Skill-based Mission Generation: A Data-driven Temporal Player Modeling Approach

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ABSTRACT

Games often interweave a story and series of skill-based events into a complete sequence—a mission. An automated mission generator for skill-based games is one way to synthesize designer requirements with player differences to create missions tailored to each player. We argue for the need for predictive, data-driven player models that meet the requirements of: (1) predictive power, (2) accounting for temporal changes in player abilities, (3) accuracy in the face of little or missing player data, (4) efficiency with large sets of data, and (5) sufficiency for algorithmic generation. We present a tensor factorization approach to modeling and predicting player performance on skill-based tasks that meets the above requirements and a combinatorial optimization approach to mission generation to interweave an author's preferred story structures and an author's preferred player performance over a mission—a kind of difficulty curve—with modeled player performance.

Categories and Subject Descriptors

I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems—*Games*; K.8.0 [**Personal Computing**]: General—*Games*

General Terms

Algorithms, Measurement, Design, Human Factors

Keywords

Procedural Content Generation, Optimization, Player Modeling

1. INTRODUCTION

Games typically involve a sequence of skill-based tasks, such as combat or puzzle-solving, motivated by story. While games are often designed with a fixed progression of task difficulty, there have been calls for dynamic tailoring of difficulty on a per-player basis [13]. Dynamic difficulty adaptation is a challenging problem; given the current broad diversity of player background skills, preferences, and motivations, this matching is typically difficult or impossible to achieve with any single, fixed progression. The solution is *Procedural Content Generation* (PCG), in which a system automatically creates game content algorithmically, with or without the involvement of a human designer. *Just-in-time PCG*, in which the algorithm uses information about a player that cannot be known *a priori*, is well suited for customization of player experiences and dynamically creating numerous variations to promote replayability.

In this paper, we explore just-in-time content tailoring to dynamically adjust the difficulty of a game and provide motivating context for the adjustments provided. Specifically, we look to solve two related problems: *challenge tailoring* and *challenge contextualization*. Challenge tailoring is the problem of matching the difficulty of skill-based challenges over the course of a game to match player abilities. Challenge contextualization is the problem of providing appropriate motivating story context for the skill-based challenges. We motivate an approach to these problems with a simple role-playing game in which skill-based challenges manifest as combat with monsters (see Figure 1), which are contextualized through common role-playing game activities such as quests and interactions with non-player characters. The solution to the challenge tailoring and challenge contextualization problems in this domain is a *mission*, a sequence of events to occur in the game world, interleaving skill-based combat with story-based background motivation. Borrowing the term from Dormans [5], missions are brief "chapters" of gameplay that are composed of sequences of events that are a subset of the complete game plotline (see Figure 2).

Just-in-time content tailoring requires a model of the player and a means to use this model to adjust content to fit the player [24, 25]. We identify five criteria for player models for the purposes of content tailoring:

1. **Predictive power**—capturing expected player behavior or experience when given a known task or situation
2. **Accuracy**—correctly inferring player behavior or experience with high confidence, particularly when faced with partial/missing player data or small amounts of player data; transferring information between players is also desirable
3. **Efficiency**—scaling to large sets of data: fine-grained, long-term, and including many players

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Figure 1: Example battle between player team (right) and monsters (left).

4. **Generative sufficiency**—usable in generative models as parameters or evaluation methods; contrasted with abstract class labels or theoretical constructs

5. **Temporal**—capturing changes in player behavior and experience over the course of experiences; capable of forecasting several steps into the future and incorporating interactions among individual experiences along a trajectory

Many existing PCG techniques have used theory-driven models guided by designer intuition or a qualitative model of player experience. This has limited these efforts to domains where players are well-understood and cleanly fit into particular *a priori* known categories. When such categories and theories are lacking, we believe that tailored content generation systems require data-driven player models based on empirical data connecting the effects of content to player responses [22]. Such player models incorporate bottom-up information from players into the system design. Accounting for temporal variations in player models (e.g. learning to play the game over time or shifting preferences over time) can further enhance generation by predicting player changes in the future and creating sequences of content tailored to these expected changes.

