Controllable Level Blending between Games using Variational Autoencoders

Anurag Sarkar[1], **Zhihan Yang**[2] and **Seth Cooper**[1]

[1]Northeastern University

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(Towards) Controllable Level Blending between Games using Variational Autoencoders

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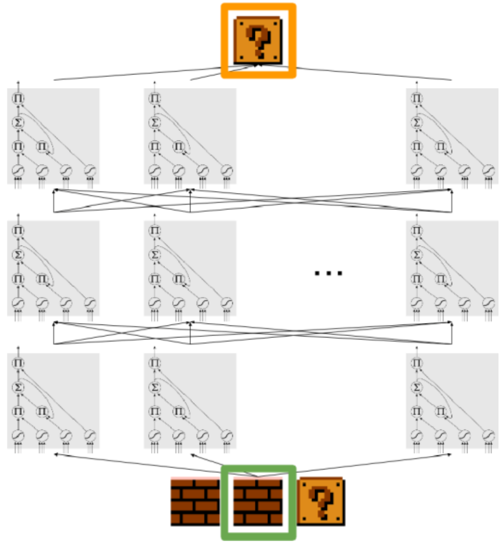
(Towards) Controllable Level Blending between Games using Variational Autoencoders

Still no playability!

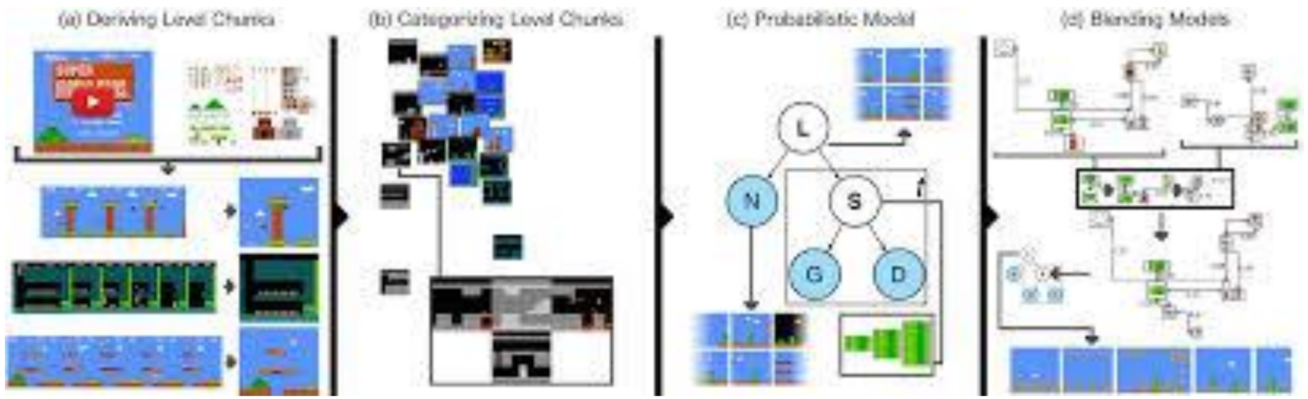
Promising results and future directions!

Motivation

- Past work on training models on existing levels to generate new levels
  - Sequence prediction using LSTMs
  - Conceptual blending using graphical models



Summerville and Mateas, 2016



Guzdial and Riedl, 2016

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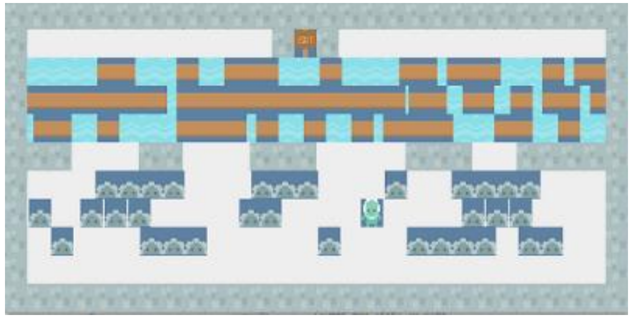
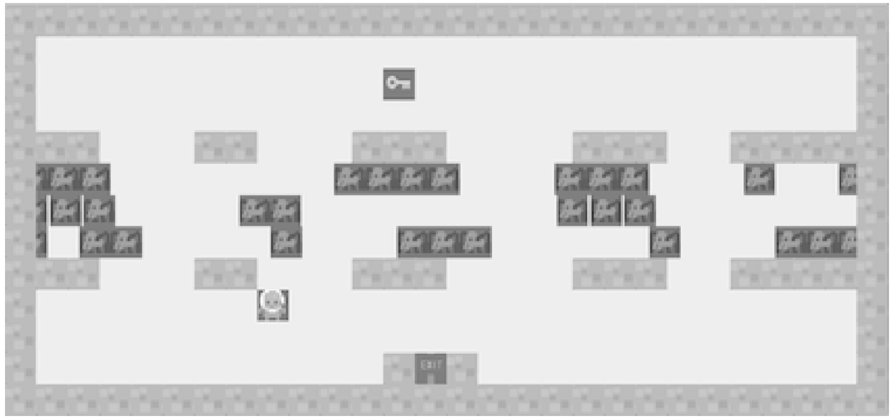


VGDL Frogger

VGDL Zelda

- Gow and Corneli proposed generating new games by blending entire games



Frolda

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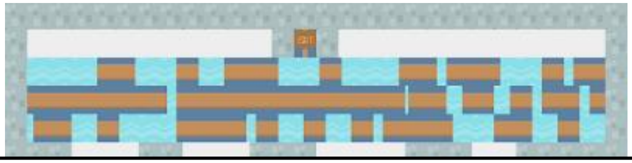
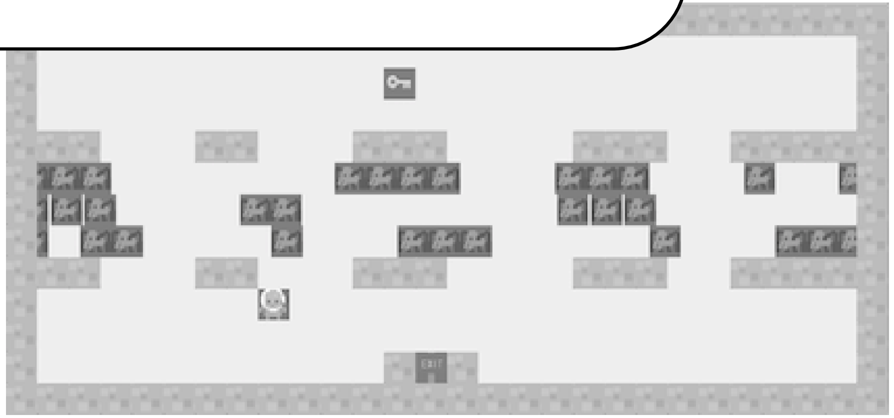
  - Concept
    graphica
- Gow and Co
  new games by blending entire games

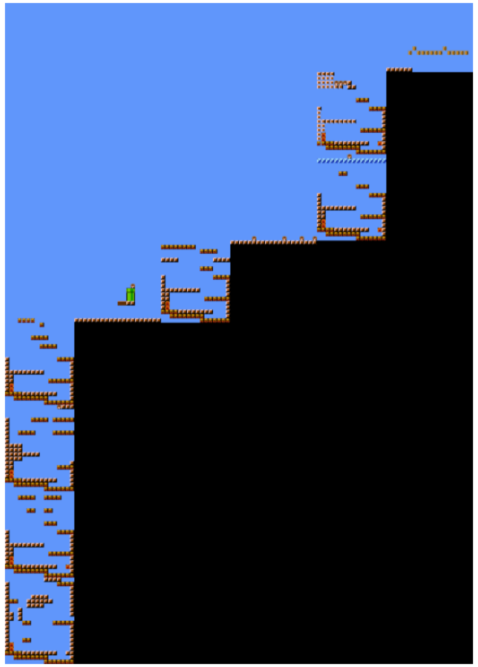


IDEA: PCGML techniques + Game Blending

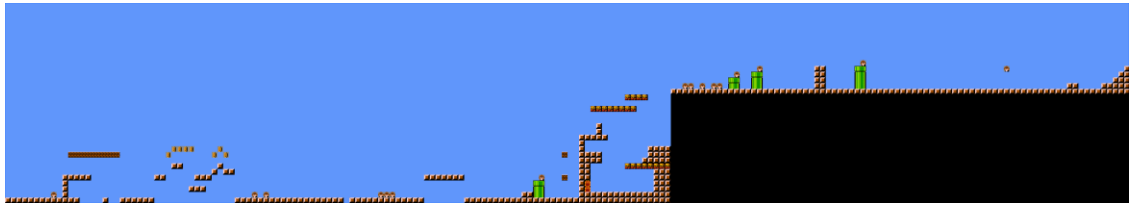


Blending Levels using LSTMs

- Trained LSTMs on levels of *Super Mario Bros.* and *Kid Icarus*
- Sampled from trained models to generate levels containing properties of both games
- Parametrized generator with weights to control approximate percentage of each game in blended level



(SMB=0.2, KI=0.8)



(SMB=0.8, KI=0.2)

