Sequential Segment-based Level Generation and Blending using Variational Autoencoders

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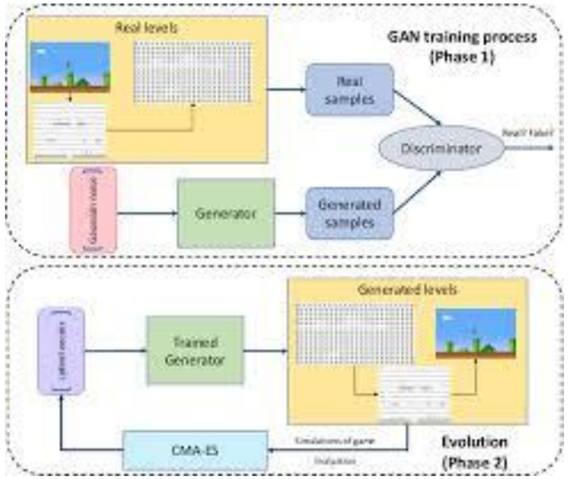
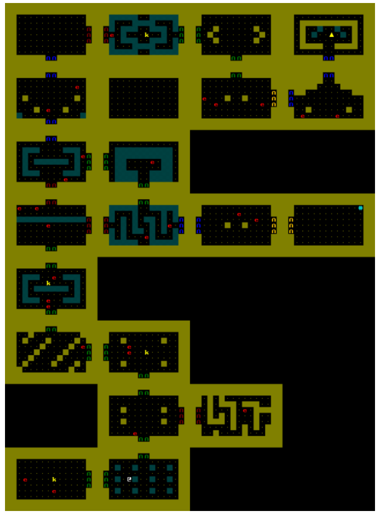
Motivation

- Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) have been used for generating platformer levels and dungeons via sampling, interpolation and evolution



Volz et al., 2017



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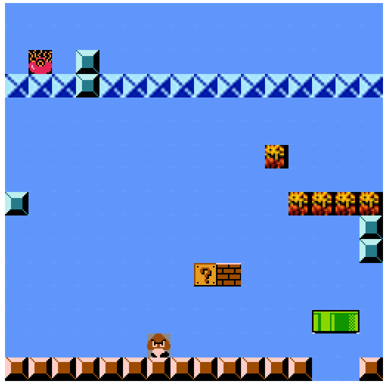

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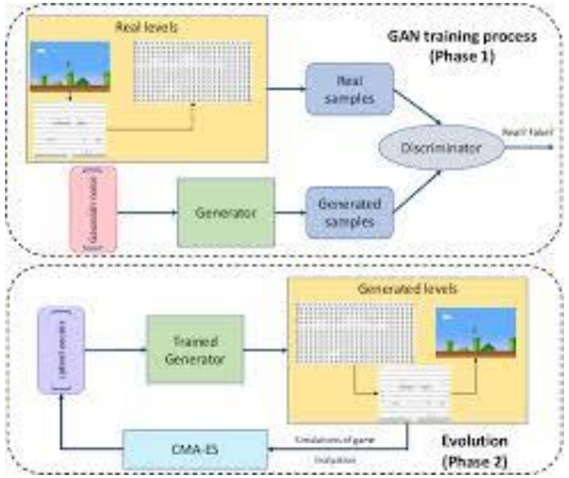

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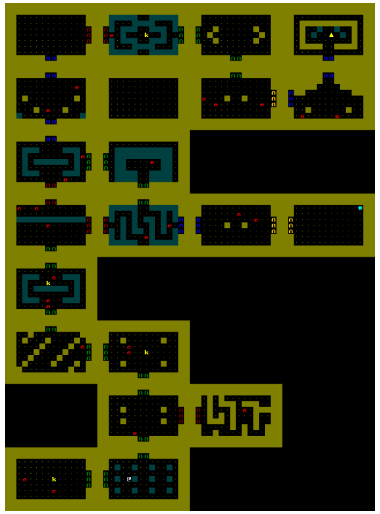

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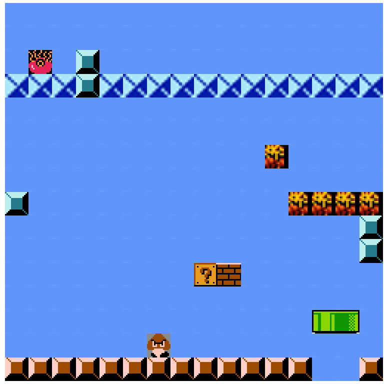

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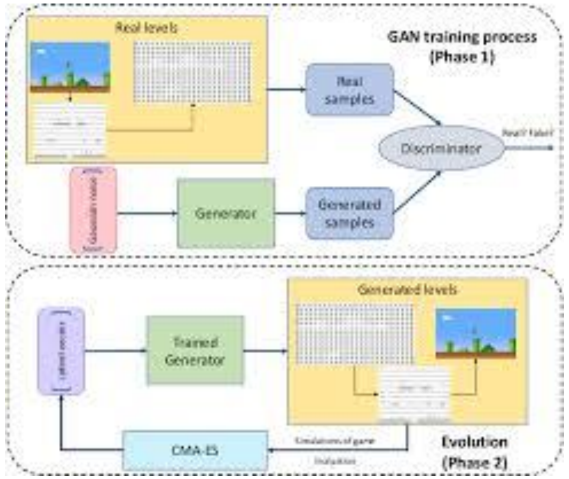

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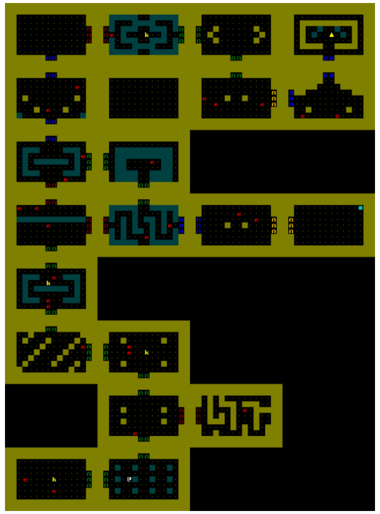

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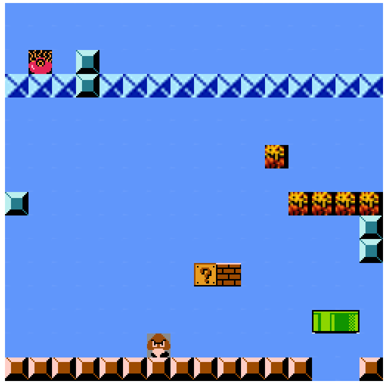

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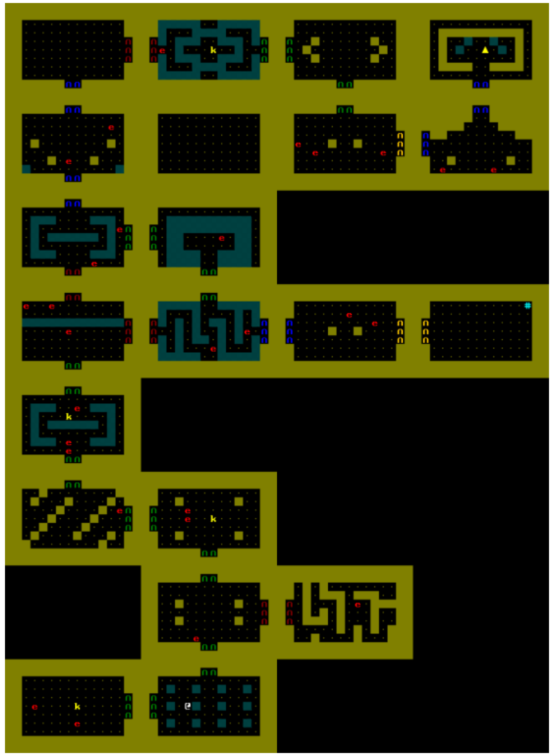

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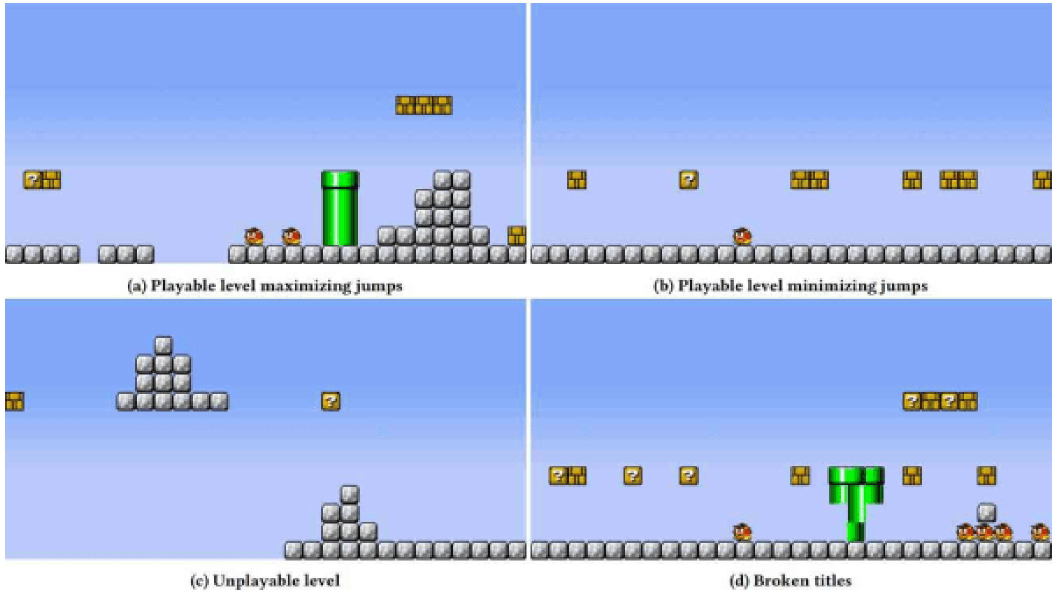

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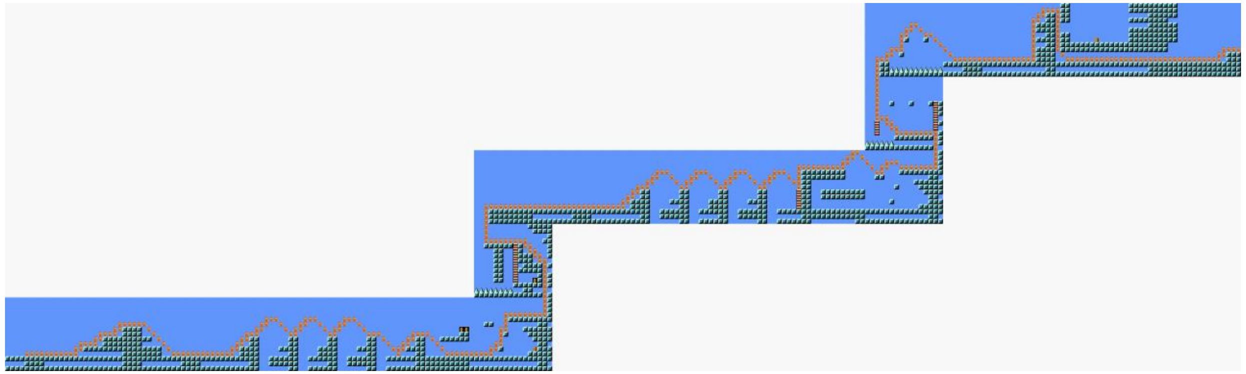

Mega Man level, source: VGLC

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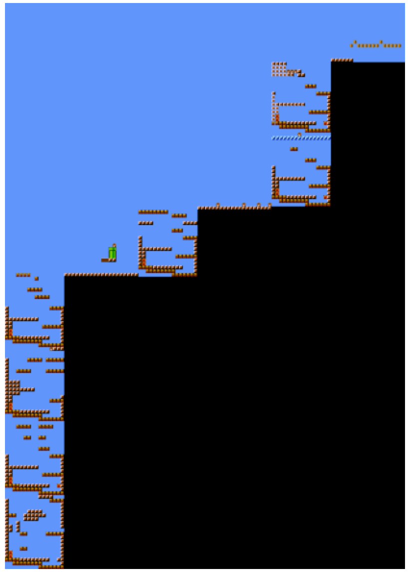

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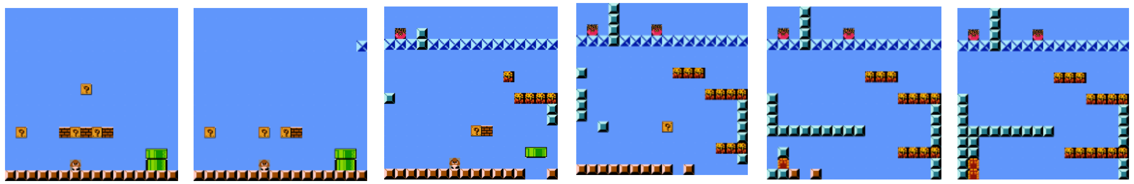

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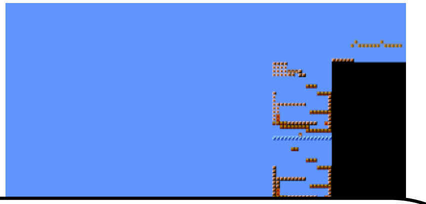

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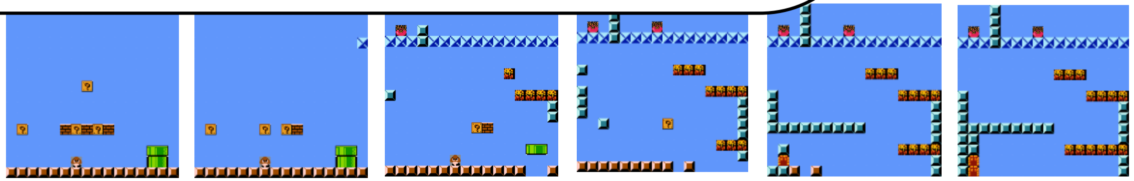
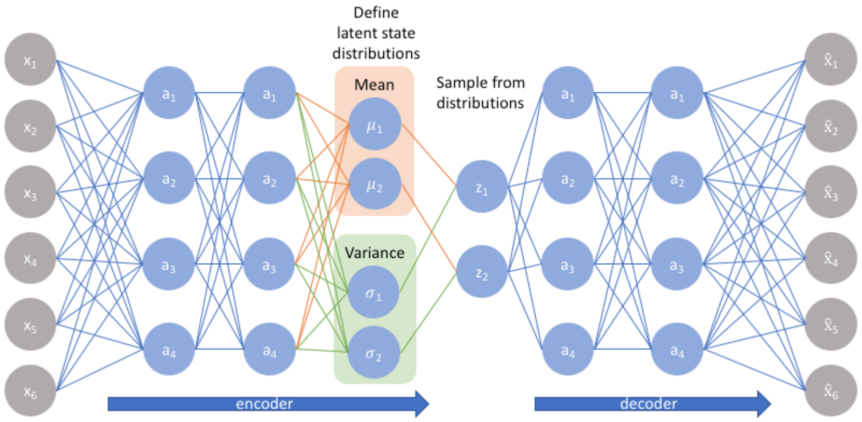
Generate and blend whole platformer levels progressing in multiple directions while still using latent variable models and their fixed-size inputs/outputs



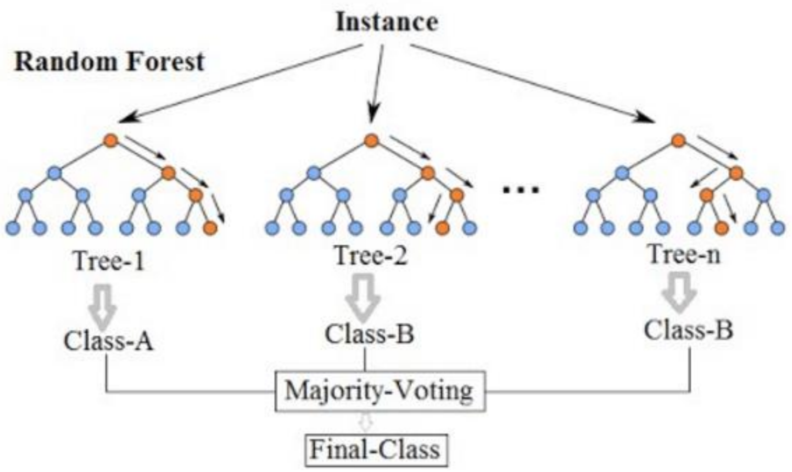
Sarkar, Yang and Cooper, 2019

Solution

- Two-step solution:
  - Modify VAE to learn encoding of next segment rather than current segment
  - Train a classifier to predict where next segment should be placed



VAE (modified), source: jeremyjordan.me



Random forest classifier

Source: https://community.tibco.com/wiki/random-forest-template-tibco-spotfire

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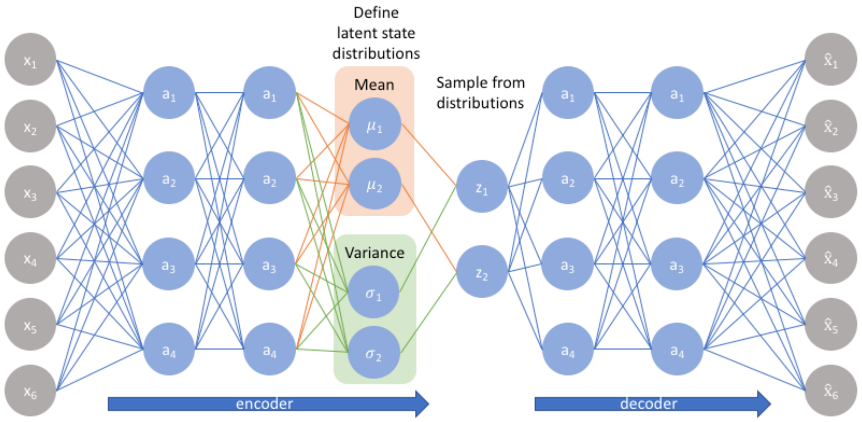
- Hybrid PCGML model which enables:
  - Generating arbitrarily long levels via iterative encoding-decoding of segments
  - Generating levels that can progress in multiple directions
  - Generating blended levels rather than segments



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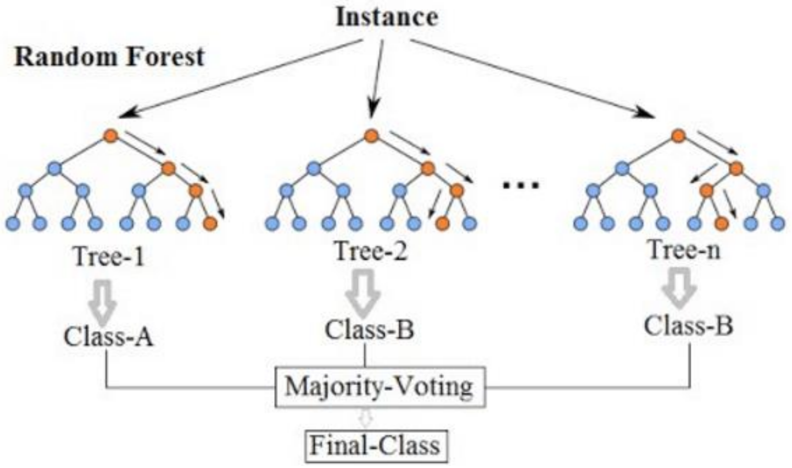

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Sequential Segment Generation

- Generative models based on VAEs trained on *Super Mario Bros* (SMB), *Kid Icarus* (KI), *Mega Man* (MM) and blended SMB-KI domain (implementation details in paper)

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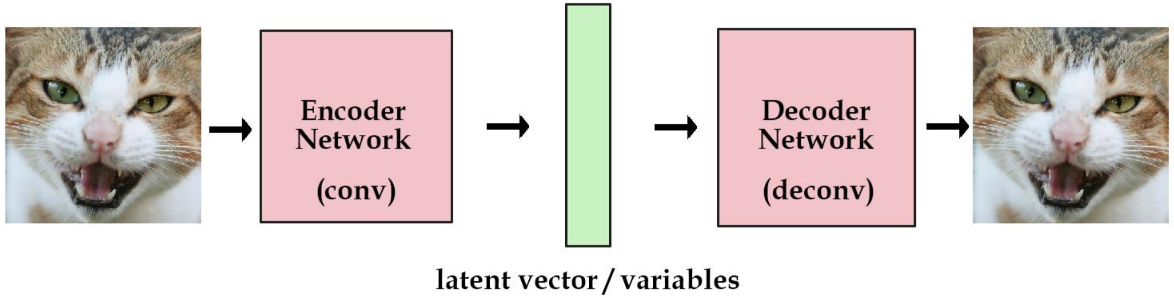
  - Encoder → input data to latent space
  - Decoder → latent space to reconstructed data



Vanilla Autoencoder

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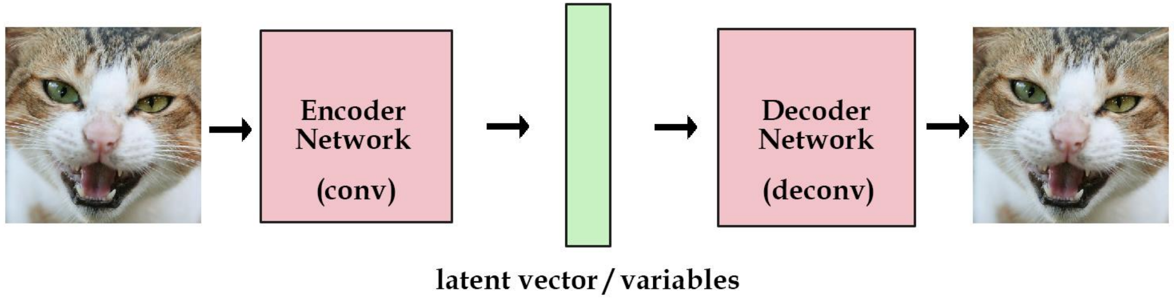
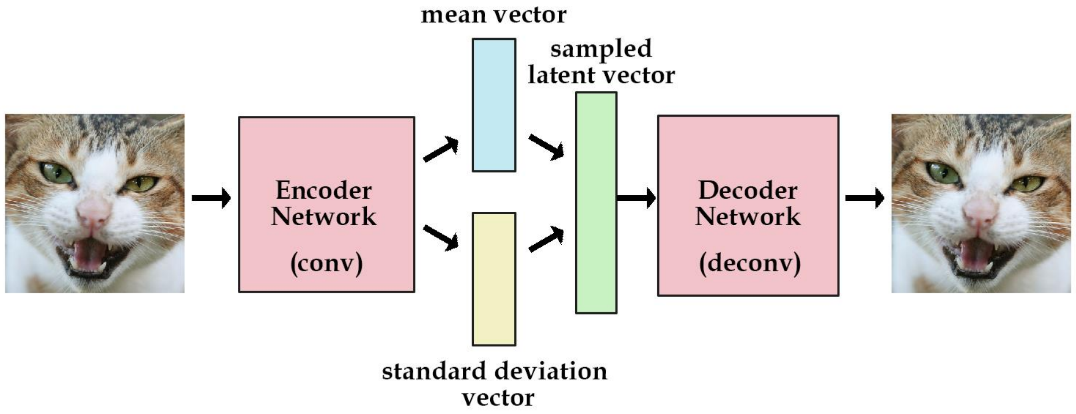


Vanilla Autoencoder

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



Variational Autoencoder

Source: kvfrans.com

Sequential Segment Generation

- VAE Loss function
  - Reconstruction error

    ---error between input segment and reconstruction of input segment
  - KL Divergence (between latent distribution and known prior)

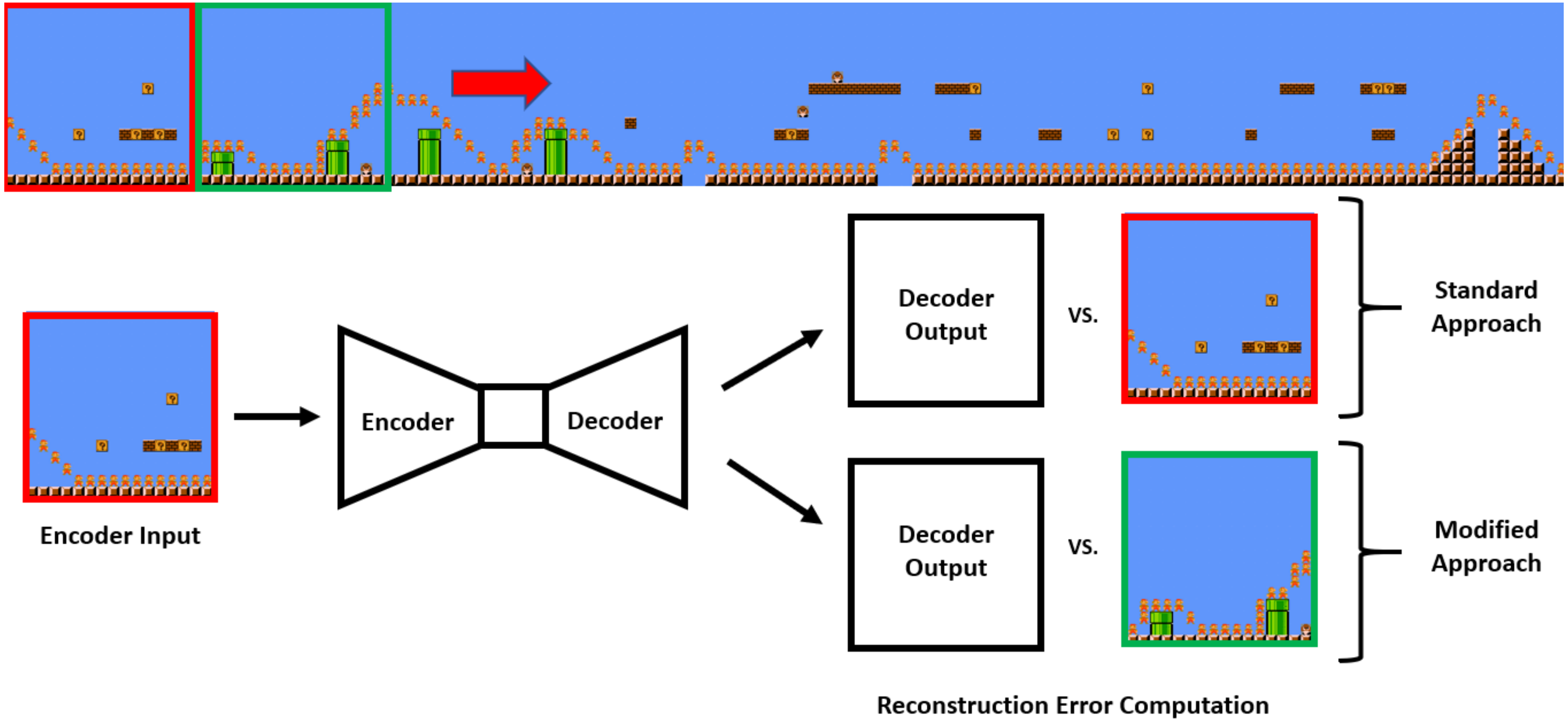
    ---forces latent space to model a continuous, informative distribution

Sequential Segment Generation

- VAE Loss function
  - Reconstruction error (modified)

    *---error between input segment and reconstruction of **next** input segment*

    ---technically, no longer 'auto'-encoding, but enables our approach



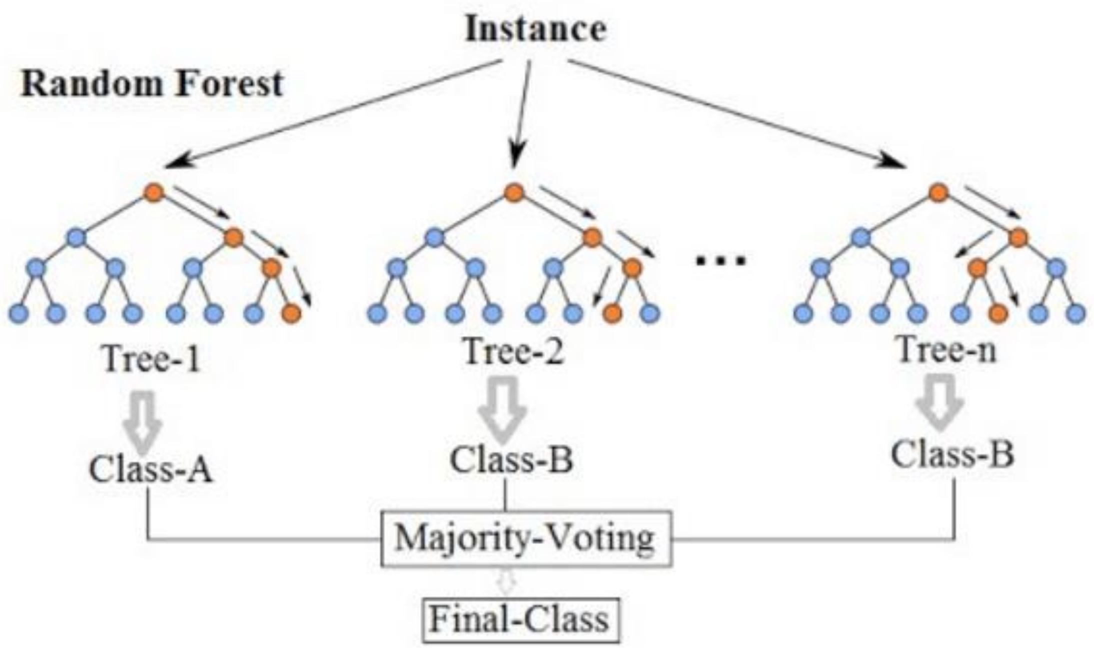
Sequential Segment Generation

Algorithm 1 GenerateLevel(init_segment, n)

```
Initialize level to init_segment
num_segments = 1
segment = init_segment
while num_segments ≤ n do
    z ← Encoder(segment)
    segment ← Decoder(z)
    Add segment to level
    num_segments += 1
end while
return level
```

Placement Classification

- To generate levels that can dynamically progress in any direction, need to determine where/how to place generated segments
- Directional classifier
  - Random forest classifier trained on segments from SMB, KI, MM and SMB-KI domain, labeled with direction of next segment in levels



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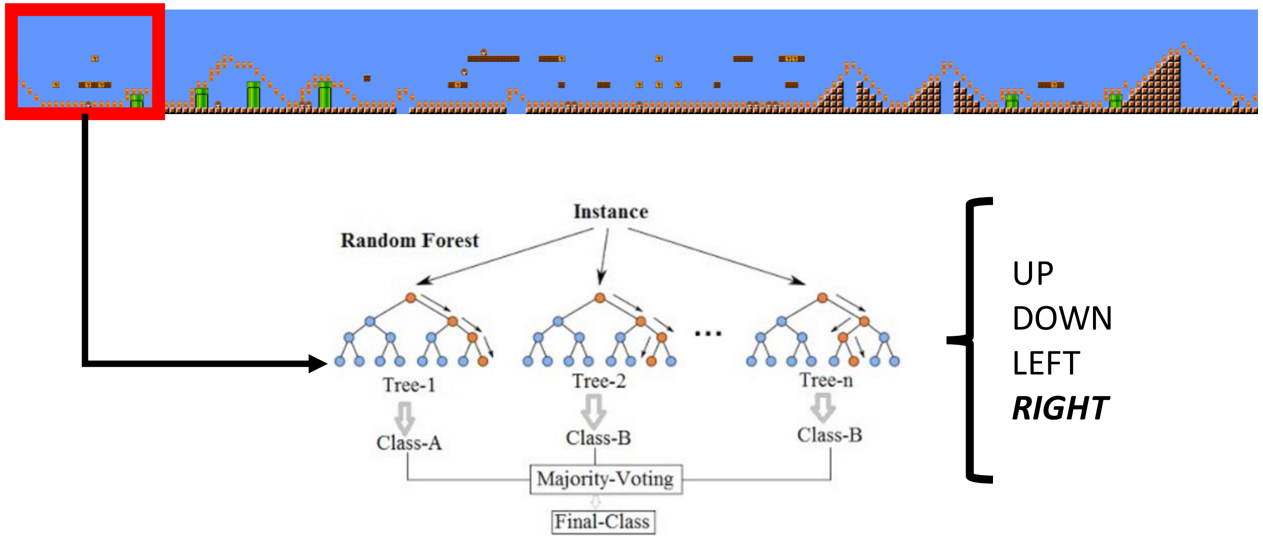
Placement Classification

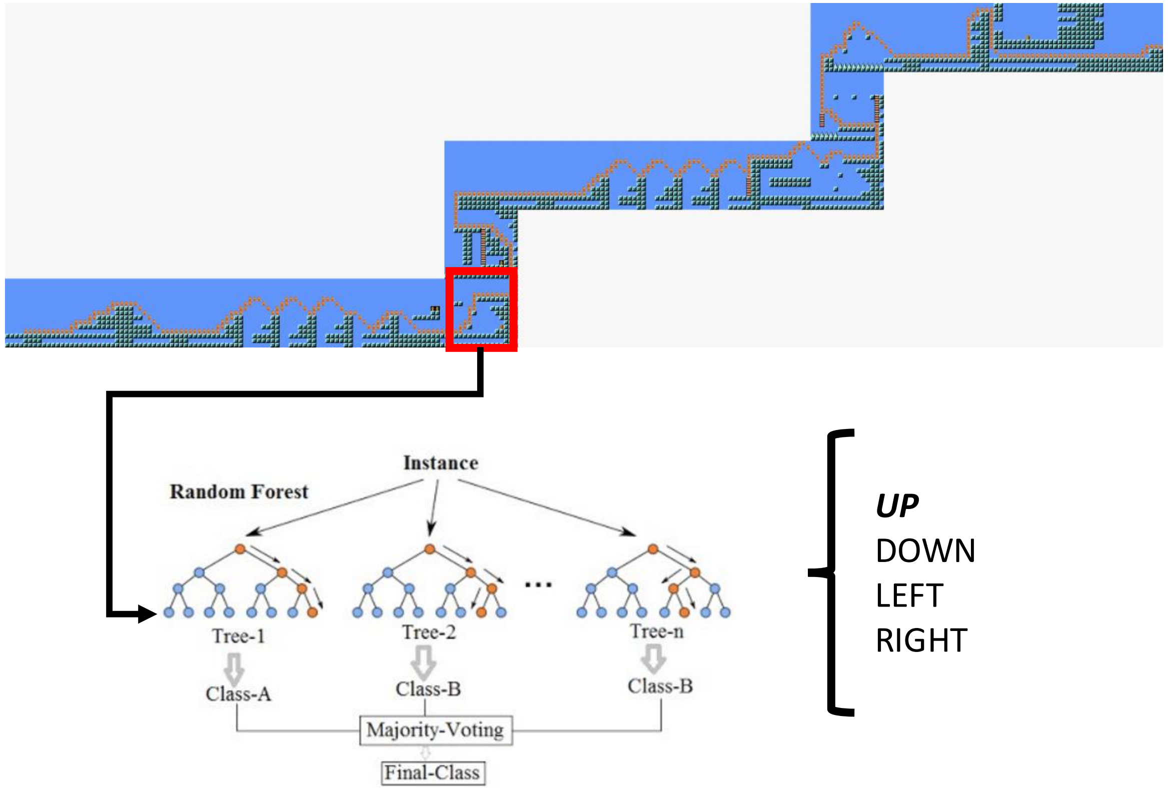
- Input: same segments as before, Label: next direction
  - SMB – right only, KI – up only, MM and SMB+KI – both
  - 70%-30% train-test split
  - 100% accuracy for SMB, KI, SMB-KI, 98.73% for MM
  - Post-processing after prediction (details in the paper)

Super Mario Bros.



UP
DOWN
LEFT
RIGHT

Mega Man



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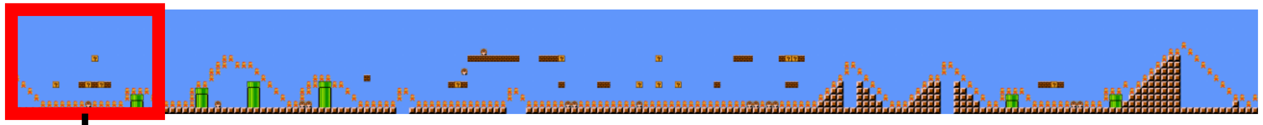

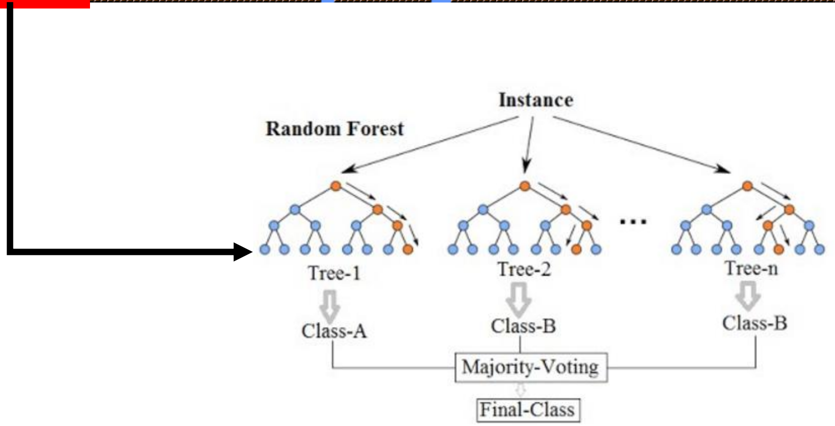

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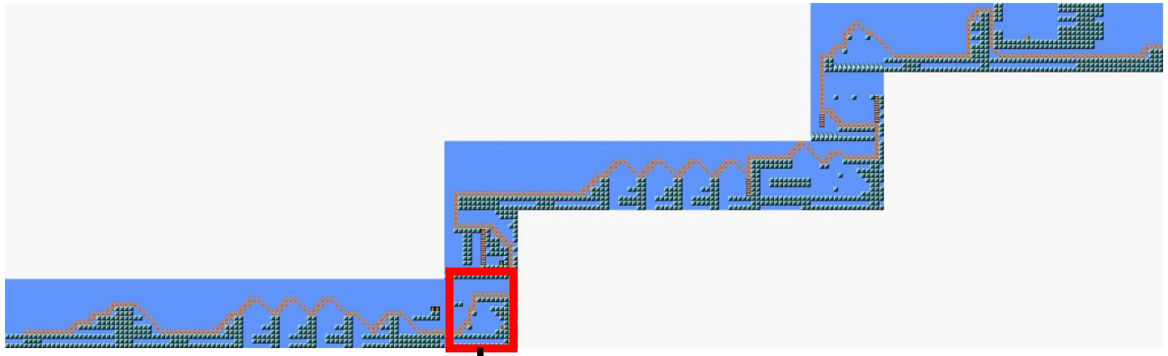
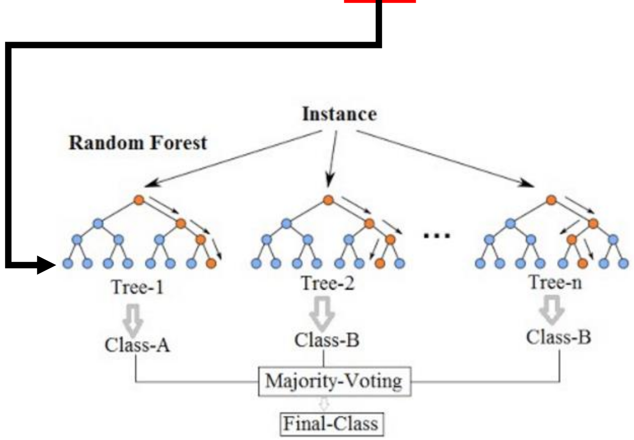




UP
DOWN
LEFT
RIGHT

Placement Classification

Algorithm 2 GenerateLevelWithDirs(init_segment, n)

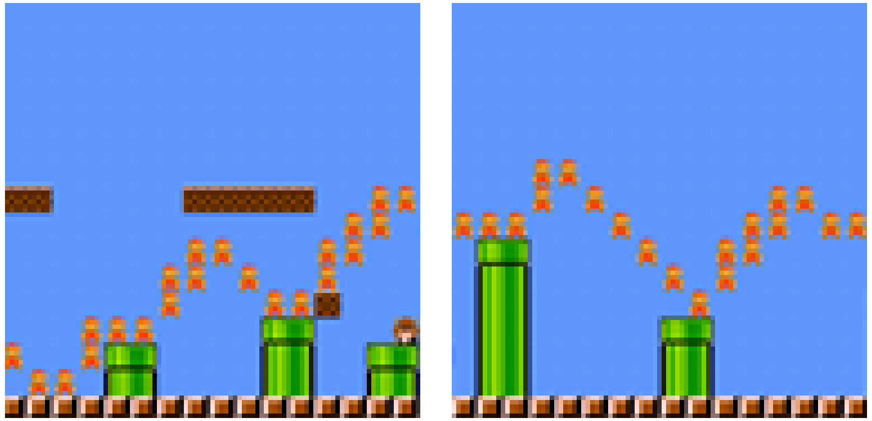
$level \leftarrow$ GenerateLevel(init_segment, n)
$level\_with\_dirs \leftarrow \emptyset$
for $segment$ in $level$ **do**
  $dir \leftarrow Classifier(segment)$
  Add $(segment, dir)$ to $level\_with\_dirs$
end for
return $level\_with\_dirs$

Evaluation

- Three-part evaluation
  - Continuous nature of generated levels
  - Properties of generated blended levels
  - Quality of arbitrarily long generated levels

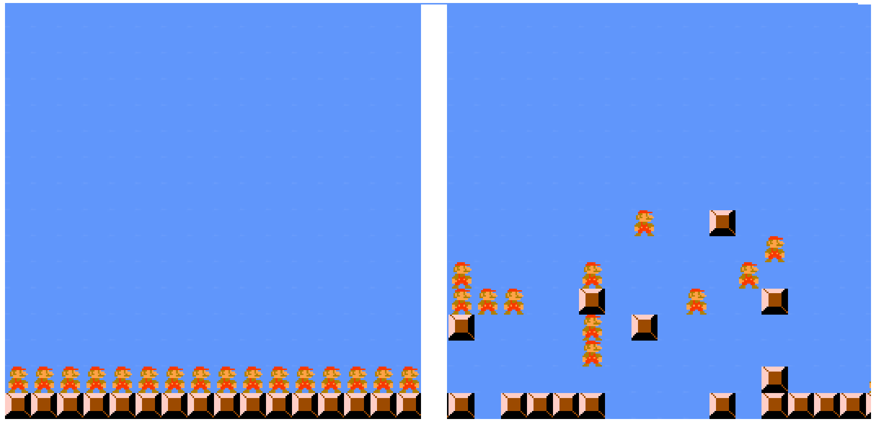
Discontinuity

- To test continuous flow of progression, introduced *Discontinuity* metric
  - Absolute distance between path tiles along the adjoining edge of two successive segments
  - Lower values → higher continuity between successive segments
  - Range from 0 (high continuity) to 16 (low continuity)



E.g. Discontinuity = 1

- Levels with better sense of progression would have a more continuous path through its segments i.e. low values of *Discontinuity* between successive pairs of segments



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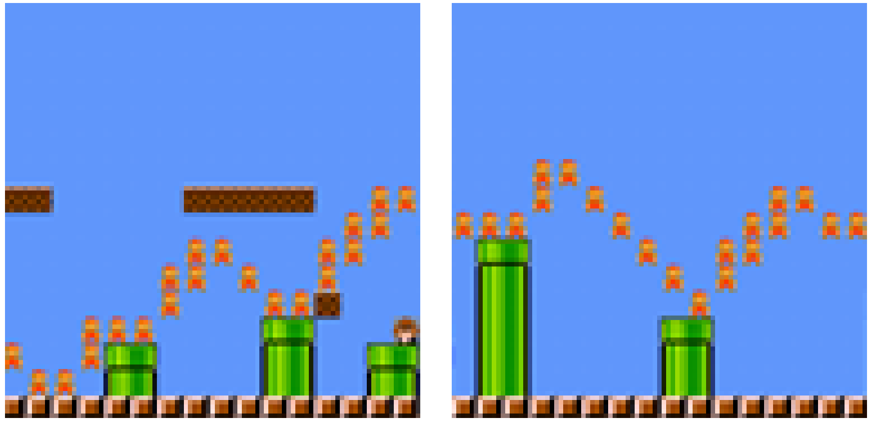

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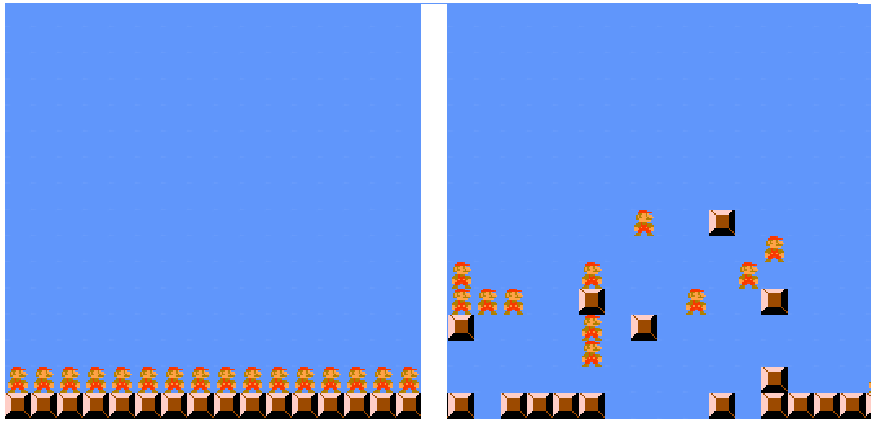

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Discontinuity

- Computed average per-segment Discontinuity for 100 generated levels each for SMB, KI, MM and SMB-KI using 2 methods for generating segments:
  - *Sequential:* using our algorithm
  - *Independent:* successive segments independent of each other
  - For both, generated segments combined using classifier

- Each generated level consisted of 12 segments for SMB, KI and SMB-KI and 16 segments for MM

- Significantly lower discontinuity values using *Sequential* for all games

Game	Sequential	Independent
SMB	3.86 ± 2.28	5.91 ± 2.04
KI	3.99 ± 2.59	7.37 ± 1.99
MM	6.54 ± 2.63	11.18 ± 1.69
SMB-KI	5.4 ± 2.42	9.84 ± 1.76

Table 1: Average per-segment *Discontinuity* values along with standard deviation. A Wilcoxon Rank Sum Test showed differences to be significant with $p < .001$ in all cases.

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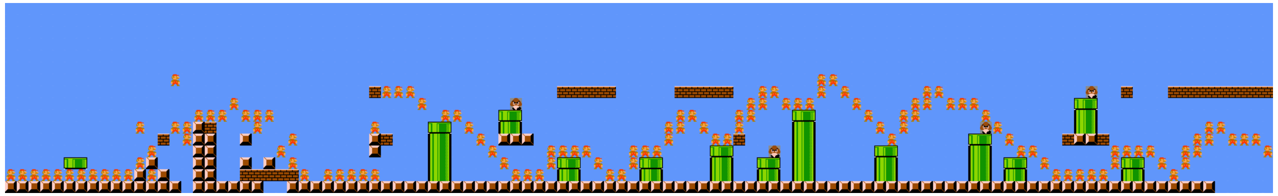
Example Levels

SMB-Sequential



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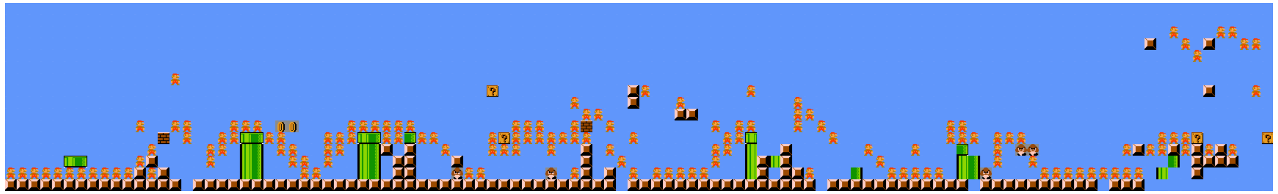
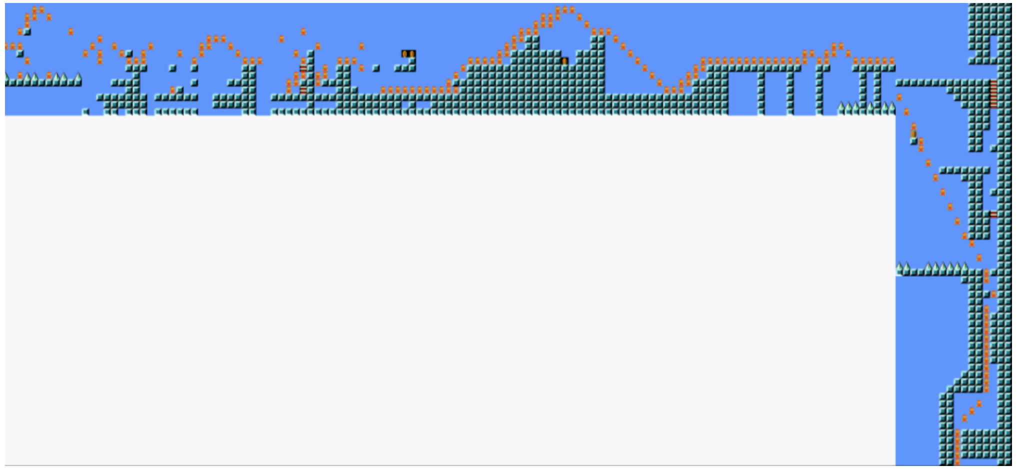
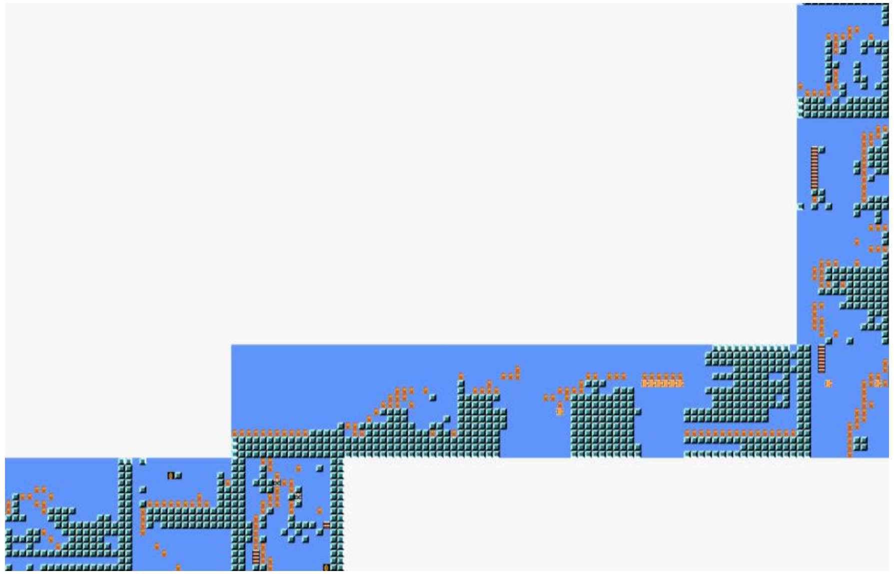




MM-Sequential



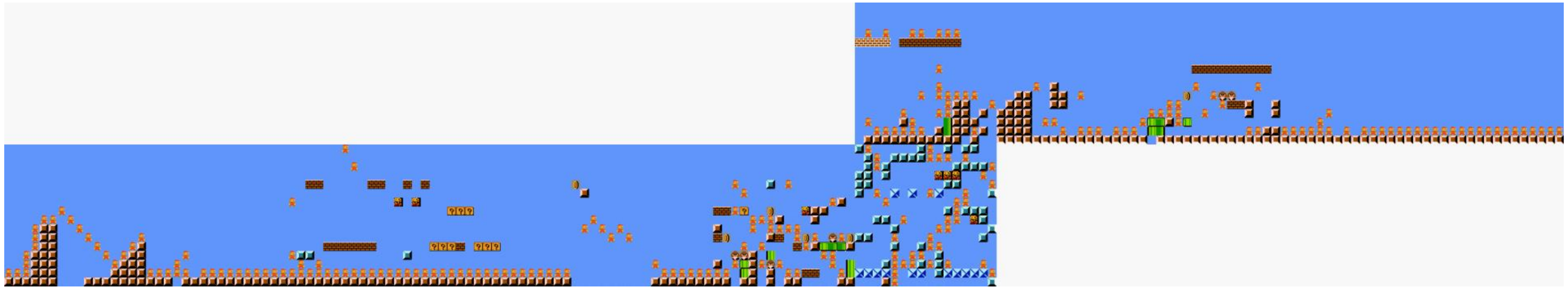
MM-Independent

KI-Sequential

KI-Independent

Example Blended Levels

Blended SMB-KI-Sequential



Blended SMB-KI-Independent

Blending

- Generated blended SMB-KI levels of 12 segments each

- 6 sets of 100 each with a different starting segment
  - Random sample from SMB-KI latent space
  - Original SMB segment
  - Original KI segment
  - 3 segments interpolated between above 2
    - SMB-25%,KI-75%
    - Both-50%
    - SMB-75%,KI-25%

Blend	SMB	KI
SMB-0	0.5	99.5
SMB-25	4	96
SMB-50	86.1	13.9
SMB-75	85	15
SMB-100	94.3	5.7
Random Blend	43.4	56.6

Table 2: Percentage of segments (out of $100x12 = 1200$**) classified as SMB-like and KI-like using the directional classifier.**

- Evaluated using directional classifier
  - Prediction: Right → Segment is more SMB-like
  - Prediction: Up → Segment is more KI-like

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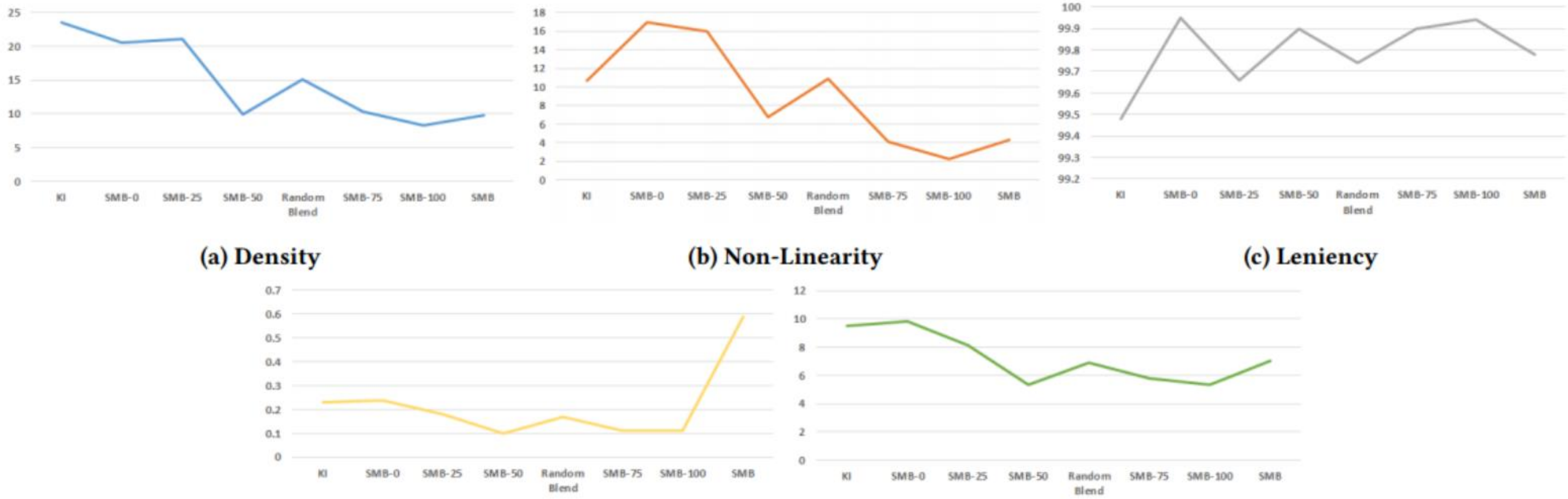
Blending

- Compared generated blended levels with original SMB and KI levels using tile metrics
  - *Density (proportion of solid tiles)*
  - *Non-Linearity (unevenness of segment topology)*
  - *Leniency (proxy for difficulty)*
  - *Interestingness (proportion of decorative/collectible items)*
  - *Path-Prop (proportion of path tiles)*



(a) Density **(b) Non-Linearity** **(c) Leniency**

(d) Interestingness **(e) Path-Prop**

Figure 2: Per-segment tile metrics for original SMB and KI levels along with different types of blends.

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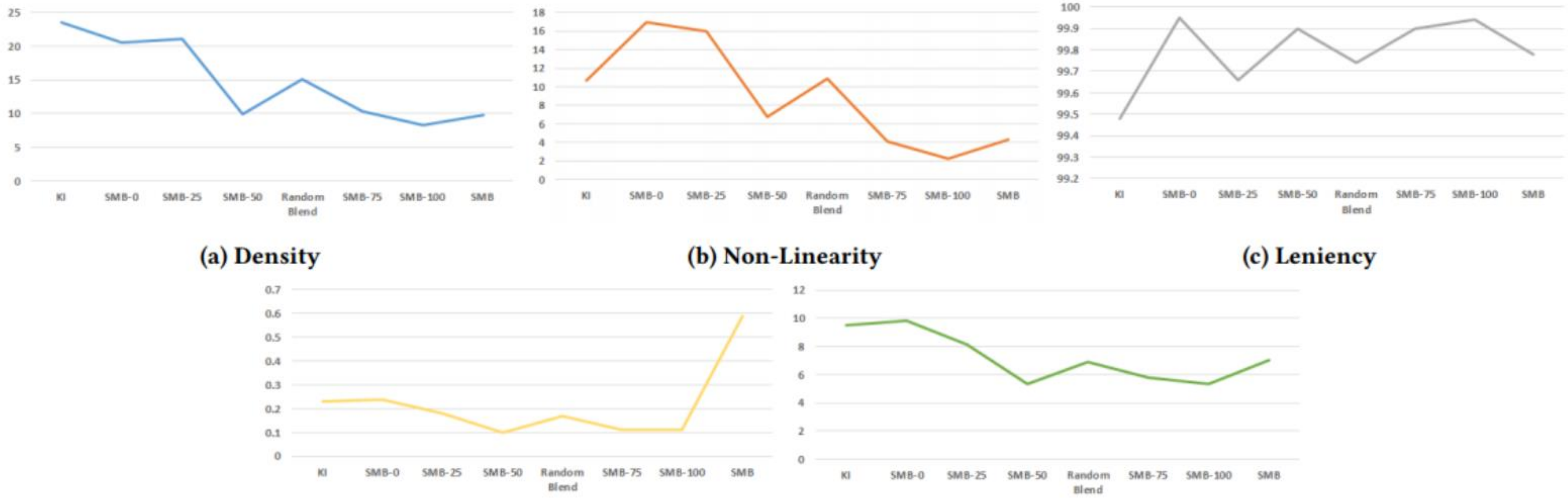
  - *Interestingness (proportion of decorative/collectible items)*
  - *Path-Prop (proportion of path tiles)*



(a) Density (b) Non-Linearity (c) Leniency

(d) Interestingness (e) Path-Prop

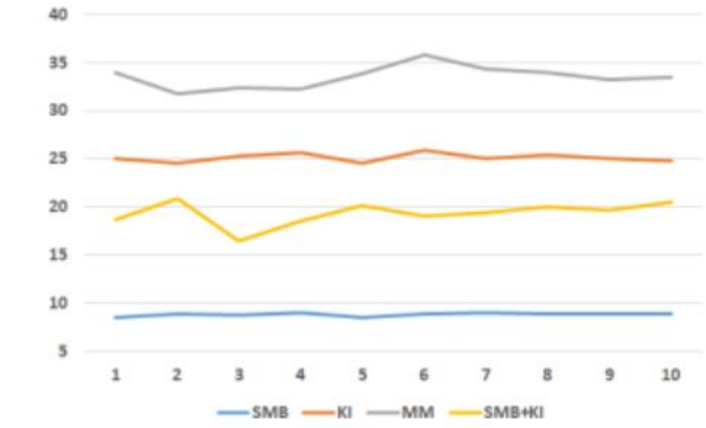
Figure 2: Per-segment tile metrics for original SMB and KI levels along with different types of blends.

