

Designer Modeling through Design Style Clustering

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Abstract—We propose modeling designer style in mixed-initiative game content creation tools as archetypical design traces. These design traces are formulated as transitions between design styles; these design styles are in turn found through clustering all intermediate designs along the way to making a complete design. This method is implemented in the Evolutionary Dungeon Designer, a research platform for mixed-initiative systems to create adventure and dungeon crawler games. We present results both in the form of design styles for rooms, which can be analyzed to better understand the kind of rooms designed by users, and in the form of archetypical sequences between these rooms, i.e., Designer Personas.

Index Terms—Procedural Content Generation, Mixed-Initiative Co-Creativity, Designer Modeling, Unsupervised Learning, Computer Games

I. INTRODUCTION

How can we best build a system that lets a human designer collaborate with procedural content generation (PCG) algorithms to create useful and novel game content? Collaboration between AI and humans to co-design and co-create content is a major challenge in AI, and the main focus of Mixed-Initiative Co-Creativity [1], [2]. These systems’ objectives are to foster creativity and provide seamless proactive collaboration; ultimately enabling a colleague relation and collaboration as described by Lubart [3]. However, there needs to be an understanding between the human designer and the AI system about what needs to be designed, ideally even a shared goal.

Reaching such a shared understanding is a hard task, even when both collaborators share significant cultural and professional backgrounds. However, we can take steps towards the goal of shared understanding. One idea is to train a supervised learning model on traces of other collaborative creation sessions and try to predict the next step the human would take in the design process. The main problem with this is that people are different, and creators will want to take different design actions in the same state. Another problem is what to do in design states that have not been encountered in the training data. To remedy this, it has been proposed to train multiple models, predicting the next step for different designer “personas” (akin to procedural personas in game-playing [4]). However, for such a procedure to be effective, we need to have sufficient training data. The more different designer personas there are, the more training data is necessary.

One way of overcoming this problem could be to change the level of abstraction at which design actions are modeled and predicted. Instead of predicting individual edits, one could

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identify different styles or phases of the artifact being created and model how a designer moves from one to another. To put this concretely in the context of designing rooms for a Zelda-like dungeon crawler [5], one could classify room styles depending on whether they were enemy onslaughts, complex wall mazes, treasure puzzles, and so on. One could then train models to recognize which types of rooms a user creates in which order. By clustering sequences of styles, we could formulate designer personas as archetypical trajectories through style space rather than as sequences of individual edits. For example, in the context of creating a dungeon crawler, some designers might start with the outer walls of the rooms and then populate it with NPCs, whereas another type of designer might first sketch the path they would like the player to take from the entrance to the exit and then add parts of the room outside the main path. These designer models could then be combined with search-based [6] or other procedural generation methods [7] to suggest ways of getting to the next design style from the current one.

In this paper, we present a method to create and identify designer personas as archetypical paths through style space and provide a prototype implementation of it. For this, we use the Evolutionary Dungeon Designer (EDD), a research platform for exploring mixed-initiative creation of adventure and dungeon crawler content [8], [9]. Data from 48 users designing game levels with the tool following different goals and styles have been used to fit the models. Based on this data, we clustered room styles to identify a dozen distinct types of rooms. To understand the typical progress of designers and validate the clustering, we visualize how typical design sessions traverse the various clusters. We also perform frequent sequence mining on the design sessions to find a small handful of designer personas.

II. BACKGROUND

Player modeling, the ability to recognize general socio-emotional and cognitive/behavioral patterns in players [10], has been appointed by the game research community as an essential process in many aspects of game development, such as designing of new game features, driving marketing and profitability analyses, or as a means to improve PCG and game content adaptation. Player modeling frequently relies on data-driven and ML approaches to create such models from user data or user-generated gameplay data [4], [11]–[13].

Modeling users and players can have different goals and use multimodal data. User data can be used to understand and enable behavior for agents in games. For instance, Melhart et al. model a user’s *Theory of Mind*, finding that players’ perception of an agent’s frustration is more a cognitive process than an affective response [11]. Alvarez and Vozaru explored

personality-driven agents, evaluating how observers judged and perceived agents using their personality data from their personality tests when encountering multiple situations [14]. Gameplay data can show player behavior, as well as help developers understand their player base. Melhart et al. used gameplay data from *Tom Clancy's The Division* to find predictors of player motivation [12], and Drachen and Canossa used playing behavior data from *Tomb Raider Underworld* and identified four types of players as behavior clusters, which provide relevant information for game testing and mechanic design [15].

Furthermore, the combination of Machine Learning (ML) with PCG has led to the rise of Procedural Content Generation via Machine Learning (PCGML), defined as the generation of game content by models that have been trained on existing game content [16]. PCGML has been used for autonomous content generation, content repair, content critique, mixed-initiative design, or content adaptation. A promising PCGML usage is in the area of content adaptation, where using player and user models are essential to adapt the generated content [17]–[19].

Content adaptation can take place as players play or use the content online or offline, building models from collected data. For instance, Duque et al. adapt and adjust the difficulty of generated content as players play the game using bayesian optimization [17]. Summerville et al. model players automatically and implicitly by learning from video traces; generating levels that correspond to the latent player models [20]. Player models can also be used to enhance and adapt design tools, specifically MI-CC tools. Migkotzidis and Liapis use player models as surrogate models to generate content assisting game designers in the creation of more relevant content for specific players [21]. Similarly, Holmgård et al. use player personas based on player archetypes as content critics to help designers adapt their content to different archetypes [4]. Their work on player personas is similar to our proposed work, yet instead of personas based on player archetypes, we propose personas based on design style.

A. Designer-centric Perspective

Mixed-initiative co-creativity (MI-CC) [1], is the subset of PCG algorithms where human users and AI systems engage in a constant mutual inspiration loop towards the creation of game content [22]–[26]. Understanding the designer’s behavior and experience, as well as predicting their intentions is key for mixed-initiative creative tools while aiming to offer in real-time user-tailored procedurally generated content.

While player modeling is key for generating content adapted to players, adapting tools, systems, and AI methods for designing games requires a shift towards a designer-centric perspective, focusing on Designer Modeling. *Designer Modeling*, akin to player modeling, refers to the creation of models of either individual designers or groups of designers informed by how they create various types of content. Liapis et al. [27], [28] introduced designer modeling for personalized experiences when using computer-aided design tools, with a focus on the integration of such in automatized and mixed-initiative

content creation. The focus is on capturing the designer’s style, preferences, goals, intentions, and iterative design process to create representative models of designers.

