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Comprehensive MLOps Interview Questions: From Basic to Advanced

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In the rapidly evolving landscape of machine learning, the role of Machine Learning Operations (MLOps) has emerged as a critical discipline, bridging the gap between model [development](#) and production deployment. As organizations strive to leverage data-driven insights, the demand for skilled [MLOps](#) professionals has surged. MLOps combines best practices from DevOps with machine learning, emphasizing collaboration, automation, and scalability throughout the ML lifecycle.

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This article provides a comprehensive [set](#) of MLOps interview questions, ranging from basic to advanced levels. Whether you're an aspiring MLOps engineer preparing for an interview or a hiring manager looking to assess candidates, these questions will help gauge proficiency in essential MLOps concepts, tools, and practices. By understanding these key areas, candidates can demonstrate their readiness to tackle real-world

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Got It !

Basic Questions for MLOps Beginners

1. What is MLOps?

MLOps, or Machine Learning Operations, is a set of practices that aim to streamline the process of deploying, managing, and monitoring machine learning models in production. It integrates machine learning system development and operations, facilitating collaboration between data scientists and IT operations teams. MLOps is essential for ensuring that models are reliable, scalable, and continuously updated based on new data and changing business needs.

2. What are the key differences between traditional software development and machine learning development?

Traditional software development involves writing deterministic code that produces consistent outputs for the same inputs, with a focus on logic and algorithms. In contrast, machine learning development relies on training models using data, which introduces variability. This means machine learning requires continuous monitoring, updating, and retraining to maintain model performance over time, especially as data distributions shift.

3. What are the main components of an MLOps pipeline?

An MLOps pipeline typically includes several key components:

- **Data Ingestion:** Collecting and aggregating data from various sources.
- **Data Preprocessing:** Cleaning and transforming data to make it suitable for training.
- **Model Training:** Applying algorithms to learn patterns from the data.

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- **Model Deployment:** Integrating the trained model into a production environment.
- **Monitoring:** Continuously tracking the model's performance and data drift, allowing for timely updates.

4. What is the role of version control in MLOps?

Version control is critical in MLOps as it enables teams to track and manage changes to both code and datasets over time. This facilitates collaboration, allows for easy rollbacks to previous versions, and ensures that experiments can be reproduced. Version control enhances accountability and reproducibility in machine learning projects, which is essential for auditing and compliance.

5. What is data versioning, and why is it important in MLOps?

Data versioning involves tracking changes to datasets, which is crucial for managing the lifecycle of machine learning models. As models are sensitive to the data they are trained on, maintaining versions of datasets allows teams to experiment with different configurations and revert to earlier versions if needed. This practice ensures consistency, reproducibility, and better management of data quality over time.

6. What are some popular MLOps tools?

Popular MLOps tools include:

- **MLflow**: For tracking experiments and managing model lifecycles.
- **Kubeflow**: Designed for deploying machine learning workflows on Kubernetes.
- **DVC (Data Version Control)**: Focused on versioning data and models.
- **TensorFlow Extended (TFX)**: A comprehensive solution for production-ready ML pipelines. These tools help automate and manage various aspects of the MLOps workflow.

7. What is the purpose of model training and validation?

Model training involves teaching an algorithm to recognize patterns by adjusting its parameters based on input data. Validation assesses how well the trained model performs on a separate, unseen dataset. This step is crucial for ensuring that the model generalizes effectively to new data and does not overfit the training set, thus enhancing its predictive performance in real-world applications.

8. What is a CI/CD pipeline, and how is it relevant to MLOps?

A CI/CD pipeline, or Continuous Integration/Continuous Deployment pipeline, automates the processes of integrating code changes and deploying applications. In MLOps, this is relevant because it allows for rapid iterations and updates to machine learning models, ensuring that changes are made seamlessly and reliably. Automation helps maintain model quality and facilitates quick responses to new data or changing requirements.

9. What metrics would you track to evaluate the performance of a

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Key performance metrics for machine learning models include accuracy, precision, recall, F1 score, and ROC-AUC. Accuracy measures overall correctness, while precision and recall provide insights into the model's performance on positive classes. The F1 score balances precision and recall, and ROC-AUC assesses the trade-off between true positive and false positive rates. Tracking these metrics helps gauge model effectiveness and informs further improvements.

