Artificial Intelligence and Games

Modeling Players

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Welcome to the Artificial Intelligence and Games book. This book aims to be the first comprehensive textbook on the application and use of artificial intelligence (AI) in, and for, games. Our hope is that the book will be used by educators and students of graduate or advanced undergraduate courses on game AI as well as game AI practitioners at large.

Final Public Draft

The final draft of the book is available [here](#).
Overview

- Player Modeling
  - Why?
  - How?
- Main tasks for AI/Machine Learning
- Holistic view
  - From Affective Computing to Game Studies to Game Analytics
- Examples
  - Player Behavior
  - Player Experience
What is Player Modeling?
• Player Modeling
  • Non human players
  • Human players

• Player Modeling vs Opponent Modeling

• Player Modeling vs Player Profiling
  • Modeling: complex dynamic phenomenon
  • Categorization of players based on static information
The study of *computational* means for the modeling of a player’s *experience* or *behavior* which is based on *theoretical frameworks* about player experience and/or *data* derived from the interaction of the player with a game.
Why Model Players?
Goal

“…understand how the interaction with a game is experienced by players.”

Why use AI for Player modelling?

• Understanding player experience
• Understanding player behavior
Why Model Players?

• Why not?
• Machines understand numbers
• Player Experience is the holy grail for design and development
• But most importantly because...
Why Model Players?

- The perfect game is tailored to you!
- We are different (and many more than before)
- If you learn to play.... it is only fair that the game learns you
Supervised/Reinforcement Learning
  Imitation
  Prediction

Unsupervised Learning
  Clustering
  Association mining
Player Modeling Examples
Experience: how you feel during play
• A set (a synthesis) of affective, cognitive and behavioral states
• Or else user states
• Emotions: Appraisal theory, ...
• Cognition/Behavior: several models (e.g. BDI,...)

Behavior: what you do during play
Player Model

Model-Based [Top-Down]
(Psychology, Cognitive Science, Game Studies, ...)

Model Free [Bottom-Up]
(Data Science, Machine Learning)
Player Model

Model-Based [Top-Down]
(Psychology, Cognitive Science, Game Studies, ...)

Model-Based
“Affective computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affect” (Wiki)

Term coined by R. Picard (1999)
Emotion is a subjective, conscious experience characterized primarily by psychophysiological expressions, biological reactions, and mental states. (Wikipedia)

NB: Emotion (and affect) is a construct with fuzzy boundaries!
Cognitive Appraisal

Cognitive appraisal

You see a shark!

Physiological Manifestation(s)

High adrenaline, increased HR, pupil dilation, increased skin conductivity

You scream, swim away, fight (?!)

Action(s)
Emotions
- Are **discrete** (states)
- Are measurable
- Can be identified through their physiological or bodily manifestations
The 6 basic emotions are culture-independent
Emotions
- Are **scalar values**
- Represented in a 2-d plane: **arousal vs. valence**
- Are measurable
- Can be identified through physiological or bodily manifestations
Games Best Realizes the Affective Loop


Experience Elicitation

Experience Detection/Modelling

Adaptation and Emotion Expression

Game Content

Game Agents

Manifestations

Emotion stimuli

Game parameter space
Neurobiology of Play

Neuroscience – via fMRI

- **Interest (or curiosity):** visual cortex (hippocampus) and endomorphin.
- **Explorer (Barter) / Easy Fun (Lazzaro) / Curiosity (Malone)** → Wonder: endomorphin (pleasure center)
- **Achiever (Bartle)** → Achievement: dopamine (pleasure center).
- **Hardcore gamers / Hard Fun (Lazzaro)** → Fiero: dopamine (pleasure center)
- **Serious Fun (Lazzaro)** → Excitement: adrenaline (fear center)
- **Socialiser (Bartle) / People Fun (Lazzaro)** → Enjoyment: oxytocin (social center) and dopamine (pleasure center)

“Fun”

- “Fun” and friends
  - Learnability
  - The right difficulty level
  - Challenge – Curiosity – Fantasy
  - Hard Fun / Easy Fun / X Fun / ...
  - Adrenalin / Dopamine
  - Arousal / Positive Emotions
  - Flow
  - ...