We propose a tensor factorization approach based on collaborative filtering as a data-driven means of modeling and predicting player performance on skill-based events such as computer game combat. This approach captures temporal variations in the relationship between player abilities and task features in influencing player performance, for building player skill models meeting the above five criteria. Our player model is incorporated into a mission generation algorithm, based on a genetic algorithm, that balances tailoring content to players with designer-specified content requirements and preferences [27]. Our system is thus capable of producing a variety of missions tailored for any given player while still meeting high-level designer intentions.

...
enter(town)
arrest(guards, companion)
battle(guards)
reveal-history-foe(companion, wizard)
...
enter(palace)
search(castle, wizard)
guard(acid-monsters, wizard)
battle(acid-monsters)
capture(wizard)
...
meet(king)
ask-rescue(king, princess)
find-clue(princess)
enter(dungeon)
battle(ice-beasts)
free(princess)
...

Figure 2: An example of a single mission containing three challenge events (in bold).

2. RELATED WORK

Research on generating or adapting games to players has investigated both generating content and modeling players. Procedural content generation (PCG) research has developed systems to construct or adapt content—including puzzles, platformer game levels, racetracks, and game stories—from a given set of domain content using a variety of algorithms (for reviews, see [22, 25]). Previous work on PCG in the role-playing game genre includes generating missions and levels [5, 8, 10, 19].

Player modeling research has investigated techniques to extract player preferences or skills given their activities in a game (e.g. [1, 14, 18, 23]). Most systems, however, have relied on theory-driven player models based on designer experience or qualitative theory that lack direct connections to the behavior of players during play. For example, Thue, et al. [21], Seif El-Nasr [6], and Magerko [11] model players of an interactive story using vectors of various archetypal player classes. Other researchers have applied data-driven techniques including evolutionary computing and machine learning methods to model players. Pedersen et al. [14] collect preferences from players of a platformer game through a questionnaire and train a neural network to predict player emotional states based on player behavior and game features. Weber, Mateas, and Jhala [23] model player retention using an ensemble of regression algorithms and a ranking of features according to their individual impact on player retention. Harrison and Roberts [7] model the temporal relationships among acquiring achievements in a massively-multiplayer online role-playing game using correlations between achievements for different players at different times. Yu and Riedl [26] use a collaborative filtering approach to predict preferences for subsequences of a choose-your-own-adventure story. Our player modeling approach differs from those above in that it is both data-driven *and* incorporates temporal variations in player performance—that is, our technique, based on tensor factorization, allows us to model change in a player's skill over time.

Educational data mining (EDM) researchers have explored a variety of models to capture player skills and preferences in the context of learning tasks (for a review, see [4]). While

we focus on games for entertainment, the fact that players learn a set of skills while playing makes EDM relevant. Among EDM approaches to player modeling, collaborative filtering techniques are most relevant to the current discussion as they meet the five requirements of predictive power, accuracy with partial data, efficiency with large data sets, sufficiency for algorithmic input, and accounting for temporal change. Recent advances have extended these models to handle temporal factors [9, 20]. Mapping to standard collaborative filtering terminology, players are treated as users, particular tasks they execute (e.g. a mathematics problem) as items, and the performance on the task as the rating.

Mission generation shares much in common with story and quest generation, in which a system autonomously produces a linear or branching sequence of events to play out in the game world. Generation of sequential content has often been approached as a planning problem, in which the system searches for a sequence of operations to transform a given domain from an initial state to a goal state, with the final sequence being the generated content. Porteous, et al. [15] developed a system that organizes a set of given key elements of a story along a dramatic arc and subsequently fills gaps between these events using a planning system. Li and Riedl's [10] system uses partial order planning to adapt quest plans to a set of player-specified requirements for events to include or exclude from an initial quest.