10. How do you handle imbalanced datasets in machine learning?

Handling imbalanced datasets can be approached through several techniques, such as:

- **Resampling Methods:** Oversampling the minority [class](#) or undersampling the majority class.
- **Using Robust Algorithms:** Employing algorithms that are less sensitive to class imbalance, like [ensemble methods](#) or tree-based models.
- **Cost-sensitive Learning:** Modifying the learning algorithm to take into account the different costs of misclassifications.
- **Different Evaluation Metrics:** Using metrics that provide a better picture of model performance in imbalanced contexts, such as precision-recall curves.

Intermediate Questions for MLOps

11. What is the difference between online and offline model training?

Online model training refers to training models in real-time as new data becomes available, allowing for immediate updates to the model. This is useful for applications where data changes frequently. Offline training, on the other hand, involves training models on a fixed dataset and is typically

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improved accuracy, it may not adapt as quickly to changes in data distributions compared to online training.

12. What is a feature store, and why is it important?

A feature store is a centralized repository for storing and managing features used in machine learning models. It enables data scientists to access, reuse, and share features across different models, promoting consistency and efficiency. Feature stores are important because they facilitate the process of [feature engineering](#), ensure data quality, and reduce the duplication of effort in preparing features for different projects.

13. How do you manage model drift in production?

Model drift occurs when the statistical properties of the input data change over time, potentially degrading model performance. To manage this, teams can implement monitoring systems to track model performance metrics over time and detect drift. If drift is detected, strategies include retraining the model with recent data, adjusting the feature set, or even deploying a different model altogether to adapt to the new data distribution.

14. What is hyperparameter tuning, and which techniques can you use?

[Hyperparameter tuning](#) involves optimizing the parameters that govern the training process of a machine learning model, as opposed to parameters learned during training. Common techniques for hyperparameter tuning include:

- **Grid Search:** Systematically trying all combinations of a specified set of hyperparameters.

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- **Bayesian Optimization:** A probabilistic model that seeks to find the optimal hyperparameters by balancing exploration and exploitation.

15. How can you ensure reproducibility in machine learning experiments?

Ensuring reproducibility in machine learning experiments can be achieved through several best practices:

- **Version Control:** Use version control for code, datasets, and models.
- **Environment Management:** Use containerization (e.g., Docker) to create consistent environments across different systems.
- **Clear Documentation:** Maintain thorough documentation of experiments, including configurations and results.
- **Experiment Tracking:** Use tools like MLflow or DVC to track parameters, metrics, and outputs associated with each experiment.

16. What are some common challenges in deploying machine learning models?

Common challenges in deploying machine learning models include:

- **Model Performance:** Ensuring the model performs well on live data, which may differ from training data.
- **Scalability:** Handling increased load and ensuring that the model can serve predictions efficiently.
- **Integration:** Seamlessly integrating the model with existing systems and workflows.
- **Monitoring:** Setting up effective monitoring to catch issues like data drift and model degradation early.

17. How do you monitor and log model performance in production?

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- **Performance Metrics:** Regularly tracking key metrics (e.g., accuracy, precision, recall) and visualizing them via dashboards.
- **Alerting Systems:** Setting up alerts to notify the team of performance drops or data anomalies.
- **Logging Predictions:** Capturing inputs, predictions, and actual outcomes to analyze discrepancies and improve the model.

18. What is A/B testing in the context of machine learning?

[A/B testing](#) involves comparing two versions of a model (A and B) to determine which performs better based on predefined metrics. In machine learning, this could mean deploying two models to different user segments and measuring their performance. The results help in making data-driven decisions about which model to scale or retain in production.

19. How can you automate the MLOps pipeline?

Automating the MLOps pipeline can be achieved by integrating various tools and processes, including:

- **CI/CD Tools:** Utilizing CI/CD tools for automated testing and deployment of models.
- **Workflow Orchestration:** Using orchestration tools like Apache Airflow or Kubeflow Pipelines to automate the flow of tasks in the ML lifecycle.
- **Monitoring and Alerts:** Automating monitoring systems to trigger alerts and retraining workflows based on performance metrics.

20. What are the best practices for securing machine learning models and data?

Best practices for securing machine learning models and data include:

- **Data Encryption:** Encrypt sensitive data at rest and in transit.

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- **Regular Audits:** Conduct regular security audits and vulnerability assessments.
- **Monitoring:** Set up monitoring to detect unauthorized access or data breaches.

Advanced Questions for MLOps

21. What is transfer learning, and how can it be applied in MLOps?

Transfer learning is a technique where a pre-trained model is fine-tuned on a new, but related task, leveraging the knowledge gained from the original training. This approach can significantly reduce the time and data required for training new models, especially in scenarios with limited labeled data. In MLOps, transfer learning allows for rapid deployment of models while maintaining high performance.

