Blending Levels from Different Games using LSTMs

Anurag Sarkar and **Seth Cooper**

College of Computer and Information Science

Northeastern University

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- Recent work on training models on existing levels to generate new levels

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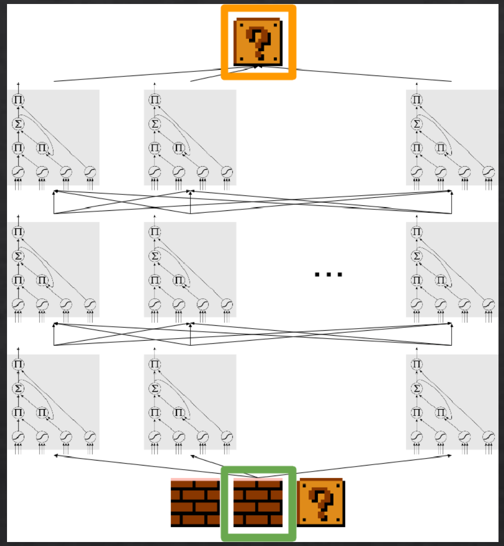
  - Sequence Prediction using LSTMs



Summerville and Mateas, 2016

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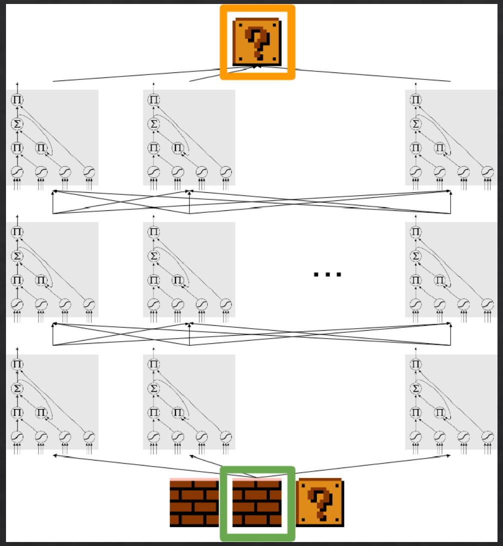

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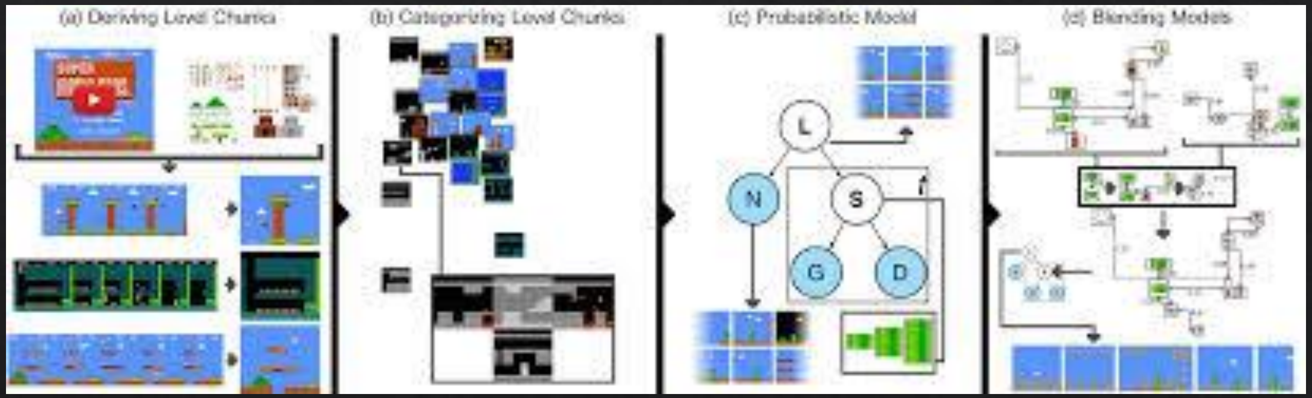

Guzdial and Riedl, 2016

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```
SpriteSet
  forest > SpawnPoint stype=log
    dense > prob=0.4 cooldown=10
      sparse > prob=0.1 cooldown=5
  structure > Immovable
      home > Door
      water
      wall
  log > Missile orientation=LEFT speed=0.1
  safety > Resource limit=2
  frog > MovingAvatar
  truck > Missile img=truck
      rightTruck > orientation=RIGHT
          fastRtruck > speed=0.2
          slowRtruck > speed=0.1
      leftTruck > orientation=LEFT
          fastLtruck > speed=0.2
          slowLtruck > speed=0.1

InteractionSet
  home frog  > killSprite scoreChange=1
  frog log   > changeResource resource=safety value=2
  frog log   > pullWithIt
  frog wall  > stepBack
  frog water > killIfHasLess resource=safety limit=0
  frog water > changeResource resource=safety value=-1
  frog truck > killSprite scoreChange=-2
  log   EOS  > killSprite
  truck EOS  > wrapAround

TerminationSet
  SpriteCounter stype=home win=True
  SpriteCounter stype=frog win=False
```

VGDL Frogger

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  sword > Flicker limit=5 singleton=True
  movable >
      link > ShootAvatar stype=sword
          nokey
          withkey
      monster > RandomNPC
          monsterQuick > cooldown=2
          monsterNormal > cooldown=4
          monsterSlow > cooldown=8

InteractionSet
  movable wall  > stepBack
  nokey door    > stepBack
  door withkey  > killSprite scoreChange=1
  monster sword > killSprite scoreChange=2
  link monster  > killSprite scoreChange=-1
  key link      > killSprite scoreChange=1
  nokey key     > transformTo stype=withkey

TerminationSet
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VGDL Zelda

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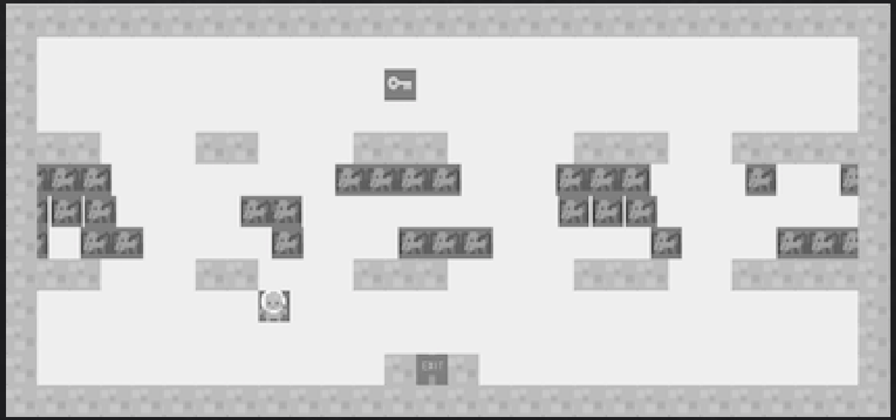
VGDL Zelda



Frolda

Motivation

- Recent work on training models on existing levels to generate new levels
  - Sequence Prediction using LSTMs
  - Concept
- Gow and C
  generating
  entire games

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 key   > killSprite scoreChange=1
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 ter   > killSprite scoreChange=-1
       > killSprite scoreChange=1
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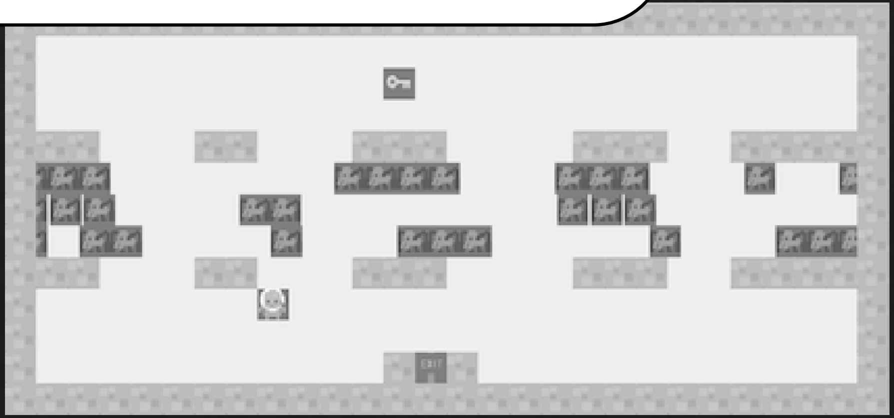
Set
 nter stype=door win=True
 nter stype=link win=False
```

GDL Zelda

IDEA: PCGML techniques + Game Blending



Frolda

Overview

- Train LSTMs on existing levels of *Super Mario Bros.* and *Kid Icarus*

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- Train LSTMs on existing levels of *Super Mario Bros.* and *Kid Icarus*
- Sample from the trained models to generate new levels that contain properties of levels from both games
- Used weights to control approximate amount of each game

Dataset

- Video Game Level Corpus (VGLC)
  - *Super Mario Bros. (15)*
  - *Kid Icarus (6)*

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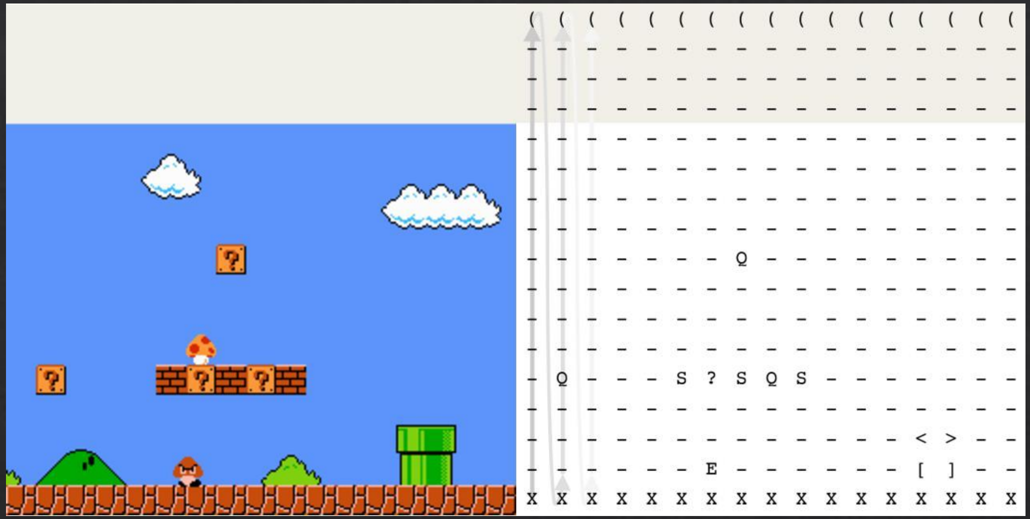
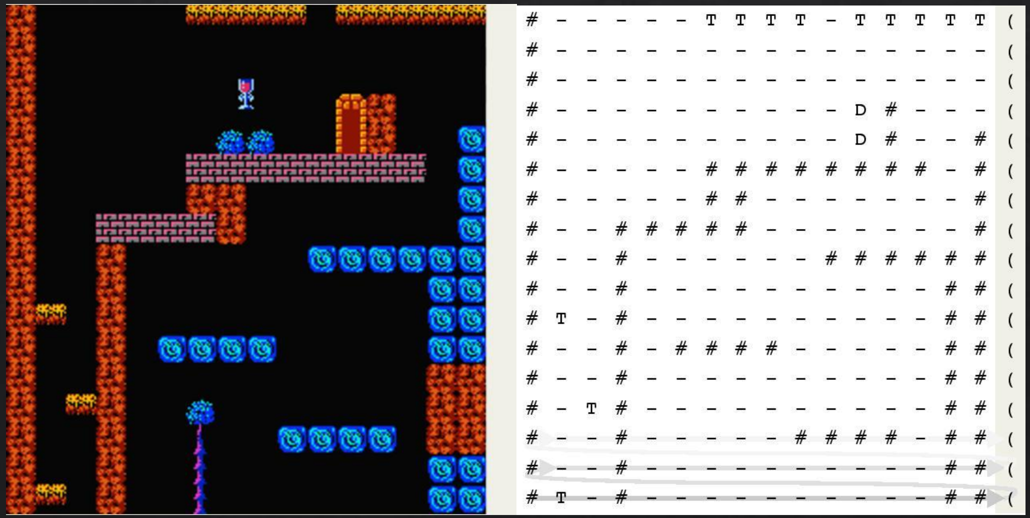


SMB Level 1-1

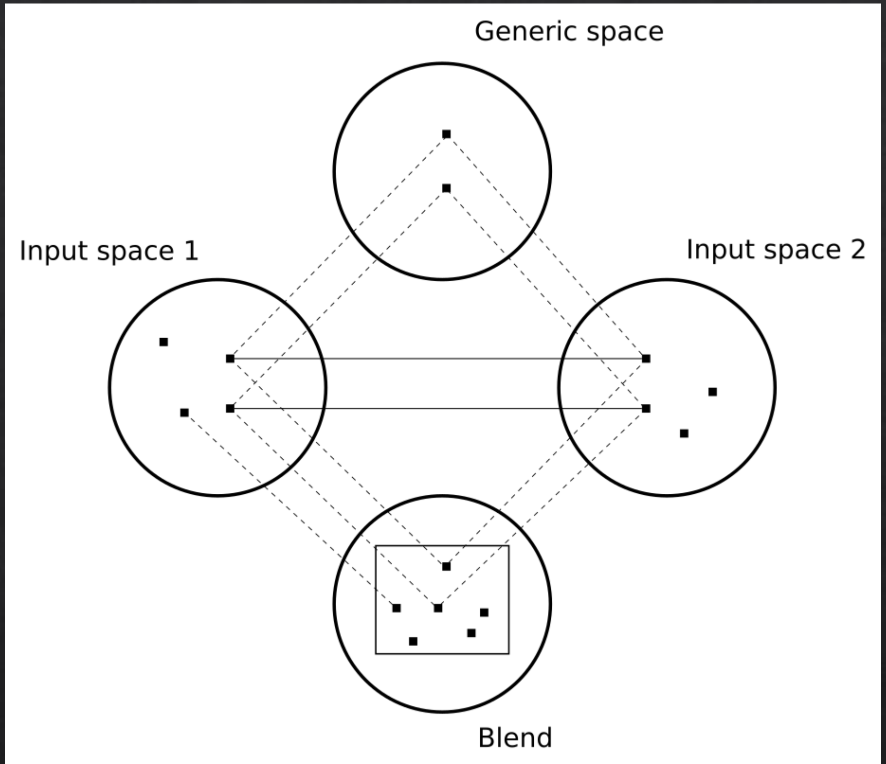
- Levels are represented as text files with each character mapping to a specific tile



