Scholar Publishing Group
International Journal of Big Data Intelligent Technology
https://doi.org/10.38007/IJBDIT.2026.070117
ISSN 2790-0932 Vol. 7, Issue 1: 140-149

Research on Model Engineering Integration Methods for AI Systems Based on Data-Driven Intelligence

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Keywords: AI systems; Machine Learning Operations (MLOps); data-driven intelligence; engineering integration; quantitative trading models

Abstract: As the practice of artificial intelligence in important fields of finance and industry rapidly advances, the design of intelligent systems with significant levels of reliability, maintenance, and ability to seamlessly evolve has turned into the most important focus of research. This paper uses quantitative trading, which is a typical high-frequency and data-heavy decision-making context, as a case study. This study concentrates on the main engineering issues in model development, including the strict data timeliness demands, model repeated reuse, and the challenges of coordinating between multi-model-based engineering, and presents and introduces an engineering methodology of AI system engineering models that are based on its data-driven intelligence. The suggested solution changes and improves the conventional quantitative research processes by incorporating MLOps toolchains (ex: MLflow and DVC) into the open-source quantitative research platform Qlib. It is useful and resolves key bottlenecks that might include delays in data updates, inadequate reproducibility of experiments, absence of model version control, and inadequate monitoring features when using models in production settings. Empirical outcomes prove that the suggested integration approach is a great way of enhancing the extent of automation of the model development process and the efficiency of team collaboration, as well as agile reactions to altering market conditions and the ongoing and consistent development of the models.This study does not only offer tangible solutions and empirical data to the engineering discipline of AI models in quantitative trading, but also presents a transferable and scalable approach to methodological modeling platform on how data-driven intelligent systems can be developed and run across a large scope of application areas.

1. Introduction

Artificial intelligence is swiftly moving out of laboratory designs to large-scale industrial applications, and data-driven and model-driven intelligent systems have become a strategic change agent in a variety of principles. Nevertheless, there remains a huge engineering disjuncture between theory and practice. Conventional paradigms of model development have been biased to make a single-point enhancement to algorithmic performance and ignore the system engineering issues of converting models into real world productivity with efficiency, reliability, and in a continuous way. This has led to the numerous AI systems in the real world having slow loops of iteration, limited flexibility in response to non-stationary data distribution, and exorbitantly high operational and maintenance expenses. In particular, these issues are acute in the areas like quantitative trading where the real-time performance and risk-resilience are strict prerequisites but they are reflective of a wider failure of end-to-end engineering integration across the lifecycle of data-driven intelligent systems.

Machine Learning Operations (MLOps) is a novel engineering paradigm that addresses these difficulties with the combination of the DevOps principles and peculiarities of machine learning. Its main focus is to have an end-to-end efficient management of the full model lifespan, the development process, its deployment, monitoring, and iteration, in a standardized, automatized and collaborative way. In spite of the fact that MLOps has proven its worth in some areas of application, the efforts to underpin it with domain-specific knowledge systems and the generalization of engineering practices, malleable through such integration, have little been investigated.

In this context, this paper transcends the perspective of one technology application, and will suggest an engineering approach to creating model-centric AI systems on the basis of data-driven intelligence. Based on MLOps as the framework, the solution offered makes significant contributions to the ideas of systems engineering and project management, attempting to present a lifecycle management system of AI models, which is both standard and reusable. An extremely complicated and dynamic process of developing quantitative trading models is taken to represent an empirical scenario. By engaging in methodological implementation and establishing its effectiveness, the study does not only attempt to elucidate tangible engineering pain points within the quantitative trading business but also evaluates to encapsulate a generalized methodology of integration, which offers both theoretical and practical directions in terms of how AI systems can be effectively and efficiently deployed in a wide variety of application parameters and continually evolve.

2. Related Work

The paradigm shift occurring in various industries is as a result of the integration and application of data-driven intelligent technologies. The current research has a pronounced developmental trend in that technological enabling progress has been going through applications scenario-specific to system-level reconfigurability. The AI system models that are being engineering-integrated in the present study reside at a critical stage of this journey and thus, need to be properly positioned with regard to a vast landscape of technological convergence and practical application. The existing studies in this field could be divided into the following directions.

