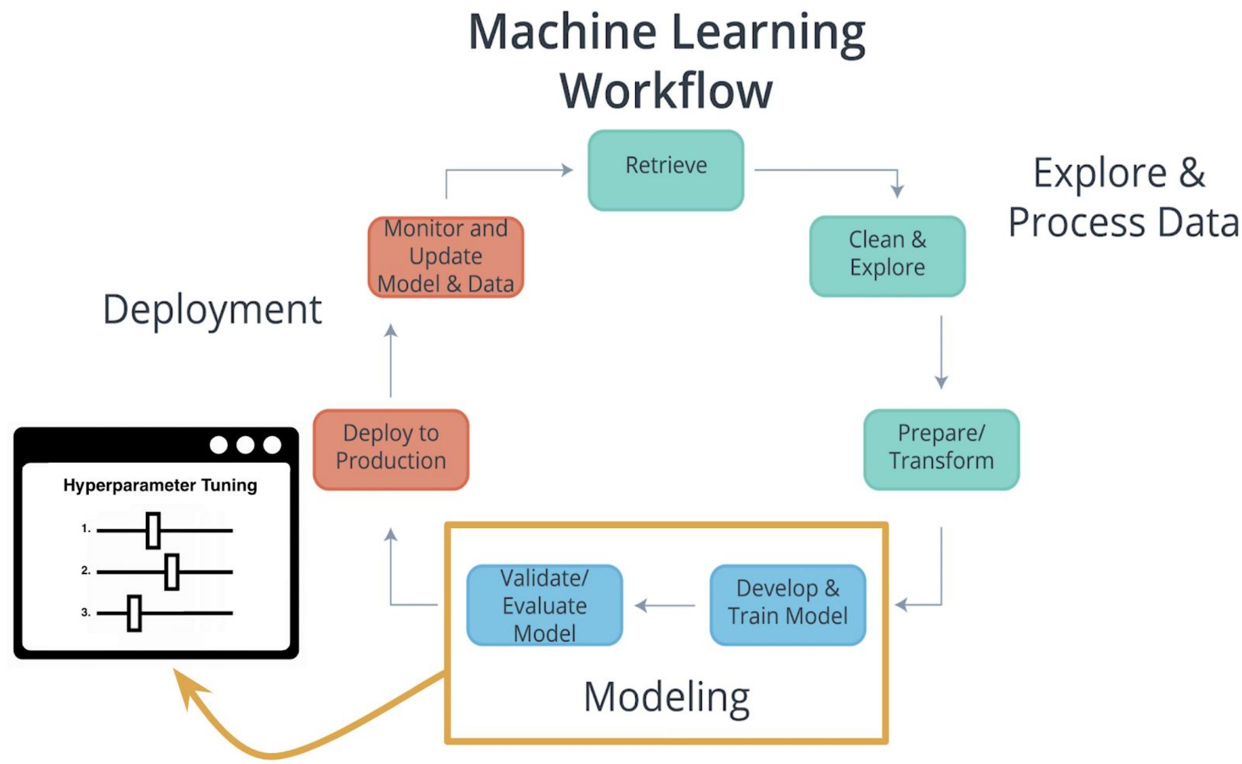
Characteristics of Deployment and Modeling

Recall that:

> ***Deployment*** to production can simply be thought of as a *method* that *integrates* a machine learning **model** into an *existing* **production environment** so that the **model** can be used to make *decisions* or *predictions* based upon *data* input into this **model**.
>
> Also remember that a ***production environment*** can be thought of as a *web*, *mobile*, or *other software* **application** that is *currently* being *used* by *many* people and must respond *quickly* to those users' requests.

Keeping these things in mind, there are a number of *characteristics* of **deployment** and **modeling** that I'm going to introduce here. These concepts are introduced *now* to provide you with *familiarity* with these concepts for when you see them discussed in *future lessons*. Specifically, these concepts are provided as ***features*** that are made easier to use within cloud platforms services than if implemented with your own code.



