Procedural Content Generation: Player Models

2019-11-04

OOB

- HW 7: SMB level generation
- Trajectory update
  - Intro: Game AI vs Academic AI; Graphs + Search
  - Taking action in a game:
    - Basic Physical Acts: Paths, Movement, Steering
    - Decisions: FSMs, D&B Trees, RBS, Plan, Meta {BB, Fuzzy}
  - **Creating & Adapting content (sans NPC decisions):**
    - **PCG, Player Modeling**
  - Adapting NPC decisions (& content) → Learning
  - Support Technologies; Design GAI; AI Based Games; Special topics (e.g. narrative); Revisits

PCG as Local Search

1. What "search" is happening? Do we seek a path to goal?
2. What is the state space? How many states do we save?
3. How memory efficient is this search?
4. Hill climbing: (PCG as parameter search part 1)
    1. L____ search
    2. What is the "landscape"?
    3. Need a function that maps p____ to f_____
5. GAs: (PCG as parameter search part 2)
    1. Good in ______ domains, where _D.K.__ is scarce or hard to encode
    2. Can also be used for ____ search
    3. Also needs a f_____ function (maps c____ to f_____)
6. Other local search techniques
    1. Gradient Descent
    2. Simulated annealing
    3. Local beam
    4. Tabu
    5. Ant Colony Optimization

PCG and GAs

1. Create a random set of *n* chromosomes (**population**)
2. Assign a fitness score to each chromosome (**fitness function**)
3. Remove the *m%* (*m* < 100) worst chromosomes
4. Cycle through remaining pairs of chromosomes and *cross-over* (with some probability)
5. Randomly mutate (during?) cross-over (with some probability)
6. Reduce new population to size *n*
7. Repeat steps 2-6 until [stepwise improvement diminishes || one individual is fit enough || # generations reached]

- Tuning parameters
  - Population size
  - Number of generations
  - Fitness function
  - Representation
  - Mutation rate
  - Crossover operations
  - Selection procedure
  - Number of solutions to keep

Search-based approach to PCG

- Core components
  - Search algorithm
  - Content representation/encoding
    - defines (and thus also limits) what content can be generated, and determines whether effective search is possible
  - Evaluation function(s)
    - f(artifact) → number indicating quality

- Very small search space or lots of time: exhaustive search
- Easy to find good solutions and important to maintain high diversity: random search
- Otherwise: search-based optimization

On content representation: Locality v Dimensionality

- Representation should have high *locality*
  - a small change to the genotype should on average result in a small change to the phenotype and a small change to the fitness value
- Lack of locality means what?
- “curse of dimensionality”
  - the larger the search space, the harder it is (in general) to find a certain solution

- Same space of content phenotypes can be represented in several different ways in genotype space
- Continuum: Direct ←→ Indirect
  - Direct, e.g. level map
  - List of positions and properties of game entities
  - Repo of reusable patterns and how they are distributed
  - List of properties, e.g. #gaps, #enemies
  - Random seed

Three class of evaluation functions

- **Direct**: base fitness calculations directly on phenotype representation of the content
  - Theory-driven: guided by intuition and/or qualitative theories of player experience
  - Data-driven: based on quantitative measures of player experience
- **Simulation-based**: use AI agents to play content and estimate quality
  - Usually calculate statistics about the agents' behavior/playing style to score game content
- **Interactive**: evaluate content based on interaction with a human
  - Explicit / reported preference
  - Implicit / inferred preference: e.g. based on how often and how long the player uses weapon

Creating computational models of a player's behavior, preferences, or skills is called player modelling. With a model of the player, we can create algorithms that create content specifically tailored to that player.

PLAYER MODELING

http://pcgbook.com/wp-content/uploads/chapter10.pdf

Player Modeling

A set of approaches that represent/quantify the player’s experience or preferences with the goal of improving future experiences. “**experience-driven procedural content generation**”

Improving the experience either:

1. Within the game, altering game elements or deciding between elements (picking which Mario Kart item)
2. Outside the game, giving feedback to designers/developers (analytics)

Model-based versus Model free

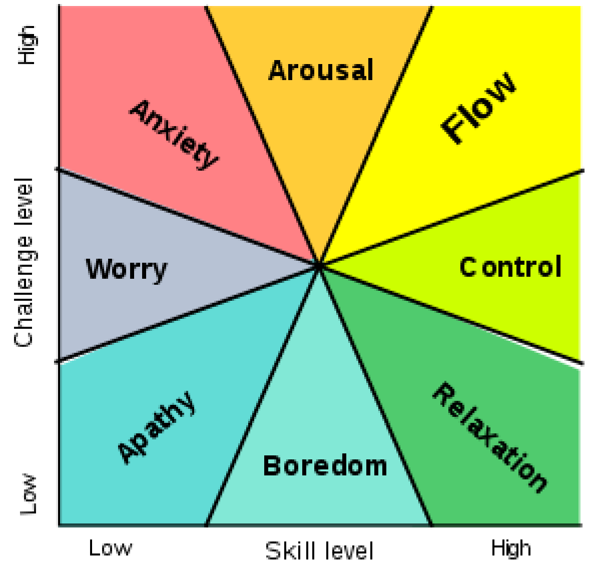
We can separate player modeling approaches into two more general groups:

– **Model-based**: Roughly corresponds to player modeling within games. It presupposes we have a set of categories or value range to assign to some part of a player’s experience

– **Model free**: Roughly corresponds to player modeling outside of games. Looks for patterns of behavior without pre-existing hypothesis, drawing on statistical/machine learning techniques

Model-based: 4 Major Models

- **Note:** This is not to say that there exists only four models, but that vast majority can be understood as derivatives of these four



1. Csikszentmihalyi's Flow (Position in space)
2. Bartle’s player types (Categories of play style)
3. Elo’s performance rating (Continuous value)
4. Drama Management (Difference between target value and .)

Model free Approaches

- Start with some data about a playerbase and game world

- **Categorize** learn what types exist
- **Regression analysis** how does x relate to y?
  - X: Input about the playerbase/game world
  - Y: Something we want to predict/understand
- **Classify** which y is x a member of?

MODEL-BASED PCG

Player Modeling

- What is optimal in PCG?
- Need a player model
  - Tells you something about the player
  - Makes predictions about player
- Challenges in player modeling:
  - What do you model?
  - Where do you get the model?
  - How do you use the model?

Player Model

- What do we want to model?

What do we want to model?

- Demographics
- Game play traces
- Stats
- Features of world when actions are performed
  - Eg: more likely to jump when X is true
- Sensors
- Preferences
  - Ask before, during, after → ratings
- Personality

Example Statistics

CAT 1: (FPS – L4D)
- Ave player health
- Shot accuracy
- # times damaged
- # times killed

CAT3: (rpg)
- Unique area visits
- Time spent exploring (straying)
- Win/loss ratio
- Time to complete level
- Items found
- Item usage

CAT2: (platformer -- mario)
- Power up blocks collected
- # deaths
- # deaths from gaps
- # times duccked
- Time between deaths
- Con blocks pressed
- # gaps jumped
- Avg width of gaps jumped

Player Model

- What do we want to model?
- Where do we get the model?

Where do we get the model?

- Observe player

Where do we get the model?

- Observe player
- Questionnaire

Where do we get the model?

- Observe player
- Questionnaire
- Social media?

Player Model

- What do we want to model?
- Where do we get the model?
- How do we use the model?

How do we use the model?

- Must be input to algorithm

How do we use the model?

- Must be input to algorithm
- Must actually make a difference

How do we use the model?

- Must be input to algorithm
- Must actually make a difference
- Machine Learning
  - Learn to make decisions based on observed data
  - Optimization seeks best mapping
    - Genetic algorithms
    - Simulated annealing

