MLOps Sales Certification

Slides and Talk Track

Certification Overview

Customer-facing staff will be certified via a Lessonly module that includes:

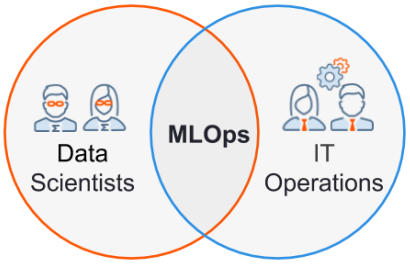
1. Slides and Talk Track
    a. Video for each slide with sample talk track
    b. Document with talk track and other instructions for presenting slide deck
    c. Video with Dan Darnell's presentation
    d. Assessment: Upload of video OR live presentation of staff presenting slides and talk track
2. Demo of the product*
    a. Video of James Johnston and Tristan Spaulding presenting short sales-appropriate demo
    b. Document with talk track and other instructions for demo
    c. Assessment: Upload of video OR live presentation of staff presenting demo
3. Lessonly instruction on history, context and triggers
    a. Slides, text, and documents as needed
    b. Assessment: Lessonly quiz
4. Additional videos from Kyle Rowe
    a. Introducing MLOps
    b. Customer stories about ML

*A separate demo and module will be created for CFDSs, Platform team & Solution Architects

Slide 1: What is MLOps?

What is MLOps?

Machine Learning Operations (MLOps) technology and practices provide a scalable and governed means to rapidly deploy and manage ML applications in production environments.



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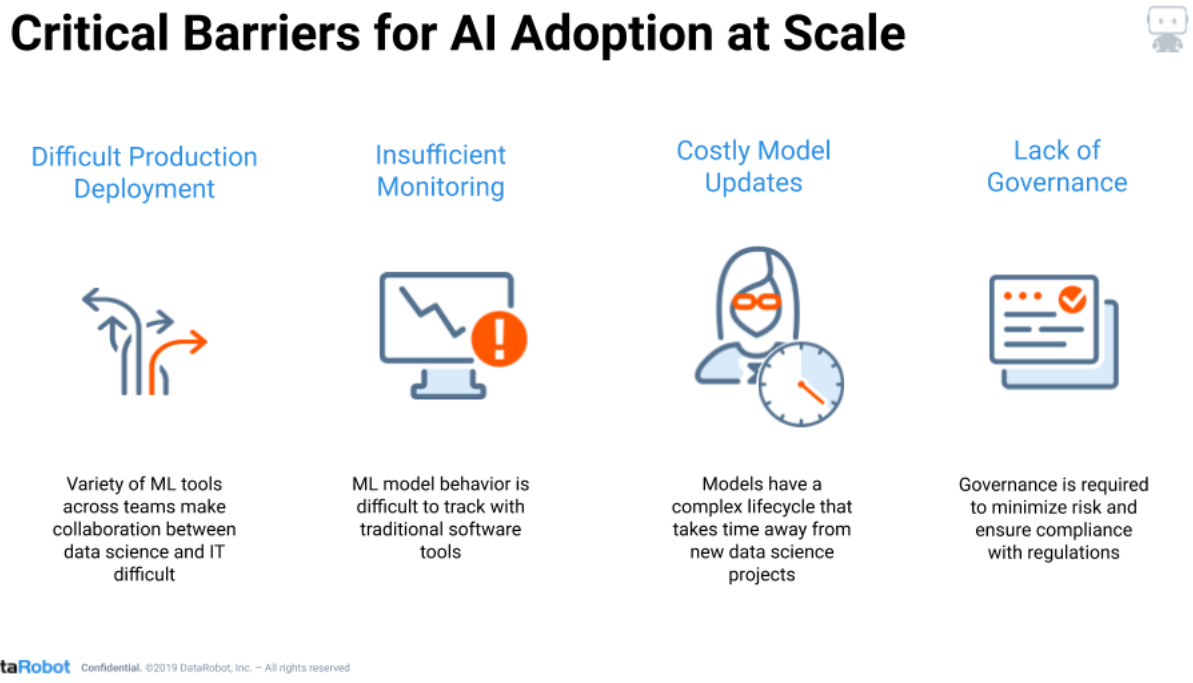
Today we'll talk about machine learning operations - also known as MLOps - and I'll provide: ● a quick overview of the key problems we face in this space and ● how DataRobot MLOps solution addresses those problems and provides value.	
What is MLOps? It's technology and a set of practices that allow your data science teams and IT operations to work together to rapidly deploy and manage machine learning models in your live production environment.	Defines ML Ops as *technology and a set of practices that allow data science teams and IT operations to work together to rapidly deploy and manage machine learning / AI applications,* using similar language to the above.
This is critical, because today there are a number of issues that companies face that prevent them from scaling their AI programs. Let's take a look at a few:	

