Performance Monitoring and Model Management in Machine Learning

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Article History

Article Submission
15 November 2020

Revised Submission
18 January 2021

Article Accepted
14 March 2021

Article Published
31 March 2021

Abstract

The paper analyzes the intricate aspects of Machine Learning Model Management and Monitoring (MLM3) while demonstrating the need for well-developed systems to handle ongoing evolutions in ML technology. An extensive research explores all aspects including procedural obstacles and implementation approaches which pertain to MLM3. The system addresses model drift together with data integrity problems and scalability issues and security requirements. The article examines three advanced techniques for ML model enhancement including adaptive learning systems together with ensemble techniques and incremental learning which boost both efficiency and reliability in model operation. The analysis presents a discussion between ML model compatibility with IT infrastructure and necessary regulatory requirements together with design considerations for ethical behavior in deployment. This review gives professionals including IT managers and policymakers deep insights into modern trends and upcoming directions as a tool to help them properly build and run advanced ML systems.

Keywords- *Adaptive Learning, Data Integrity, Machine Learning, Model Drift, Model Management, Scalability, Security*

I. INTRODUCTION

Many business sectors have experienced fundamental operational changes because ML technologies enable the automation of advanced decision-making and data-based insights extraction from big data collections. Office processes and fundamental infrastructure components continue to adopt machine learning technology which requires a sophisticated system for managing and monitoring Machine Learning Model Management and Monitoring (MLM3). The analysis investigates MLM3 complexities through examination of both procedural difficulties and implementation methods and it discusses why adaptation must occur according to technological progress and oversight standards.

ML technology has seen explosive growth during the last ten years because of faster computers combined with new algorithm development and large data collections. The operational success and competitive advantage of organizations today heavily rely on ML models for predictive analytics in finance and diagnostic assistance in healthcare purposes [1]. The implementation of these models faces numerous real-world difficulties which emerge from both their inherent complexity together with dynamic characteristics of the processed data.

The complete life trajectory from creation to ongoing management of ML models is more complex compared to standard software applications. ML models become complex because their probabilistic operations depend strongly on input data quality and features. Continuous drift occurs across evolving data patterns that results in sustained performance degradation of models according to study [2]. Moreover, the black-box nature of certain ML algorithms, particularly in deep learning, exacerbates the challenges of transparency and traceability [3].

ISSN: 2250-0839

Several vital elements need focus in order to achieve effective MLM3:

- Model drift together with performance degradation happens when models in production environments face changes in their underlying data patterns. This effect is known as model drift. Monitoring systems along with adaptive measures must be implemented to maintain model performance continuity [4].
- The process of integrating ML models with existing IT systems while ensuring their capability for increasing workload needs robust infrastructure design and efficient resource handling mechanisms [5].
- Security and adversarial attack prevention requires modern security implementations to protect sensitive information along with preventing wrongful modification of model output [6].
- ML applications must adhere to increasing regulatory specifications and maintain ethical principles especially regarding information privacy and transparency alongside fairness compliance [7].

The paper performs an in-depth analysis of the present-day MLM3 development standards:

- Analyse both technological foundations and operational complications which ML models encounter when deployed for production.
- Examine sophisticated monitoring methods which both identify problems as they emerge and run automated solutions to correct them.
- The paper examines frameworks in addition to deployment tools which manage ML model life cycles across development to deployment and maintenance until decommissioning.
- Review practical MLM3 deployment examples and their achieved results from industries worldwide through specific case analyses.
- Analyze upcoming industry developments to discover new ways which will improve the reliability and operation efficiency of MLM3 implementation methods.

Through this paper the authors deliver crucial resources for professionals in data science and ML who also include IT managers and policymakers thus helping them develop advanced ML systems which run effectively with responsible management.

The strategic role of effective MLM3 becomes increasingly vital since ML drives innovation in all sectors. Organizations can achieve maximum potential from ML investments along with risk reduction and compliance to ethical standards through correct solutions of technical issues and advanced monitoring tools.

II. CHALLENGES IN MACHINE LEARNING MODEL MANAGEMENT AND MONITORING

2.1 Model Drift

Temporal degradation of machine learning predictive models creates one of the major challenges which diminishes their accuracy along with their reliability throughout the time period. When the real-world environment transforms the data used for models becomes less effective which diminishes model performance. The phenomenon displays itself through two fundamental types which are covariate shift and concept drift.

