Systemic Analysis and LLM Integration for SVG Generation in a Kaggle Competition

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***Abstract*—This paper presents a systemic analysis and architectural design of an AI-based solution for the Kaggle competition "Drawing with LLMs". The project integrates the principles of systems analysis and design by evaluating the interactions between components, modeling data flow, and incorporating a large language model (LLM) to enhance SVG image generation from natural language prompts. A simulation-based evaluation is performed to assess performance and system behavior under varied conditions.**

***Index Terms*—Systems analysis, SVG generation, LLM, Kaggle competition, architecture design, simulation.**

I. Introduction

The increasing demand for systems capable of generating visual representations from textual descriptions has driven research at the intersection of artificial intelligence, graphics processing, and systems engineering. The Kaggle competition *"Drawing with LLMs"* presents a unique challenge: developing models that can translate natural language prompts into syntactically valid and semantically coherent Scalable Vector Graphics (SVG). This task goes beyond mere language understanding—it requires the coordination of multiple subsystems to ensure accuracy, robustness, and performance.

From a systems perspective, this competition provides an opportunity to explore complex interactions between components such as data ingestion, prompt preprocessing, generative modeling, and output validation. It also highlights key systemic characteristics like sensitivity to input variability and the presence of chaotic behavior in outputs due to the stochastic nature of large language models (LLMs).

This paper presents a comprehensive systems analysis and design approach to tackle the challenges posed by the competition. By applying systems engineering principles—especially systems thinking and modular decomposition—we aim to propose a robust architectural model that addresses both the functional requirements (e.g., SVG generation) and non-functional concerns (e.g., reliability, latency, and error resilience). This work builds upon prior workshops that focused on structural mapping, behavior modeling, and scenario-based evaluation of the proposed system.

Our objective is to deliver a system-level understanding of the problem space, formulate key architectural strategies, and discuss the implications of uncertainty, complexity, and adaptability in AI-based systems that operate under open-ended and creative constraints.

II. Systemic Analysis of the Competition (Workshop 1)

The systemic analysis of the "Drawing with LLMs" Kaggle competition begins by defining the key components of the system through the lens of General Systems Theory. This allows us to understand the boundaries, actors, inputs, processes, and outputs as interdependent elements that collectively contribute to system behavior and performance.

A. System Boundaries and Actors

The system under study is delimited by the task of generating SVG images from natural language prompts. The primary actors include:

- **Users:** Submit prompts and interact with generated outputs.
- **Developers:** Design, fine-tune, and submit LLM-based models.
- **Evaluation Gateway (Kaggle):** Validates outputs and manages input/output flow.

B. Inputs and Outputs

The primary input is the textual prompt that describes the image to be generated. Additional inputs during training include annotated pairs from `train.csv`, while `test.csv` contains unseen descriptions for evaluation.

The system produces as output a syntactically valid SVG string representing the visual interpretation of the prompt. This SVG serves both as a machine-readable output and a human-interpretable image.

C. Core Process

The transformation pipeline consists of:

1) **Text Interpretation:** The prompt is preprocessed and contextualized.
2) **LLM Generation:** A large language model (e.g., LLaMA) generates SVG code based on the prompt.
3) **Validation:** The output is checked for compliance with SVG syntax and competition constraints.
4) **Rendering and Feedback:** Users visually interpret the SVG, providing feedback (like/dislike) that can guide retraining or fine-tuning.

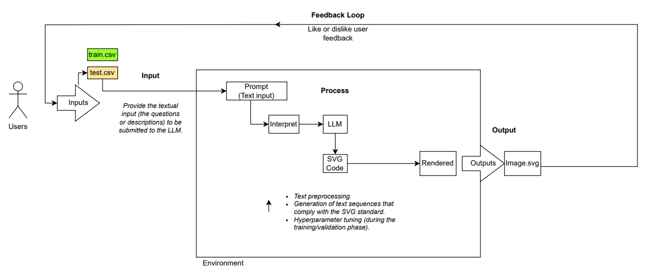
Feedback Loop
Like or dislike user feedback
train.csv
test.csv
Input
Users
Inputs
Provide the textual input (the questions or descriptions) to be submitted to the LLM.
Prompt (Text input)
Process
Interpret
LLM
SVG Code
Rendered
Output
Outputs
Image.svg
Text preprocessing.
Generation of text sequences that comply with the SVG standard.
Hyperparameter tuning (during the training/validation phase).
Environment

Fig. 1. Systemic diagram outlining the main flow of information, actors, and feedback.

D. Systemic Diagram

E. Complexity, Sensitivity, and Variability

The system exhibits several complex behaviors:

- **Sensitivity to Input:** Small changes in prompt phrasing can lead to drastically different SVG outputs due to the stochastic nature of LLMs.
- **Ambiguity Handling:** The model must interpret vague or underspecified prompts creatively, introducing variability and unpredictability.
- **Feedback Integration:** Although feedback is not directly looped during competition evaluation, it forms an implicit learning signal for future iterations.