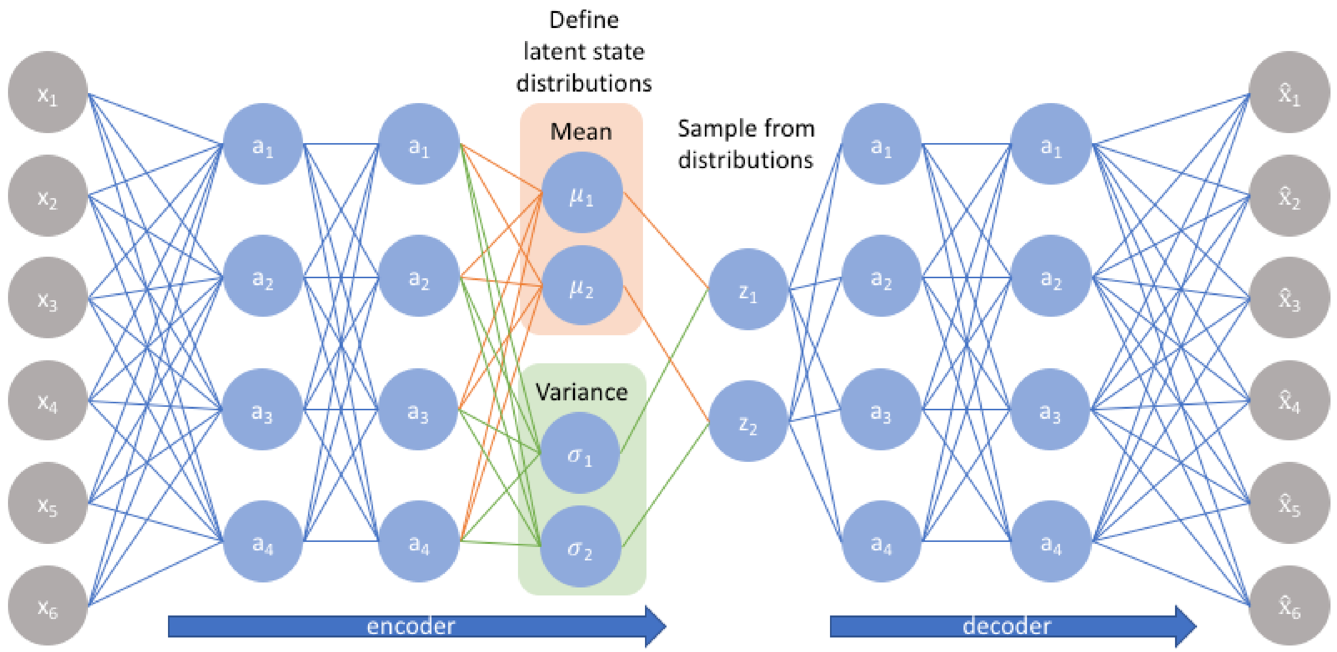
Drawbacks

- Blended levels by taking turns between *Super Mario Bros.* and *Kid Icarus*

- Allowed control of proportion of each game in blended level but no control over more fine-grained tile-based properties

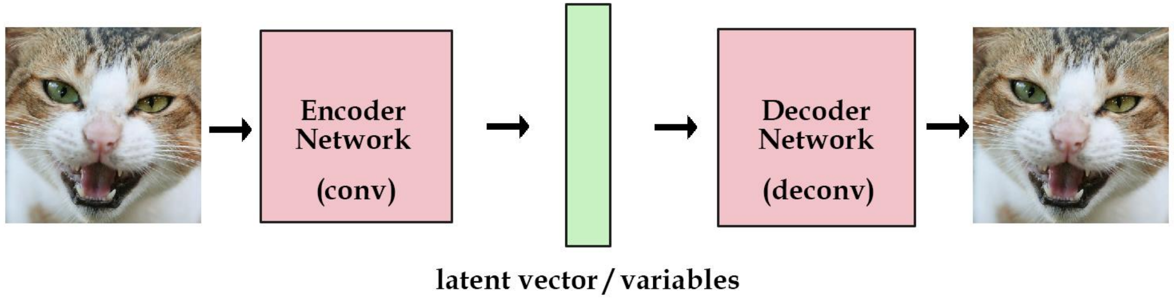
Solution: Variational Autoencoder (VAE)

- Enables more holistic blending of level properties by capturing latent space across both games
- Allows generation of segments satisfying specific properties
- More conducive to co-creative level design



Variational Autoencoder

- Autoencoders are neural nets that learn lower-dimensional data representations
  - Encoder → input data to latent space
  - Decoder → latent space to reconstructed data



Vanilla Autoencoder

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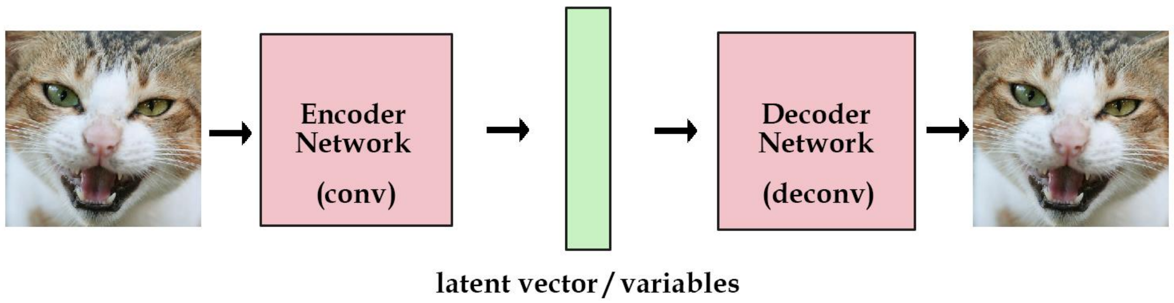
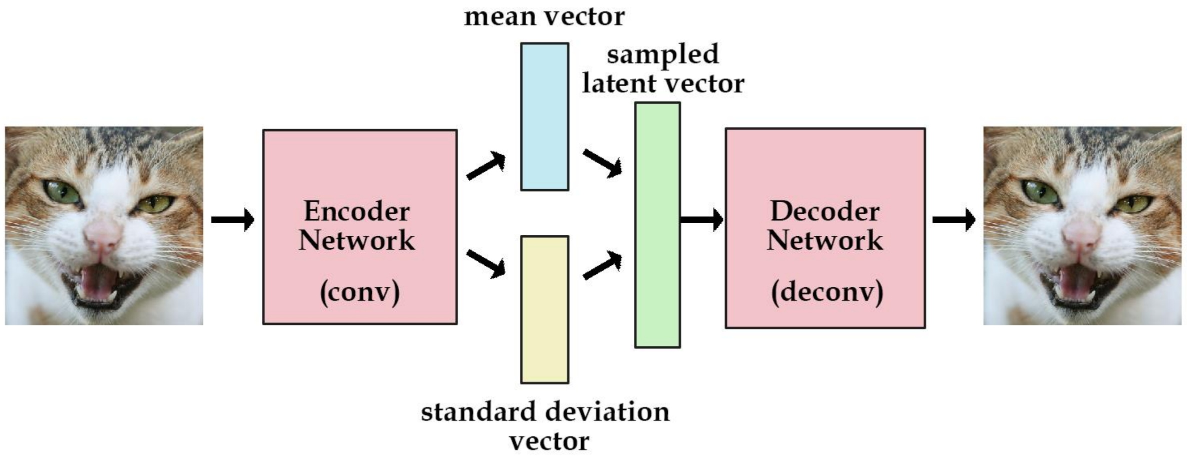


Vanilla Autoencoder

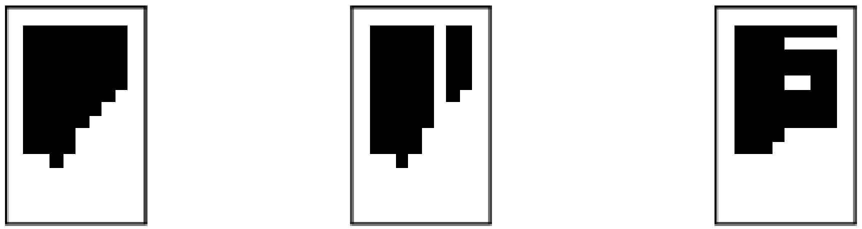
- VAEs make latent space model a probability distribution (e.g. Gaussian)
  - Allows learning continuous latent spaces
  - Enables generative abilities similar to those of GANs



Variational Autoencoder

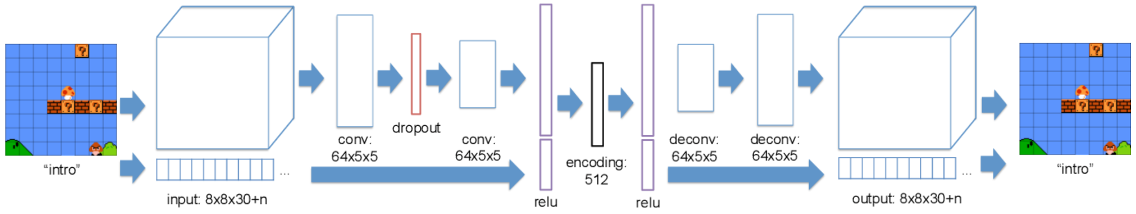
Motivation for VAE

- Past work in using autoencoders for Mario level generation
    - Autoencoders for Level Generation, Repair and Recognition, Jain et al. (2016)
    - Explainable PCGML via Design Patterns, Guzdial et al. (2018)



(a) Original (b) Unplayable (c) Repaired

Jain et al. (2016)



Guzdial et al. (2018)