On the scale of technological integration and intelligent decision support, the current literature is more concerned with integrating the key technologies that include big data, artificial intelligence, and the Internet of Things to improve the analytics and decision-making processes. Take the example of Paramesha M. et al. [1]who tried to systematically explore the role of combining these technologies in enhancing decision support in business intelligence systems. These studies are the definitive technological paradigm of data model connection-connectivity-intelligent that is eligible as a pre-integration of the intelligent systems.

At these higher levels of cross-domain applications and practical issues, the data-driven has been intensively embraced into various situations, and at the same time revealing similar and problem-specific questions. On a larger scale, Bachmann N. et al. [2] examined the duo effect of data-driven technologies on the Sustainable Development Goals, showcasing both their potential to enable it and cross-cuts such as the data governance, ethics, and energy efficiency. Gomez-del Rio T.

et al. [3] revealed in the engineering education sector that advanced manufacturing technologies with project-based learning can greatly promote the results of learning. The central role of model performance optimization in specific application set-ups was exemplified by Yang I. et al. [4] that optimised trading strategies based on models like the long short-term memory (LSTM) networks in the most dynamic areas of decisions (such as finance). The studies taken together paint an articulate picture of the intelligence application using data and the difficulty in 1 achieving successful engineering deployment in heterogeneous contexts.Moreover, in the quest of seeking combining visions about complex systems in the future, recent studies have started to investigate system-oriented architectures that will go beyond individual applications. Brauner P. et al. [5] introduced the notion of the so-called Production Internet and focused on its global coordination and optimization of manufacturing systems provided by the means of digital twins, cross-domain data sharing under control and hybrid model-data-driven modeling. These researches lead to the advanced goals of system engineering, i.e. the exceptional integration of distributed data abilities, model aptitudes, and business procedures so that to create sustainable, dynamic, and transfusiveness intelligent ecosystems.

Collectively these lines of research constitute a coherent image: in spite of ongoing progress in technological integration, more profound application scenarios, and broader systemic perspectives, there is an essential gap in the lack of systematic engineering techniques to reliably, efficiently and maintainably incorporate technical elements into the systems of AI capable of perpetual development. Located in this compromising zone, this study seeks to develop an engineering integration approach based on MLOps and to test and streamline it using a representative quantitative trading case, thus filling in the engineering gap between applications on technology and engineering critical deployment.

3. Construction and Implementation of an AI System Model Engineering Integration Method

3.1 MLOps-Based Model Engineering Integration Framework Design.

In order to overcome the underlying issues related to the engineering implementation of data-driven intelligent systems, this paper suggests a universal engineering-level integration system based on the MLOps paradigm. The framework will combine fragmented data, model development process, and operational processes systematically to create an automated, collaborative, and constantly evolving pipeline. The framework follows the principle of consistent data-model-service evolution whereby all the layers are interconnected in a bottom-up architecture, where each level is structurally interconnected to manage effectively the full lifecycle of AI models.

A single and reliable chain of data supply is the basis of the framework. By introducing standardized data governance, multi-source heterogeneous data is introduced to automated cleaning, validation and version controlled storage. The framework makes the data lineage traceable and manage change by the data of the code paradigm. The layer offers quality guaranteed, structured data inputs to upstream model development to reduce the issue of instability in model performance due to data inconsistency at the source. On this strong data base the framework also dwells in the aspect of governance and enhancement of efficiency on the model development phase. An experiment management system will be designed as a system to appropriately store the entire context of a given experiment, the version of data, the version of code, every hyperparameter setting, and every metric of evaluation. This design designates and characterizes experimental processes, an assetization and templating of experimental procedures essentially eradicates the black-box character of conventional experimentation and the problem of irreproducible outcomes. In addition, it allows to optimize hyperparameters in an efficient way that has been automated and allows researchers to focus more on algorithmic innovations than on tracking experiments manually.

