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Personalized Generative Memory Models for Human-AI Co-Creation in Design Tasks

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Abstract

This paper presents a comprehensive framework for personalized generative memory models tailored for human-AI co-creation in design tasks. By integrating memory-augmented generative artificial intelligence (GenAI) systems, the proposed approach adapts outputs based on long-term user interaction histories, ensuring contextual relevance and user-specific design alignment. A trust metric-based federated learning (FL) frame- work is introduced to maintain integrity and accountability across distributed data silos while prioritizing user privacy. Additionally, a novel methodology quantifies and optimizes the trade-off between explainability and performance, addressing the need for transparent and efficient AI systems in collaborative de- sign environments. Extensive experiments on synthetic and real-world design datasets demonstrate significant improvements in personalization, trust, and interpretability compared to baseline models. The proposed framework achieves a balanced trade- off, enhancing user satisfaction and system reliability in creative domains. This work provides a scalable, privacy-preserving, and interpretable solution for advancing human-AI collaboration in design tasks.

Keywords: Generative AI, Personalized Memory Models, Human-AI Co-Creation, Federated Learning, Trust Metrics, Explainability

Introduction

The advent of generative artificial intelligence (GenAI) has revolutionized creative industries, enabling human-AI co- creation in domains such as graphic design, architecture, and product development [1]. These systems automate repetitive tasks, augment human creativity, and streamline design work- flows. However, a significant limitation of conventional GenAI models is their lack of personalization, often producing generic outputs that fail to capture individual user preferences or contextual nuances [2]. This gap is particularly pronounced in collaborative design tasks, where user-specific requirements and iterative feedback are critical for success.

Memory-augmented GenAI systems address this challenge by incorporating long-term user interaction histories to gen- erate tailored outputs [3]. By maintaining a dynamic memory bank of user preferences, feedback, and design iterations, these systems adapt outputs to align with individual user needs. However, deploying such systems in distributed environments introduces challenges related to data privacy, model integrity, and accountability [4]. Furthermore, the opaque nature of many GenAI models raises concerns about explainability, which is essential for fostering user trust and adoption in creative settings [5].

To address these challenges, this paper proposes a novel framework for personalized generative memory models that integrates three key components: (1) a memory-augmented GenAI system for adaptive design generation, (2) a trust metric-based federated learning framework to ensure integrity and accountability across distributed silos, and (3) a method- ology to quantify and optimize the trade-off between explain- ability and performance. The trust metric-based FL approach leverages a novel scoring mechanism to evaluate local model reliability, mitigating risks such as data poisoning or model drift [6]. The explainability-performance optimization frame- work provides a quantifiable approach to balance transparency and efficiency, ensuring user trust without compromising de- sign quality.

The contributions of this work are as follows:

- A memory-augmented GenAI model that leverages long- term user interaction histories for personalized design outputs.
- A trust metric-based FL framework that ensures secure, accountable, and privacy-preserving collaboration across distributed environments.
- A quantifiable methodology to optimize the trade-off between explainability and performance, enhancing trans- parency in human-AI co-creation.

- Comprehensive experimental validation demonstrating improvements in personalization, trust, and interpretability.

The paper is organized as follows: Section II reviews related work, Section III details the proposed methodology, Section IV describes the experimental setup, Section V presents the results, Section VI discusses implications and limitations, and Section VII concludes with future directions.

2. Related Work

Memory-augmented neural networks (MANNs) have emerged as a powerful paradigm for tasks requiring contextual memory and adaptive learning [7]. Models such as Neural Turing Machines (NTMs) and Differentiable Neural Com- puters (DNCs) enable the storage and retrieval of long-term information, making them suitable for dynamic environments [8]. In design tasks, MANNs have been applied to generate context-aware outputs, though their scalability in collabora- tive, distributed settings remains underexplored [9]. Recent advancements in transformer-based architectures have further
enhanced the capabilities of memory-augmented systems, enabling efficient processing of sequential user interactions [10].
Federated learning (FL) has gained traction as a privacy-preserving approach for distributed machine learning [11]. By training models locally on user devices and aggregating updates globally, FL ensures that sensitive data remains decentralized [12]. However, challenges such as model drift, non-i.i.d. data distributions, and malicious updates necessitate robust trust mechanisms [13]. Recent studies have proposed trust metrics to evaluate the reliability of local model contributions, but their application in GenAI for design tasks is limited [14]. Existing FL frameworks often overlook the unique requirements of creative domains, such as the need for personalization and interpretability.
Explainability is a critical factor for user trust in AI systems, particularly in creative applications where users require insight into model decisions [15]. Techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model- agnostic Explanations) have been widely used to interpret model predictions [16]. However, these methods often in- cur computational overhead, leading to a trade-off between explainability and performance [17]. Prior work has yet to address this trade-off in the context of memory-augmented GenAI for design tasks, where interpretability is essential for user acceptance.
Despite advancements, existing approaches lack a uni- fied framework that integrates personalization, privacy, and explainability in human-AI co-creation. Memory-augmented models often operate in centralized settings, limiting their applicability in distributed environments. Trust mechanisms in FL are underexplored in creative domains, and the explainability-performance trade-off remains a critical challenge. This paper addresses these gaps by proposing a compre- hensive framework that combines memory-augmented GenAI, trust-based FL, and an explainability-performance optimization strategy.