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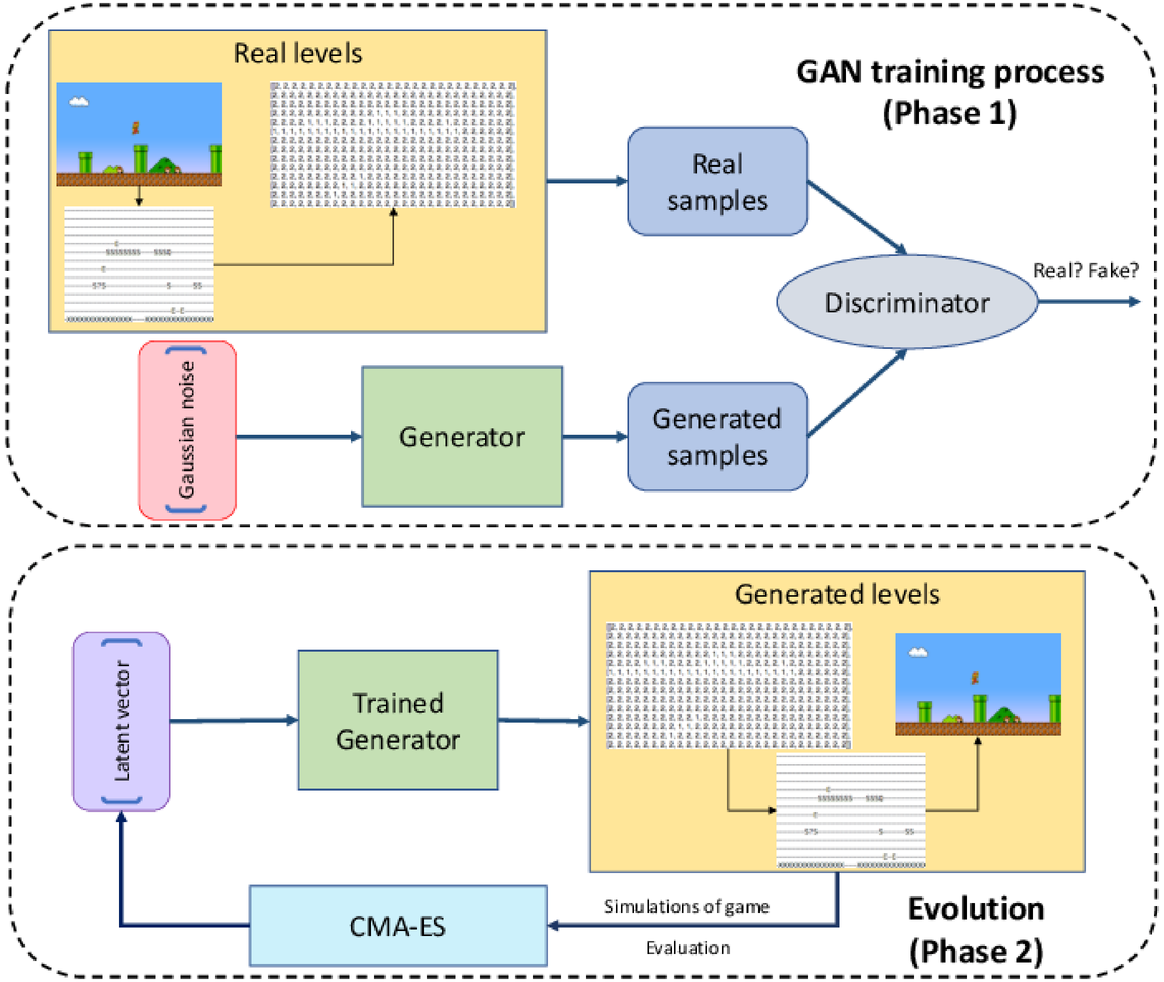
- Evolving Mario Levels in the Latent Space of a DCGAN (i.e. MarioGAN), Volz et al. (2018)



Volz et al. (2018)

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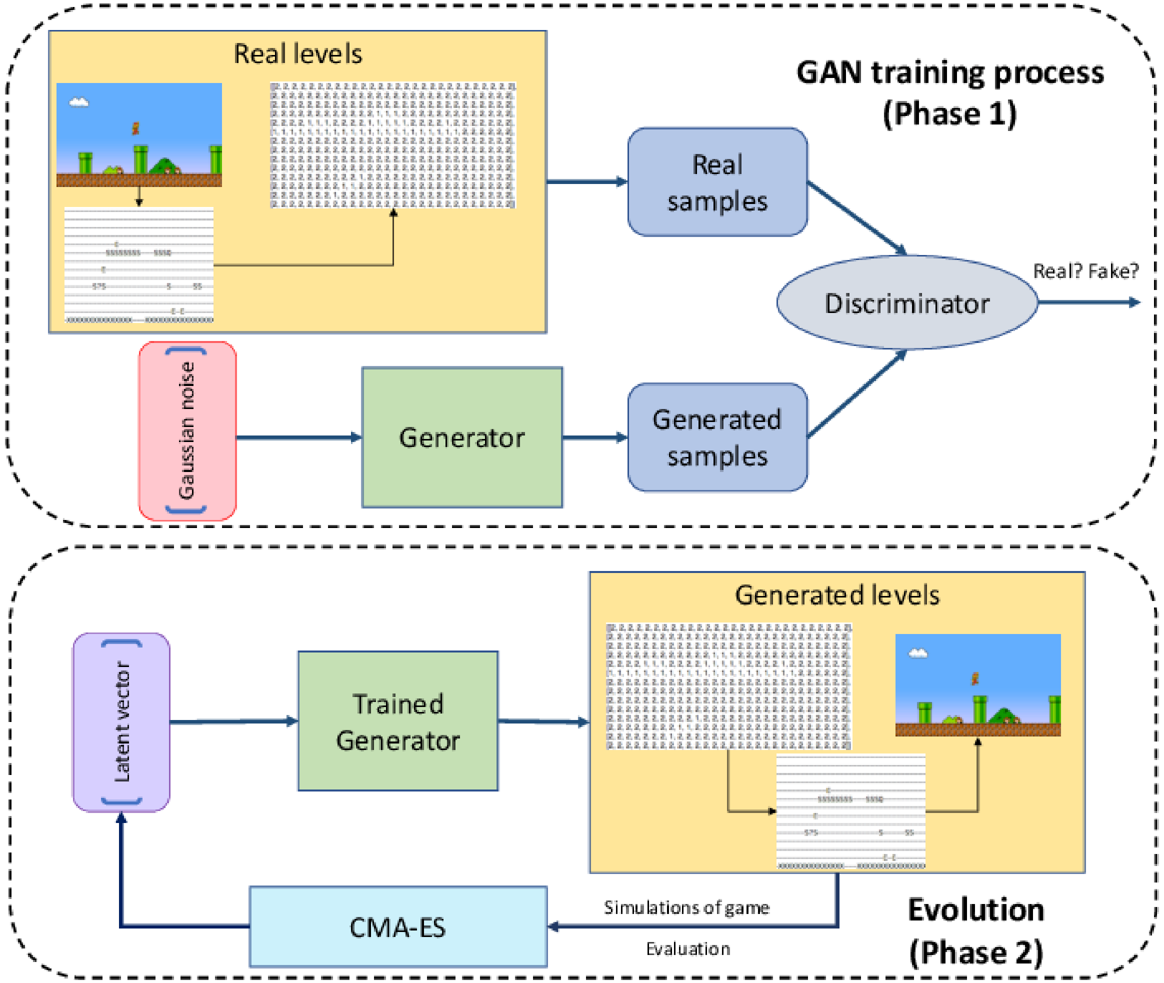
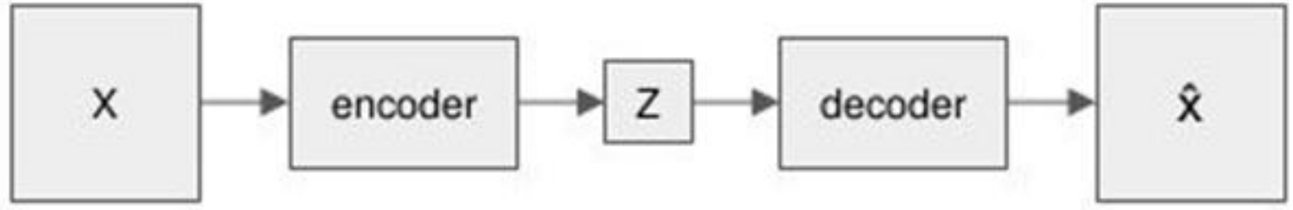
- Evolving Mario Levels in the Latent Space of a DCGAN (i.e. MarioGAN), Volz et al. (2018)
- Use MarioGAN-based approach to capture latent space of 2 games instead of 1



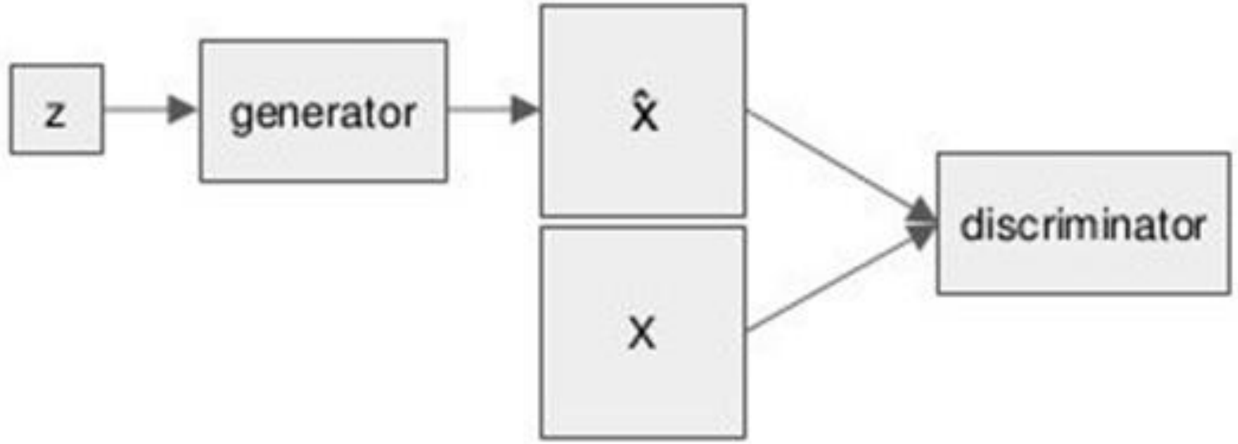
Volz et al. (2018)

Why VAE over GAN?

