MarioGPT: Open-Ended Text2Level Generation through Large Language Models

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UNIVERSITY OF INFORMATION TECHNOLOGY

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- ▶ Background and Related Work
- ▶ Open-Ended Level Generation through LLMs
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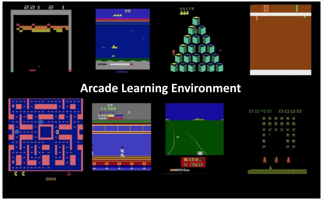
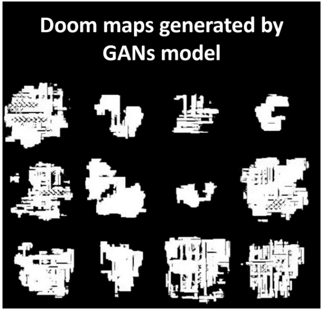
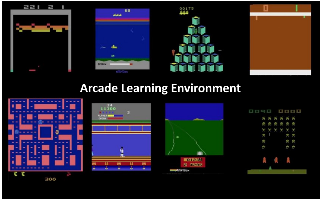
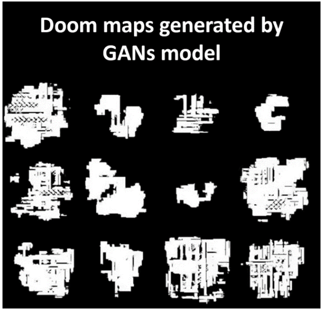
PCG and Machine Learning





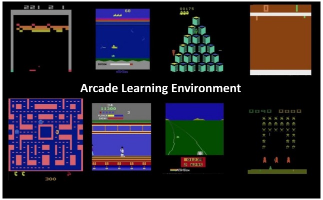
- PCG for evaluating generalization capabilities of trained agents.
  - Offer more diverse and challenging scenarios.
  - A better way to test the adaption and generalization of trained agents.

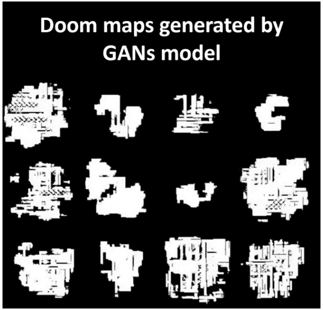




- PCG for evaluating generalization capabilities of trained agents.
  - Offer more diverse and challenging scenarios.
  - A better way to test the adaption and generalization of trained agents.

- Incorporation of machine learning-based approaches in PCG systems.
  - GANs for generating levels (Doom, Super Mario Bros)





Challenges

- **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.

Contributions

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

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

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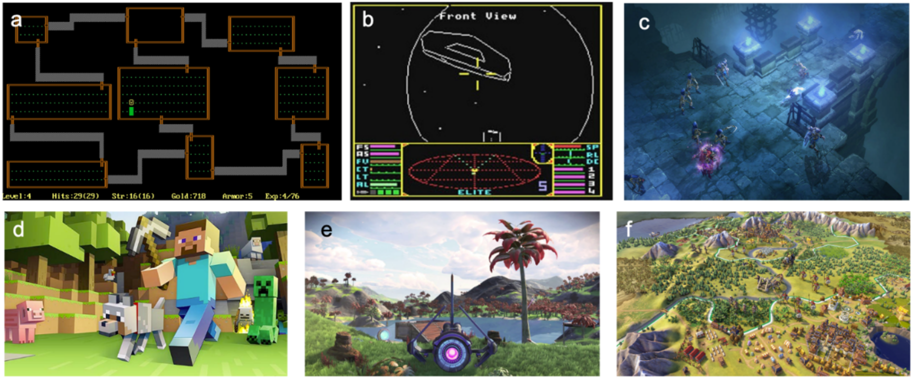
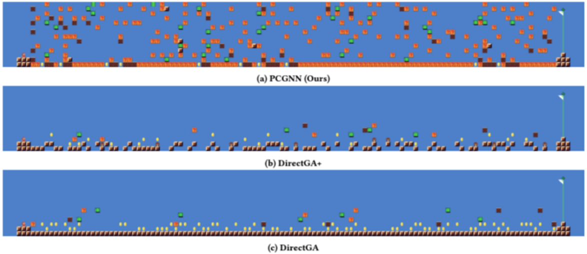
Procedural Content Generation (PCG)