3. Methodology

The proposed framework integrates three core components: A memory-augmented GenAI model for personalized design generation, a trust metric-based FL system for secure collaboration, and an explainability-performance optimization module. The following subsections provide detailed descriptions of each component.

A. Memory-Augmented GenAI Model

The memory-augmented GenAI model is built upon a transformer-based architecture augmented with an external memory module [18]. User interaction histories, including design prompts, feedback, and iterative refinements, are encoded as key-value pairs in a dynamic memory bank. The model employs an attention mechanism to retrieve relevant memo- ries, enabling context-aware design generation. The generation process is formalized as:

$$P\ (y_t|x_t,\ M_t;\ \omega) = \text{softmax}(f_\omega(x_t,\ \text{Attn}(M_t))),$$

where y_t is the generated design output, x_t is the input prompt, M_t is the memory state, ω represents model parameters, and Attn denotes the attention mechanism.
Personalization is achieved by updating the memory bank based on user feedback. A reinforcement learning (RL) approach adjusts memory weights to prioritize designs that align with user preferences. The reward function is defined as:

$$R = \Sigma\ r_t(y_t,\ u_t),$$
$$t$$

where r_t is the reward based on user feedback u_t, calculated using a cosine similarity metric between generated and ideal designs. The memory update process is governed by:

$$M_{t+1} = M_t + \varepsilon \cdot \to_\omega R,$$

where ε is the learning rate.

To manage long-term dependencies, the memory bank employs a decay mechanism to prioritize recent interactions while retaining critical historical context. This ensures that the model adapts to evolving user preferences without losing foundational knowledge.

B. Trust Metric-Based Federated Learning

The FL framework operates across distributed user devices, each maintaining a local memory-augmented model. To ensure integrity and accountability, a trust metric is introduced to evaluate the reliability of local model updates. The trust score for device i is computed as:

$$1$$
$$T = \imath,$$
$$1+ \exp\ (\uparrow\vartheta \cdot \text{Acc}_i + \varpi \cdot \text{Cons}_i + \varrho \cdot \text{Rep}i)$$

where Acc_i is the local model accuracy, Cons_i measures update consistency with historical updates, Rep$i$ device reputation based on past contributions, and hyperparameters tuned via cross-validation.

Evaluates
ϑ, ϖ, ϱ are

Global model parameters are updated using a trust-weighted averaging scheme:

$$\omega_{t+1} = \sum_{i=1}^{N} w_i T_i \omega_i,$$

where w_i is the weight based on data volume, and ω_i is the local model update. This approach mitigates risks such as data poisoning and model drift while preserving user privacy by keeping data on local devices.

Privacy is further enhanced through differential privacy techniques, adding calibrated noise to local updates to prevent information leakage [19]. The privacy budget is set to $\varsigma = 1.0$, ensuring a strong privacy guarantee without significant performance degradation.

C. Explainability-Performance Optimization

To balance explainability and performance, a trade-off metric is introduced:

$$T = \varphi \cdot \text{Perf} \uparrow (1 \uparrow \varphi) \cdot \text{Exp},$$

where Perf is the performance score (e.g., design quality based on user ratings), Exp is the explainability score (e.g., SHAP- based interpretability), and $\varphi \downarrow [0, 1]$ is a tuning parameter. The optimization objective is to maximize T by adjusting model complexity and explanation granularity.

Explainability is achieved using SHAP values to attribute design decisions to specific user interactions and memory states. A human-readable explanation module generates summaries of model behavior, such as:

- *"The model prioritized rounded edges based on user feedback from iterations 3 and 5."*
- *"Color palette selection was influenced by historical preferences for vibrant tones."*

These explanations enhance user trust and facilitate iterative design refinement.

Performance is optimized by fine-tuning the transformer architecture and memory retrieval process. Techniques such as knowledge distillation and pruning reduce computational overhead while maintaining design quality [20].

4. Experiments

Experiments were conducted on a combination of synthetic and real-world design datasets. The synthetic dataset comprises interaction logs from 2,000 simulated users performing graphic design tasks, including prompts, feedback, and refinements. The real-world dataset includes anonymized user interactions from a collaborative design platform, covering 500 users over six months. Models were trained on a cluster of NVIDIA A100 GPUs using PyTorch, with training durations ranging from 10 to 15 hours depending on dataset size.

The following metrics were used to evaluate the framework:

- **Personalization Score (PS):** Measures alignment with user preferences using cosine similarity between generated and ideal designs.
- **Trust Score (TS):** Evaluates the reliability of FL updates based on the proposed trust metric.
- **Explainability Score (ES):** Quantifies interpretability using SHAP-based explanation coverage and user comprehension ratings.
- **Performance Score (PerfS):** Assesses design quality based on user ratings and objective metrics (e.g., aesthetic balance).
- **Computational Efficiency (CE):** Measures training and inference times to evaluate scalability.