- VAE architecture more conducive to co-creative level design
    - Designers don't have to directly use latent space vectors
    - More explicit control in defining inputs to the system
    - More useful to blend/interpolate between known segments rather than latent vectors



VAE Architecture

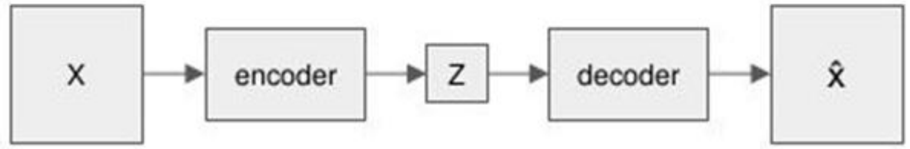


GAN Architecture

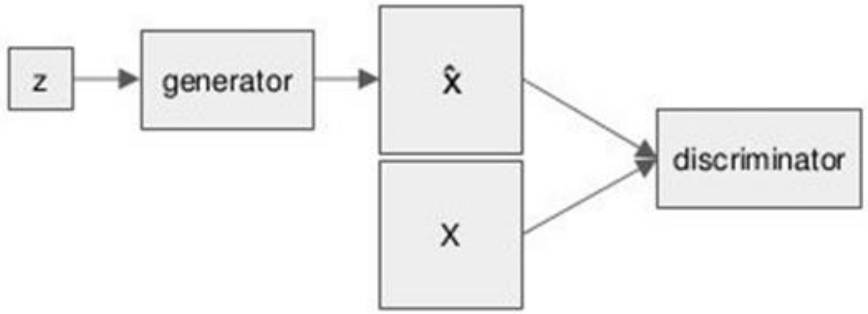
VAE vs GAN vs VAE-GAN

- Trained a GAN and a VAE-GAN in addition to the VAE to compare generative capabilities in a level blending context

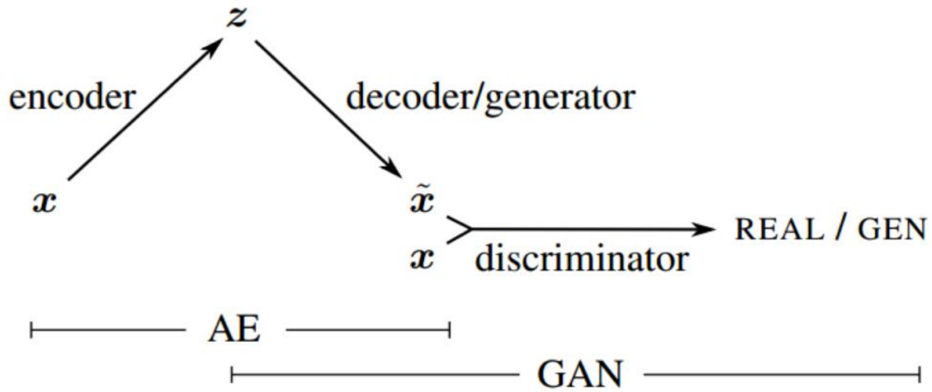
- VAE-GAN is a hybrid generative model
    - Combines VAE and GAN by collapsing VAE decoder into a GAN generator



VAE



GAN



VAE-GAN (Larsen et al. 2016)

Dataset and Training

- Trained on a level each from SMB (Level 1-1) and KI (Level 5) taken from the Video Game Level Corpus (VGLC)

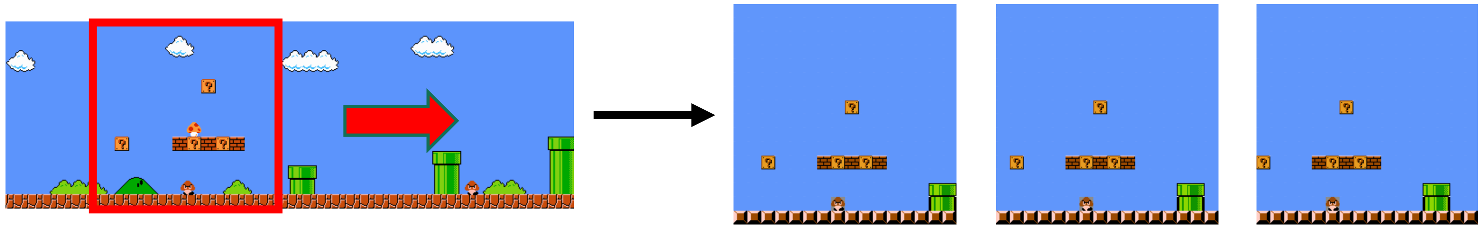
- Each level is a 2D character array

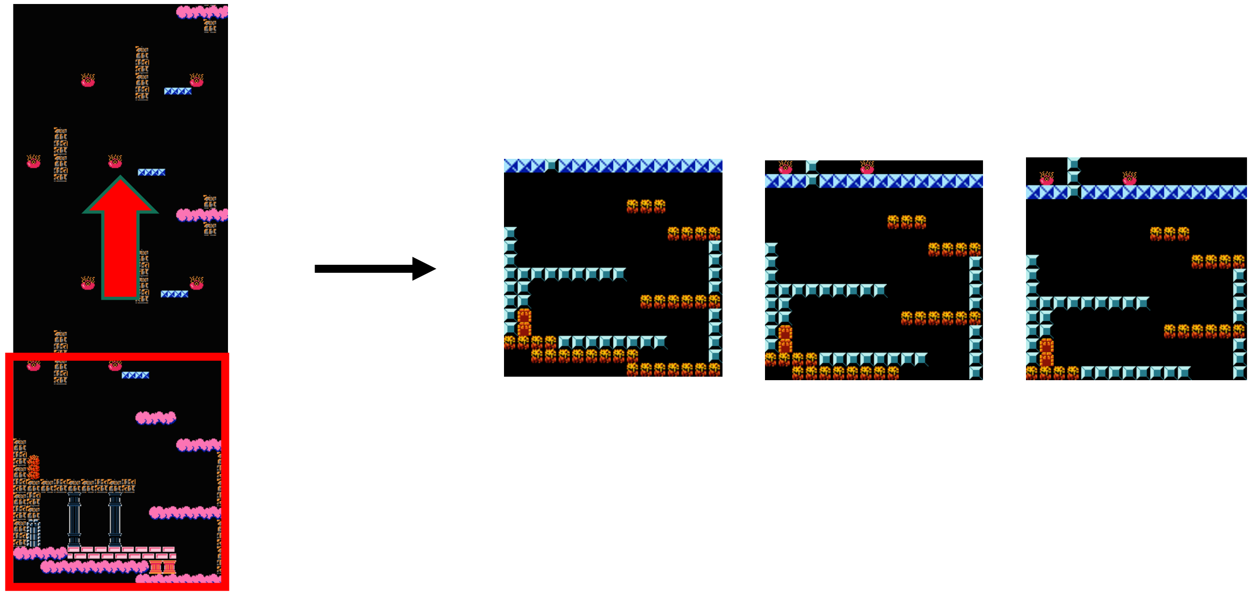
- Each tile type was encoded using an integer and then with one-hot encoding for training

Tile Type	*VGLC*	*Integer*	*Sprite*
SMB Ground	X	0	
SMB Breakable	S	1	
SMB Background	-	2	
SMB Full Question	?	3	
SMB Empty Question	Q	4	
SMB Enemy	E	5	
SMB Pipe Top Left	<	6	
SMB Pipe Top Right	>	7	
SMB Pipe Bottom Left	[	8	
SMB Pipe Bottom Right	]	9	
SMB Coin	o	10	
KI Platform	T	11	
KI Movable Platform	M	12	
KI Door	D	13	
KI Ground	#	14	
KI Hazard	H	15	
KI Background	-	16	

Dataset and Training

- To account for orientation, used 16x16 sliding window
- 187 segments of SMB + 191 segments of KI = 378 total segments
- Models learned to generate 16x16 blended level segments
- VAE, GAN and VAE-GAN all trained using same number of segments and with similar training conditions





