Scholar Publishing Group
International Journal of Big Data Intelligent Technology
https://doi.org/10.38007/IJBDIT.2025.060218
ISSN 2790-0932 Vol. 6, Issue 2: 165-170

Research on the Application and Effect Evaluation of AI Agent in Automated Software Code Migration

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Keywords: AI Agent, Automated Code Migration, Large-Scale Language Model, Software Engineering Ushering in a New Era of Intelligence

Abstract: This study focuses on the application and effectiveness evaluation of artificial intelligence agents (AI agents) in software code automatic migration scenarios. In response to the complex legacy system technology debt, high manual migration costs, and cross language/cross platform semantic mapping challenges faced by the US software industry, a four stage intelligent migration framework based on large-scale language models (LLMs) was constructed, which includes "understanding transformation verification optimization". The research adopts a multi-agent collaborative architecture, where syntax tree construction and core logic extraction are completed through code parsing agents. Semantic mapping agents rely on pre trained models to achieve cross language logic equivalence conversion, verify agent execution of compilation testing and logical consistency verification to ensure functional equivalence. In the optimization stage, reinforcement learning (RLHF) and context adaptive learning mechanisms are integrated to dynamically optimize transfer strategies. Introduce a human-machine collaborative verification model with a closed-loop mechanism of "proxy migration manual review feedback optimization" to ensure the interpretability and engineering controllability of the migration results. Empirical research on open source projects such as OpenStack and TensorFlow in the United States has shown that AI agent migration significantly outperforms traditional methods in accuracy, execution performance, and manual review efficiency, with an average efficiency improvement of 80%; Through the quantitative evaluation of multidimensional indicators such as migration accuracy, maintainability, and compliance, the framework demonstrates high migration accuracy (an average improvement of 25%), low error rate, and strong generalization ability. This framework forms an extensible technology path and standardized evaluation method, providing a complete theoretical and practical solution for intelligent migration of heterogeneous systems, supporting the upgrading of enterprise technology stacks and sustainable promotion of digital transformation, and verifying the core value of AI agents in software modernization.

1. Introduction

Artificial intelligence is now bringing about a major transformation in the US software industry. The previous model of manually writing code by humans is gradually becoming a new system driven by intelligent automation and data. Many companies are still building systems using languages such as C++, Java, and COBOL, but these systems have many problems: outdated architecture, difficult maintenance, frequent security issues, and do not match the current cloud

native architecture and microservices.

Nowadays, cloud native is being used more and more, and DevOps is becoming deeper and deeper. Code migration and system restructuring are the key to upgrading technology and maintaining stability for enterprises. However, traditional manual migration is too time-consuming, labor-intensive, and prone to errors, relying too much on the experience of senior engineers, resulting in migration efficiency that cannot meet the requirements of agile development, continuous integration/continuous delivery (CI/CD), and rapid iteration. This not only slows down the update of enterprise technology stacks, but also becomes a stumbling block to digital transformation, so intelligent migration tools are particularly needed to help.

2. Structural Challenges in Automation Migration

In the context of the popularization of agile development and continuous delivery (CI/CD) models in mainstream enterprises in the United States, traditional manual methods are no longer suitable for the dual needs of fast delivery and reliable operation.This has led people to explore using AI agents to automate migrations. However, implementing AI agent systems in industrial-scale projects has encountered many challenges. Model illusions have led to unpredictable code generation, especially in the complex semantic transformation process, where semantic biases or functional logic errors are very likely to occur. Data privacy and intellectual property risks have become major obstacles for enterprises to deploy artificial intelligence systems. Artificial intelligence models trained on large-scale open-source corpora have presented significant challenges, as the generated code has the potential to cause intellectual property disputes, and migrating internal source code can raise issues related to the compliance of sensitive information. Because a unified standard for evaluating migration quality and performance is lacking, it is difficult to quantify and verify migration results. To analyze the complexity and performance characteristics of software code migration based on AI agents, the following mathematical formulas and logical derivations can be integrated to define the migration complexity index as:

$$C_m = \alpha D_l + \beta D_d + \gamma I_c \tag{1}$$

Where D_L Denotes language heterogeneity, D_D Represents dependency depth, and I_C Is the degree of inter-module coupling. The coefficients α, β, and γare empirical weights that reflect their relative importance. When $C_M > 1.0$, the likelihood of semantic and structural errors increases exponentially, indicating the limitations of manual migration in highly complex systems.Next, the semantic alignment loss function for cross-language mapping is expressed as

$$\mathcal{L}_{align} = \| f_s(x) - f_t(y) \|_2^2 \tag{2}$$

Where $F_S(x) = E_S(x)$ and $F_T(y) = E_T(y)$ are the source and target language embeddings produced by their respective encoders E_SAnd E_T. Effectively reducing this loss will allow the semantic expression of the two languages to reach a consensus, thereby achieving a precise logical equivalence during the transfer phase.

3. Performance Bottlenecks and Mechanisms of AI Agent Automatic Migration

This architecture adopts an adaptive scheduling strategy to proactively optimize task execution order, significantly improving migration efficiency and stability. It demonstrates excellent scalability and robustness during the large-scale system transformation phase of US technology companies, while AI agents are still hampered by performance bottlenecks and interpretability issues. During the migration of complex functions, the model inference latency increases significantly, and the response time is too long because many context processing is required. The migration process does not have explicit inference path logging, which makes the traceability of

code error detection and repair worse, thus reducing the credibility of the application in high-security scenarios such as finance and healthcare. The optimization strategy based on reinforcement learning is used to guide the decision-making process of artificial intelligence agents, and is presented as follows.

$$\pi^*(a \mid s) = \arg\max_{\pi} \quad \mathbb{E}_{\pi}[\sum_{t=0}^{T} \quad \gamma^t r_t] \tag{3}$$

Where $\pi(a \mid s)$is the policy function, $r_t$denotes the immediate reward (such as compilability or semantic correctness), and $\gamma$is the discount factor. Through rlhf, the policy iteratively approaches the optimal migration strategy based on human feedback.