KI Level 1

Blending

- Conceptual blending
  - Two input spaces
  - A generic space
  - A blend space



Blending

- Conceptual blending
  - Two input spaces
  - A generic space
  - A blend space

- Input spaces were VGLC SMB and KI corpora

```
{
    "tiles" : {
        "X" : ["solid","ground"],
        "S" : ["solid","breakable"],
        "-" : ["passable","empty"],
        "?" : ["solid","question block", "full question block"],
        "Q" : ["solid","question block", "empty question block"],
        "E" : ["enemy","damaging","hazard","moving"],
        "<" : ["solid","top-left pipe","pipe"],
        ">" : ["solid","top-right pipe","pipe"],
        "[" : ["solid","left pipe","pipe"],
        "]" : ["solid","right pipe","pipe"],
        "o" : ["coin","collectable","passable"]
    }
}
```

SMB Mapping

```
{
    "tiles" : {
        "#" : ["solid","ground"],
        "-" : ["passable","empty"],
        "D" : ["solid","openable","door"],
        "H" : ["solid","damaging","hazard"],
        "M" : ["solidtop","passable","moving","platform"],
        "T" : ["solidtop","passable","platform"]
    }
}
```

KI Mapping

Blending

- Conceptual blending
  - Two input spaces
  - A generic space
  - A blend space
- Input spaces were VGLC SMB and KI corpora
- For generic space, mapped semantically common elements to a uniform representation and preserved unique elements

```
generic_mapping = {
    # already generic
    "-": "-",

    # mario to generic
    "X": "X",
    "E": "E",
    "Q": "Q",
    "?": "?",
    "<": "<",
    ">": ">",
    "[": "[",
    "]": "]",
    "o": "o",
    "S": "S",

    # icarus to generic
    "#": "X",
    "H": "E",
    "T": "T",
    "M": "M",
    "D": "D"
    }
```