Characteristics of Modeling

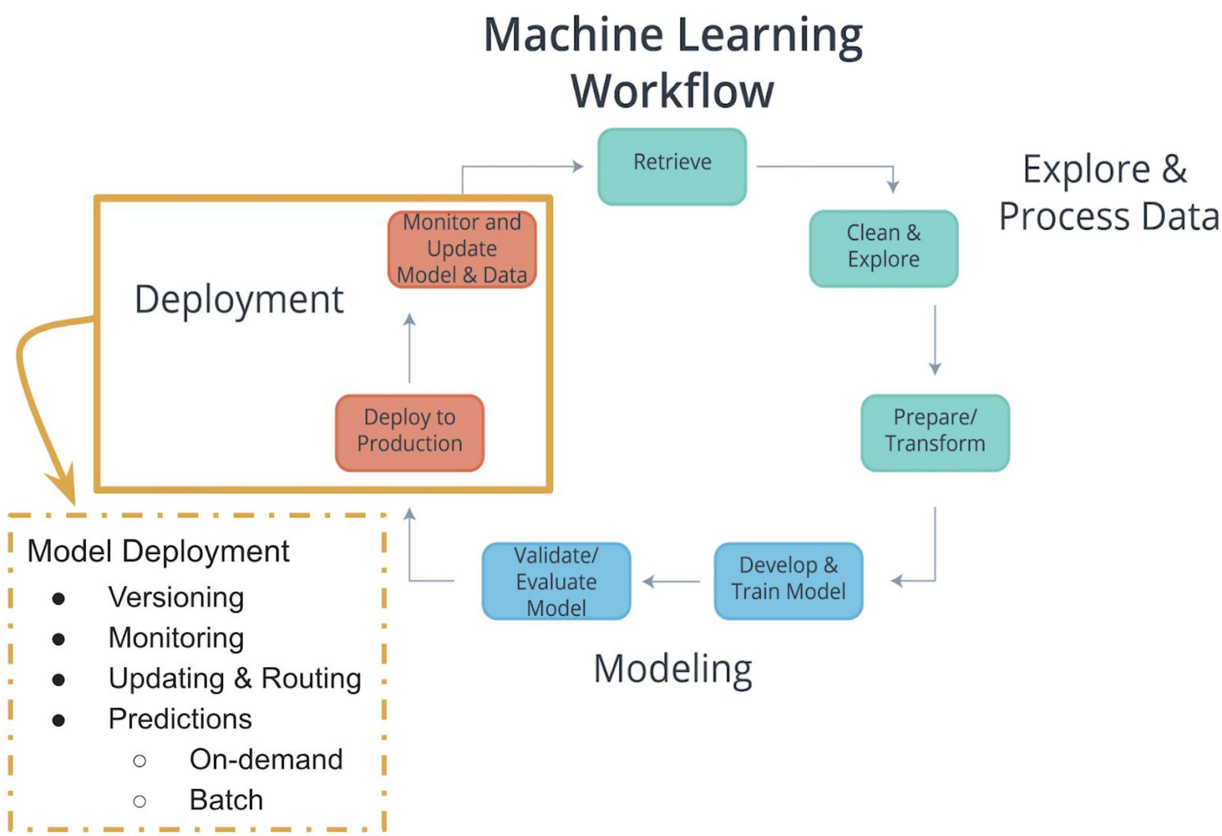
Hyperparameters

In machine learning, a **hyperparameter** is a parameter whose value *cannot* be estimated from the data.

- Specifically, a **hyperparameter** is *not directly* learned through the estimators; therefore, their value must be *set* by the model developer.
- This means that **hyperparameter** *tuning* for optimization is an ***important part*** of *model training*.

- Often cloud platform machine learning services provide methods that allow for **automatic hyperparameter** *tuning* for use with model training.

If the machine learning platform fails to offer an *automatic* **hyperparameter** option, one option is to use methods from scikit-learn Python library for **hyperparameter** *tuning*. Scikit-learn is a free machine learning Python library that includes *methods* that help with **hyperparameter** *tuning*.



Characteristics of Deployment

Model Versioning

One characteristic of deployment is the **version** of the model that is to be deployed.

- Besides saving the **model version** as a part of a *model's metadata* in a database, the *deployment platform* should allow one to indicate a deployed **model's version**.

This will make it easier to maintain, monitor, and update the *deployed model*.

Model Monitoring

Another characteristic of deployment is the ability to easily **monitor** your deployed models.

- Once a model is deployed you will want to make certain it continues to meet its performance metrics; otherwise, the application may need to be updated with a *better* performing model.

Model Updating and Routing

The ability to easily **update** your deployed model is another characteristic of deployment.

- If a deployed model is *failing* to meet its performance metrics, it's likely you will need to **update** this model.

If there's been a *fundamental change* in the *data* that’s being input into the model for predictions; you'll want to **collect** this *input data* to be used to **update** the model.

- The *deployment platform* should support **routing** *differing* proportions of *user requests* to the deployed models; to allow *comparison* of performance between the deployed model *variants*.

Routing in this way allows for a test of a model *performance* as *compared* to other model *variants*.

Model Predictions

Another characteristic of deployment is the *type* of **predictions** provided by your deployed model. There are *two common* types of **predictions**:

- **On-demand predictions**
- **Batch predictions**

On-Demand Predictions

- **On-demand predictions** might also be *called*:
    - online,
    - real-time, or
    - synchronous predictions
- With these type of predictions, one *expects*:

    - a *low latency* of response to each prediction request,
    - but allows for possibility *high variability* in request volume.
- Predictions are returned in the response from the request. Often these requests and responses are done through an API using JSON or XML formatted strings.
- Each prediction request from the user can contain *one* or *many* requests for predictions. Noting that *many* is limited based upon the *size* of the data sent as the request. Common cloud platforms **on-demand prediction** request size limits can range from *1.5(ML Engine)* to *5 Megabytes (SageMaker)*.

On-demand predictions are commonly used to provide customers, users, or employees with real-time, online responses based upon a deployed model. Thinking back on our *magic eight ball web application* example, users of our web application *would be* making **on-demand prediction** requests.

Batch Predictions

- **Batch predictions** might also be *called*:
    - asynchronous, or
    - batch-based predictions.
- With these type of predictions, one *expects*:
    - *high volume* of requests with more *periodic submissions*
    - so *latency* won't be an issue.
- Each batch request will point to specifically *formatted data file* of requests and will return the predictions to a file. Cloud services ***require*** these files will be *stored* in the cloud provider's cloud.

- Cloud services typically have *limits* to how much data they can process with each batch request based upon *limits* they impose on the *size of file* you can store in their cloud storage service. For example, *Amazon's SageMaker* limits batch predictions requests to the size limit they enforce on an object in their S3 storage service.

Batch predictions are *commonly* used to help make *business decisions*. For example, imagine a business uses a complex model to predict customer satisfaction across a number of their products and they need these *estimates* for a *weekly* report. This would require processing customer data through a **batch prediction** request on a *weekly basis*.

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