22. How do you implement a model monitoring system?

Implementing a model monitoring system involves:

- **Defining Key Metrics:** Identify which metrics (e.g., accuracy, latency) are important for the business context.
- **Setting Up Data Pipelines:** Create pipelines to collect and process data for monitoring.
- **Using Monitoring Tools:** Employ monitoring tools (e.g., Prometheus, Grafana) to visualize and track model performance in real-time.
- **Feedback Loops:** Establish processes to use monitoring data to inform model retraining and improvements.

23. Explain the concept of explainability in machine learning models.

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building trust, ensuring compliance with regulations, and enabling stakeholders to interpret model outcomes. Techniques for enhancing explainability include using interpretable models, feature importance scores, and post-hoc analysis methods such as LIME and SHAP.

24. What is the role of containerization in MLOps?

Containerization involves encapsulating applications and their dependencies into a single package, or container, which can run consistently across different computing environments. In MLOps, containerization (e.g., using Docker) ensures that machine learning models can be deployed seamlessly across various platforms, facilitating reproducibility and simplifying deployment processes. It also helps manage dependencies and configuration issues.

25. How would you handle a situation where your model is underperforming in production?

If a model is underperforming in production, I would first investigate potential causes by reviewing monitoring data for any signs of data drift or changes in input features. I would then consider retraining the model with more recent data, evaluating feature importance, and checking for biases. Implementing A/B tests to compare alternative models or configurations can also help identify more effective solutions.

26. What is continuous training, and why is it important?

Continuous training is the practice of regularly retraining machine learning models using fresh data to ensure they remain relevant and accurate over time. This is important because models can degrade in performance due to changes in data distributions, a phenomenon known as model drift.

27. How do you manage dependencies in machine learning projects?

Managing dependencies in machine learning projects can be achieved through:

- **Environment Management Tools:** Using tools like Conda or virtualenv to create isolated environments for different projects.
- **Docker:** Containerizing applications to ensure consistent environments across development and production.
- **Requirements Files:** Maintaining requirements files that [list](#) all necessary packages and their versions to ensure reproducibility.

28. What are the differences between batch and real-time inference?

Batch inference involves processing a large volume of data at once, typically at scheduled intervals. It is suited for scenarios where immediate results are not necessary. Real-time inference, on the other hand, processes data and generates predictions instantly as requests are received, making it suitable for applications requiring immediate responses, such as [recommendation systems](#) and fraud detection.

29. How do you evaluate the effectiveness of feature engineering?

The effectiveness of feature engineering can be evaluated through:

- **Model Performance:** Analyzing the impact of new features on model accuracy and other performance metrics.
- **Cross-Validation:** Using techniques like k-fold [cross-validation](#) to assess how well the model generalizes with different feature sets.
- **Feature Importance Scores:** Utilizing algorithms that provide insights

30. What is the significance of data pipelines in MLOps?

Data pipelines automate the flow of data from collection through preprocessing to model training and deployment. They are significant in MLOps because they ensure a consistent, repeatable process for managing data. Efficient data pipelines enhance the scalability and reliability of machine learning workflows, allowing teams to focus on developing models rather than managing data logistics.

Expert Questions for MLOps Engineer

31. How can you implement a rollback strategy for machine learning models?

Implementing a rollback strategy involves:

- **Versioning Models:** Keeping track of all deployed models and their versions.
- **Monitoring Performance:** Continuously monitoring model performance metrics to identify degradation.
- **Automated Rollbacks:** Creating automated processes to [switch](#) back to a previous model version if the new deployment fails or underperforms significantly.

32. What are the key considerations when scaling an MLOps system?

Key considerations for scaling an MLOps system include:

- **Infrastructure:** Ensuring that computational resources can handle increased workloads.
- **Model Management:** Implementing robust version control and monitoring systems to manage multiple models efficiently.

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- **Collaboration:** Facilitating communication and collaboration among cross-functional teams to maintain efficiency as the system scales.

33. How do you handle sensitive data in machine learning applications?

Handling sensitive data involves:

- **Data Anonymization:** Removing or encrypting personal identifiers to protect user privacy.
- **Compliance:** Adhering to regulations such as GDPR or HIPAA that govern data usage and protection.
- **Access Controls:** Implementing strict access controls to limit who can view and process sensitive data.
- **Secure Storage:** Using encrypted databases and secure cloud storage solutions to protect data integrity.