Generic Mapping

Blending

- Conceptual blending
  - Two input spaces
  - A generic space
  - A blend space
- Input spaces were VGLC SMB and KI corpora
- For generic space, mapped semantically common elements to a uniform representation and preserved unique elements
- Common elements were solid ground, enemy/hazard and the background character

```
generic_mapping = {
    # already generic
    "-": "-",

    # mario to generic
    "X": "X",
    "E": "E",
    "Q": "Q",
    "?": "?",
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    # icarus to generic
    "#": "X",
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Generic Mapping

Training on Level Data

- Used Long Short Term Memory networks (LSTMs) for training

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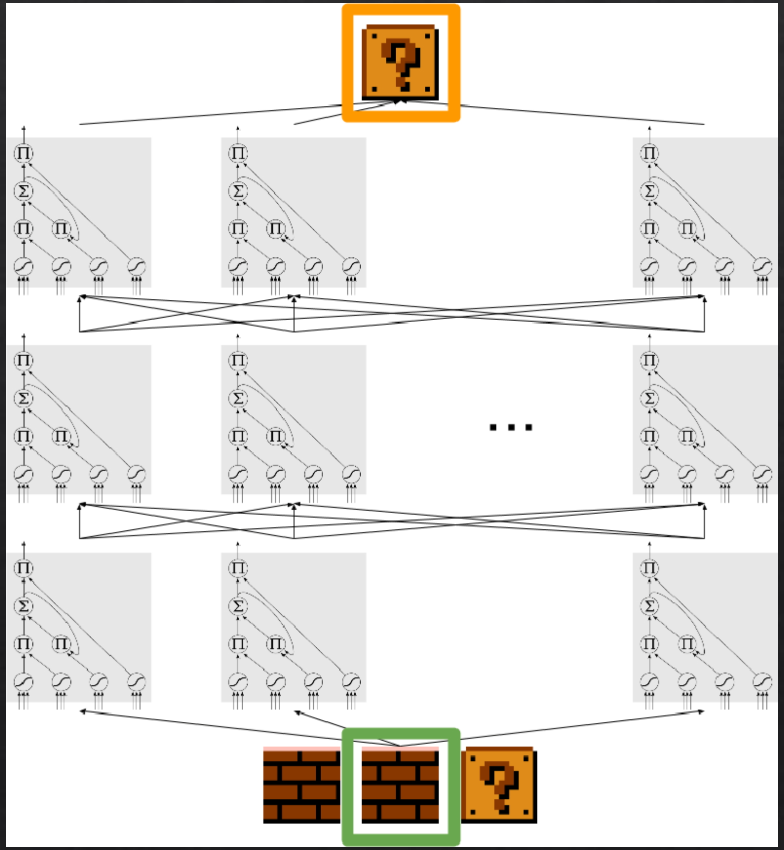
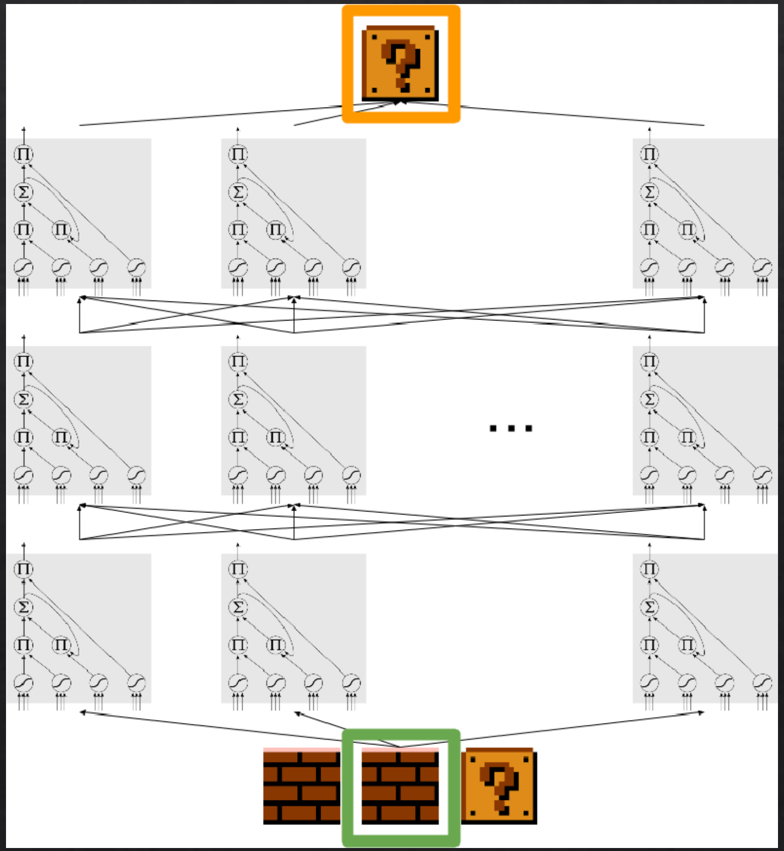


Summerville and Mateas, 2016

Training on Level Data

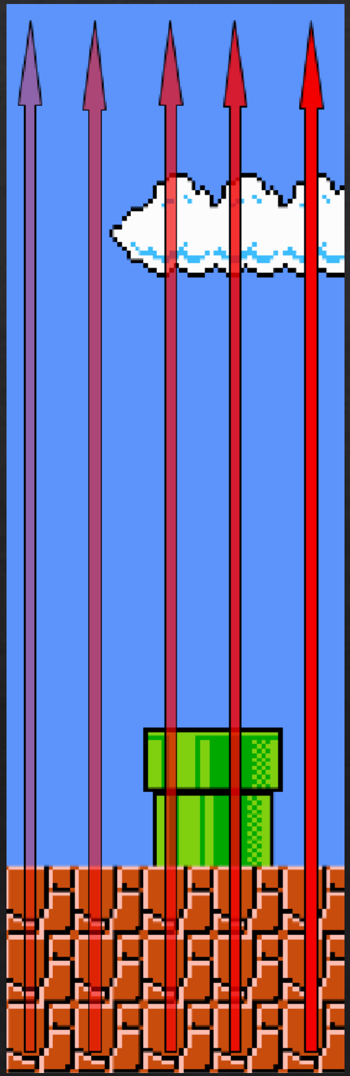
- Used Long Short Term Memory networks (LSTMs) for training
  - Predicts next item in a sequence given the sequence thus far using learned probability distribution
  - Past success in generating SMB levels



Summerville and Mateas, 2016

Training on Level Data

- Each level is a collection of sequences and each tile is a point in a sequence



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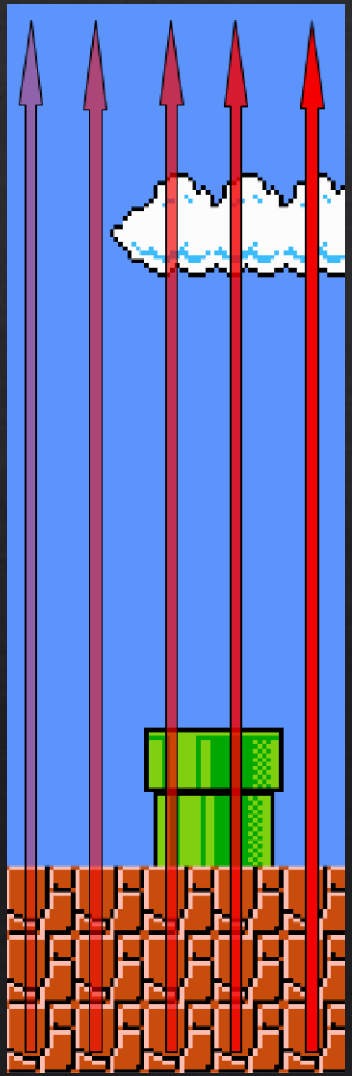
Training on Level Data

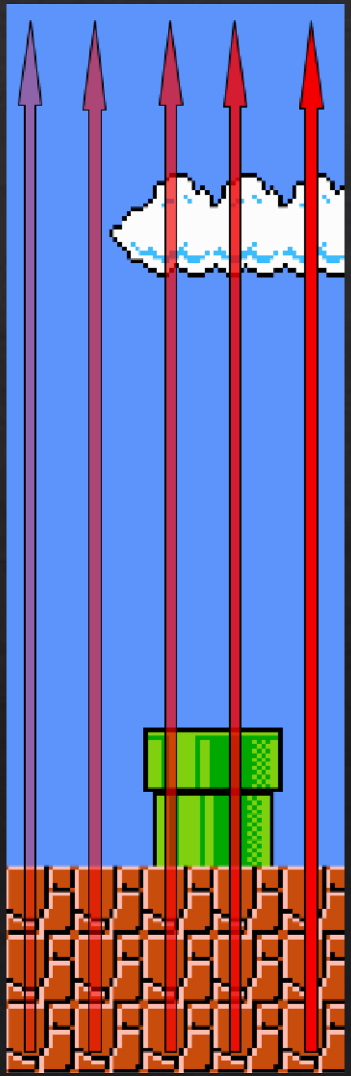
- Each level is a collection of sequences and each tile is a point in a sequence
- SMB → feed in sequences of columns from left to right
  KI → feed in sequences of rows from bottom to top



Summerville and Mateas, 2016

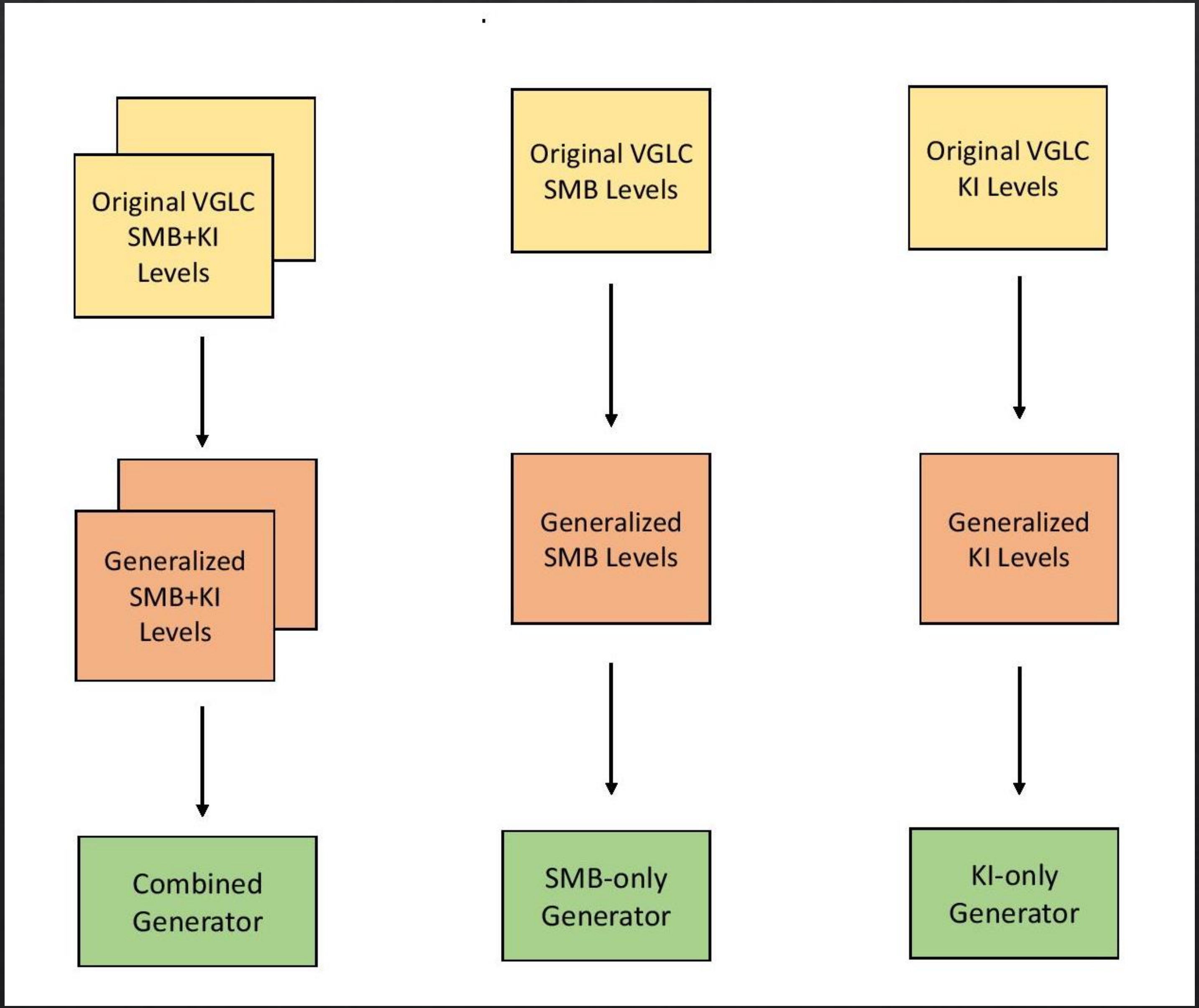
Training on Level Data

- Each level is a collection of sequences and each tile is a point in a sequence
