Introduction

- Virtual experience management
  - AI problem
- Player modelling
- AI planning
- Emotion modeling
Virtual Experience

- Entertainment
- Training
Inherent complexity of physical phenomena and personnel activities
• Concurrent crises
• Limited resources
• Information overload
• Considerable uncertainty
• Psychological stress
• Very limited real-life practice

Simulated DC environment: DC-Train 2.0
Learning Player Preferences for Better Interactive Stories
Lost Operative

Scanner Results:
- Lorek: Rich

Anomaly Detected!
- Element Zero: 3500
- Indium: 4000
- Platinum: 2000
- Palladium: 4500

Launch Probe
30 Probes
Three Different Players

Lost Operative

Lost Operative

Lost Operative

All screenshots from http://guides.ign.com
Three Different Players

Lost Operative

Lost Operative

Lost Operative

10

All screenshots from http://guides.ign.com
Three Different Players

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All screenshots from http://guides.ign.com
Three Different Players

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All screenshots from http://guides.ign.com
How can we do better?

Lost Operative

2
How many will the average player see?
Suppose that average players see 70% of available N7 missions.

How many will the average player see?
A Given Single Player
A Given Single Player
70% of available N7 missions
A Given Single Player
70% of available N7 missions
How can we do better?

Lost Operative

2

All screenshots from http://guides.ign.com
How can we do better?
Three Different Players

- Lost Operative
- Lost Operative
- Archeological Dig Site

All screenshots from http://guides.ign.com
If you know about your audience, you can tell a better story.
Our Goals

More Fun

More Agency

by automatically learning about each player,
and selecting content that’s best for them
PaSSAGE
Player-Specific Stories via Automatically Generated Events
Model Updates

Encounter Manager

Encounters

Player Model

Game Engine

Model Values

(Convey)

Audio/Video

(Interpret)

Encounters

Model Updates

(Decide)

Actions

(Gather)

Player
Learning Player Preferences
Player Model

Player types come from Robin's Laws of Good Game Mastering (Laws 2002)
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Player types come from Robin's Laws of Good Game Mastering (Laws 2002)
Better Interactive Stories
Archeological Dig Site

Lost Operative

Endangered Research Station

Captured Mining Facility
Archeological Dig Site
Endangered Research Station
Lost Operative
Captured Mining Facility
Archeological Dig Site

Lost Operative

Endangered Research Station

Captured Mining Facility

Fighter
Method Actor
Storyteller
Tactician
Power Gamer
Archeological Dig Site

Endangered Research Station

Lost Operative

Captured Mining Facility

Method Actor

Storyteller

Tactician

Power Gamer
First Testbed
Increasing Player Fun

LITTLE RED RIDING HOOD

David Thue, Eric Waslyishen, Michael Webb
Vadim Bulitko, Marcia Spetch
Evaluation
Results for Increasing Fun

114 players  mean age 19.5  1/3 male

(Thue et al., AIIDE 2010)
Evaluation
Results for Increasing Fun

114 players  mean age 19.5  1/3 male

Player-Specific Stories are more Fun: 93% Confidence

(Thue et al., AIIDE 2010)
Our Goals

More Fun  More Agency

by automatically learning about each player, and selecting content that’s best for them.
Our Goals

More Fun ✔️ More Agency

by automatically learning about each player, and selecting content that's best for them
PaSSAGE 2.0
Player-Specific Stories via Automatically Generated Events
Protests over ending of *Mass Effect* 3 show fan investment in story control

By Kyle Orland | Published 7 days ago

Many *Mass Effect* 3 players feel kind of like Commander Shepard in this image, watching helplessly as events transpire out of their control.

*Mass Effect* 3's ending didn't match up with the reality.

*Mass Effect* 3 sold 890,000 copies in its first hours on the market, but not everyone is pleased with the game's ending.

One fan is reportedly so peeved that he filed a false advertising complaint with the Federal Trade Commission.

“Looking through the list of promises about the game they made in their campaign and PR interviews, it was clear the product we got did not live up to any of the ads,” user El_Spiko wrote on the forums, according to gamepur.com.
Proposed Approach
Inspiration from Psychology

The Control Heuristic

When our decisions lead to desirable outcomes, our perceived agency is increased.

(Thompson et al., Psychological Bulletin 1998)
Proposed Approach
Inspiration from Psychology

The Control Heuristic

When our decisions lead to desirable outcomes, our perceived agency is increased.

(Thompson et al., Psychological Bulletin 1998)

Our goal is to maximize the desirability of the content that occurs as a result of player decisions.
Lord of the Borderlands

Vile beast! You will regret running into us this day!

1. We will kill you!
2. I bet we'll get a reward if we bring you in alive!
3. Bluff: We are scouts from the army!
4. Whisper: Colin, make a distraction!
5. Intimidate: It's two on one, monster. Leave while you can!