"Fun"
Fun = Learning

Complex training signals / patterns \(\rightarrow\) Learning Difficulty \(\rightarrow\) Frustration \(\rightarrow\) No Fun!

Seen (and mastered) training signals / patterns \(\rightarrow\) Boredom \(\rightarrow\) No Fun!
Fun of an AI agent

= Learnability during the game (dynamic “fun” fitness function)

Lazzaro’s 4 Fun-factor Model

(c) Nicole Lazzaro, www.xeodesign.com
Problems with “Fun”

Way too many
• Complex – composite of other things…
  – Engagement, interest, immersion, ...? Who knows?
• Quasi/Fake Emotion (not real!)
• Nowhere in any model of emotion
• No device can measure “fun”

But
• People can still express it...
• Ask 4-yo children if they are immersed....
Flow is the state of “happiness”

When in Flow:
1. focused concentration on the present moment
2. loss of reflective self-consciousness
3. sense of personal control or agency over the situation or activity
4. a distortion of temporal experience (subjective experience of time is altered)
5. experience of the activity as intrinsically rewarding
Flow (Csikszentmihalyi, 1975)
Challenge

- Uncertainty of achieving a goal due to e.g. variable difficulty level, multiple level goals, hidden information, and randomness.

Fantasy

- Show (or evoke) images/situations/context not present
  - Extrinsic: depends on the skill used in a game
  - Intrinsic: related to the use of that skill.

Curiosity

- What will happen next to the game?
  - Sensory curiosity
  - Cognitive curiosity – it can be aroused via incomplete/inconsistent knowledge structures

Entertainment Modelling based on Malone

Prey/Predator Games

Playware Playground

Evolving Racing Tracks Based on Malone

Summary of Top-Down Player Modeling

One Theory After all?

Some Examples

• Explorer (Barter) / Easy Fun (Lazzaro) / Curiosity (Malone)
• Achiever (Bartle) / Serious Fun (Lazzaro)
• Killer (Bartle) / Hard Fun (Lazzaro) / Challenge (Malone) / Flow aspects
• Socialiser (Bartle) / People Fun (Lazzaro) / Shared Involvement (Calleja)
Player Model

Model Free [Bottom-Up]
(Data Science, Machine Learning)

Model-free: From Theory to Data
Game Analytics
Basic Definitions

- **Game analytics**: application of analytics to game development and research.
- **Goal**: support decision making, at operational, tactical and strategic levels for design, art, programming, marketing, user research, etc.
- **Game metrics**: interpretable measures of something related to games
  - User/Player metrics
    - User: customer, gameplay community
    - Gameplay: interface, in-game
  - System metrics
What’s the Problem?

- Understanding players
  - Behaviour
  - Player Experience
- How do people play a game?
- Do they play the game as intended?
What’s the Problem?

- Debugging costs!
  - Code debugging
  - Experience debugging
- Play testing costs!
- Non-linear games
  - Testing is challenge
- Improve next game release costs!
- ...
Game Data Visualization
Very important to visualise data prior to further processing

Lots of information is hidden in basic statistics and analytics
Heatmaps

- Plot specific information over the map of a level
- Typically, counts of a particular event in a map location
- The higher the count, the higher the temperature
Heatmaps in *Halo*


Number of deaths

Player navigation
Heatmap in *Just Cause 2*

Drachen and Shubert. **Spatial Game Analytics**, in El-Nasr et al (Eds.) *Game Analytics: Maximizing the value of Player Data.*
Drachen and Schubert. **Spatial Game Analytics**, in El-Nasr et al (Eds.) *Game Analytics: Maximizing the value of Player Data.*
Player Click Heatmaps

Drachen and Schubert. **Spatial Game Analytics**, in El-Nasr et al (Eds.) *Game Analytics: Maximizing the value of Player Data.*
Can be viewed as a service to

- **Game Developers** (publishers, designers, programmers etc.)
- **Third Parties** (recommendation systems, adverts, etc.)
- **Players** (own performance, tailored challenges, game aids, etc.)
• Tracking data in games is a common practice
• The amount of data is usually huge
• One does not simply spot patterns in the data
• Data mining provides methods for finding regularities and anomalies

Game Data Mining: What can it do for you?

- Supplementary approach to traditional testing
- Imitate human playing styles
- Identify player profiles
- Spot cheating
- Spot game design flaws (e.g. “sweet spots” and frustrating sections)
Game Data Mining: What can it do for you?