- SMB → feed in sequences of columns from left to right
  KI → feed in sequences of rows from bottom to top
- LSTM was trained on sequences of 16 characters



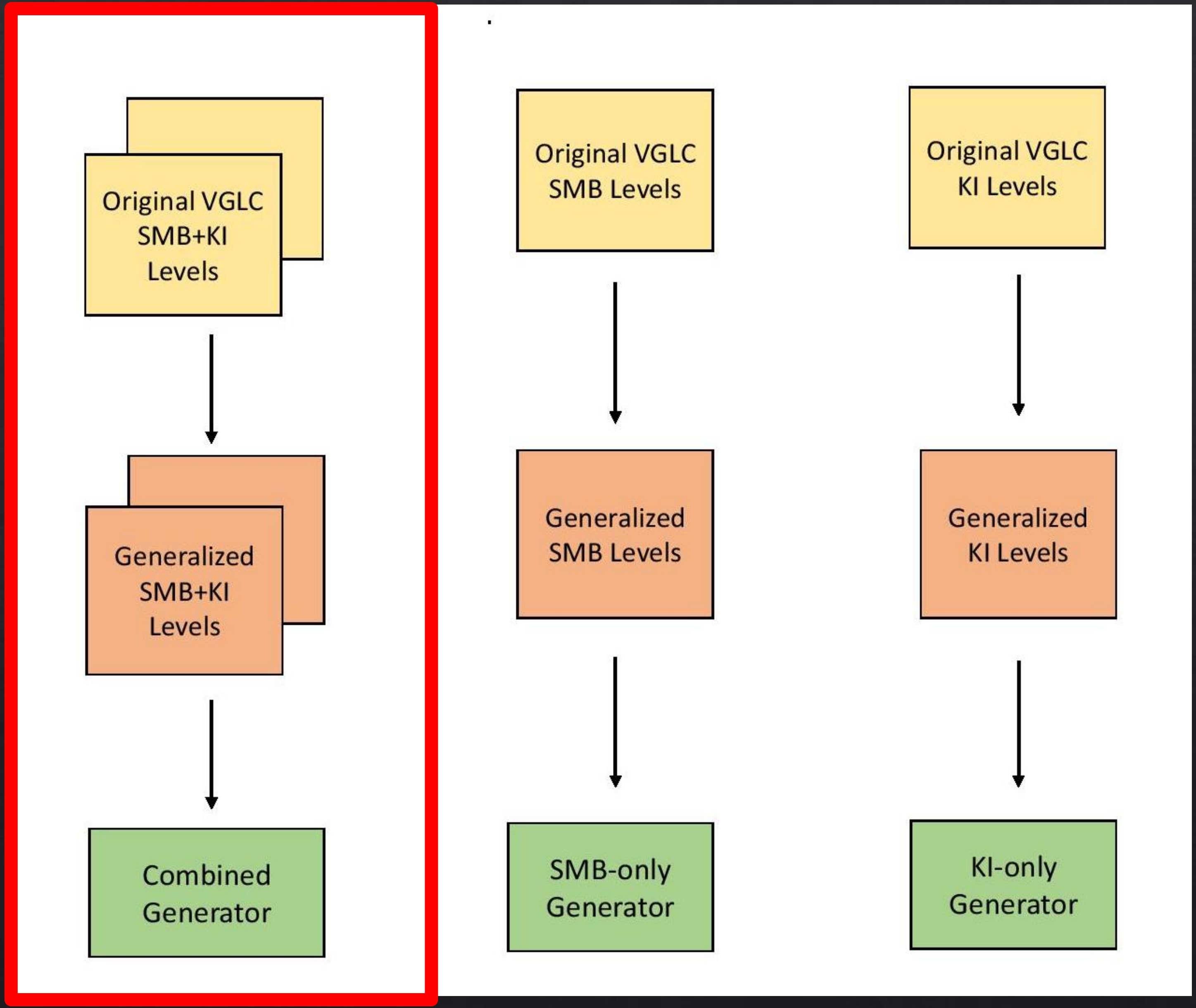
Summerville and Mateas, 2016

Models



Original VGLC SMB+KI Levels
Original VGLC SMB Levels
Original VGLC KI Levels
Generalized SMB+KI Levels
Generalized SMB Levels
Generalized KI Levels
Combined Generator
SMB-only Generator
KI-only Generator

Models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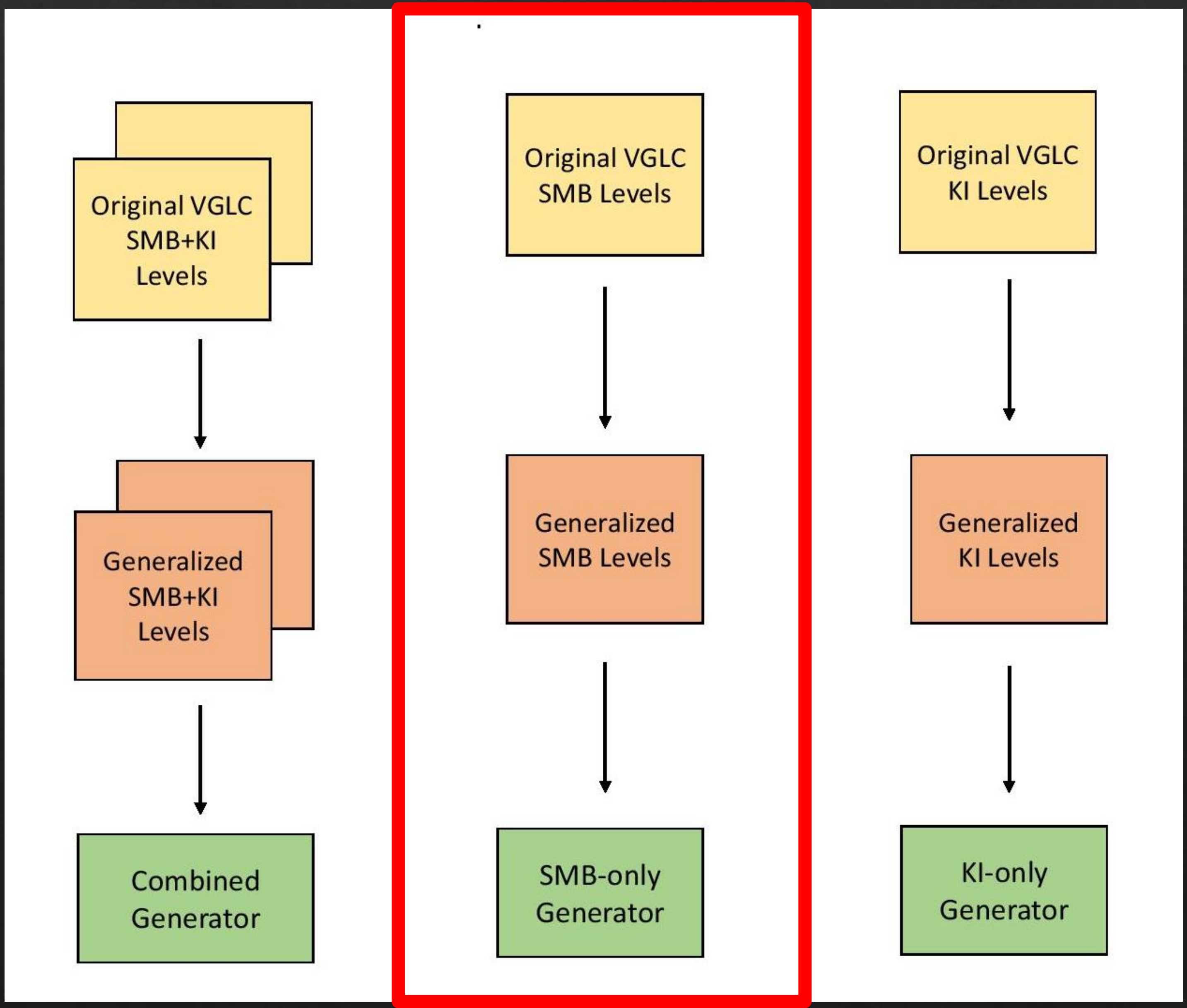

Original VGLC SMB+KI Levels
Generalized SMB+KI Levels
Combined Generator
Original VGLC SMB Levels
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SMB-only Generator
Original VGLC KI Levels
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KI-only Generator

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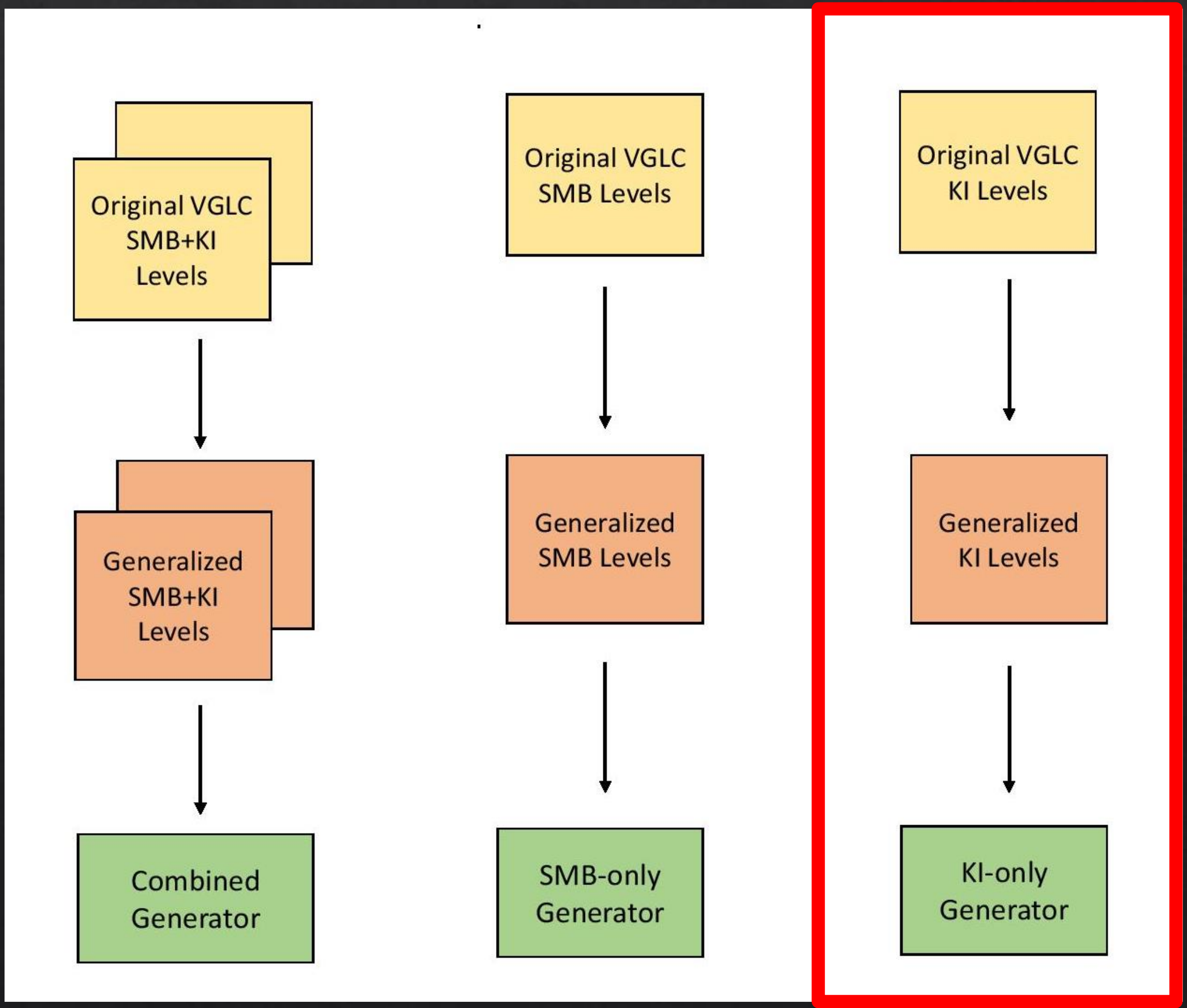

Original VGLC SMB+KI Levels
Generalized SMB+KI Levels
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Original VGLC SMB Levels
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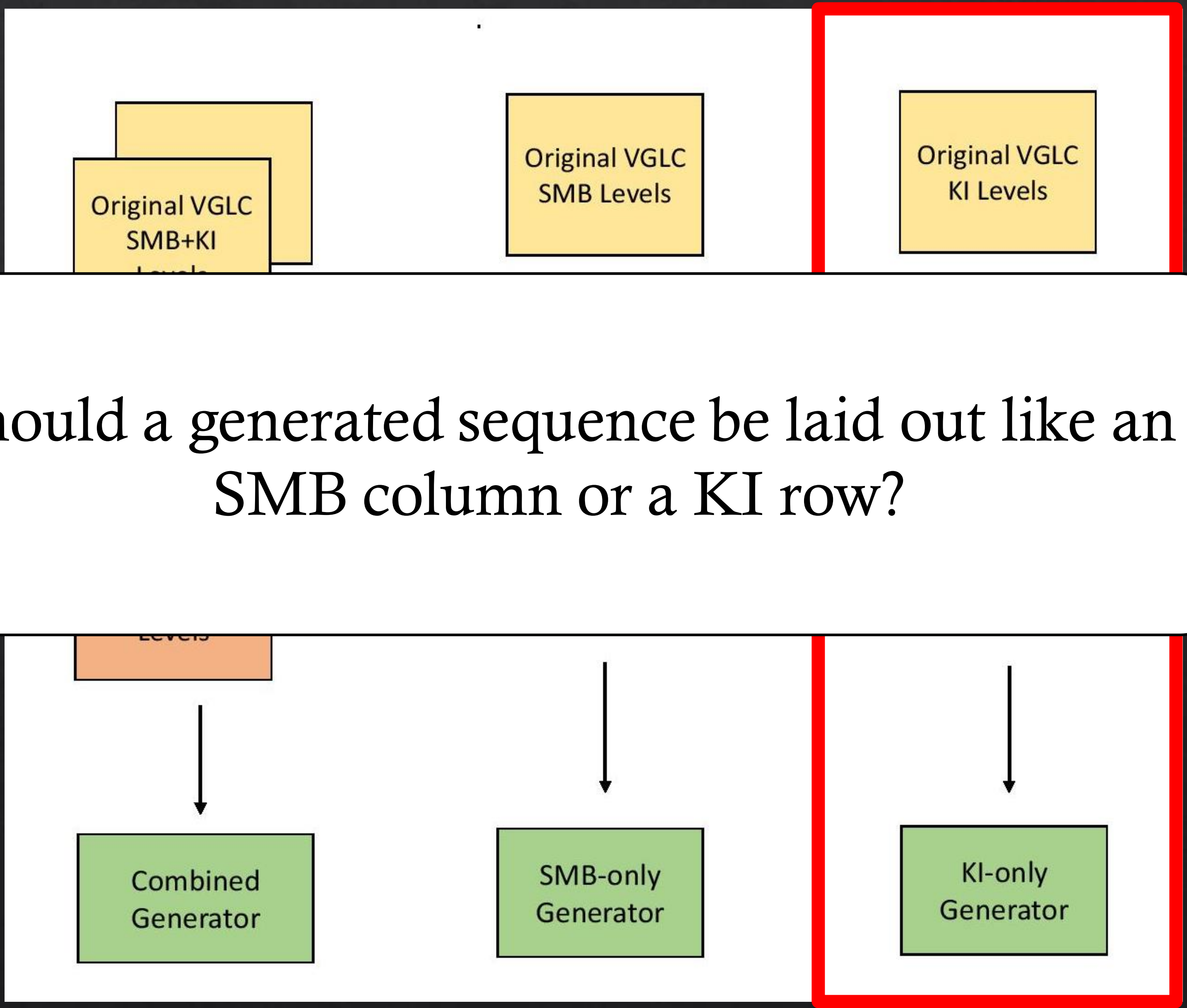
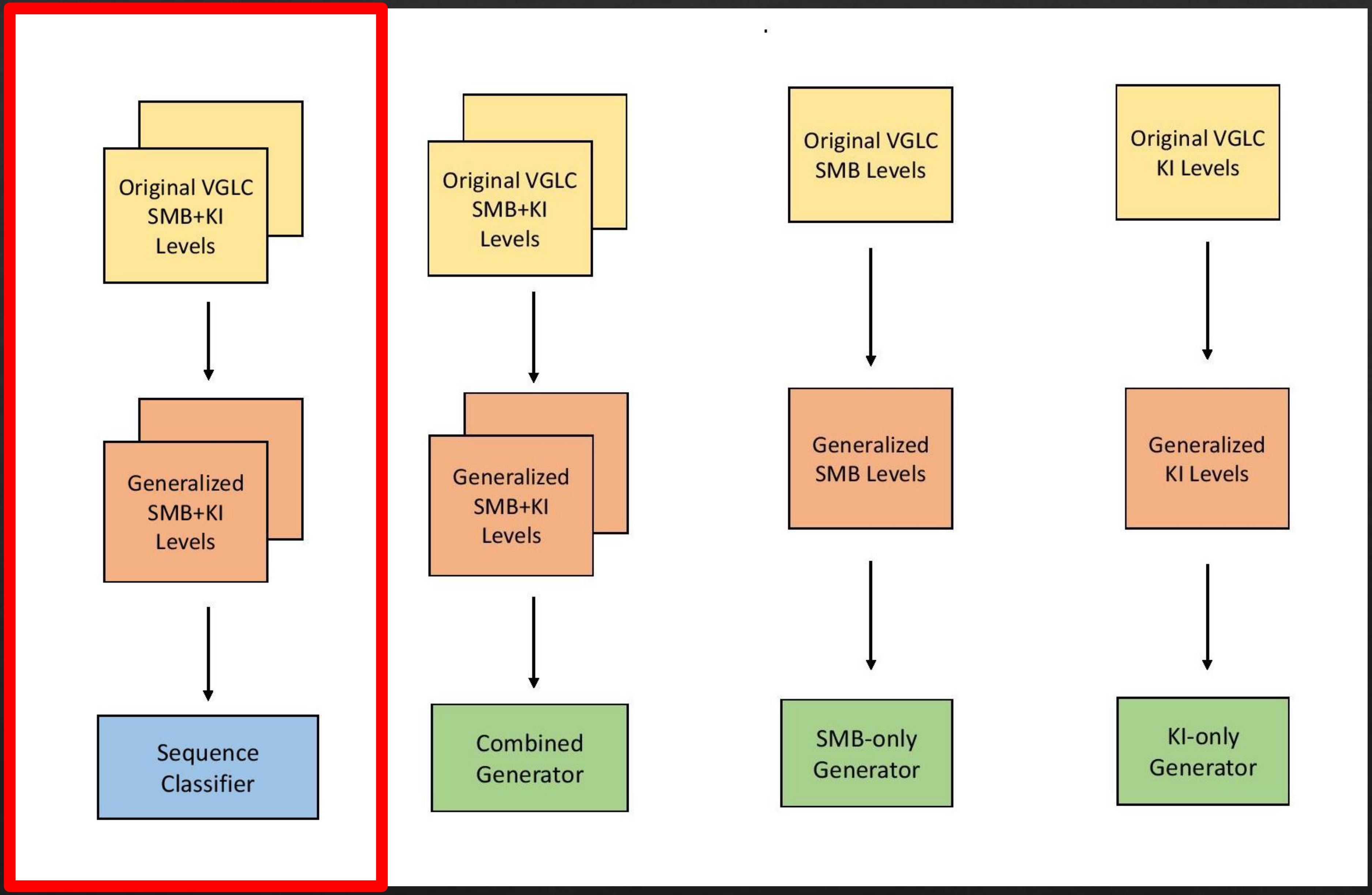


Should a generated sequence be laid out like an SMB column or a KI row?

Models



Original VGLC SMB+KI Levels
Generalized SMB+KI Levels
Sequence Classifier
Original VGLC SMB+KI Levels
Generalized SMB+KI Levels
Combined Generator
Original VGLC SMB Levels
Generalized SMB Levels
SMB-only Generator
Original VGLC KI Levels
Generalized KI Levels
KI-only Generator

Level Generation

- Forward an initial level seed through the LSTM which repeatedly predicts next most likely character given previous characters in the string until full level is generated

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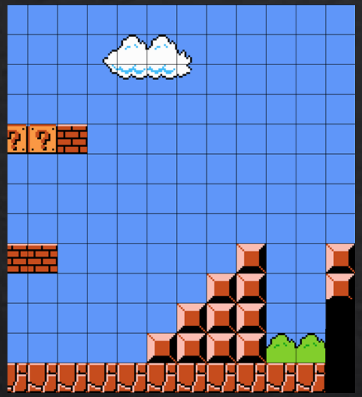