Alternative approaches to content generation for stories have explored the use of machine learning and evolutionary computation techniques. Roberts et al. [16] used a reinforcement learning technique—targeted-trajectory distribution Markov Decision Processes—to direct an agent to construct appropriate stories from a space of possible stories given sequences of player actions. Sorenson and Pasquier [19] combine a feasible-infeasible 2-population genetic algorithm with constraint satisfaction techniques to generate challenge-based game levels. As with the planning systems above, these efforts are based on *a priori* known models of player experiences: TTD-MDP's rely on author specified distributions, and Sorenson and Pasquier's challenge metric is predefined by an author and tuned using level exemplars independent of player performance. We integrate our player model into a combinatorial optimization approach—using a genetic algorithm—that integrates given author-specified evaluation criteria with player performance-derived criteria [27]. We advance previous work by incorporating dynamic models of players into the generation process while also leveraging additional knowledge of how players learn over time.

3. TAILORING GAME MISSIONS

Our goal is to generate missions—sequences of skill-based challenge events and story events. Challenge events are tasks that assess player skills, such as battles that assess player combat abilities or spatial puzzles that assess player spatial problem-solving abilities. In contrast, story events provide motivating plot or character developments for a game world, such as narrated plot points or conversations with characters. Generating missions requires solving both the *challenge tailoring problem* and *challenge contextualization problem*. The challenge tailoring problem requires finding a sequence of skill-based challenge events that produces a given progression of predicted player performance. To determine whether a particular sequence of challenges is appropriate,

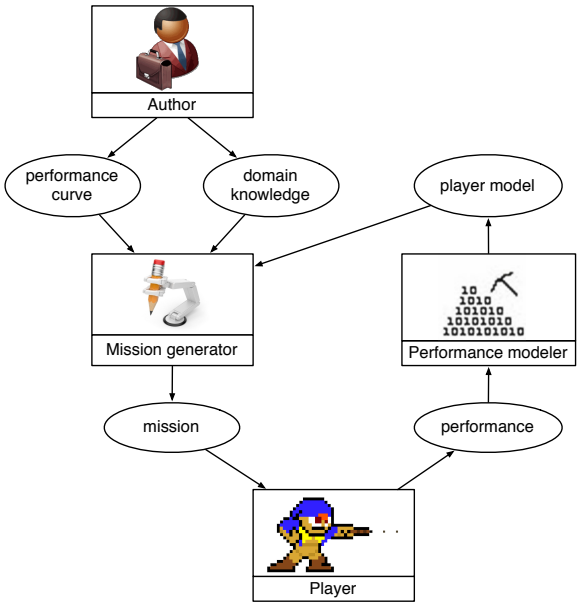

Figure 3: Framework for model training and mission generation.

the game designer specifies a *performance curve*—a progression of player performance over the course of a mission—to guide generation. For example, a performance curve describing a reduction of player performance over time can create the feeling of increasing challenge. Designers may specify any form of performance curve desired, representing arbitrary shapes such as fluctuating peaks and valleys or a rise and subsequent drop in performance.

In missions, skill-based challenge events, such as battles, do not exist in isolation from the other aspects of game play. The challenge contextualization problem is the creation of story content that motivates game play in between challenges, sets up challenges, and varies the game play to increase replayability. The fragments of a single, full mission shown in Figure 2 contain numerous story events that contextualize the battles. Challenge contextualization is a simplified form of story generation. Whereas story generation provides causally linked narratives that incorporate a sequence of required events and end with a given consequence, challenge contextualization provides interesting interactions with characters and short-term quests to motivate the player's activities without concern for a coherent overarching narrative. In challenge contextualization, contextualizing story events are selected and instantiated from a set of known possible event types.