Model-based: 4 Major Models

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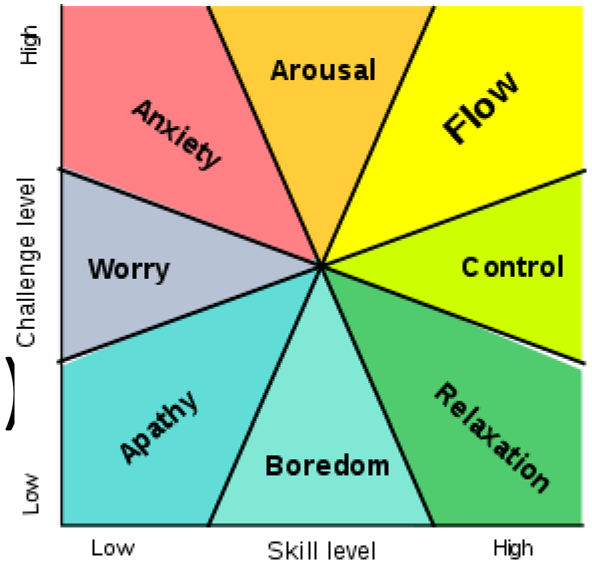
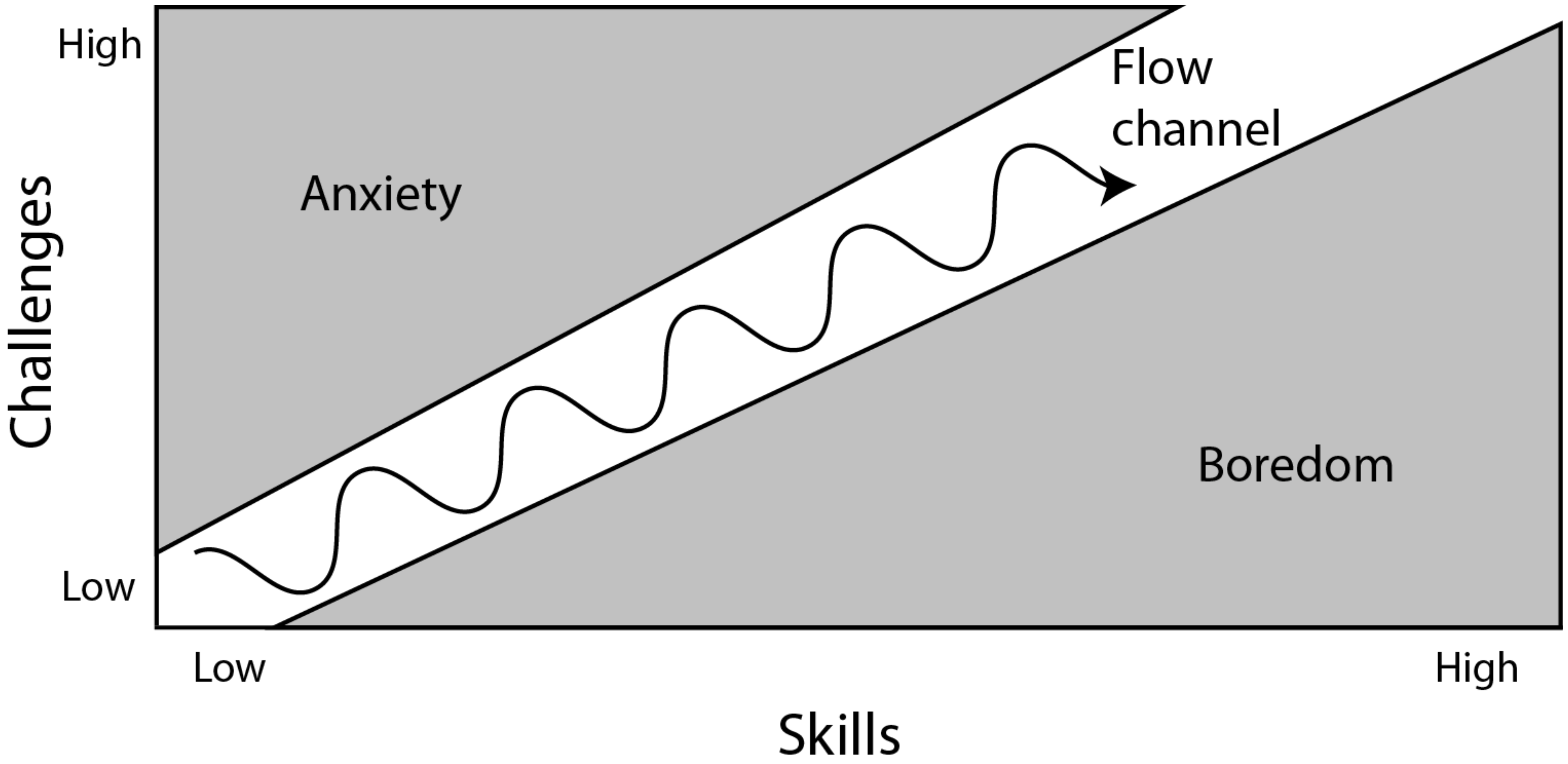
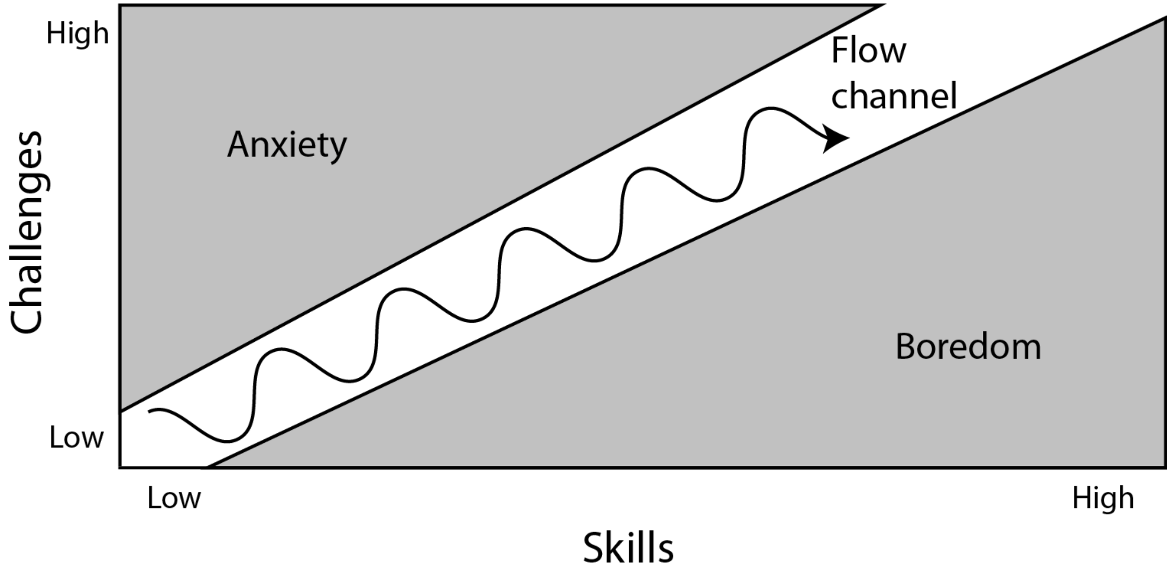


FLOW

Flow


High
Low
Challenges
Anxiety
Flow channel
Boredom
Low
High
Skills

Mario Kart: Flow



Input: Skills (player placement in race), and Challenges (power-ups of enemies)

Output: A position in space.

Decision: What do we do about it?

Flow

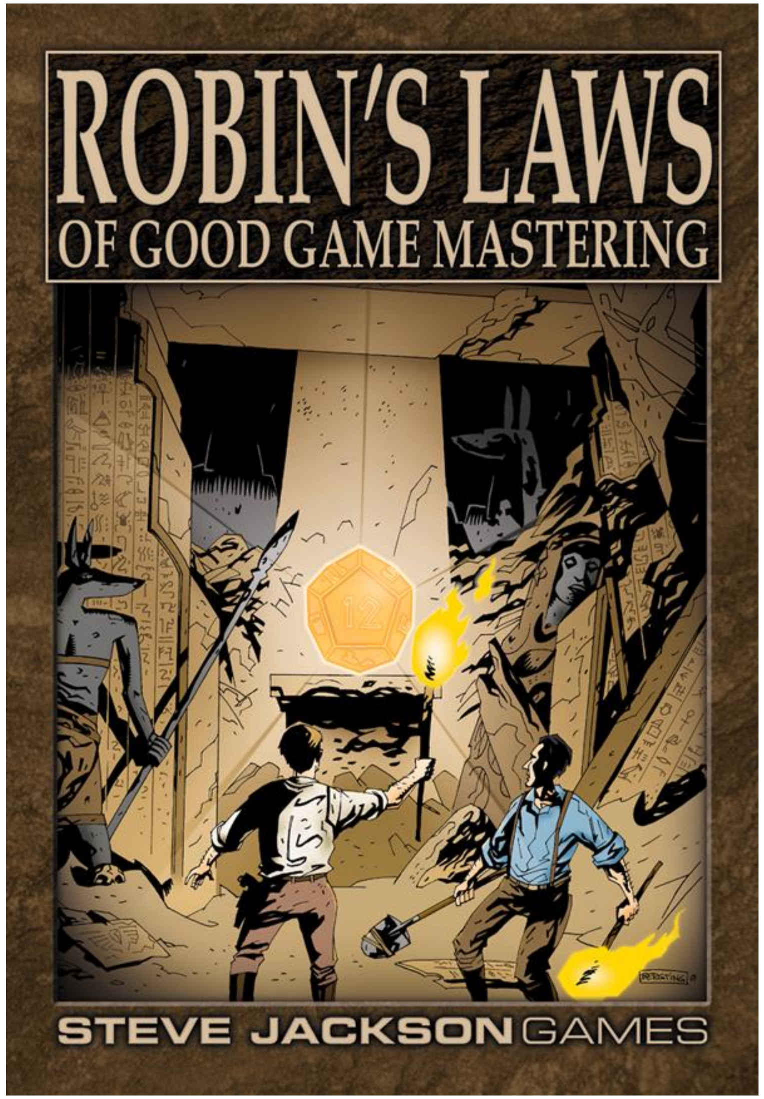
- Advantages
  - Intuitive
  - Matches player experience
- Disadvantages
  - Need to design reliable measures for player challenge and skill, not possible in all games
  - Difficult for non-competitive multiplayer games

MODELS: ROBIN, BARTLE, YEE, ELO, TRUESKILL

Robin’s Laws of Good (tabletop RPG) Gamemastering

Five player archetypes:

- Fighter
  - prefers combat
- Power Gamer
  - gaining special abilities and riches
- Method Actor
  - taking dramatic actions
- Tactician
  - prefers thinking creatively & solving problems
- Storyteller
  - prefers complex plots



Player Types within a game Example: Dragon Age Prototype

Five types, what motivates?