Generation

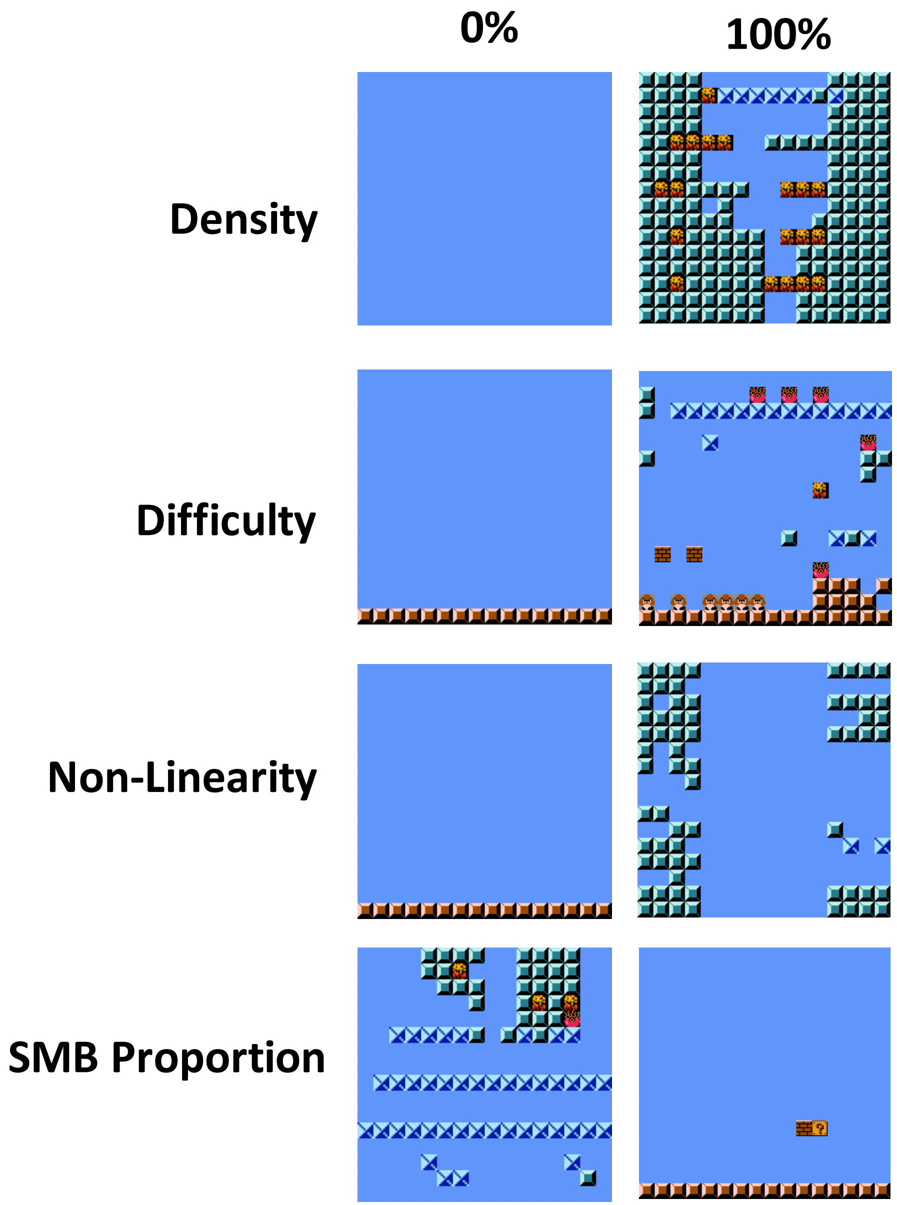
- Trained models generate 16x16 segments in combined *SMB-KI latent level design space*

- Generation involves feeding a latent vector into the VAE’s decoder which outputs a one-hot encoded array which is converted to the 16x16 level segment

- Two generation methods
  - Like GANs, use random latent vectors or evolve optimal vectors using search
  - Unlike GANs, generate segments based on input segments

Evaluation

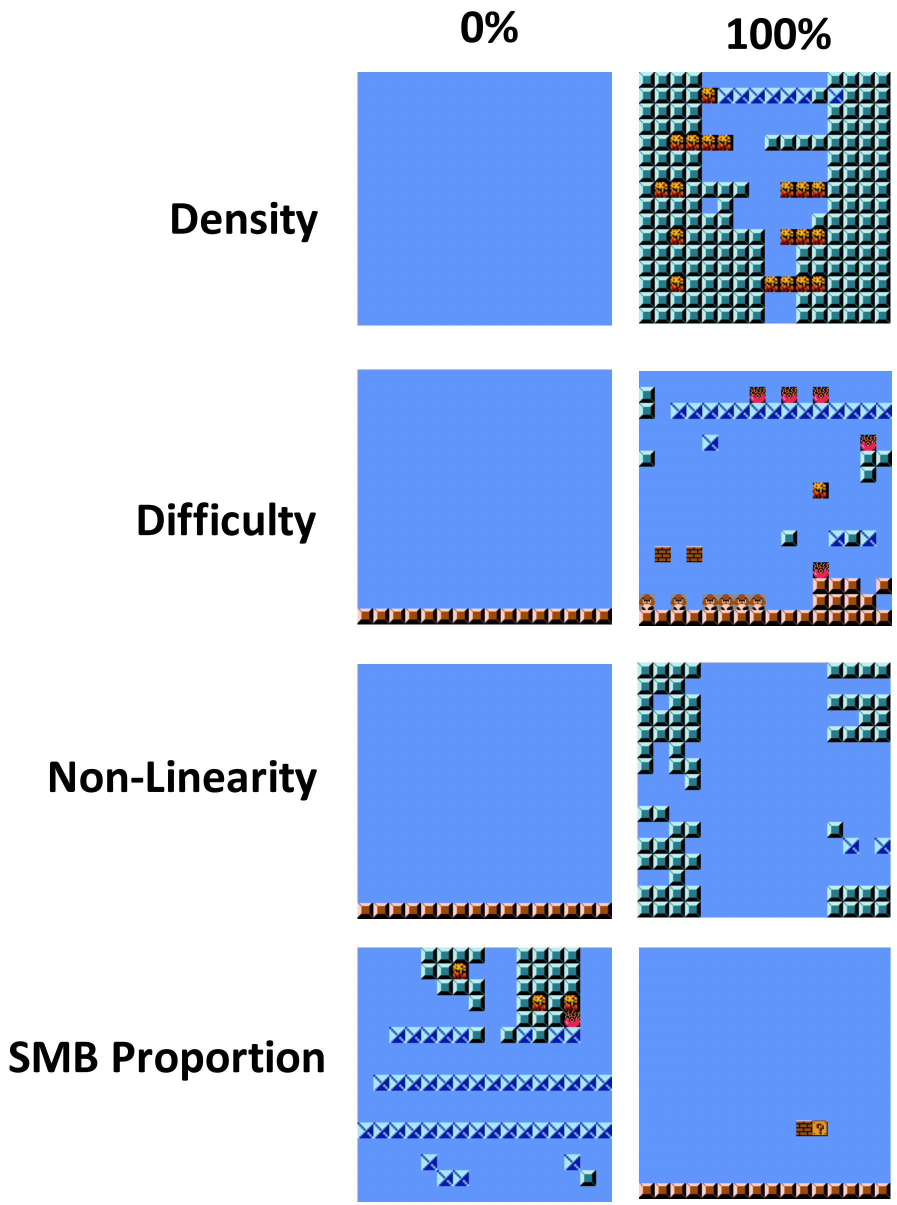
- Used four metrics for evaluation
  - *Density*
  - *Difficulty*
  - *Non-Linearity*
  - *SMB Proportion*



Evaluation

- Used four metrics for evaluation
  - *Density*
  - *Difficulty*
  - *Non-Linearity*
  - *SMB Proportion*

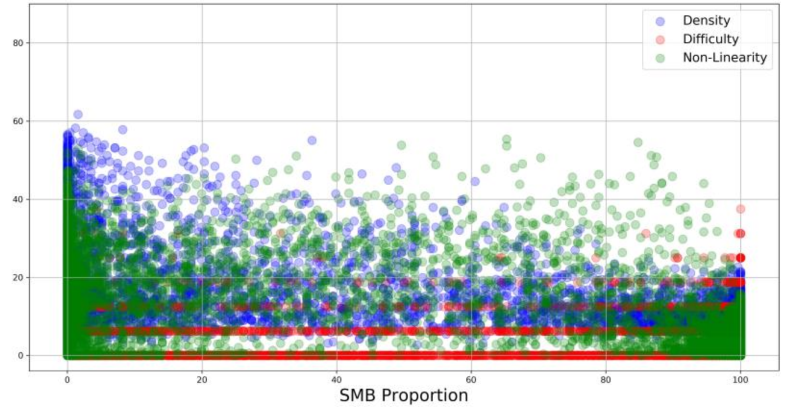
- Compared generative performance of VAE with that of GAN and VAE-GAN
  - How well models capture latent space spanning both games → computed above metrics for 10K random latent vectors
  - Accuracy of evolving desired segments using CMA-ES → evolved 100 segments with target values of 0%, 25%, 50%, 75%, 100% for each metric