- 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

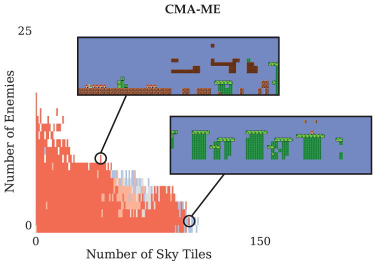
Procedural Content Generation (PCG)



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

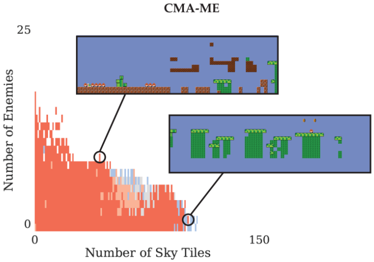


Using neural networks (Beukman et al.[1])



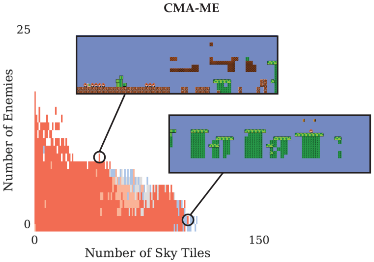
Searching in the latent space of GANs (Matthew et al.[2])

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



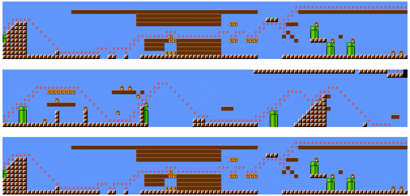
Searching in the latent space of GANs (Matthew et al.[2])

- 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.*



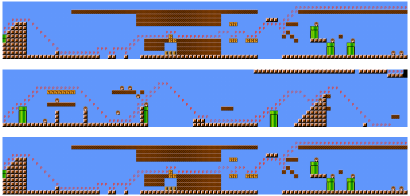
Searching in the latent space of GANs (Matthew et al.[2])

