Computationally expensive**
 - **Requires program structure analysis**
-

- **Works out of the box**
- **Leverages LLM training**

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Machine Learning-Assisted Crossover

- Deep Neural Crossover
 - Adaptive crossover
 - Requires pre-training and fine-tuning
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- No pre-training or fine-tuning needed
- No extra data required

LIMITATIONS - FUTURE WORK

LIMITATIONS

Generalisa-
bility

SOLUTIONS

more
models

more
benchmarks

more tools

more
repetitions

LIMITATIONS - FUTURE WORK

LIMITATIONS

Generalisa-
bility

LLM non
determinism

SOLUTIONS

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Prompt
Engineering

Temperature
Confidence

THANK YOU FOR YOUR ATTENTION!



https://github.com/SOLAR-group/LLM_Assisted_Crossover



KEY TAKEAWAYS

**Initial Exploration of
LLMs for Crossover in
GI of Software**

**Provided Support for LLM
Assisted Crossover in the
MAGPIE Framework**

-8.5% runtime

**25.6 % faster to
reach milestones**

**4.8% more viable
variants**

**LLM assisted crossover is promising.
Future work should focus on more experiments!!!**