• Tell you when and why players stop playing
• Enable player-driven adaptive games
• Overall, help you make better games
  — Project management
  — Marketing
  — Customer care
Game Data Mining: What can it do for you?

A few examples

- Find weak spots in the design of game
- Which assets that are not getting used
- Figure out how players spend their time when playing
- Predict when they will stop playing
- Predict what they will do while playing
- Discover gold farmers in an MMORPGs
- Explore and use of social grouping
- Figure out how to convert non-paying to paying users
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Player Modelling: In a nutshell
Yannakakis et al., Player Modeling, in Dagstuhl Seminar on AI/CI in Games, 2013

Theory (model-based)  Data (model-free)
Model-based (theory-driven):
- The majority of models have not been tested on or derived from interactive media
- Models are not cross-validated (they should be!)
- Agent-based models (OCC, BDI) – rather limited to agent-based interaction (it’s limited in games)

Model-free (data-driven):
- Big data, crowdsourcing, elegant ML (e.g. deep learning / sequence mining), sensor technology
- Supreme and obvious given the availability of big data and crowdsourcing
- Problems: quality / quantity of data
- Problems: garbage in – garbage out
Player Modelling: Hybrid Approaches
Yannakakis et al., Player Modeling, in Dagstuhl Seminar on AI/CI in Games, 2013

Theory (model-based)

Data (model-free)
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Input
- Gameplay
- Objective
- Context
- Player Profile
- Linked Data
Gameplay
Gameplay Input

- Player game preferences, behavioral patterns
- Examples: tactics, strategy, play patterns, clickthroughs, deaths, weapon selection, character selection, etc...

- **Common features:** Micro vs macro actions
- **Pros:** real-time efficiency
- **Challenge:** we can’t tell much beyond player behavior...
Objective Input

- Bodily and physiological manifestations of gameplay
- **Pros:** reliable measures of user experience
- **Challenges:** many; let’s see them in more detail
Objective Input – ways

- **Cameras**
  - Face
  - Body movement
  - Eye movement

- **Other sensors/devices**
  - Physiology (heart rate, skin conductance, ...)
  - Muscle activation (EMG)
  - Brain activity (EEG)
  - Speech
• **Common features:** summarization, time and frequency domain
• **Pros:** directly linked to arousal – immediate response
• **Challenges:** signal denoising/normalization; control for subjectivity of physiological responses, law of initial values, habituation, rebound
Common features: action unit detection, head pose stats

Pros: every laptop has a camera, off-the-shelf cheap solution, natural interaction

Challenges: do we really express emotions (facially) while playing? Head-pose might be more relevant? Models rely on posed/acted expressions
Tools for Video-Based Affect Detection
Eye-tracking

- **Common features:** blinks and gaze fixation (indicators of attention and engagement); total time spent looking at particular objects
- **Pros:** you know where your player looks at/focuses on/pays attention to
- **Challenges:** practicality, lab conditions (illumination), pupilometry doesn’t really work in games

• **Common features:** frequency-based, detection of spoken words and other communication components (e.g. laughter and pauses)

• **Pros:** speech (pitch, loudness, quality) is linked to emotions (arousal/valence); useful in game-child interaction studies

• **Challenges:** verbal cues are rare; environment noise; multi-player games
https://audeering.com/technology/opensmile/

Context Matters!

a  

b  

c  

d
• Player profile
  • Information about ones’ personality, demographics, culture, age, gender, experience with games etc...
  • In general information that does not change due (or not altered via) games – at least not that rapidly...

• A player profile can form additional input(s) to a player model
• What are the differences?
  • A **profile** is built on *static* data and not influenced by the game
  • A **model** is built on *dynamic* data from the gaming interaction and is (temporally) influenced by the game
Linked Data

- FB emoticons
  - User daily state, emojis, tags
- Twitter-based – semantic info/analysis
- Game reviews
- ...
Input
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Input
- Gameplay
- Objective
- Context
- Player Profile
- Web of Data

Output Data Types
- Interval
- Nominal
- Ordinal

Supervised Learning
- Regression
- Classification
- Preference Learning

Output (Behavior)
- Micro-actions vs. Macro-actions
Input:
- Gameplay
- Objective
- Context
- Player Profile
- Web of Data