- ***Covariate Shift:*** The distribution of input data shifts during covariate shift although the connection between input data and output remains unaltered. Data distribution adaptation methods serve as common mitigation techniques since they modify model settings according to new data without requiring whole retraining processes [8].
- ***Concept Drift:*** The more challenging situation happens when concept drift occurs because it disrupts the relationship between input and output variables. Model maintenance methods for concept drift include either adapting existing models through new data collection or shifting to adaptive models which automatically modify their operating principles in response to changing data patterns [9].

Page-Hinkley tests operate with statistical which use sequential analysis methods to detect process average alterations [10]. Regular test monitoring systems produce alerts that start procedures to review and modify the model.

2.2 Data Integrity and Quality

Machine learning models build their effectiveness on stellar data quality. Model performance deterioration occurs substantially when data includes missing values as well as outliers and errors in the data. Data integrity requires strict preprocessing procedures that should be applied to ensure reliable results.

ISSN: 2250-0839

- ***Data Cleaning:*** The Z-scores and IQR methods combined with iterative methods and K-Nearest Neighbor approach serve as essential data cleaning techniques for training dataset reliability [11].
- ***Data Validation:*** A system of regular checks should validate incoming data to verify both its expected format and correct range. The implementation of automated scripting solutions with data validation frameworks including TensorFlow Data Validation or Great Expectations helps automate this procedure [12].

2.3 Scalability Challenges

A growing number of machine learning applications makes computational resource management progressively more intricate to handle. Several key aspects need attention to carry out effective management.

- ***Resource Allocation:*** The development of flexible resource allocation systems must be implemented to maximize computational resource use which simultaneously lowers costs and accelerates responses [13].
- ***Model Optimization:*** It includes two techniques namely model quantization that decreases numerical precision in computations and pruning which eliminates nonessential model sections to achieve higher speed and reduced size without significant accuracy deterioration [14].
- ***Distributed Computing:*** Distributed systems equipped with Apache Spark or Hadoop enable parallel execution of data processing and model training to manage big data and elaborate computations through distributed computing [15].

2.4 Security Considerations

Machine learning model security has risen to critical status because of increasing frequency of data breaches alongside cybersecurity threats. Several approaches exist to deliver better security measures.

- ***Adversarial Training:*** It integrates adversarial examples into model development which strengthens their resistance against attack attempts [16].
- ***Regular Audits:*** Security audits together with penetration tests establish a method to discover machine learning system weaknesses prior to adversary exploitation [17].
- ***Data Encryption:*** Data Encryption through homomorphic encryption permits secure processing of protected information in its encrypted state particularly for vital data [18].

2.5 Regulatory Compliance and Ethical Considerations

Machine learning system deployment requires strict adherence to authorized standards alongside ethical guidelines according to financial and healthcare sectors.

- ***Transparency and Explainability:*** A mandatory requirement for GDPR compliance involves right to explanation automation that delivers clear decision explanations to users through models deployed in their systems [19].
- ***Bias Mitigation:*** The integration of bias mitigation strategies that detect and neutralize machine learning model biases will produce fair outcomes together with preventing discrimination [20].

III. ADVANCED METHODOLOGIES FOR MACHINE LEARNING MODEL MANAGEMENT AND MONITORING

3.1 Introduction to Advanced Methodologies

Modern data science needs strong methodologies to keep an eye on and manage machine learning (ML) models due to constant field developments. Advanced methods serve an essential purpose in operational adaptation as they support model accuracy during changing operational situations. Machine learning models require effective management paired with monitoring systems as the fundamental requirement for complete utilization because these systems ensure high performance together with scalability and security and compliance with evolving governing standards [21].

3.2 Adaptive Learning Systems

Systems that learn adaptively function independently to modify their operations based on changes in input data because environments with evolving data need these systems. The systems guarantee reliability through automatic techniques which handle emerging patterns alongside anomalies without manual human involvement.

3.2.1 Ensemble Techniques

Multiple model combination processes through ensemble techniques leads to better robustness and accuracy in predictions. The streaming data challenge of concept drift finds its solution through Online Bagging and Boosting which excel at this task. The methods decrease errors by letting different models share their biases and variances through a model averaging process which creates consistent predictions that remain stable throughout time [22].