We need strength as the monsters besiege our Empire in the North, along with all the wisdom and cunning you've got.

David Thue, Trevon Romanuik, Charles Crittenden, Vadim Bulitko, Marcia Spetch
Congratulations, students.
My boy! My boy! You’ve been locked up in that school for far too long. It is good to see you!
My boy! My boy! You've been locked up in that school for far too long. It is good to see you!
You’re the lord’s nephew? They told me that I was going to face you in a duel! I guess that plan went awry.
Fucked up in that school for far too long to see you!
Come no closer!
Your people don't trust me or my fellow rebels yet, but I'm sure that a few words from you will get us what we need: weapons, armor, and supplies.
My boy! My boy! You've been locked up in that school for far too long. It is good to see you!
You're the lord's nephew? They told me that I was going to face you in a duel! I guess that plan went awry.
Evaluation
Results for Increasing Agency

141 players  mean age 19.4  38% male
Player-Specific Stories give a feeling of more Agency:  96% Confidence

(Thue et al., AIIDE 2011)
Our Goals

More Fun ✔ More Agency

by automatically learning about each player, and selecting content that's best for them.
Our Goals

More Fun ✓ More Agency ✓

by automatically learning about each player, and selecting content that’s best for them.
By dynamically selecting story content based on a learned model of player preferences, we can increase the amount of fun and agency that players perceive.
Automated Planning and Player Modelling for Interactive Storytelling
The Agency Maximization Problem

Authorial
- Story trajectories
- Resources

Experience Manager
- Increase player fun and agency
- Procedural generation

Evaluation
- Measure perception
Experience Management as a Formal Problem
Experience Management as a Formal Problem

Game states
- Goals
Experience Management as a Formal Problem

Game **states**
- Goals

Player **actions**
- Player’s **policy**

![Diagram of state transition with action](image)
Experience Management as a Formal Problem

Game states
- Goals

Player actions
- Player’s policy

Transition function
Experience Management as a Formal Problem

Game states
- Goals

Player actions
- Player’s policy

Transition function

Reward function

![Diagram showing states, actions, rewards, and transitions in a game context.]
Experience Management as a Formal Problem

Game **states**
- Goals

Player **actions**
- Player’s **policy**

**Transition** function

**Reward** function

**Trajectory**
Experience Management as a Formal Problem

Game states
  ◦ Goals

Player actions
  ◦ Player’s policy

Transition function

Reward function

Trajectory

Markov Decision Process
Generative Experience Managers
Generative Experience Managers
Generative Experience Managers

Generative Experience Managers

Intervention

Accommodation

ASD
ASD

Automated Story Director (Riedl et al., 2008)
ASD

Automated Story Director (Riedl et al., 2008)

Ruptures = inconsistencies

Planning fixes inconsistencies
- Longbow
- ASD Three-tiered Planning
ASD

Automated Story Director (Riedl et al., 2008)

Ruptures = inconsistencies

Planning fixes inconsistencies
  ◦ Longbow
  ◦ ASD Three-tiered Planning

Procedural generation

Evaluation
PAST

Player-specific Automated Storytelling
(Ramirez and Bulitko, 2012)
Player-specific Automated Storytelling
(Ramirez and Bulitko, 2012)
PAST

\[ s_0 \xrightarrow{\text{greet}} s_1 \xrightarrow{\text{kill wolf}} ? \xrightarrow{\text{introduce grendel}} g \xrightarrow{\text{resurrect wolf}} s' \xrightarrow{\text{?}} s'' \]
PAST

\[ s_0 \xrightarrow{\text{greet}} s_1 \xrightarrow{\text{kill wolf}} ? \xrightarrow{\text{resurrect wolf}} s' \xrightarrow{\text{introduce grendel}} g \xrightarrow{\text{Player model}} \]
PAST

\[s_0 \xrightarrow{\text{greet}} s_1 \xrightarrow{\text{kill wolf}} s'' \xrightarrow{\text{introduce grendel}} g\]

\[s' \xrightarrow{\text{resurrect wolf}} s_1\]
Goal

Evaluate planning-based experience managers for **fun** and **agency**
Goal

Evaluate planning-based experience managers for **fun** and **agency**
Evaluation Design

- Text-based prototype
- Two-way ANOVA
- Fun and agency
- Gamers vs. non-gamers
User Study 1

Agency

Fun
User Study 1

Agency

Fun

[Bar chart showing agency scores for gamers and non-gamers. The chart indicates that gamers have a significantly higher agency score compared to non-gamers.]
User Study 1

Agency

Fun

---

Fixed  ASD

---

Fun Score

0  0.1  0.2  0.3  0.4  0.5  0.6  0.7  0.8  0.9  1

Gamers  Non-gamers
User Study 2

Agency

Fun

72
User Study 2

Agency

Fun

72

Fixed  ASD  PAST

Agency Score

Gamers  Non-gamers
User Study 2

Agency

Fun

72

Fun Score

Gamers
Non-gamers
User Study 3

Agency

Fun
User Study 3

Agency

Fun

![Bar chart showing agency scores for gamers and non-gamers. The chart indicates that gamers have higher agency scores compared to non-gamers.]

