

Replicating Super Mario as a String

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Original Paper

- Title - Super Mario as a String: Platformer Level Generation Via LSTMs
- Authors - Adam Summerville and Michael Mateas
- Year - 2016
- Published at -
<https://doi.org/10.48550/arXiv.1603.00930>

THE PROBLEM

(With human-designed levels)



- Time
- Design Skills
- Creativity
- Time

CHALLENGES (of generating levels)



Limited Data Set

Limited Data

Most games have a maximum of hundreds of levels, but even more are far below that.



Long Levels

Each level is thousands of characters long.



Patterns

Levels are made up of complicated design patterns,

MOTIVATION

T

TIME

Level Design takes a significant amount of time.

S

SKILL-INTENSITY

Due to the number of skills needed to design a level, it is difficult to learn.

C

COMPLEXITY

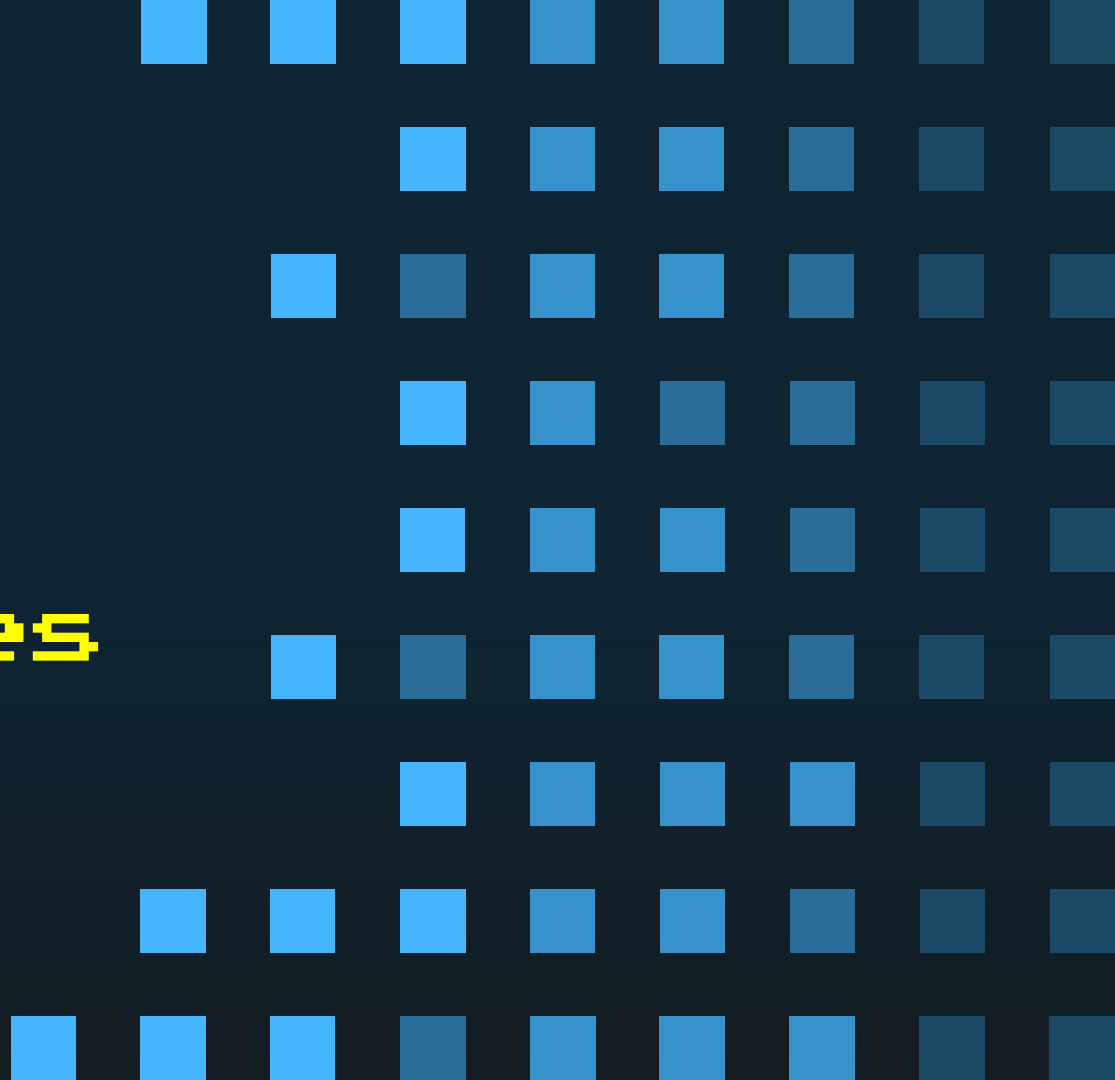
The design of a level is but one tiny part of a massive program.