Our framework for mission generation is shown in Figure 3. Given an author-specified performance curve plus additional required domain knowledge, the mission generator constructs a mission—a sequence of story and challenge events—to be played through by the player. Actual performance on challenge events is tracked and once the mission is complete, the player model is updated for the next time a mission is generated.

We demonstrate our challenge tailoring and challenge contextualization system on a custom game designed to test our algorithms. The game consists primarily of a sequence of battles in the model of traditional turn-based role-playing

games (RPGs). Battles are interspersed with periods where players can interact with NPCs and go on quests that serve as opportunities to set up and contextualize the battles. Our game domain was constructed to focus on deliberative tasks during combat such that players are forced to make the best choice of action for the given situation while having limited time to consider the options available.

Battles consist of a sequence of discrete turns taken by characters on a player team and enemy team. On each turn, the player (or enemy) character has a set of available actions—magical spells—that they may select among (see Table 1). The player's team consists of four characters each with a different subset of spells they may use; the player has 10 seconds to cast a spell before his or her turn is skipped. Each battle presents a different enemy team of four enemies.

Each spell is associated with a *type* that defines its effectiveness against opponents of a particular type. For example, a fire type spell is effective against an ice type character and ineffective against a water type character. We vary spell effectiveness into three levels: super-effective, effective, and ineffective. Table 1 presents the effectiveness matrix of spell types cast on particular character types. As an example, a player may battle an enemy ice beast. In this case, since the ice beast is ice type, casting a fire spell is super-effective, casting an earth spell is merely effective, and casting a lightning spell is ineffective. Each player character in the game was designed to have a partially overlapping set of spells, while each battle is generated with varying sets of enemy types. This situation forces players to make choices based on what is available to them and learn which spells are most effective in a given situation. Spell naming was intentionally obscure to require players to learn the effectiveness matrix over play, rather than using pre-existing knowledge of game conventions. The player's skill at the game consists of knowing which spell to choose for each of his or her teams' characters to perform against any given enemy.

Each mission consists of a sequence of 10 battles. Each battle yields data on each spell the player cast on each turn, enabling us to model player proficiency at selecting the best available spell in each situation. The battle interface is shown in Figure 1. Our game system allows us to record: which spells a player casts, how long they spend deciding to cast a spell, which opponent they target, the battle and turn number in which the action was taken, and the effectiveness of that spell. As spells vary in the amount of damage they inflict players will vary in the length of their play traces based on their spell choices. Our system is able to accommodate these length variations by using a data structure that allows for play traces up to the maximum length observed, with shorter traces having missing values for unobserved future time points.

4. PLAYER MODEL

Solving the challenge tailoring problem requires a model of the player and a set of desired performance requirements. We focus on the player modeling task of predicting player performance in future battles given a player's history.

We approach this task using collaborative filtering, specifically tensor factorization. Collaborative filtering, which learns to make predictions from similarities across a large number of people, is a well-known technique for making accurate predictions with relatively little data about any one particular individual. It thus meets our first four player model requirements: predictive power, accuracy, efficiency, and generative sufficiency. Collaborative filtering techniques are particularly powerful in combining data across users. With initial data from one set of users these models can predict new user performance on a given task based on averages across other users on similar tasks. Thus, collaborative filtering models can provide principled baseline predictions without existing data on a new user, and improve on these predictions by incorporating additional data on that user's performance.

Tensors generalize matrices to add additional dimensions to the matrix structure, moving from the two-dimensional arrangement of a matrix to higher orders. Tensors that add a time dimension extend collaborative filtering to make predictions about how a player is expected to change in the future, thus handling the fifth criteria, temporality. We use tensor-based collaborative filtering to predict player performance for different possible parameterizations of battles across time, thus modeling skill improvement.

Our mission generator takes as input both predicted player performance and a designer-specified performance curve, such as that shown in Figure 4. Battles with appropriate parameterizations are selected to match the desired performance level at the desired point in time and sequenced to produce a full progression of player performance. Players then play through the mission, yielding performance ratings that the performance modeler uses to update the player model for the next round of mission generation.