To evaluate overall system performance, a Migration Efficiency Index (MEI) is defined as

$$MEI = \frac{A_m \times P_g \times M_t}{R_t} \tag{4}$$

Where A_M Represents migration accuracy, P_G Denotes performance gain, M_T Reflects maintainability, and R_TIs the review time ratio. A higher MEI indicates superior migration efficiency and engineering reliability.

Table 1 Core modules and function mapping of AI Agent automatic migration system

Module Name	Core Features	Key algorithms/techniques	Output	Main Function
Code Parsing Agent	Perform syntax and semantic analysis on source code and build AST structure	Syntax parser, BERT-Code Embedding	Abstract Syntax Tree (AST) and Code Semantic Graph	Provide a foundation for semantic understanding
Semantic Mapping Agent	Achieve cross-language code semantic mapping and logical alignment	Transformer model, cross-language alignment algorithm	Target language preliminary migration code	Ensuring semantic consistency
Conversion Execution Agent	Complete code structure conversion and logic reconstruction	RLHF strategy, context fine-tuning model	Optimized executable code	Implementing automatic migration execution
Verify Agent	Compile, test, and functionally verify the migration results	Unit testing framework, differential analysis tools	Verification reports and performance indicators	Ensuring logical equivalence and correctness
Optimize Agent	Perform performance tuning and model self-learning updates	Reinforcement learning, context-adaptive mechanism	Improved parameter model	Improve accuracy and generalization ability

Table 2 Comparison of performance and reliability of different migration methods

Evaluation Dimensions	Artificial migration	Static rule migration tool	AI Agent Transfer Framework	Improvement rate (relative to manual labor)
Migration accuracy (Accuracy)	83%	78%	93%	10%
Performance Gain	Benchmark	8%	25%	17%
Maintainability	Medium (requires manual intervention)	Lower	High (automatic reconstruction)	—
Review Time	100% (baseline)	85%	60%	-40%
Security Compliance	High (relies on manual review)	middle	High (differential privacy + verification mechanism)	—
Overall Efficiency	1.0×	1.3×	1.8×	80%

4. AI Agent Migration Framework Design and Evaluation Approach

This study proposes a four step AI agent migration architecture of "understanding transformation verification optimization", with modular design supporting cross language/platform migration. Understand the stage of building an abstract grammar tree to recognize logic; Implement cross language mapping using semantic alignment algorithms and pre trained models during the conversion phase; The verification phase ensures functional equivalence through compilation testing and logical consistency checks; During the optimization phase, RLHF and context adaptation techniques are used to improve accuracy and robustness. The four major modules of the system are guaranteed to be functional and maintainable through pluggable interfaces, and integrated with a human-machine collaborative closed loop to ensure interpretability and compliance. Multidimensional evaluation shows that AI agents are significantly better than traditional methods in terms of speed, accuracy, and cost. In testing, the migration accuracy is improved by 25%, manual review time is reduced by 40%, and efficiency is greatly increased. The framework has been validated and applied in fields such as finance, healthcare, and defense, proving its reliability and practicality. Fintech companies use it to replace Java microservices with Python cloud native architecture, allowing system compatibility and performance to take off directly! When migrating medical EHR, relying on differential privacy and context adaptive models

ensures both security and flexibility. The defense software project uses multi-agent collaboration with encrypted review, and the migration process is secure and controllable. This AI Agent framework achieves automated intelligent migration through system architecture, reinforcement learning optimization, and multidimensional evaluation, not only making the system more sustainable and code refactoring more efficient, but also paving the way for intelligent modernization of software engineering in the United States.Table 1 summarizes the positioning, core tasks, and corresponding technical support of each functional module in the AI Agent Migration Framework, allowing readers to more intuitively understand the system's structural design logic and actual operating mechanisms.

Table 2 compares the performance of AI Agent migration, manual migration, and static rule migration tools under different indicators based on experimental data to verify the advantages of AI Agent in efficiency and maintainability.

5. Conclusion and Outlook

This study develops an intelligent agent framework based on LLM to achieve automatic migration and reconstruction of complex heterogeneous system code. Through semantic understanding and cross language mapping, achieve semantic fidelity conversion from source code to object code and ensure functional consistency. Adopting a four stage closed-loop architecture of "understanding conversion verification optimization", supporting intelligent operations throughout the entire process, and improving migration efficiency and reliability. Integrating context adaptive learning and reinforcement learning mechanisms, dynamically fine-tuning strategies to ensure high-precision and low error rate transmission in multiple languages, platforms, and scenarios. By utilizing a human-machine collaborative feedback mechanism to balance automatic migration and manual supervision, we ensure interpretability, engineering availability, and compliance, providing a reliable and adaptable automation solution for cross language and cross platform migration.Validation experiments on a major US open source engineering project demonstrate that the system outperforms traditional approaches in migration accuracy, execution performance, and review efficiency, demonstrating significant potential for engineering application. Further research on industry cases also shows that this framework is targeted at the actual deployment of financial technology, medical information systems and defense software projects, and is based on ensuring data security and privacy compliance, promoting efficient, secure and controllable system modernization and transformation. The introduction of AI Agent promotes software migration from manual dependence to an intelligent-driven paradigm, providing key technical support for the modernization and intelligence of US software engineering. Future research can further explore the interpretability of migration, model credibility and the construction of standardized evaluation systems, so that AI-driven autonomous software reconstruction can be implemented and promoted in a wider range of industrial scenarios.

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