



MarioGPT: Open-Ended Text2Level Generation through Large Language Models

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UNIVERSITY OF
INFORMATION
TECHNOLOGY



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- ▶ Experiments and Results
- ▶ Conclusion



Procedural Content Generation (PCG)

1 Introduction

- Procedural Content Generation (PCG) refers to techniques that can automatically create game content (e.g. levels, maps, or characters).
 - Increasing the replayability
 - Reducing production costs



Procedural Content Generation (PCG)

1 Introduction



a) Rouge b) Elite c) Diablo III d) Minecraft e) No Man's Sky f) Civilisation VI

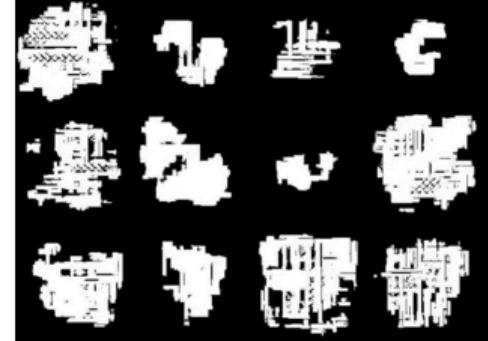


PCG and Machine Learning

1 Introduction



Doom maps generated by
GANs model





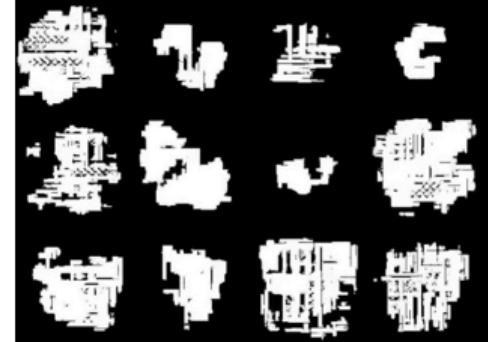
PCG and Machine Learning

1 Introduction

- PCG for evaluating generalization capabilities of trained agents.
 - Offer more diverse and challenging scenarios.
 - A better way to test the adaption and generalization of trained agents.



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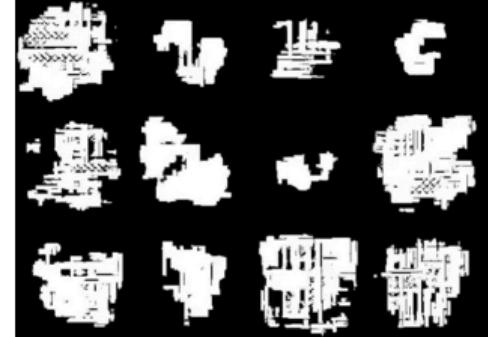
PCG and Machine Learning

1 Introduction

- PCG for evaluating generalization capabilities of trained agents.
 - Offer more diverse and challenging scenarios.
 - A better way to test the adaption and generalization of trained agents.
- Incorporation of machine learning-based approaches in PCG systems.
 - GANs for generating levels (Doom, Super Mario Bros)



Doom maps generated by
GANs model





Challenges

1 Introduction

- **Costly** searching in the latent space of neural networks.
- Desire to **directly condition** a generator for creating levels with specific properties, ideally in natural language. (**prompt**)



Contributions

1 Introduction

1. Introduction of MarioGPT, a text-to-level model generating Mario levels based on natural language prompts.



Contributions

1 Introduction

1. Introduction of MarioGPT, a text-to-level model generating Mario levels based on natural language prompts.
2. Combining MarioGPT with novelty search for producing diverse levels.



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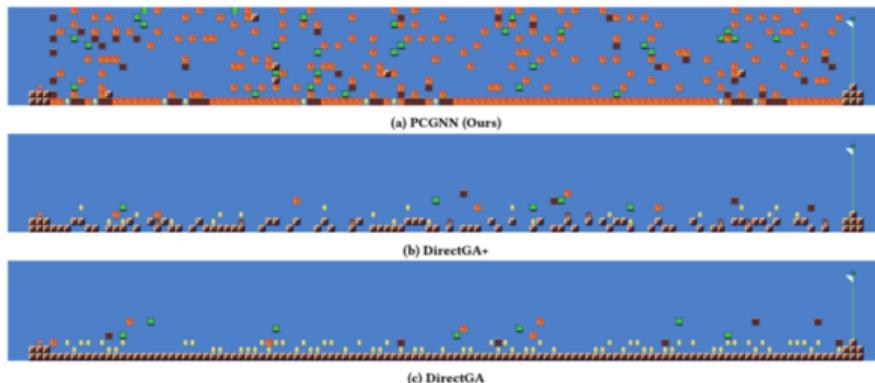
2 Background and Related Work

- ▶ Introduction
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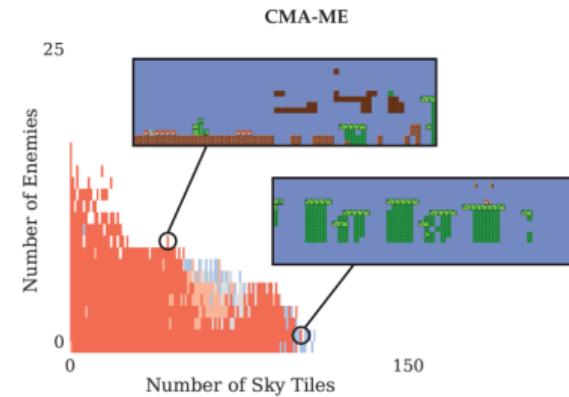


Neural Network-based Level Generation

2 Background and Related Work



Using neural networks ([Beukman et al.\[1\]](#))



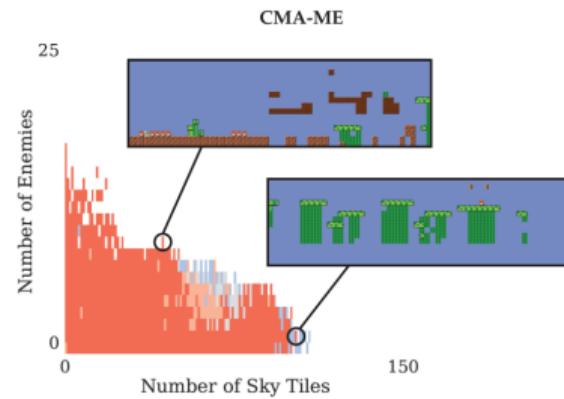
Searching in the latent space of GANs
([Matthew et al.\[2\]](#))



Neural Network-based Level Generation

2 Background and Related Work

- Guided sampling of the latent space could result in a diverse set of levels.
- The abilities to control characteristics in generated levels.



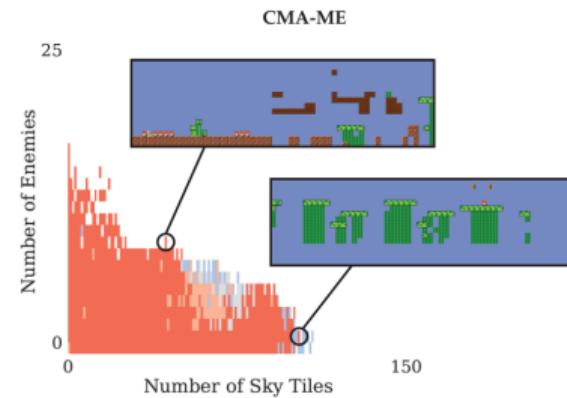
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Neural Network-based Level Generation

2 Background and Related Work

- Guided sampling of the latent space could result in a diverse set of levels.
- The abilities to control characteristics in generated levels.
- *Using A* agent to measure whether the generated levels were playable.*



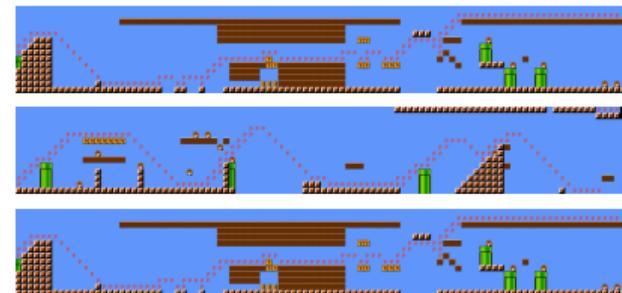
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Open-Endedness Paradigm

2 Background and Related Work

- The open-endedness paradigm focuses on algorithms that can produce infinite innovation.



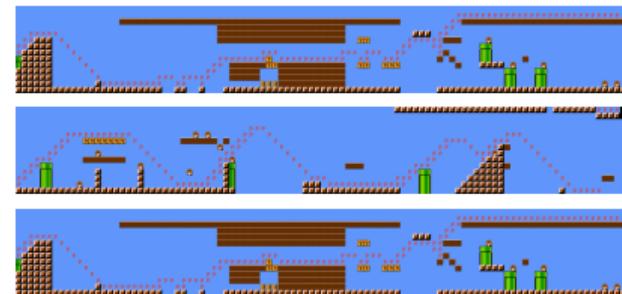
Diversity but not-playable cases



Open-Endedness Paradigm

2 Background and Related Work

- The open-endedness paradigm focuses on algorithms that can produce infinite innovation.
- Must balance the hard task of generating content with **diversity** as well as **playability**



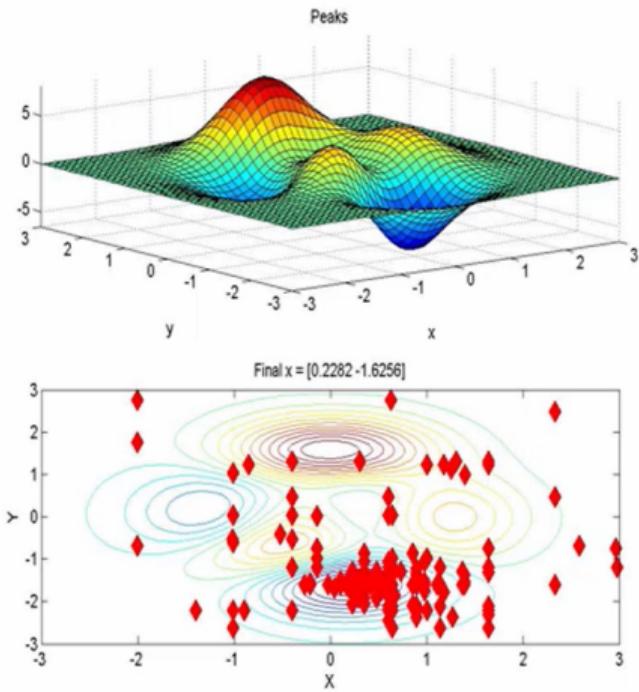
Diversity but not-playable cases



Genetic Algorithms

2 Background and Related Work

- Uses concepts from *evolutionary biology*

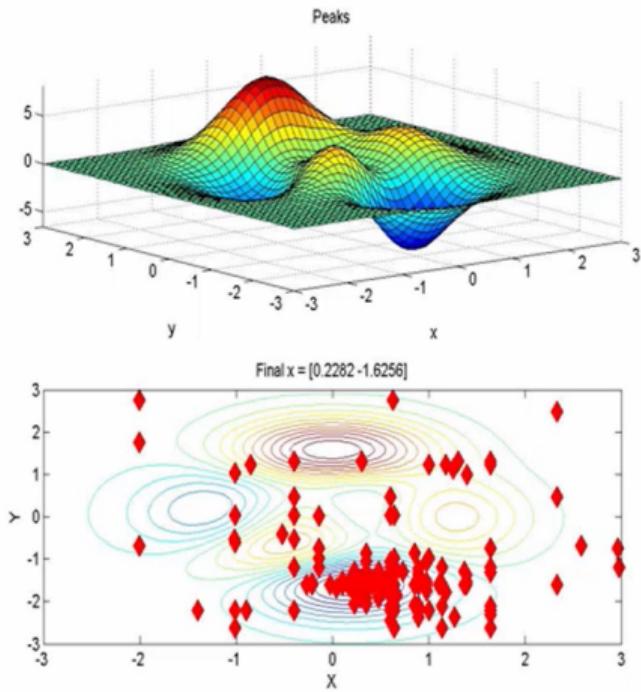




Genetic Algorithms

2 Background and Related Work

- Uses concepts from *evolutionary biology*
- Start with an initial generation of candidate solutions that are tested against the objective function