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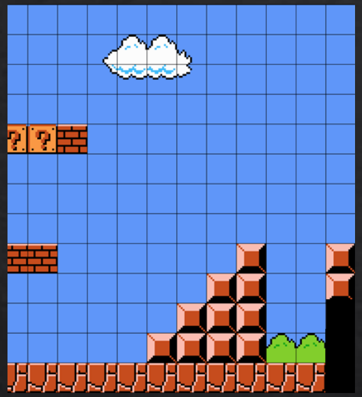

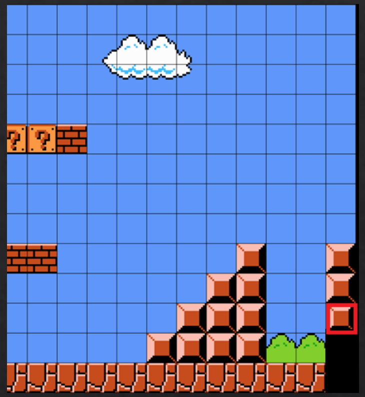

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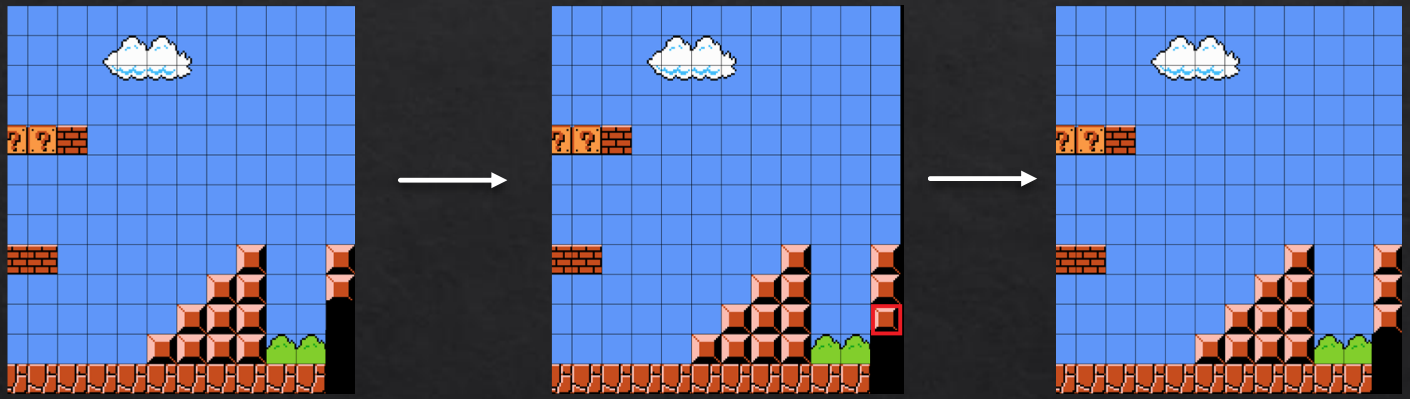

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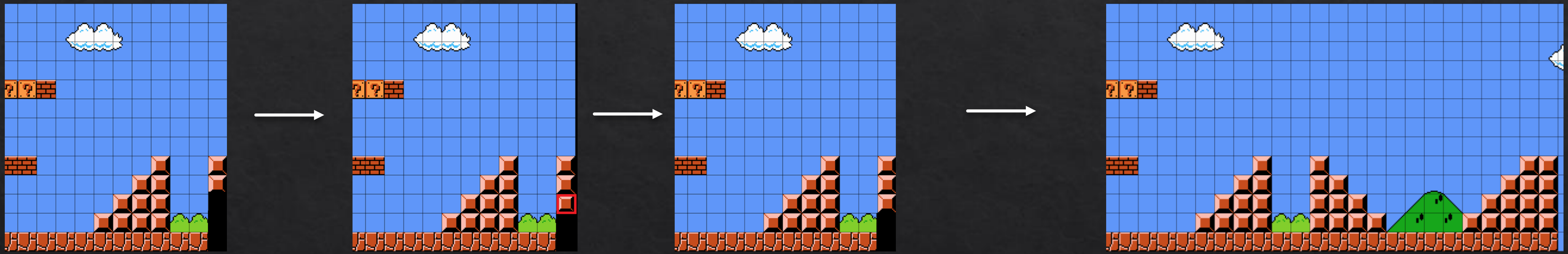

Credit: Adam Geitgey, Medium

Level Generation

- Three generators

Level Generation

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  - Unweighted generator UW that used model trained on combined dataset

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- For UW, generated levels consisting of 200 sequences

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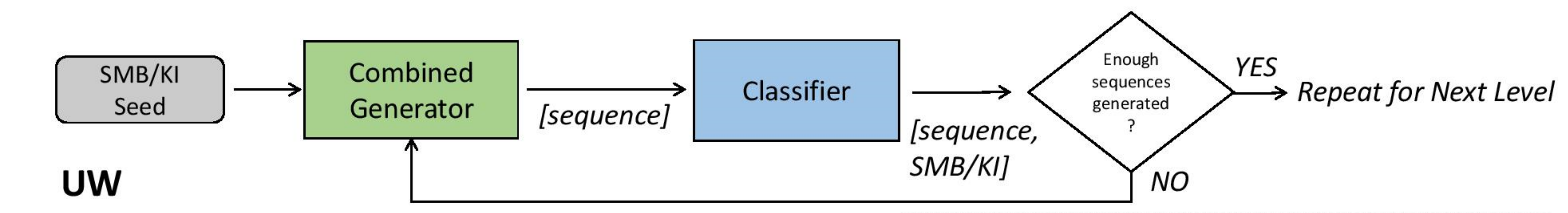
  - Weighted generator WC that used model trained on combined dataset
  - Weighted generator WS that used the models trained separately i.e. consisted of an SMB-only sub generator and a KI-only sub generator

- For UW, generated levels consisting of 200 sequences

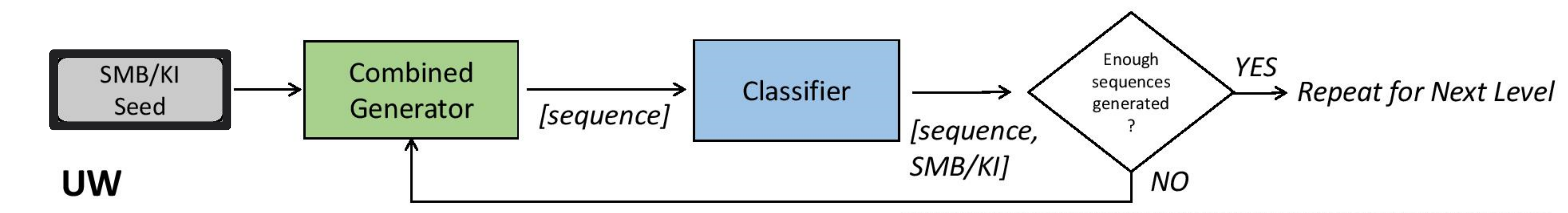
- For both WC and WS, generated levels consisting of 10 segments of 20 sequences each

Level Generation



Unweighted Generator

Level Generation



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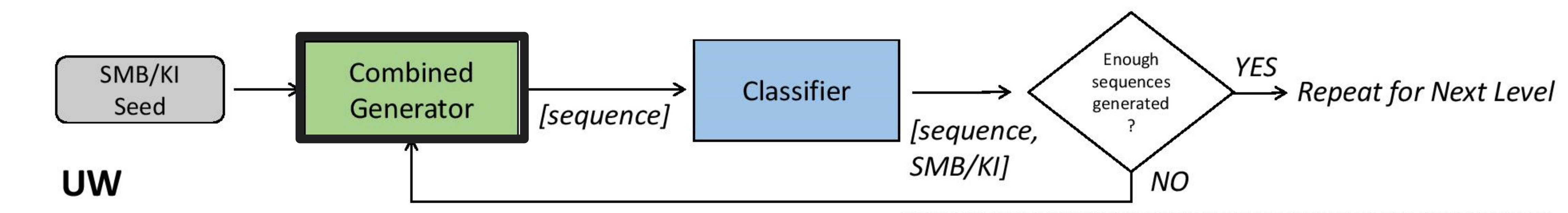

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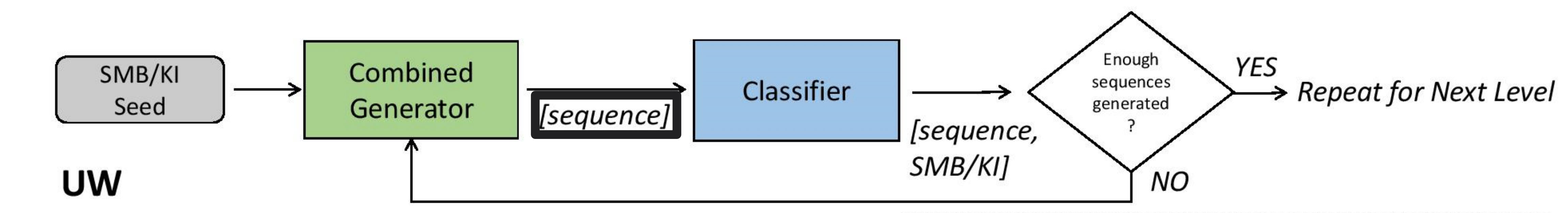

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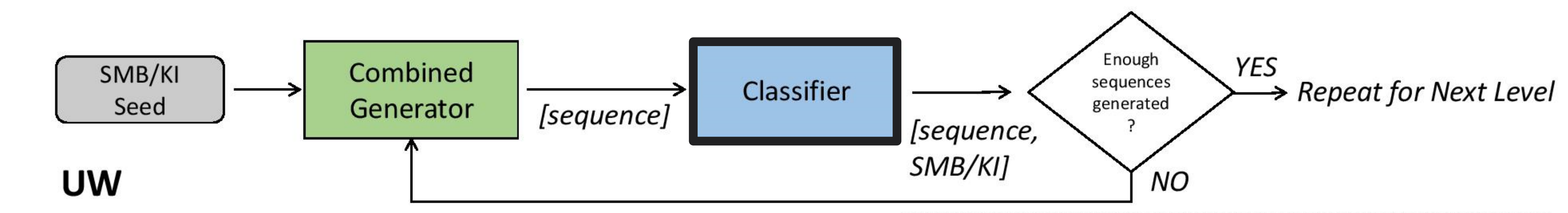
Level Generation



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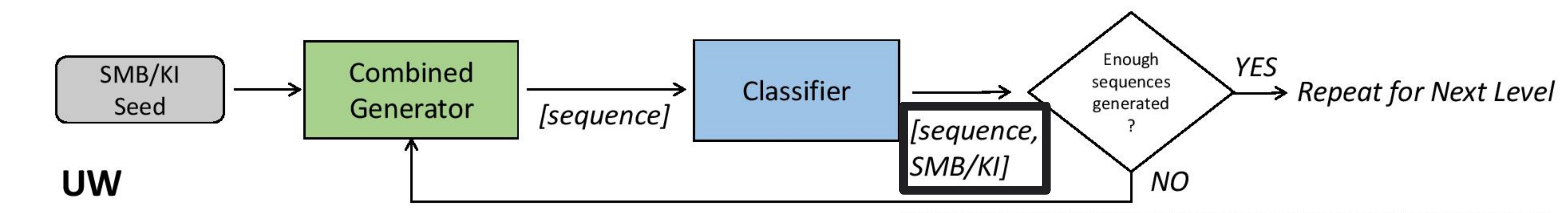

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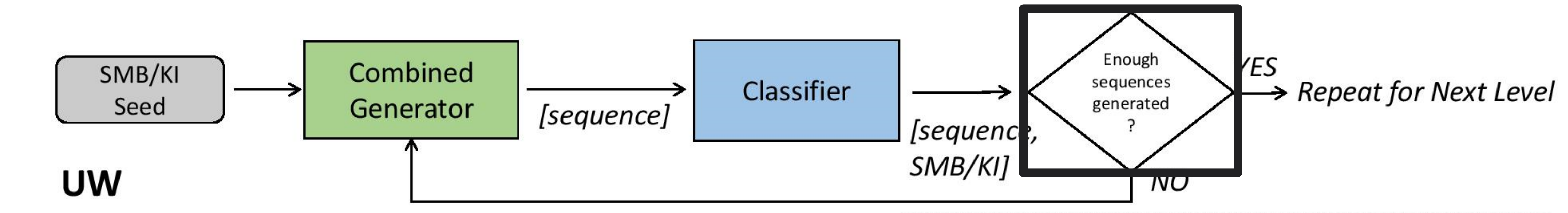
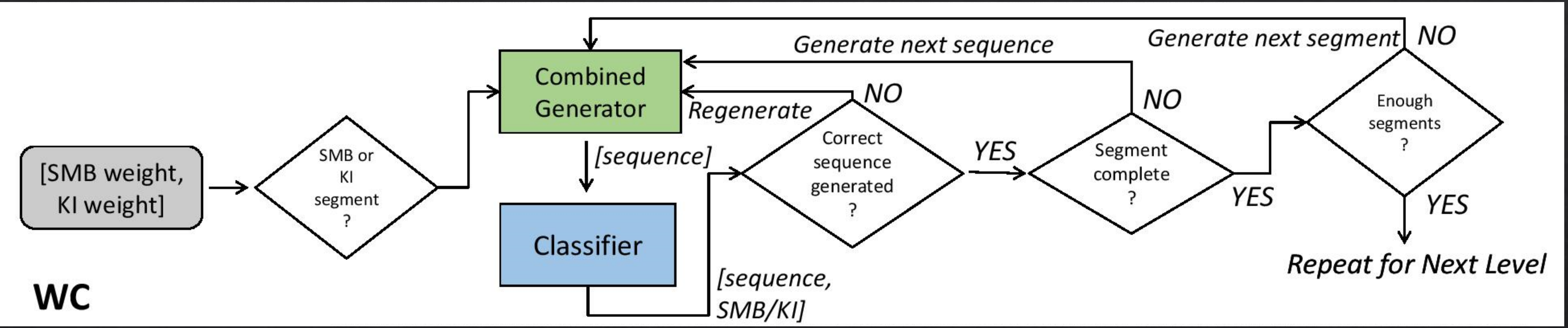


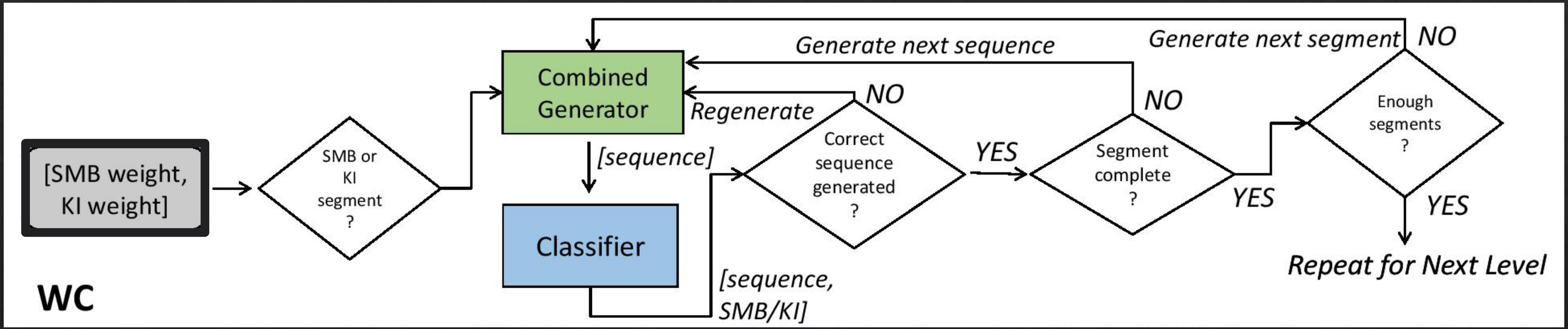
Unweighted Generator