EXplainable AI (XAI) is an emergent research field that holds substantial promise for improving model explainability while maintaining high-performance levels [29], [30]. Explanations should be aligned with the users’ understanding to not hinder the usability of systems, as demonstrated by Nourani et al. [31], who discuss the effects of meaningful and meaningless explanations to users of an AI interactive systems.

Zhu et al. [32] proposed the field of eXplainable AI for Designers (XAID) as a human-centered perspective on MI-CC tools. This work discusses three principles of mixed-initiative, *explainability*, *initiative*, and *domain overlap*, where the latter focuses on the study of the overlapping creative tasks between game designers and black-box PCG systems in mixed-initiative contexts. This work deems of high relevance the inclusion of data-driven and trained artifacts to facilitate a fluent bi-directional communication of the internal mechanisms of such a complex co-creative process in which *the designer provides the vision, the AI provides capabilities, and they merge that into the creation*. Mapping the designer’s internal model to the AI’s internal model is suggested as a meaningful way for creating a common ground that establishes a shared language that enables such communication. Our method, and designer modeling in general, aims to develop this designer’s internal model to enhance MI-CC tools by adapting the AI’s functionality towards designers’ needs and aligning to their objectives.

Moreover, Guzdial et al.’s [33] discuss the insufficiency of current approaches to PCGML for MI-CC, as well as the need for training on specific datasets of co-creative level design. Guzdial et al. work on the mixed-initiative Morai Maker [34] shows the relevance of exploring the ways designers and AI interact towards co-creation, identifying four human-AI relationships (friend, collaborator, student, and manager), as well as the different ways they impact on the designer-user experience. Our study advocates for the importance of designer modeling through ML as the generation of surrogate models of designer styles by training on existing designer-generated data, aiming for an improvement in quality and diversity in computational creativity and, in particular, MI-CC tools.

B. The Designer Preference Model in EDD

EDD is an MI-CC tool where designers can create dungeons and rooms; meanwhile, a PCG system analyzes their design and proposes suggestions to the designer [9], [35]. EDD uses *Interactive Constrained MAP-Elites* (IC MAP-Elites) [8], an evolutionary algorithm that combines Constrained MAP-Elites [36] with interactive and continuous evolution.

The work presented in [37] introduced the Designer Preference Model, a data-driven solution that learns from user-generated data based on their choices while using EDD. Both systems constantly interact and depend on each other, so that the Designer Preference Model learns from the selected suggestions, and IC MAP-Elites uses the Designer Preference Model as a designer’s surrogate model to complement the

fitness evaluation of new individuals. The results showed the need for stability and robustness in the data-driven model, to counterbalance the highly dynamic designer's creative process.

III. CONCEPTS AND DEFINITIONS

Our work draws from ideas, concepts, and definitions introduced by Liapis et al., such as the core designer model loop when using CAD tools, what can be modeled: preferences, style, goals, processes, and their definition, and particularly, the use of designer modeling as an individual or collective model [27]. We support our approach on the idea of style as a particular type of designer's preference, and that a collective model can be used to form a stable and static design space, which after being interacted with by designers, can be adapted towards them.

A. Design Style

There exist many different styles when creating content, especially levels, that designers can create and adapt to accomplish their goals and the experiences they want for players. On a general level, *Design Style* encompasses the creative process from conceptualization, prototyping, reflection, adaptation, especially when following different processes or constraints during collaboration. Taking a more concrete and operational level, *Design Style* can be analyzed as overarching goals that different designers have when creating a dungeon. For instance, dungeons in games such as Zelda [5] or The Binding of Isaac [38], represent a particular playing style planned by the designer. In the former, low tempo, exploring the dungeon, and secret rooms define the style of the dungeons, whereas in the latter, high tempo, optimizing time and resources, small rooms, and in general high-challenge define the dungeons.

While interesting and relevant to understanding the designers' holistic design process and the expected player experience, *Design Style* can also be discussed on an individual room basis. Rooms have their own set of characteristics and styles that can be identified and modeled to understand their design process. Some would prefer to create the room's architecture first to then create the goals within, whereas others would like to place strategic objectives around and then create the architecture around it or alternating between both. Even with such a division, how to reach those design styles is not straightforward and does not require the same strategy, which also shows the preference and style of individual designers. For instance, if the goal is to create a challenge to reach a door, the designer could create a room with a substantial number of enemies, create a concentrated high-challenge in the center of the room, or divide the room into smaller choke areas. Therefore, in this paper, we take a simplified view of *Design Style* and treat it as the style designers follow to create a room, informed by the individual steps each has taken connected to their preferences and goals.

IV. ROOM STYLE CLUSTERING

This paper presents an approach and method for the implementation of designer personas: an analysis of designer style clustering to isolate archetypical paths that can later be used

TABLE I
BEST PERFORMING SETUP BASED ON THEIR INTERNAL VALIDATION AND VISUALIZATION OF CLUSTERED DATA POINTS.

Algorithm	Data	K	\diamond	\square	\triangle	ARI	ARI(R)
K-Means	Tiles-PCA	9	0.43	0.73	9437.23	0.941	0.581
*K-Means	Tiles-PCA	12	0.41	0.77	9436.57	0.935	0.775
K-Means	Dimensions-PCA	12	0.43	0.73	7738	0.84	0.876
K-Means	Combined-PCA	10	0.41	0.73	8455.34	0.931	0.866
Agglomerative compl.	Tiles-PCA	6	0.501	0.64	4221.34	0.719	0.419

\diamond Silhouette Score \square Davies Bouldin Index \triangle Calinski-Harabasz Index

to build ML surrogate models of archetypal designers. Such models would allow for a stable and static design and solution space to be traversed by designers, adapting it to them as they explore their creative process.

The proposed system builds on top of EDD's Designer Preference Model and preliminary results [37], expanding it to classify the designers' designs based on clusters developed using previously hand-made design sequences by expert and non-expert designers. Figure 1 illustrates our approach in five sequential stages, from data collection to experimentation and results. The first four stages are explained in the following subsections, whereas Section V shows the experimental results.