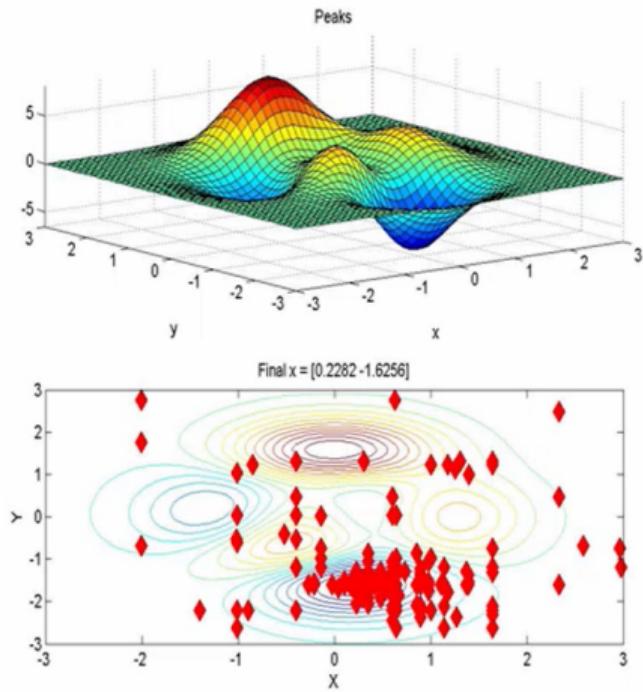




Genetic Algorithms

2 Background and Related Work

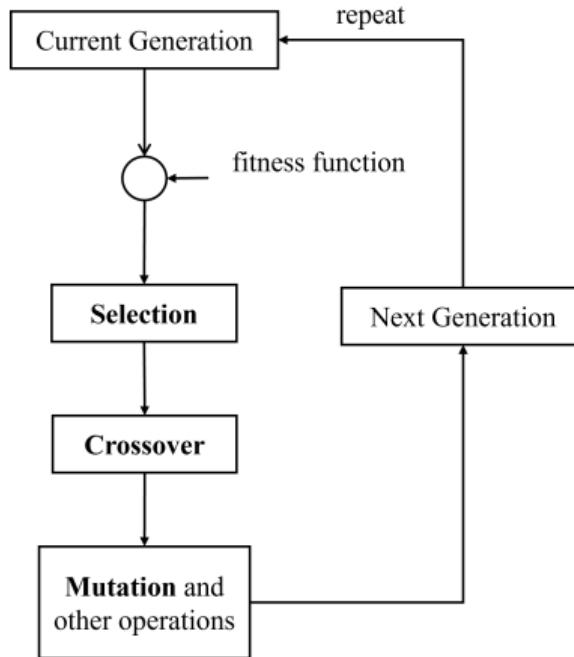
- Uses concepts from *evolutionary biology*
- Start with an initial generation of candidate solutions that are tested against the objective function
- Subsequent generations evolve from the 1st through *selection*, *crossover* and *mutation*





Genetic Algorithms

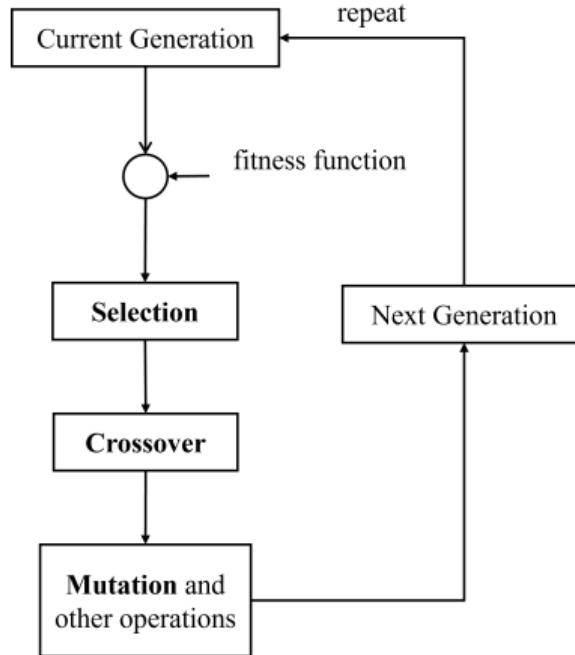
2 Background and Related Work





Genetic Algorithms

2 Background and Related Work

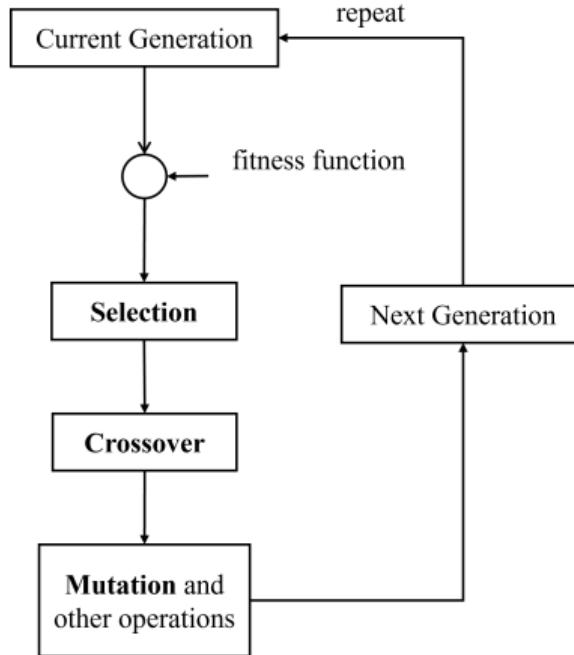


- First generation is arbitrarily, or $x = \text{random}()$



Genetic Algorithms

2 Background and Related Work

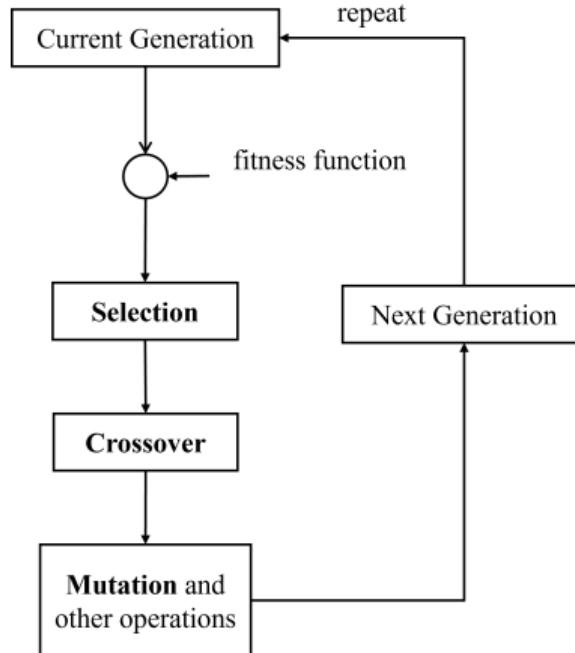


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*



Genetic Algorithms

2 Background and Related Work



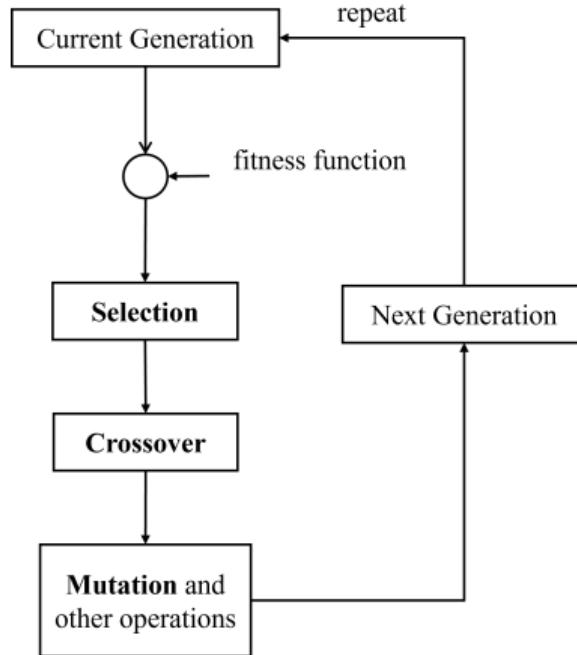
- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*

$$\text{fitness}(x) = f(x)$$



Genetic Algorithms

2 Background and Related Work

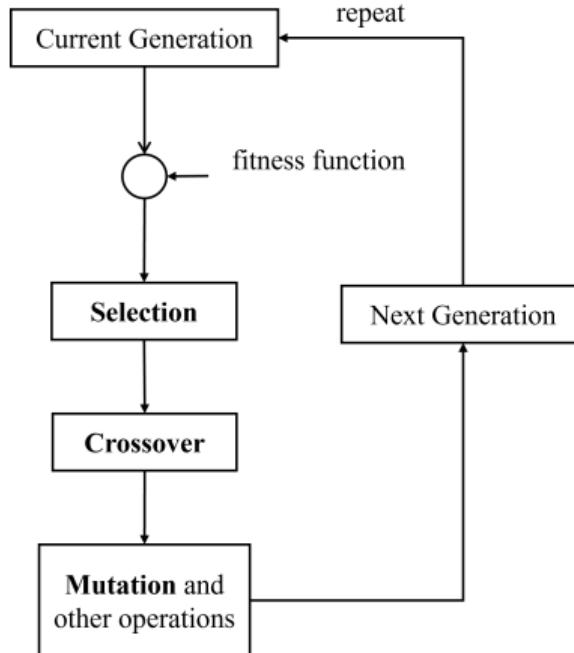


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:



Genetic Algorithms

2 Background and Related Work

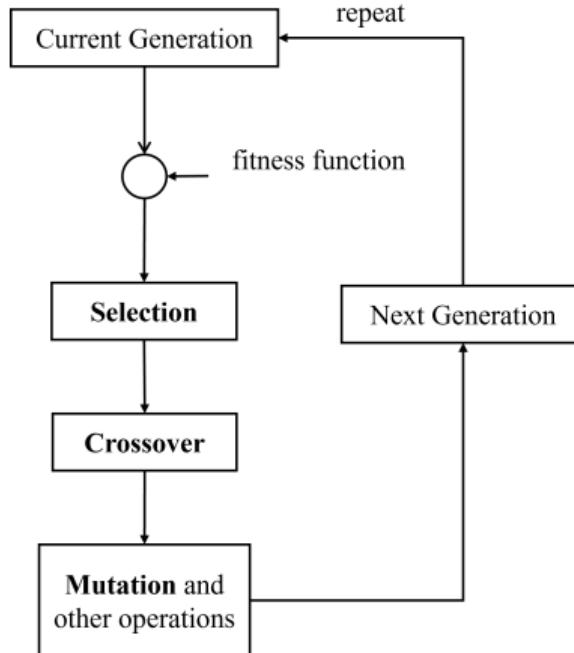


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic



Genetic Algorithms

2 Background and Related Work

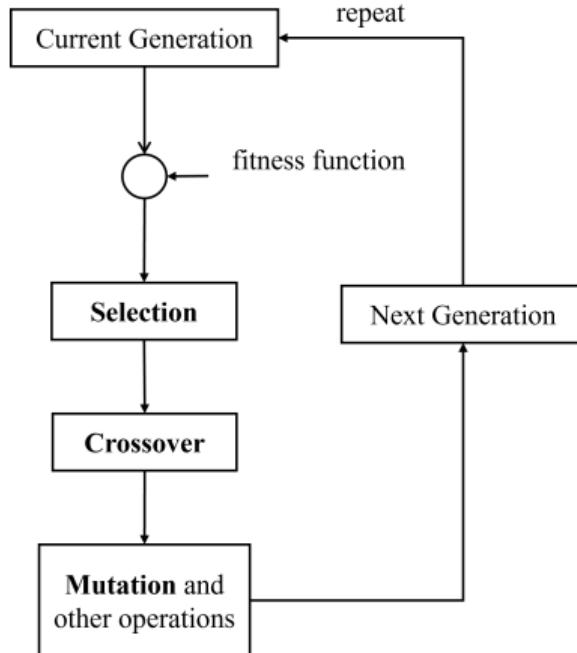


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic: Elitism
 $\text{argmax}_x \text{fitness}(x)$



Genetic Algorithms

2 Background and Related Work

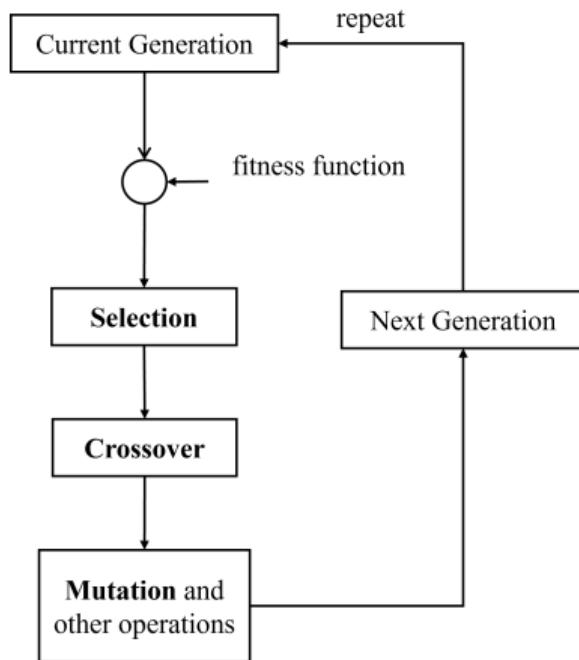


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic
 - Stochastic



Genetic Algorithms

2 Background and Related Work



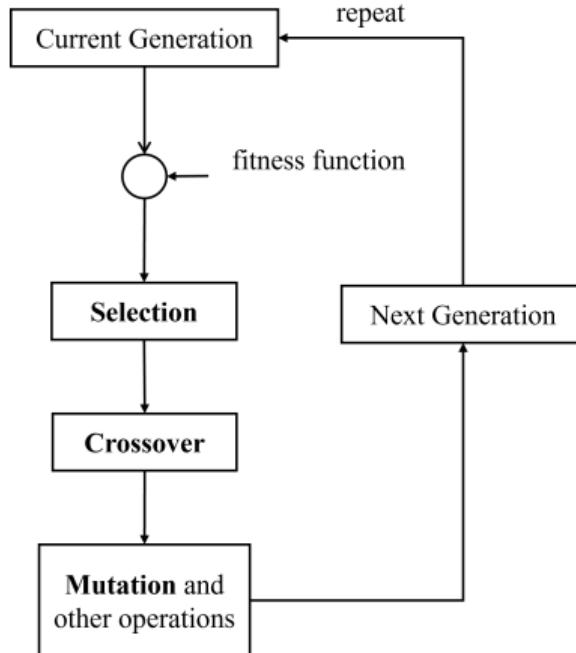
- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic
 - Stochastic: Roulette wheel selection

$$P(x) = \frac{\text{fitness}(x)}{\sum \text{fitness}(x)}$$



Genetic Algorithms

2 Background and Related Work

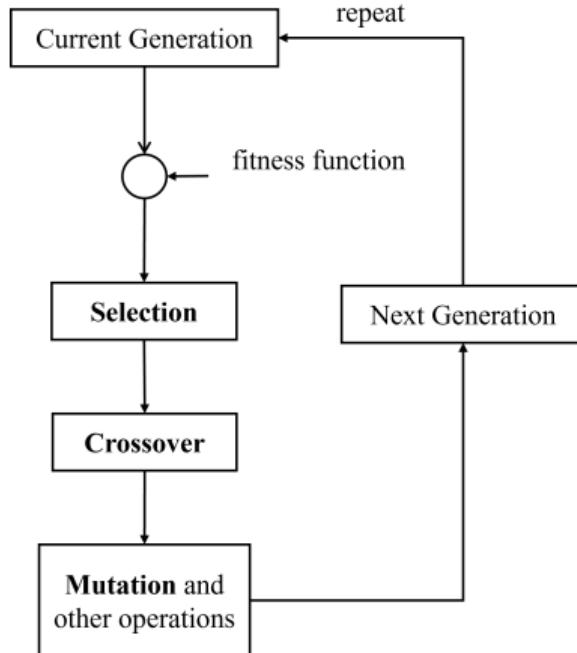


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Genetic Algorithms

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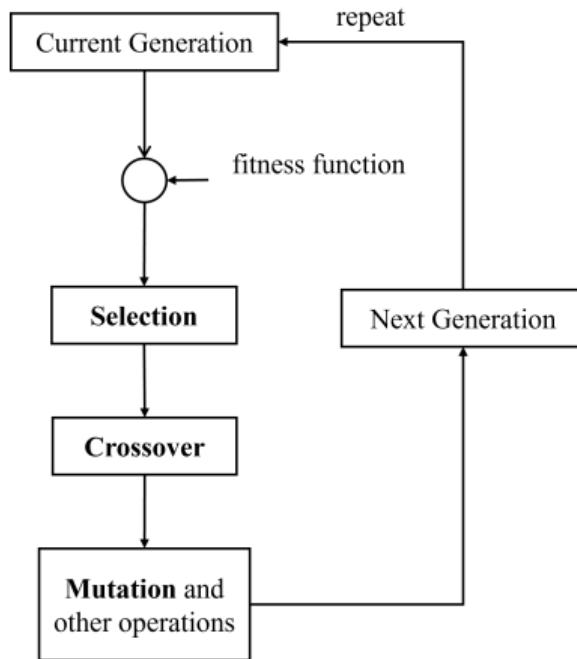


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic
 - Stochastic
- Implement crossover operation on the reproduced chromosomes



Genetic Algorithms

2 Background and Related Work



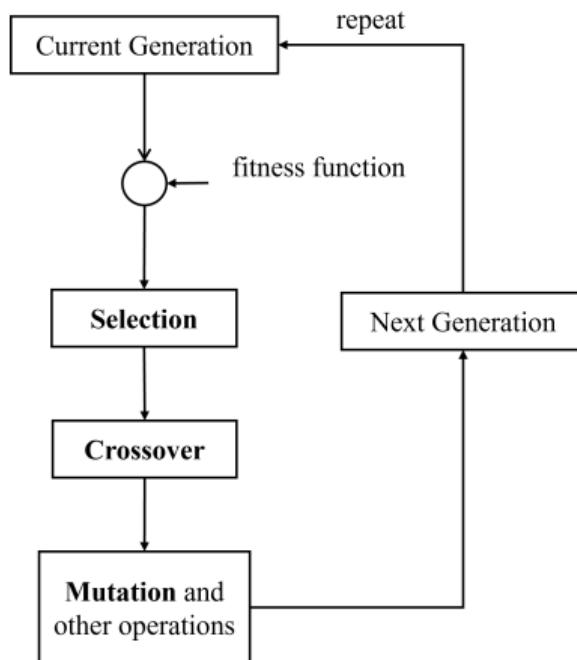
- First generation is arbitrarily, or $x = \text{random}()$
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$$\text{Crossover}(x_1, x_2) = y$$



Genetic Algorithms

2 Background and Related Work

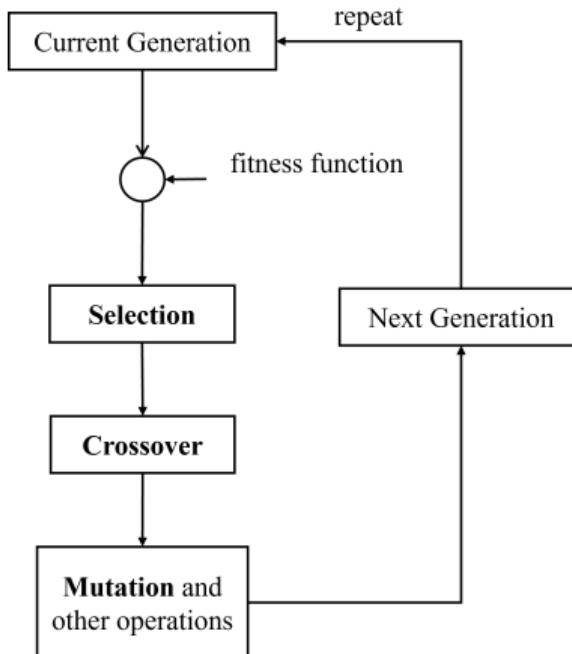


- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness*
- Select members of the population:
 - Deterministic
 - Stochastic
- Implement *crossover* operation on the reproduced chromosomes
$$\text{Crossover}(x_1, x_2) = y$$
- Execute *mutation* operation with low probability