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



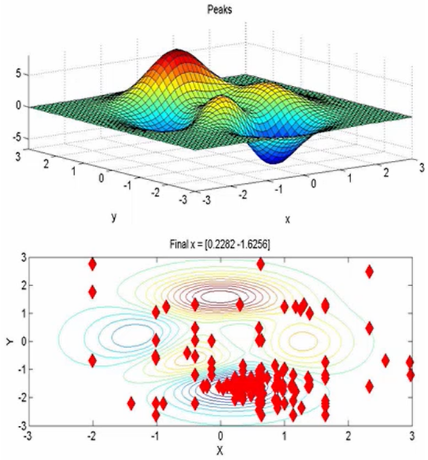
Diversity but not-playable cases

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

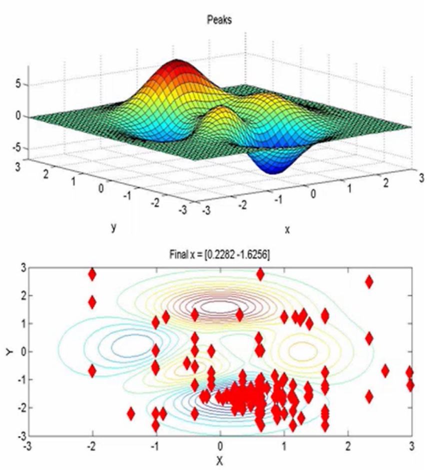


Diversity but not-playable cases

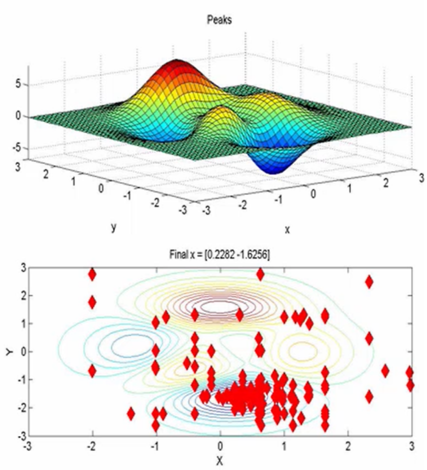
- Uses concepts from *evolutionary biology*



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

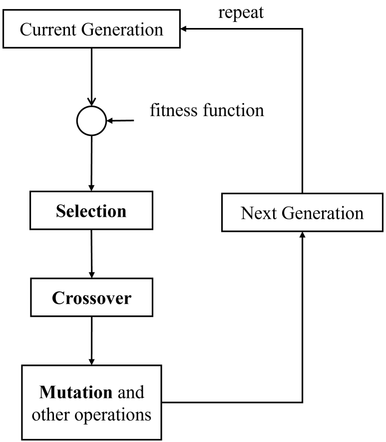


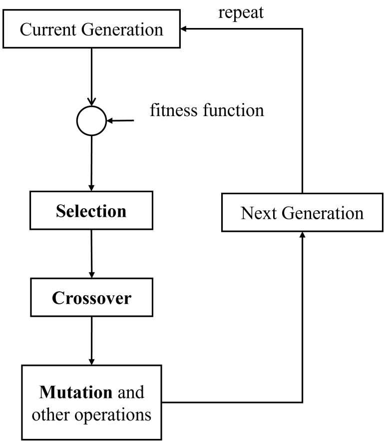
- Uses concepts from *evolutionary biology*
- Start with an initial generation of candidate solutions that are tested against the objective function
- Subsequent generations evolve from the 1st through *selection*, *crossover* and *mutation*



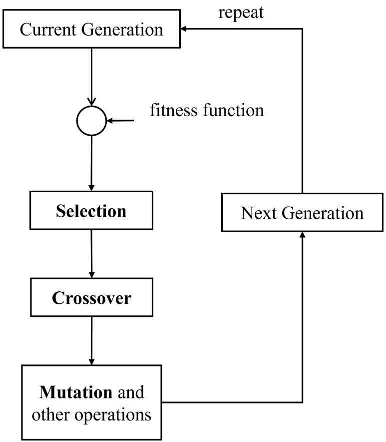
Genetic Algorithms

2 Background and Related Work

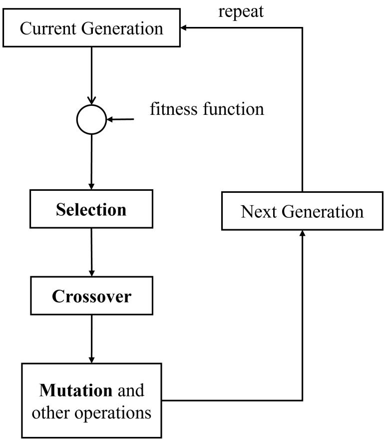




- First generation is arbitrarily, or $x = random()$



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



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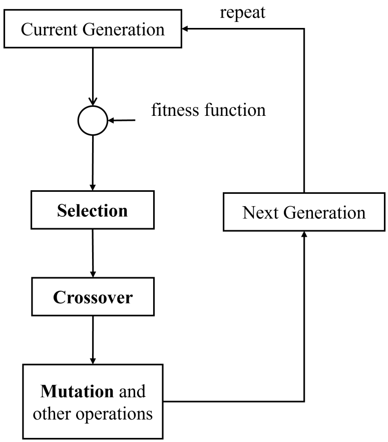
- Evaluate their *fitness*