A. Data Collection

We conducted two user studies where participants were tasked with designing and creating a dungeon with interconnected rooms without restrictions, using all the available tiles i.e. floor, wall, treasure, enemy, and boss tiles. All participants were introduced to the tool before the design exercise. User-generated data was gathered during the complete design session, creating a new data entry every time the designer edited the dungeon. In total, we had 40 participants, 25 of these (i.e. NYU participants) were industry or academic researchers within the Games and AI field, and the other 15 (i.e. MAU participants) were game design students. This resulted in a diverse dataset composed of 180 unique rooms like the ones depicted in Figure 1, that was pre-processed and clustered in the subsequent stages.

B. Dataset pre-processing

From the 180 unique rooms, we extracted and used each room's design step sequence, from their initial design to the more elaborated end-design, to compose a richer dataset that could capture the design process of a designer rather than focusing on the end-point. This resulted in a dataset with 8196 data points. Moreover, five different copies of the dataset were created to analyze and compare the performance of the clustering stage using the following image pre-processing methods:

- 1) **Room:** No pre-processing. Room images are fed into the next stage as they were created by the designer, with a resolution of $1300 \times 700 \times 3$, corresponding to width, height, and RGB (3 color channels).
- 2) **Tiles:** Each room tile type is mapped to a single-color pixel and the rooms are simplified to a pixel-tile based representation, as shown in the second stage of Figure 1. The dimensions are downsampled to $13 \times 7 \times 3$.

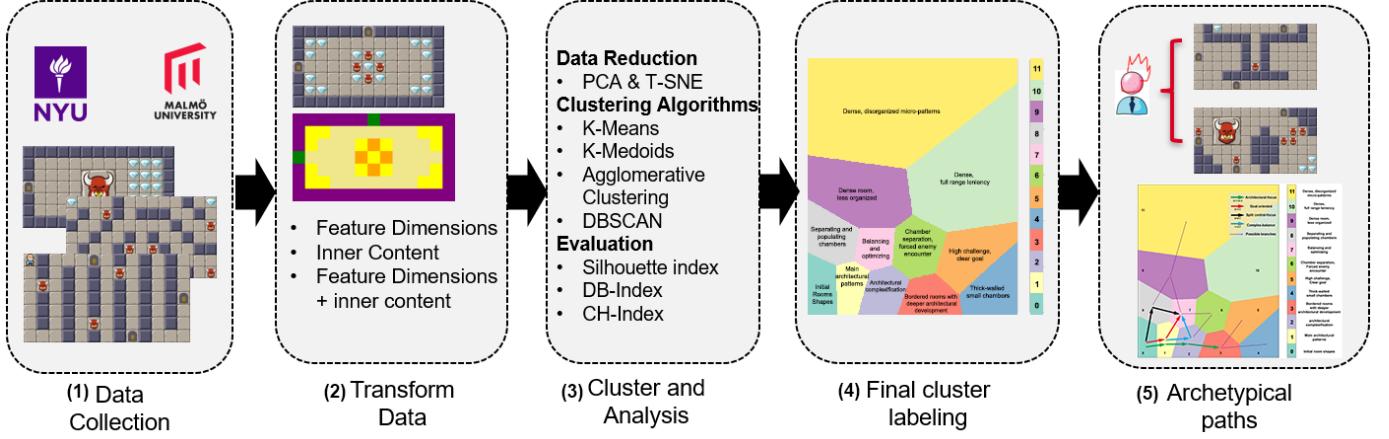


Fig. 1. The stages of the design style clustering development: (1) Data was first collected through two user studies. (2) Then, using the design sequences, the data was processed into five different datasets, one using the room images, a second using the tiles information, and three using tabular information. (3) A data reduction technique was applied to different datasets, and then they were clustered and internally evaluated. (4) The clusters were formed, picked from the best performing methods, and labeled based on the data points within each cluster. The clusters were evaluated by visualizing how a typical design session traverse the various clusters, and K-Means ($K=12$) was chosen as the final approach. (5) Finally, using this final approach all the sequences were clustered and archetypical paths were identified.

- 3) **Dimensions:** Each room is described by its five IC MAP-Elites feature dimension values, excluding the similarity scores: LINEARITY, LENIENCY, #MESOPATTERNS, #SPATIALPATTERNS, and SYMMETRY. A complete description of these features can be found in [39].
- 4) **Inner Content:** Each room is described by 12 values, related to the count, sparsity, and density of the enemy, treasure, floor, and wall tiles contained in it.
- 5) **Combined:** A combination of the **Dimensions** and **Inner Content** methods.

C. Clustering and Analysis

We used the Scikit-learn machine learning toolset [40] to run all setups, data reduction and clustering algorithms, and to internally evaluate the clusters. To obtain the best set of clusters, we ran different setups with the above datasets. The data was reduced to two meaningful dimensions with two different data reduction algorithms, Principal Component Analysis (PCA) and T-Distributed Stochastic Neighbor Embedding (T-SNE). For both dimension reduction algorithms, we fit the algorithms with each individual dataset, setting to two principal components and in the case of T-SNE using PCA as an initializing algorithm, and transforming the data into a *pca_dataset* and *tsne_dataset*. Each two-dimensional point in the new datasets represents a step in the sequences described above. Preliminary tests without dimensionality reduction using the same distance metrics were conducted for all datasets except for **Room** and **Tiles** since the amount of dimensions made it computationally infeasible. These did not result in good space partition, achieved worse internal indices, and produced disjointed clusters. For detailed information, see the supplementary material.

All the resulting datasets were then clustered using K-MEANS, K-MEDOIDS, AGGLOMERATIVE CLUSTERING, and DBSCAN. K-Means was initialized using the standard k-means++ implementation in scikit-learn, which initializes all

centroids distant from each other. K-Medoids was initialized similarly, using the standard k-medoids++, and tested using the *coseine*, *euclidean*, and *manhattan* distances. Agglomerative clustering is a hierarchical clustering approach using a bottom-up approach implemented in scikit-learn using four different linkage criteria for comparing data points: *Ward*, *Complete*, *Average*, and *Single*. Finally, DBSCAN clusters points based on density separated by low-density areas; thus, DBSCAN automatically finds k based on two parameters, ϵ describing the maximum distance between points and *min_samples* describing the minimum amount of samples within a group to be considered a cluster. K-Means, K-Medoids, and Agglomerative clustering were tested using multiple K values ranging from 3 to 13, and DBSCAN was tested with several ϵ values ranging from 0.3 to 1.0, and *min_samples* ranging from 2 to 9.