Genetic Algorithms

2 Background and Related Work

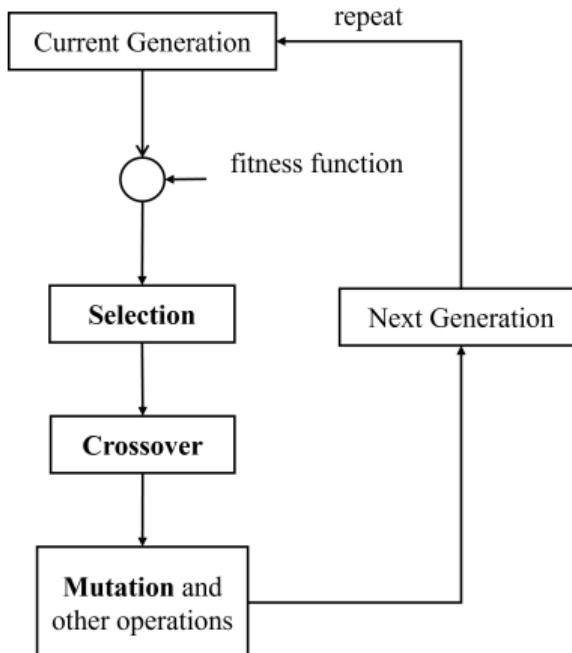


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$$\text{Crossover}(x_1, x_2) = y$$
- Execute *mutation* operation with low probability
$$\text{Mutation}(y) = y', \text{ with } p_m$$



Genetic Algorithms

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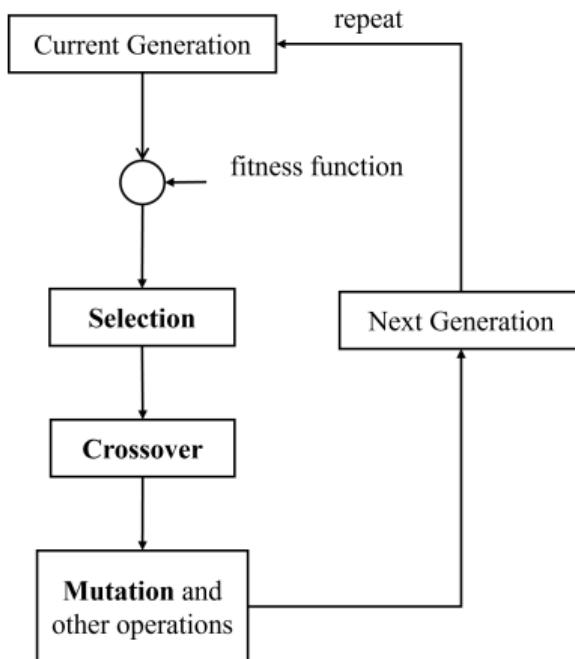


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- Execute *mutation* operation with low probability
$$\text{Mutation}(y) = y', \text{ with } p_m$$
- Allow the integration of multiple objectives



Genetic Algorithms

2 Background and Related Work



- First generation is arbitrarily, or $x = \text{random}()$
- Evaluate their *fitness* a **fitness gradient may not always be available**
- Select members of the population:
 - Deterministic
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- Implement crossover operation on the reproduced chromosomes
$$\text{Crossover}(x_1, x_2) = y$$
- Execute *mutation* operation with low probability
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Novelty Search

2 Background and Related Work

- *Exploiting open-endedness to solve problem through the search for novelty*
- **Lehman et al., 2008**
- Replaces the search for a greater fitness by a search for novel individuals, aim at finding the most novel solutions at each generation
- Increasingly diverse solutions in an open-ended fashion!



Novelty Score

$$\rho(x) = \frac{1}{k} \sum_{k=1}^k dist(x, \mu_i)$$

- $\{\mu_1, \mu_2, \dots, \mu_k\}$: the set of k -closest individuals to x in archive
 - $\rho(x)$: sparseness of x
 - $dist$: distance metric
-
- The set of individuals used to measure the novelty of new solutions corresponds to the current population, plus an archive of previous individuals.



Novelty Score

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- The set of individuals used to measure the novelty of new solutions corresponds to the current population, plus an archive of previous individuals.
 - NS guides generation towards increasingly diverse solutions in an open-ended fashion.



Sequence Modelling and Transformer

2 Background and Related Work

- Classic approaches to sequence modelling are RNNs ([Rumelhart et al.](#)[4]) and LSTM networks ([Hochreiter et al.](#) [3])
 - fading memory
 - limited scalability
- Transformers ([Vaswani et al.](#)[5]) can address both challenges, can be parallelized and achieve good scalability!



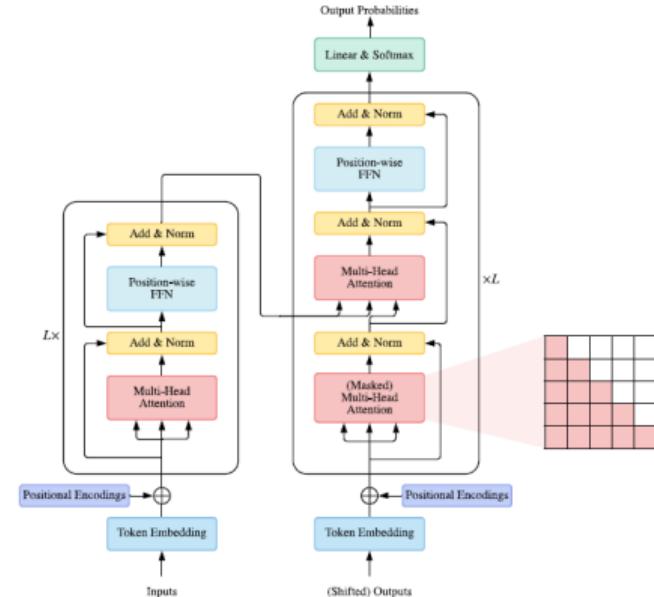
Sequence Modelling and Transformers

2 Background and Related Work

- "Attention is all you need" ([Vaswani et al., 2017](#))

- **Encoder:**

- **Decoder:**

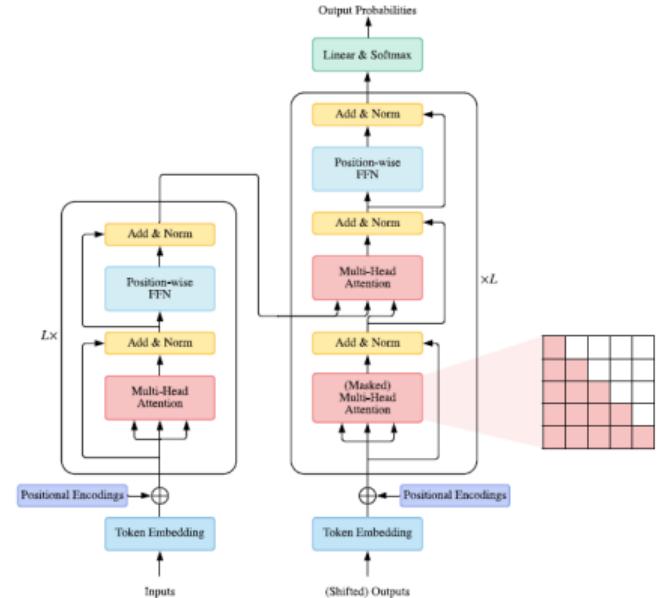




Sequence Modelling and Transformers

2 Background and Related Work

- "Attention is all you need" ([Vaswani et al., 2017](#))
- **Encoder:**
 - N identical layers (Multi-Head Attention and FFN)
 - Residual connections
- **Decoder:**

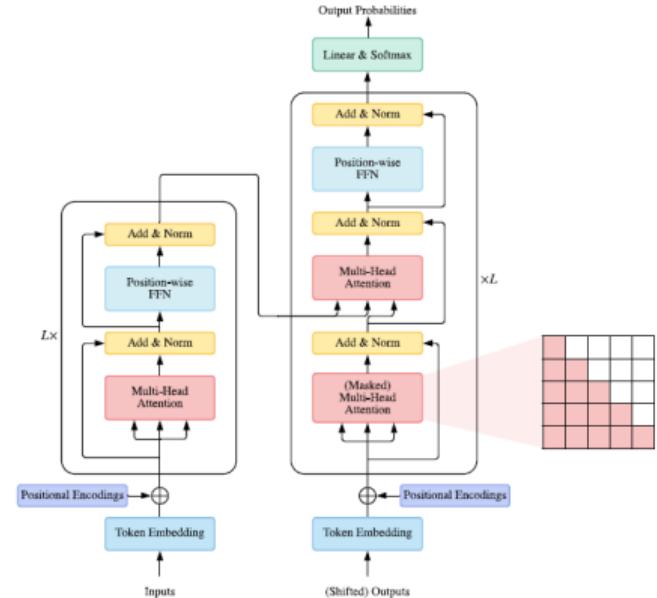




Sequence Modelling and Transformers

2 Background and Related Work

- "Attention is all you need" ([Vaswani et al., 2017](#))
- **Encoder:**
 - N identical layers (Multi-Head Attention and FFN)
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- **Decoder:**
 - N identical layers (Multi-Head Attention, FFN and Masked Multi-Head Attention)
 - Residual connections

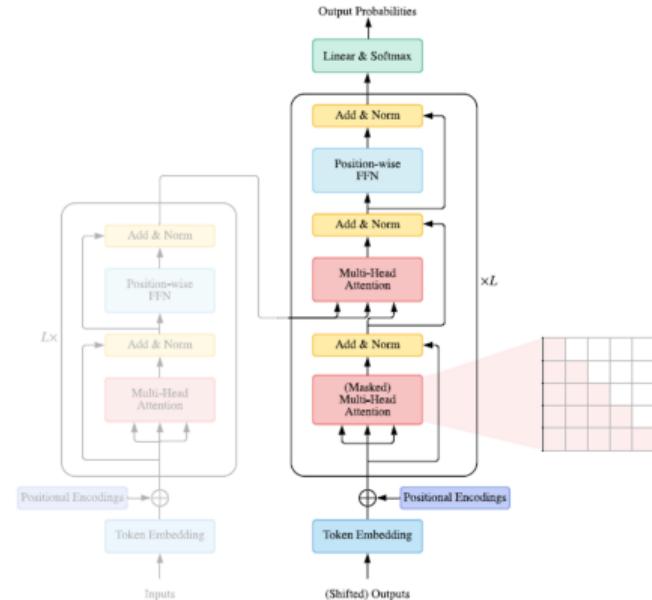




Sequence Modelling and Transformers

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- *GPT consists of a stack of decoder layers.*

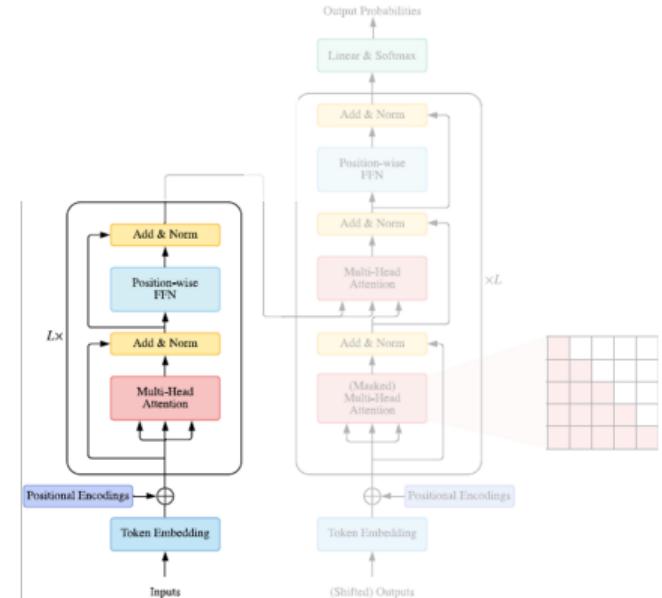




Sequence Modelling and Transformers

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- **Decoder:**
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 - Residual connections
- *BERT consists of a stack of encoder layers.*