Mathematical Formulation:

$$Y_{agg}(x) = \frac{1}{n}\sum_{i=1}^{n} M_i(x) \tag{1}$$

Here, $M_i(x)$ represents the prediction by the i^{th} model for input x, and n is the number of models in the ensemble.

3.2.2 Incremental Learning

The process of updating ML models through incremental learning operates by accepting new data bits incrementally since this approach serves dynamic environments including financial markets and real-time user interaction applications. The methodology enables a model to stay current without complete retraining requirements therefore delivering powerful resource savings together with minimized response times [23].

Mathematical Formulation:

$$\theta_{t+1} = \theta_t + \alpha \nabla L(M(x_t, \theta), y_t) \tag{2}$$

The model parameters θ along with α learning rate and L loss function and fresh input vector x_t and output vector y_t make up the optimization step.

3.2.3 Feedback Mechanisms

Feedback systems integrated in models allows them to update predictions by learning from previous decision outcomes. Continuous learning represents a major advantage in systems which require predictive accuracy for safe user experiences because it happens in autonomous driving and personalized medicine applications [24].

3.3 Real-time Analytics and Performance Metrics

Real-time analysis serves as a critical tool for model health checks which allows operators to track performance indicators through established boundaries until the system identifies abnormal data activities.

3.3.1 Key Performance Indicators (KPIs)

The assessment of KPIs including accuracy and precision along with recall and F1-score through continuous monitoring gives instant analytical information about ML model performance. The applied metrics enable the identification of model degradation caused by concept drift and detection of unknown data types which the training set did not contain [25].

Mathematical Formulation:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The values of true positives (TP) and false positives (FP) and false negatives (FN) represent the respective counts used in calculations.

3.3.2 Predictive Performance Metrics

Manufacturers deploy ROC-AUC alongside log-loss to estimate model performance patterns and detect potential deterioration. The predictive methodology enables organizations to perform early modifications which prevent significant deterioration of performance [26].
Mathematical Formulation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2 \quad (5)$$

This MSE formula calculates the average of the squared differences created by evaluating $(\hat{y})$ estimated data against actual (y) observations.

3.3.3 Monitoring Tools and Technologies

Real-time analysis and reporting for model metrics becomes possible through the employment of monitoring systems that combine Prometheus for performance tracking with Grafana for data visualization. The described tools form an essential foundation for development of agile responses to operational uncertainties in dynamically changing environments [27].

3.4 Proactive Anomaly Detection

The detection of emerging risks by employing proactive anomaly detection methods remains essential since it allows operational administrators to prevent security issues that can harm model functions.

3.4.1 Anomaly Detection Techniques

Two anomaly detector solutions known as Isolation Forests and Neural Networks combine to automatically detect data points which diverge too far from normal patterns. The detection tools work effectively in large-scale data environments that make standard statistical measures ineffective [28].
Mathematical Formulation:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \quad (6)$$

The calculation of expected path length for anomalies within isolation forest depends on $E(h(x))$ while $c(n)$ performs normalization functions.

3.4.2 Application in Cybersecurity

Anomaly detection systems in cybersecurity enable quick detection of security breaches during their initial stages to deploy immediate response measures that protect both sensitive data and installation infrastructure [29].

3.5 Scalability and Distributed Processing

The growth of both data quantities and modeling complexity requires scalable systems alongside effective distributed processing methods to preserve system speed and reaction times.

3.5.1 Data Partitioning and Load Balancing

Data distribution combined with load balancing techniques guarantee balanced processing demands which stop any part of the system from performance deterioration. The data processing efficiency improves through this method while also decreasing the response time [30].
Mathematical Formulation:

$$n = H(x) \quad (7)$$

Here, the distributed system utilizes H as its hash function to establish data point assignments between x and n.

3.5.2 Cloud-based Solutions

AWS together with Google Cloud and Microsoft Azure operate scalable platforms for managing the deployment and administration of ML models. Through online platform services organizations can establish dynamic resource management that helps them expand ML operations through existing needs with minimal initial capital outlays [31].

3.6 Regulatory Compliance Automation

The process of regulatory compliance management stands essential for delivering effective ML systems which meet legal standards and ethical requirements.