Since we lack a labeled dataset (i.e. ground truth) for cluster validation, we evaluated the results from all setups using the internal indices below. However, good values in internal indices are indicative and do not imply the best information retrieval, which is why we also manually inspect the clusters and the rooms grouped together.

- **Silhouette Score (\diamond):** The Silhouette Score shows how similar a data point is to the cluster it is associated with, through calculating the difference between the *distance* from the point to the points in the nearest cluster and the *distance* to the points in the actual cluster. The value is bounded from -1 to +1, with values closer to +1 indicating a good separation of the clusters, and closer to -1 meaning that some points might belong to another cluster.
- **Davies-Bouldin Index (\square):** The DB-index is the ratio between the within-cluster distances and between-clusters distances. With this, we can have an insight into the average similarity of clusters with their closest cluster. The value is bounded from 0 to +1, where values closer to 0 relate to clusters that are farther apart from each other and less dispersed, thus, this index is more crucial

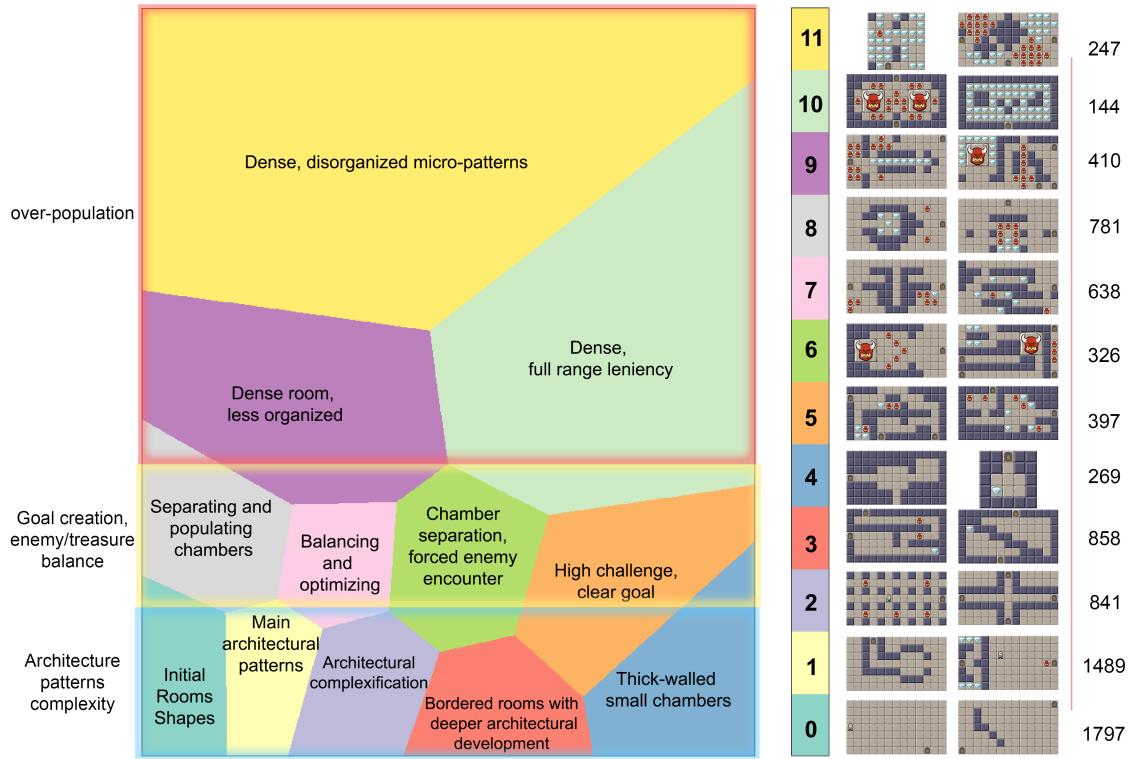


Fig. 2. Best resulting cluster set. K-Means ($K=12$), using the **Tiles** Dataset. While it scores slightly less in the internal indices than other setups, a qualitative analysis successfully gives us more granularity by subdividing the main bottom clusters, to label and cluster the design process of designers. Sample rooms belonging to each cluster are displayed on the right, next to the total number of rooms in the cluster.

when we have more dense representations.

- **Calinski-Harabasz Index (Δ):** The CH-index is another index related to the density of the clusters and how well separated they are. The score is the ratio between the within-cluster dispersion (compactness) and the between-cluster dispersion (separation). The CH-index is positively unbounded, and the higher the score the better.
- **Adjusted Rand Index (ARI):** ARI computes the similarity between two sets of clusters. We tested our setups by using 70% of the data as training set to fit the cluster algorithm and the other 30% to analyze how the fitted clusters clustered unseen data. Then, using our setups fitted with the full dataset, we compared these 30% test set using ARI , giving us an estimated performance value with unseen data. Additionally, we computed $ARI(R)$ by splitting the data based on the room sequences rather than on the individual design steps to remove any relation between training and test set.

D. Cluster Labelling

Table I shows the best performing setups according to their internal indices scores and manual qualitative analysis of the clusters, rooms clustered together, and sequence analysis (further explained in section V). The algorithm selection process followed a systematic analysis of each algorithm with each dataset from the lowest to the highest hyper-parameter value for each algorithm. We focused on the setups that both scored the best in the different indices (as a combination) and using

the *elbow method*, which is a common heuristic in clustering to select the best k . We filtered our results by $k \geq 6$ as it gave more meaningful partitions and better groups overall. Some setups with lower k values gave good overall internal indices scores but logically, tended to make big clusters and supersets. For instance, K-Means ($k=3$) using **Tiles** dataset scores $\Diamond = 0.55$, $\Box = 0.66$, and $\Delta = 9049.65$. However, the three clusters acted as supersets, dividing the space into an upper "over-population" cluster, and into two smaller bottom partitions, one to the left accounting for the architecture of the rooms and one to the right focused on challenge and leniency. By using $k \geq 6$, we guarantee that at least the big clusters would be divided into meaningful subsets such as the ones shown in figure 2.