L

LEARNING

While this project may not directly help any current game development projects, what I learned from this can be used to make impactful models for future projects

Related Works/ Approaches



RELATED WORK/APPROACHES 1

Title: Online Level Generation in Super Mario Bros via Learning Constructive Primitives

Author: Peizhi Shi and Ke Chen

Year: 2016

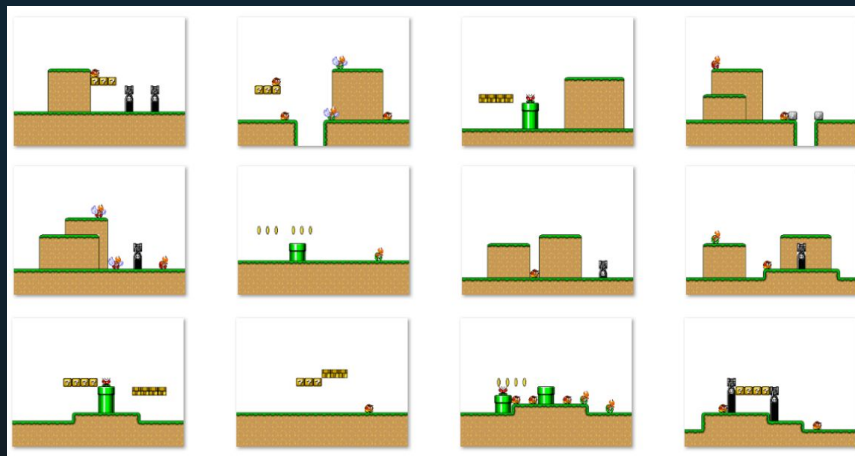
Published at: [2016 IEEE Conference on Computational Intelligence and Games \(CIIG\)](#)

Approach:

- Learning-based procedural content generation (LBPCG)
- CURE clustering algorithm
- Weighted random forests

Pros:

- High degree of control
- High Playable Rate



Cons:

- High degree of manual labor

Figure 1:
Sampled level segments, Peizhi Shi and Ke Chen

RELATED WORK/APPROACHES 2

Title: MarioGPT: Open-Ended Text2Level Generation through Large Language Models

Author: Shyam Sudhakaran, Miguel González-Duque, Claire Glanois, Matthias Freiberger, Elias Najarro, and Sebastian Risi

Year: 2023

Published at: [arXiv](#)

Approach:

- Transformers
- LLMs
- DistilGPT2
- Repeated Slicing

Pros:

- User-friendly
- High degree of control
- Multiple Paths

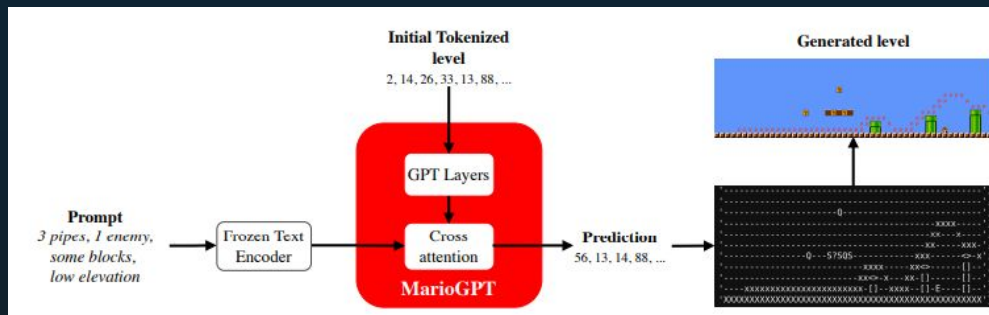


Figure 2:
Sampled level segments, Sudhakaran, Shyam, et al

Cons:

- Tradeoff between uniqueness and quality
- Enemy problems

My Approach/
Method

Quick Note on contributions

For my project, I heavily modified Zhihan Yang's attempt of replicating the same paper.