While we employ our model's predictions to generate full missions (as described in Section 5), these results can also be employed to predict player performance over single events and make adaptations to an existing mission or incrementally build a mission. For single event predictions tensor factorization models include temporal shifts in player performance over time and thus provide a more nuanced view of player performance than the static models of traditional matrix factorization and related approaches. While our current approach employs offline training and adaptation recent work in machine learning has developed techniques for online training for matrix factorization that applies to our problem [12]. We first present our matrix factorization approach to player performance modeling, then describe our genetic algorithm approach to mission generation.

4.1 Matrix Factorization

Matrix factorization techniques model player performance by considering the relationships between players and tasks with respect to the observed performance ratings. Performance ratings are decomposed into sets of latent factors describing underlying features of players and tasks. Task factors describe a latent space of features possessed by a task. Player factors describe a latent space of capabilities of players at those task factors. Performance predictions are made using an inner product of these latent factors [20].

Formally, we have sets of players ("users") U, tasks ("items") I, and performance scores P. Player performance data for a given task is collected in a $U \times I$ matrix with entries corresponding to the performance of player u on task i. In the time-varying case (three-dimensional tensor) we add a dimension to the matrix corresponding to the time of observations T. The resulting tensor $Z = U \times I \times T$ is a tensor of player u's performance on task i at time t. This tensor is decomposed into a set of factors according to:

Table 1: Spell Effectiveness Matrix

Attack ↓ Defense →	fire	water	acid	ice	lightning	earth	force	undeath
fire	1	0	1	2	1	2	1	0
water	2	1	0	1	0	1	2	1
acid	1	2	1	0	1	0	1	2
ice	0	1	2	1	2	1	0	1
lightning	1	2	1	0	1	0	1	2
earth	0	1	2	1	2	1	0	1
force	1	0	1	2	1	2	1	0
undeath	2	1	0	1	0	1	2	1

$$Z \approx \sum_{k=1}^{K} \lambda_k w_k \circ h_k \circ q_k$$

where $\circ$ is the outer product, λ_k are positive weights on the factors, w_k are player factors, h_k are task factors, and q_k are time factors. K is the rank of approximation made by the decomposition, keeping the set of the K most important factors. Tensors may incorporate variable-length traces of player data by ensuring the T dimension is the length of the longest player trace, with other players having missing data for time points they have not yet acted in. Prediction on these missing future tasks becomes:

$$\hat{p}_{uiT^*} = \sum_{k=1}^{K} w_{uk} h_{ik} \Phi_{T^*k}$$

where $\hat{p}_{uiT^*}$ is predicted performance of player u on task i at the current time T^* and:

$$\Phi_{T^*k} = \frac{\sum_{t=T^*-L}^{T^*-1} q_{tk} p_t}{L}$$

with L defining the number of previous time steps to use for performance. Φ_{T^*k} are averaged performances of players over the last L times performing this task, based on the factors describing the time of the task and the observed performance. Future performance is predicted by taking a weighted sum of the latent factors describing the player, task, and averaged performances. The weight factors are derived using root mean square error for optimization by stochastic gradient descent.

Prediction can be improved by including bias terms to account for baseline features of both the players and tasks. This alters the model to:

$$\hat{p}_{uiT^*} = \mu + b_u + b_i + \sum_{k=1}^{K} w_{uk} h_{ik} \Phi_{T^*k}$$

where μ is the global average performance on a task, b_u is a bias term encoding the proficiency of a player, and b_i is a bias term encoding the difficulty of a task. The player and task biases are computed as the averaged performance differences from the global average over all players or tasks, respectively.