Output Data Types:
- Interval
- Nominal
- Ordinal
- No Output

Player Model:

Model-Based [Top-Down]
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Unsupervised Learning

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Output (Behavior):
- Micro-actions vs. Macro-actions
Example (Player Experience Modeling)
Mazeball Dataset – http://hectormartinez.com/
Sequence Mining (General Sequential Pattern)

Martinez and Yannakakis, *Mining Multimodal Sequential Patterns: A Case Study on Affect Detection*, ICMI, 2011 [Outstanding Student Paper Award]
Mazeball’s Model of Fun
Martinez and Yannakakis, *Mining Multimodal Sequential Patterns: A Case Study on Affect Detection*, ICMI, 2011 [Outstanding Student Paper Award]
Convolution for Affect Detection
Martinez, Bengio and Yannakakis, Learning Deep Physiological Models of Affect, IEEE Computational Intelligence Magazine, 2013
Deep Fusion of Events and Signals
Martinez and Yannakakis, *Deep multimodal fusion: Combining discrete events and continuous signals*, *Proceedings of the 16th International conference on multimodal interaction*, 2014
Example (Player Behavior Modeling)

Tomb Raider: Underworld

• How do people play TRU?
• User testing: Do people play TRU as intended?
• Player modeling using *metrics* via machine learning ➔ alternative quantitative approach to traditional qualitative approaches of user and playability testing
Clustering in TRU

- Commercial major game test-bed: Tomb Raider Underworld
- Large-scale data collection (1365 players)
- Data is clean and live: gathered in a natural setup via an industrial logging system and a commercial web service
- First application of SOMs on high-level behaviors of completed games
- Directly addressing game-industry requirements
  - limitations of scalability and commercial-game practicality are minimized
  - bridging the AI gap
• **EIDOS Metrics Suite software**
  – Record gameplay data (*metrics*) of EIDOS games
  – Data are stored in an SQL-server via ELT process
  – Several Features are extracted (work done by *Crystal Dynamics*)
    ▪ 3D coordinates, completion time, # deaths etc.

• **Live Data** (xBox Live!)
  – Published version of TRU played in gamers’ natural habitats
  – Data free from laboratory bias and experiment expectancy effects

• **Data collection during November 2008**
  – 25240 Players
  – 1365 of those completed the game
  – Data are stored for all 7 levels (100 map units)
• **Causes of Death (% over total number of deaths)**
  - **Opponent** – 28.9% of all deaths – Min: 6%, Max: 60%
  - **Environment** – 13.7% of all deaths – Min: 2%, Max: 45%
  - **Falling** – 57.2% of all deaths – Min: 27%, Max: 83%

• **Total Number of Deaths** – 140 on average – Min: 16, Max: 458

• **Completion Time** – 550 min on average – Min: 3h, Max: 29h

• **Help-on-Demand (# hint + answer requested)**
  – 29 on average – Min: 0, Max: 148
Emergent Self-Organizing Maps (ESOMs)

- Unsupervised learning through self-organization of a neuron map
- Dimensionality reduction to 2D
- Training
  - Batch
  - Toroid topology (50X100 neurons)
  - Rectangular grid
- Performance Measures
  - Topographic error
  - Quantization error
Clustering in TRU (ESOMs)

Feature Planes

Cause of Death: Opponent

Cause of Death: Environment

Cause of Death: Falling
Feature Planes

- Number of Deaths
- Completion Time
- Help on Demand (HoD)
Video: Four Resulting Player Clusters

https://www.youtube.com/watch?v=HJS-SxgXAI4
Analysing Player Behaviour in

*Tomb Raider: Underworld*

https://www.youtube.com/watch?v=A89ZDjF51Nk
Player Model

**Model-Based [Top-Down]**
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**Output Data Types**
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**Supervised Learning**
- Regression
- Classification
- Preference Learning

**Unsupervised Learning**

**Output (Behavior)**
- Micro-actions vs. Macro-actions

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Unsupervised Learning

Output (Experience)
- Free Response vs. Forced Response
- First Person vs. Third Person
- Discrete vs. Continuous
- Time-Discrete vs. Time-Continuous
- Pre vs. During vs. Post
- Ratings vs. Classes vs. Ranks
- Absolute vs. Relative

Output (Behavior)
- Micro-actions vs. Macro-actions
Labels are Key!
Why Output (Annotation) is Key?