When the model is meticulously tested in the academic setting, the framework uses an automated, continuous delivery chain that shifts the model to the production setting in an effective and dependable manner. It is a combination of the best practices of continuous integration and continuous deployment and includes the machine learning model-specific design elements. Upon satisfying a series of quality constraints, including performance measures and equitability tests, the model will be automatically packaged to execute isolated environment testing and secure deployment to convert high-risk manual releases into automated procedures of uniform quality and reproducibility. Deployment is not the final part of the process, the frame works will create a smart layer of monitoring in the production environment not only of the infrastructure traditionally monitored but also affording a full layer of monitoring of the performance drift of the models and data anomalies in funding the input data, and the business effects therefrom. The monitoring layer which uses configured alert rules and real-time dashboards to identify performance degradation early enough and rollback operations or retraining model operations in response to identified performance degradation are part of a complete loop between monitoring and optimization and will allow the intelligent system to dynamically adapt to environmental changes.

The organic functionality of these four layers and close loop operation of these layers make the concept of MLOps functionalized into a concrete, manageable engineering system. Each stage has core tasks and output requirements that are well understood, and the design is focused on automation and standardization that fuses the disconnect between data, algorithms, and operations and gives a solid engineering blueprint of developing highly reliable, maintainable, and ever-evolving data-driven intelligent systems. A standardized pipeline can be identified as the operational logic of the closed-loop mechanism of the framework, as Figure 1 demonstrates. The pipeline is initiated with data governance and provisioning, encompassing the reliability and traceability of input data; model testing and model development to support swift strategy experimentation and manageable deployment; a CI/CD pipeline, which incorporates quality gates to provide security and automated deployment of models into production space; and real-time monitoring of model performance and business metrics during deployment and service monitoring. The most important innovation is the closed loop feedback mechanism that is initiated at the monitoring stage (dashed lines in the figure), under which, the system is able to provide self-diagnostic messages like data drift or model performance decline and will automatically result in the update of data layers or retraining/rollbacking of the models. This way, the MLOps paradigm is implemented as a manageable and controllable dynamic system of engineering, which provides a relevant basis to experimental implementation in the future.

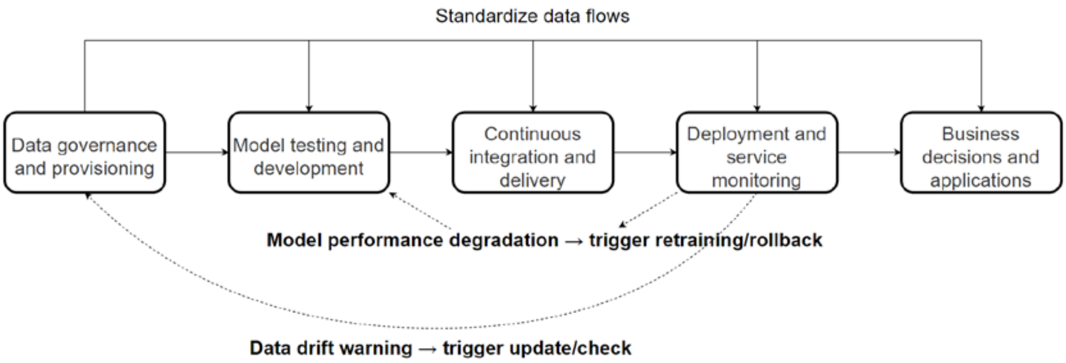

Figure 1. A history polygraph of model engineering architecture of an MLOps-based AI system integration pipeline of data-driven intelligence.

3.2 Application Path of integration technique in the quantitative trading situations.

The route of engineering integration of the above named engineering integration framework in quantitative trading, which is a high dynamic, real-time and risk sensitive data environment, appears in a closed loop of data to decisions, and decisions to data. The rational for this implementation is supported by real business needs and capabilities contained in the framework and creates a complete engineered process that includes strategy development, deploying operations, and continuous monitoring.