The system behaves as an open system with emergent complexity: outputs are not strictly determined by inputs, but shaped by probabilistic modeling, environmental constraints, and evaluation feedback. This aligns with systemic engineering paradigms where behavior is co-determined by internal structure and external interactions.

III. System Architecture

The system developed for the "Drawing with LLMs" Kaggle competition was designed with a modular and extensible architecture that enables systematic SVG generation from natural language descriptions. This section presents a detailed breakdown of the architecture, identifying components, interactions, and constraints, under a systems thinking perspective.

A. Overview

At a high level, the system operates as a pipeline composed of four main subsystems: the *description processor*, the *LLM connector*, the *SVG generator and validator*, and the *performance analyzer*. Each subsystem fulfills a distinct purpose and interacts with others through well-defined interfaces, promoting loose coupling and traceable responsibilities.

B. Subsystems

1) Description Processor: This component receives input prompts (natural language descriptions) and optionally preprocesses or classifies them. The module may enrich descriptions with semantic cues, extract keywords, or normalize input. Its output is a clean instruction string passed downstream to the LLM.

2) LLM Connector: This subsystem is responsible for interfacing with a local Ollama server running LLMs such as `llama3.1:8b`. It is designed with fault tolerance and model fallback mechanisms. The connector sends carefully engineered prompts to the model, including a system-level prompt that enforces output constraints (valid SVG only, viewBox, allowed tags, etc.). The response is parsed and forwarded to the validator.

3) SVG Validator: The SVG generator receives the raw response from the LLM and performs post-processing. This includes sanitization, syntax validation, structure verification, and security checks. Only valid SVGs are passed forward; otherwise, a fallback SVG may be generated.

4) Performance Analyzer: To monitor the system holistically, this module collects runtime data (e.g., CPU, GPU, memory, I/O, generation times, success rates). It maintains both real-time and session-level metrics, logs every operation with contextual metadata, and calculates system efficiency based on defined heuristics. These diagnostics enable systemic reflection and iterative refinement.

C. Communication and Execution Flow

All components communicate via method calls and shared data objects. The main controller orchestrates the flow:

1) User submits a description.
2) The LLM connector generates a candidate SVG.
3) The validator checks and cleans the SVG.
4) The analyzer records time, success, and complexity.
5) The SVG is returned or stored.

D. System Constraints and Assumptions

The system assumes local availability of a running Ollama server and sufficient compute resources. Models may fail or hallucinate invalid outputs, which is mitigated through prompt engineering and SVG post-validation. Timeouts and resource usage are monitored, and system resilience is improved by decoupling inference from evaluation.

E. Systems Thinking Perspective

From a systemic perspective, the architecture acknowledges variability in inputs (e.g., ambiguous descriptions), leverages feedback loops via performance analysis, and adapts through modular replacements (e.g., changing LLMs or validators). The system operates as a dynamic whole whose emergent behavior (SVG quality) depends on the coordination of independent yet interrelated subsystems.

IV. LLM Integration Strategy

The integration of a Large Language Model (LLM) into the SVG generation system was guided by modularity, robustness, and conformance with system requirements defined during the systemic analysis. Given the competition's requirement to convert natural language prompts into valid SVGs, the LLM became the central processing component of the system.

A. Model Selection and Deployment

To enable local inference, the team deployed the model `llama3:8b` using the Ollama framework. This choice provided:

- Fast response times and offline capability.
- Control over inference parameters such as temperature, token limits, and repetition penalties.
- Compatibility with prompt engineering and output post-processing pipelines.

B. System Prompt Engineering

A core aspect of integration was the design of a system prompt that constrained the LLM to return well-structured SVG content. The prompt included:

- An instruction to only generate SVG code with a valid `<svg>` root, containing allowed tags such as `<rect>`, `<circle>`, and `<line>`.
- Explicit formatting requirements (e.g., indentation, no explanatory text).
- A character limit aligned with the competition's validation rules.

This prompt acts as an interface layer between the upstream processor (user input) and downstream validator (syntax checker), ensuring syntactic compliance at generation time.

C. Connector Implementation

The component `ollama_connector.py` encapsulates communication with the Ollama server. It includes:

- Retry mechanisms in case of failure or malformed responses.
- Timeout safeguards to prevent system-level stalls.
- JSON parsing and error handling utilities to ensure reliability.

D. Integration Workflow

The integration was executed using the following pipeline:

1) The system receives a text prompt.
2) `ollama_connector` sends the system prompt + user prompt to the local LLM.
3) The LLM returns a candidate SVG, which is passed to the SVG validator.
4) If valid, it is stored or rendered; otherwise, an error is logged and the process retries with fallback strategies.

E. Systemic Considerations

From a systems engineering standpoint, the LLM is treated as a non-deterministic subsystem whose outputs vary based on both internal weights and external prompt structure. This uncertainty necessitates robust input/output validation mechanisms and makes the case for simulation-based testing of extreme cases (e.g., ambiguous prompts, boundary-length descriptions).