• Annotation is the labelling of experience
• This is ultimately the *ground truth* (golden standard) of experience
• This is the **training signal** for your computational models
Key Questions of Labelling

- Who annotates?
- When?
- How often?
- How?
### Who Annotates?

- **Third Person**
  - Usually a domain expert (game designer) or a psychologist

- **First Person**
  - The person actually experiencing the emotion/affect

<table>
<thead>
<tr>
<th></th>
<th>Third person</th>
<th>First person</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>+</strong></td>
<td>• Expert knowledge</td>
<td>• Reported true experience</td>
</tr>
</tbody>
</table>
| **-**      | • Assumptions about the true emotion  
  • Reporting effects | • Self-deception  
  • Reporting effects  
  • No expert knowledge |
How is Player Experience Represented?

- Discrete states (e.g. fun, engagement, frustration)
- Continuous dimensions (e.g. arousal and valence)
How Often to Annotate?

- Time-Discrete (e.g. self-assessment manikin)
- Time-Continuous (e.g. FeelTrace, AffectRank)
How Often to Annotate?

• Depends on
  • Application (speed of interaction: e.g. games vs. movies vs. e-learning apps)
  • Signal (e.g. physiology is slower than body movement and speech)

• No gold standard
When to Annotate?

- Before play (**Pre**-Experience)
- **During** (real-time) experience
- After play (**Post**-experience)

<table>
<thead>
<tr>
<th>Before</th>
<th>During</th>
<th>After</th>
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</table>
| • Set the baseline of a player's state prior to playing a game  
  • Information that enriches our models  
  • Detecting the *relative* change from baseline | • Report on the spot!  
  • Real experience (better ground truth?)  
  • Limited memory effects | • Controlled  
  • Non-intrusive |
| • No data about experience | • Highly intrusive  
  • Distorts the experience (first person) | • Self-deception  
  • Various reporting effects |
A note about time and self-report!

- Self-reports are time-dependent
- Real experience vs. Post-experience
  - Few seconds → Real experience
  - Few minutes/hours → Episodic memory (context retrieval)
  - More → Semantic Memory (beliefs)

NB. The gap between our memory of experience and our experience is more prominent when we report unpleasant emotions such as anger, sadness and tension. Also: The experience felt near the end of a session (e.g. a game level or a game) affects our report – aka peak-end rule.
Which Annotation (Data) Type?
Which Annotation (Data) Type?

- Scalar (Likert scale, arousal/valence score, SAM) – Rating
- Binary value or a class – Class
- Preference between two or more options – Rank
Examples: Geneva Wheel, SAM, Likert Scales, PAD values
Examples:
• This facial expression is **happy**! (Eckman)
• Arousal values higher than 0.6 belong to class **aroused**
• This skin conductance peak denotes **stress**
Rank

X is more/less frustrating than Y

- Requires at least two instances!
- N-Alternative Forced Choice (4-AFC is popular)

☐ X is more/less frustrating than Y
☐ Both are equally frustrating
☐ Neither is frustrating
<table>
<thead>
<tr>
<th>Class</th>
<th>Scalar</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Easy to analyse and process. Only one instance (to be annotated) is required. Part of subjectivity is eliminated.</td>
<td>Easy to analyse and process. Only one instance (to be annotated) is required.</td>
<td>Controls for reporting memory effects (increasing/decreasing the memory window). Eliminates subjectivity biases. It is natural to compare (key trend in marketing research). Evidence from neuroscience.</td>
</tr>
<tr>
<td>Assumptions made about classification. What is the “gold” threshold value that splits classes?</td>
<td>Highly subjective; Use of scale-bias; Culture-bias, Personality (temperament, interests)-bias; Increased between-participants effects; Logical errors: confused by ordinal scales. Primacy and Recency order effects. Memory effects. Key fundamental issues (see next slide).</td>
<td>Primacy and Recency order effects. Memory effects.</td>
</tr>
</tbody>
</table>

Which Annotation (Data) Type? Summary
What is the Value of Player Experience?
A thesis: emotions are intrinsically ordinal (relative)