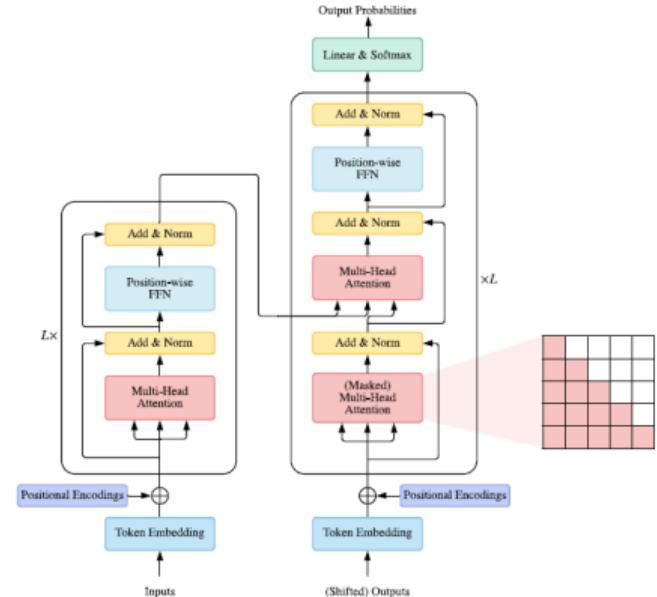




Sequence Modelling and Transformers

2 Background and Related Work

- Enable LLMs to learn from massive datasets

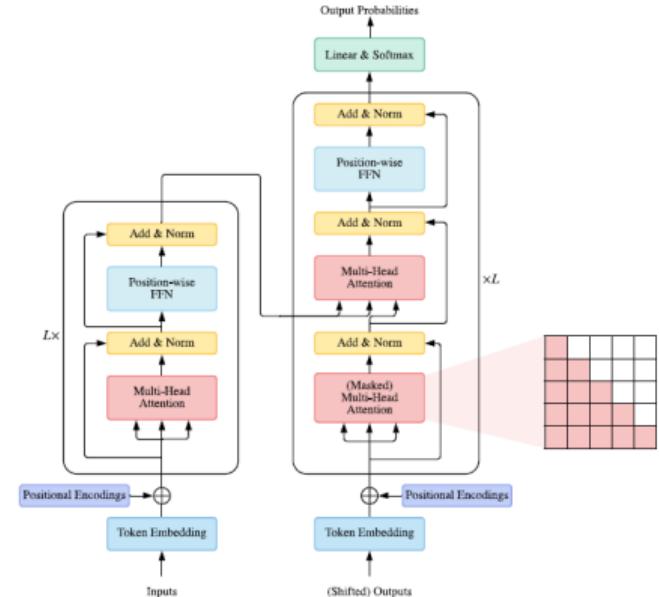




Sequence Modelling and Transformers

2 Background and Related Work

- Enable LLMs to learn from massive datasets
 - Using pre-trained model weights as a weight initialization for new tasks.

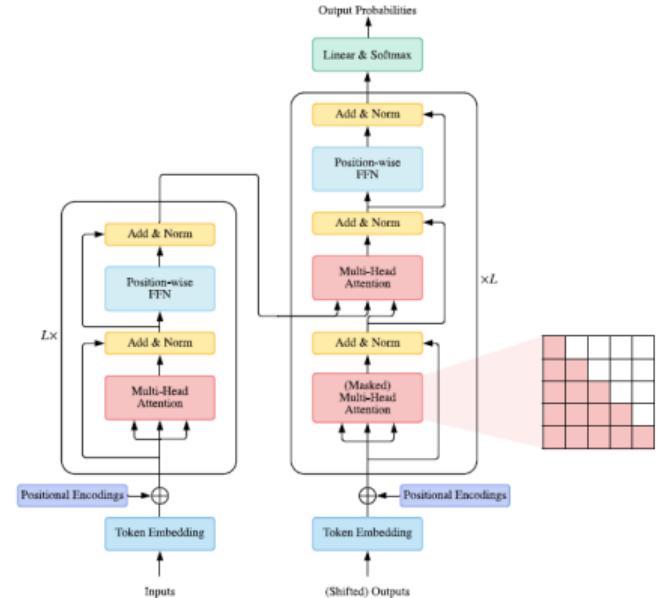




Sequence Modelling and Transformers

2 Background and Related Work

- Enable LLMs to learn from massive datasets
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- *Evolution through Large Models (Lehman et al., 2022)*

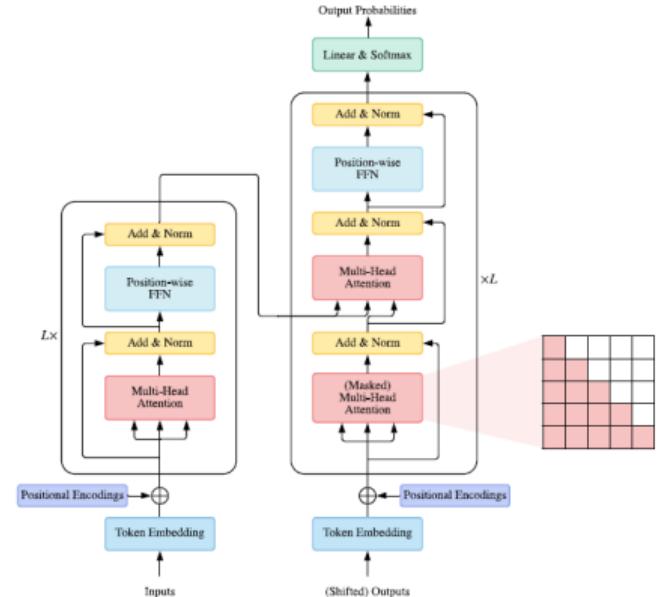




Sequence Modelling and Transformers

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 - LLM diff model
 - used as a "mutation operator"





Sequence Modelling and Transformers

2 Background and Related Work

- Enable LLMs to learn from massive datasets
 - Using pre-trained model weights as a weight initialization for new tasks.
- *Evolution through Large Models (Lehman et al., 2022)*
 - LLM diff model
 - used as a "mutation operator"
- Produce incredibly diverse mutations, vary increasingly over the course of the GA!

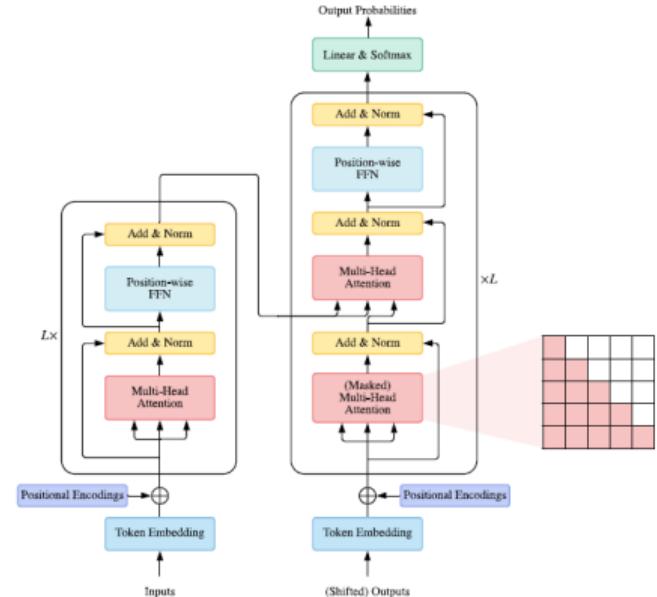




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Level Representation

3 Open-Ended Level Generation through LLMs

- Use the levels provided in the Video Game Level Corpus ([Summerville et al., 2016](#))



Level Representation

3 Open-Ended Level Generation through LLMs

- Use the levels provided in the Video Game Level Corpus ([Summerville et al., 2016](#))
- Utilize a set of path-annotated levels, taken from Super Mario Bros. and Super Mario Bros.: The Lost Levels (in total 37 levels)



Level Representation

3 Open-Ended Level Generation through LLMs

- Use the levels provided in the Video Game Level Corpus ([Summerville et al., 2016](#))
- Utilize a set of path-annotated levels, taken from Super Mario Bros. and Super Mario Bros.: The Lost Levels (in total 37 levels)
 - Stitch selected levels together, make one giant level!



Level Representation

3 Open-Ended Level Generation through LLMs

- Use the levels provided in the Video Game Level Corpus ([Summerville et al., 2016](#))
- Utilize a set of path-annotated levels, taken from Super Mario Bros. and Super Mario Bros.: The Lost Levels (in total 37 levels)
 - Stitch selected levels together, make one giant level!
- Tokenize string representation into discrete values using Byte Pair Encoding.



Level Representation

3 Open-Ended Level Generation through LLMs

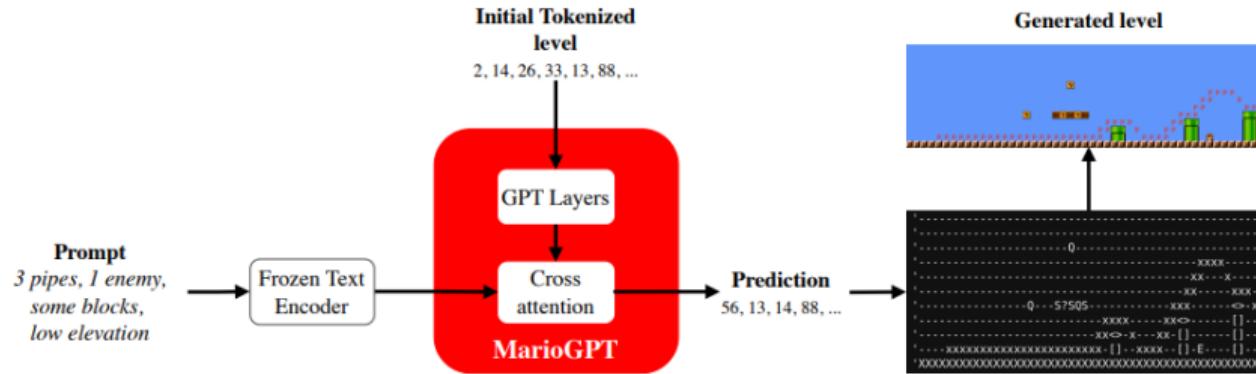
Tile Type	Symbol	Visualization
Empty	-	
Unbreakable	X	
Breakable	S	
Question Block	? / Q	
Coin	o	
Enemy	E	
Left pipe top	<	
Right pipe top	>	
Left pipe lower	[
Right pipe lower]	
Cannon Top	B	
Cannon Body	b	
Path	x	

Unique Mario tiles ([Sudhakaran et al., 2023](#))



MarioGPT Model

3 Open-Ended Level Generation through LLMs

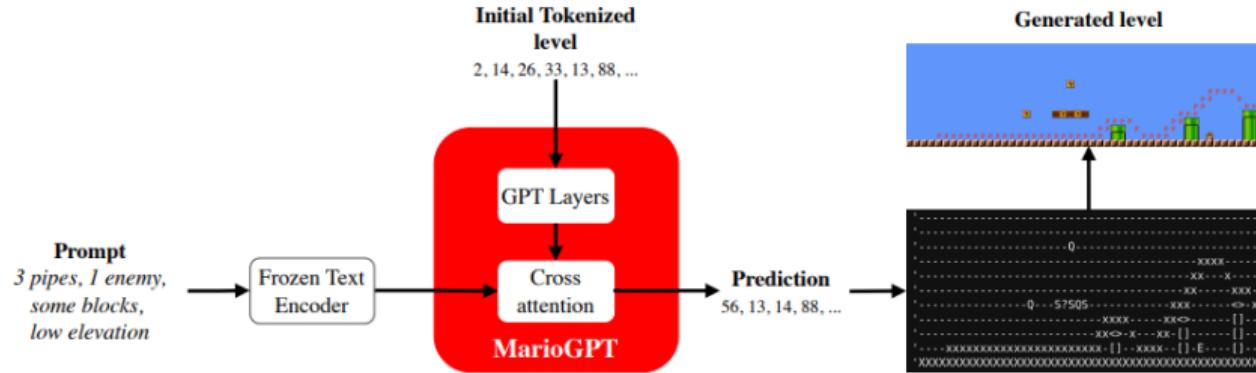


- DistilGPT2 ([Li et al., 2021](#)) is MarioGPT's backbone.