- Fighters (combat)
- Power Gamers (gaining special items)
- Tacticians (creative thinking)
- Storytellers (complex plot)
- Actors (dramatic actions

http://www.aaai.org/Papers/AIIDE/2007/AIIDE07-008.pdf

How it worked

- Each player has a vector
  - (Fighter, MethodActor, Storyteller, Tactician, PowerGamer)
- Every action is tagged with one or more of these roles.
- Every time a player takes an action, update the value of the vector index of the associated role(s).
- System chooses reward to incentivize the maximal role(s)

Example

- Player A has vector (F: 0, MA: 0,S: 0,T: 0,PG: 0)
- Player A asks for a reward for a quest, an action which is strongly tagged with the PowerGamer role (value of 100)
- Player A now has a vector (F: 0, MA: 0,S: 0,T: 0,PG: 100)

- Later on Player A will be offered more powerful items if their vector remains unchanged

Player Types

- Advantages
  - Can allow designers to understand player base
  - Can broaden the appeal of a game
- Disadvantages
  - Different games/genres need their own player types designed, a tricky task
    - E.g. “Whales” in free-to-play mobile games
  - In-game usage of this model requires a lot of extra knowledge authoring

Robin's Laws of Good Gamemastering

- Suppose actions, decisions, and/or choice points are tagged with types and strengths
  - e.g. Action X has *method-actor* = 8
- Player model is vector of accumulated strengths (normalized?)

<*F*, *PG*, *MA*, *T*, *S*>

<1, 141, 81, 1, 1>

- Incrementally build model

Robin’s Laws of Good Gamemastering

- How does world/actions translate to model?

Robin's Laws of Good Gamemastering

- How does world/actions translate to model?
- How does model map to design?

Robin’s Laws of Good Gamemastering

- How does world/actions translate to model?
- How does model map to design?

ACTIONS ---> MODEL ---> ACTIONS

FEATURES ---> MODEL ---> FEATURES

Robin's Laws of Good Gamemastering

- How does world/actions translate to model?
- How does model map to design?

ACTIONS ---> MODEL ---> ACTIONS

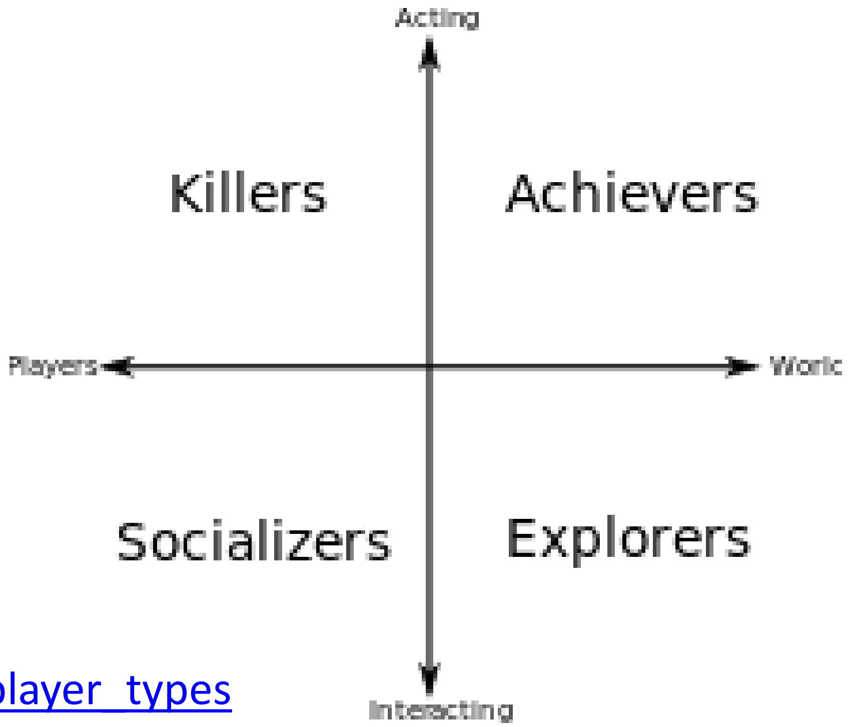
FEATURES ---> MODEL ---> FEATURES

- Player simulation

- See http://www.sjgames.com/robinslaws/

Bartle: MUD Player Modeling

- MUD = Multi-user Dungeon
- 4 things people typically enjoy doing in MUDs:
  - Achievement (preset in-game goals eg kill, aquire)
  - Exploration
  - Socializing
  - Killers (Imposing on other players)



https://en.wikipedia.org/wiki/Bartle_taxonomy_of_player_types

Bartle's Player Types

- Most commonly used today in the design of MMORPG's, to motivate these different "types" of players

- Example: World of Warcraft
  – Experience for killing mobs (killer)
  – completing quests (achievers)
  – exploring (explorers)
  – battlegrounds (socializers)

MUD Player Modeling

- Everyone has a primary type
  - Bit of each, tendency towards one
- Take the Bartle Test!
- Suggests a feature vector

<*killer*, *achiever*, *explorer*, *socializer*>

< 0.0, 0.7, 0.1, 0.2 >

- See (no really, follow the 1st link)
  - http://www.mud.co.uk/richard/hcds.htm
  - http://en.wikipedia.org/wiki/Bartle_Test

Yee Player Model

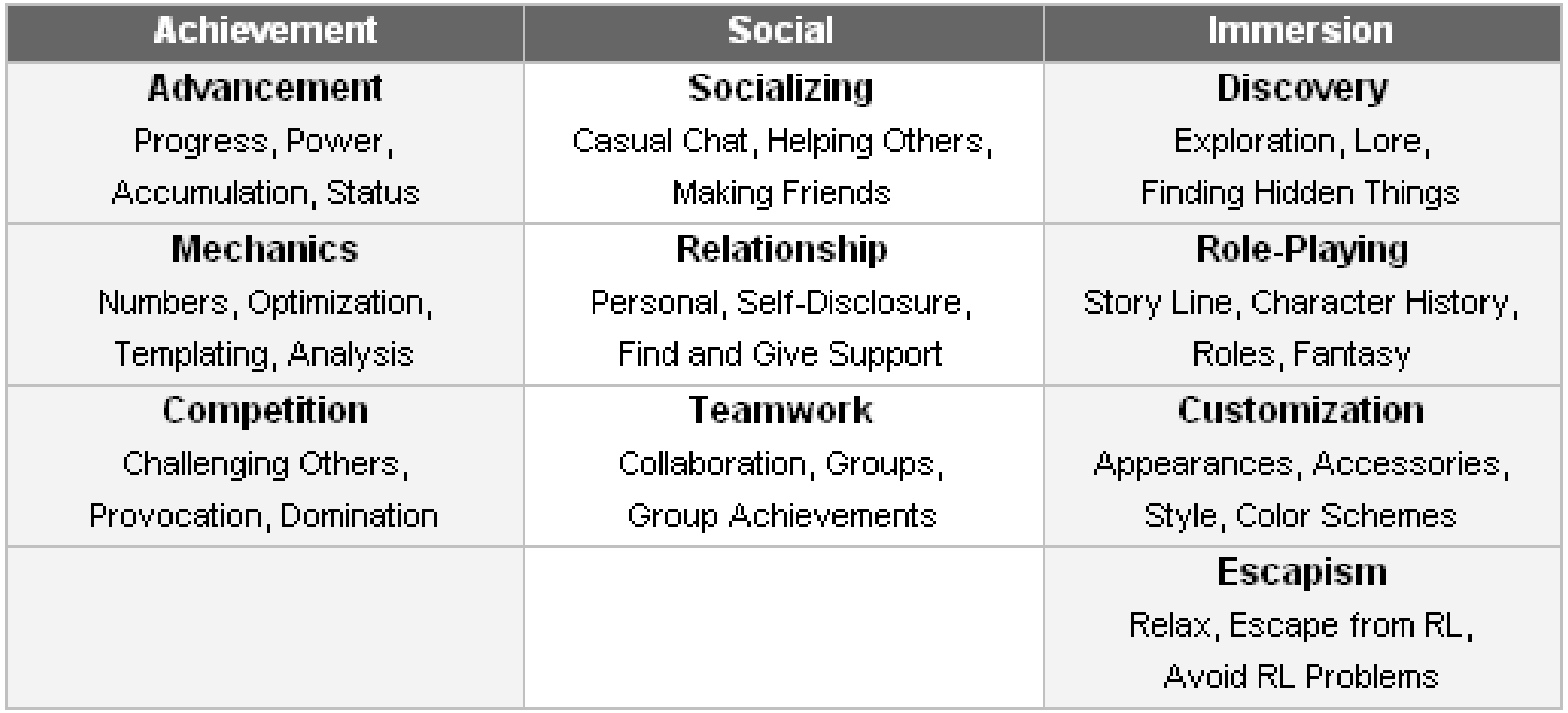
- Used iterative process to validate, expand and refine a player motivation model **empirically**
- Based on open-ended questions about motivation
  - *"I feel powerful in the game."*
  - *"I like to be immersed in a fantasy world."*
- See
  - http://www.nickyee.com/daedalus/archives/001298.php