Slide 2: Critical Barriers for AI Adoption at Scale



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First, it's difficult to put AI or machine learning applications into production. ● Businesses are now using a huge variety of tools but when they are ready to deploy models, IT doesn't have the tools or understanding of machine learning to be helpful. ● This barrier between the IT and data science organizations - in terms of tools, languages, and how they operate - prevents projects from moving into production. ● *Example*: data scientists create a model in Python, but when it's ready to deploy, the IT team will doesn't speak Python and wants to convert it to Java or some other language that they understand. And the project dies right there.	Addresses first key barrier using similar language to the following: *It's difficult to put machine learning into production because Data Science and IT use different tools and speak different languages that make it difficult for them to work together to deploy models.* Speaks convincingly of customer problems around the difficulty of and need for monitoring

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The next barrier: once a model goes into a production environment, it needs to be monitored. ● But traditional IT and tools for managing software programs just don't work for machine learning. ● They monitor whether a program is consuming more memory or CPU than usual or if responses are off. ● But even as a machine learning model decays over time and the accuracy degrades, it responds in a timely fashion and produces responses that look right. ● So with traditional tools, there's really no way to monitor Machine Learning model performance. ● If you're a business needing to deploy models and realize there is no way to know when they start to decay, then you may decide not to deploy. ● Or you can deploy the models, and invest data science time and CPUs to retrain the models frequently - which detracts from building new models.	Addresses second key barrier using similar language to the following: *It's not possible to monitor model performance using traditional IT and software tools – they can't monitor accuracy or detect decay or drift.* *So consequently, you either don't deploy the model or you invest resources in frequent retraining, which limits the new models you build.* Speaks convincingly of customer problems around the difficulty of and need for monitoring
The third barrier is the cost of retraining– both in CPU time and data science time. Because Data Scientists are frequently the only ones who understand the languages that the models are built in, they must create the scripts for any manual deployments and become heavily involved in the day-to-day management of the model once it's in production, including any retraining processes. ● It's not unusual to take data science teams multiple weeks to retrain a model and then more time for approval processes. For that reason, businesses frequently end up not retraining models as often as they should. ● It's important to be able to retrain quickly and easily so that you can update models when you need to and keep your predictions accurate. ● Plus, the data science team should be focused on data science - and not be heavily involved in production, unless there's an issue where their unique expertise is needed.	Addresses third key barrier using similar language to the following: *Because Data Scientists are the only ones who understand their models, they have to help with day-to-day updates and management which is a waste of their valuable resources and prevents them from doing data science.* Speaks convincingly of customer problems around cost of manual retraining using similar language to the following:

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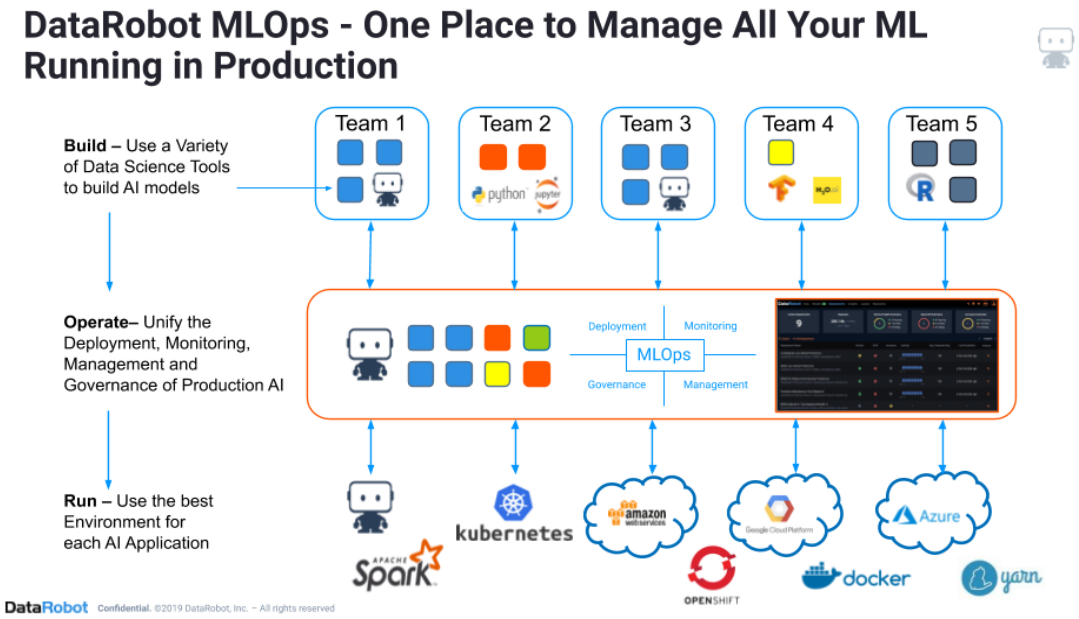
And last, especially for heavily regulated industries like financial services, there's a need for systematic governance of models. Often a company plans to deploy a model and then finds they are introducing a massive operational risk to the business. ● They don't have proper governance tools to controls access to the model in production and who can update it ● And they have no way to audit the model, to track when it was changed and what version was in production when a particular inference was made. ● Without governance, deploying models is a massive operational risk. Without access controls and traceability, businesses in regulated industries may not be able to put the model into production.	Addresses fourth key barrier using similar language to the following: *For heavily regulated industries, governance is required - control over access and who updates, and an audit trail that can trace predictions back to a particular model.* *Without governance, deploying models is an operational risk.* Speaks convincingly of customer problems around lack of governance:
In summary, there are a number of issues from the lack of a common language and framework for IT operations and data science: ● The inability to monitor performance and understand when models are starting to degrade; ● The overall time and expense of data science involvement in the model management process; ● And last, without governance, the impossibility of deploying in regulated industries. **Ultimately, it's all about scale.** If you're deploying one or two models, you can handle it manually. But frequently, once you start to see success and generate positive results, the business quickly wants not a few more, but a few hundred more models. They recognize all the other areas of the business that could be transformed with machine learning and AI, but **you simply can't scale without an automated way to deploy and monitor performance and some method of governance, that both data science and IT can work with.**	Summarizes barriers in context of inability to scale, including language similar to the following: *Your simply can't scale without an automated way to deploy and monitor performance and some method of governance, that both data science and IT can work with.*

Slide 3: DataRobot MLOps



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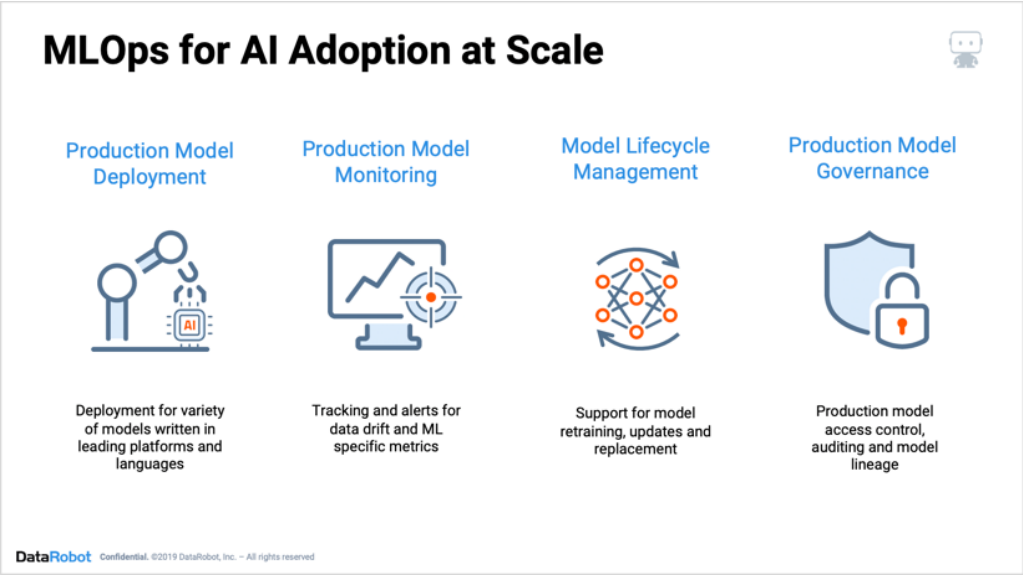
DataRobot MLOps gives you the ability to scale – it's one place where you can manage all of your ML running in production. Your teams can use a variety of platforms and frameworks like Python and R to build models You then use DataRobot MLOps to deploy and manage the models from a single console. Best of all, you can run models on whatever environment makes the most sense for you - in the cloud or on prem or on platforms like Kubernetes, Kubernetes running any of the major cloud platforms, Kubernetes platforms like OpenShift on premise, and still monitored from the MLOps console. So DataRobot MLOps give you the ability to build models using a variety of tools and run those models wherever makes the most sense for your business, and still have unified operations around those models.	Addresses flexibility and comprehensive functions of ML Ops, using language similar below : *DataRobot's MLOps provides a unified deployment monitoring management and governance layer for all your models, no matter what system was used to create them or where they were deployed.*