When using the **Dimensions** and **Combined** datasets, the clusters perform well in certain indices than when using the **Tiles** dataset with certain algorithms. However, when analyzing the resulting setups, they missed a clear relationship between the clustered rooms, which was exacerbated when analyzing sequences on these setups, where they missed continuity between clusters and either jump around clusters or had close to no movement between them. When using these datasets and analyzing the sequences, we notice that there are sequences where the cluster set is robust to seemingly meaningless changes, whereas jumps occurred when something important changed (or was added), and in other sequences, the clusters are very sensitive to changes. We believe this is because similar rooms (one or a few steps in difference) could have a big impact on several dimensions within these

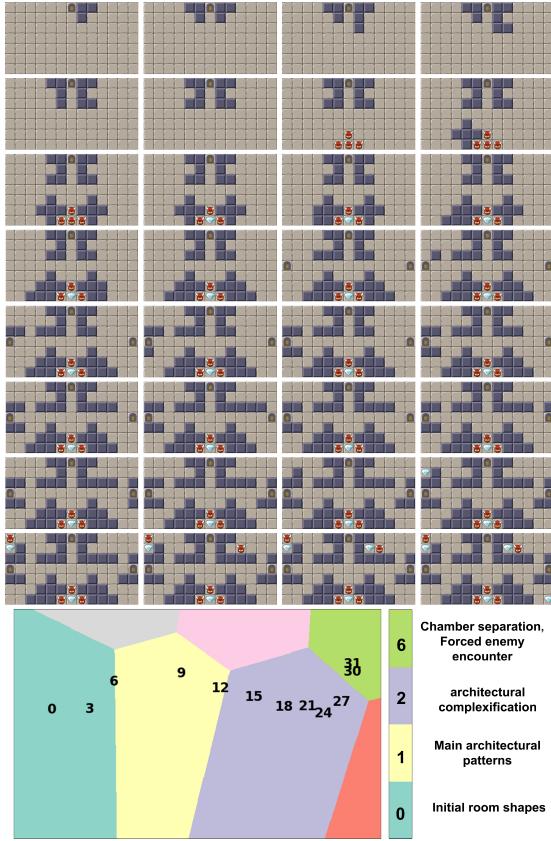


Fig. 3. Example of a room's design step sequence and its clustering. At the top, we present the design steps of one of the rooms in the dataset starting at the top left with the first design step. At the bottom, it is the actual trajectory of the design in the cluster space. Numbered and in black (every 3 steps), it is shown how each step of the design process is clustered by our approach

datasets, such as a room becoming more symmetric and fully linear by simply adding a few walls. This, combined with the lack of natural continuity in many of the analyzed examples, negatively affected their evaluation.

Conversely, given that we are creating tile-based rooms and dungeons, the **Tiles** dataset had more representative features, which when used, generally performed better in the evaluated internal indices, and the clusters meaningfully separated the data. Similar robustness and beneficial behavior as when using the **Dimensions** and **Combined** datasets was also encountered while showing a clear continuity between designs that supports its usability (further discussed in section V). Figure 2 shows the best-resulting cluster set found among all the experiments run. K-Means ($K=12$) with the **Tiles** dataset was chosen as the best cluster set. While K-Means ($K=9$) performs better in all indices, $K=12$ gave us more granularity within the bottom clusters. In our case, this was more important, especially since the difference was minimal, as the bottom area of the design space is denser than others containing much of the early design steps and their refinement.

In the figure, we have plotted on top of the clusters the labels describing in general, the content that is within them. Labels were defined based on the rooms that were clustered together and surrounding clusters' content. The following is a description of the clusters and rooms clustered together:

0. Empty-Initial rooms: This cluster relates mostly to the initial designs made by the designers. These designs are from completely empty rooms to initial work-in-progress structures.

1. Main architectural shapes: Similar to other clusters within the same layer, this cluster relates to the development and definition of main architectural patterns that are somewhat symmetrical.

2. Architectural complexification: This cluster relates mostly to the complexification of wall structures by having dense wall chunks, representative architectural patterns, or symmetrical patterns.

3. Bordered rooms with deeper architectural development: This cluster relates mostly to rooms with an added wall border by the designer, and where the focus is to shape chambers and develop more visual structures.

4. Thick-walled small chambers: This cluster to the far right region in fig. 2, relates to more highly-linear, confined and maze-like rooms.

5. High challenge, clear goal: This cluster relates to well-shaped rooms with clear wall structures and goals, towards more challenge.

6. Chamber separation with forced enemy encounter: This cluster relates to rooms that are in the process of a clear segmentation into corridors and chambers, and that enforce to some extent enemy encounters for the player.

7. Balancing and optimizing: This cluster contains a mix between corridors and chambers within rooms with a focus on balancing rooms and optimizing their design towards certain goals.

8. Separating and populating chambers: This cluster relates to the process of separating rooms into distinct chambers, focusing on the center of the room, and starting to populate rooms with enemies and treasures.

9. Dense, less organized: This cluster contains rooms that still have a certain objective but are moving towards more disorganized distributions of micro-patterns in relation to their density.

10. Dense, full range leniency: Focusing on density as the other two clusters within the same layer, this cluster relates to rooms that are in the full range of leniency from very rewarding treasure rooms to very challenging boss rooms.

11. Dense, disorganized micro-patterns: This cluster contains the extreme rooms that contain a high density of tiles, other than floor-tiles, without a clear structure or objective for the player.