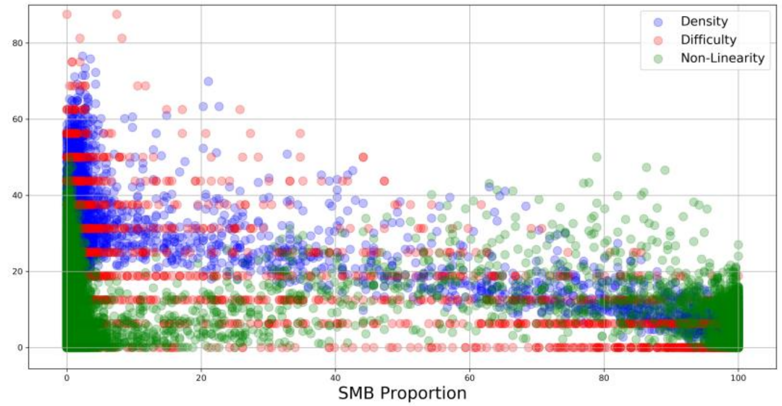
Results

- VAE does best at generating segments that are a mix of either game while GAN and VAE-GAN generate segment with mostly SMB or mostly KI elements

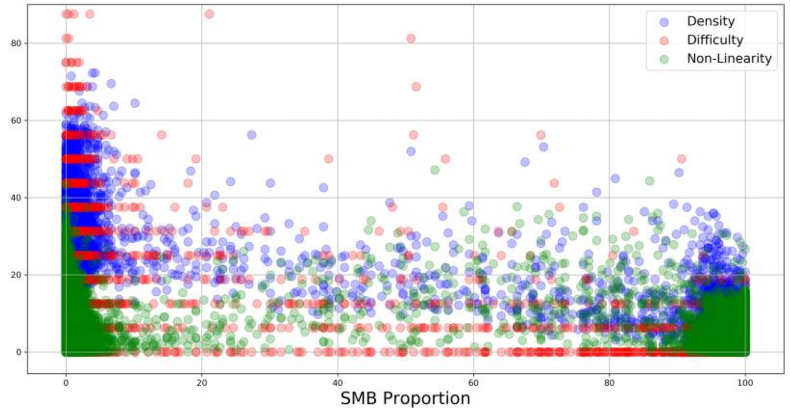
VAE



GAN



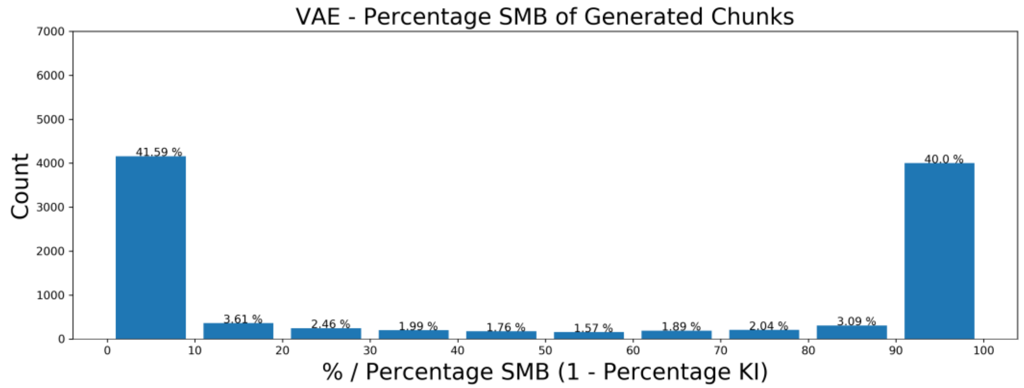
VAE-GAN

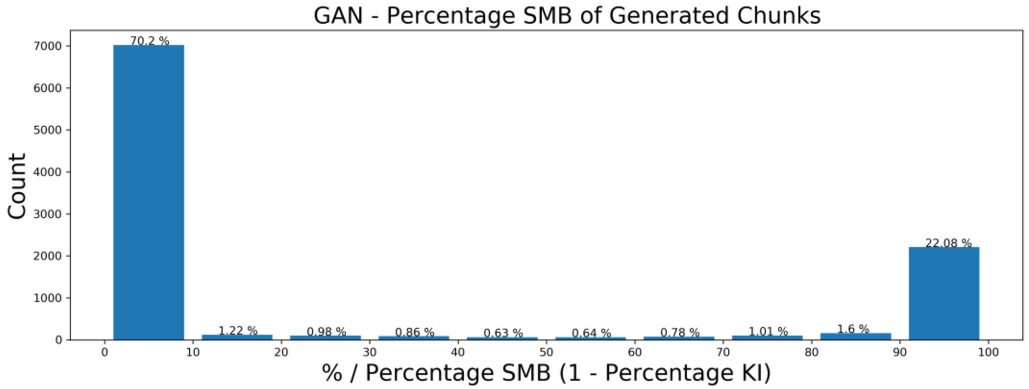


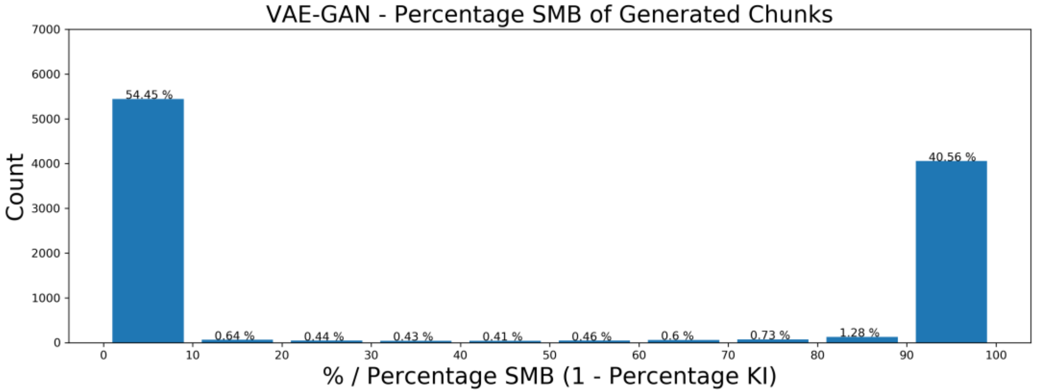
Results

- VAE does best at generating segments that are a mix of either game while GAN and VAE-GAN generate segment with mostly SMB or mostly KI elements

- VAE is better at capturing the latent space spanning both games as well as the space in between
    - 18% of VAE segments have elements of both games
    - 8% for GAN
    - 5% for VAE-GAN

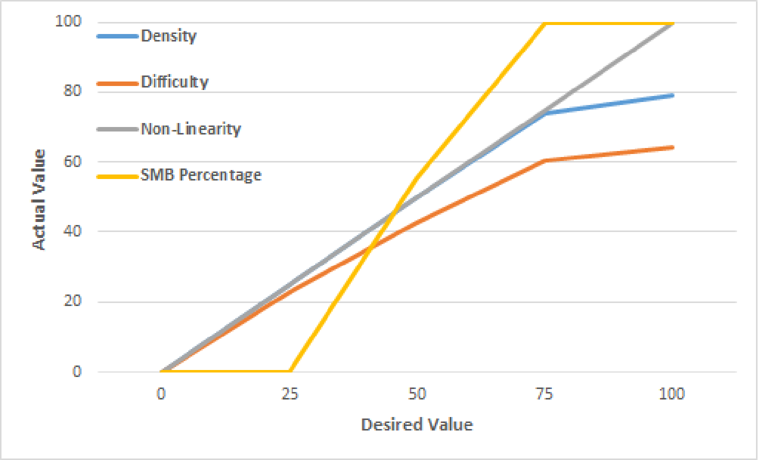




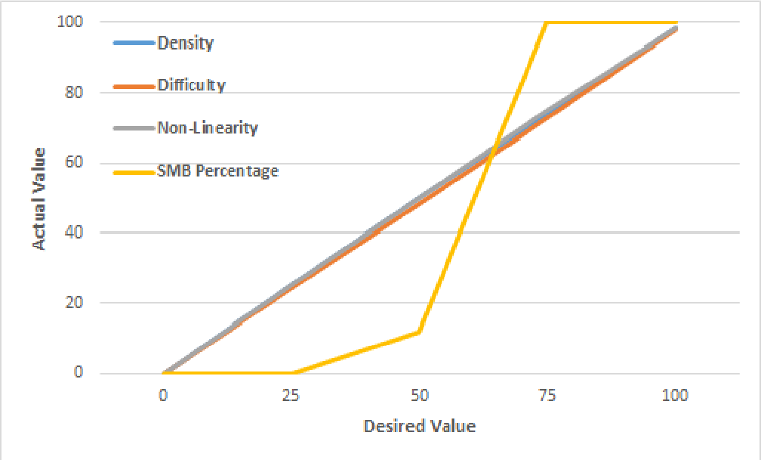


Results

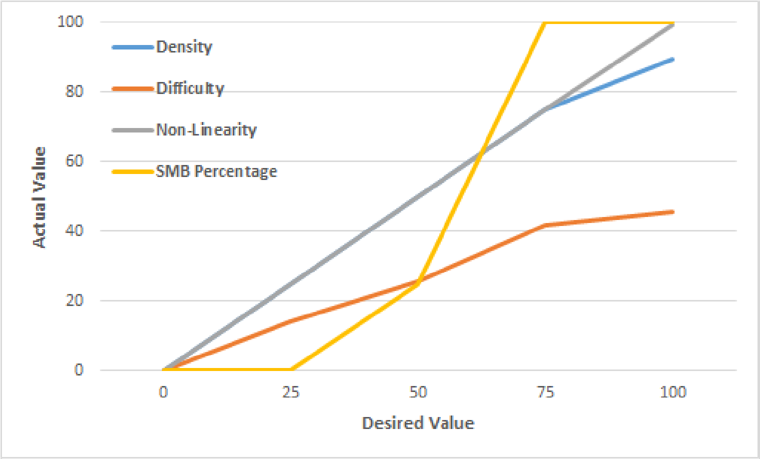
- GAN does better than VAE only for 100% Density and 75% and 100% Difficulty