Yang's GitHub:

<https://github.com/zhihanyang2022>

The Project Itself:

https://github.com/zhihanyang2022/super_mario_as_a_string

What is **Not Original**

- The Original Mario Level Data
- *Most* of the Data Pre-processing
- Creating the seed for level generation
- A tool that turns text levels into pngs

What is **Original**

- Everything else, including:
- The Model
- The Training
- The Generation
- Snaking, Pathing, and Column Depth
- Metric Calculation and Evaluation

Pre-Processing

1

Combine Levels Into One
File

2

Modify each Level for
Snaking/ Pathing/ Column
Depth

3

Get the number of
unique characters in the
levels

4

Divide each level string into
overlapping sequences of 200
characters

5

Split sequences into Inputs
and Targets

6

One-Hot Encode the
Inputs

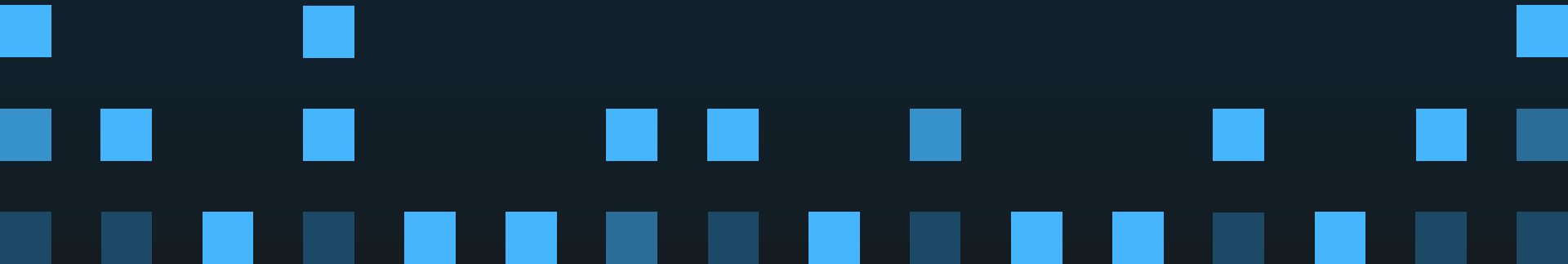
Input and Target Sequences

Input Sequence:

..asldhfuoasdufhao8sdufhnlfawoe8iufhapodufhbasdsadfasdfa..

Target Sequence:

..asldhfuoasdufhao8sdufhnlfawoe8iufhapodufhbasdsadfasdfa..



[illegible]

Input Sequence:

[illegible]

Target Sequence:

...318337458734592394720093459234012093492304943439534523...

So what are LSTMs?

LSTMs are a type of artificial neural network designed for sequential data processing. LSTMs address the vanishing gradient problem in traditional recurrent neural networks (RNNs) by introducing specialized memory cells with gating mechanisms. These gates enable LSTMs to selectively store, update, and retrieve information, allowing them to capture long-range dependencies. Effectively, LSTMs create sequences that have good global and local coherence.