In our game we collect player data on actions taken during combat. Each data point consists of a tuple (u, i, t, p) where u is the player, i is the task, t is the turn number in the full play trace, and p is the performance. i is recorded as a concatenation of the enemy being attacked and the particular spell being cast. As an example, casting an earth spell on an ice beast would be recorded as "ice_beast-earth". Performance ratings are based on the defined spell efficacy matrix above—super-effective, effective, and ineffective are mapped to 2, 1, and 0, respectively. For the above case, the full tuple may be (player01, ice_beast-earth, 15, 1) when player01 performs the earth spell as her 15^{th} action and where casting earth is effective and thus scored 1. Given this data we model and predict player performance based on the tensor factorization techniques outlined above.

To bypass an early period of identical predictions across players we begin all players with a fixed initial mission that serves both as a tutorial and initial source of player data. The player model is trained using this data (approximately 100 data points per player, requiring 15 minutes of gameplay) and existing data from all other players and then used to predict player performance and generate a mission. Collaborative filtering techniques minimize the amount of per-user data required by leveraging data from other users to generate baseline predictions and rapidly improve performance with additional data. For example, Yu et al. [26] achieved over 90% accuracy for new users with 9 data points per new user using training data from 31 users with 18 data points per training user. We expect our additional data for training users should compensate for the additional complexity of our tensor model. The model is updated after a player completes each mission and used to generate the next mission. We anticipate reducing training frequency when data sets become large to avoid substantial delays in mission generation. Reducing model update frequency is acceptable as larger data sets enable more information to be shared between players and thus enable more accurate predictions without additional data from the new player.

4.2 Performance Modeling

To generate a mission our system requires a set of skill-based challenge events (combat) associated with particular skill (spell) types and a designer-specified performance curve of desired player performance over the full mission. Figure 4 shows an example of a target performance curve, specifying that the designer wishes to have player performance decrease during combat over the course of the mission. The solid line depicts the author-specified desired levels of player performance over the course of the mission. This particular curve approximates a mission that will *appear* to steadily increase in difficulty. Dotted lines depict the predicted performance of players over the mission and black boxes depict combat events within the mission, with intervening periods occupied by non-combat events. The particular parameterization of combat events in Figure 4 results in player B's predicted performance to be nearer the author's intended performance profile than that of player A.

Other curves may be used to approximate the shape of an

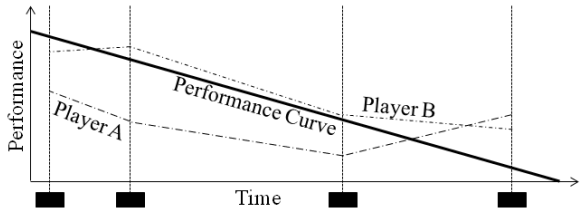

Figure 4: Example performance curve illustrating desired and predicted player performance. Boxes indicate skill-based (combat) events set at different times in the mission. The solid curve depicts desired performance over the course of the mission. Dashed curves depict performances for two different players on these events.

Aristotelian dramatic arc, or create rhythms of alternating periods of low and high performance, or capture common design heuristics such as having high early performance, a middle period of low performance, and a final increase in performance that gives the player a sense of mastery.

Note that we model player *performance*, instead of game *difficulty*. Player performance is directly observable during play in the form of the choices made in given circumstances and evaluated by the game that directly "scores" these actions. In our game domain these scores come in the form of combat attacks being super-effective, effective, or ineffective; the notion generalizes to any actions that have some implications for how well a player is doing. For example: in a shooter game performance may be measured through player firing accuracy, in a racing game performance may be measured by time to complete track segments, or in a puzzle game performance may relate to the number of moves players take to complete particular parts of puzzles.

Content difficulty is not necessarily equivalent to performance as many factors impact player performance beyond difficulty alone, such as ambiguity in the context, level of player attention or fatigue, prior player knowledge, or familiarity with interface controls. Further, difficulty itself may be multidimensional, subdividing into terms based on speed of actions, precision of action timing and execution, or complexity of action composition. To bypass these complications we focus on the task of performance prediction, where we assume some of the latent factors may implicitly describe the notion of difficulty. Our system is able to accommodate multiple performance notions through training separate tensor factorizations for these separate dimensions.