3.6.1 Compliance Frameworks

Organizations must implement automated compliance platforms because these systems verify their ML systems comply with necessary regulations including GDPR for data privacy and HIPAA for healthcare data protection. The use of these frameworks serves essential purposes which include maintaining transparency alongside protecting data and ensuring deployment accountability in ML frameworks [32].

3.6.2 Impact of Regulations on Model Deployment

The regulatory standards direct the strategy of ML model development alongside enforcement of maximum transparency and fairness and accountability requirements for these systems. South Bank University points out ML technologies depend on this compliance since they establish fundamental public trust in these systems [33].

New advanced AI-driven techniques together with methodologies will lead the way for future developments in ML model management and monitoring practice. The combination of quantum computing and blockchain technology would boost ML systems capabilities by enabling advanced processing and security capabilities. Future advancements in machine learning capabilities will expand operational possibilities in order to spark industrial revolutions [34].

IV. LITERATURE REVIEW

Manufacturers depend more heavily on machine learning (ML) models in operational settings so they need ongoing enhancements of model administration and surveillance as well as anomaly identification strategies and security measures and regulatory conformity systems. During the previous decade researchers intensively studied these challenges until they achieved the creation of adaptive learning systems as well as real-time analytics and explainable AI alongside scalable ML architecture development. The reviewed research papers undergo thorough examination in this review for their significant impact on ML model management and monitoring practices. The analyzed studies provided the foundation for modern methodology development which establishes reliable and moral AI technology.

4.1 Adaptive Learning Systems for Model Management

The authors from [35] developed a framework for self-adjusting learning which helps machine learning models detect evolving data patterns throughout execution. The research examines the critical role of concept drift detection systems and uses Page-Hinkley tests as statistical methods to detect ML model performance decline. This methodology elevates the durability of models operating in changing environments which includes financial projection and medical diagnosis systems.

The authors in [36] utilize ensemble learning approaches to create better adaptive model management systems. Online Bagging and Boosting in combination demonstrate in the study how ensembling multiple learners produces superior results on non-stationary data streams. A weighted voting mechanism according to the authors permits an ongoing model weight adjustment through real-time accuracy measurements which establishes superior protection against drift-caused errors.

Researchers introduce in [37] a new framework that solves the problems associated with persistent model retraining. Through their approach ML models can efficiently receive new data while bypassing full-scale

retraining procedures that cut down processing requirements. The technique delivers optimal results when applied to real-time IoT analytics because repeated retraining operations cannot obey resource limitations.

The research in [38] demonstrates an adaptive system which controls automatic learning rate adjustments through performance decay patterns. The authors use an active error correction system to stop models from following recent trends which maintains their generalizability throughout time. The proposed framework demonstrates success during evaluation through high-frequency trading data by reaching 30% better accuracy than static models.

The research in [39] presents a solution for adaptive learning by merging knowledge distillation technology to maintain previous knowledge throughout the process of adapting to new data. Catastrophic forgetting is dealt with effectively by their approach which enables ML systems to maintain past learning knowledge without accuracy degradation.

The authors of [40] develop a reinforcement learning-based method that trains models for automatic detection of optimal retraining periods according to changing data distributions. An algorithm joins Q-learning with policy gradients to decrease useless model modification and therefore reduce resource usage.

The authors in [41] develop an active learning framework to specify annotation requests from new data points. The method performs cost-effective labeling by targeting high-uncertainty predictions thus making it suitable for medical imaging together with fraud detection scenarios that require expensive labeled data acquisition.

4.2 Real-time Analytics and Performance Monitoring

The authors in [42] established a streaming analytics framework that combines real-time anomaly detection methods with model performance tracking for continuous ML model surveillance needs. Real-time detections of model drift and concept evolution in large-scale industrial applications become possible through their system based on Apache Kafka and Spark Streaming.

The authors in [43] created a probabilistic degradation detection algorithm which predicts forthcoming performance declines through Bayesian learning. The system demonstrates better performance than standard monitoring tools due to its ability to detect near-future failures thus benefitting maintenance scenarios.

The authors of [44] describe in their paper a self-healing framework for managing ML models during real-time monitoring sessions. The reinforcement learning mechanism within this system allows it to adjust model hyperparameters automatically because of changing input distributions thereby reducing maintenance needs and enhancing system stability.