MarioGPT Model

3 Open-Ended Level Generation through LLMs

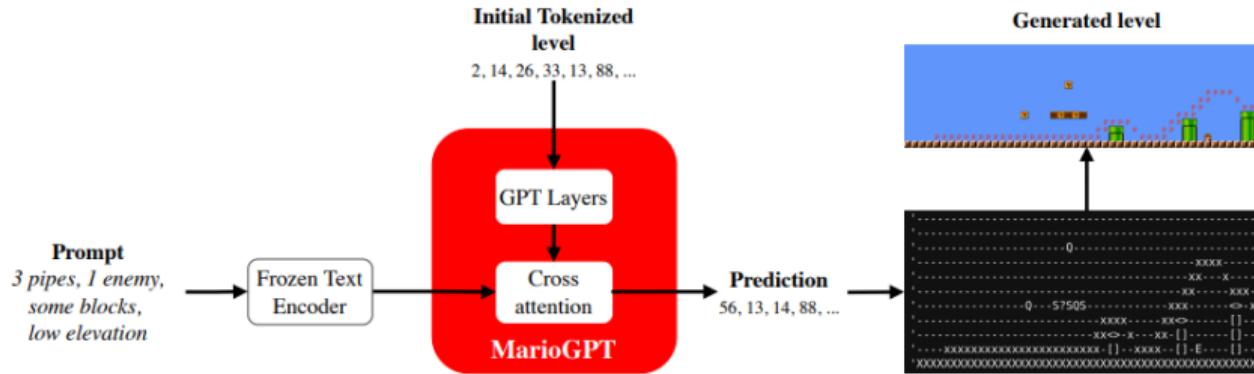


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- Cross attention layer takes prompt information into account.



MarioGPT Model

3 Open-Ended Level Generation through LLMs

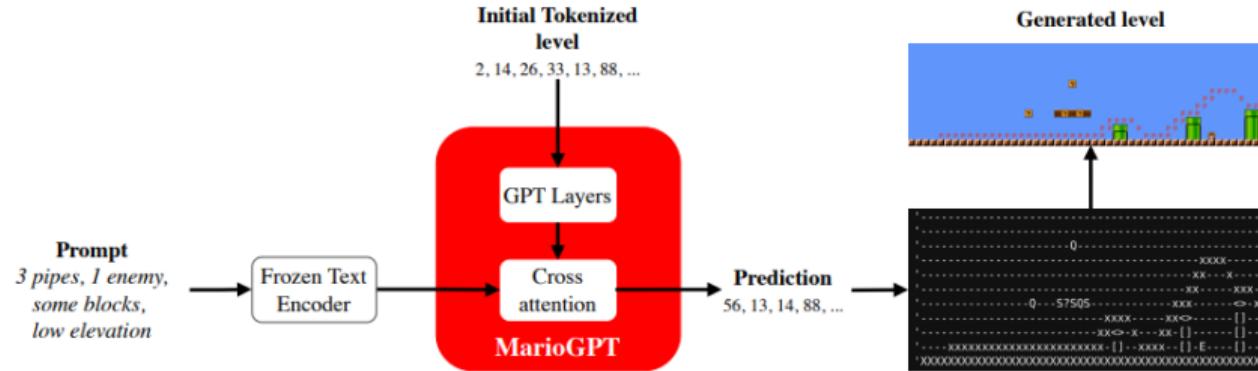


- DistilGPT2 (Li et al., 2021) is MarioGPT’s backbone.
 - Cross attention layer takes prompt information into account.
 - 96M parameters of DistilGPT2 (86M) and Cross attention weights (10M).



MarioGPT Model

3 Open-Ended Level Generation through LLMs

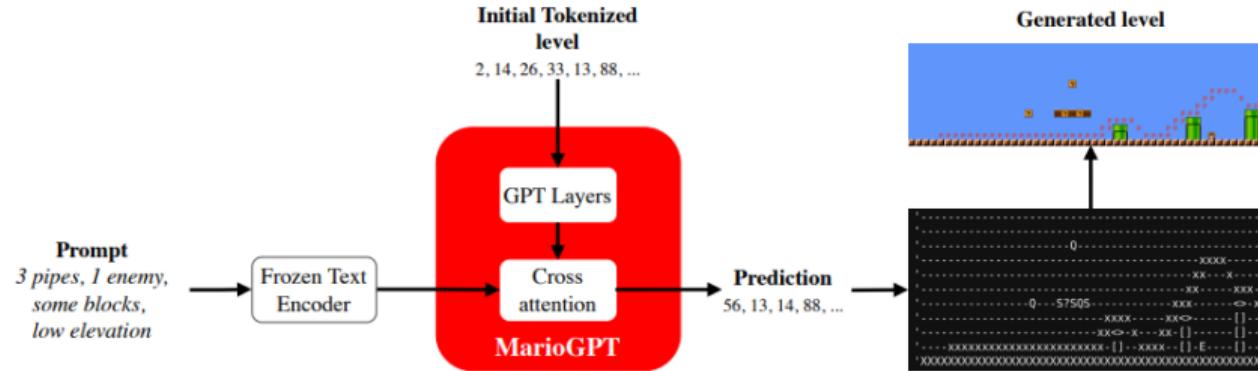


- Prompts are encoded through BART ([Lewis et al., 2019](#)).



MarioGPT Model

3 Open-Ended Level Generation through LLMs



- Prompts are encoded through BART ([Lewis et al., 2019](#)).
- Prompt's feature vector is combined with the actual level sequence in the cross attention layers.



MarioGPT Model

3 Open-Ended Level Generation through LLMs

- Prompts:
 - { no, little, some, many, [0-1000] } pipes
 - { no, little, some, many, [0-1000] } enemies
 - { little, some, many, [0-1000] } blocks
 - { low, high } elevation



MarioGPT Model

3 Open-Ended Level Generation through LLMs

- Prompts:
 - { no, little, some, many, [0-1000] } pipes
 - { no, little, some, many, [0-1000] } enemies
 - { little, some, many, [0-1000] } blocks
 - { low, high } elevation
- Example:
 - "no pipes, many enemies, low elevation"
 - "many pipes, many enemies, many blocks"



MarioGPT Model

3 Open-Ended Level Generation through LLMs

tile	no	little	some	many
pipes	0	1	2	5
enemies	0	1	3	7
blocks	0	50	75	176

Prompt Quantiles and corresponding
counts within a 50 column window



Open-Ended Mario Level Generation with Novelty Search

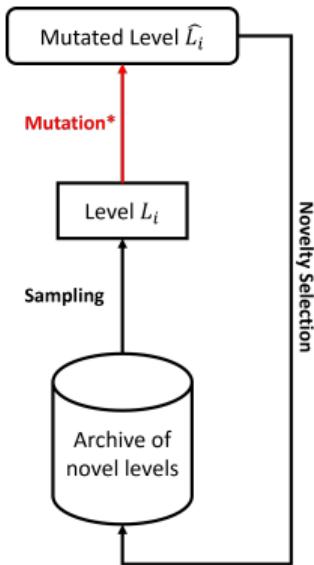
3 Open-Ended Level Generation through LLMs

- Not only generate levels with diverse physical features, but also elicit a wide range of **player behavior**.
 - a challenge for many algorithms
 - the use of an external agent for evaluation
- **NS-MarioGPT**
 - integrate MarioGPT within a novelty search augmented genetic algorithm



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs

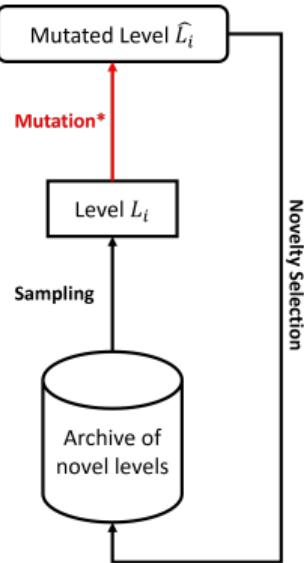


- Initialize archive with 30 levels.



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs



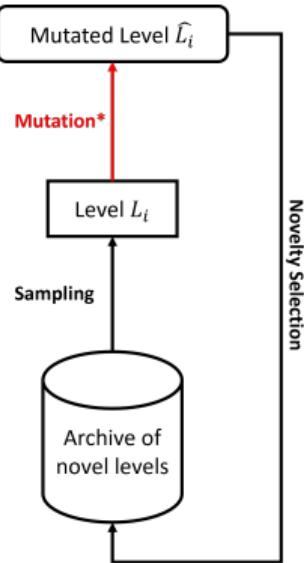
- Initialize archive with 30 levels.
- Novelty score: k -means

$$\rho(x) = \frac{1}{k} \sum_{k=1}^k \text{dist}(\varphi_B(x), \varphi_B(\mu_i))$$



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs



- Initialize archive with 30 levels.
- Novelty score: k -means

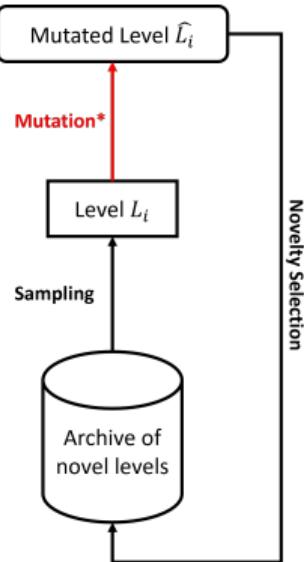
$$\rho(x) = \frac{1}{k} \sum_{k=1}^k \text{dist}(\varphi_B(x), \varphi_B(\mu_i))$$

- Use **predicted** player paths as basis for φ_B .