Moreover, besides the local relation between clusters, the clusters are implicitly divided in three layers on the Y-axis. From bottom to top, (a) architectural patterns complexity, relating to clusters composed of rooms with clearer or complex shapes created with walls, from empty rooms to chambers. (b) Goal creation, enemy/treasure balance, with clusters containing the strategic addition of enemies and treasures to establish objectives in the room for the player. In terms of EDD, these rooms are composed of more meso patterns. And (c), over-population, which relates to clusters filled with less organized and dense rooms where the addition of enemy or treasure does not necessarily need to follow any clear objective. Identifying the designer in a layer, and the path they have taken to get there

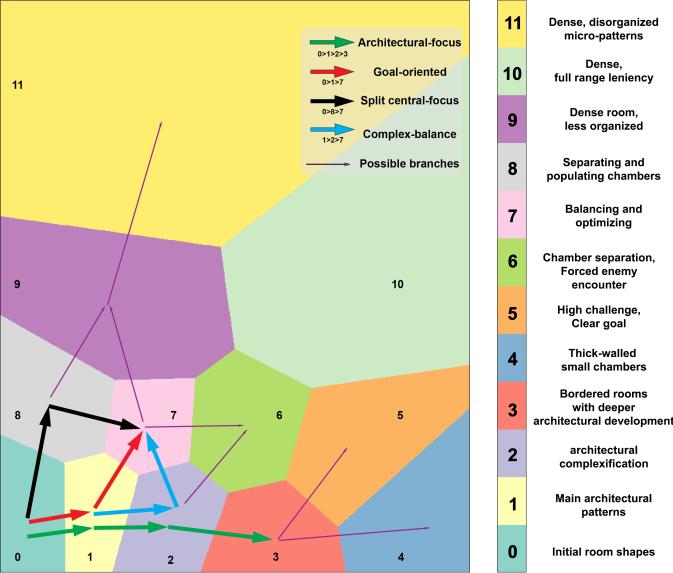


Fig. 4. Final and common designer trajectories. The archetypical paths are represented with thick arrows, and were calculated using the frequencies of subsequences from 180 diverse rooms. Each color represent a unique trajectory; with green the ARCHITECTURAL-FOCUS, with red the GOAL-ORIENTED, with black the SPLIT CENTRAL-FOCUS, and with blue the COMPLEX-BALANCE. Finally, thinner purple arrows extending from clusters traversed by the archetypical paths show the multiple possible branches that an archetypical path can deviate or extend to.

could show meaningful information in the design process. For instance, the intentions of the designer or in what phase of the design process they are at the moment; i.e. trying the tool or observing how the tool reacts or scraping their current goal towards a new goal within the room.

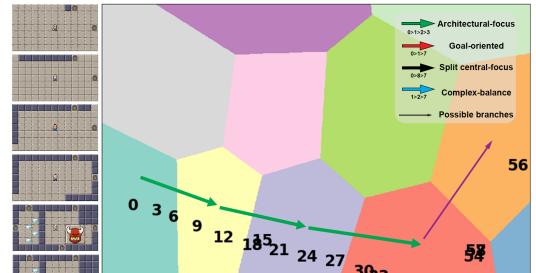
V. DESIGNER PERSONAS

Once we created, evaluated, and labeled the room style clusters, we were able to cluster and visualize the paths of a typical design session. Figure 3 presents an example of the design sessions, where we cluster each step of the design. This sequential process revealed that there is an interesting continuity between room style clusters, even capturing when a designer applied one of the procedural suggestions due to bigger steps in the room style clusters. Further, through this process, we could understand the progress of designers in their design process and represent their design style and trajectory in relation to the traversed room style clusters rather than individual editions.

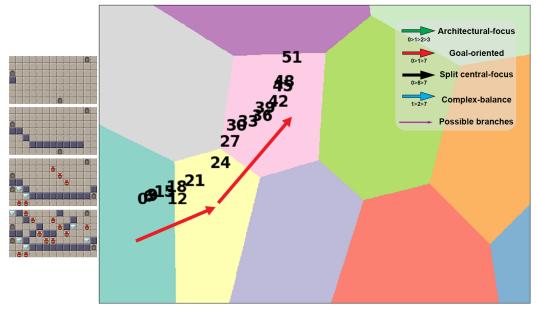
A. Unique Trajectories

Using the room style clusters in Figure 2, we clustered the design session of all the 180 designs. This resulted in trajectories where each individual design step was associated to some room style cluster. For instance, the design session in fig. 3 resulted the trajectory: $Trajectory = \{0>0>0>0>0>0>0>1>1>1>1>1>2>2>2>2>2>2>2>2>2>2>2>2>2>2>6>6>6\}$.

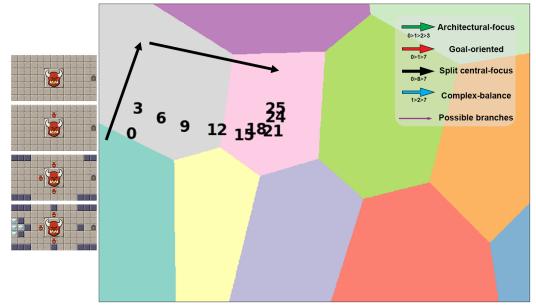
We then converted these trajectories to their unique trajectory, which would convert the previous $Trajectory$ into



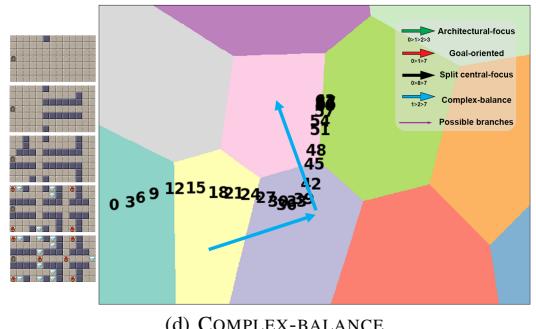
(a) ARCHITECTURAL-FOCUS



(b) GOAL-ORIENTED



(c) SPLIT CENTRAL-FOCUS



(d) COMPLEX-BALANCE

Fig. 5. Example archetypical paths from different frequent sequences used to create the clusters. To the left of each subfigure, we present each key step in the trajectory i.e. when the design entered a new room style cluster. (a) presents the ARCHITECTURAL-FOCUS where the focus is firstly on creating the structural design of the rooms; the design process jumps back and forth suddenly to room style cluster 5 (one of the possible branches) due to the designer adding a boss, and removing it immediately. (b) presents the GOAL-ORIENTED where the design focus on a minimal architecture complexity and mix between adding structural changes and enemies/treasures. (c) shows the SPLIT CENTRAL-FOCUS where, intentionally, the designer creates a center obstacle with a boss and build around it. Finally, (d) presents the COMPLEX-BALANCE; the designer focuses on building complex, uncommon structures first and then add some goal with enemies and treasures, taking advantage of the spaces.