$$fitness(x) = f(x)$$



- First generation is arbitrarily, or $x = random()$
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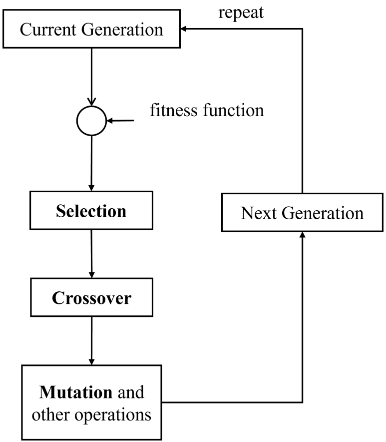
- *Select* members of the population:

Genetic Algorithms



- First generation is arbitrarily, or $x = random()$
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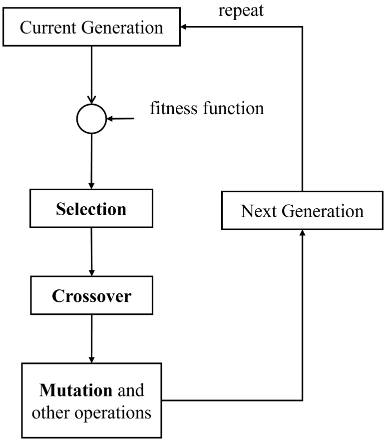
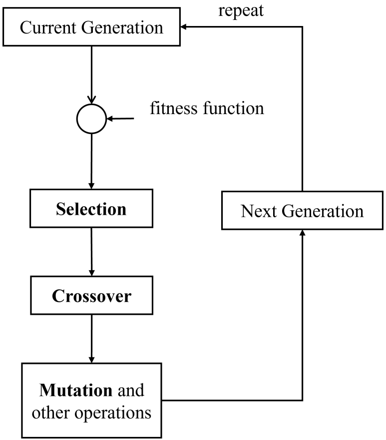
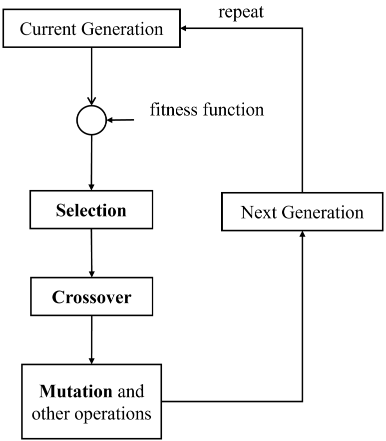
- *Select* members of the population:
  - Deterministic



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

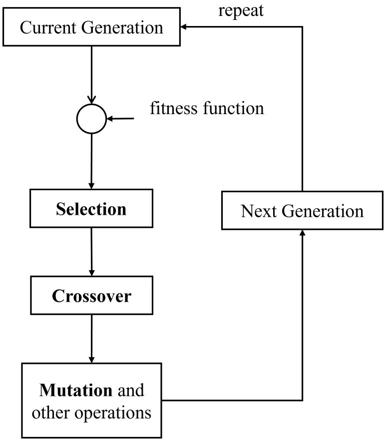


- First generation is arbitrarily, or $x = random()$
- Evaluate their *fitness*
- *Select* members of the population:
  - Deterministic
  - Stochastic



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

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



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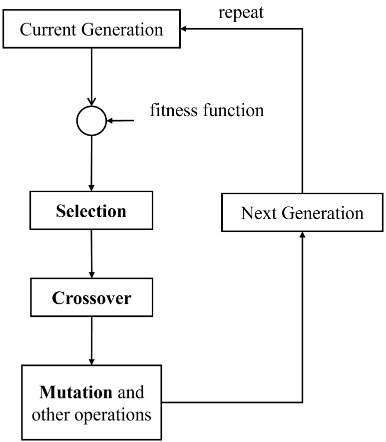