The thesis is supported by theoretical arguments and empirical evidence across disciplines

It reframes the way emotions are viewed, represented and analysed computationally
Mapping the intensities of responses to particular stimuli

That is basic to AC/HCI/UX/GUR...: we call it labelling

Two approaches have a long history

• The older (Fechner) was based on comparing stimuli, and finding ‘just noticeable differences’

• Much later, Stevens introduced ‘magnitude estimation’ – asking people to give a number. Twenty years ago, psychologists tried a magnitude estimation approach to labelling. The data are in, and we know it doesn’t work as straightforwardly as they hoped.
When people are presented with a piece of data and asked to assign a magnitude describing an emotional response, they tend to disagree quite substantially.

Or else...

....there is **seriously** no point in this....

Why? Multivalued Emotion...
Why? Adaptation Level...
**Magnitude** is deeply context-dependent

**Pairwise comparison** is robust! A reference point is forced

We encode values in a **relative** fashion
The ordinal (relative) approach

Some Evidence for the Ordinal Nature of Experience
Classified Ratings vs Ranked Ratings

Martinez et al., Don’t classify ratings of affect; Rank them! IEEE Trans. on Affective Computing, 2014
AffectRank: Ordinal Emotion Annotation

https://github.com/TAPeri/AffectRank
Tools @ emotion-research.net
X is more/less engaging than Y
Both are equally engaging
Neither is engaging

Ratings (Likert) vs Preferences (Ranks)

Yannakakis and Martinez, *Ratings are Overrated! Frontiers in Human-Media Interaction*, 2015
Stress Annotation: Classes vs Preferences

Treat ratings as **ordinal data**: rank them!

\[ X \text{ is more/less challenging than } Y \]

- frustrating
- arousing
- boring
- fearful
- ...

---

Martinez, Yannakakis and Hallam, *Don’t classify ratings of affect; Rank them*, IEEE Transactions on Affective Computing, 2014
To sum it up: don’t do this...

- Wasteful Info due to
  - Scale-bias
  - Personal-bias
  - Labels are NOT numbers
  - High inconsistency (randomness)
  - ...

Do this instead...

☐ I like Julian’s class more/less than Georgios’ class
☐ I like them both equally
☐ I like neither

You gain on:
  • Reliability
  • Validity
  • Generality

How does this video compare to other YouTube videos you watched this week?

  - One of the worst
  - A poor video
  - About average
  - A great video
  - One of the best videos
  - Don’t remember/haven’t watched it

SUBMIT
An Ordinal Perspective

1\textsuperscript{st} vs. 3\textsuperscript{rd} person: depends on the application

Try to get reports as close to the \textit{true experience} as possible (time-wise)

No report is ideal (they suffer from biases)

Annotate experience as \textbf{ranks} whenever possible

If ratings are available

\begin{itemize}
  \item Regression of ratings is \textbf{fundamentally wrong}
  \item Do not convert them to classes – it will cost you on model performance
  \item \textbf{Convert them to ranks} (treat them as ordinal scales)!
\end{itemize}
How Can we Model Players?
Supervised Learning

Data collection

Feature extraction and selection

Modelling
Supervised Learning

• The output of the model is the *estimated experience*
• The **ground truth** is given by annotated experience given as
  ▶ Nominal values (e.g. sample A is frustrated)
  ▶ Numerical values (e.g. sample A is 0.86 frustrated)
  ▶ Ordinal values
    - Ranks (e.g. sample A is more frustrating than sample B)
    - Ratings (e.g. sample A is ‘extremely frustrating’ and sample B is ‘fairly frustrating’
Which Training Method?

- Preference learning
- Classification
- Regression
Example: modeling *fun* ratings

How much *fun* was that game?