Unique = {0>1>2>6}, where the first and last element of the sequence are respectively, the starting- and end-points, with all the unique intermediate steps in between.

These unique trajectories varied in the starting point, length, and end-point, however, when analyzing the trajectories we identified common patterns among them. To gather the common patterns from the trajectories, we applied the Generalized Sequential Pattern (GSP) algorithm, which locates frequent subsequences in the analyzed trajectories. For instance, given three trajectories (a) {8>1>2>6>9}, (b) {8>1>2>6>10}, and (c) {0>1>2>6}, none of these is a perfect match in its entirety, but GSP can spot that subsequences {1>2>6}, {1>2}, {2>6}, among others, appear with frequency = 3.

After doing a preliminary analysis, we identified some steps that we classified as “border designs”: steps that are borderline between two room style clusters. These *border designs* disrupted the sequence pattern mining with noise in the unique trajectories, specifically when these *border designs* entered a different room style cluster for just a few steps. Therefore, we filtered them out by applying a threshold $\theta = 3$, so that all subsequences inside one room style cluster with less than θ steps are removed from the main sequence. For instance, the sample trajectory {0>0>0>0>8>8>8>7>8} turns into {0>8} instead of {0>8>7>8}. Through this, we were able to reduce the noise and the search space, obtaining meaningful and frequent patterns.

B. Archetypical Paths through Style Space

In Figure 4, we present the archetypical paths, represented as thicker arrows to denote direction, which show the most frequent paths taken by designers either through their whole design process or as the initial meaningful steps. From all the collected unique trajectories, we have identified 4 main archetypical paths, labelled, ARCHITECTURAL-FOCUS, GOAL-ORIENTED, SPLIT CENTRAL-FOCUS, and COMPLEX-BALANCE. In addition, we have numbered each archetypical path for easier visualization and referencing. In the figure, we also include thinner purple arrows pointing to different room style clusters from several of the room style clusters that are part of the main paths. These are *possible branches* presented in the unique trajectories and added based on their frequency. Through these possible branches, the design of an archetypical session, can vary and extended or deviate the final design. Each archetypical path is defined and explained as follows:

1) *Architectural-focus*: The path followed by this archetype focuses first on designing the architecture of the room with walls. Through this, the design focuses on shaping the visual patterns, chambers, and corridors to give a clear space for adding goals and objectives with enemies and treasures. The sequence is denoted with a green arrow in Figure 4, and following the sequence {0>1>2>3}.

2) *Goal-oriented*: Design processes following this archetypical path, create the rooms in a more standard way, combining simpler symmetric wall structures with distributed placement of enemies and treasures. Thus, rather than focusing extensively on an individual part of the room, the rooms have an initial structure and then they are populated

with some specific goal. The sequence is denoted with a red arrow in Figure 4, and following the sequence {0>1>7}.

3) *SPLIT central-focus*: This archetypical path focuses on designing rooms with obstacles placed in the center of the room in the shape of enemies, treasures, or wall structures that clearly split the room into different areas. The design process is less organized than the other archetypes since it searches to achieve the split goal with any of the available tiles. The sequence is denoted with a black arrow in Figure 4, and following the sequence {0>8>7}.

4) *Complex-balance*: This archetypical path focuses on building complex symmetric shapes with a clear objective for the player and adapting the spaces with a balance of enemies and treasures. In general, the rooms created following this path are more unique and typically balanced. The sequence is denoted with a blue arrow in Figure 4, and following the sequence {1>2>7}.

Furthermore, using these archetypical paths, we can then categorize certain room style clusters as key clusters based on their contribution to the paths, their frequency, and their usage. Most of the paths go through or end in cluster 7 (“Balancing and optimizing”) and cluster 1 (“Main architectural patterns”), which relate to rooms that have a more explicit mix between corridors and small chambers, and more clear architecture. The rooms in those clusters are or shaped as end rooms, as in the case of cluster 7, or architecturally shaped to be “optimized” to a specific goal e.g. a dense bordered room. Similarly, most of the sequences start from cluster 0 (“Initial room shapes”), with 134 out of the 180 designs, which correlates to the type of designs encountered in that clusters. Thus, it is understandable that most of the archetypical paths pass through these three clusters.

Nevertheless, it is the steps in-between that creates a clear differentiation between the archetypical paths, which is the benefit of observing the design process as a whole in the clustered room style space. For instance, in fig. 4, it can be observed that SPLIT CENTRAL-FOCUS starts in the same room style cluster as three other paths, and tentatively ends in the same room style cluster as three other. However, the designs following SPLIT CENTRAL-FOCUS are more different from the other trajectories, since it enters a room style cluster that is denser with several tile types in principle, and where designers seem to have a clearer goal.

Moreover, in figure 5, we present examples of each of the designer personas by visualizing the sequence of steps done in representative design sessions, showing what these paths would look like in practice. Each visualization of a designer persona has the key design steps to the left, where each image is in a sequence: the first is the first edition of the designer, the last is the final edition, and the in-between represent entering a new room style cluster.

Figure 5a shows the ARCHITECTURAL-FOCUS, where the designer first created the border of the room with a clear chamber division. As the designer adds and subsequently removes the boss, the design jumps to cluster 10, which is one of the possible branches, adding a high challenge.

Figure 5b shows the GOAL-ORIENTED, where the designer sketched the main shape of the room followed by alternating