34. What is multi-cloud deployment in MLOps, and what are its benefits?

Multi-cloud deployment refers to utilizing multiple cloud service providers to host machine learning models and infrastructure. Benefits include:

- **Flexibility:** Avoiding vendor lock-in and choosing the best services from different providers.
- **Resilience:** Enhancing redundancy and reliability by distributing workloads across clouds.
- **Cost Optimization:** Taking advantage of competitive pricing and services tailored to specific needs.

35. Explain how you would design a feedback loop for a deployed model.

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- **Monitoring Performance:** Continuously tracking key metrics to assess model effectiveness.
- **Collecting Feedback Data:** Gathering data on model predictions and actual outcomes to evaluate performance.
- **Data Pipeline Integration:** Integrating this feedback into the data pipeline to facilitate retraining or adjustments.
- **Model Updates:** Using the feedback to inform when to update or retrain models to improve accuracy and adaptability.

36. What is the importance of model governance?

Model governance ensures that machine learning models are developed and deployed responsibly, transparently, and ethically. It involves setting policies and standards for model development, deployment, and monitoring. This is important for compliance with regulations, managing risks, and ensuring that models are fair, unbiased, and aligned with organizational values.

37. How can you ensure ethical considerations in AI and MLOps?

To ensure ethical considerations in [AI](#) and MLOps, organizations should:

- **Implement Fairness Audits:** Regularly assess models for bias and fairness to ensure equitable outcomes.
- **Maintain Transparency:** Clearly document model development processes and decision-making criteria.
- **Engage Stakeholders:** Involve diverse stakeholders in the development process to identify potential ethical concerns.
- **Continuous Monitoring:** Monitor deployed models for unintended consequences and take corrective actions when necessary.

38. What are adversarial attacks, and how do you protect against

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Adversarial attacks involve manipulating input data to deceive machine learning models into making incorrect predictions. To protect against these attacks, strategies include:

- **Adversarial Training:** Training models on adversarial examples to improve robustness.
- **Input Validation:** Implementing rigorous input validation to detect and filter out potentially malicious inputs.
- **Model Robustness Testing:** Regularly testing models against adversarial scenarios to identify vulnerabilities.

39. How do you balance model accuracy and interpretability?

Balancing model accuracy and interpretability can be challenging, as more complex models (e.g., deep learning) often yield higher accuracy but lower interpretability. To achieve this balance:

- **Choose Simple Models:** Start with simpler, interpretable models and use them as baselines.
- **Model Explainability Tools:** Utilize tools like LIME or SHAP to provide insights into complex models' decisions.
- **Stakeholder Communication:** Engage with stakeholders to understand their interpretability needs and make informed decisions about model selection.

40. Describe your experience with serverless architectures in MLOps.

Serverless architectures allow developers to build and run applications without managing server infrastructure. In MLOps, this can streamline deployment processes by automatically scaling resources based on demand. My experience with serverless architectures includes using

Scenario-Based Questions

41. Describe a time when you had to troubleshoot a production issue with an ML model.

In a previous role, I encountered a production issue where a deployed model's performance dropped significantly. I began troubleshooting by examining logs and monitoring metrics for signs of data drift. After identifying a change in input data distribution, I collaborated with the data engineering team to update the [data preprocessing](#) pipeline. Retraining the model with the new data improved performance, and I implemented monitoring to catch similar issues in the future.

42. How would you approach integrating a new model into an existing MLOps pipeline?

To integrate a new model into an existing MLOps pipeline, I would start by reviewing the current pipeline architecture to understand its components. Then, I would ensure that the new model aligns with the existing data preprocessing and feature engineering processes. Next, I would conduct thorough testing in a staging environment to validate the new model's performance and integration. Finally, I would update monitoring and logging systems to track the new model once deployed.

43. If a model's performance degrades over time, what steps would you take?

If a model's performance degrades, I would first conduct a thorough analysis of the input data and model predictions to identify potential causes. This includes checking for data drift, changes in user behavior, and feature relevance. I would then consider retraining the model with recent

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determine the effectiveness of different models or configurations before full deployment.

44. How would you design an experiment to compare two different models?

To design an experiment comparing two models, I would define clear performance metrics aligned with business goals. I would then split the data into training, validation, and test sets, ensuring that both models are evaluated on the same test data. I would implement A/B testing to deploy both models in a controlled environment, randomly assigning users to each model. Finally, I would analyze the results based on the defined metrics and determine which model performs better.

