Making the Familiar Strange: A Computational Approach to Defamiliarization in Creativity Support

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Abstract

Defamiliarization—originating in literary theory and later adapted into Critical and Speculative Design—seeks to disrupt habitual perception and invite renewed engagement through “slight strangeness,” and has been extensively used to provoke critical engagement in design and interactive systems. However, existing approaches remain subjectively designer-controlled, limiting generalizability in interactive creative systems, while generative-AI tools introduce unexpected elements without offering structured, user-level control over estrangement. To address this gap, we present Familiarity–Estrangement Space, which projects textual materials (e.g., design concepts and invented stories) along three personalized dimensions—Familiarity, Positive Estrangement, and Negative Estrangement—empowering creators to modulate the exact degree of strangeness they desire. By extracting latent topics and inviting users to identify which topics to retain, amplify, or minimize, our approach transforms defamiliarization from a designer-imposed intervention into an adjustable parameter for creativity support. This enables creators to navigate and discover fresh thematic collisions or reinforce familiar patterns, offering a structured framework for AI-assisted creative exploration that balances coherence with deliberate estrangement.

Introduction

Defamiliarization, introduced by Victor Shklovsky in literary theory (Shklovsky 1965), describes making the familiar strange to disrupt habitual perception and foster renewed engagement. Dunne and Raby (Dunne 2008) (Dunne and Raby 2001) later applied this concept to Critical and Speculative Design, using slight strangeness to challenge technological norms and provoke alternative interpretations of design artifacts. Their approach leverages deliberate friction to shift passive interaction into active reflection, where interactive systems subtly interrupt ingrained behaviors to expose underlying technological assumptions.

Defamiliarization has been extensively used to provoke critical engagement in design and interactive systems. Reflective Design (Sengers et al. 2005) and Critical Computing (Bell, Blythe, and Sengers 2005) show how subtle disruptions can reveal hidden technological structures. However, these approaches rely on predefined estrangement levels decided by designers, rather than permitting users to adjust them.

At the same time, Creativity Support Tools (CSTs) and AI-assisted creative tools have focused on preserving coherence or maximizing novelty (Lubart 2005) (Frich et al. 2019). Although generative AI can produce a wide variety of outputs, these variations are often random rather than systematically controlled (Franceschelli and Musolesi 2024), offering creators no mechanism to modulate the degree of estrangement in their work. This leaves creators to sift through and fine-tune an abundance of AI outputs—an effort that underscores the need for proper metrics to evaluate and guide selection (Li et al. 2024).

To address this gap, we present the *Familiarity–Estrangement Space (FES)*, a conceptual model that quantifies— and makes adjustable— the defamiliarization of textual materials (e.g., design concepts, invented stories) by combining human creative vision with topic-modeling techniques, thereby structuring creative exploration and enabling AI to cultivate controlled strangeness.

Topic Modeling as a Mechanism for Defamiliarization

Topic modeling, an NLP approach that aims to automatically extract latent topics from extensive collections of texts (corpus) (Blei, Ng, and Jordan 2001), has introduced new methods for structuring creative exploration. While typically applied to retrieval and categorization, topic modeling can also serve as a mechanism for controlled estrangement by surfacing unexpected thematic pairings that challenge conventional thinking.

By integrating Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan 2001) as a creative disruptor, Familiarity–Estrangement Space generates structured thematic collisions, discovering new inspiration pathways. This approach repurposes topic modeling from a content structuring tool to a computationally guided defamiliarization mechanism that enhances creative exploration.

Research Gap and Motivation

Although prior research in Critical and Speculative Design has explored defamiliarization, existing approaches remain