VAE



GAN



VAE-GAN

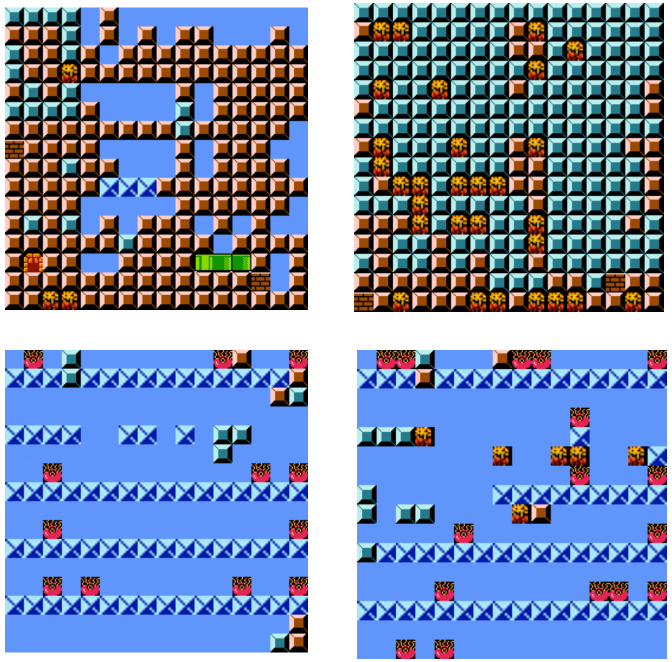
Results

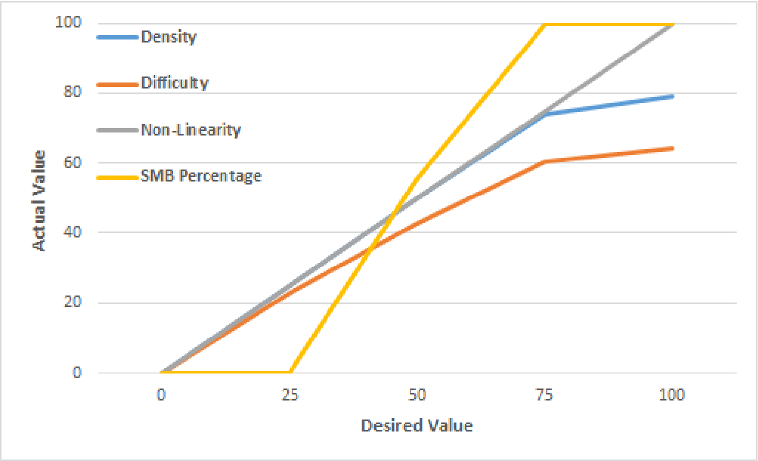
- GAN does better than VAE only for 100% Density and 75% and 100% Difficulty
- Ignore structures in training levels since actual segments would not be 100% solid nor have 16 enemies and hazards

75% 100%

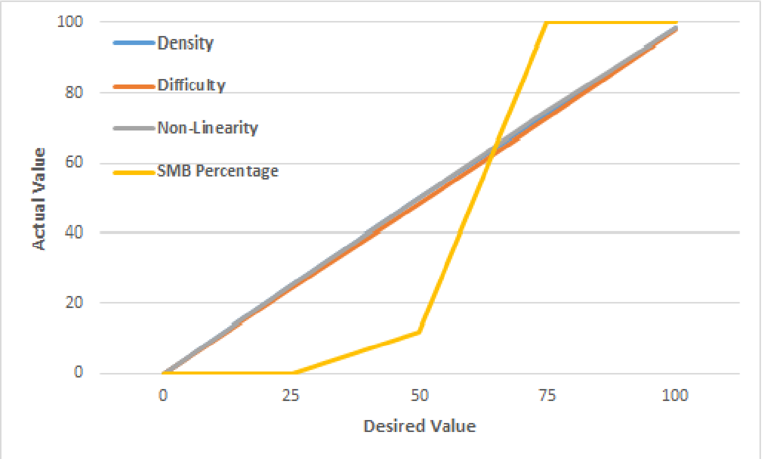
Density

Difficulty

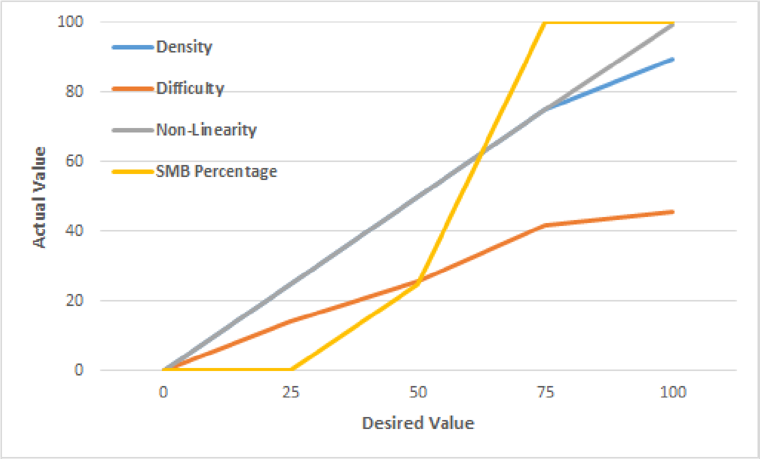




VAE



GAN

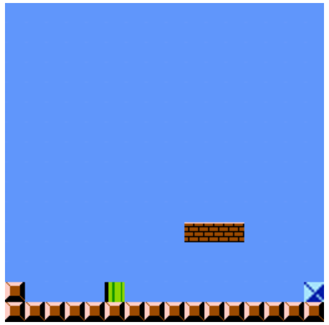


VAE-GAN

Results

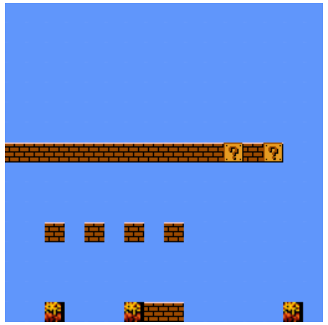
- No model does particularly well in blending desired SMB and KI proportions but VAE does well for the 50% case

- With similar training, VAE learns a latent space that is more representative while having more variation to enable better blending