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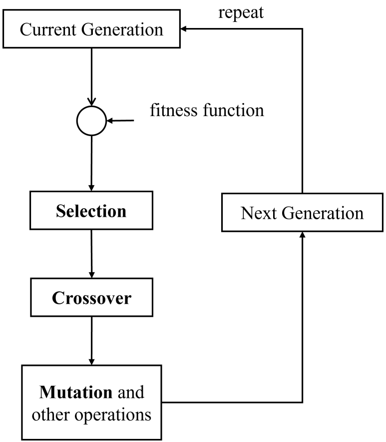
  - Novelty Selection



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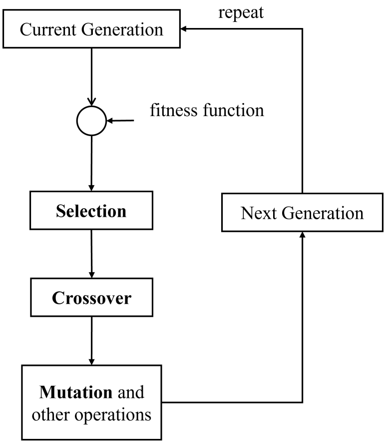

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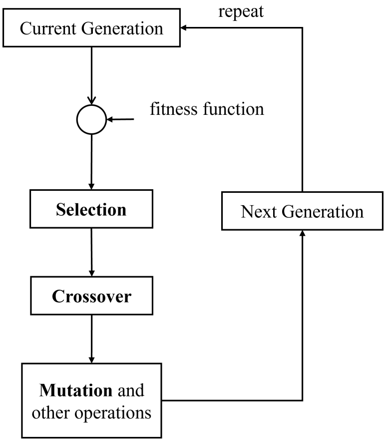
- Implement *crossover* operation on the reproduced chromosomes



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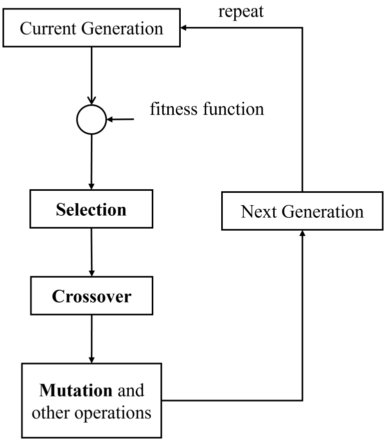
$$Crossover(x_1, x_2) = y$$



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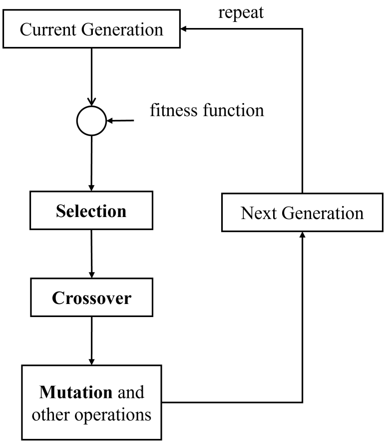

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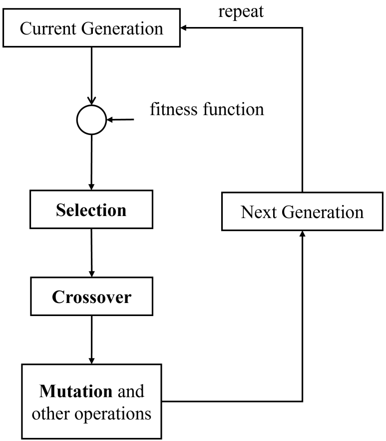
$$Mutation(y) = y', \text{ with } p_m$$



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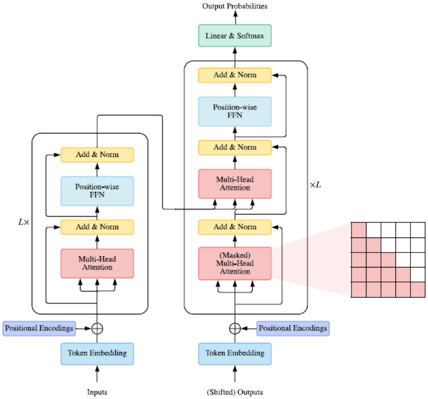
- *Allow the integration of multiple objectives*

Sequence Modelling and Transformer

- 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!

