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Deploying to Production

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Adapted from “Introducing MLOps”
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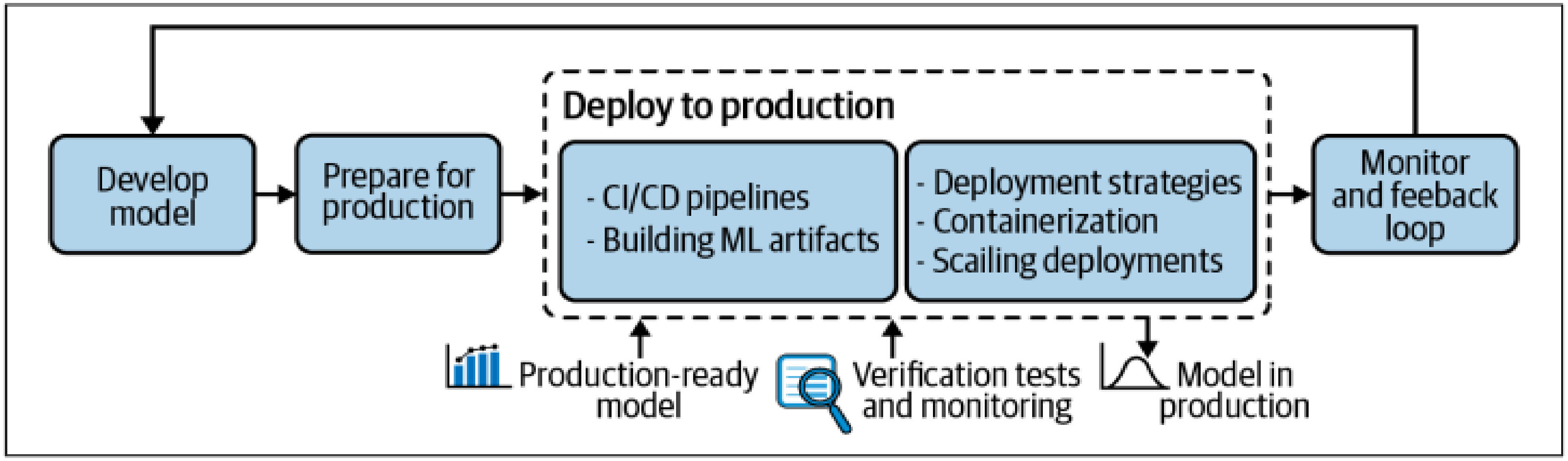
Deploying to Production

- Business leaders view rapid deployment of systems into production as key to maximizing business value
  - only true if deployment can be done smoothly and at low risk

- Lets dive into the concepts and considerations when deploying machine learning models to production
  - that impact and drive—the way MLOps deployment processes are built



Deployment to production highlighted in the larger context of the ML project life cycle

CI/CD Pipelines

A common acronym for continuous integration and continuous delivery (or put more simply, deployment)

- Forms a modern philosophy of agile software development and a set of practices and tools
  - to release applications more often and faster, while also better controlling quality and risk

- Ideas are decades old and already used to various extents by software engineers
  - different people and organizations use certain terms in very different ways

- Essential to keep in mind that
  - these concepts should be tools to serve the purpose of delivering quality fast
  - first step is always to identify the specific risks present at the organization

- CI/CD methodology should be adapted based on the needs of the team and the nature of the business.

CI/CD for ML

- CI/CD concept apply just as well to machine learning systems
  - are a critical part of MLOps strategy

- An example of such pipeline could be:
  1. Build the model
     a. Build the model artifacts
     b. Send the artifacts to long-term storage
     c. Run basic checks (smoke tests/sanity checks)
     d. Generate fairness and explainability reports
  2. Deploy to a test environment
     a. Run tests to validate ML performance, computational performance
     b. Validate manually
  3. Deploy to production environment
     a. Deploy the model as canary
     b. Fully deploy the model

CI/CD for ML(2)

- Many scenarios are possible, depend on the application,
  - the risks from which the system should be protected
  - and the way the organization chooses to operate

- Generally, an incremental approach to building a CI/CD pipeline is preferred:
  - a simple or even naïve workflow on which a team can iterate
  - often much better than starting with complex infrastructure from scratch

- A starting project does not have the infrastructure requirements of a tech giant
  - can be hard to know up front which challenges deployments will present