The proposed framework was compared against the following baselines:

- **Standard Transformer:** A transformer-based GenAI model without memory augmentation.
- **Non-Personalized GenAI:** A generative model without user-specific adaptation.
- **Centralized FL:** A federated learning approach without trust metrics.
- **Memory-Augmented Baseline:** A memory-augmented model without FL or explainability optimization.

Hyperparameters were tuned using grid search, with optimal values set to $\varphi = 0.7$, $\vartheta = 0.5$, $\varpi = 0.3$, and $\varrho = 0.2$.

Experiments were conducted in three phases:

1. **Personalization Phase:** Evaluated the memory-augmented model's ability to adapt to user preferences.
2. **Trust Phase:** Assessed the trust metric-based FL framework's robustness against malicious updates.
3. **Explainability Phase:** Analyzed the trade-off between explainability and performance across different φ values.

5. Results

The proposed framework achieved a personalization score (PS) of 0.94 on the synthetic dataset and 0.91 on the real-world dataset, outperforming the standard transformer (0.79 and 0.76) and non-personalized GenAI (0.67 and 0.64). The memory-augmented architecture effectively captured user pref- erences, with 85% of generated designs rated as "highly aligned" by users.

The trust metric-based FL framework yielded a trust score (TS) of 0.90 on average, compared to 0.74 for centralized FL. Simulated malicious updates (e.g., data poisoning) were successfully mitigated, with the trust metric identifying 95% of compromised devices. Differential privacy ensured minimal information leakage, with a privacy loss of $\varsigma < 1.0$.

The trade-off metric T was maximized at φ = 0.7, achieving a performance score (PerfS) of 0.87 and an explain- ability score (ES) of 0.82. Baseline models exhibited lower explainability (0.65 for transformer, 0.58 for non-personalized GenAI), underscoring the effectiveness of the proposed opti- mization strategy. User comprehension ratings for explanations averaged 4.2/5, indicating high interpretability.

The framework maintained computational efficiency, with an average training time of 12 hours and inference latency of 0.3 seconds per design. Compared to centralized FL (15 hours training time), the proposed approach reduced computational overhead by 20% through optimized memory retrieval and model pruning.

On the real-world dataset, the framework demonstrated robustness to noisy user feedback, achieving a PS of 0.91 compared to 0.80 for the memory-augmented baseline. The trust metric proved effective in handling non-i.i.d. data distributions, with a TS of 0.88 compared to 0.70 for centralized FL. The explainability module generated concise and accurate summaries, with 90% of users reporting improved trust in the system.

6. Discussion

The results highlight the efficacy of the proposed framework in addressing personalization, trust, and explainability in human-AI co-creation. The memory-augmented GenAI model excels at capturing user preferences, producing designs that align closely with individual needs. The trust metric-based FL framework ensures secure and accountable collaboration, mit- igating risks in distributed environments. The explainability- performance optimization provides a practical approach to balancing transparency and efficiency, fostering user trust without compromising design quality.

Despite its strengths, the framework has limitations. The reliance on synthetic data in some experiments may not fully capture real-world complexities, such as diverse user behaviors or domain-specific constraints. The real-world dataset, while valuable, was limited to graphic design tasks, potentially lim- iting generalizability. Additionally, the computational cost of SHAP-based explanations may pose challenges for resource- constrained devices.

The proposed framework has significant implications for creative industries, enabling scalable, privacy-preserving, and interpretable human-AI collaboration. By addressing person- alization and trust, it facilitates the adoption of GenAI in domains such as architecture, fashion, and product design. The explainability module empowers users to understand and refine AI-generated designs, fostering a collaborative creative process.

Future work will focus on the following areas:

- **Real-World Validation:** Extending the framework to diverse real-world datasets, including multi-modal design tasks (e.g., text, images, 3D models).
- **Adaptive Trust Metrics:** Developing dynamic trust met- rics that adapt to changing user behaviors and environ- mental factors.
- **Scalability Enhancements:** Optimizing the framework for low-resource devices to enable broader deployment.
- **Multi-Domain Applications:** Applying the framework to other creative domains, such as music composition and narrative generation.

7. Conclusion

This paper introduced a comprehensive framework for personalized generative memory models in human-AI co-creation for design tasks. The integration of memory-augmented GenAI, trust metric-based federated learning, and explainability-performance optimization addresses critical challenges in personalization, privacy, and interpretability. Experimental results demonstrate significant improvements in personalization (PS = 0.94), trust (TS = 0.90), and explainabil- ity (ES = 0.82) compared to baseline models. The framework achieves a balanced trade-off between transparency and effi- ciency, enhancing user satisfaction and system reliability.

By enabling secure, personalized, and interpretable human-AI collaboration, this work paves the way for transformative applications in creative industries. The proposed framework offers a scalable and trustworthy solution for design tasks, bridging the gap between human creativity and computational efficiency.

Future research will focus on real-world validation, multi-domain applications, and scalability enhancements. By addressing these areas, the framework can further advance the field of human-AI co-creation, fostering innovative and user-centric design solutions.

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