The authors in [45] describe an explainable monitoring system that enables the identification of precise features along with data biases causing ML performance changes. SHAP and LIME-based interpretability models combine to assist businesses in checking for errors and biases during real-time operations.

Edge computing for ML monitoring is examined in research conducted by [46] through which decentralized monitoring systems run directly on IoT devices. The method decreases both processing delays for data transmission and boosts operational speed for real-time decision systems.

4.3 Anomaly Detection and Security in ML Monitoring

Manufacturing environments now struggle to assure safety for ML models. The research in [47] demonstrates how adversarial attacks affect real-time predictions which results in critical damage to security-dependent applications. A defensive mechanism based on adversarial retraining developed by the authors enables substantial improvement to model robustness.

The study [48] presents a progressive self-supervised anomaly detection system which permits ML systems to detect anomalies through unlabeled training data. Through their contrastive learning technique they have shown better performance than standard approaches to find fraudulent transactions in bank transaction records.

An innovative monitoring system for detecting malignant changes in running ML models presents itself in research [49] by introducing resistant backdoor fingerprinting techniques. The approach helps maintain both security and integrity of autonomous vehicle and smart surveillance models.

ISSN: 2250-0839

The authors in [50] developed homomorphic encryption to execute models securely on encrypted information without decryption procedures. The proposed method maintains data privacy in healthcare AI applications which need to protect patient information at all times.

4.4 Scalability and Distributed ML Model Monitoring

The necessity to scale increases alongside the growth of ML model size and complexity. Using distributed deep learning they developed a framework that combines Apache Spark with Hadoop to support scalable model training according to the authors of [51].

The research paper in [52] introduces federated learning to enable distributed training of numerous ML models across decentralized devices that protect user privacy. Kept security levels intact the method successfully enhances performance in mobile AI applications.

The study in [53] establishes a framework of model optimization to improve resource management without accuracy loss. Deep learning applications achieve enhanced performance through their work which reduces inference time.

The authors of [54] discussed how Docker and Kubernetes help operate ML pipelines in containers allowing models to run dynamically without the need for manual resource management.

4.5 Regulatory Compliance and Ethical Considerations

AI compliance frameworks have become essential because of rising attention dedicated to AI regulations. The authors of [55] establish an automated system which embeds GDPR and HIPAA together with CCPA regulations as verification elements within ML pipelines.

The paper in [56] explores methods to reduce discrimination through fairness-aware retraining as it applies to loan approvals and hiring processes.

The research in [57] establishes XAI principles to produce clear explanations of AI outputs which brings clarity to criminal justice systems that use AI applications.

The authors in [58] established an AI ethical framework that specifies development responsibilities for AI programmers aiming to decrease unintended model bias.

A report in [59] creates federal AI governance strategies which feature standardized benchmarks to check AI performance for fairness and consistency.

The authors of [60] and [61] provide a discussion about AI regulations by examining policy frameworks which determine safety and accountability standards.

The literature review receives a comparative depiction through the data presented in Table 1.

Table 1: Comparative analysis of literature review

Ref. No.	Focus Area	Methodology	Key Findings	Relevance to MLM3
[35]	Adaptive Learning Systems	Self-adjusting learning framework, Page-Hinkley tests for drift detection	Improves long-term model reliability in dynamic environments	Helps detect and adapt to model drift
[36]	Ensemble Learning for Adaptation	Online Bagging and Boosting techniques	Weighted voting improves model resilience against drift	Reduces errors in non-stationary data streams
[37]	Incremental Learning	Continuous update of ML models without full retraining	Reduces computational overhead while maintaining accuracy	Useful for real-time applications where full retraining is costly
[38]	Feedback Loop in Adaptive Systems	Active error correction and dynamic learning rate adjustments	Prevents overfitting while ensuring long-term generalization	Improves model stability in high-frequency environments
[39]	Knowledge Distillation for Adaptation	Retains old knowledge while adapting to new data	Prevents catastrophic forgetting in ML models	Useful for long-term AI systems requiring continuous learning
[40]	Reinforcement Learning-based Adaptation	Policy gradient and Q-learning for retraining decisions	Reduces unnecessary updates, optimizing retraining cycles	Helps automate retraining based on performance decay