Level Generation



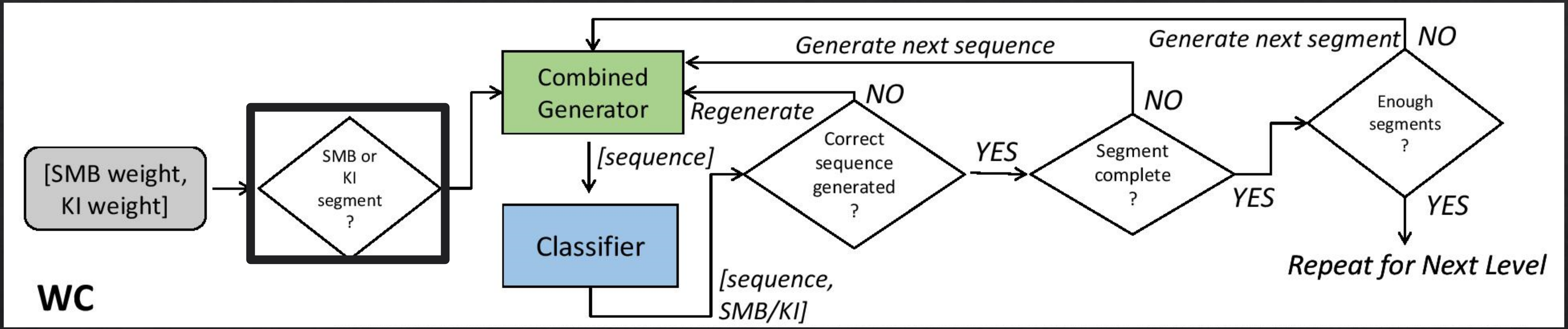
Weighted Generator 1

Level Generation



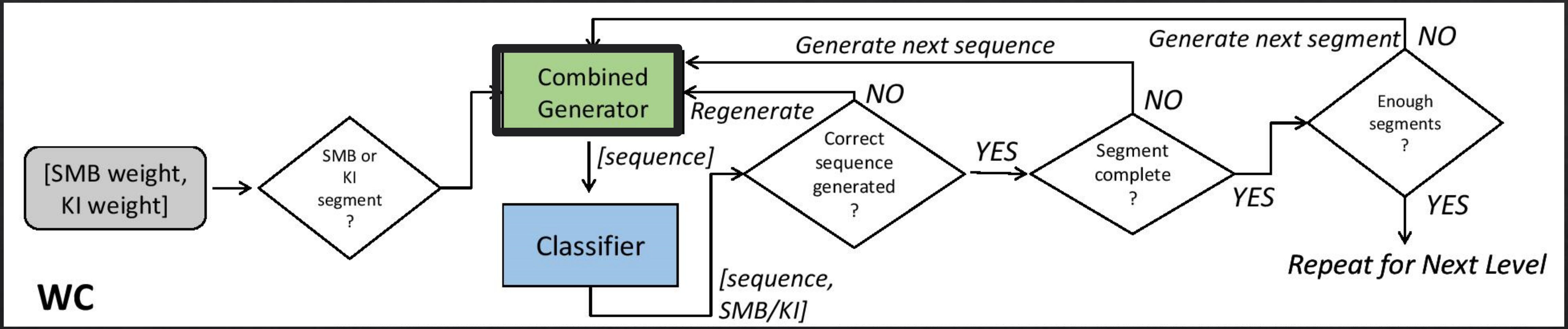
Weighted Generator 1

Level Generation



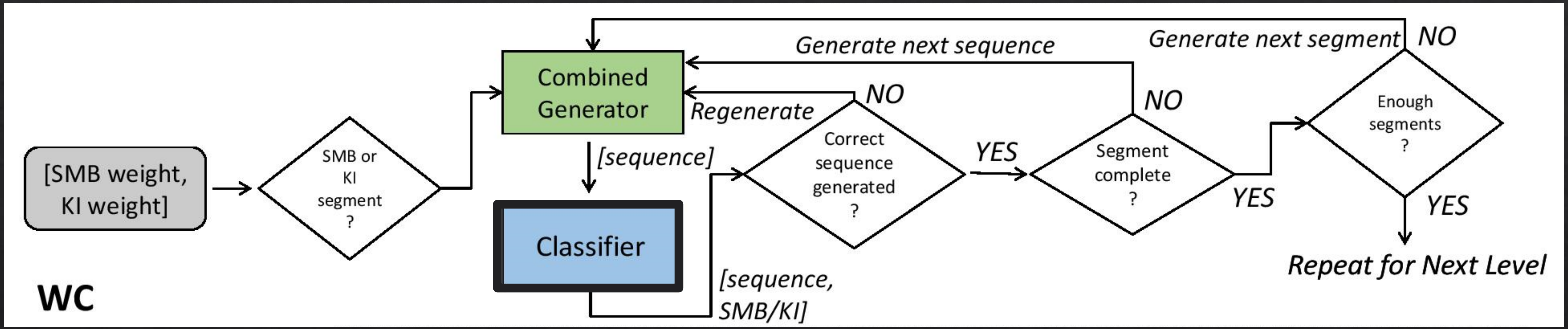
Weighted Generator 1

Level Generation



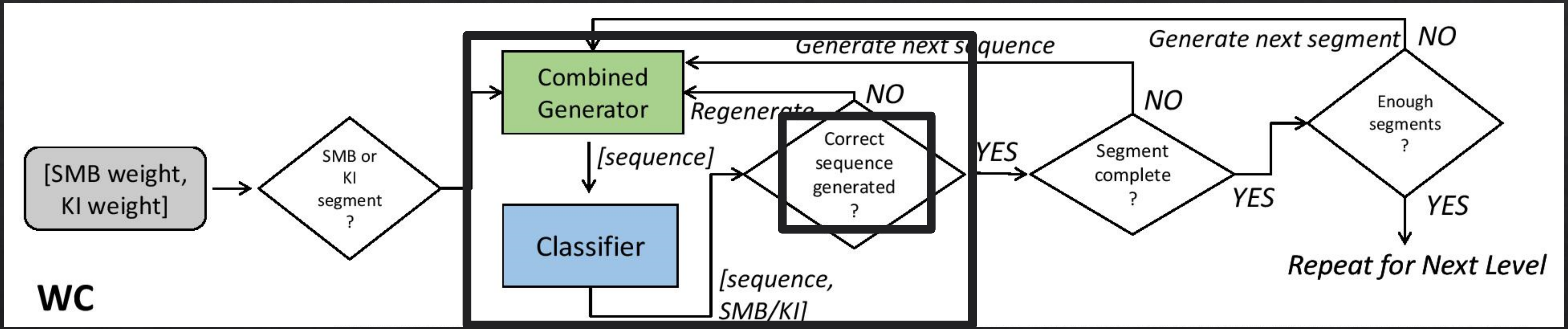
Weighted Generator 1

Level Generation



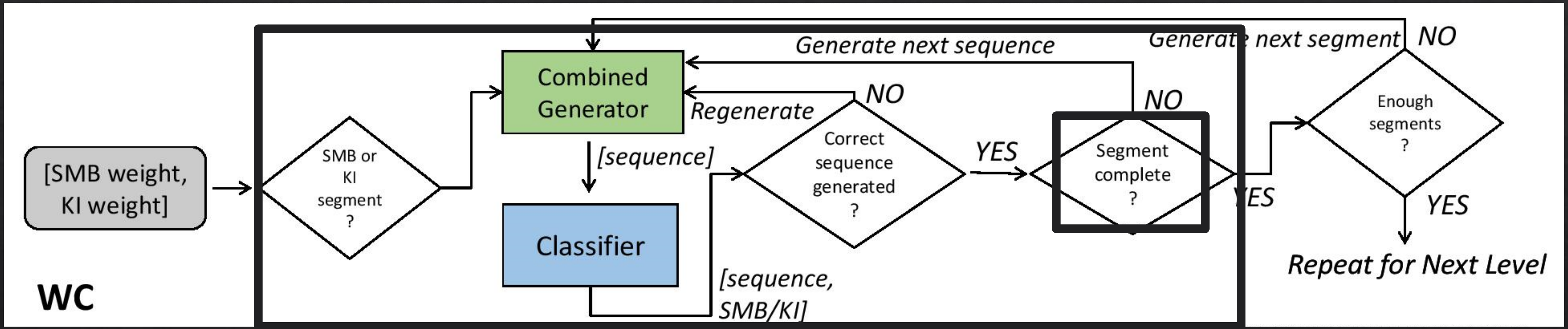
Weighted Generator 1

Level Generation



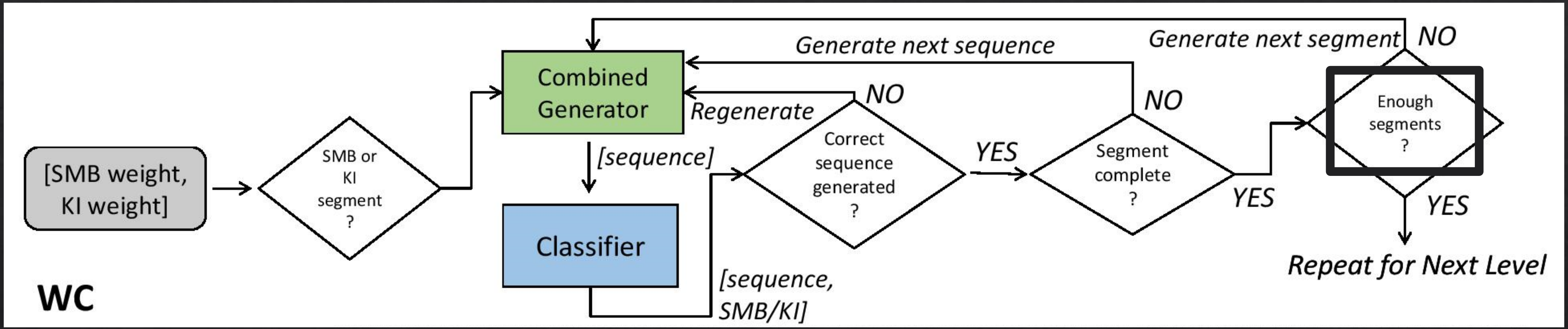
Weighted Generator 1

Level Generation



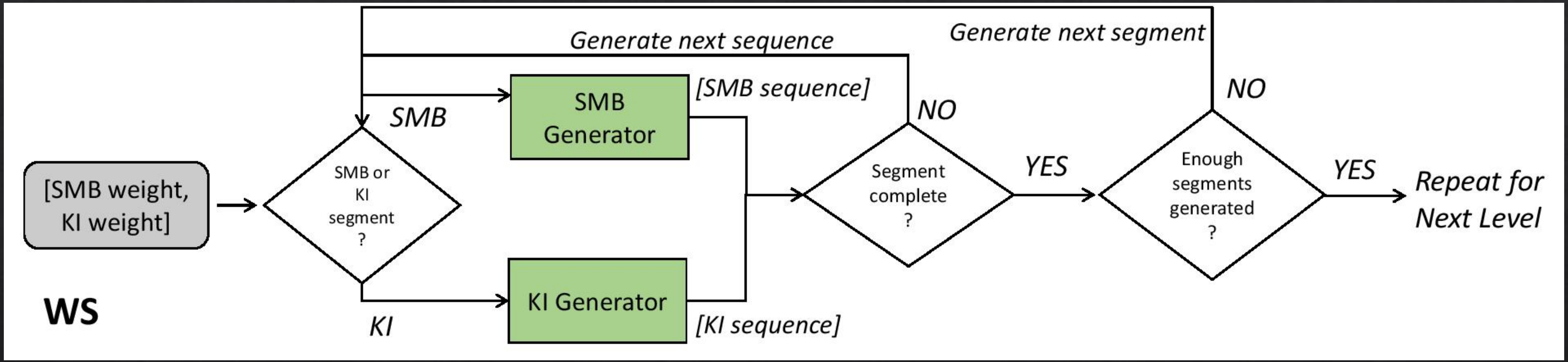
Weighted Generator 1

Level Generation



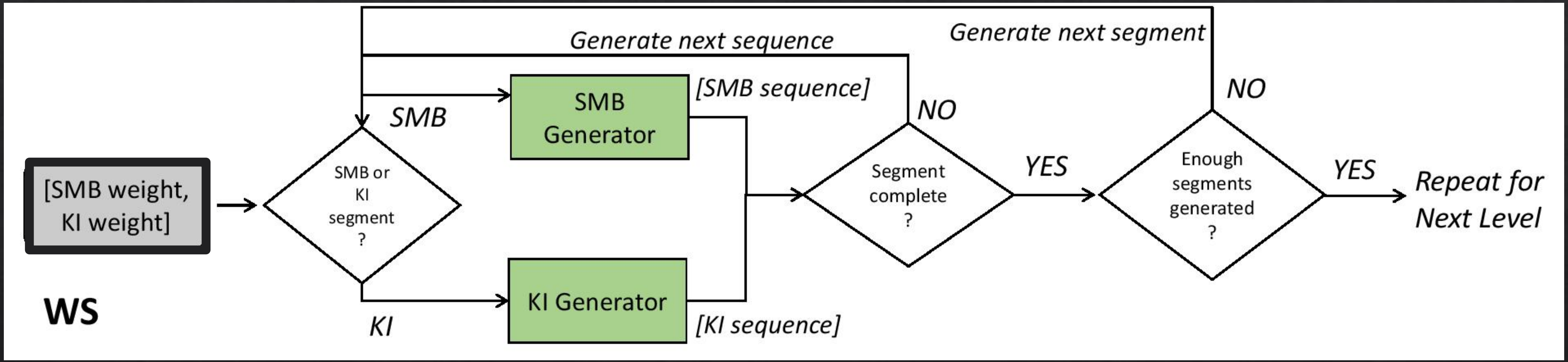
Weighted Generator 1

Level Generation



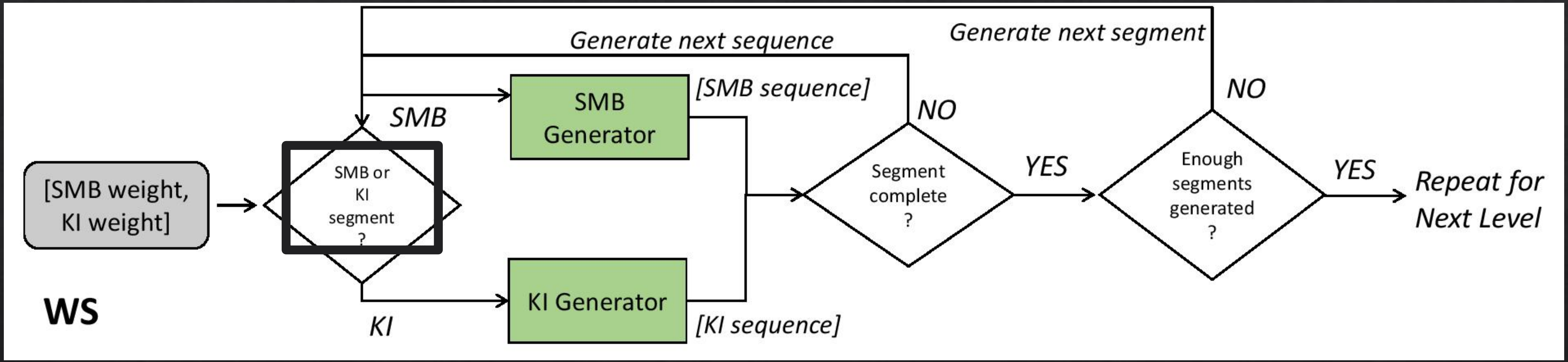
Weighted Generator 2

Level Generation



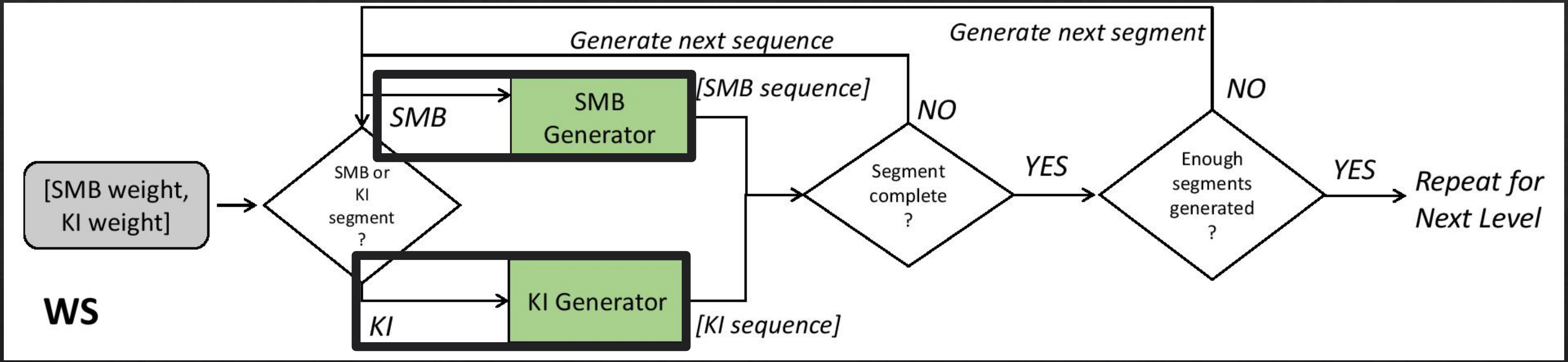
Weighted Generator 2

Level Generation



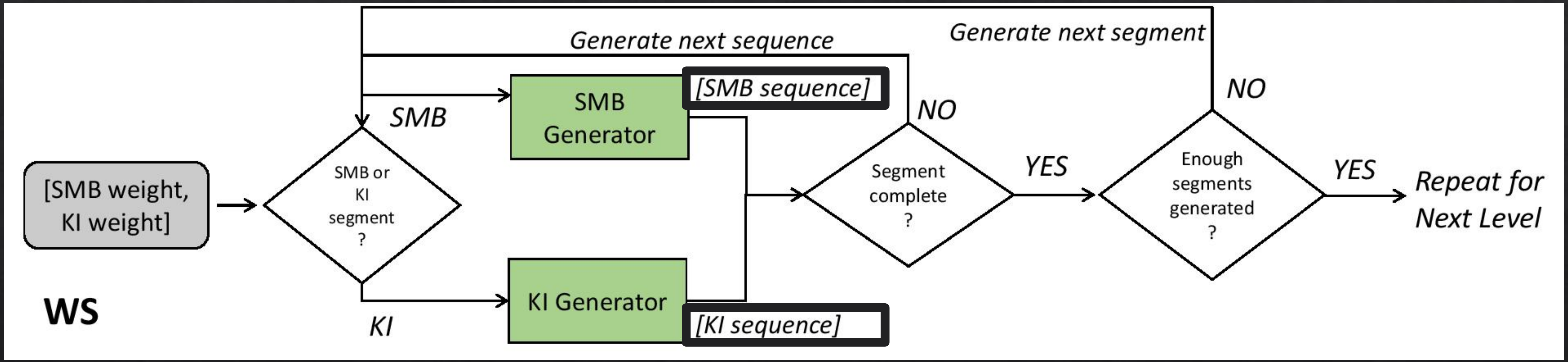
Weighted Generator 2

Level Generation



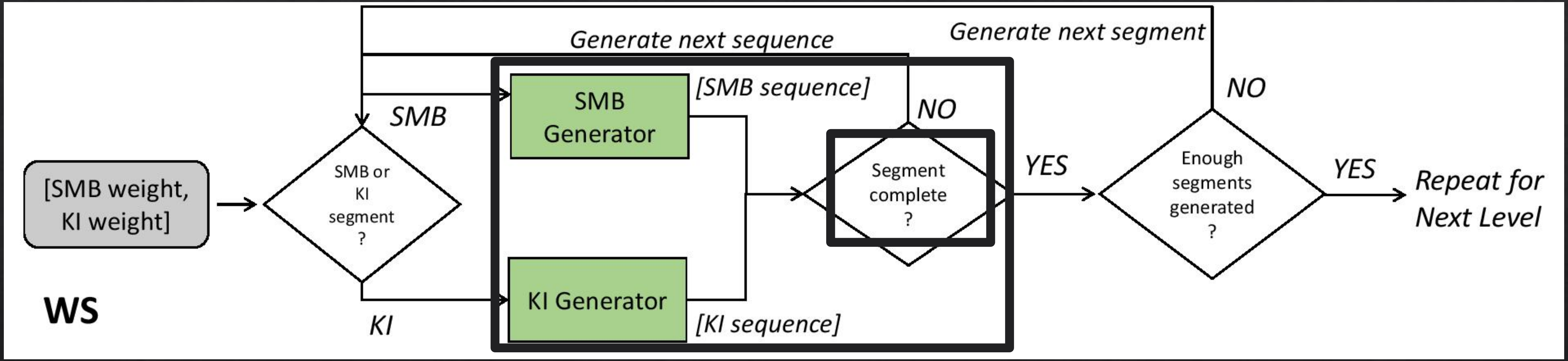
Weighted Generator 2

Level Generation



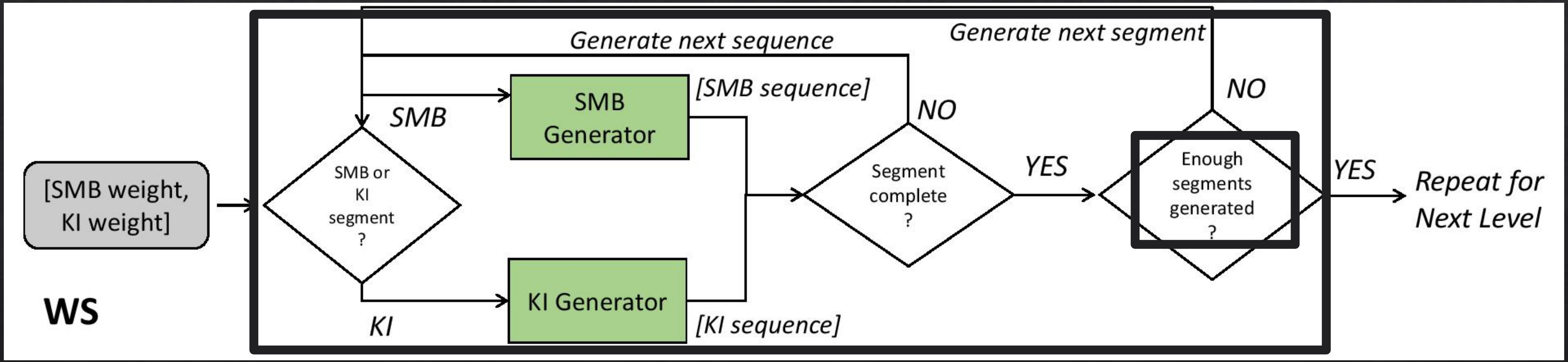
Weighted Generator 2

Level Generation



Weighted Generator 2

Level Generation



Weighted Generator 2

Layout

- Generated sequences are laid out using a basic algorithm

Layout

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- Three cases:
  - Column after column/Row after row
  - Row after column
  - Column after row

Layout

- Generated sequences are laid out using a basic algorithm

- Three cases:
  - Column after column/Row after row
    - Stack one after another
  - Row after column
  - Column after row

Layout

- Generated sequences are laid out using a basic algorithm
- Three cases:
  - Column after column/Row after row
  - Row after column
    - Align row with topmost point of column on which player can stand
  - Column after row

Layout