Yee Player Model: Factors

- Relationship
- Manipulation
- Immersion
- Escapism
- Achievement

“Performed factor analysis on data to separate the statements into clusters where items within each cluster were as highly correlated as possible while clusters themselves were as uncorrelated as possible” – Yee

Yee Player Model



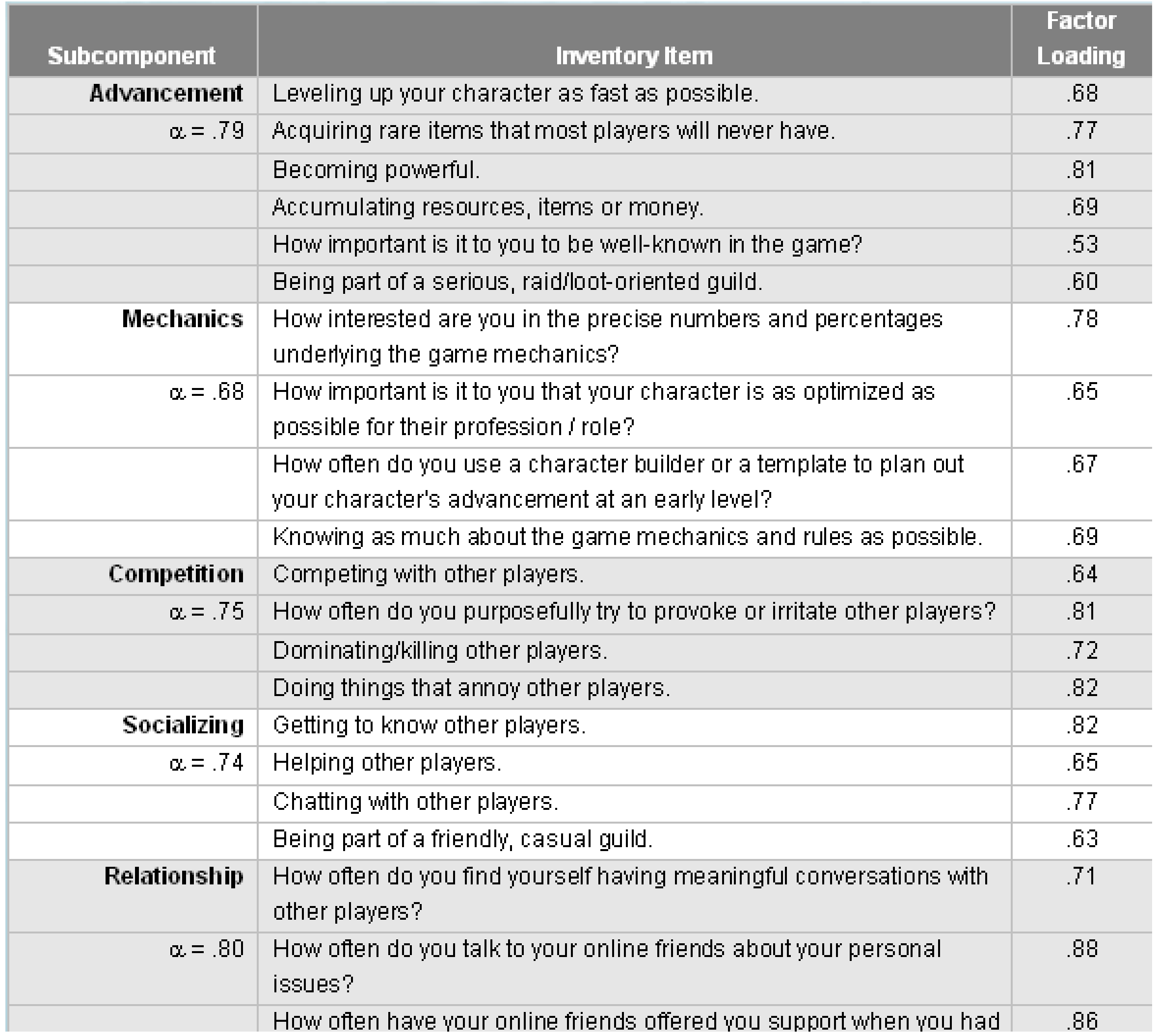
Achievement	Social	Immersion
Advancement Progress, Power, Accumulation, Status	**Socializing** Casual Chat, Helping Others, Making Friends	**Discovery** Exploration, Lore, Finding Hidden Things
Mechanics Numbers, Optimization, Templating, Analysis	**Relationship** Personal, Self-Disclosure, Find and Give Support	**Role-Playing** Story Line, Character History, Roles, Fantasy
Competition Challenging Others, Provocation, Domination	**Teamwork** Collaboration, Groups, Group Achievements	**Customization** Appearances, Accessories, Style, Color Schemes
		Escapism Relax, Escape from RL, Avoid RL Problems

http://www.nickyee.com/daedalus/archives/001298.php?page=4

Motivations do not "suppress"

"The subcomponents generated by the factor analysis are NOT player types.

- It is NOT the case that we have come up with 10 boxes that we can put players in, but rather, we have revealed 10 subcomponents that co-exist and together reveal the motivations of a player.
- Bartle assumed that your underlying motivations "suppressed" each other. In other words, the more of an Achiever you were, the less of a Socializer, Explorer and Killer you could be, but just because you like ice-cream doesn't mean you will hate pasta.
- The assumption of polarized motivations is also not supported by the correlations of the current data set."

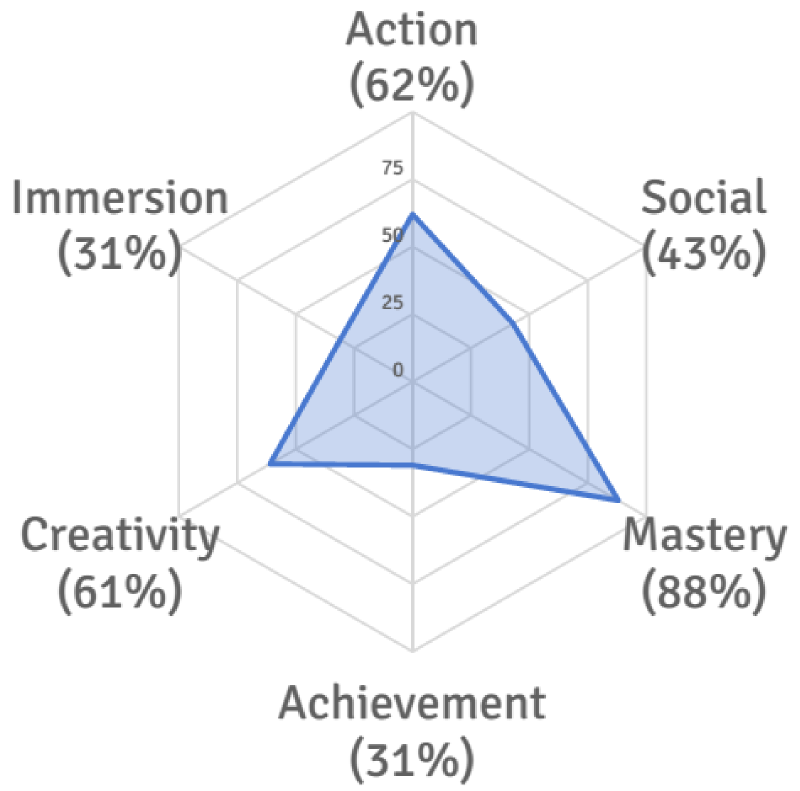


Subcomponent	Inventory Item	Factor Loading
Advancement	Leveling up your character as fast as possible.	.68
α = .79	Acquiring rare items that most players will never have.	.77
	Becoming powerful.	.81
	Accumulating resources, items or money.	.69
	How important is it to you to be well-known in the game?	.53
	Being part of a serious, raid/loot-oriented guild.	.60
Mechanics	How interested are you in the precise numbers and percentages underlying the game mechanics?	.78
α = .68	How important is it to you that your character is as optimized as possible for their profession / role?	.65
	How often do you use a character builder or a template to plan out your character's advancement at an early level?	.67
	Knowing as much about the game mechanics and rules as possible.	.69
Competition	Competing with other players.	.64
α = .75	How often do you purposefully try to provoke or irritate other players?	.81
	Dominating/killing other players.	.72
	Doing things that annoy other players.	.82
Socializing	Getting to know other players.	.82
α = .74	Helping other players.	.65
	Chatting with other players.	.77
	Being part of a friendly, casual guild.	.63
Relationship	How often do you find yourself having meaningful conversations with other players?	.71
α = .80	How often do you talk to your online friends about your personal issues?	.88
	How often have your online friends offered you support when you had	.86

http://www.nickyee.com/daedalus/archives/001298.php?page=8

Where do you fit?