[41]	Active Learning for Efficient Data Labeling	Selective data query for annotation	Reduces labeling cost while improving model accuracy	Ideal for ML applications with expensive data annotation
[42]	Real-time Anomaly Detection	Apache Kafka and Spark Streaming	Enables immediate detection of model drift and concept evolution	Enhances real-time monitoring capabilities
[43]	Bayesian Performance Degradation Prediction	Probabilistic modeling	Predicts when models will fail before actual performance drop	Helps in proactive model maintenance
[44]	Self-Healing ML Management	Reinforcement learning for automatic hyperparameter tuning	Dynamically adjusts ML models to adapt to changing data	Reduces manual intervention in ML model maintenance
[45]	Explainability-driven Monitoring	SHAP and LIME-based interpretability tools	Diagnoses performance drops due to feature importance changes	Ensures transparency and fairness in ML decisions
[46]	Edge Computing in ML Monitoring	Decentralized ML model monitoring on IoT devices	Reduces data transmission latency	Useful for real-time applications in low-latency environments
[47]	Adversarial Attack Detection	Adversarial retraining for robust models	Strengthens ML models against attack manipulations	Essential for security-sensitive ML applications
[48]	Self-supervised Anomaly Detection	Contrastive learning for fraud detection	Detects anomalies without labeled data	Increases robustness in fraud and cybersecurity applications
[49]	Backdoor-resistant ML Models	Fingerprinting ML model integrity	Detects unauthorized modifications in deployed models	Prevents security breaches in AI systems
[50]	Privacy-preserving ML	Homomorphic encryption for secure model execution	Ensures encrypted data processing	Critical for confidential and healthcare AI applications
[51]	Distributed Deep Learning	Apache Spark and Hadoop-based training	Enables scalable ML training	Helps manage large-scale ML workloads
[52]	Federated Learning	Decentralized model training across multiple devices	Improves privacy and security	Reduces data-sharing risks in sensitive ML applications
[53]	Model Optimization	Pruning and quantization	Speeds up inference while maintaining accuracy	Useful for deploying ML models on edge devices
[54]	Scalable ML Pipelines	Docker and Kubernetes for containerized deployment	Automates ML model scaling	Ensures efficient resource utilization in production
[55]	Automated Compliance Verification	GDPR, HIPAA, and CCPA integration in ML pipelines	Ensures legal adherence	Crucial for regulatory compliance in AI deployments
[56]	Bias Mitigation	Fairness-aware retraining	Reduces discrimination in AI models	Ensures ethical AI decision-making
[57]	Explainable AI (XAI)	Transparency-focused ML frameworks	Improves interpretability	Enhances user trust in ML models
[58]	AI Ethics Framework	Responsibility guidelines for AI developers	Mitigates unintended model bias	Promotes responsible AI development
[59]	AI Governance Strategies	Standardized performance benchmarks	Ensures fairness and reliability	Helps in AI risk assessment and compliance
[60]	Future AI Regulations	Policy frameworks for AI safety and accountability	Discusses evolving regulations to standardize AI governance	Helps organizations anticipate regulatory changes
[61]	Societal Impact of AI	Ethical and societal considerations in AI deployment	Examines AI risks and mitigation strategies	Ensures responsible AI adoption in public and private sectors

V. CONCLUSION

The review paper clearly identifies essential factors together with modern obstacles within the Machine Learning Model Management and Monitoring field. The results prove effective MLM3 serves as a core requirement to maximize ML technologies across sectors thus maximizing sustainable returns from ML investments. The paper establishes a framework to boost model reliability and performance by studying IT system-model integration and security vulnerability resolution and regulatory standard implementation. Future advancements in MLM3 will focus on new technology applications of quantum computing and blockchain to enhance ML system capabilities as described in the paper. The research findings along with their methods create a significant foundation for better strategy regarding ML model deployment while supporting innovative practices and competitive success in the fast-evolving technological environment.

ACKNOWLEDGMENT

The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g”. Avoid the stilted expression, “One of us (R.B.G.) thanks . . .” Instead, try “R.B.G. thanks”. Put applicable sponsor acknowledgments here; DO NOT place them on the first page of your paper or as a footnote.

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