The fundamental aim at the data provisioning stage is to have a stable, reliable, traceable digital financial supply chain of data. With multi-source heterogeneous data (market data, fundamental data and alternative data) the system incorporates the standardized modules of data ingestion to have un-ified collection and uses a stream-batch integrated processing architecture to combine real-time and historical data. The feature engineering is represented through the reusable feature operators that are simultaneously computational efficient and allow combining features dynamically and managing versions. Any processed data are all stored in a version controlled way so that each data state used to train and backtest a model can be re-reproducibly obtained to provide a strong base of consistent strategy iteration based on the original data.

The implementation path undertaken at the stage of strategy development focuses on systematics and collaborative watch of the experiment. Since most quantitative trading involves factor discovery, parameter optimization and a number of strategies are being compared, the platform offers a standardized search environment of strategy research. In its entirety, the researchers are able to execute the entire analytical procedure, signal creation and portfolio building, to execution of performance, and the full context of every experiment, such as data variants, code slices, parameter settings, and execution results are captured and stored automatically. The mechanism does not just guarantee reproducibility and auditability of the strategy research, but it also enables internal comparison and knowledge base, thus contributing much to the effectiveness and scientific rigor of strategyization.

When the strategy is validated, the implementation route utilizes the capabilities of automated continuous delivery to assist in the straightforward movement between the research and the production environment. The system is based on predefined deployment pipelines to automatically package models, compliance checks, paper-trading validation and incremental live deployment. In the process, a complete strategy asset map is made by packaging the model version, dependency environment and training data correspondingly and storing them in an immutable way. The strategy facilitates both the traceability of implemented strategies and provides fast and secure rollback to previously stable strategies in case the performance of the strategies reduces.

The implementation path also defines a monitoring system specific to the nature of quantitative trading, including conventional measures of performance its returns, Sharpe ratio and maximum drawdown, and concentrating on the risks of possible occurrence of market condition changes, degradation of factors and abnormal trading costs. Monitoring system depends on dynamic threshold and statistical tests to automatically determine the presence of changes to the strategy effectiveness and based on predetermined rules to issue a warning, revise positions, or switch to reserve strategies. The next iteration of the strategies is automatically updated with new data and a new market feedback produced by the live functioning and strategies can continuously adjust to the market evolution within a closed loop mechanism.

This implementation path provides the integration framework a complete change of this methodology into engineering practice in the quantitative trading field. Designed experimental outcomes show that such a strategy is an effective method of enhancing engineering efficiency in strategy formulation, the consistency of production implementation, as well as ensuring robust and active strategy adaptability throughout the entire lifecycle, as a feasible paradigm, data-driven intelligence can be applied in the finance sector at the industrial level.

4. Online Testing and Performance

4.1 Full-scale assessment of Engineering productivity and business performance

In a bid to holistically justify the efficiency and excellence of the suggested method of integration, this paper uses quantitative trading as an empirical situation, and develops a two-dimensional method of evaluation incorporating both engineering performance and business excellence. This system, in contrast to traditional evaluation methods which use only one metric of performance, focuses on a holistic examination of the evaluation process through systems engineering that includes the entire model development and operation process, and thus better represents support value of engineering integration method to the actual business performance.

To prevent the possible bias of comparing on the basis of the single indicator, this research makes another step, integrating engineering efficiency and business performance in one assessment framework and is creating an overall effectiveness evaluation functional as presented in. formula

$$E=\alpha\cdot E_{eng}+\beta\cdot E_{biz},\alpha+\beta=1$$

In this case, E_{eng} is the engineering efficiency measure which is mainly employed to provide an indication of engineering characteristics (degree of automation, deployment efficiency and recovery of the experiment) when developing AIs, and E_{biz} is the business performance measure which quantifies the risk-adjusted returns and stability of the models in actual trades including Sharpe ratio, maximum drawdown and volatility of returns. α and β are weighting factors suggesting the relative contribution of engineering efficiency and business performance to measurements under various application conditions.