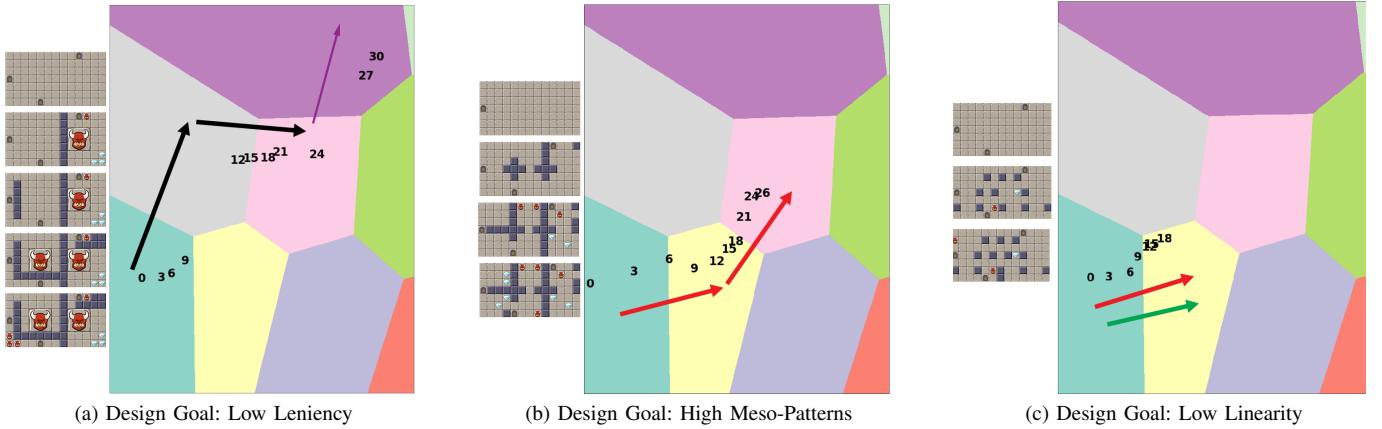


Fig. 6. Example sequences created with specific design goals orthogonal to the designer personas. (a) and (b) are categorized as SPLIT CENTRAL-FOCUS and GOAL-ORIENTED, respectively. While (c) is uncategorized (with two possible designer personas).

between enemies, treasures, and walls to adjust the room towards the goal for the player. In this example, the designer ends the design close to cluster 9, with a disorganized placement of tiles and a less aesthetical room, but forming small choke areas balancing the placement of enemies and treasures.

Figure 5c shows the SPLIT CENTRAL-FOCUS, where the designer directly started by adding a boss in the center of the room and using this as a reference point, shaped the rest of the room. Figure 5d shows the COMPLEX-BALANCE, where the designer focused on creating an uncommon structure and followed by adding enemies and treasures symmetrically, with clear individual areas for the player to approach.

Finally, further analyzing figure 5, it can also be observed an interesting dual tendency of the designers in the archetypical paths. This dual tendency is to either focus on the aesthetic configuration of the room based on what is perceived in the editor exemplified the personas: ARCHITECTURAL-FOCUS and SPLIT CENTRAL-FOCUS, and to focus on the player experience exemplified the personas: GOAL-ORIENTED and COMPLEX-BALANCE. Nevertheless, both are not mutually exclusive, instead this illustrates adequately the dualistic role the designer has when using the tool and designing rooms. That of creating an aesthetically pleasing object as it is seen in the editor, and that of creating an experience.

C. Preliminary Evaluation

We recorded three design sessions with specific design goals orthogonal to the archetypical trajectories to preliminary evaluate our approach. These are shown in figure 6 with the design goals: figure 6a) Low Leniency (i.e., challenging room), figure 6b) high meso-pattern level (i.e., large quantity of guard, treasure, enemy, and ambush rooms), and figure 6c) low linearity (i.e., several paths between doors). Both figure 6a and figure 6b fitted two of the archetypical trajectories, SPLIT CENTRAL-FOCUS and GOAL-ORIENTED. Figure 6c shows a design achieving its goal but identified as an early design, aligned with two possible designer personas. This last example shows the situations we expect to normally encounter during design sessions, namely, uncertainty and adaptation. If the

designer continued elaborating the level's architecture, they would align with the ARCHITECTURAL FOCUS else they would probably align with the GOAL-ORIENTED.

While these results requires a larger study that analyses and verifies the different possibilities and properties of using Designer Personas, especially, in-the-wild; this evaluation helps to understand and visualize how unseen design sessions map and align to possible archetypical paths regardless of the designer's design goal.

VI. DISCUSSION

Our work draws on many of Liapis et al.'s [27], [28] ideas, concepts, and goals but differs on the tool and type of game being created and the methods to create designer models. These differences strengthen the importance and usefulness of designer modeling and highlight this designer-centric perspective's holistic and generic properties.

The archetypical paths presented in sec. V-B relate to EDD and the options that exist within it. However, while important for EDD's development, this is used to demonstrate what can be done and as an exemplification of the method to model designers. Our method focuses on designer modeling through clustering the design space and the room style based on level design step sequences, resulting in archetypical paths. We leverage a collective dataset to build a collective cluster model of a set of designers and utilize this to mitigate, to some extent, problems regarding lack of individual designer data and continuous model adaptation [37]. Our method allows us to better understand, cluster, categorize and isolate designer behavior. A virtual model of the designer's style could allow to better drive the search process for procedurally generating content that is valuable for designers and aligned with the designers' intentions, observed as well by Liapis et al. [27].

We expect that work on similar domains and tools working with level design could discuss these archetypical paths in relation to what designers create. They can build on and adapt the proposed method to model designers to their respective domains, identifying valuable and applicable designer personas. Then, these could be used to understand what designers create

and to design adaptive systems and better Human-AI collaborations and interactions. The resulting Designer Personas have the potential to be used in many different scenarios. For instance, as objectives for a search-based approach to enable a more style-sensitive system, to evaluate the fitness of evolutionary generated content, or to train PCG agents via Reinforcement Learning [7].

VII. CONCLUSIONS

This paper presents a novel method and meaningful steps towards designer modeling through an experiment on archetypical design trajectories analysis in an MI-CC environment. Through this, we characterize several representative design styles as designer personas. We have first run and compared several clustering setups to find the best partitioning of the room style using the design step sequence of the collected 180 unique rooms, ending in 8196 data points, and resulting in a set of twelve cohesive and representative room style clusters. We have then mapped these 180 design sequences in terms of these clusters, applying frequent sequence mining to find four frequent and unique designer styles, with related common sub-styles. As a result, we have presented a roadmap of design styles over a map of data-driven room style clusters.

Recognizing the designers' current style and the path taken so far, which would indicate a possible designer persona, would open the possibility for recognizing their intentions, preferences, and goals. This traced roadmap of designer personas could let a content generator anticipate a designer's next moves without heavy computational cost, just by identifying their current location on the map and offering content suggestions that lie in the most promising clusters to be visited next. Conversely, it would also identify designers who do not follow a certain path, i.e., deviating from the pattern, trying to understand their objective through their design style. Finally, we aim at implementing our approach in a functional system within EDD to assess and validate the benefits and usability of these adaptable systems with human designers.

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