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs



- Initialize archive with 30 levels.
- Novelty score: k -means

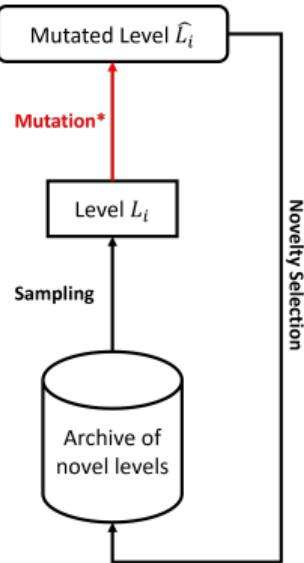
$$\rho(x) = \frac{1}{k} \sum_{k=1}^k \text{dist}(\varphi_B(x), \varphi_B(\mu_i))$$

- Use **predicted** player paths as basis for φ_B .
- Archive only stores levels with an acceptable novelty score ($\rho(x) > \text{threshold}$).



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs



- Initialize archive with 30 levels.
- Novelty score: k -means

$$\rho(x) = \frac{1}{k} \sum_{k=1}^k dist(\varphi_B(x), \varphi_B(\mu_i))$$

- Use **predicted** player paths as basis for φ_B .
- Archive only stores levels with an acceptable novelty score ($\rho(x) > threshold$).
- In this paper, $k = 4$.

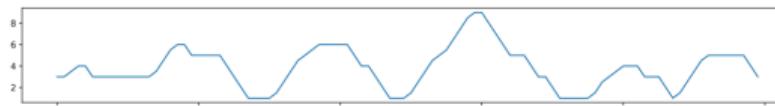


Open-Ended Mario Level Generation with Novelty Search

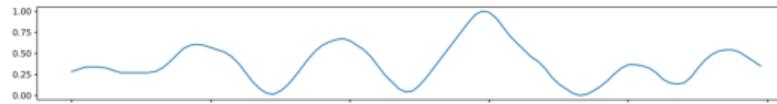
3 Open-Ended Level Generation through LLMs



(a) Generated level



(b) Extracted path from level

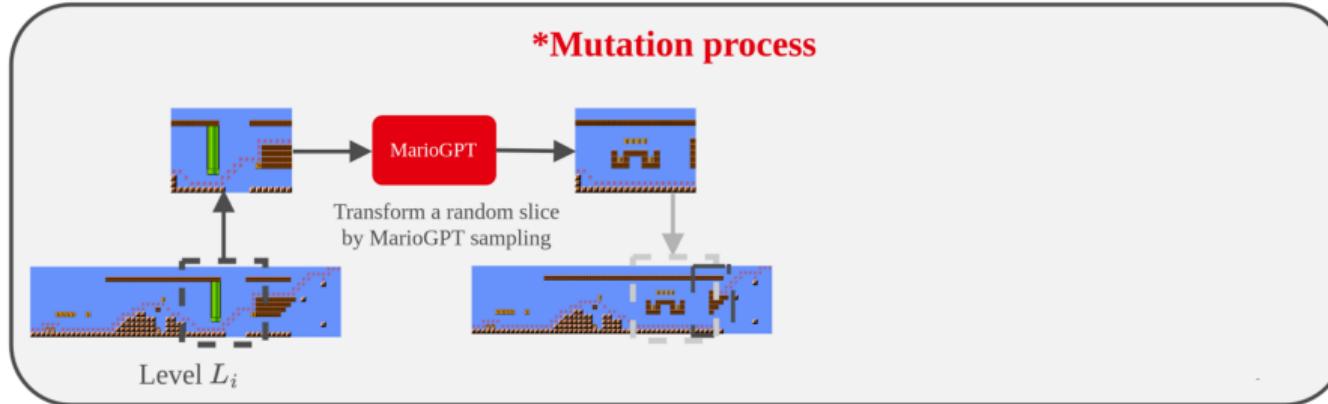


(c) Behavior characteristic of level: smoothed path using a moving average with a window of 5 coordinates



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs

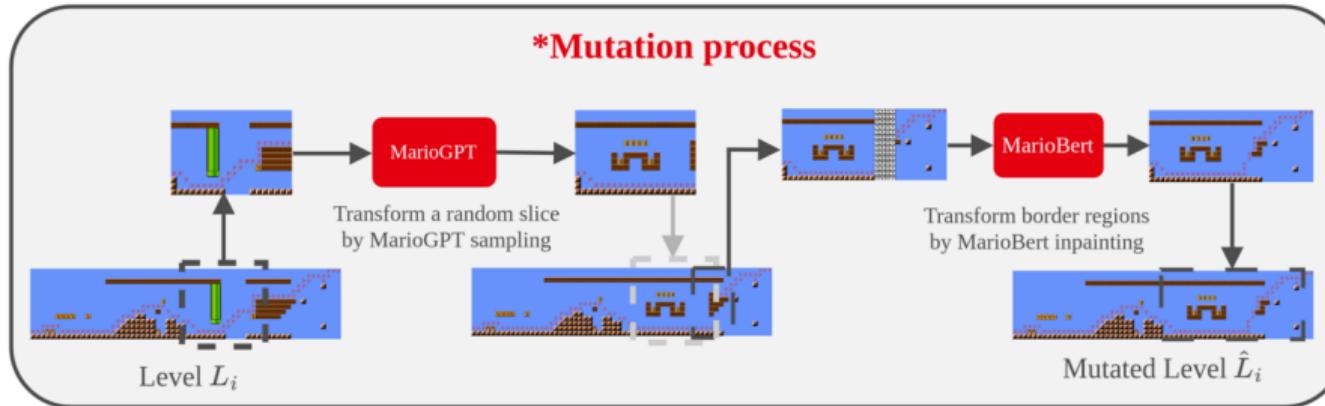


- Model transforms a *randomly* picked slice (40-80 columns) of a level with **MarioGPT**.



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs

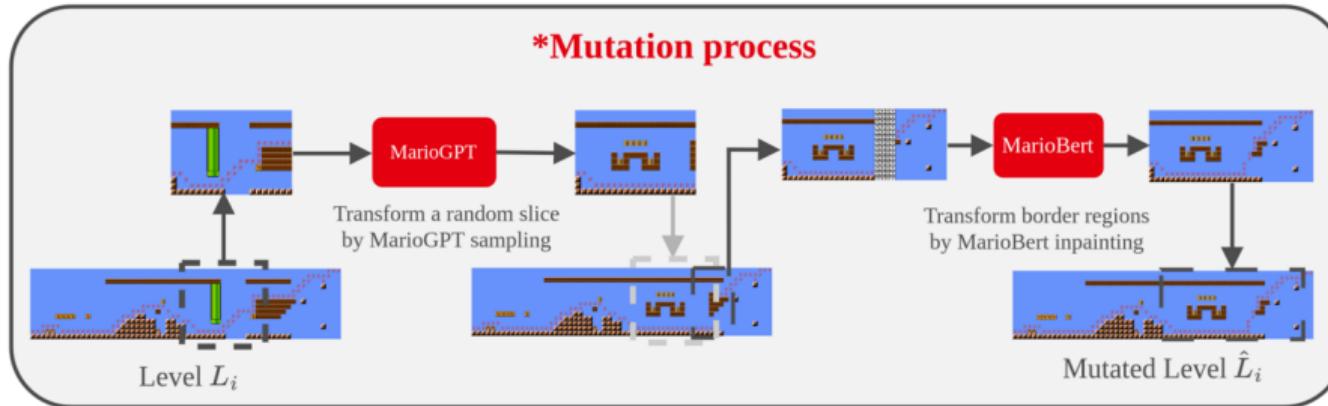


- Model transforms a *randomly* picked slice (40-80 columns) of a level with **MarioGPT**.
- To further improve path consistency, **MarioBert** (fine-tuned mask prediction model) is used to inpaint its border region.



Open-Ended Mario Level Generation with Novelty Search

3 Open-Ended Level Generation through LLMs



- Model transforms a *randomly* picked slice (40-80 columns) of a level with **MarioGPT**.
- To further improve path consistency, **MarioBert** (fine-tuned mask prediction model) is used to inpaint its border region.
- Smoothly join the mutated slice and the rest of level.



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4 Experiments and Results

- ▶ Introduction
- ▶ Background and Related Work
- ▶ Open-Ended Level Generation through LLMs
- ▶ Experiments and Results
- ▶ Conclusion



Reconstruction and Sampling Quality

4 Experiments and Results

It's proved in original paper that MarioGPT (using a pretrained GPT2 model) outperforms other baselines with regards to tile prediction.

Model	Tile Acc.	Path Acc.	Promptable?
LSTM	46%	39%	NO
from-scratch MarioGPT	31%	23%	YES
adapter MarioGPT	21%	11%	YES
MarioGPT	93%	91%	YES

Table: Training Reconstruction Accuracy – Validation Set



Reconstruction and Sampling Quality

4 Experiments and Results

To assess MarioGPT's capability in generating diverse and playable levels, we focus on two questions :

- 1. Playability of levels generated by MarioGPT** : Are MarioGPT's generated levels solveable?
- 2. Learning capability of MarioGPT**: Is MarioGPT memorizing?



Reconstruction and Sampling Quality

4 Experiments and Results

(1) Measuring Playability of Levels

- To test for playability, we deploy Robin Baumgarten's A* agent in generated levels, each level was played for 5 times.
 - Playable levels : 201
 - Not playable levels : 39

83.75% generated levels can be solved(it is 88.33% in original paper.)



Reconstruction and Sampling Quality

4 Experiments and Results

(1) Measuring Playability of Levels

- To test for playability, we deploy Robin Baumgarten's A* agent in 240 generated levels, each level was played for 5 times.
 - Playable levels : 201
 - Not playable levels : 39

83.75% generated levels can be solved(it is 88.33% in original paper.)

Playable	Not Playable	All
1.8009	8.68538	2.4375

Table: MAE between paths suggested by model and Baumgarten's A* agent **in original paper.**

Playable	Not Playable	All
1.14	4.55	1.55

Table: MAE between paths suggested by model and Baumgarten's A* agent **in our experiment.**



Reconstruction and Sampling Quality

4 Experiments and Results

(1) Measuring Playability of Levels

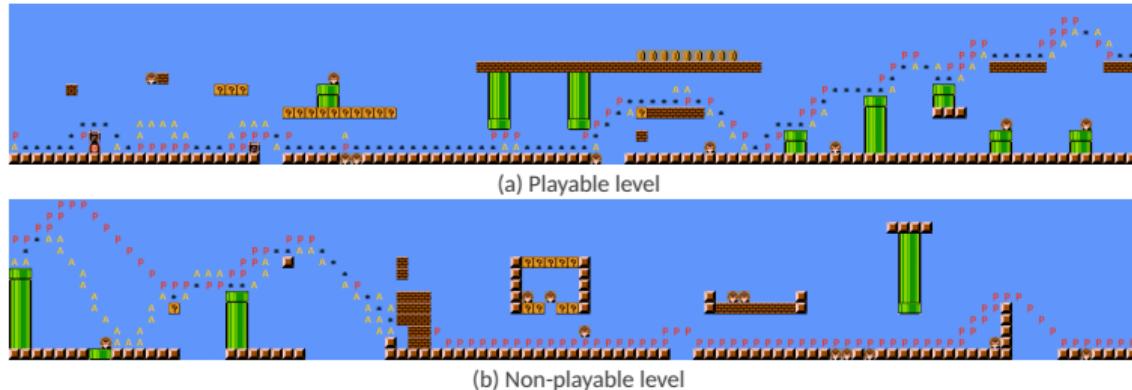


Figure: A* vs. MarioGPT generated paths. A* agent (denoted as A), and model suggestion (denoted as P) Positions where both trajectories overlap are marked with *.