- ”Attention is all you need” (Vaswani et al., 2017)
- **Encoder**:
- **Decoder**:



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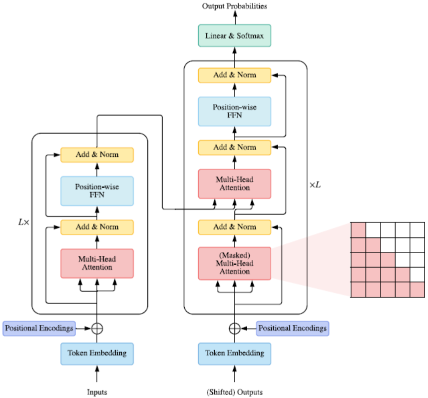
  - N identical layers (Multi-Head Attention and FFN)
  - Residual connections
- **Decoder**:



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- **Decoder**:
  - N identical layers (Multi-Head Attention, FFN and Masked Multi-Head Attention)
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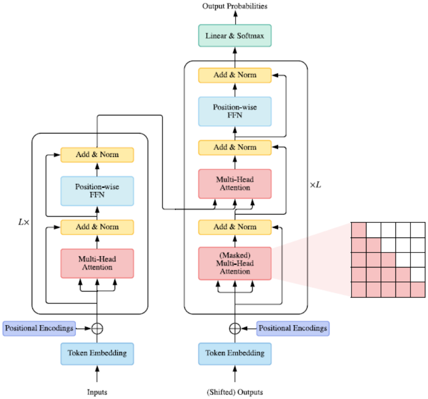

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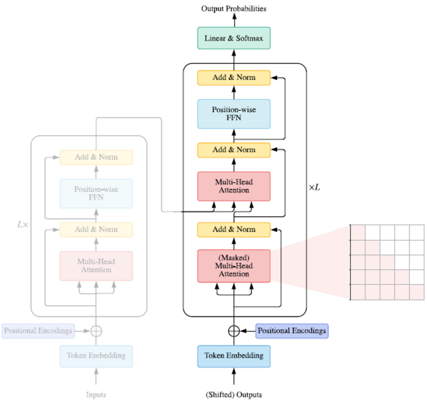
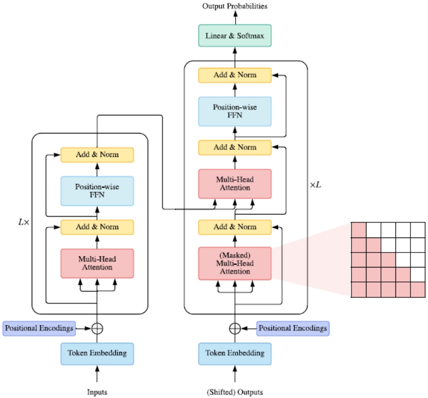
- *GPT consists of a stack of decoder layers.*



- 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”



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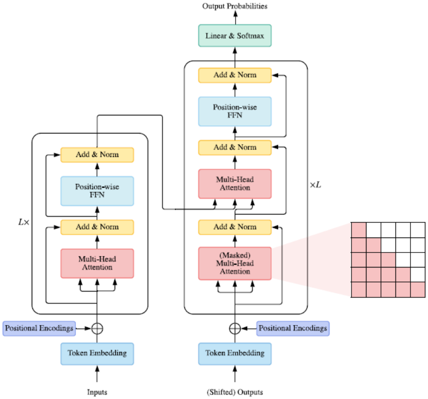
- Produce incredibly diverse mutations, vary increasingly over the course of the GA!



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MarioGPT: Open-Ended Text2Level Generation through Large Language Models *Thank you for listening!*

Any questions?