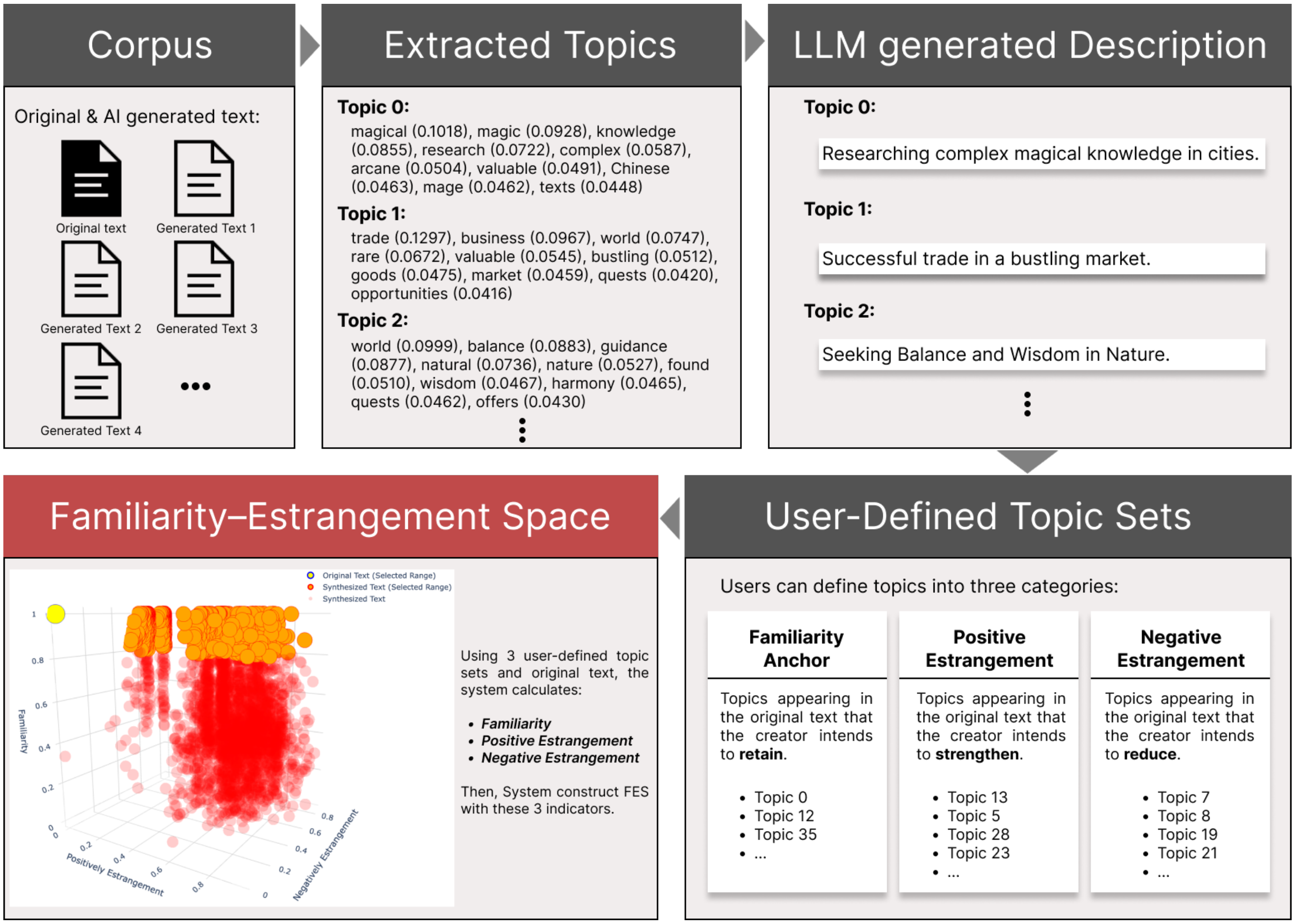


Figure 1: **A Topic Modeling-Based Framework for Familiarity–Estrangement Space Co-Construction**.

subjectively designer-controlled, limiting generalizability in interactive creative systems, while generative-AI tools introduce unexpected elements without structured user control over strangeness, treating estrangement as an incidental side effect rather than a deliberate, adjustable parameter.

To address these limitations, FES introduces:

- *A computational model of defamiliarization, formalized through three quantifiable indicators: Familiar, Positive Estrangement, and Negative Estrangement.*
- *A topic modeling-based framework for conceptual defamiliarization, leveraging LDA to extract unexpected but semantically meaningful thematic disruptions. (As illustrated in Fig. 1.)*

In the following sections, we formulate the Familiarity–Estrangement Space, define its fundamental components, and conclude with preliminary results from a game character design scenario.

Familiarity-Estrangement Space Overview

Since creativity is inherently subjective, the construction of Familiarity–Estrangement Space is user-centered: the system collects user's aesthetic preferences to construct a customized FES. FES maps generated outputs by their alignment with prior stylistic conventions (familiarity) and degree of intentional deviation (estrangement).