Progression

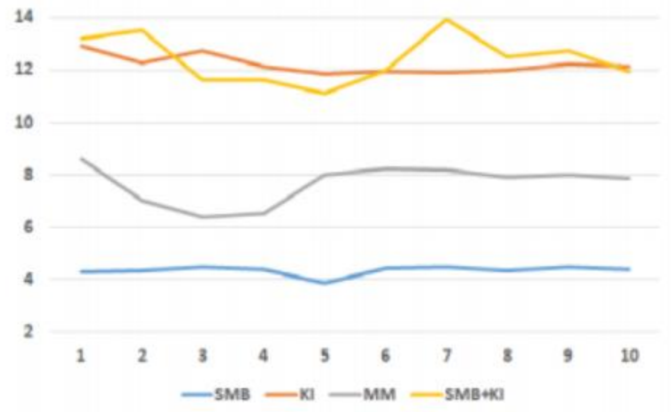
- Generate arbitrarily long levels without deteriorating quality

- Generated 100 levels of 120 segments each for SMB, KI and SMB-KI and 160 segments each for MM (approx. 10x size of average actual levels)
  - Computed average per-segment Discontinuity and tile-based metrics for each of the 10 subsections of each level
  - That is, track if/how these values change as more segments are generated conditioned on the previous ones

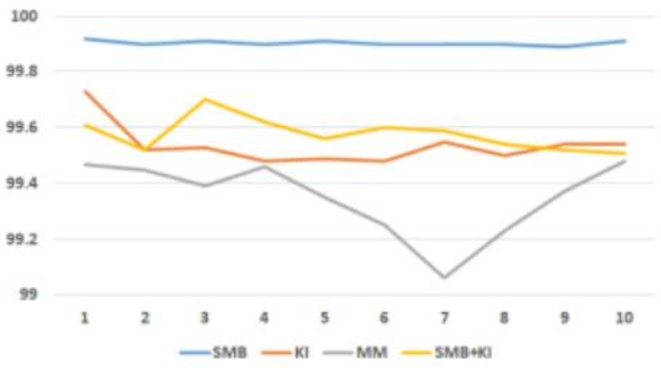
Progression



(a) Density

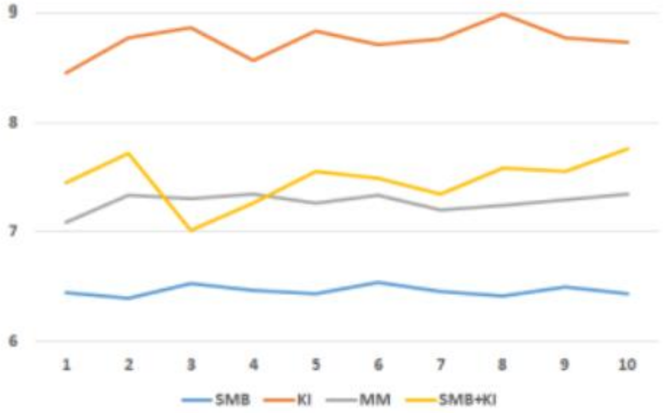


(b) Non-Linearity

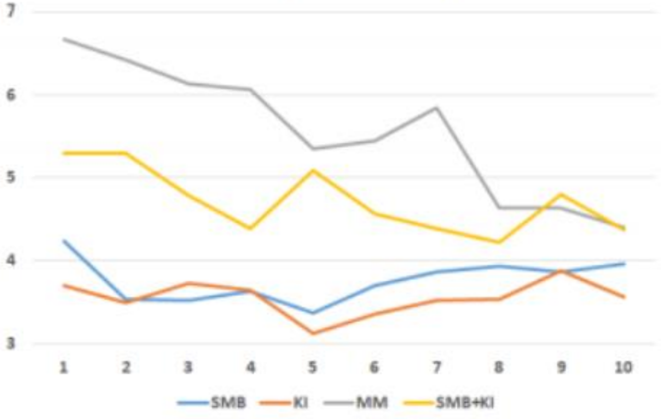


(c) Leniency

(d) Interestingness



(e) Path-Prop



(f) Discontinuity

Figure 3: Per-segment metric values plotted for each grouping of 16 segments for MM and each grouping of 12 segments for the other games. x-axis values indicate 1st such grouping, 2nd such grouping etc. y-axis indicates average metric value for the corresponding group of segments.

Progression

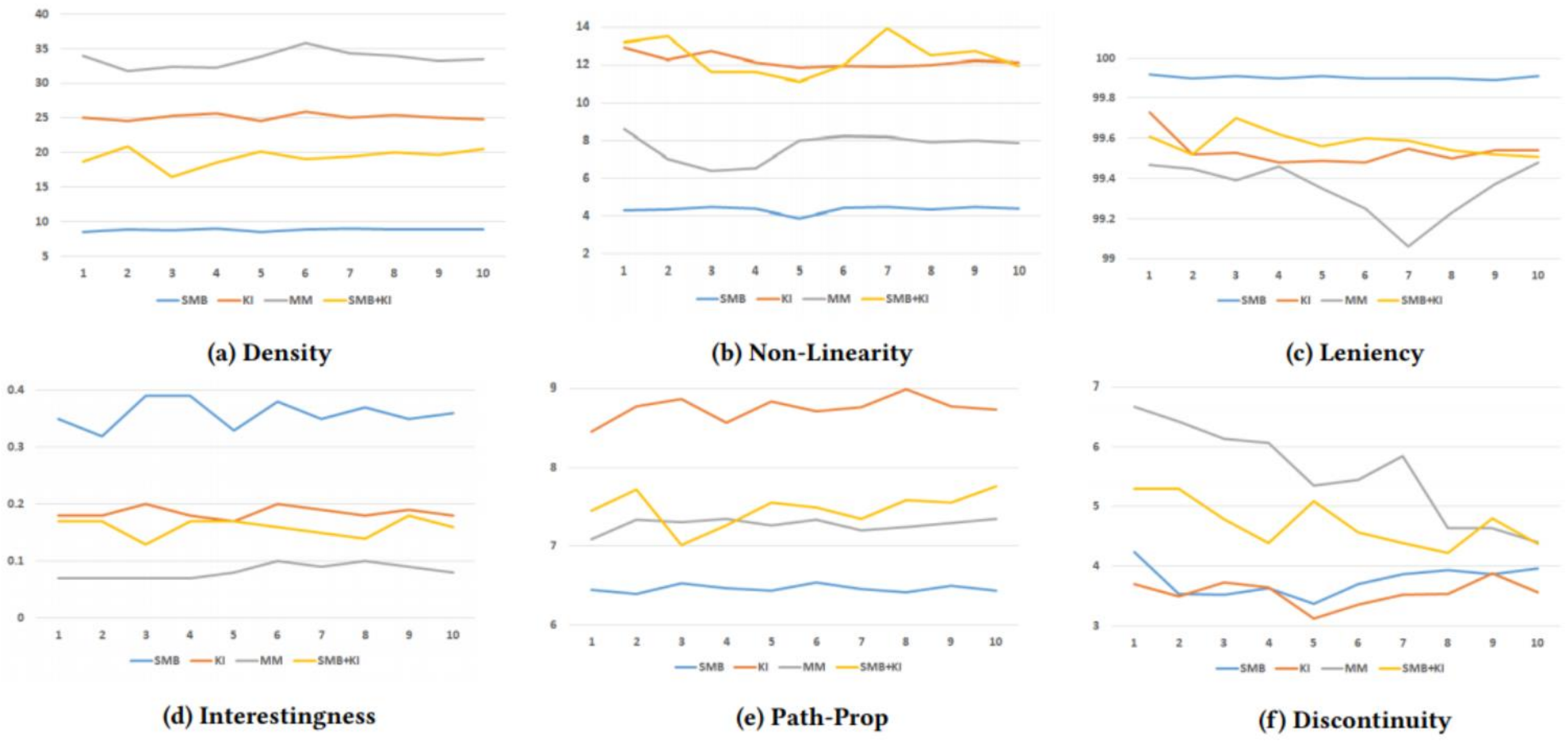


Figure 3: Per-segment metric values plotted for each grouping of 16 segments for MM and each grouping of 12 segments for the other games. x-axis values indicate 1st such grouping, 2nd such grouping etc. y-axis indicates average metric value for the corresponding group of segments.

Conclusion

- Novel PCGML approach for sequential platformer level generation and blending
- Generate arbitrarily-long coherent platformer levels
- Generate platformer levels progressing in multiple directions
- Blend levels from platformers progressing in different directions

Future Work

- Investigate other placement strategies (e.g. heuristics vs. classifier)
- Improve generation quality (particularly for Mega Man)
- Empirically test generation of left-to-right progressing levels (such as in Ninja Gaiden)
- Add controllability of generation beyond choice of initial segment

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