Reconstruction and Sampling Quality

4 Experiments and Results

(2) Is MarioGPT memorizing?

- LLMs are incredibly powerful, but sometimes overfit extremely and end up regurgitating training data.
- Add some randomness in predictions in the form a tunable *temperature* parameter.



Reconstruction and Sampling Quality

4 Experiments and Results

(2) Is MarioGPT memorizing?

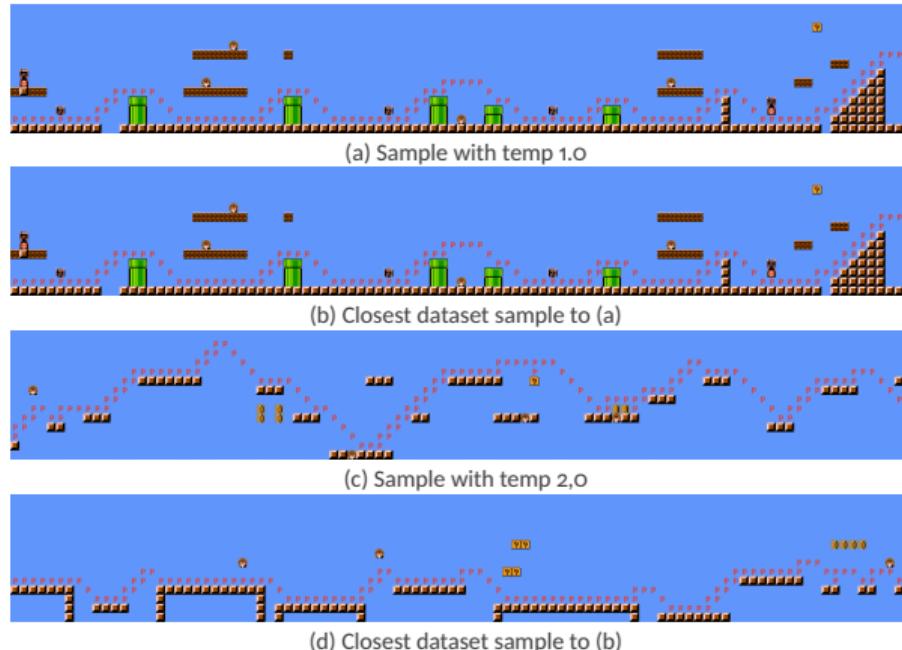


Figure: Generated levels vs closest in dataset.



Guided Level Generation via Prompting

4 Experiments and Results

- Evaluate the prompting ability of MarioGPT by comparing generated levels with the prompt descriptions.

pipes	enemies	blocks	elevation
75%	66.25%	81.25%	76.25%

Table: Prompt vs actual description accuracy **in our experiments**.

pipes	enemies	blocks	elevation
81%	68%	92%	76%

Table: Prompt vs actual description accuracy **in original paper**.



Guided Level Generation via Prompting

4 Experiments and Results

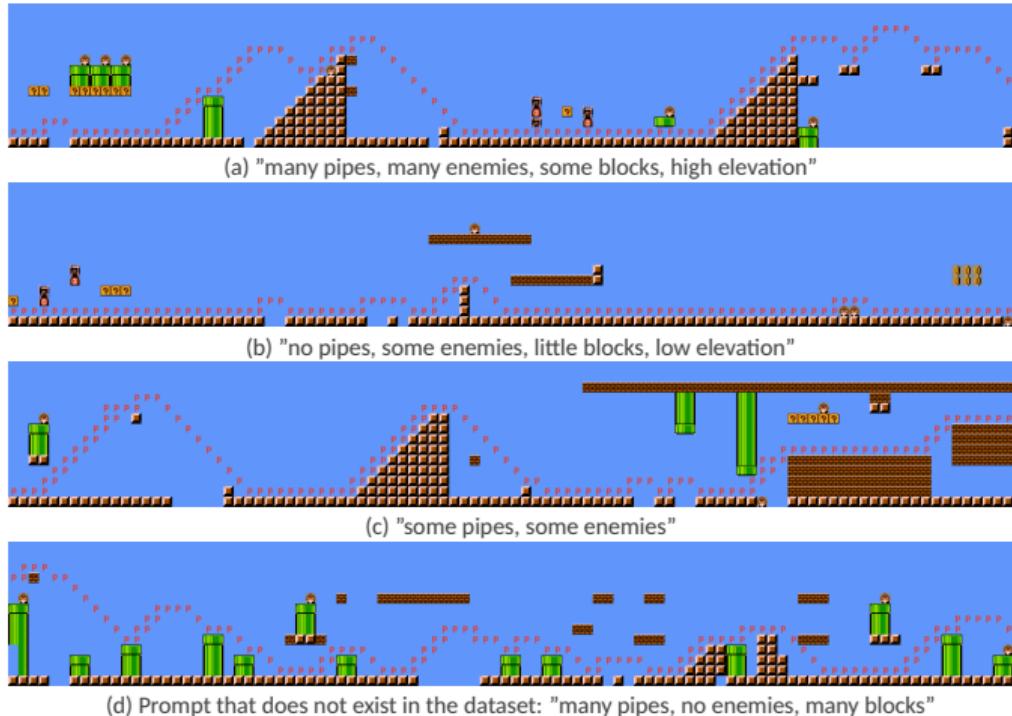
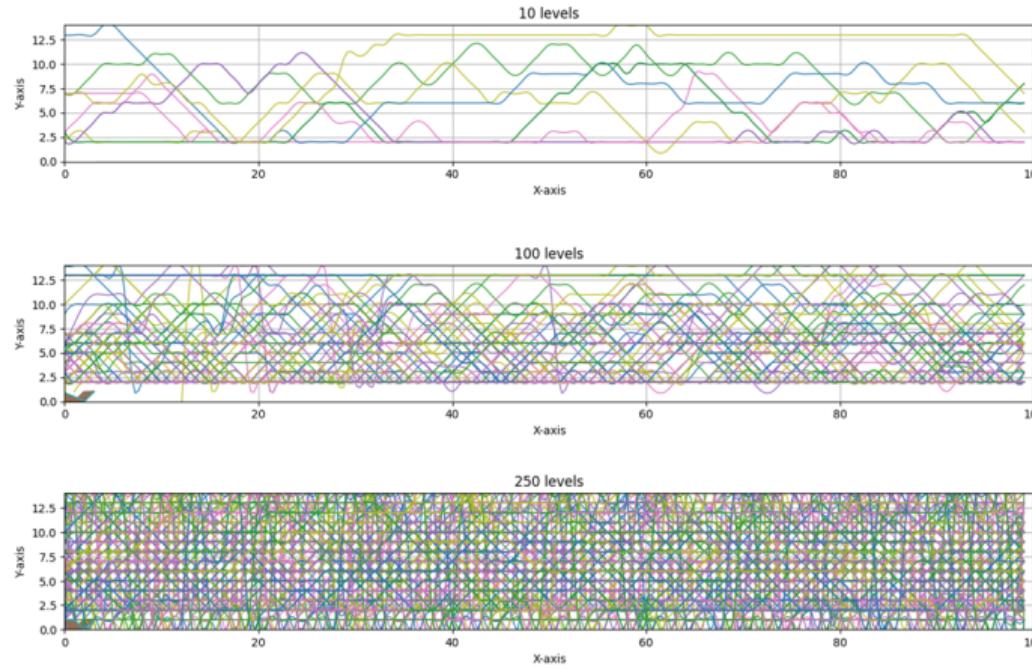


Figure : Multiple prompt generations from a single seed block.



Generating Diverse Levels with Novelty Search

4 Experiments and Results



Archive after 10, 100, 250 levels.

Figure: Generated path populations during novelty search. Each line is a path through a level.



Generating Diverse Levels with Novelty Search

4 Experiments and Results

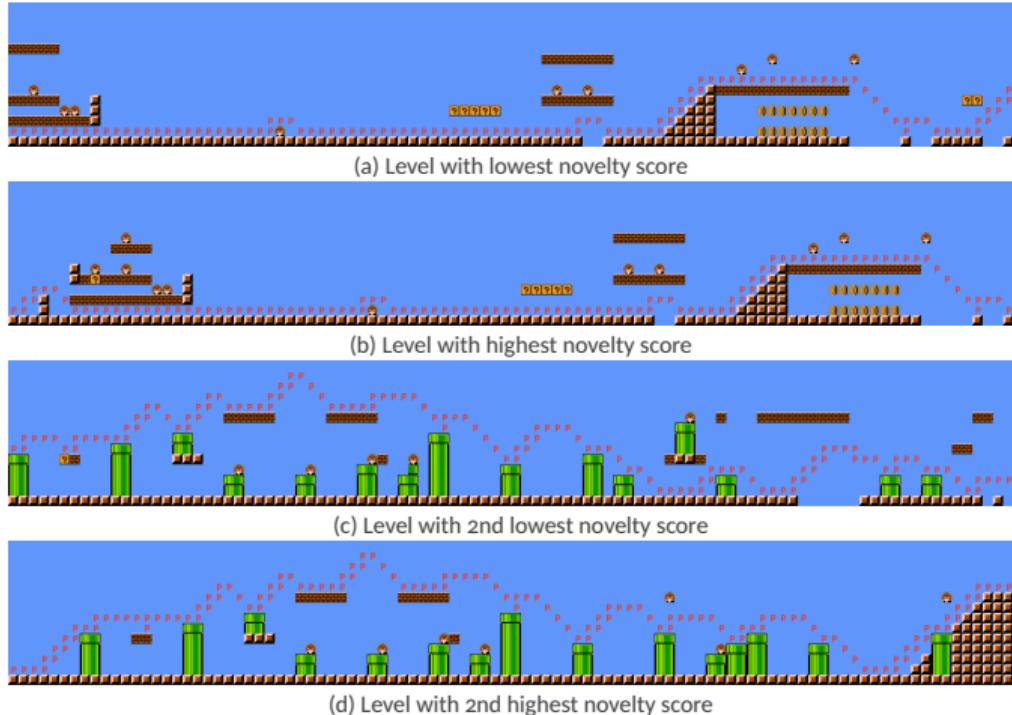


Figure: Comparison of most and least novel levels in the archive.



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5 Conclusion

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Conclusion

5 Conclusion

- MarioGPT is a fine-tuned LLM based on GPT2, capable of generating diverse and guided levels through language prompts.
- MarioGPT is able to :
 - predict player interaction in generated levels.
 - generate diverse and playable environments.
 - reduce the need for expensive. external agent interactions (MarioGPT can generate playable levels approximately 82% of the time)
- MarioGPT can generate open-ended and functional content with a diversity-driven algorithm (novelty search).



Future Work

5 Conclusion

- Leverage the scalability of LLMs and train MarioGPT on bigger, more detailed annotated levels.
- Incorporating human feedback into the level generation process through reinforcement learning from human feedback (RLHF).
- Opens the door to more controllable and diverse PCG systems.