Given a set of challenge events and an an author-specified performance curve, a mission generation system can use the player model to predict a player's performance on the challenge events and compare the predicted performance to the author's desired performance. The selection, spacing, and parameterization of challenge events to reduce the discrepancy between performance model and predicted player performance is described in the next section.

5. MISSION GENERATION

The mission generator creates sequences of events consisting of story events interspersed with challenge events. In the case of our RPG domain, challenge events are battles consisting of combinations of enemies meant to have players achieve particular levels of performance on particular skills, as determined by player model predictions and a given performance curve. Challenge tailoring is thus the parameterization of the sequence of battles based on how closely a specific sequence matches the performance curve. Challenge tailoring involves solving the exact parameterization of each battle in the sequence and determining the timing of each battle. Our mission generator is designed to apply to any domain where player performance can be assessed with respect to a set of concrete tasks used repeatedly in the course of a larger sequence. The full details of our mission generator are described by Zook et al. [27].

To solve the *challenge tailoring* problem a system must compose a sequence of battles that matches predicted player performance to a desired performance curve. To solve the *challenge contextualization* problem a system must intersperse story events within a given sequence of combat events, ensuring these events meet author requirements and preferences. Since challenge tailoring and challenge contextualization are highly interrelated—adding story events impacts timing of battles and thus impacts performance curve matching—we solve the two problems simultaneously.

When solving these problems we seek both to provide designers some control over generation and to create multiple distinct missions from a given set of input to meet the general PCG goal of enhancing replayability without designer effort. In this paper we focus on the task of fitting player performance to the performance curve expressing a designer's intended course of performance. Our previous work describes methods to incorporate designer control over domain content and the evaluation of story content [27].

The mission generator attempts to find the best sequence of events that incorporates the set of performance skills and performance curve, authored story content and evaluation, and player performance predictions. To meet these diverse requirements we use combinatorial optimization, specifically a Genetic Algorithm (GA). Genetic algorithms attempt to find one or more structures that maximize a given evaluation function. They are particularly suitable for problems where there are many soft requirements that describe ideal relationships between different aspects of the structure, but few binary requirements such as necessitated goal states.

A genetic algorithm starts with a population of randomly generated potential solutions—in this case missions—and attempts to modify and/or combine aspects of different members of the population to improve the fitness of the population according to the given evaluation function. Our GA uses an evaluation function involving a number of weighted components. The first component addresses challenge tailoring by matching a designer-specified performance curve to predicted player performance. That is, given a performance curve and player model, the GA is able to evaluate each mission event sequence created in terms of the distance between predicted player performance and designer-desired player performance in battles. The GA thus searches for the optimal fit between battles and desired performance by varying the parameterization and timing of battles over the mission. Scenarios are penalized using a Euclidean distance metric summing over all battles to encourage a smooth convergence toward battles meeting designer specifications. The other components of the evaluation function include numeric evaluation functions and an evaluation grammar. The nu-

meric functions assess story aspects such as frequency with which characters are reused and story length. The evaluation grammar encodes author preferences over combinations of events, such as having players receive a quest and subsequently receive clues on how to complete the quest. Additional details are provided in our previous paper [27]. Ensuring global properties of items is a difficult problem for GAs; we employ a planner to post-process the results produced by our GA to meet this global coherence need, similar to using constraint-satisfaction approaches in other GA-based systems [19].