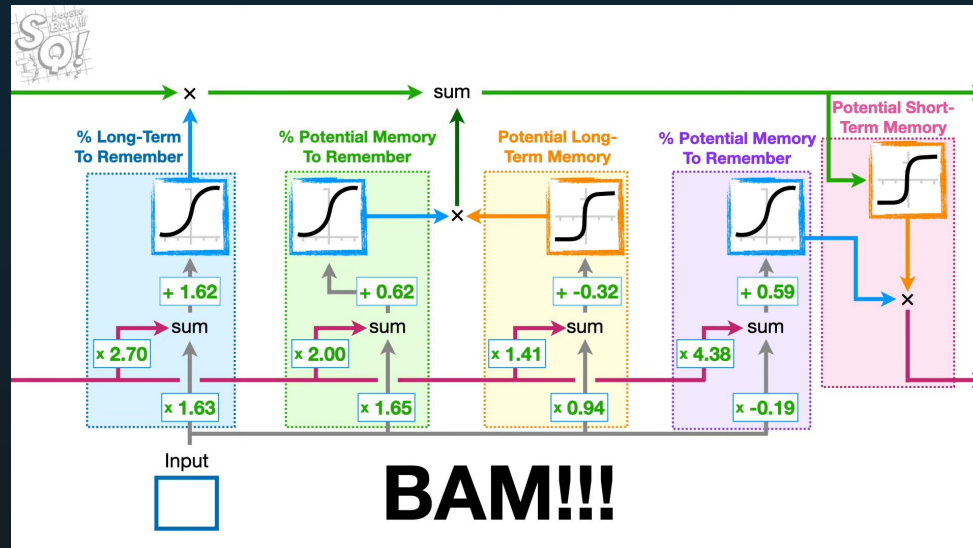


Figure 3:
LSTM Diagram, Josh
Starmer

THE MODEL

Model Parameters:

Num_layers = 3

Vocab_size = 14-16

Hidden_size = 516

Dropout = 0.5

This project's LSTM Model

```
1 import torch
2 import torch.nn as nn
3 import torch.nn.functional as F
4 class LSTMModel(nn.Module):
5     def __init__(self, vocab_size, hidden_size, num_layers, dropout):
6         super().__init__()
7
8         self.hidden_size = hidden_size
9         self.num_layers = num_layers
10
11         self.lstm = nn.LSTM(vocab_size, hidden_size, num_layers, dropout=dropout, batch_first=True)
12         self.fc = nn.Linear(hidden_size, vocab_size)
13
14         #The reason I have the h0 and c0 is so I can predict the next char in a sequence later
15         #This isn't used during training
16         def forward(self, x, h0=None, c0=None):
17             if h0 is None or c0 is None:
18                 h0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size).requires_grad_().to(x.device)
19                 c0 = torch.zeros(self.num_layers, x.size(0), self.hidden_size).requires_grad_().to(x.device)
20
21             #We need to detach as we are doing truncated backpropagation through time (BPTT)
22             #If we don't, we'll backprop all the way to the start even after going through another batch
23             out, (hn, cn) = self.lstm(x, (h0.detach(), c0.detach()))
24
25             # Index hidden state of last time step
26             out = self.fc(out)
27
28             return out, (hn, cn)
```