Given a creator's original text d_o (e.g., a manuscript, a design draft, etc.) and a related corpus $D = \{d_1, d_2, \ldots, d_m\}$ (either existing or AI-generated), FES is a three-dimensiona space constructed by the Familiarity $\mathcal{F}$ (Equation (4)), Positive and Negative Estrangement $\mathcal{E}$ (Equation (7)) indicators:

- **Familiarity–Estrangement Space**:

$$\begin{aligned}\forall d_x \in D, \quad FES(d_x, d_o) = \Big(&\mathcal{F}(d_x^{(T_{anc})}, d_o^{(T_{anc})}),\\ &\mathcal{E}(d_x^{(T_{pos})}, d_o^{(T_{pos})}),\\ &\mathcal{E}(d_x^{(T_{neg})}, d_o^{(T_{neg})})\Big).\end{aligned} \tag{1}$$

Here, T_{anc}, T_{pos}, and T_{neg} denote user-defined *topic sets*. Leveraging these topic sets, the system computes tailored Familiarity and Estrangement indicators, enabling users to efficiently retrieve texts and locate content that matches their desired level of defamiliarization.

User-Defined Topic Sets

Firstly, the system performs topic modeling over corpus D, extracting k representative topics $T = \{t_1, t_2, \ldots, t_k\}$, and computing a topic-weight distribution to quantify each text with a $\mathbb{R}^k$ vector:

$$\begin{aligned} &\forall d_i \in D, \quad d_x \overset{T}{\mapsto} d_i^{(T)} = \left(w_1^{(x)}, w_2^{(x)}, \ldots, w_k^{(x)}\right) \in \mathbb{R}^k, \\ &\text{s.t.} \quad w_j^{(x)} \geq 0, \quad \sum_{j=1}^{k} w_j^{(x)} = 1. \end{aligned} \tag{2}$$

Next, the system summarizes the text-to-topic weights and invites creators to define three mutually exclusive topic sets $T_* \subseteq T$ that reflect their aesthetic preferences:

- **Familiarity Anchor** (T_{anc}): Topics appearing in the original text that the creator intends to *retain*.
- **Positive Estrangement** (T_{pos}): Topics appearing in the original text that the creator intends to *strengthen*.
- **Negative Estrangement** (T_{neg}): Topics appearing in the original text that the creator intends to *reduce*.

Given a topic set T_* and any text $d_x \in D$, the system projects $d_x^{(T)}$ into the corresponding subspace by zeroing out topics *not* in T_*:

$$\begin{aligned} &\forall d_x \in D, \quad d_x^{(T)} \overset{T_*}{\mapsto} d_x^{(T_*)} = \left(w_1'^{(x)}, w_2'^{(x)}, \ldots, w_k'^{(x)}\right) \in \mathbb{R}^k, \\ &\text{s.t.} \quad w_j'^{(x)} = \begin{cases} w_j^{(x)}, & t_j \in T_* \\ 0, & t_j \notin T_* \end{cases}. \end{aligned} \tag{3}$$

These subspaces capture user's creative intentions and form the basis for computing three indicators.

Familiarity and Estrangement Indicators

By anchoring on the user-defined topic sets and original text, the system computes *Familiarity*, *Positive Estrangement*, and *Negative Estrangement* indicators of texts with the following equations:

Familiarity indicator (4) computes a familiarity score between any text d_x and d_o. To capture how well d_x preserves topics in T_{anc}, we introduced *Weight-Kept* (5) to measure how much topic weights of d_o is retained in d_x, and defined the *Cosine Similarity* in the Topic Space (6) to quantify the structural similarity of their topic distributions. Finally, a weighted harmonic mean merges these two metrics ($W_{w\text{-}kept}$ and $W_{\cos}$ are hyperparameters):

$$\begin{aligned} &\mathcal{F}\left(d_x^{(T_{anc})}, d_o^{(T_{anc})}\right) \\ &= \frac{W_{w\text{-}kept} + W_{cos}}{\dfrac{W_{w\text{-}kept}}{\textit{w-kept}\left(d_x^{(T_{anc})}, d_o^{(T_{anc})}\right)} + \dfrac{W_{cos}}{\cos\left(d_x^{(T_{anc})}, d_o^{(T_{anc})}\right)}} \end{aligned} \tag{4}$$