- Generated sequences are laid out using a basic algorithm

- Three cases:
  - Column after column/Row after row
  - Row after column
  - Column after row
    - Align topmost point of column on which player can stand with the row

Layout

- Generated sequences are laid out using a basic algorithm

- Three cases:
  - Column after column/Row after row
  - Row after column
  - Column after row

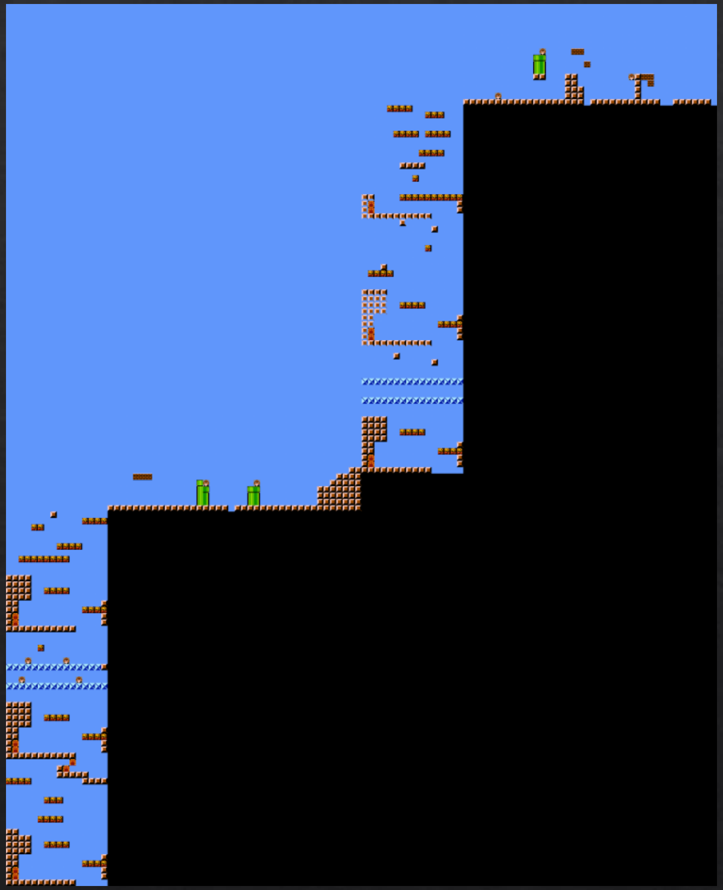
- Layout function separate from generation

Example Levels

Unweighted Generation

Example Levels

WC

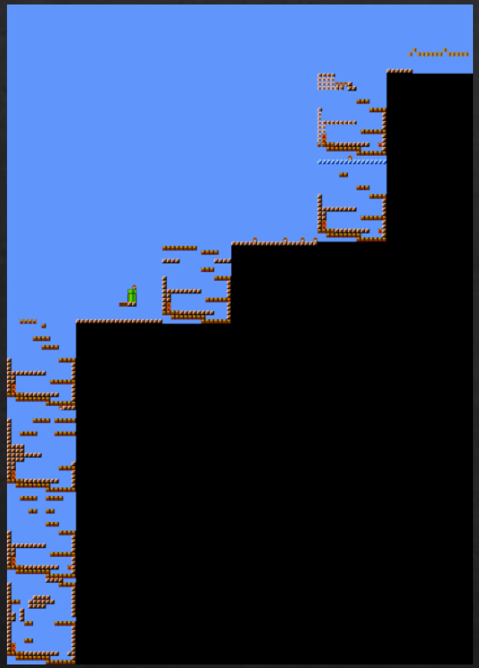


WS

Weighted Generation (0.5, 0.5)

Weighted Generation

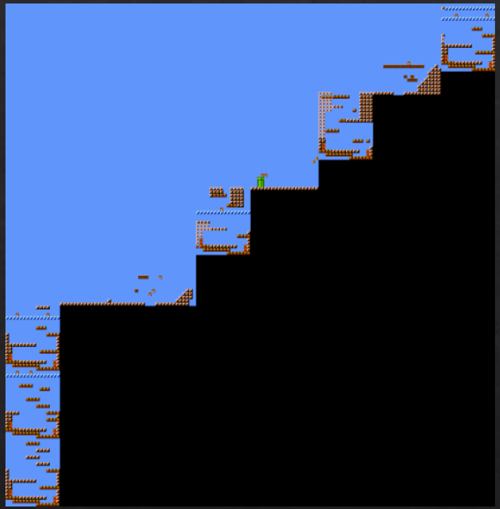
Weighted Generation



(SMB=0.2, KI=0.8)

Weighted Generation

(SMB=0.2, KI=0.8)

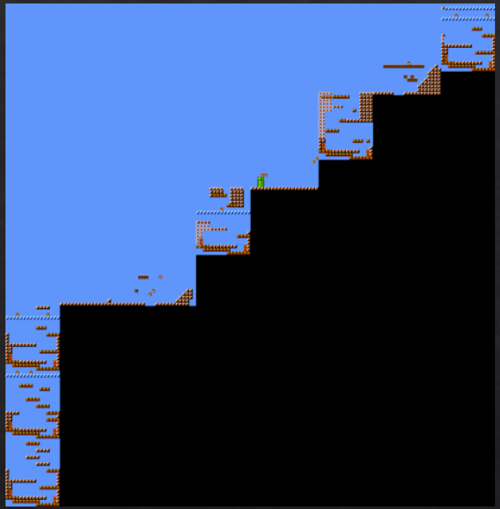


(SMB=0.4, KI=0.6)

Weighted Generation

(SMB=0.5, KI=0.5)

(SMB=0.2, KI=0.8)

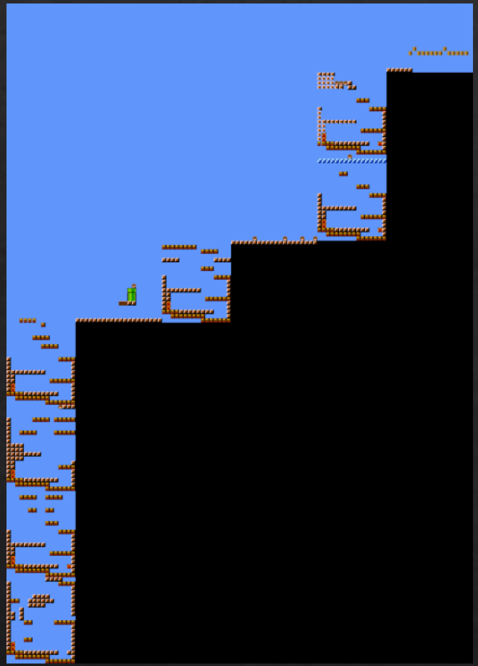


(SMB=0.4, KI=0.6)

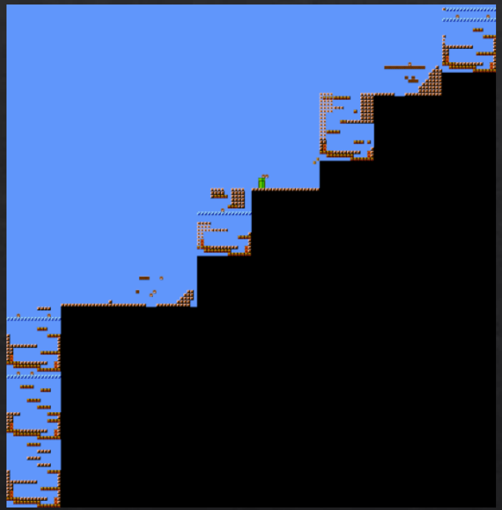
Weighted Generation

(SMB=0.5, KI=0.5)

(SMB=0.6, KI=0.4)



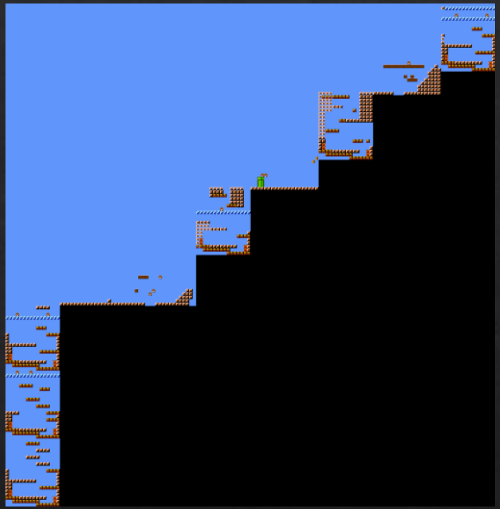
(SMB=0.2, KI=0.8)



(SMB=0.4, KI=0.6)

Weighted Generation

(SMB=0.2, KI=0.8)



(SMB=0.4, KI=0.6)

(SMB=0.5, KI=0.5)

(SMB=0.6, KI=0.4)

(SMB=0.8, KI=0.2)

Measures

Measures

$$Leniency = \frac{-(\#\ Enemy\ Sprites + (0.5 \ast \#\ Gaps))}{\#\ Sequences\ in\ Level}$$

Measures

$$Leniency$$

$$\frac{-(\#\ Enemy\ Sprites + (0.5\ * \#\ Gaps))}{\#\ Sequences\ in\ Level}$$

$$Density$$

$$\frac{(\#\ Ground + \#\ Platform)}{\#\ Sequences\ in\ Level}$$

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$$Sequence\ Density$$
$$\frac{\#\ Sequences\ in\ level\ in\ training\ set}{\#\ Sequences\ in\ Level}$$

$$Sequence\ Variation$$
$$\frac{\#\ Unique\ Sequences\ in\ level\ in\ training\ set}{\#\ Sequences\ in\ Level}$$

Measures