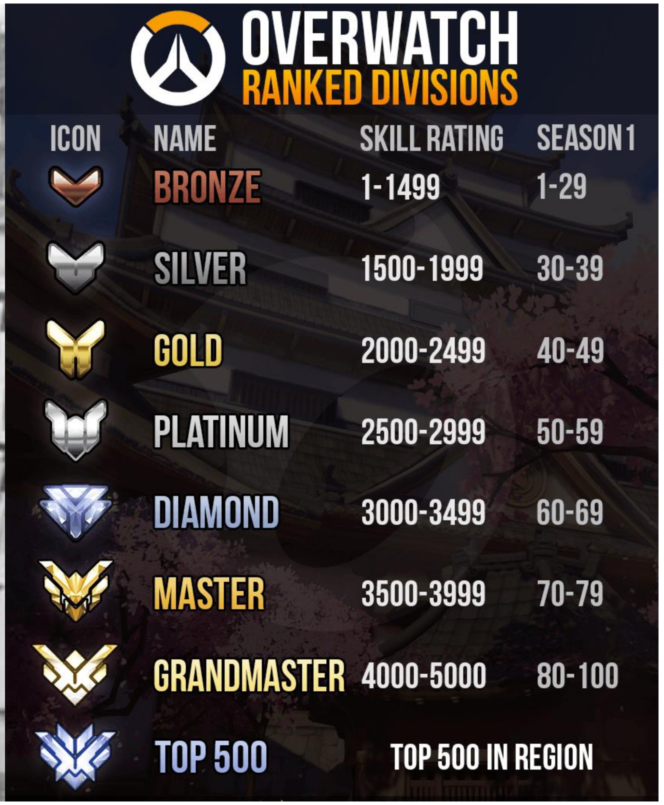
- Proficient, Relaxed, Competitive, Grounded, and Inquisitive



After filling out a brief survey (5-7 minutes), this profile tool will generate a customized report and a list of recommended games for you. The report will describe the traits that were measured, and how you compare with other gamers.

https://apps.quanticfoundry.com/lab/gamerprofile/

ELO



OVERWATCH
RANKED DIVISIONS

ICON	NAME	SKILL RATING	SEASON 1
	BRONZE	1-1499	1-29
	SILVER	1500-1999	30-39
	GOLD	2000-2499	40-49
	PLATINUM	2500-2999	50-59
	DIAMOND	3000-3499	60-69
	MASTER	3500-3999	70-79
	GRANDMASTER	4000-5000	80-100
	TOP 500	TOP 500 IN REGION	

Elo’s Performance Rating

- Algorithm:
  - For each win, add your opponent’s rating plus 400
  - For each loss, add your opponent’s rating minus 400
  - Divide this sum by the number of played games
- Formula:

  (Total of opponents’ ratings + 400(Wins –Losses))/ Games

Quick Note: Elo rating naming confusion

Many games do not make use of this exact rating algorithm, but you will still hear references to “Elo rating”/Elo hell

At a high level this phrase refers to any approach to update player skills given wins/losses and prior player skills

– Probability distribution

Elo Rating

- Advantages
  - Requires very little designer authoring
  - Does a surprisingly good job of keeping competitive games fair
- Disadvantages
  - Player's do not like seeing this value drop
    - Solution: Many games have "hidden" true Elo ratings
  - Limited to competitive experiences of 2 players
    - Only makes sense when comparing players to others

See also https://en.wikipedia.org/wiki/TrueSkill http://www.moserware.com/2010/03/computing-your-skill.html

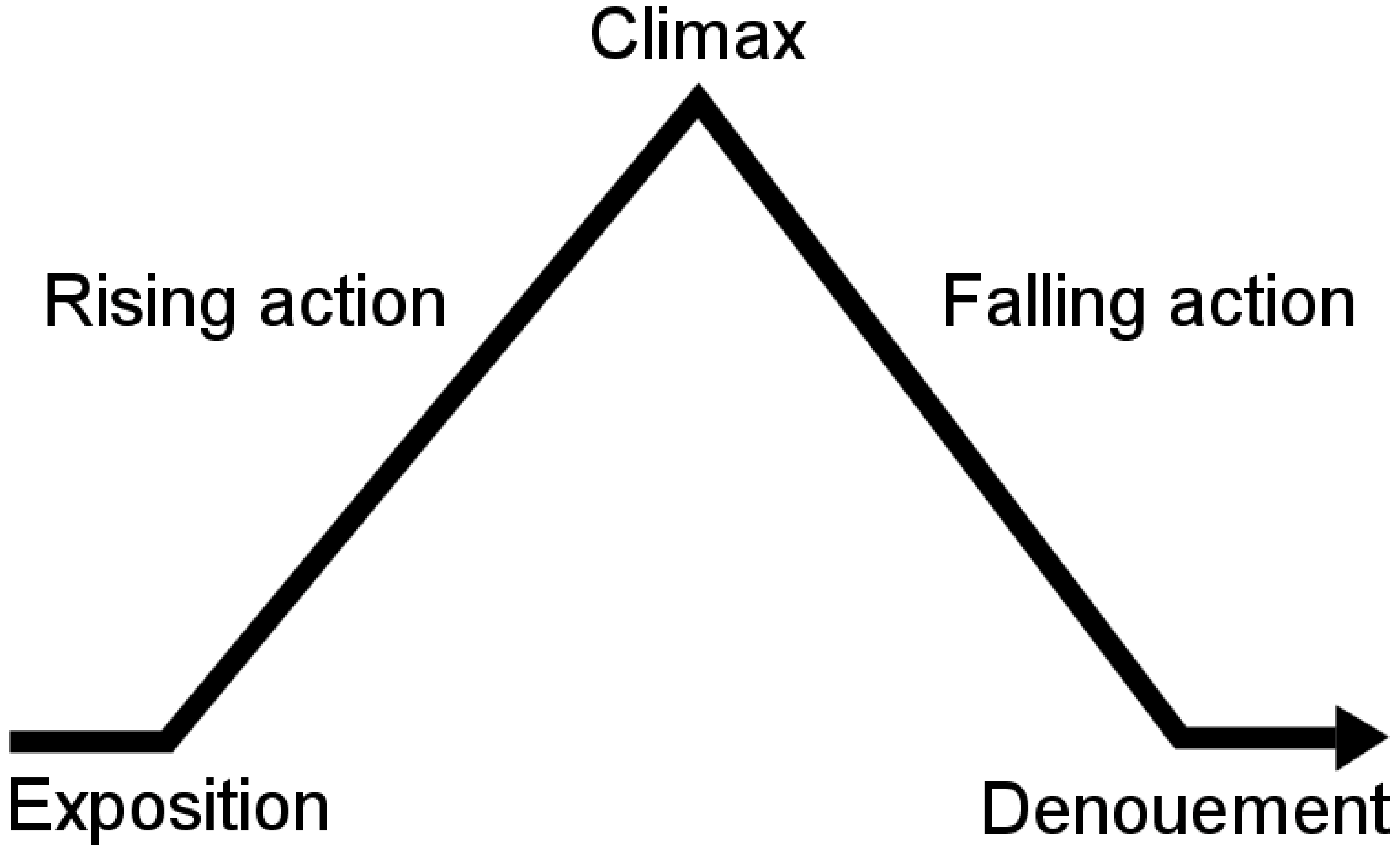
MS TrueSkill ™

- The TrueSkill (Bayesian) ranking system is a skill based ranking system for Xbox Live developed at Microsoft Research. The purpose of a ranking system is to both identify and track the skills of gamers in a game (mode) in order to be able to match them into competitive matches. TrueSkill has been used to rank and match players in many different games, from Halo 3 to Forza Motorsport 7.
- An improved version of the TrueSkill ranking system, named TrueSkill 2, launched with Gears of War 4 and was later incorporated into Halo 5.
- In particular, the ELO ranking system has been used successfully by a variety of leagues organized around **two-player games**, such as world football league, the US Chess Federation or the World Chess Federation, and a variety of others.
- In video games many of these leagues have game modes with more than two players per match. **ELO is not designed to work under these circumstances. In fact, no popular skill-based ranking system is available to support these games**. Many one-off ranking systems have been built and are in use for these games, but none of them is general enough to be applied to such a great variety of games.