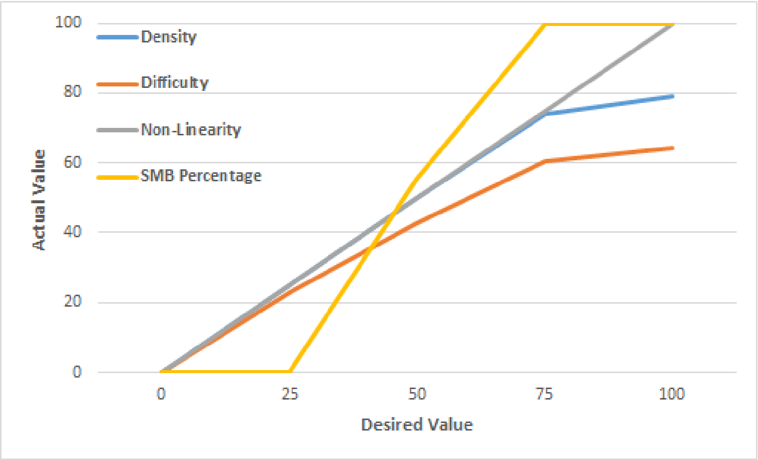


VAE

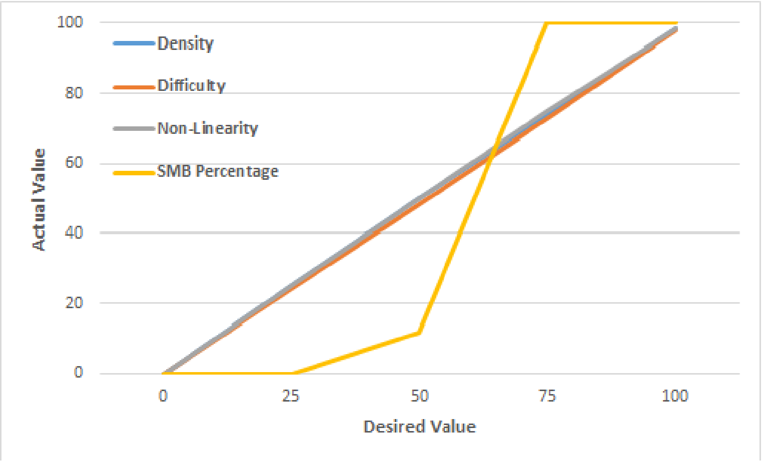
GAN



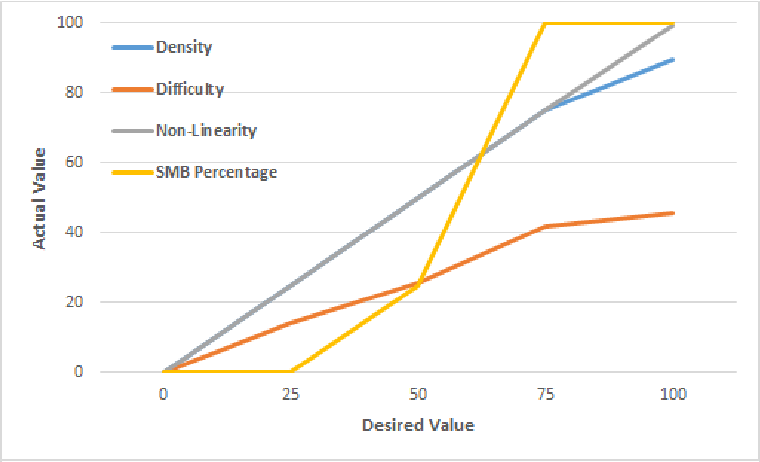
VAE-GAN



VAE



GAN

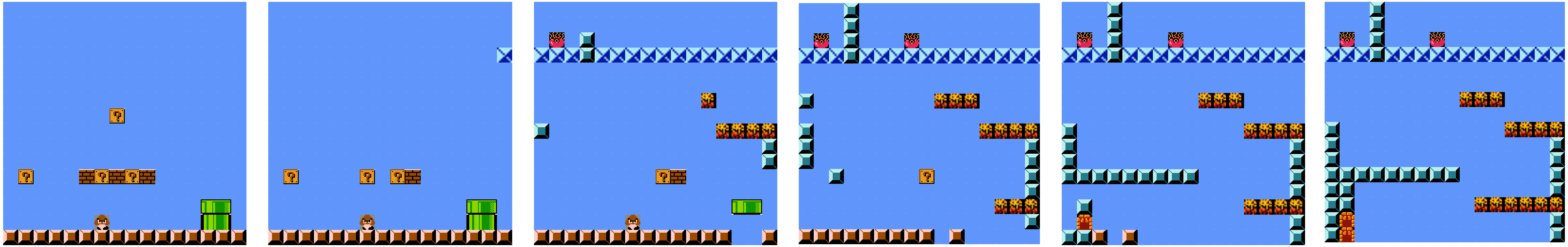


VAE-GAN

Application in Co-Creative Design

Application in Co-Creative Design

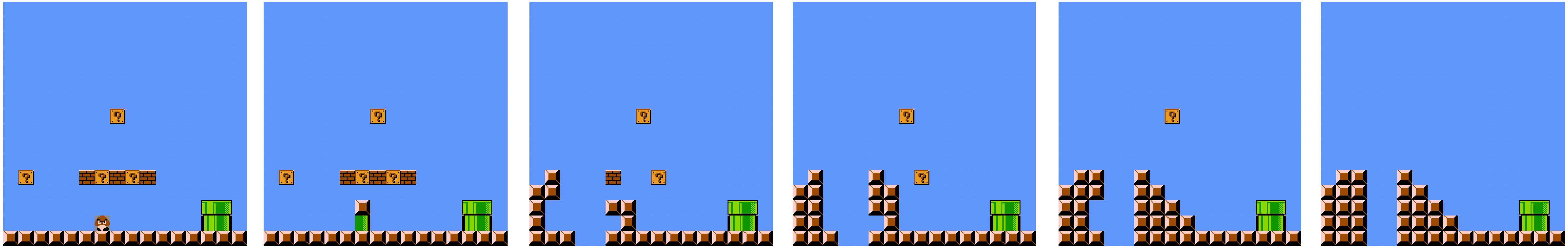
- Interpolation between games



SMB 1-1 Segment **KI Level 5 Segment**

Application in Co-Creative Design

- Alternate connections between segments

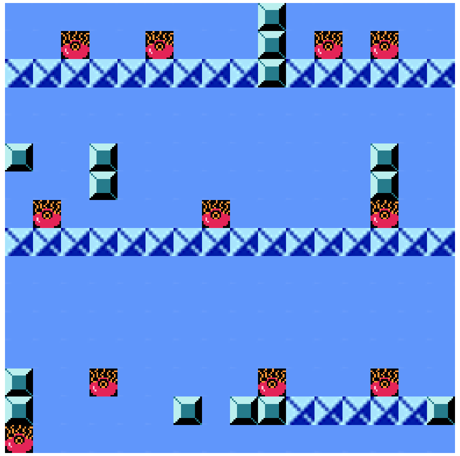


SMB 1-1 Segment 1

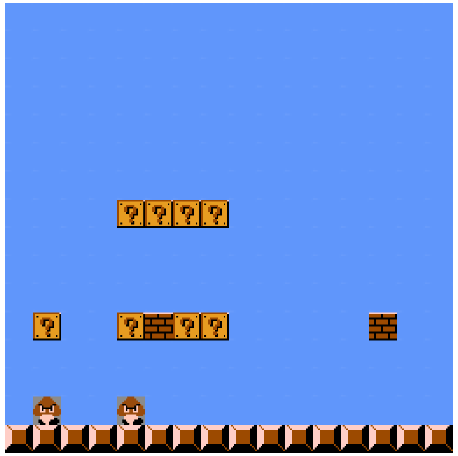
SMB 1-1 Segment 2

Application in Co-Creative Design

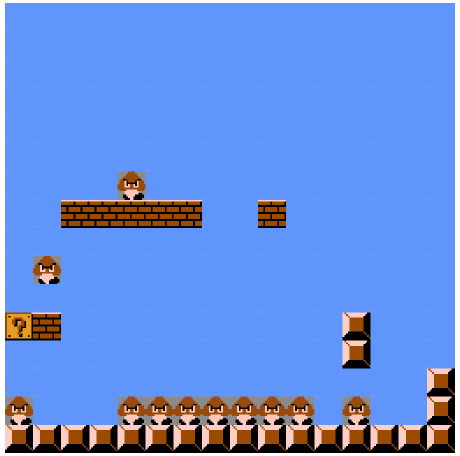
- Generating segments satisfying specific properties



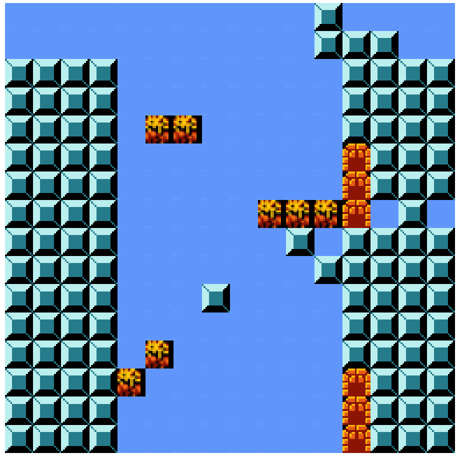
KI Hazards



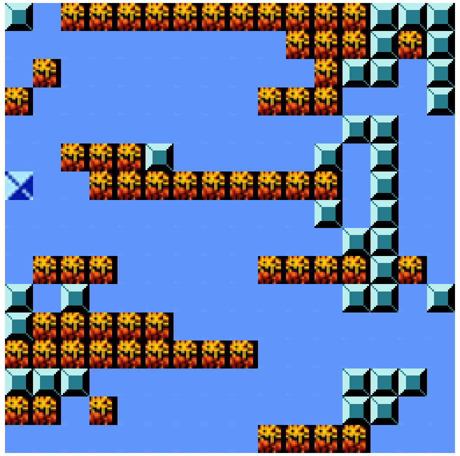
SMB ?-Marks



SMB Enemies



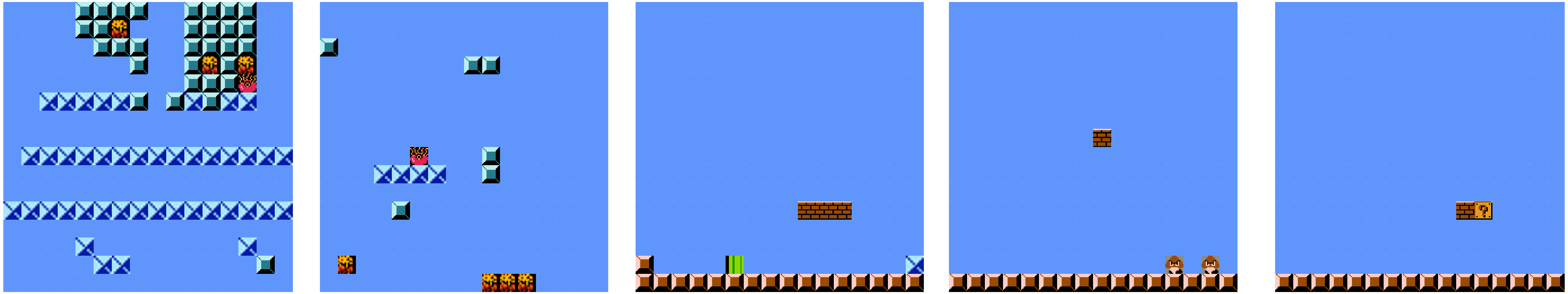
KI Doors



KI Platforms

Application in Co-Creative Design

- Generating segments with desired proportions of different games



0% SMB **25% SMB** **50% SMB** **75% SMB** **100% SMB**

Future Work

- Playability

Future Work

- Playability
- Vector math in level design space

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- Playability
- Vector math in level design space
- Co-Creative Level Design Tool

Future Work

- Playability
- Vector math in level design space
- Co-Creative Level Design Tool
- Multiple Games and Genres

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Contact

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