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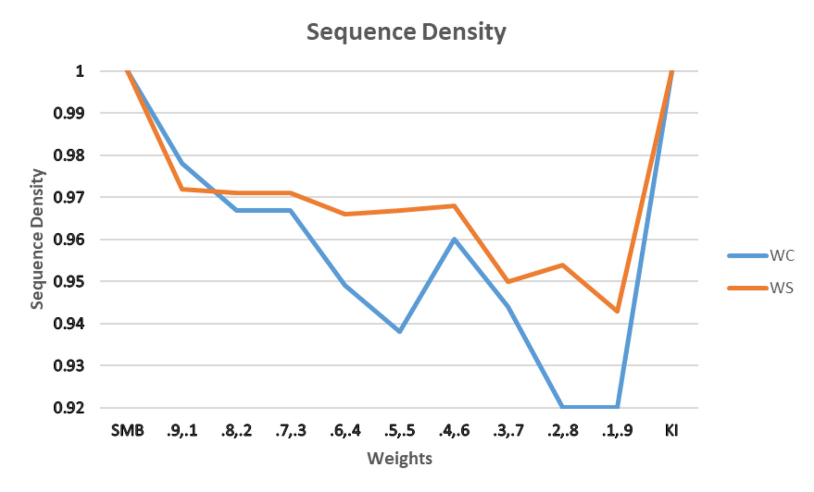
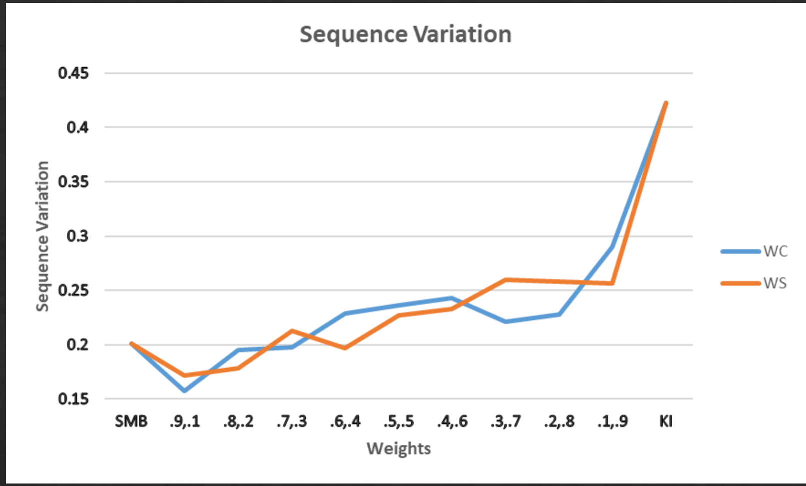
$$Sequence\ Variation = \frac{\#\ Unique\ Sequences\ in\ level\ in\ training\ set}{\#\ Sequences\ in\ Level}$$

$$Aspect\ Ratio = \frac{\#\ Rows\ in\ Level}{\#\ Columns\ in\ Level}$$

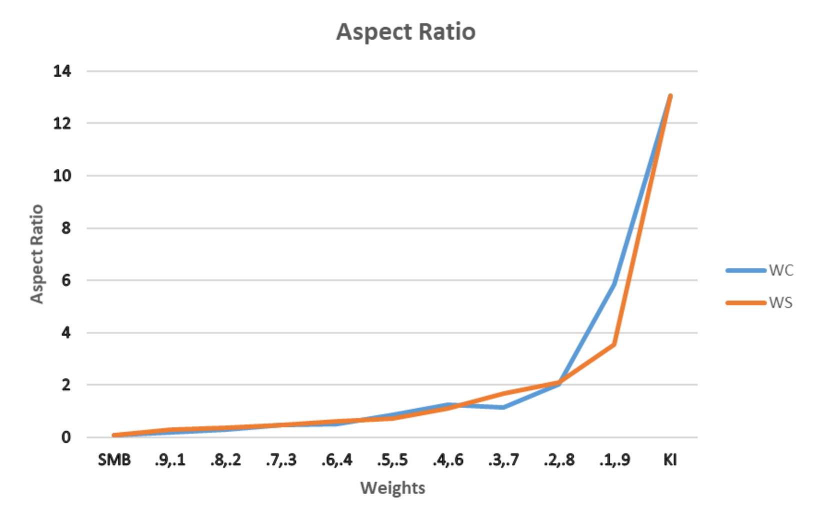
Results



Sequence Density

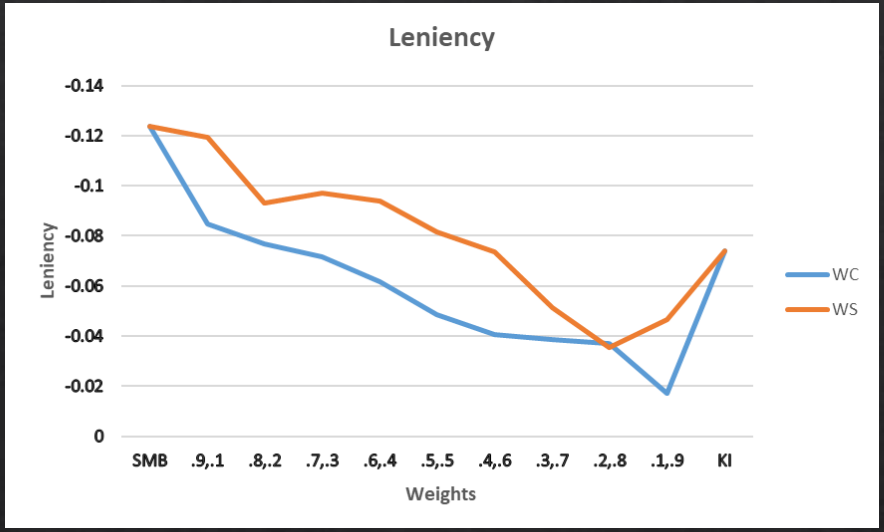


Sequence Variation

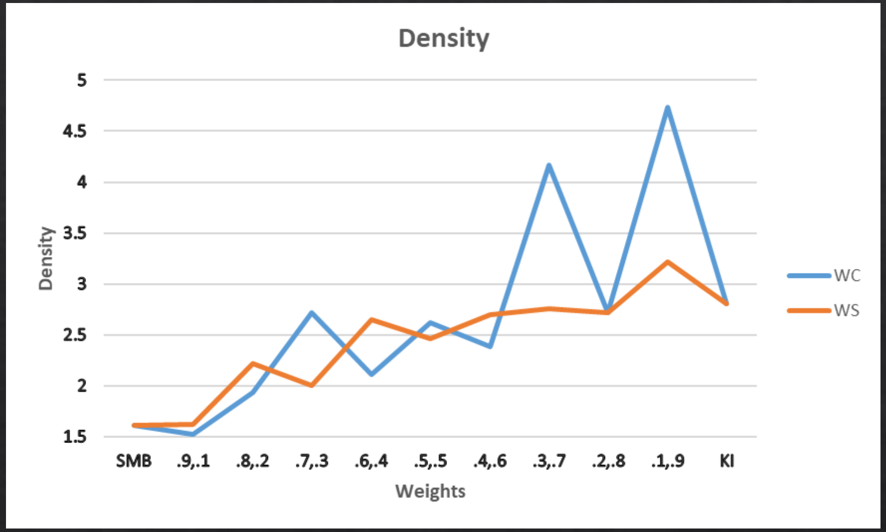


Aspect Ratio

Results



Leniency



Density

Discussion

- Altering weights impacted the type of levels generated and roughly interpolated between SMB and KI

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- Altering weights impacted the type of levels generated and roughly interpolated between SMB and KI
- Possible to generate levels that are a mix of levels from 2 games but can also be made to be more like one than the other
- Deviations suggest that these methods can also produce some novelty

Future Work

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- No playability tests were run nor playability/path-based information used in training, thus levels are currently not completable; using an agent to carve-out a path post-generation or encoding path info into training corpus could help

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Future Work

- No playability tests were run nor playability/path-based information used in training, thus levels are currently not completable; using an agent to carve-out a path post-generation or encoding path info into training corpus could help
- Blended levels necessitate blended mechanics to be fully playable
- Other techniques such as evolutionary algorithms to evolve game mechanics

Contact

Anurag Sarkar
Northeastern University
sarkar.an@husky.neu.edu