- Weight-Kept:

$$\begin{aligned} &\textit{w-kept}\left(d_x^{(T_*)} - d_o^{(T_*)}\right) \\ &= \min\left(\frac{\sum_{i=1}^{k} \min\{w_i'^{(x)}, w_i'^{(o)}\}}{\sum_{i=1}^{k} w_i'^{(o)}}, 1\right). \end{aligned} \tag{5}$$

- Cosine Similarity:

$$\begin{aligned} &\cos\left(d_x^{(T_*)} - d_o^{(T_*)}\right) \\ &= \frac{\sum_{i=1}^{k} w_i'^{(x)} w_i'^{(o)}}{\sqrt{\sum_{i=1}^{k} \left(w_i'^{(x)}\right)^2} \sqrt{\sum_{i=1}^{k} \left(w_i'^{(o)}\right)^2}}, \end{aligned} \tag{6}$$

Estrangement indicator (7) evaluates *value* and *structural* differences between d_x and d_o to reflect the creator's desired estrangement. We introduced *Positive/Negative Difference* (8) to compute the cumulative increase or decrease of topic weights in T_{pos} or T_{neg}, and *Positive/Negative Count* (9) to indicate how these increases or decreases are distributed among topics:

$$\begin{aligned} &\mathcal{E}\left(d_x^{(T_*)}, d_o^{(T_*)}\right) = \\ &\frac{W_{\textit{diff}} + W_{\textit{count}}}{\dfrac{W_{\textit{diff}}}{R_d\left(\textit{diff}\left(d_x^{(T_*)}, d_o^{(T_*)}\right)\right)} + \dfrac{W_{\textit{count}}}{R_c\left(\textit{count}\left(d_x^{(T_*)}, d_o^{(T_*)}\right)\right)}}, \end{aligned} \tag{7}$$

- Positive/Negative Difference:

$$\begin{aligned} &\textit{diff}\left(d_x^{(T_*)} - d_o^{(T_*)}\right) \\ &= \begin{cases} \sum_{i=1}^{k} \left(w_i'^{(x)} - w_i'^{(o)}\right), & \text{if } T_* = T_{pos}, \\ \sum_{i=1}^{k} \left(w_i'^{(o)} - w_i'^{(x)}\right), & \text{if } T_* = T_{neg}. \end{cases} \end{aligned} \tag{8}$$

- Positive/Negative Count:

$$\begin{aligned} &\textit{count}\left(d_x^{(T_*)} - d_o^{(T_*)}\right) \\ &= \begin{cases} \sum_{i=1}^{k} \mathbf{1}[w_i'^{(x)} > w_i'^{(o)}], & T_* = T_{pos}, \\ \sum_{i=1}^{k} \mathbf{1}[w_i'^{(x)} < w_i'^{(o)}], & T_* = T_{neg}. \end{cases} \end{aligned} \tag{9}$$

Two rescaling functions

$$R_d(\textit{diff}(.)) = \frac{\textit{diff}(.)}{2}, \quad R_c(\textit{count}(.)) = \frac{\textit{count}(.)}{|T_*|}$$

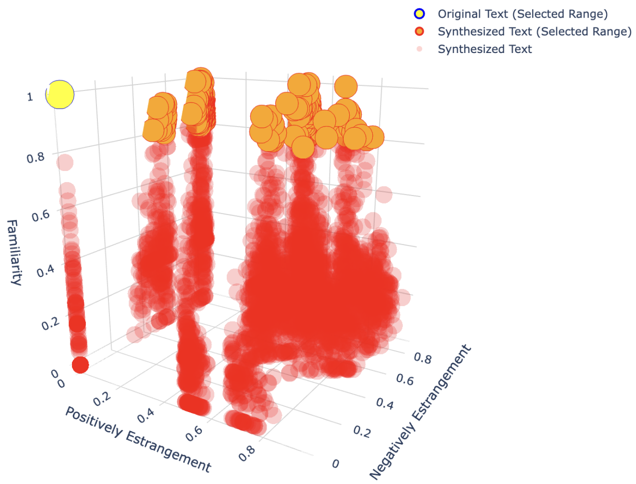
align the metrics' value ranges. Substituting T_{pos} or T_{neg} gives:

$$\begin{aligned} \textit{Positive Strangeness} &= \mathcal{E}\left(d_x^{(T_{pos})}, d_o^{(T_{pos})}\right), \\ \textit{Negative Strangeness} &= \mathcal{E}\left(d_x^{(T_{neg})}, d_o^{(T_{neg})}\right) \end{aligned}$$