Approach Steps

Initialize
Model

1

Split Inputs
and Targets
into Training
and evaluation

2

3

Train (LSTM)
Model

Clear
Gradients

Forward Pass

Calculate
Loss

Backward pass/
Compute gradients

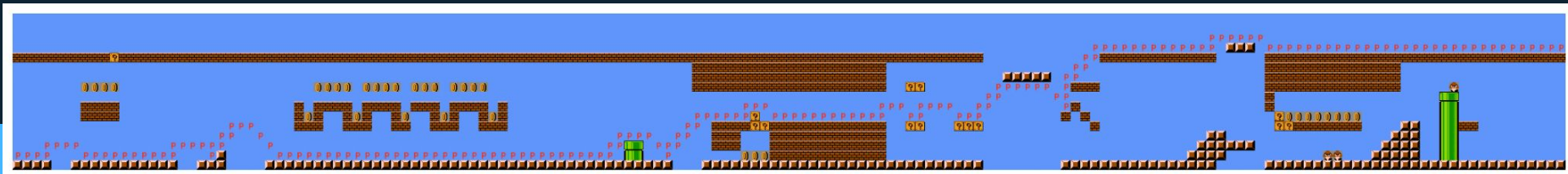
Update
Weights

Repeat
Until
Loss
Plateau

4

Generate
Levels

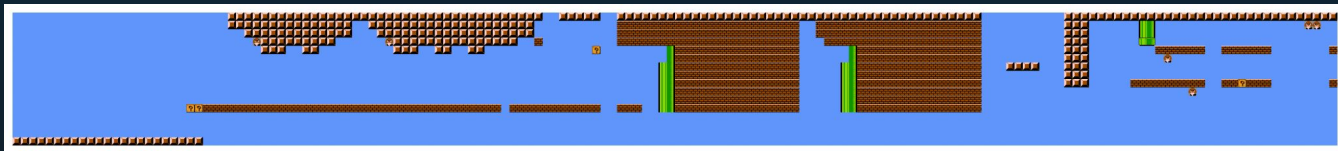
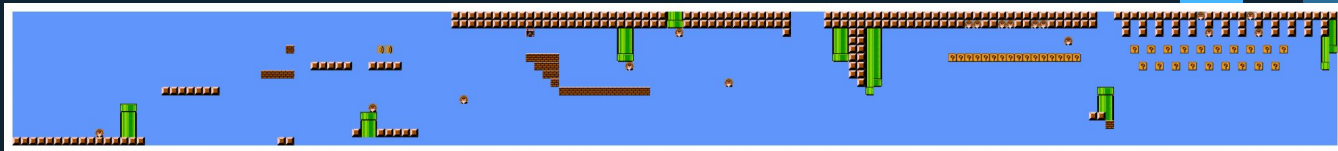
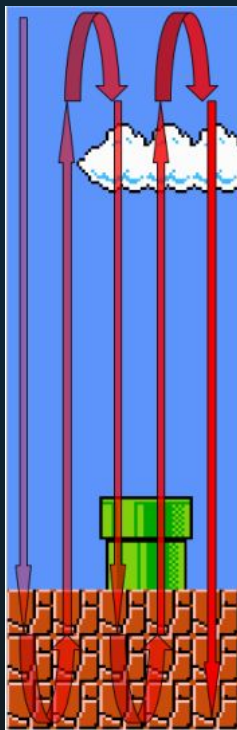
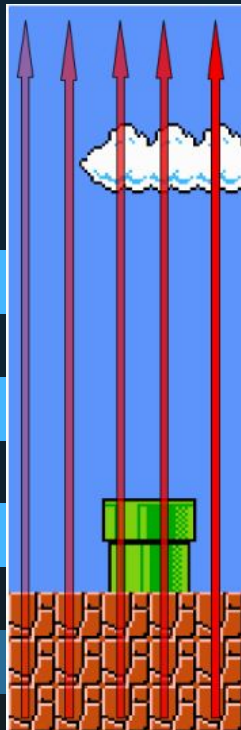
Generated Levels Results



Snaking Results

Normal

Snaking



Main Observations

- The LSTM model can successfully generate playable levels at a reasonable rate
- Snaking the input is **Not** recommended, as it can cause the levels to flip around and create strange artifacting
- It takes an average of 6.5 seconds to generate each level. This means the model successfully fixes our problem of time taken to design and build levels

Closing Remarks

Thank you for your time and attention.

The Project Github can be found at
<https://github.com/Ninjaikl/ITCS5156Project>

Suggestion for Future Work

- Test different hyperparameter combinations
- Attempt using a LLM instead of a LSTM
- Expand dataset to include more original mario levels

References

- Shi, Peizhi, and Ke Chen. “Online level generation in Super Mario Bros via learning constructive primitives.” *2016 IEEE Conference on Computational Intelligence and Games (CIG)*, Sept. 2016, <https://doi.org/10.1109/cig.2016.7860397>.
- Sudhakaran, Shyam, et al. “MarioGPT: Open-Ended Text2Level Generation through Large Language Models”, *arXiv*, Feb. 2023, <https://doi.org/10.48550/arXiv.2302.05981>.
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- Starmer, J. (2023, January 24). Long short-term memory with pytorch + lightning. YouTube. https://www.youtube.com/watch?v=RHGIXPuo_plI