45. What strategies would you use to communicate model results to non-technical stakeholders?

To communicate model results to non-technical stakeholders, I would focus on clarity and relevance. This includes:

- **Using Visualizations:** Presenting results through clear charts and graphs that highlight key findings.
- **Avoiding Jargon:** Simplifying technical terms and explaining concepts in layman's terms.
- **Focusing on Business Impact:** Relating the model's performance to business outcomes, such as revenue or customer satisfaction.
- **Encouraging Questions:** Creating an open environment for stakeholders to ask questions and express concerns about the model.

General Questions

46. What are the latest trends in MLOps that you find interesting?

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- **Increased Focus on Explainability:** There is a growing emphasis on developing models that are interpretable and understandable to stakeholders.
- **Integration of Automated Machine Learning (AutoML):** This simplifies model development by automating various stages, making it more accessible.
- **Rise of Feature Stores:** Feature stores are becoming essential for managing and sharing features across projects, improving efficiency.
- **Ethical AI Practices:** There is an increasing focus on ensuring ethical considerations are integrated into AI and machine learning processes.

47. How do you stay updated with advancements in MLOps and machine learning?

I stay updated by following industry blogs, attending conferences, and participating in online courses related to MLOps and machine learning. I also engage with communities on platforms like GitHub and LinkedIn, where practitioners share insights and advancements. Additionally, I subscribe to newsletters from leading AI organizations and regularly read research papers to keep abreast of the latest developments.

48. Can you discuss any open-source contributions you've made related to MLOps?

In my previous roles, I contributed to several open-source projects focused on MLOps tools, such as adding features to MLflow for better model tracking and integrating DVC with existing data pipelines. I also contributed to documentation and tutorials for these projects to help other users implement best practices in MLOps.

49. What are your thoughts on the future of MLOps?

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management. There will be a stronger focus on ethical AI practices and explainability, as stakeholders demand transparency in AI decision-making. Furthermore, the collaboration between data scientists and IT operations will deepen, leading to more efficient workflows and better model performance in production.

50. How do you foster collaboration between data scientists and operations teams in MLOps?

Fostering collaboration between data scientists and operations teams can be achieved by:

- **Regular Meetings:** Organizing joint meetings to discuss project updates, challenges, and solutions.
- **Cross-Training:** Encouraging team members to learn from each other's domains to build mutual understanding.
- **Shared Goals:** Establishing shared objectives and metrics that align both teams' efforts toward common outcomes.
- **Using Collaborative Tools:** Implementing tools that facilitate communication and project management, such as Slack or Jira.

Wrap-Up Questions

51. What do you believe is the biggest challenge in implementing MLOps?

The biggest challenge in implementing MLOps is often the cultural shift required within organizations. Bridging the gap between data science and IT operations necessitates changes in processes, tools, and mindsets. Additionally, managing the complexities of model deployment, monitoring, and maintenance can be daunting without a clear strategy and effective collaboration.

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I am drawn to MLOps because it combines my passion for machine learning with the operational aspects of software development. The opportunity to work on bridging the gap between data science and production environments excites me, as it allows for practical applications of AI that can drive significant business impact. I enjoy solving complex problems and believe that MLOps is at the forefront of transforming how organizations leverage machine learning.

53. What skills do you think are most critical for success in MLOps?

Key skills for success in MLOps include:

- **Technical Proficiency:** Strong understanding of machine learning concepts and tools.
- **Software Development Skills:** Knowledge of software engineering practices and version control.
- **Collaboration and Communication:** Ability to work effectively with cross-functional teams and communicate technical concepts to non-technical stakeholders.
- **Problem-Solving:** Analytical skills to troubleshoot issues and optimize processes.

54. How would you handle conflicts between teams in an MLOps project?

To handle conflicts between teams, I would prioritize open communication and understanding the underlying concerns of each party. I would facilitate discussions to ensure all voices are heard and aim for a collaborative approach to find common ground. Establishing clear goals and roles can also help mitigate misunderstandings and foster a more cooperative environment.

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In my previous roles, I worked on several projects that involved MLOps principles, including developing a real-time recommendation system for an e-commerce platform. This project required implementing a robust CI/CD pipeline for model deployment, monitoring model performance, and establishing a feedback loop for continuous improvement. I also contributed to optimizing data preprocessing pipelines and ensuring compliance with data governance standards.

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