Slide 4: DataRobot MLOps Capabilities



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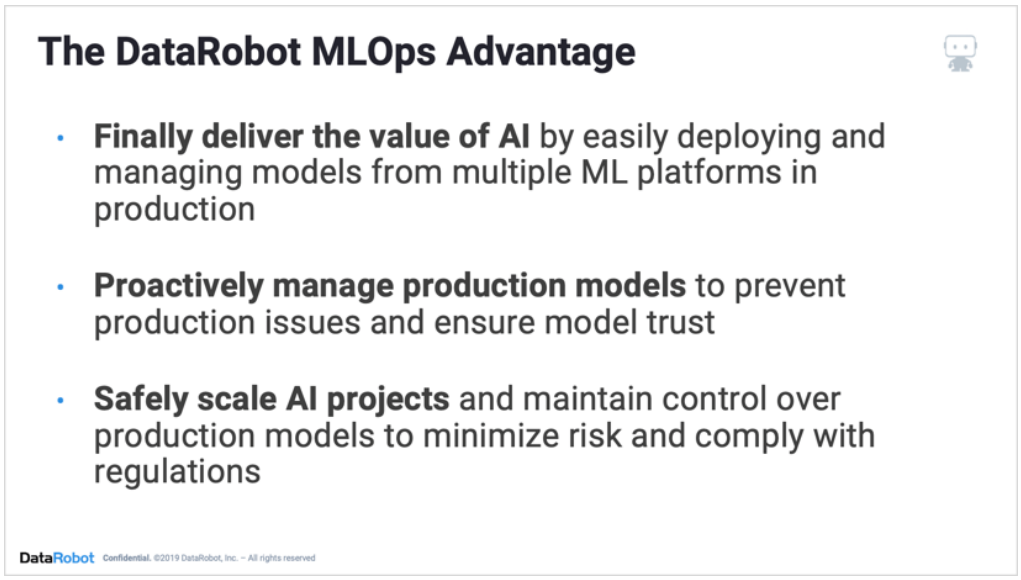
DataRobot MLOps removes the barriers to deploying and managing machine learning at scale. Data Scientists can continue to use their own framework based on their experience and skill set or because a certain framework is the best fit for the problem they're trying to solve. Monitoring is specifically designed for ML models and includes data drift and ML metrics tracking and alerts. Models can be updated in production without needing help from your data science team. The entire platform is built with governance in mind so you know you have control over your production models and that you can meet regulatory needs.	Addresses flexibility and comprehensive functions of ML Ops, using language similar below : *DataRobot's MLOps removes the barriers to deploying and managing machine learning models at scale.* Addresses each of the four functions: ● *Ability to track models regardless of framework* ● *Monitoring of ML-specific metrics* ● *Easy updating of models* ● *Governance*

Slide 5: The DataRobot MLOps Advantage (optional)



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So the advantage of DataRobot MLOps is: ● You have the ability to deliver on all your investments in data science and all the projects that your teams are working on by streamlining deployment and management across your organization. ● The system provides real-time monitoring dashboards and alerts on ML centric metrics so your teams can proactively manage your production models and head off problems before they become issues for your business. ● And, you can now safely scale your data science out and up with built-in capabilities for production model governance to minimize organization risk and ensure compliance.	Summarizes the advantages and value of MLOps.