The above overall assessment mechanism can be used to quantitatively define engineering capabilities and business value on a scale, which will formally serve as the means of systematically evaluating the offered integration approach both on an engineering and business front.

In the perspective of engineering efficiency the assessment is on the development efficiency, reliability of the system and process standardization. The assessment of major engineering indicators before and after the implementation of the integrated framework helps to depict the significant difference the latter produced. In particular, the mean duration of the cycle between test runs to achieve production readiness was dramatically reduced, which is primarily because the many manual steps were removed by the use of automated pipelines. Experimental reproducibility improved to close to 100 percent, making any past strategy reproducible such that any version-controlled data, code, and environment allowed scientific rigor and auditability of the study to be substantially improved. Furthermore, due to standardized model registration and deployment procedures, the possible problems with models version conflicts or the lack of dependencies in the production environment were totally avoided which greatly enhanced system stability. Moreover, the metrics used in monitoring shows that the system can automatically monitor over 90% of the warnings of a performance degradation failure due to data drift or changes in market mechanisms and cause automated response procedures which facilitates proactive intelligent running of operations.

The business aspect of the performance will focus on whether or not the approach empowers and enhances stability and quality of the core business decision making. This translates into the stability of investment strategies and the risk-adjusted returns of the investment strategy in quantitative trading. Experimental findings indicate that in the identical strategy rationale, continuously-evolved portfolios created by the presented framework in question were characterized by a significantly higher Sharpe and Calmar ratio than the isolated development methods used conventionally. This has been enhanced not because of the breakthroughs in the single-model prediction accuracy, but the framework has enabled higher-frequency systematic strategy selection and portfolio maximization. More to the point, through an unremitting tracking of strategy consistency and trading cost anomaly, the structure provides maximum drawdown in extreme market conditions, which has much better environmental adaptability and risk-resilience. This is an extreme level of inter-weaving of engineering surveillance and business risk assessment, which the conventional procedures of model development deprives them of.

Through uniting engineering and business evaluation outcomes, this combination way is entirely proven to be valuable. It is not merely an assortment of instruments that augment development efficiency but an overall empowerment tool that squarely connects data, models and business targets by means of standardization, automation and closed circle administration. The results of practical use confirm that the systematic approach to engineering integration can transform the data-driven intelligence which originally largely relied on the individual experience and the workshop-like model into the industrialized production model that was scaled, sustainable, and had risk control and represented a practical and reliable reference point to the reliable use of AI systems in critical fields.

4.2 Iterative Optimization of the Framework and Cross-Scenario Applicability Analysis

According to the empirical feedbacks provided by the quantitative trading sphere, the offered framework of integration proves both the ability of self-improvement and prospect to expand to other directions. Framework optimization is not a studied procedure but rather it happens dynamically as the different data and signals that are created within the system operation feed on it. In the meantime, the principles of the modular and standardized design are the basis of successful transfer to various data-driven situations.

The framework is based on the iterative optimization mechanism, which is dependent on internal monitoring and feedback loops. As a matter of fact, the framework is not a passive solver of problems, on the contrary, it also actively takes advantage of the monitoring of production, pipeline records, and strategy outcomes performance to adjust the evolution of the framework. As an illustration, through the study of correlation between initial patterns of model performance degradation and market conditions, the system would be able to dynamically adjust the thresholds by which they are sensitive and robust in terms of triggering model retraining. Likewise, in a resource scheduling case efficiency studies of every phase within the continuous delivery pipeline may indicate a constriction in resource distribution or wastefulness in procedure conception, and thus direct dynamic calculation resource scheduling or ease pipeline steps. The ability of this evidence-based, go-round fine tuning to allow the framework to advance through complex operational conditions, to become a movable tool set then an organic mechanism able to learn and adjust.