1. not at all
2. slightly
3. moderately
4. fairly
5. extremely

Example: modeling *fun* ratings

$x$: input features

$fun(x)$
(1) Initialise to random weights

(2) For each training pattern p:
   (a) Present input pattern $\mathbf{x}^{(p)}$
   (b) Compute output(s) using forward mode
   (c) Compute output error $E^{(p)}$
   (d) Compute error derivatives $-\eta \frac{\partial E}{\partial w_{jk}}$
   (e) Update weights by $\eta \frac{\partial E}{\partial w_{ij}}$

(3) Is error small?
   - Yes: then STOP
   - No: loop to step (2)
The **bad**: Regression

- Remember: ratings are **NOT** numbers!
  - Not everyone uses scales in the same way
  - Items in the scale are not equidistant
Regression with Backpropagation

\[ E_k = \frac{1}{2} (d_k - a_k)^2 \]

- Output (\( f(x) \))
- Inputs (\( x \))

Sum of squared deviations

Training patterns (d) (red)
ANN prediction (a) (blue)
• Converting ratings into classes eliminates a lot of information and it can introduce biases.

• Same as regression but with one output per class

Sum of squared deviations

\[ E_k = \frac{1}{2}(d_k - a_k)^2 \]
The **good**: Preference Learning

- Learn only the ordinal relations
- Valid whenever the annotator is consistent on her use of the scale

![Graph showing preference learning with input features and function values](image)
(Deep) Preference Learning

- Error function maximizes the distance between the output for the preferred sample \((d^A)\) and the output for the non preferred sample \((d^B)\)

\[
E = \max(0, 1 - (d^A - d^B)) \quad \frac{\partial E}{\partial w_{ij}} = \begin{cases} 
-\frac{\partial d^A}{\partial w_{ij}} + \frac{\partial d^B}{\partial w_{ij}} & \text{, if } d^A - d^B < 1 \\
0 & \text{, otherwise}
\end{cases}
\]
The concept of learning from pairs of preferences can be implemented in most supervised learning methods by adapting the error/fitness function:

- Neuroevolution
  - Fitness that rewards match of pairs
- Rank-based ANN (RankNet)
- SVMs (RankSVM)
- Decision Trees
- ...

(Deep) Preference Learning Beyond BP
Preference Learning Toolbox

http://plt.institutedigitalgames.com/
Preference Learning Examples
Player Experience Modeling in Super Mario

- 327 subjects (1308 games)
- Input: Playing Behavior and Content Features
- Output: Engagement, Frustration, Challenge self-reported ranks (pairwise) of short games
- ANN trained via Neuroevolutionary Preference Learning
- Player experience model accuracy: 73-92%
Three Player experience states modelled:

- Engagement, Frustration, Challenge

Player Experience is self-reported (post-experience) via a 4-alternative forced choice questionnaire:

- Game A is more/less engaging than Game B
- Both are equally engaging
- Neither is engaging

Super Mario Bros Example: The Annotated Experience (ANN output)
Super Mario Bros Example: The Modeling Approach

Platformer Experience Dataset

http://ped.institutedigitalgames.com/
**Input**
- Gameplay
- Objective
- Context
- Player Profile
- Web of Data

**Output Data Types**
- Interval
- Nominal
- Ordinal
- No Output

**Player Model**

**Model-Based [Top-Down]**
(Psychology, Cognitive Science, Game Studies, ...)

**Model Free [Bottom-Up]**
(Data Science, Machine Learning)

**Supervised Learning**
- Regression
- Classification
- Preference Learning

**Unsupervised Learning**

**Output (Experience)**
- Free Response vs. Forced Response
- First Person vs. Third Person
- Discrete vs. Continuous
- Time-Discrete vs. Time-Continuous
- Pre vs. During vs. Post
- Ratings vs. Classes vs. Ranks
- Absolute vs. Relative

**Output (Behavior)**
- Micro-actions vs. Macro-actions
Input
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- Objective
- Context
- Player Profile
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Player Model

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Output (Behavior)
- Micro-actions vs. Macro-actions

Output Data Types
- Interval
- Nominal
- Ordinal
- Reward
- No Output

Supervised Learning
- Regression
- Classification
- Preference Learning

Reinforcement Learning
- Unsupervised Learning
• Given utilities (rewards) show me believable gameplay
• Useful for human-standard game testing
• RL
  – MCTS
  – NeuroEvolution
  – ...
• Inverse RL
Welcome to the Artificial Intelligence and Games book. This book aims to be the first comprehensive textbook on the application and use of artificial intelligence (AI) in, and for, games. Our hope is that the book will be used by educators and students of graduate or advanced undergraduate courses on game AI as well as game AI practitioners at large.

**Final Public Draft**

The final draft of the book is available [here](gameaibook.org).