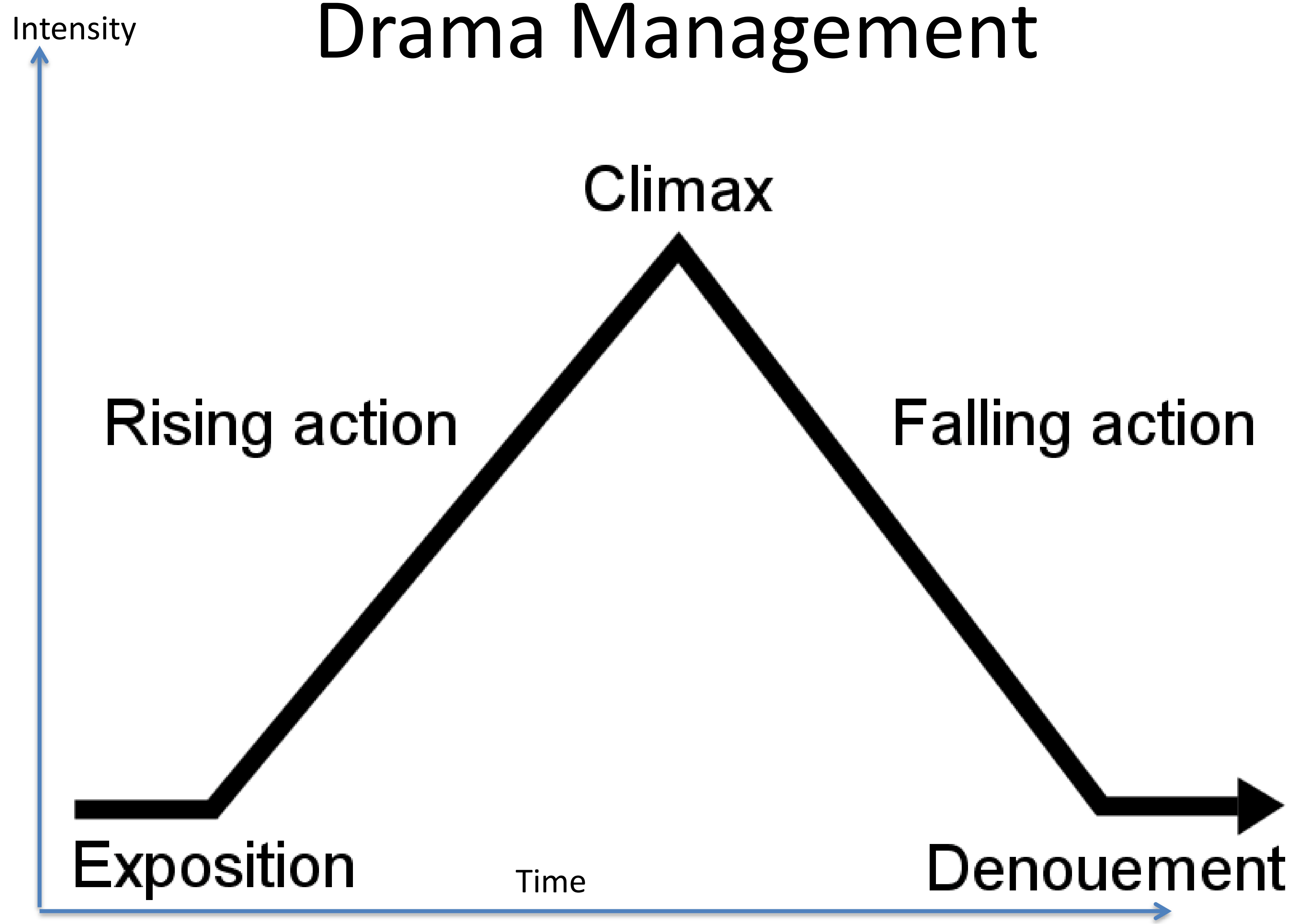
https://www.microsoft.com/en-us/research/project/trueskill-ranking-system/
https://www.microsoft.com/en-us/research/wp-content/uploads/2007/01/NIPS2006_0688.pdf
https://www.microsoft.com/en-us/research/uploads/prod/2018/03/trueskill2.pdf

DRAMA MANAGEMENT

Drama Management



Drama Management



Left4Dead AI Director

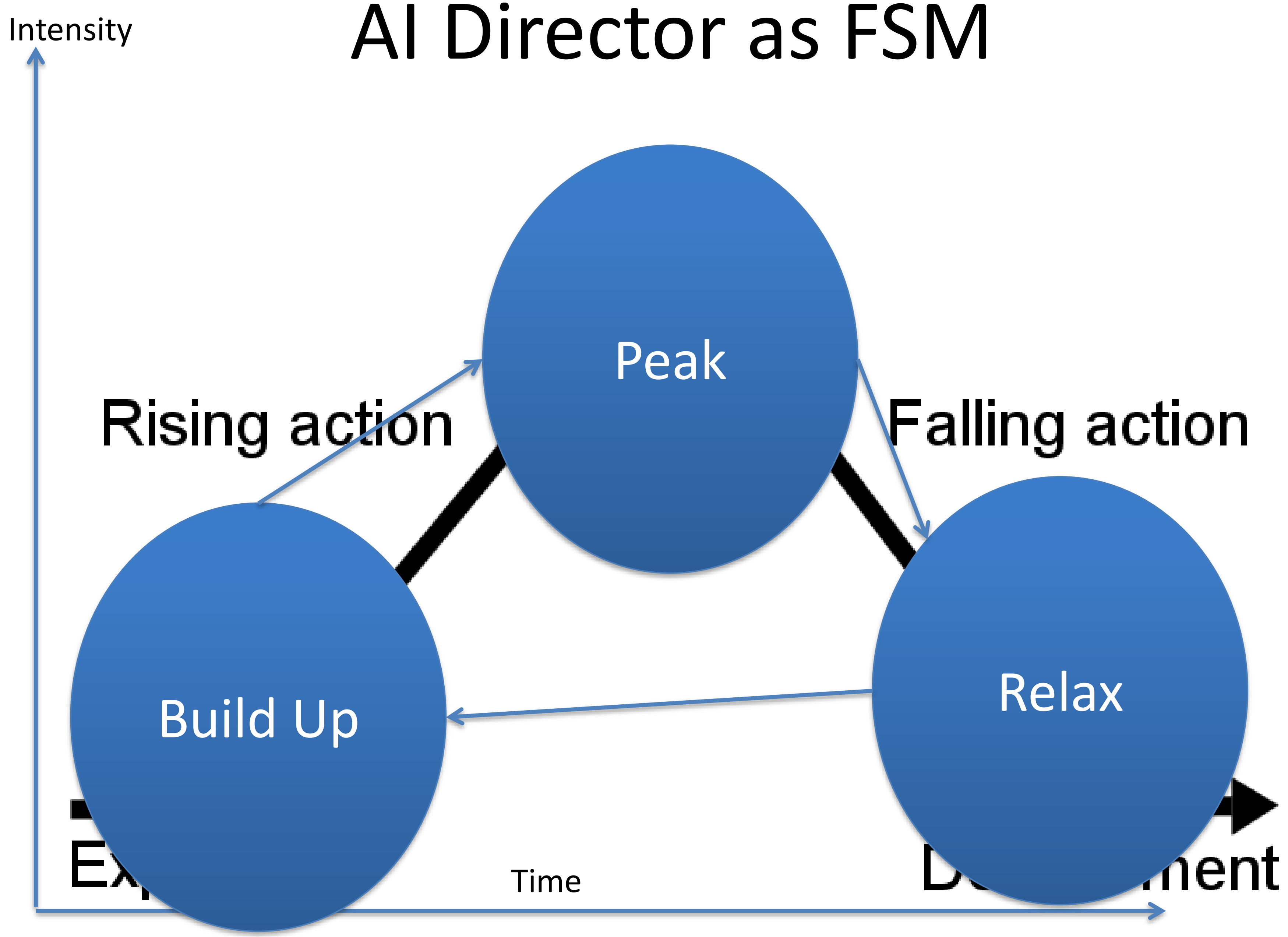
- Constantly measures player “intensity”
  - Intensity increases when attacked/killing
  - Players hit max when incapacitated
  - Players slowly drop intensity when nothing is happening and reset at the start of a new stage

  - (This is a lot like challenge in flow)

Left4Dead AI Director

- Three “modes”
  - **Build up**: AI Director attempts to increase tension
  - **Peak**: Intensity reaches max, director stops spawning enemies
  - **Relax:** Director spawns helpful items/alters path to decrease tension