The universal applicability of the framework in other realms exists in the fact that it can find out and properly tackle the shared engineering problems of data-driven intelligent systems. It could be financial trading, industrial forecasting, or personalized services, but the key thing would be to put the data into models and finally in actionable decisions. These situations prove to be faced with some problems like development and operations gaps, unorganized experiments control, and high levels of deployment risk. The generality of the framework does not mean that the operational solution is a universal one, but the set of principles and interface standard to be maintained by engineers is widely applicable. As a case in point, the concept of data versioning can be used in a financial application to store real-time snapshots of market data, whereas in manufacturing can be used to trace historical states of data sensor of equipment. In like manner, most of these quantitative trading strategies have backtesting reliability that verifies the consistency of the experiment in quantitative trading surely and A/B-testing of a new product recommendation algorithm of Value e-commerce fairness.

The framework when applied to a new scenario is configured and extended specifically due to domain knowledge. The transfer can only be successful by being aware of certain constraints and core value chain of the target situation, and realigning the general framework. To give an example, real-time bidding of online advertisement may need better real-time feature computation, and ultra-low-latency model deployment. Compliance verification and audit functionality should be extensively incorporated in model experimentation and monitoring in medical decision support situations where high safety and interpretability considerations are paramount. This means that the integration technique basically offers an extremely adaptable system engineering architecture, outlining significant elements, uniformizing interaction standards and incorporating confirmed industry best practices. Various spheres can use this blueprint to create specific cases that meet the overall requirements of engineering practices as well as fulfilling the requirements of the business and the regulations.

The worth of this integrated framework has been earmarked through the quantitative trading setting by taking the form of comprehensive practice and verification. It is not only able to conduct continuous self-optimization through its own feedback systems but also it can incorporate inherent engineering problems, which means that it can be widely applicable. This approachology offers an organization a valid implementation route and a structured way of employing construction so that it can develop data-driven intelligence off pilot projects in exploration into footing dependable and stable core business capabilities.

5. Conclusion and Outlook

This research will also cover the widespread engineering issues that are associated with industrial adoption of data-intensive intelligent systems and suggest an AI system model engineering integration framework based on MLOps. This methodology creates a durable infrastructure including standardized data management, reproducible model experimentation, automatic continuous delivery, and intelligent systems oversight, and coordinates hitherto widely separated workflows of development and operation automated systems into a single workflow that can undergo continuous iteration and optimization.

The most important input of this work is in that MLOps is no longer a concept of technical practices but a system engineering methodology with a developed architecture, procedures, and tangible evaluation criteria. An empirical study was chosen on a high-frequency, high-altering market situation and is referred to as quantitative trading that proves that the proposed method promotes higher efficiency in R&D, system stability and superior adaptability of the trade strategy and better collaboration among the team. The findings show that this combined method is effective to test the gap between theoretical research and actual production implementations where data-driven intelligence is no longer a historically experience-based, exploratory process but rather a convenient, quantifiable, and industrialized ability. In addition, to its practical application in dealing with particular engineering issues in quantitative trading, the design is modular and based on principles and so can be generalized to other data-intensive decision-making tasks, offering a high degree of reference.

In spite of these successes, a number of restrictions exist, which reflect the way forward in further studies. First, the intelligence of the framework especially in the context of surveillance, notification, and automated optimization can be enhanced. It can be future that a way of merging meta-learning and causal learning, and other implementations could lead the system to be able not only to identify problems but also automatically define the causes of the problem, and develop optimization strategies, overcoming the limit of a paradigm of problem detection and only passive response. Second, although the cross-domain nature of the method is theoretically justified, additional empirical testing and implementation in various areas of application including smart manufacturing, healthcare, and smart energy are required to define and establish the overallizability of the method as a universal engineering method. Also, with data security and algorithm governance laws still evolving, the requirement to incorporate compliance measures, including algorithm decipherability, fairness auditing, and data privacy protection requirements, into the engineering pipeline in the coming generation of trustworthy AI systems will be a challenging issue requiring a substantial response. Lastly, it is essential to encourage the maturation of supporting toolchain and building an open-source ecosystem to reduce implementation hurdles enabling the whole process toward widespread adoption, and achieving real-world industrial value.

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