As an example, the system may be given the performance curve in Figure 4 that specifies decreasing player performance across four battles during the mission. In addition, the system is provided knowledge of ice king and fire fairy monsters. Given a player with a history of initially casting super-effective spells on the fire fairy but later mostly casting effective or ineffective spells on fire fairies, the system will generate predictions that over time player performance against fire fairies will decay. If the player also has a history of casting super-effective spells against the ice king the player model will predict the player to remain at a relatively high level of performance, assuming that most other players show a similar pattern of learning and mastering spell effectiveness. From this information the system would generate a combat sequence starting with a battle against an ice king and with a battle late in the sequence against a fire fairy. Once a player plays through one of the generated missions the system updates the player predictions to reflect the new model and generates a new set of missions based on the updated player performance predictions.

6. TOWARD GENERATION OF FULLY REALIZED GAMES

Our future work involves evaluating the mission generation system. First, we intend to evaluate our tensor factorization player model to assess how accurately it can predict human player performance over time, and how many trials and users are required to train the model for any particular individual. Second, it is necessary to evaluate the extent to which our particular data-driven player modeling approach can affect noticeable change in a "closed-loop" system where missions are generated and played. As Cook, Colton, and Gow [3] note there can be differences between evaluation function ratings and human player ratings. As the primary function of performance evaluations is to tailor content to author requirements for player actions we avoid issues of player subjectivity by focusing on author goals. Third, we plan to examine the relationship between perceived difficulty, preference, and measured performance. Our study incorporates collecting player subjective ratings of perceived battle difficulty and enjoyment in addition to performance metrics to determine the extent to which our performance metrics provide useful correlations to player experience.

Currently, our game is limited to a fixed virtual environment. Future work with our system will explore the generation of spatial game content. Spatial layout of role-playing games has been previously explored [8, 19]. Hartsook et al. [8] especially advocate a pipeline approach where a mission is generated first, and then a space is constructed to support that mission. We believe it may be more beneficial to take spatial context into account when generating missions, as the time to navigate a large virtual world will affect game pacing and the way skill events align with a performance curve. We anticipate modifications to both our modeling and generation techniques due to the additional complexity added by spatial information. Modeling methods require appropriately abstracting spatial location, potentially applying kernel learning techniques found successful for complex spatial modeling in the machine learning literature [17].

Additional advances to our mission generation approach may involve altering the dynamics of the game itself—for example, simplifying or complexifying the spell system with additional spell types or levels of spell effectiveness. These extensions could potentially alleviate boredom when players "master" a given game system or simplify a system that proves too complex for novice players. We anticipate building on previous work looking at evolving game systems while extending these efforts to alter complexity based on player performance (cf., [2, 3]). These efforts also require adapting NPC behavior appropriate to altered game rule sets.

7. CONCLUSIONS

We describe five criteria for data-driven player models—predictive power, accuracy, efficiency, general sufficiency, and temporality—that serve generation and demonstrate techniques to create such models and incorporate them into the process of generating game missions that combine combat and story events. Player models should predict player performance accurately, particularly when faced with large amounts of data that may be only partially filled for a given player. Temporal forecasting in player models is also a central requirement for predictions to account for the ways player performance or preferences fluctuate over time and to enable generation of sequential content. We believe collaborative filtering algorithms in general meet the first four criteria in a domain-independent fashion, especially when data for any one player is sparse but data can be collected for many players. We employ a particular form of matrix factorization, called tensor factorization, to account for the additional criteria of temporality. Future work includes evaluating the accuracy of our player modeling technique.

Mission generation solves the challenge tailoring and challenge contextualization problems by combining data-driven player modeling with designer preferences such as the performance curve and other knowledge about appropriate combinations of story content. A genetic algorithm can incorporate a variety of competing factors into a single fitness function, meeting requirements from combat-related and story-related content. Temporal performance models combined with known combat content allows our mission generator to tailor sequences of battles to steer player performance toward an author-specified performance curve.

Procedural content generation techniques coupled with data-driven player modeling techniques hold great promise for automatically tailoring content to players' skill levels and preferences. We believe data-driven player modeling techniques meeting the five criteria we outline will help realize this potential and can expand efforts toward domain-independent PCG and adaptation solutions.

8. ACKNOWLEDGMENTS

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