ASD

PAST

34
User Study 3

Agency

Fun

34

![Bar chart showing fun scores for gamers and non-gamers. The chart indicates that gamers have higher fun scores compared to non-gamers.](chart.png)
Discussion

User Studies

- ASD increases **fun** and **agency**
- PAST increases **agency**
- Adequate content **distribution** is important
Emotion Modelling
AI for Emotion Modelling

- Emotional state/response of the player/trainee
  - a core point of art
  - important for training
- Cannot craft the experience *a priori* for interactive stories
  - AI needs to manage the experience for a desired emotional response
    - a model of the player/trainee
    - emotional trajectory from the author
Related Work

- Shaping experience to keep the player on an emotional trajectory
- Facade [Mateas, Stern 2003]
- AI Director in Left4Dead [Booth 2009]
- Emotion model has to be player-specific
Our Approach

- ASD to plan candidate narrative repairs in response to a rupture
- Select the one that keeps the player on an author-given emotional trajectory
- Predict player’s emotional reaction
  - PaSSAGE to model the player
    - infer his/her intentions/beliefs
  - Appraise those w.r.t. a candidate repair: CEMA [Bulitko, et al., 2008]
Psychological Underpinnings

Figure 1: The cognitive-motivational-emotive system. Adapted from Smith and Lazarus’ (1990)
## Table 1: Appraisal Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relevance</td>
<td>Does the event require attention or adaptive reaction</td>
</tr>
<tr>
<td>Desirability</td>
<td>Does the event facilitate or thwart what the person wants</td>
</tr>
<tr>
<td>Causal attribution</td>
<td></td>
</tr>
<tr>
<td>Agency</td>
<td>What causal agent was responsible for an event</td>
</tr>
<tr>
<td>Blame and Credit</td>
<td>Does the causal agent deserve blame or credit</td>
</tr>
<tr>
<td>Likelihood</td>
<td>How likely was the event; how likely is an outcome</td>
</tr>
<tr>
<td>Unexpectedness</td>
<td>Was the event predicted from past knowledge</td>
</tr>
<tr>
<td>Urgency</td>
<td>Will delaying a response make matters worse</td>
</tr>
<tr>
<td>Ego Involvement</td>
<td>To what extent does the event impact a person’s sense of self (social esteem, moral values, cherished beliefs, etc.)</td>
</tr>
<tr>
<td>Coping potential</td>
<td></td>
</tr>
<tr>
<td>Controllability</td>
<td>The extent to which an event can be influenced</td>
</tr>
<tr>
<td>Changeability</td>
<td>The extent to which an event will change of its own accord</td>
</tr>
<tr>
<td>Power</td>
<td>The power of a particular agent to directly or indirectly control an event</td>
</tr>
<tr>
<td>Adaptability</td>
<td>Can the person live with the consequences of the event</td>
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[from Gratch and Marsella 2004]
### Table 3: Emotion categorization and intensity rules

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<tr>
<th>Appraisal Configuration</th>
<th>Emotion</th>
<th>Intensity</th>
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<tr>
<td>Desirability(p) &gt; 0, Likelihood(p) &lt; 1.0</td>
<td>Hope</td>
<td>Desirability(p) × Likelihood(p)</td>
</tr>
<tr>
<td>Desirability(p) &gt; 0, Likelihood(p) = 1.0</td>
<td>Joy</td>
<td>Desirability(p) × Likelihood(p)</td>
</tr>
<tr>
<td>Desirability(p) &lt; 0, Likelihood(p) &lt; 1.0</td>
<td>Fear</td>
<td></td>
</tr>
<tr>
<td>Desirability(p) &lt; 0, Likelihood(p) = 1.0</td>
<td>Distress</td>
<td></td>
</tr>
<tr>
<td>Desirability(p) &lt; 0, causal attribution(q)=blameworthy</td>
<td>Anger</td>
<td></td>
</tr>
<tr>
<td>Desirability(q ≠ p) &lt; 0, causal attribution(p)=blameworthy, causal agent = p</td>
<td>Guilt</td>
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## EMA subset used in CEMA

### Table 3: Emotion categorization and intensity rules

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Conclusions

- Player/trainee **experience management**
  - need AI for mass-deployment/consistency
    - **procedural accommodations**
- **Player/trainee modelling**
  - play styles
  - goals/beliefs/intentions
  - emotions