- There are common tools and best practices,
  - but there is no one-size-fits-all CI/CD methodology
  - means the best path forward is starting from a simple (but fully functional) CI/CD workflow
  - then introducing additional or more sophisticated steps along the way as quality or scaling challenges appear

Building ML Artifacts

- The goal of a continuous integration pipeline is
  - to avoid unnecessary effort in merging the work from several contributors
  - also to detect bugs or development conflicts as soon as possible

- The very first step is using centralized version control systems
  - unfortunately, working for weeks on code stored only on a laptop is still quite common

- The most common version control system is Git, an open source software
  - majority of software engineers across the world already use Git,
  - increasingly being adopted in scientific computing and data science
- Git allows for
  - maintaining a clear history of changes,
  - safe rollback to a previous version of the code,
  - multiple contributors to work on their own branches of the project before merging to the main branch, etc

- Git is appropriate for code, but not designed
  - to store other types of assets common in data science workflows,
    - such as large binary files (for example, trained model weights),
  - or to version the data itself

ML Artifact

- Once code and data is in a centralized repository,
    - a testable and deployable bundle of the project must be built
    - are usually called artifacts in the context of CI/CD

- Each of the following elements needs to be bundled into an artifact
    - that goes through a testing pipeline and is made available for deployment to production:
        - Code for the model and its preprocessing
        - Hyperparameters and configuration
        - Training and validation data
        - Trained model in its runnable form
        - An environment including libraries with specific versions, environment variables, etc.
        - Documentation
        - Code and data for testing scenarios

The Testing Pipeline

- Testing pipeline can validate a wide variety of properties of the model contained in the artifact
  - good tests should make it as easy as possible to diagnose the source issue when they fail

- Automating tests as much as possible is essential and is a key component of efficient MLOps

- A lack of automation or speed wastes time,
  - also discourages the development team from testing and deploying often,
  - which can delay the discovery of bugs or design choices that make it impossible to deploy to production

Deployment concepts

- Integration
  - Process of merging a contribution to a central repository and performing more or less complex tests
  - typically merging a Git feature branch to the main branch

- Delivery
  - Same as used in the continuous delivery (CD) part of CI/CD,
  - Process of building a fully packaged and validated version of the model ready to be deployed to production

- Deployment
  - Process of running a new model version on a target infrastructure
  - Fully automated deployment is not always practical or desirable

- Release
  - In principle, release is yet another step, directing production workload to model
  - deploying a model version (even to the production infrastructure) does not necessarily mean that the production workload is directed to the new version
    - multiple versions of a model can run at the same time on the production infrastructure

Categories of Model Inferences

Two ways to approach model deployment

- Batch scoring,
  - where whole datasets are processed using a model, such as in daily scheduled jobs

- Real-time scoring,
  - where one or a small number of records are scored,
  - such as when an ad is displayed on a website and a user session is scored by models to decide what to display

- In both cases, multiple instances of the model can be deployed
  - to increase throughput and potentially lower latency

Considerations When Sending Models to Production

- When sending a new model version to production, first consideration is often to avoid downtime,
  - in particular for real-time scoring

- Blue-green or red-black— deployment
  - basic idea is that rather than shutting down the system, upgrading it, and then putting it back online,
  - a new system can be set up next to the stable one
  - and when it's functional, the workload can be directed to the newly deployed version
  - and if it remains healthy, the old one is shut down

- Canary deployment
  - idea is that the stable version of the model is kept in production,
  - but a certain percentage of the workload is redirected to the new model, and results are monitored
  - usually implemented for real-time scoring, but a version of it could also be considered for batch

Maintenance in Production

Once a model is released, it must be maintained

- At a high level, there are three maintenance measures:
  - Resource monitoring
  - Health check
  - ML metrics monitoring

- Resource monitoring
  - Just as for any application running on a server, collecting IT metrics such as CPU, memory, disk, or network usage
  - can be useful to detect and troubleshoot issues

- Health check
  - Need to check if the model is indeed online and to analyze its latency
  - simply queries the model at a fixed interval (on the order of one minute) and logs the results

- ML metrics monitoring
  - about analyzing the accuracy of the model and comparing it to another version or detecting when it is going stale
  - may require heavy computation, this is typically lower frequency

- Finally, when a malfunction is detected, a rollback to a previous version may be necessary
  - critical to have the rollback procedure ready and as automated as possible;
  - testing it regularly can make sure it is indeed functional

Thank You!

In our next session: