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
Sarkar, Summerville, Snodgrass, Bentley, Osborn, 2020
Sarkar and Cooper, 2020
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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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    --- post-training process independent of the model
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  • Run search in latent space to evolve desired vectors
    --- post-training process independent of the model
    --- sometimes limited controllability

• 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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Snodgrass and Sarkar, 2020

Sarkar, Summerville, Snodgrass, Bentley, Osborn, 2020

Sarkar and Cooper, 2020
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)

(source: jdykeman.github.io/ml/2016/12/21/cvae.html)
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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

source: jdykeman.github.io/ml/2016/12/21/cvae.html
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

source: jdykeman.github.io/ml/2016/12/21/cvae.html
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 $\rightarrow$ 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 $\rightarrow$ set bit to 1
  • Absent $\rightarrow$ set bit to 0
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 $\rightarrow$ all elements present

- None $\rightarrow$ none of the elements present
Game Elements

Super Mario Bros.

Kid Icarus

Mega Man
## Game Elements

| Random | (a) SMB | Random | (b) KI | Random | (c) MM |
|--------|---------|--------|--------|--------|--------|
| ![Image](image1) | ![Image](image2) | ![Image](image3) | ![Image](image4) | ![Image](image5) | ![Image](image6) |

- **SMB**
  - 000001
  - 000100
  - 001000
  - 010000
  - 100000

- **KI**
  - 00001
  - 00101
  - 01010
  - 10100
  - 10001

- **MM**
  - 00001
  - 00010
  - 00100
  - 01000
  - 10000
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

Enemy Horde (EH): group of 2 or more enemies
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Mario Design Patterns
Design Patterns
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
Game Blending

• Label accuracy evaluation issues:
  • Hard to automatically detect blending
  • No ground truth for blended levels
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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
Game Blending

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  • No ground truth for blended levels

• 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> \(\rightarrow\) very high % of SMB predictions
  • Conditioning with blended game label (e.g. <110>, <101>)
    --- more variance among predictions
    --- e.g. using <101> \(\rightarrow\) moderately high % for both SMB/MM, but not too high, low % for KI
Game Blending

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

• 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*
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*
Game Blending
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
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)
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