AI Director as FSM



Drama Management Summary

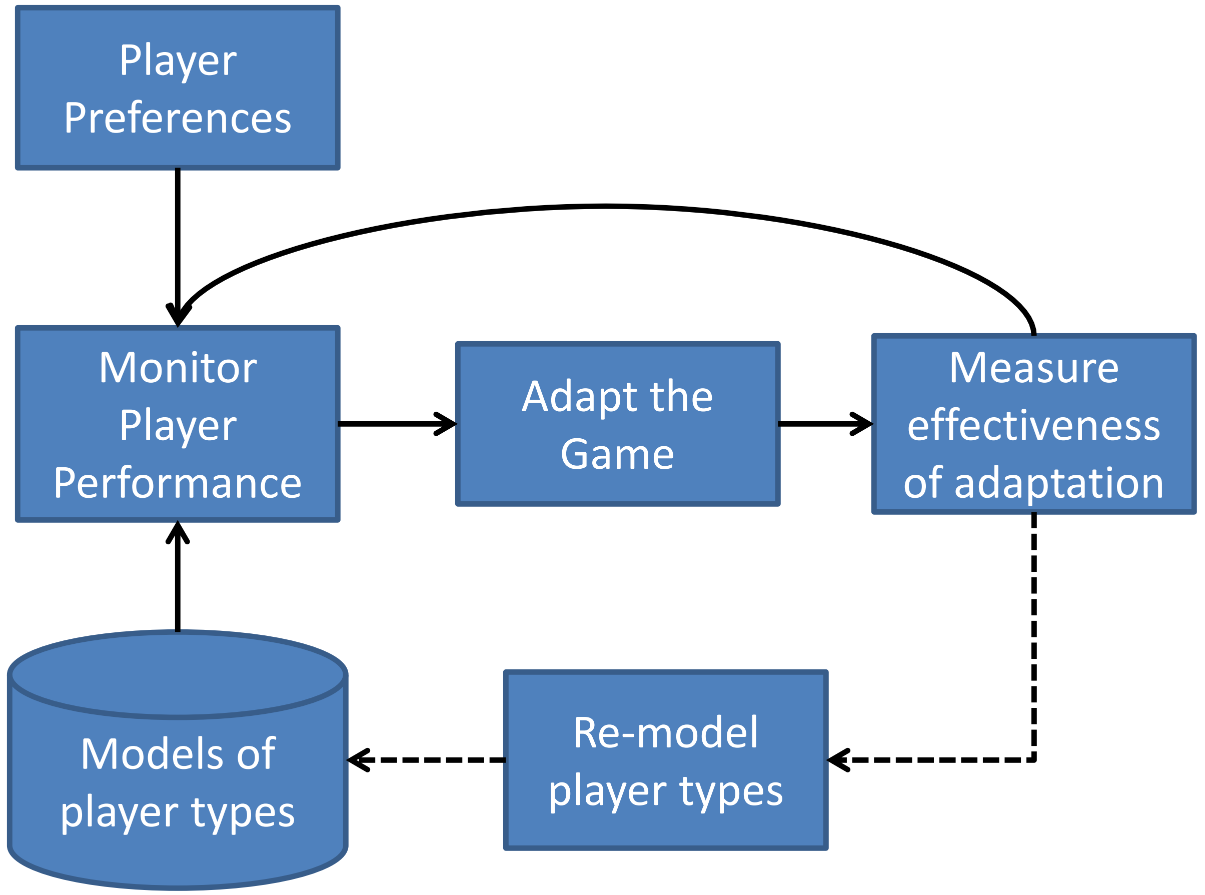
- Advantages
  - Most effective, highly praised
  - Gives players another level of strategy
- Disadvantages
  - Fair amount of authoring (less than Player Types, more than Flow)
  - All the downsides of FSMs

PCG: STEPPING BACK

Player Model Process

e.g. feature vector

Can simulate performance



Concerns

Concerns

- Player desires

Concerns

- Player desires
- Privacy

Concerns

- Player desires
- Privacy
- Testing

Concerns

- Player desires
- Privacy
- Testing
- Player experience

Summary

Authoring burden for using in a game:
player types > drama management > flow > ELO

Ultimately: Decision of when to use what depends on the type of game and desired player experience

THOUGHT EXPERIMENT: SMB LEVEL GENERATION

Mario Level Generation

- Predict users’ emotional response to level:
  - Fun
  - Challenging
  - Boring
  - Frustrating

Mario Level Generation

- Controllable features

Mario Level Generation

- Controllable features
- {#gaps, gap_width, spatial_diversity}

Mario Level Generation

- Controllable features
- {#gaps, gap_width, spatial_diversity}
- Fixed: #coins, #enemies, # ?-boxes, #powerups, etc.

Building the Model

- Option #1: Pairwise Ordering
- For each pair of levels, ask:

  Level A is more <adj> than Level B

  Levels A and B are equally <adj>

  Neither Level A nor Level B are <adj>

  Where <adj> = {fun, challenging, boring, frustrating}

Building the Model

- Option #2: Use ANN to learn to predict question-answering

Building the Model

- Option #2: Use ANN to learn to predict question-answering
- Need a function that maps features to a measure of quality:

  f (gaps, width, spatial_diversity) → **R**

Building the Model

- Other option: Learn decision tree with continuous variables
- Benefit of trained neural network: The network ***IS*** your fitness function.

Using the Model

- Search for optimal feature set for a player

Using the Model

- Search for optimal feature set for a player
- State is 3-tuple {G, W, SD} – Could brute-force

Using the Model

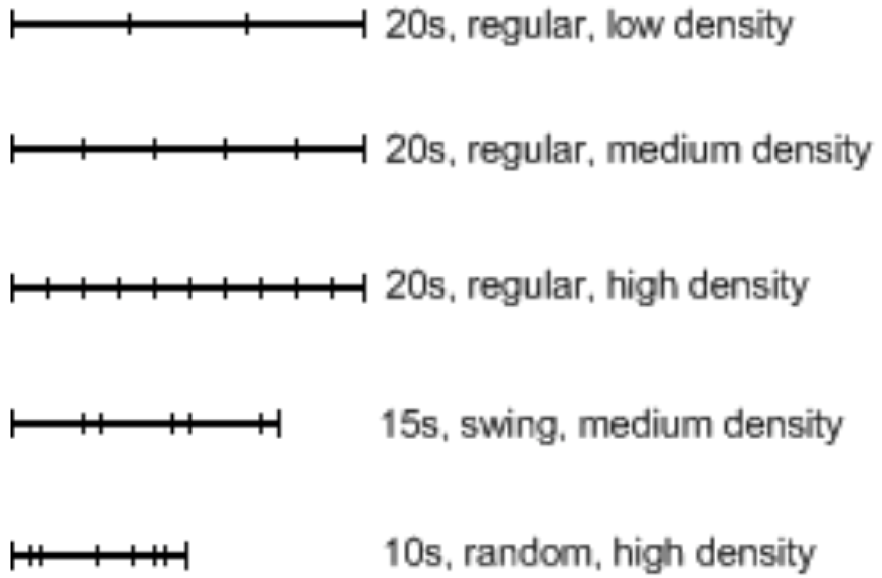
- Search for optimal feature set for a player
- State is 3-tuple {G, W, SD} – Could brute-force
- Optimization search – Genetic algorithms, hill-climbing, simulated annealing