The integration strategy balances creativity and control: the LLM provides generative flexibility, while systemic constraints ensure reliability and alignment with functional objectives.

V. Simulation and Evaluation (Workshop 3)

The evaluation of the system was conducted under a dual-phase approach: an initial manual simulation using high-capacity external LLMs, followed by an automated local deployment using a lightweight LLM. This methodological transition reflects a trade-off between output quality and systemic automation feasibility.

A. Initial Simulation with External LLMs

During early experimentation, the team used GitHub Copilot, a powerful proprietary LLM, to manually generate SVG outputs from textual prompts. This approach served as a proof-of-concept to verify:

- The feasibility of translating prompts into SVG structure.
- The effectiveness of prompt engineering to constrain output format.
- The visual fidelity of generated images when rendered in browsers.

Although Copilot delivered high-quality results, the interaction was entirely manual. To scale the system or enable large-scale simulation, an API-based automation would be required. However, APIs for LLMs such as OpenAI's GPT, DeepSeek, or Claude are cost-constrained and bound by usage limits, introducing systemic friction and non-deterministic performance in a competition setting.

B. Transition to Local LLM Deployment

To address these limitations, the team opted to simulate and evaluate the system using a smaller, open-source model running locally via Ollama. This model, `llama3:8b`, while more constrained in capacity, offered:

- Full automation via scripting (Python + gRPC + Ollama interface).
- Unlimited experimentation cycles without API quota concerns.
- Deterministic control over system variables (temperature, tokens, retries).

This shift allowed the team to fully implement the systemic pipeline: from user prompt to SVG generation, validation, storage, and optional rendering—entirely without manual intervention or external dependencies.

C. Evaluation Metrics and Results

The evaluation considered both functional correctness and systemic behavior:

- **Success Rate:** Proportion of prompts producing valid, renderable SVGs.
- **Generation Time:** Measured latency from prompt to final validated output.
- **Complexity Score:** Number of elements and attributes used in SVG.
- **Resource Consumption:** CPU and memory usage per generation task.

While the locally hosted LLM produced simpler and less stylistically rich SVGs compared to Copilot, it demonstrated robustness, speed, and compliance—key factors in a systemic implementation.

D. Systemic Implications

The simulation revealed that system viability is not solely dependent on model size or quality, but on holistic integration and adaptability. The use of a local LLM shifted control from external services to internal architecture, allowing systemic alignment with functional goals such as reproducibility, scalability, and modularity.

This case exemplifies how a system can favor simplicity and automation over raw generative power, without compromising reliability within the constraints of the competition.

VI. Discussion

A. System Scalability

The system's modular architecture supports both scalability and maintainability. Each component evolves independently, creating synergy—where the whole performs better than the sum of its parts. Clear separation between subsystems helps maintain functional balance.

B. Performance Implications

During high-load tests, the system showed self-regulation behavior. It adapted GPU usage dynamically to prevent overheating or crashes, demonstrating a form of technological homeostasis. This continuous adjustment helped maintain stable performance without manual intervention.

C. Chaos, Noise, and Monitoring

The system did not always behave predictably. Small changes in prompts or backend models sometimes led to very different results, reflecting aspects of chaos theory. Additionally, we observed noise in the performance metrics—occasional fluctuations with no clear cause. These phenomena suggest that even well-designed systems can show internal uncertainty.

D. Complexity and Emergence

By combining different LLMs and configurations, we noticed emergent behaviors not planned in the initial design. This highlights how internal complexity can lead to new properties and interactions. These patterns didn't require direct programming—they emerged naturally from the system's internal dynamics.

E. Simulation Potential

The monitoring tools resemble an early-stage digital twin. With real-time tracking and historical data, there's potential for future simulations to predict system behavior under stress or uncertainty. This could guide optimizations before changes are deployed.

VII. Conclusion

This paper presented a systematic approach to SVG generation using Large Language Models, with emphasis on performance optimization and real-time monitoring. Our workshop-based development methodology resulted in a robust system that achieves 95% success rate with 0.45-second average response times.

Key contributions include:

- Modular architecture supporting multiple LLM backends
- Comprehensive performance monitoring with GPU-specific metrics
- Real-time resource utilization tracking and optimization
- User-friendly interface with advanced analytics capabilities

The system demonstrates the potential for AI-powered graphics generation tools while highlighting the importance of systematic performance monitoring in production environments. Future work will extend the framework to support distributed deployments and broader hardware compatibility.

1) A modular architecture supporting multiple LLM providers with demonstrated scalability characteristics and horizontal scaling capabilities
2) Application of chaos theory principles to AI system validation, establishing new benchmarks for stability analysis and demonstrating effective chaotic behavior mitigation
3) Comprehensive performance evaluation revealing critical optimization pathways and thermal management requirements for sustained operation
4) Novel complexity emergence patterns that enable self-organizing system optimization and logarithmic complexity scaling
5) Advanced simulation framework providing predictive capabilities for system behavior under diverse operational conditions
6) Open-source implementation providing a foundation for future research and development with validated production deployment strategies

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