Conditional Level Generation and Game Blending

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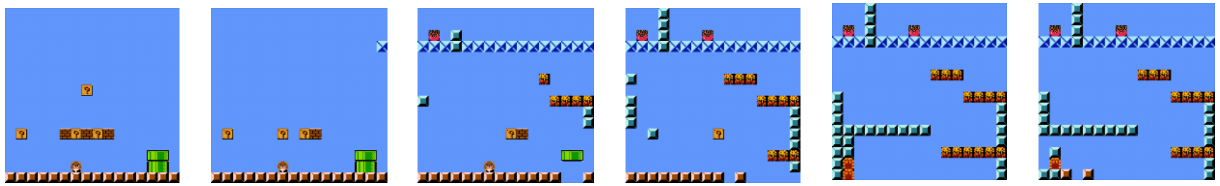
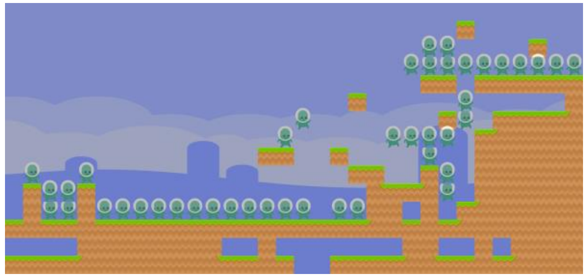
Motivation

- Variational Autoencoders (VAEs) have been used for generating and blending game levels



Sarkar, Yang and Cooper, 2019

Snodgrass and Sarkar, 2020



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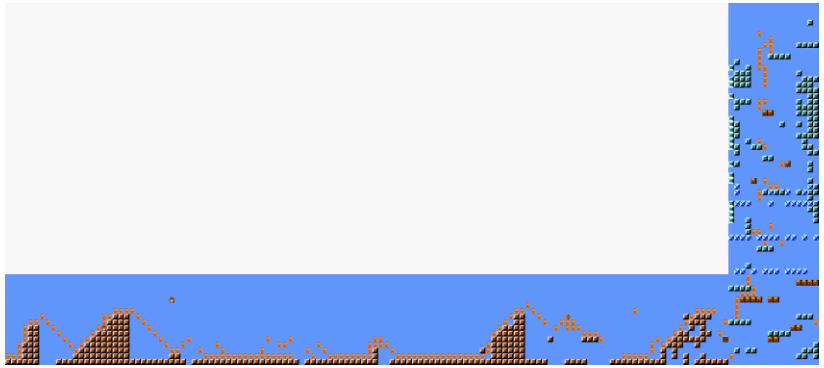

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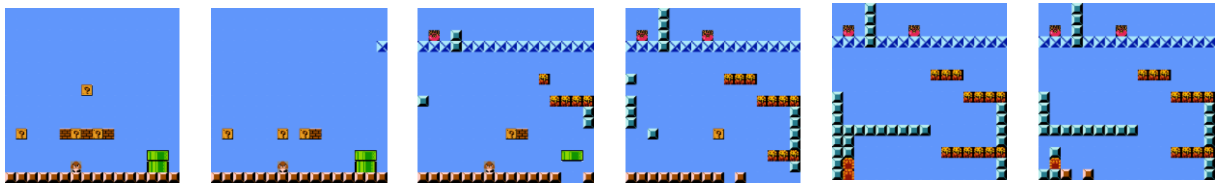
- Controllability via latent vector evolution
  - Define objective function
  - Run search in latent space to evolve desired vectors



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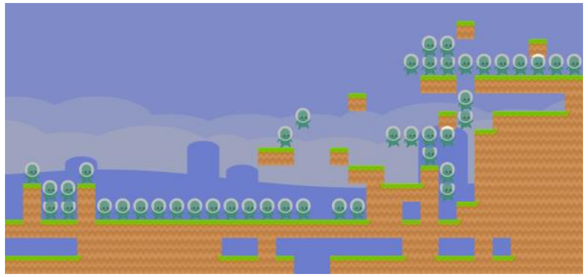

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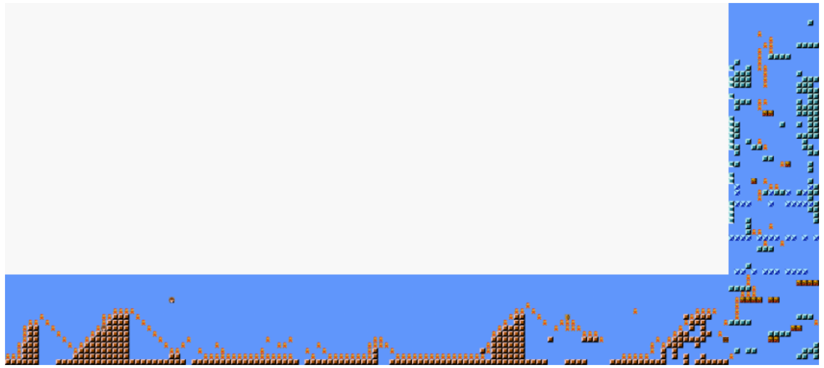

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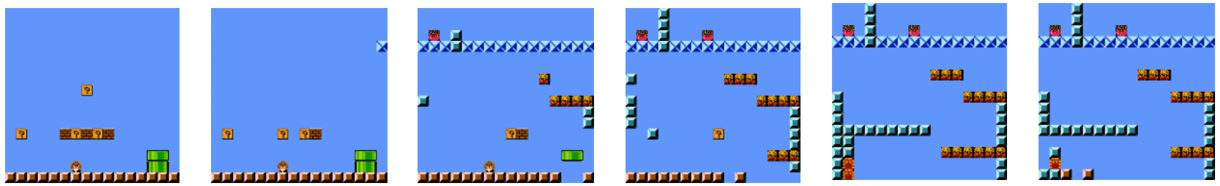

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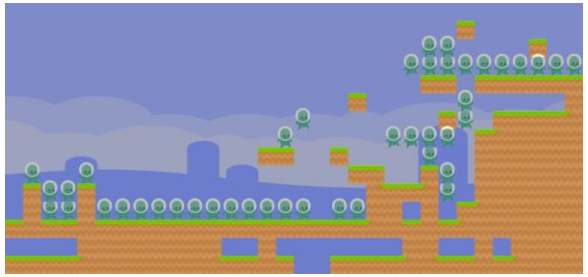

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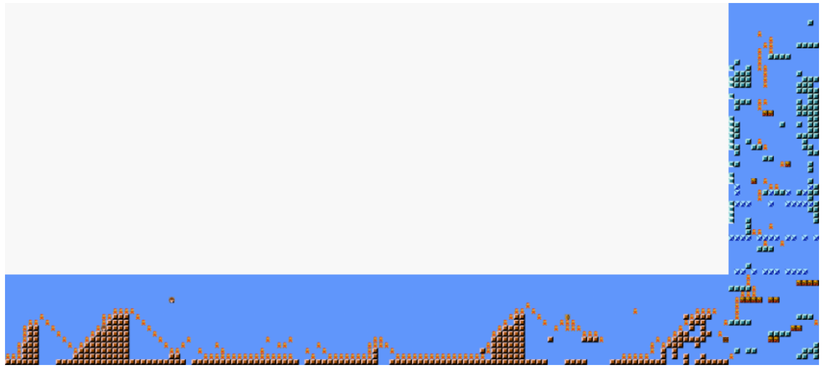

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    --- post-training process independent of the model
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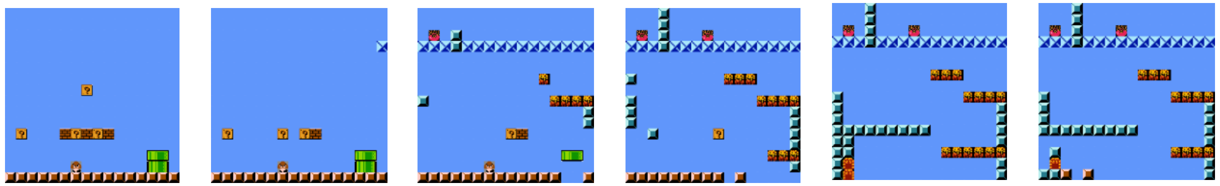
- Conditional VAEs enable controllability as part of the model itself
  - Train on labeled data
  - Generation conditioned on input labels
  - Various design affordances



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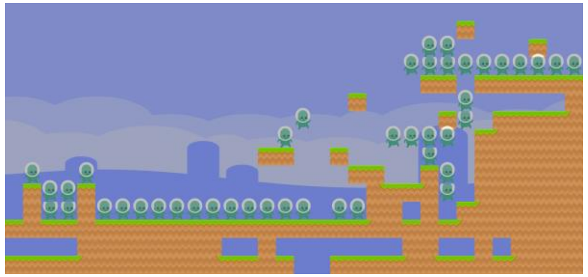

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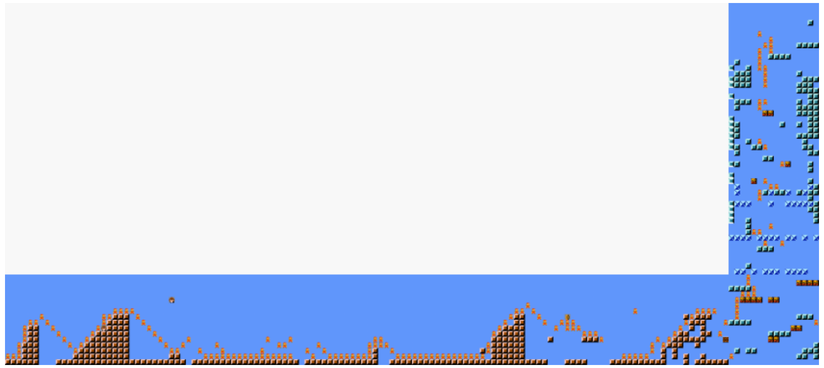

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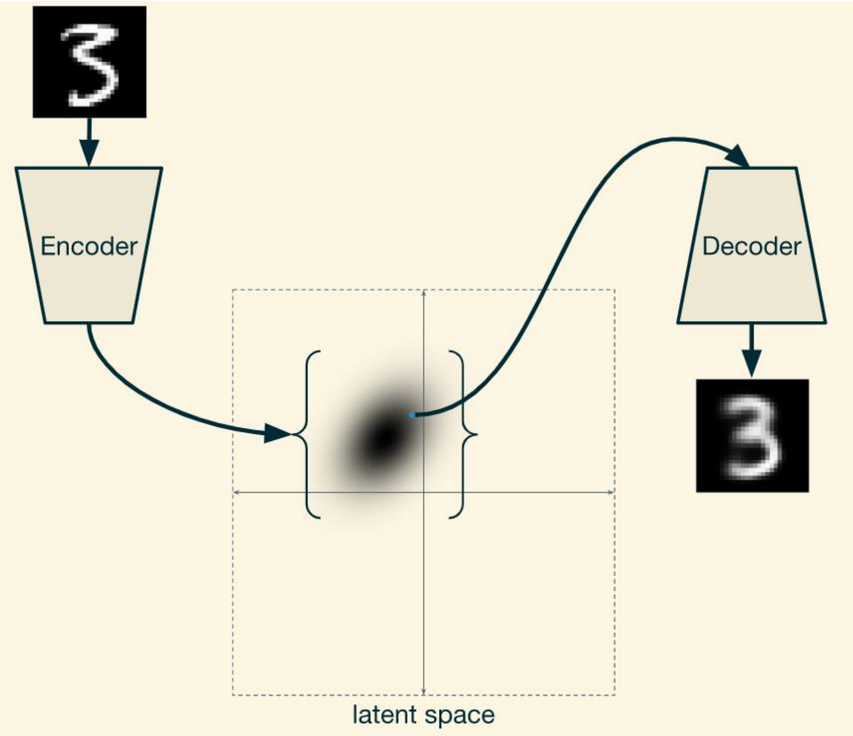
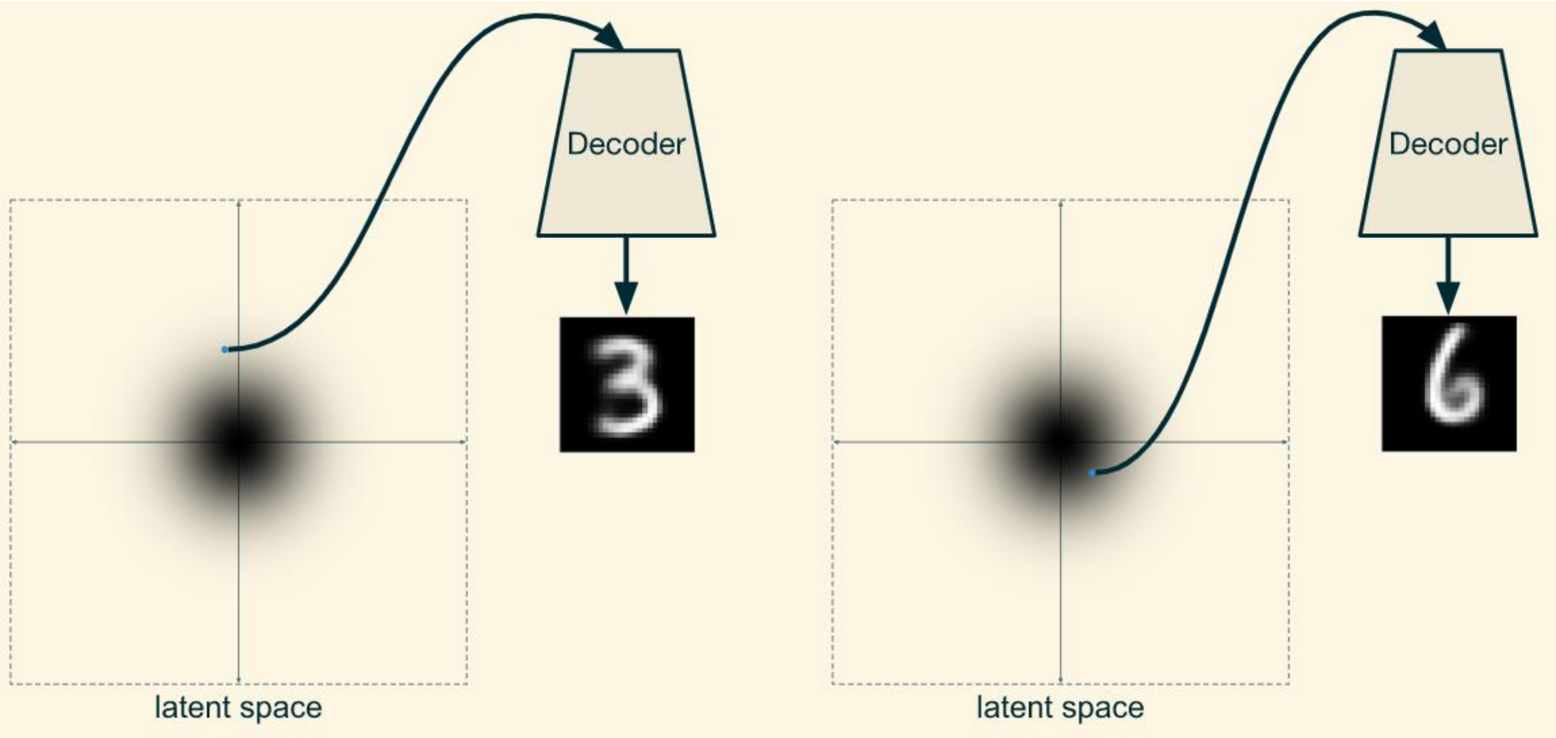
Variational Autoencoder (VAE)

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





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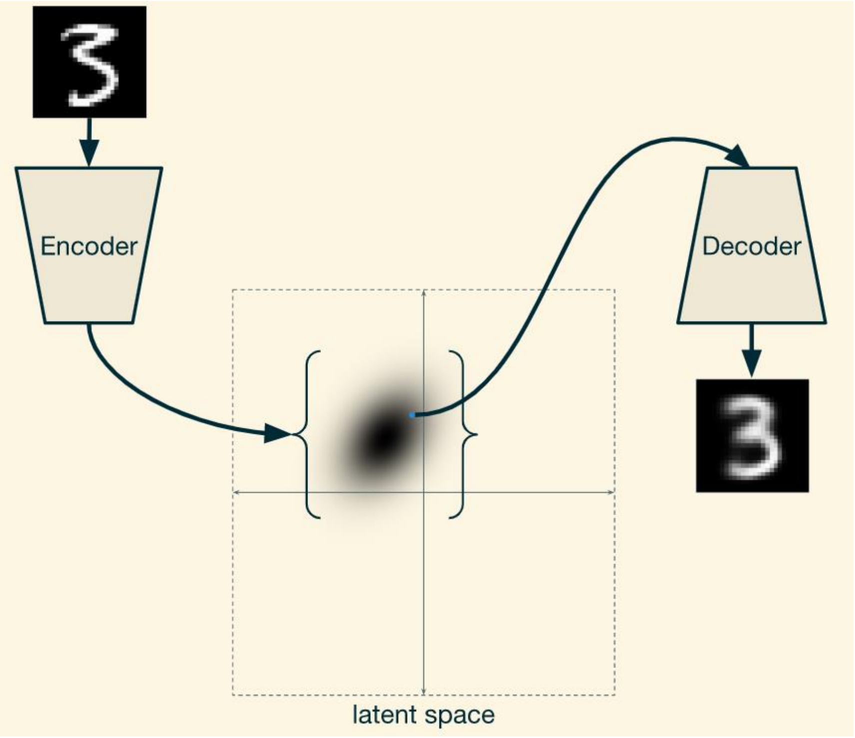

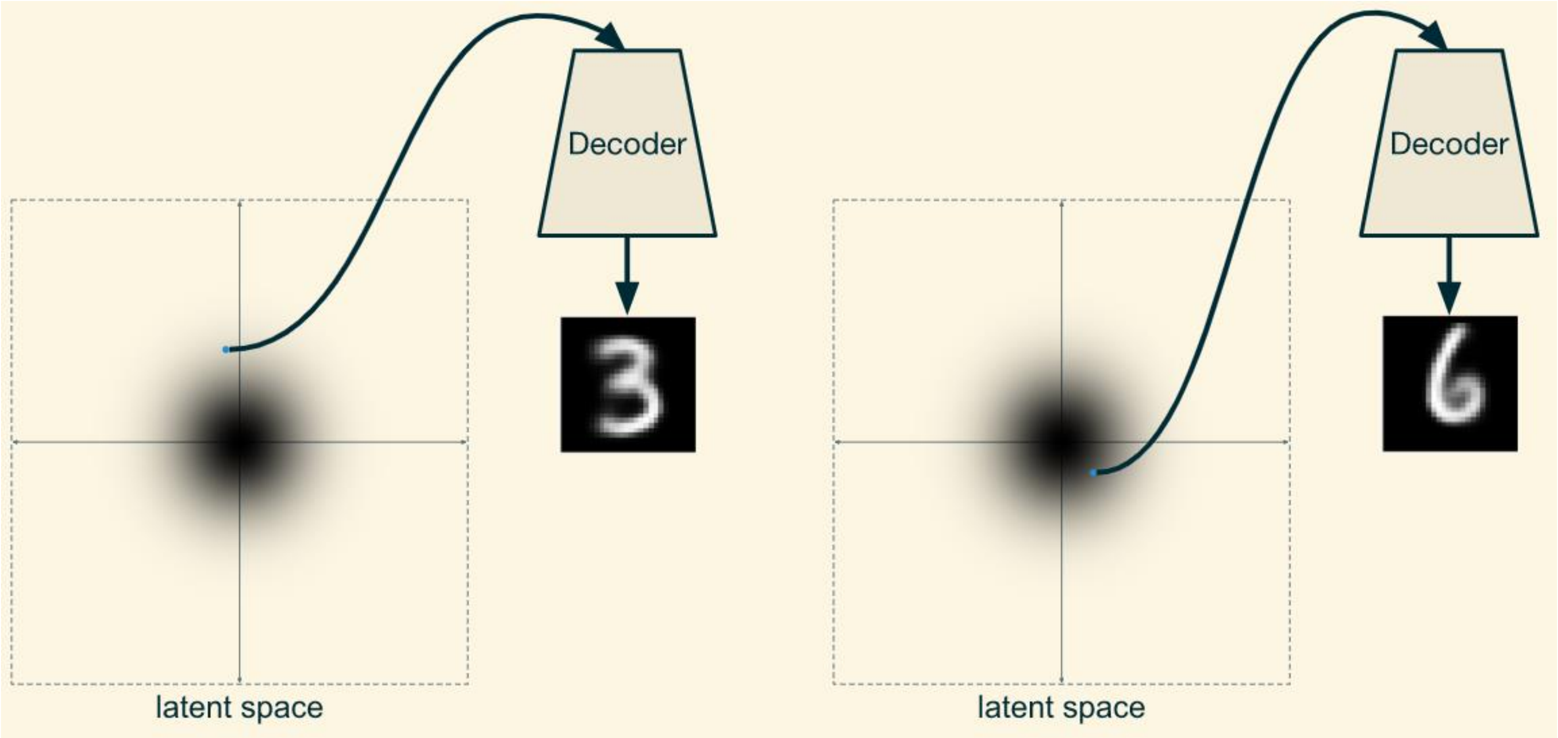

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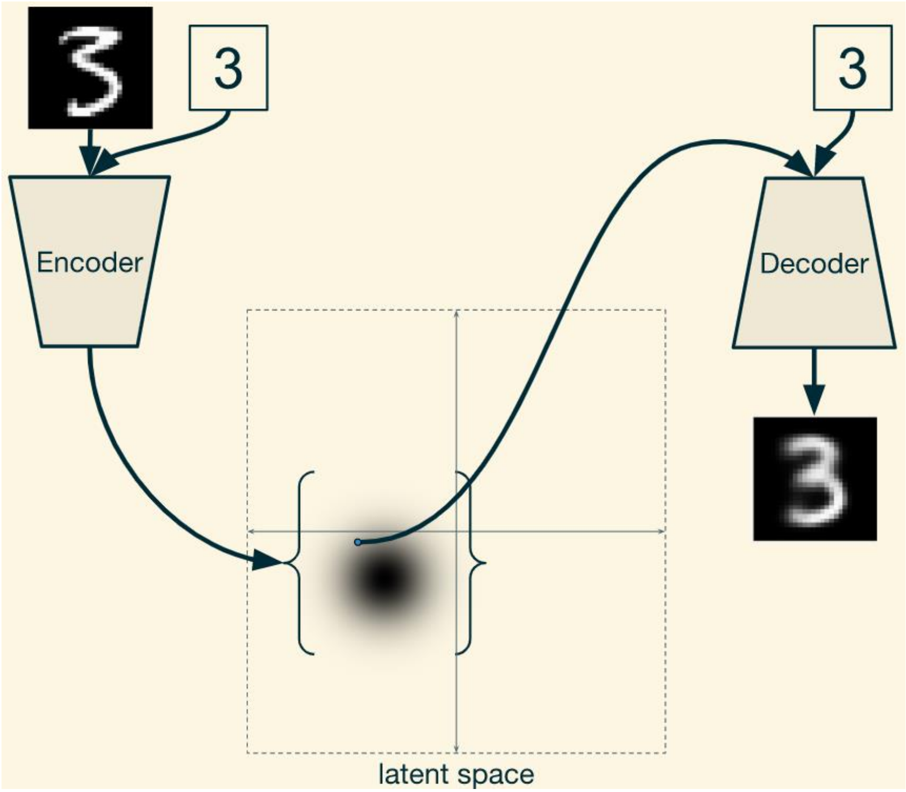
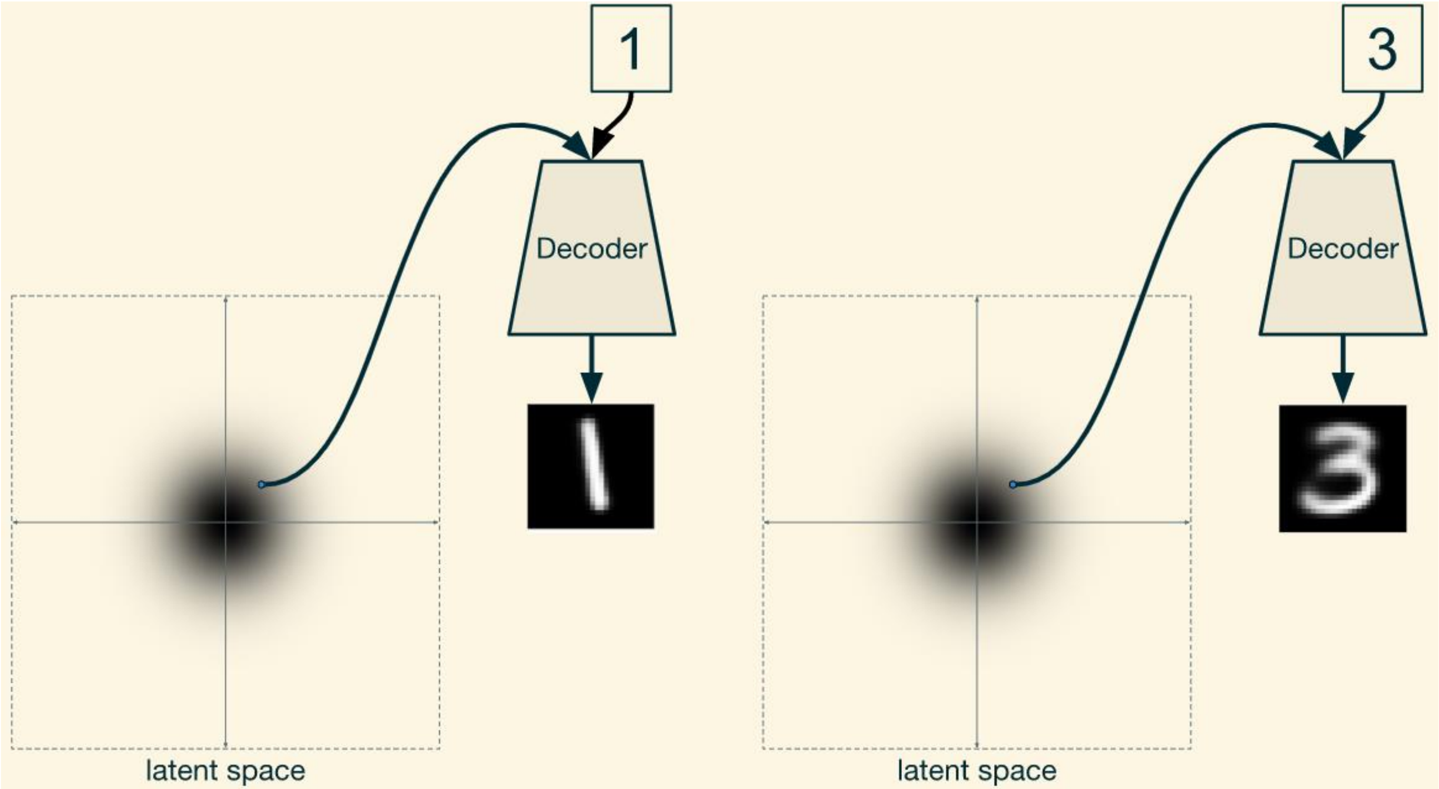
Conditional VAE (CVAE)

- CVAEs associate input data with labels during training
- Encoder uses label to learn latent encodings of inputs
- Decoder uses same label to learn how to reconstruct input from latent encoding
- Same latent vector can produce different outputs by varying label





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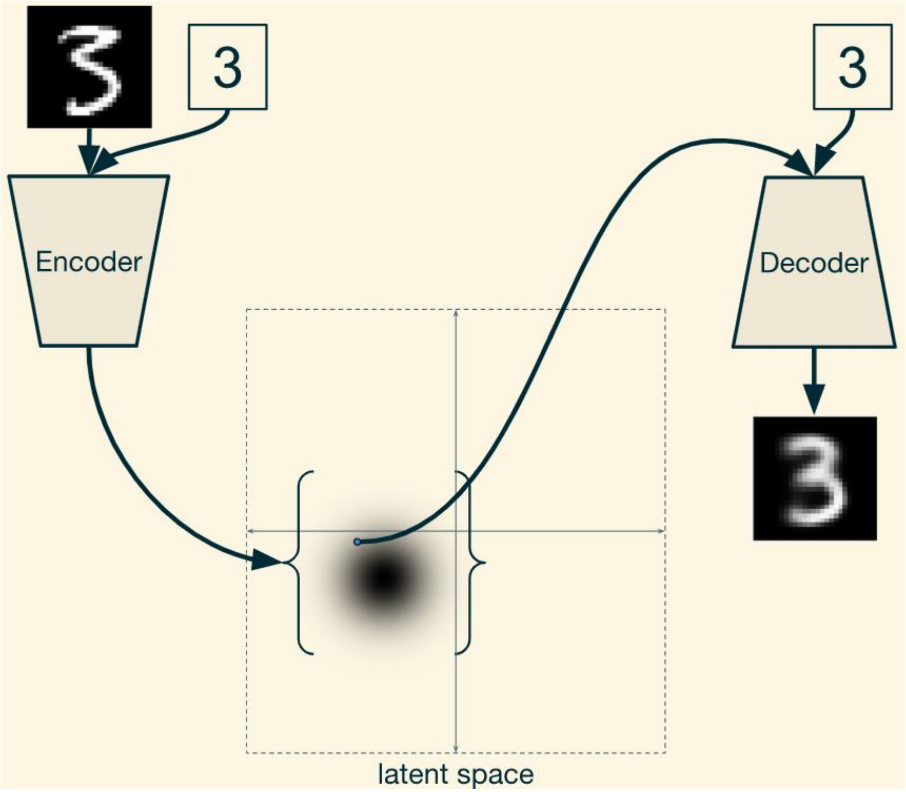
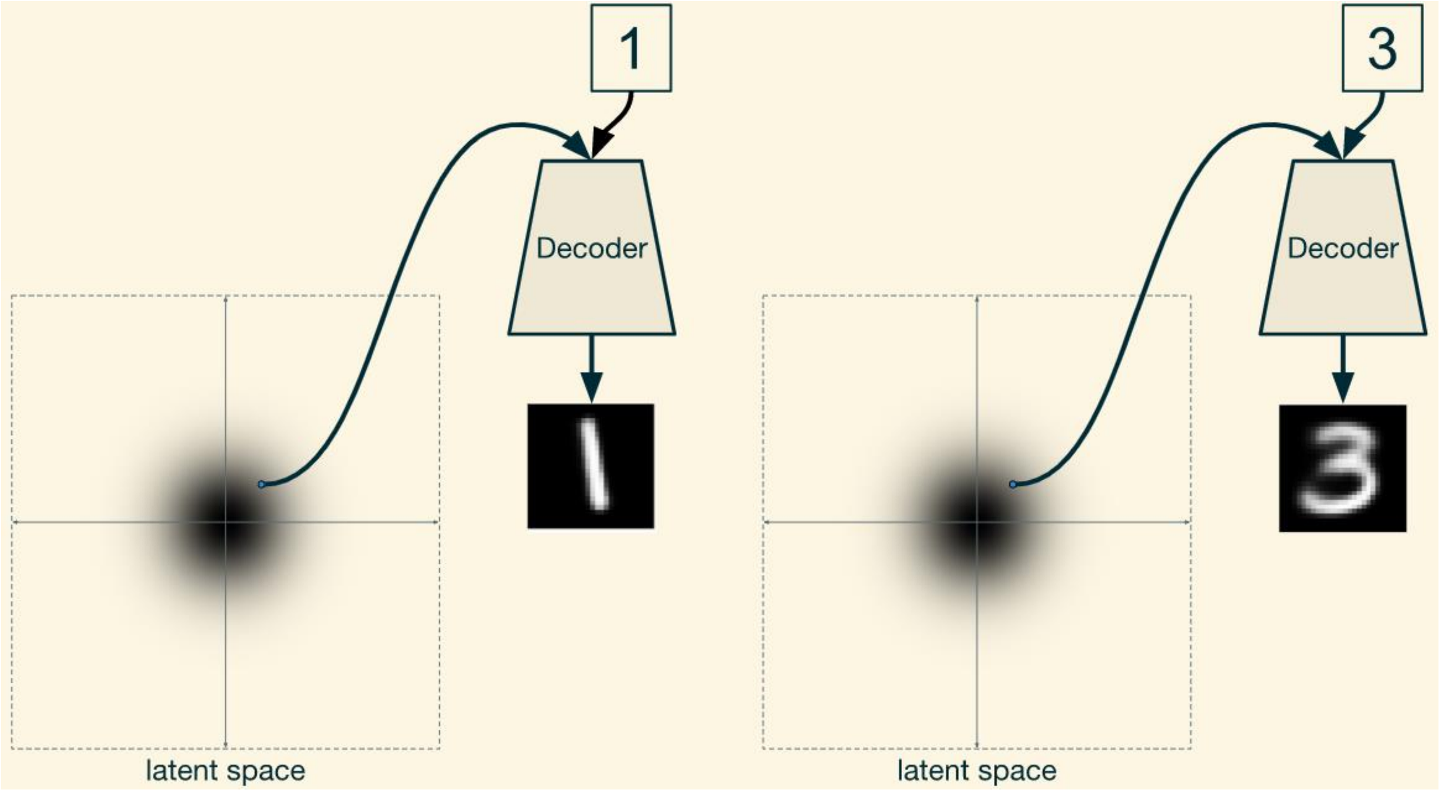
Conditional VAE (CVAE)

- CVAE could inform level design/generation by:
  - Enabling controllable generation by using labels to produce desired content
  - Generate variations of existing content by decoding it using different labels





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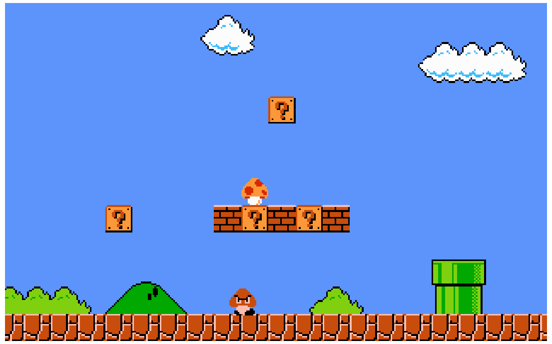
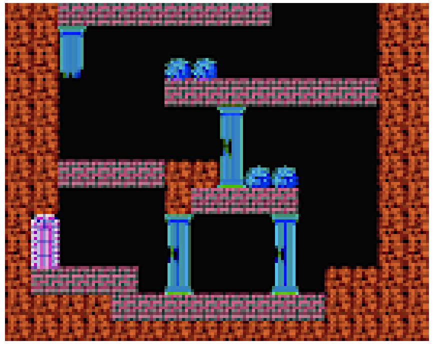
Approach

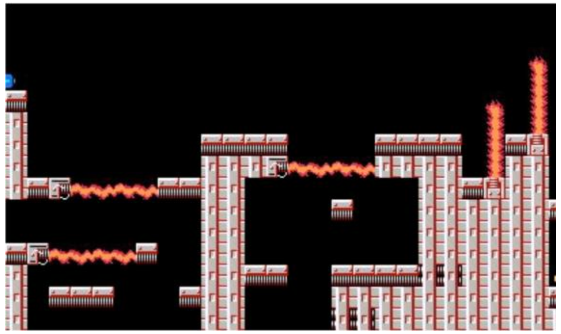
- Games:



Super Mario Bros.



Kid Icarus



Mega Man

- Three conditioning approaches:
  - Game elements
  - Mario design patterns
  - Game blending

- For all cases:
  - 16x16 segments
  - Binary-encoded vectors as labels
  - 3 latent dimensions per model (32, 64, 128)

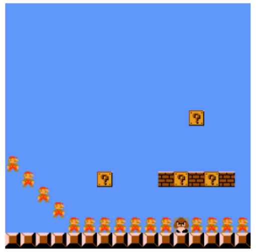
Game Elements

- Unique set of conditioning labels for each game

- Label length → number of different elements
  - 5 for SMB/MM, 4 for KI
  - Each unique label corresponds to a unique combination of elements

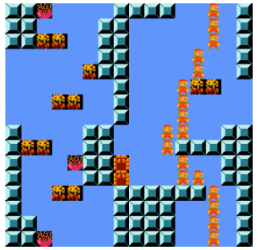
- Trained separate CVAE for each game

- Labels for training segments determined by checking for the relevant game elements within that segment
  - Present → set bit to 1
  - Absent → set bit to 0



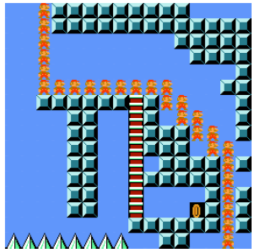
SMB - $\langle 10011 \rangle$

< Enemy, Pipe, Coin, Breakable, ?-Mark >



KI - $\langle 1101 \rangle$

< Hazard, Door, Moving, Stationary >



MM - $\langle 10101 \rangle$

< Hazard, Door, Ladder, Platform, Collectible >

Game Elements

- Conditioning Accuracy Evaluation:
  - For each game, sampled 1000 latent vectors

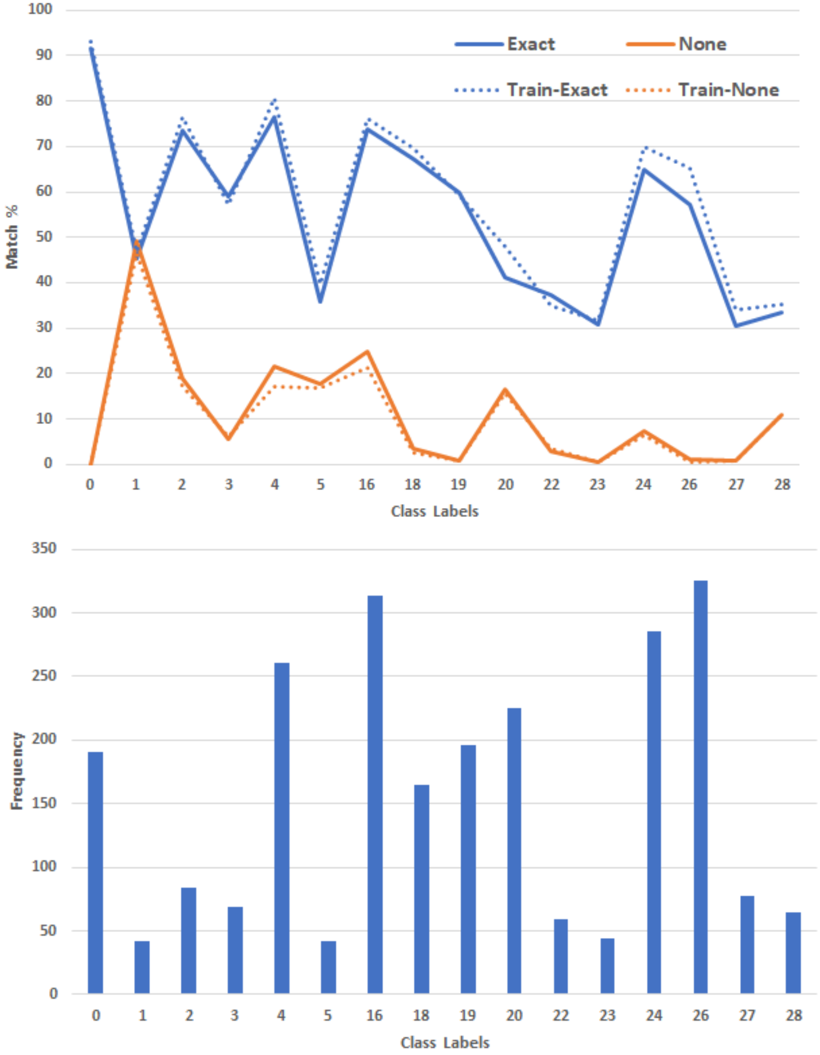
  - Conditioned generation of each using each possible label (32 for SMB/MM, 16 for KI)

  - Compared elements in generated segments with labels used for generation

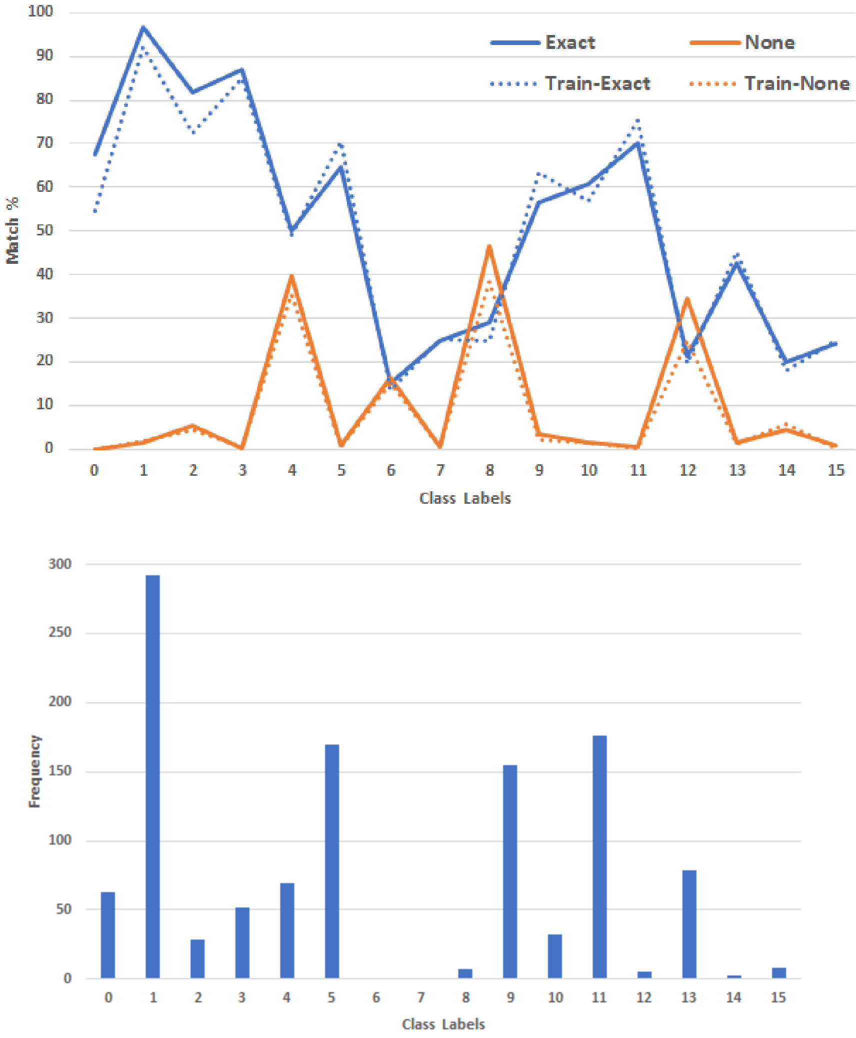
  - Exact → all elements present

  - None → none of the elements present

Game Elements



Super Mario Bros.



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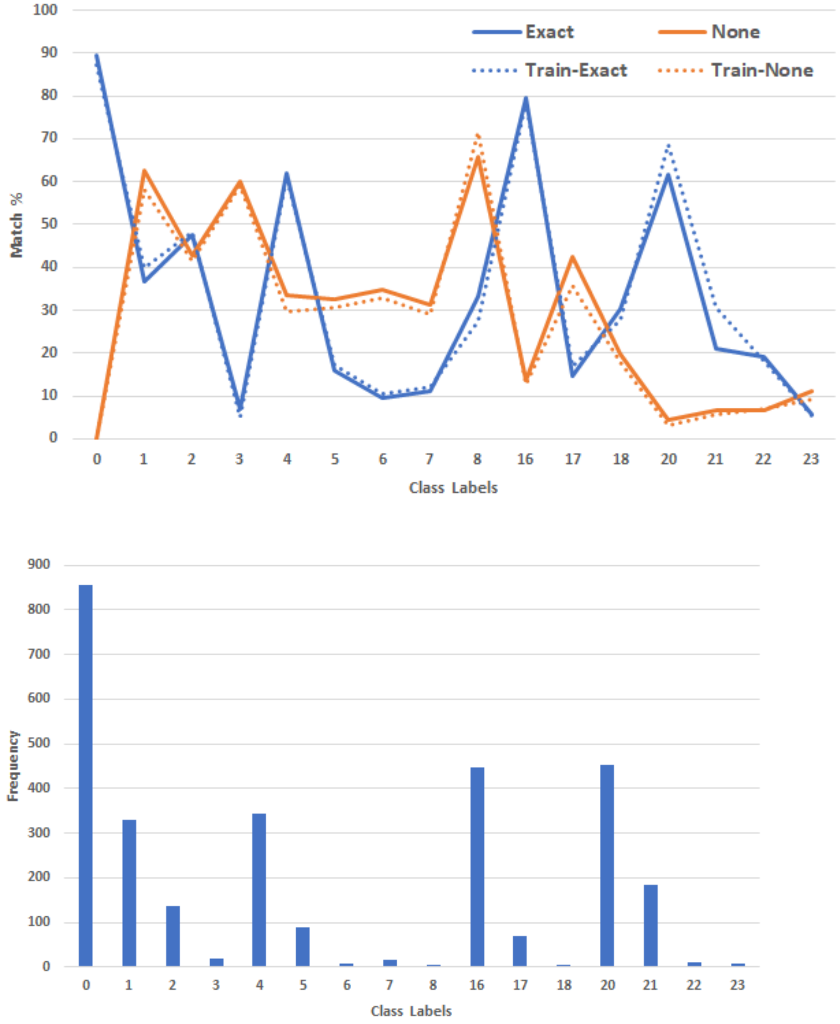
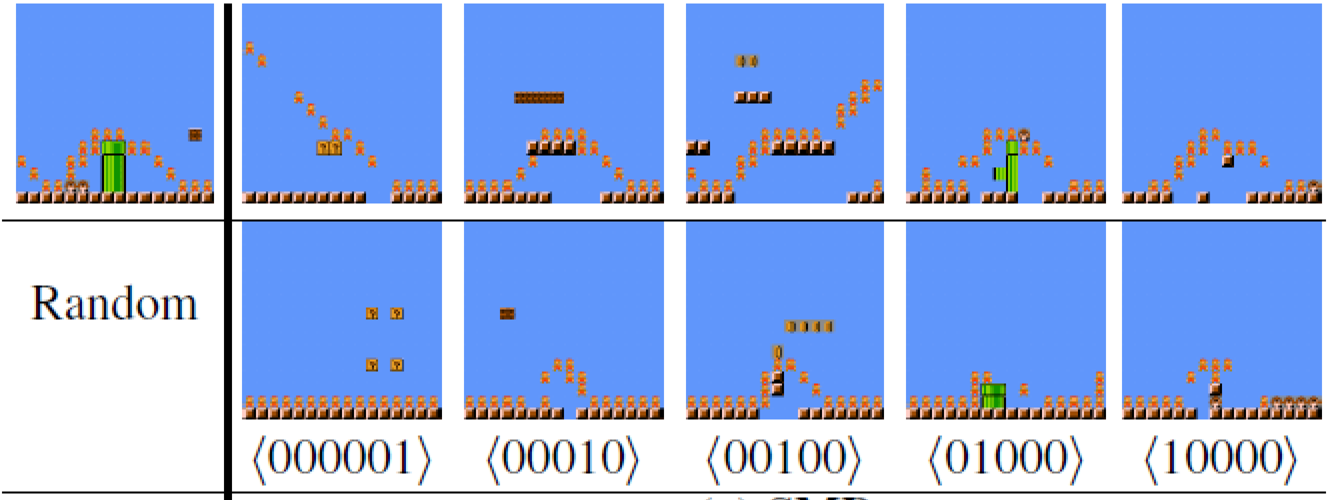
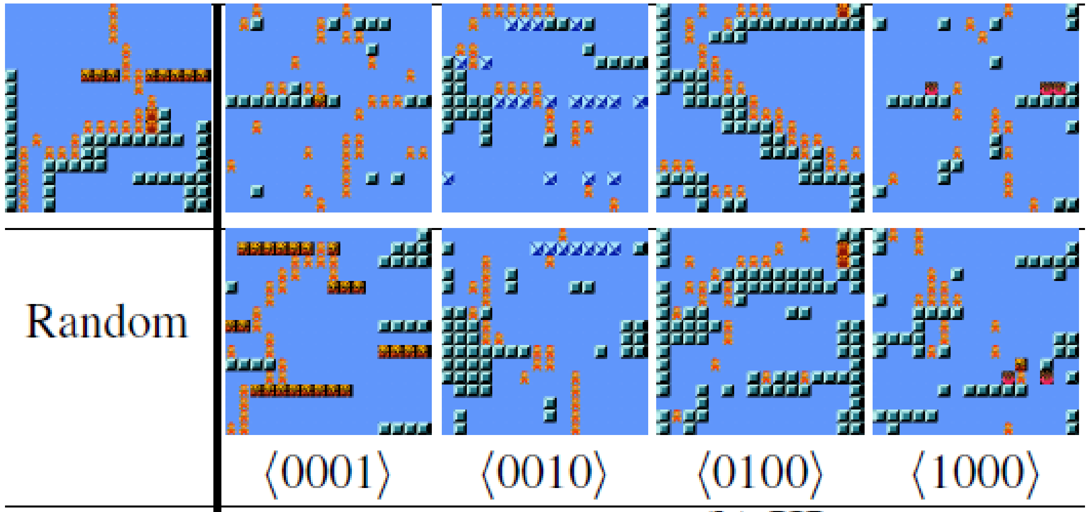


Mega Man

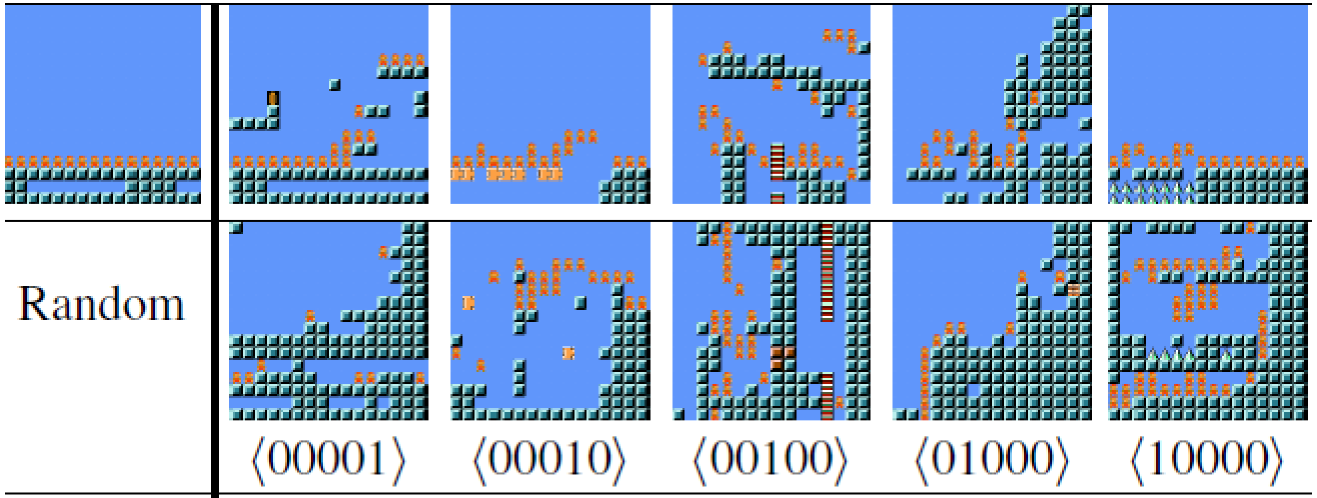
Game Elements



(a) SMB



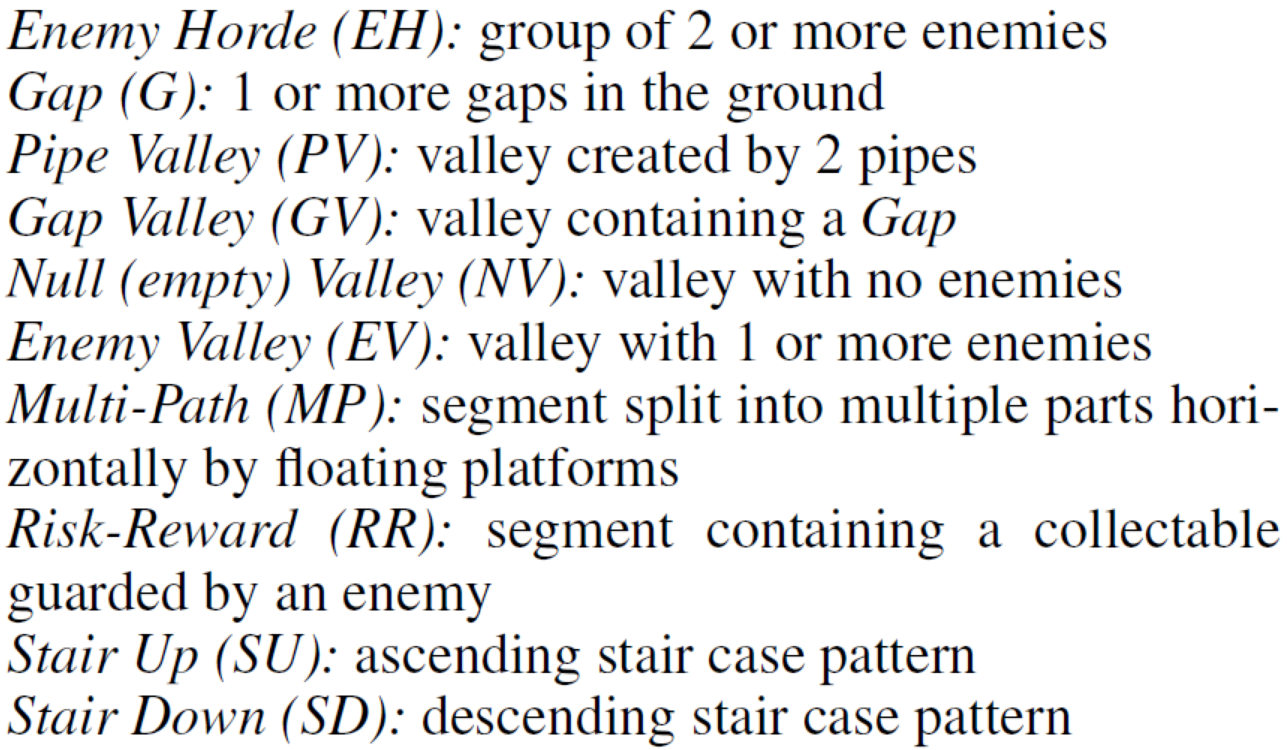
(b) KI



(c) MM

Design Patterns

- 10 SMB design patterns adapted from Dahlskog and Togelius, *“Patterns and Procedural Content Generation: Revisiting Mario in World 1 Level 1”*, 2012
- Binary labels of length 10
- Used levels from
  - Super Mario Bros.
  - Super Mario Bros II: The Lost Levels
- Labels assigned manually based on visual inspection

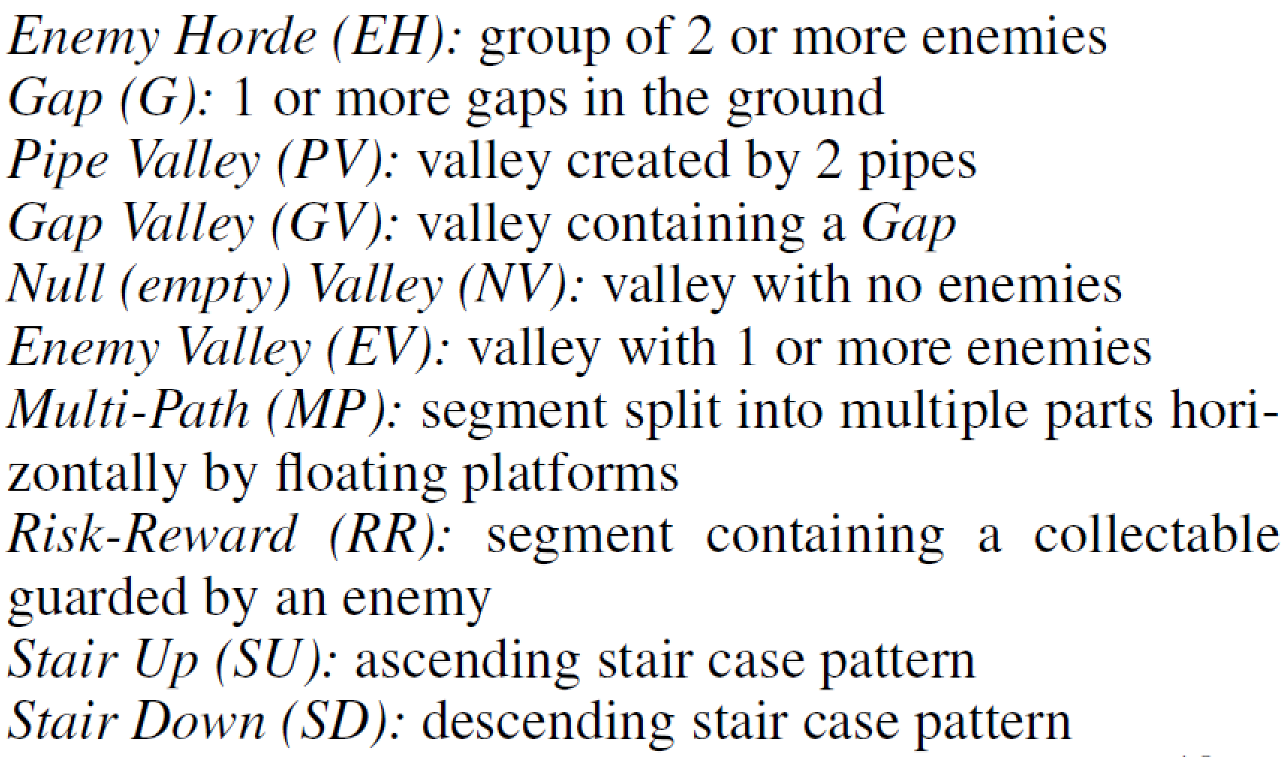


Enemy Horde (EH): group of 2 or more enemies
Gap (G): 1 or more gaps in the ground
Pipe Valley (PV): valley created by 2 pipes
Gap Valley (GV): valley containing a *Gap*
Null (empty) Valley (NV): valley with no enemies
Enemy Valley (EV): valley with 1 or more enemies
Multi-Path (MP): segment split into multiple parts horizontally by floating platforms
Risk-Reward (RR): segment containing a collectable guarded by an enemy
Stair Up (SU): ascending stair case pattern
Stair Down (SD): descending stair case pattern

Mario Design Patterns

Design Patterns

- More challenging to evaluate
  - Unlike game elements, couldn’t automatically check for design patterns
  - Couldn’t automatically determine label matches
  - No success in training a classifier due to low amount of data relative to number of unique labels
  - Currently, restricted to visual inspection



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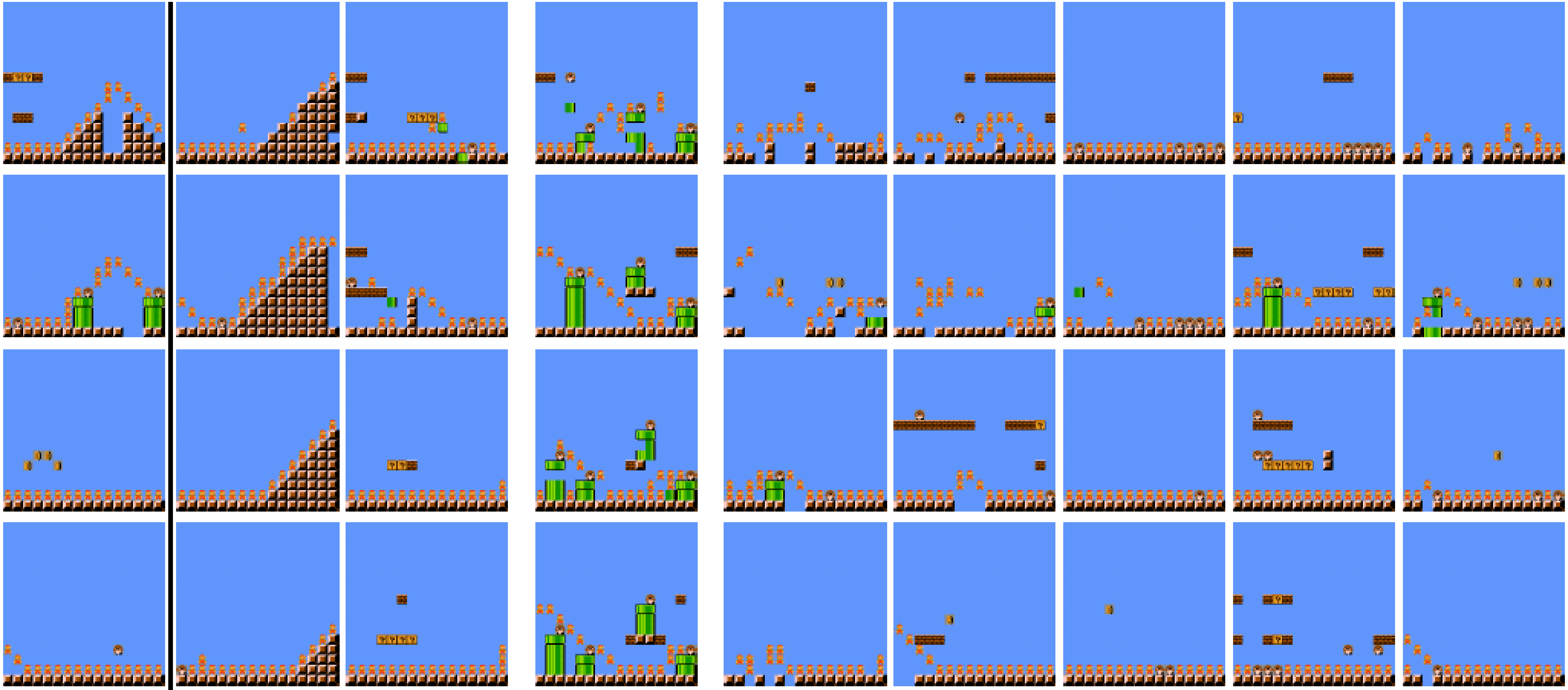
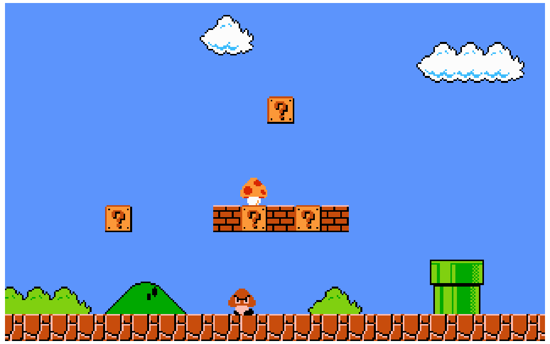


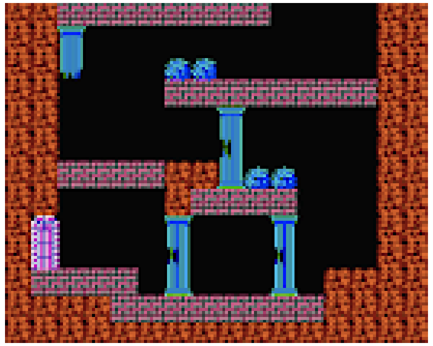
Original $\langle SU\rangle$ $\langle MP\rangle$ $\langle PV\text{-}NV\text{-}MP\rangle$ $\langle G\rangle$ $\langle G\text{-}MP\rangle$ $\langle EH\rangle$ $\langle EH\text{-}MP\rangle$ $\langle EH\text{-}G\rangle$

Game Blending

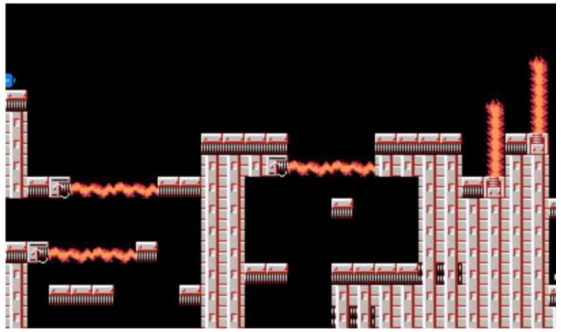
- Trained on segments from all 3 games taken together
- 3-element labels indicating which game a segment belonged to
- Blending by conditioning generation using blended labels
    - <110> → SMB + KI
    - <011> → KI + MM
    - <101> → SMB + MM



Super Mario Bros.: <100>



Kid Icarus: <010>



Mega Man: <001>

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- Proxy evaluation:
  - Train a classifier on original segments to predict which game they belong to
  - Test to see how predictions on CVAE-generated segments change with different conditioning labels
  - Sample 1000 latent vectors
  - Condition generation of each using each of 8 possible conditioning labels
  - For each, compute % of generated segments predicted as SMB, KI or MM by classifier

Game Blending

- Expectations
  - Conditioning with an original game label (<100>,<010>,<001>)

    --- e.g. using <100> → very high % of SMB predictions
  - Conditioning with blended game label (e.g. <110>, <101>)

    --- more variance among predictions

    --- e.g. using <101> → moderately high % for both SMB/MM, but not too high, low % for KI

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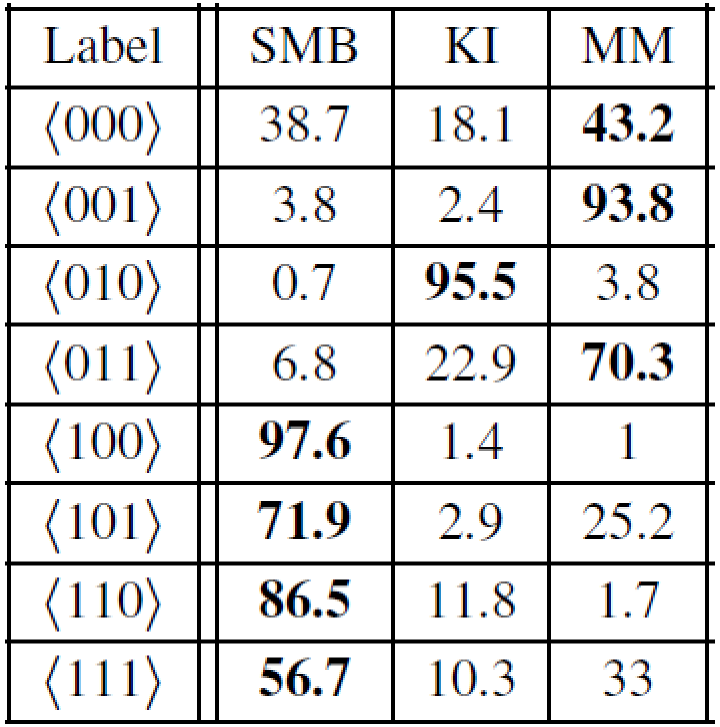
- Results
  - True to expectations
  - <100>, <010>, <001> → high% for SMB, KI, MM respectively
  - More variance among labels with multiple 1s (i.e. blended)
  - Most variance using <000> and <111>



Label	SMB	KI	MM
⟨000⟩	38.7	18.1	**43.2**
⟨001⟩	3.8	2.4	**93.8**
⟨010⟩	0.7	**95.5**	3.8
⟨011⟩	6.8	22.9	**70.3**
⟨100⟩	**97.6**	1.4	1
⟨101⟩	**71.9**	2.9	25.2
⟨110⟩	**86.5**	11.8	1.7
⟨111⟩	**56.7**	10.3	33

Blending Classification

Game Blending

- Further evaluation:
  - Compare distributions of levels obtained using each label with original game distributions
  - Generated 1000 segments using each blend label
  - Computed E-distance between each set of 1000 vs. each of SMB, KI and MM
  - Lower the E-distance between 2 distributions, more similar they are
  - Used 4 tile-based metrics – *Density, Leniency, Nonlinearity, Interestingness*

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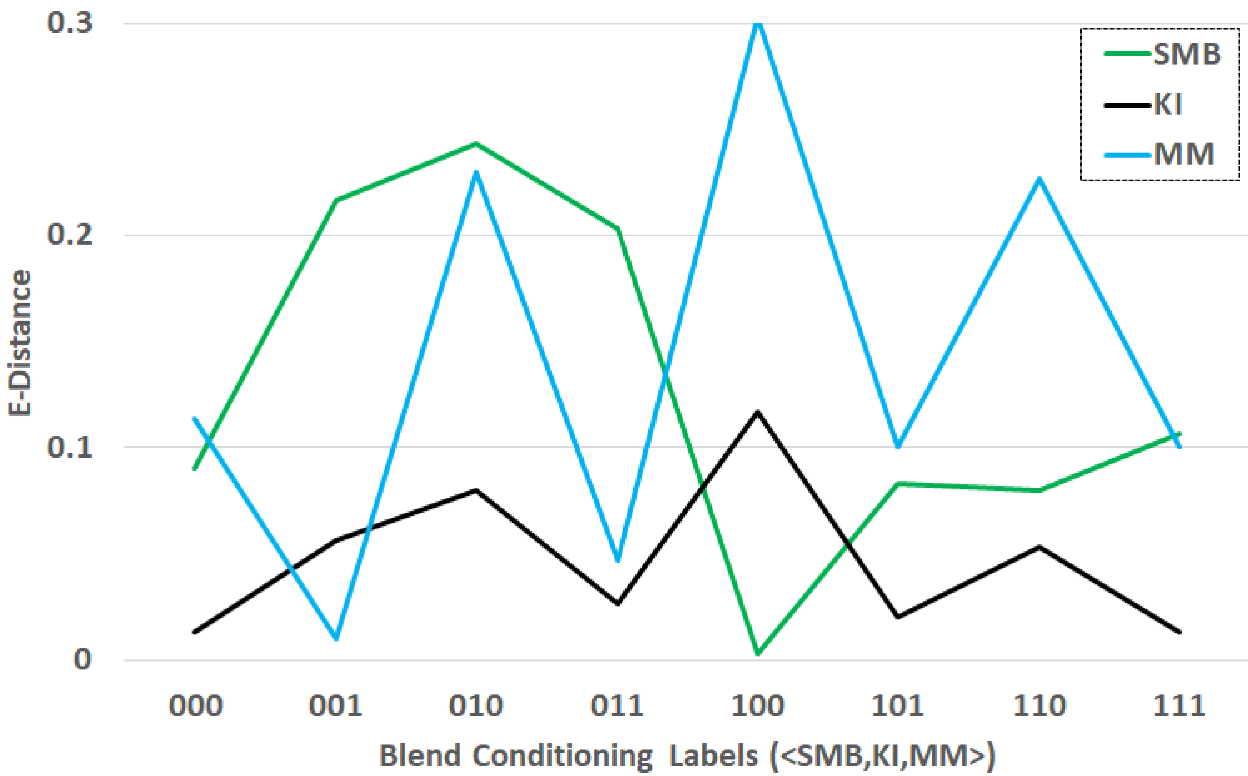

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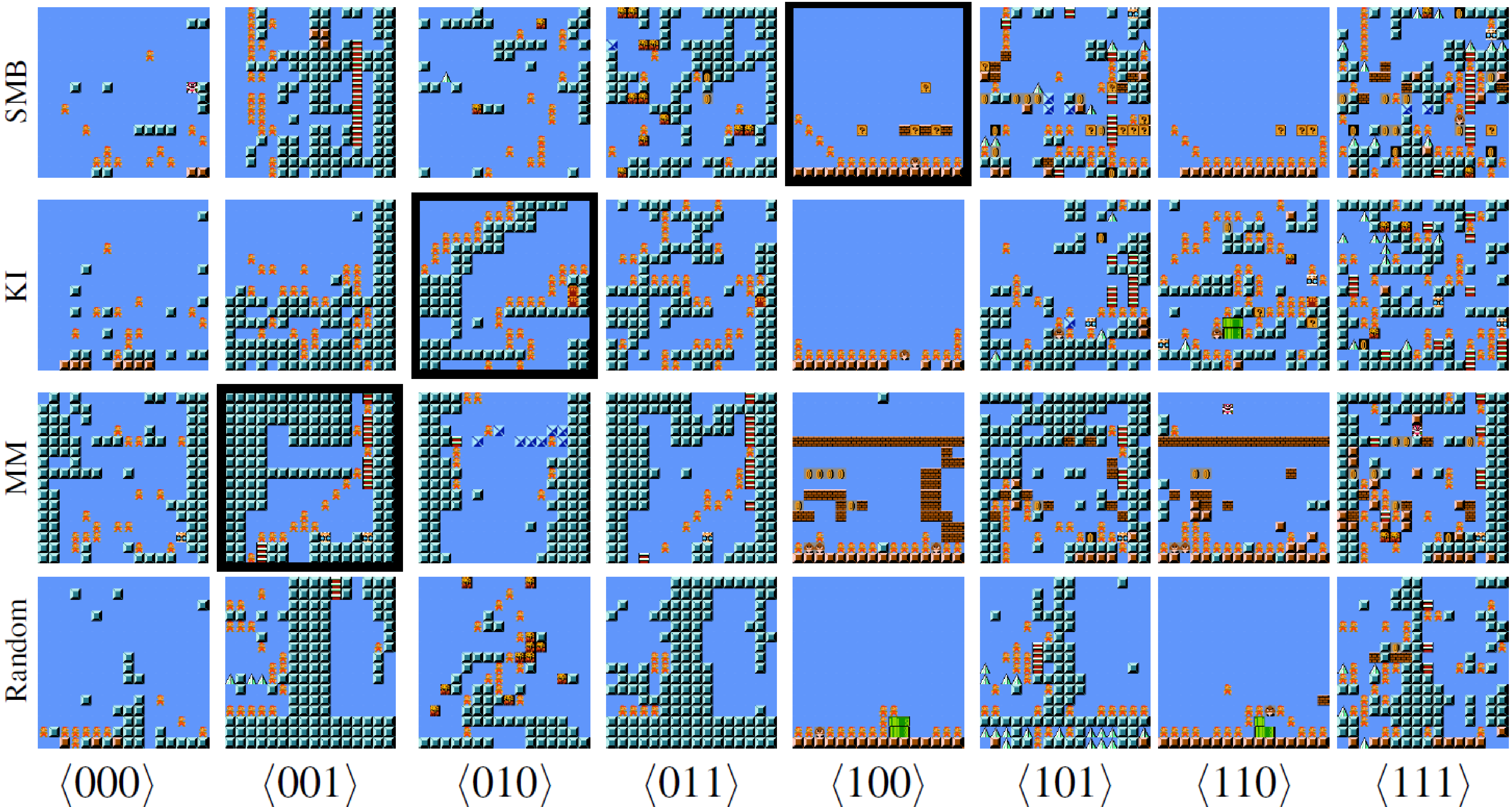

Conclusion

- Explored the use of conditional VAEs for PCGML
- Enable controllable level generation and blending
- Editing and producing novel variations of existing levels

Future Work

- Combine with evolutionary search for further controllability
- Blending – improve quality, more controllability
- More thorough focus on design patterns, more robust evaluations (user-study, playability)
- Combine with our sequential model for enabling conditional generation of whole levels
- Incorporate into co-creative tools

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