Smith, Treanor, Whitehead, Mateas {FDG, 2009}

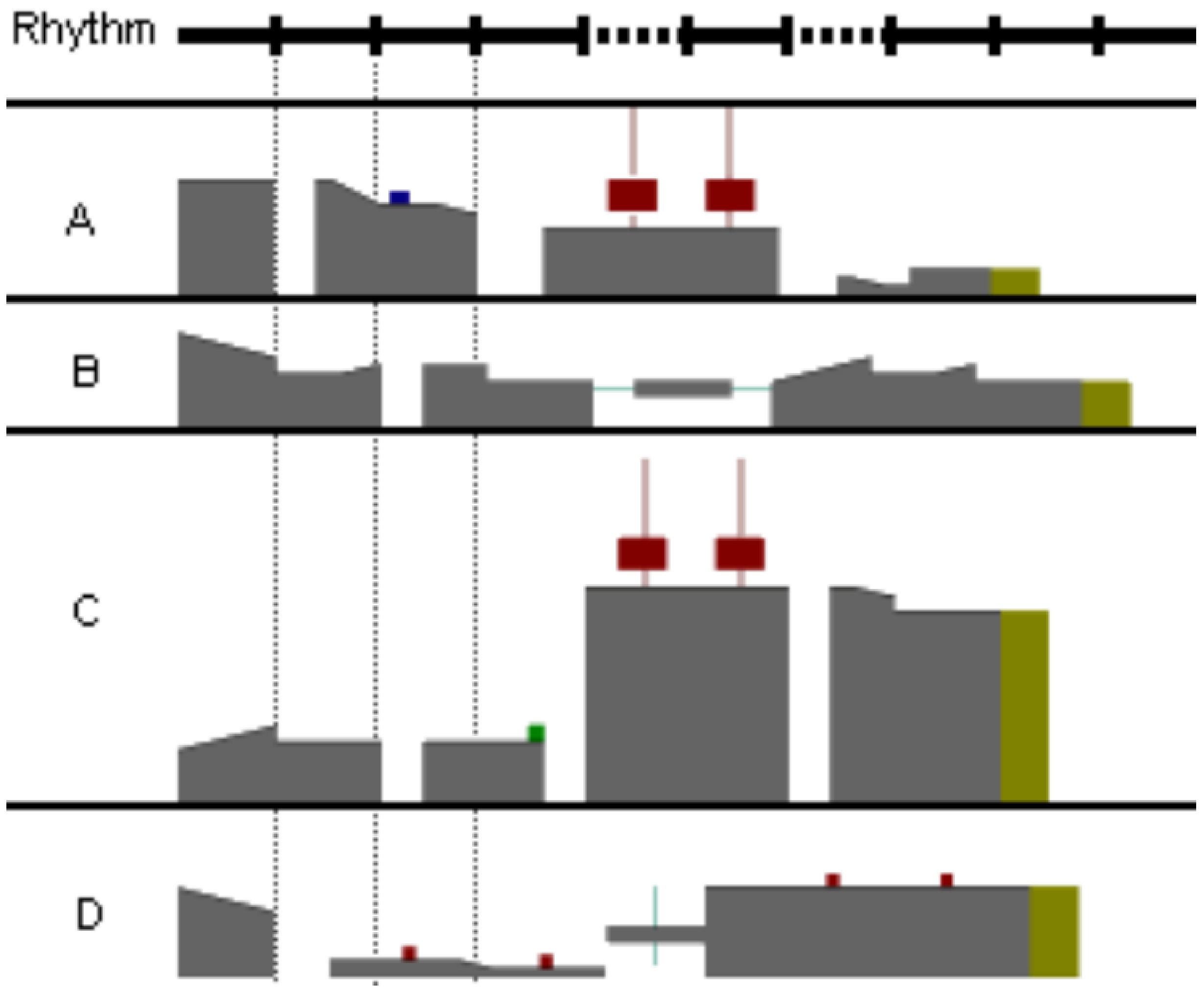
RHYTHM-BASED PLATFORMER LEVEL GENERATION

Rhythm based level-generation

- Patterned set of moves

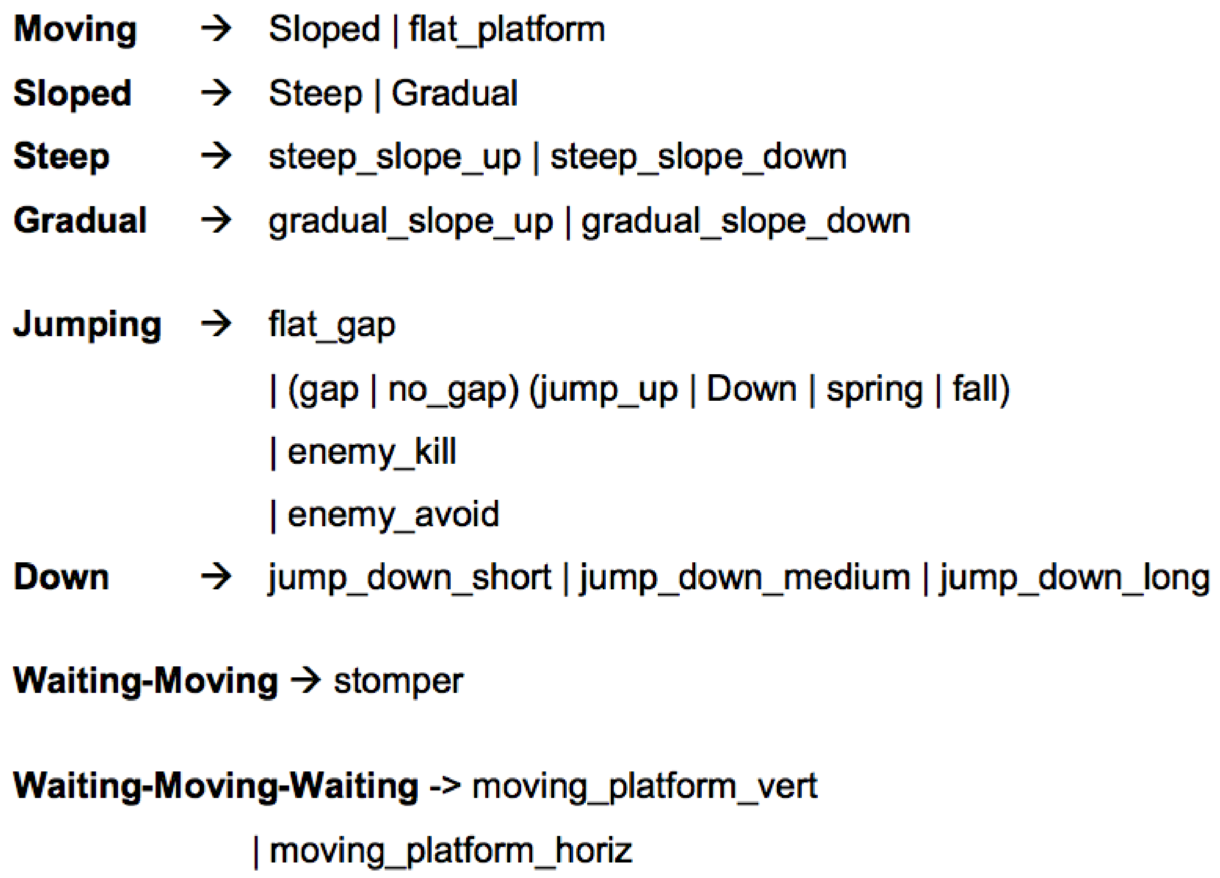

20s, regular, low density
20s, regular, medium density
20s, regular, high density
15s, swing, medium density
10s, random, high density

```
move 0 5
jump 2 2.25
jump 4 4.25
move 6 10
jump 6 6.5
jump 8 8.5
```


Rhythm
A
B
C
D

Geometry grammar

- Rhythm determines what roots
- Terminals determine specific content element selections



```
Moving    →  Sloped | flat_platform
Sloped    →  Steep | Gradual
Steep     →  steep_slope_up | steep_slope_down
Gradual   →  gradual_slope_up | gradual_slope_down

Jumping   →  flat_gap
             | (gap | no_gap) (jump_up | Down | spring | fall)
             | enemy_kill
             | enemy_avoid
Down      →  jump_down_short | jump_down_medium | jump_down_long

Waiting-Moving → stomper

Waiting-Moving-Waiting -> moving_platform_vert
             | moving_platform_horiz
```

Grammar generation problems

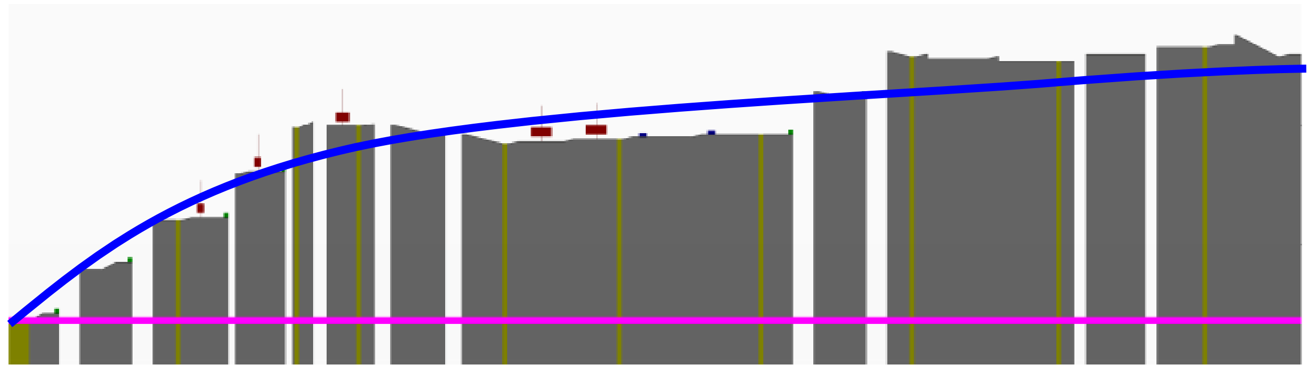
- Over-generation
- Global constraints

Problems with Grammars

- Problem with grammars: global context
- Can you fix grammars?
- Generate-and-test with some evaluation function
- Backtrack?
- Planning: Search for a sequence of actions that meet a goal
  - Heuristics meant to speed up search
  - Heuristics can also be used to guide algorithm toward more preferable solutions
- HTN planning: Tasks decompose to sub-tasks

Critics

- Generate-and-test: generate a bunch of levels and pick the one that scores best
- Critics are pieces of code that evaluate and select
- Line distance critic
  - Given a path the level should follow
- Component style critic
  - Consistency of components
  - Jumping caused by gaps vs. monsters



Control lines
for line critic