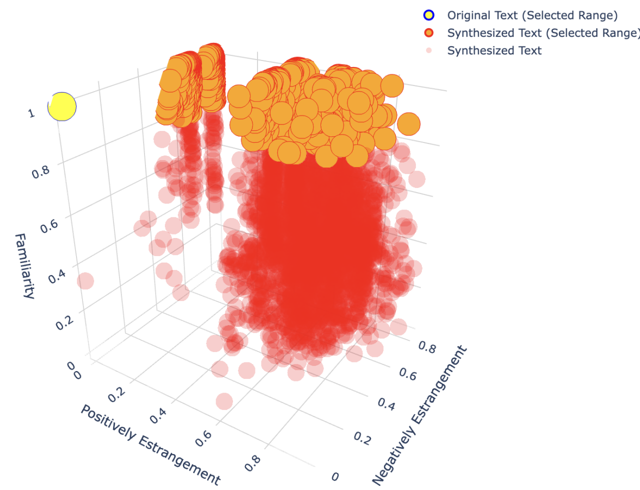
Finally, the system applies the projections according to Equation (1) and constructs a Familiarity–Estrangement Space as illustrated in Figure 2.

Preliminary Results

Figure 2 visualizes two distinct Familiarity–Estrangement Spaces, demonstrating the diversity and personalization nature of the FES. The corpus contains 3,779 game-character



(a) • T_{anc}: $\{1, 5, 6\}$ • T_{pos}: $\{3,8\}$. • T_{neg}: $\{2,10\}$.



(b) • T_{anc}: $\{2,10\}$. • T_{pos}: $\{0,7,11\}$. • T_{neg}: $\{1, 5, 6\}$

Figure 2: Familiarity–Estrangement Spaces derived from **the same corpus and original text** yet **different topic set configurations**. The original text (yellow) serves as a reference for synthesized texts (red/orange). Texts exceeding the familiarity threshold (0.8) are highlighted in orange.

profiles generated by Persona Hub (Ge et al. 2024). To accelerate brainstorming during the game design process, the authors provided the LLM with the game's world-building information and prompted it to re-imagine real-world personas as characters situated within that fictional universe.

Since familiarity and estrangement indicators define the three dimensions of FES, different topic-set configurations can yield markedly distinct FES representations. For instance, in Figure 2a, most synthesized profiles occupy a lower-familiarity region (red points, *Familiarity* < 0.8), whereas in Figure 2b, more appear in a high-familiarity region (orange points, *Familiarity* ≥ 0.8). I.e., far fewer synthetic profiles exhibit strong weights on topics $\{1, 5, 6\}$ (T_{anc} set of Figure 2a) than on topics $\{2, 10\}$; hence the creator must lower the familiarity threshold to discover a broader set of "strange" profiles. The detailed profile distributions displayed in the interactive versions of Figures 2a and 2b (see footnote[1]) reveal that identical coordinates in the two spaces can correspond to entirely different profiles (see footnote[2] for Topic Details). Overall, the FES organizes all profiles by indicators that faithfully reflect user-defined topic sets, enabling customized exploration across the entire corpus.

Discussion and Future Work

We introduced Familiarity–Estrangement Space (FES), which quantitatively models defamiliarization in a personalized context and reframes the defamiliarization from a designer-imposed strategy into a flexible framework. Grounded in FES, we are developing an interactive estrangement calibration interface that enables users to modulate strangeness in generative AI outputs and co-create with AI agents to attain a desired degree of defamiliarization. Leveraging evaluation approaches like *Creativity Support Index* (Cherry and Latulipe 2014), we will systematically assess creators' multifaceted satisfaction with the integrated system and conduct in-depth interviews to uncover user needs and refine the system.

Looking ahead, we will equip FES with real-time generators that populate its currently "empty" coordinates and incorporate *multimodal topic modeling*, expanding the framework across diverse creative domains to further boost human–AI co-creativity.

[1]Interactive Figures:
2a: https://reurl.cc/2Kz9qX
2b: https://reurl.cc/VYNxOR

[2]Topic Details: https://reurl.cc/parNGd

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