Production: Introduction to ML Systems

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$ echo "Data Science Institute"
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Introduction

Agenda

- **1.1 Overview of ML Systems**
  - When to Use ML
  - ML in Production
  - ML vs Traditional Software
- **1.2 Introduction to ML System Design**
  - Business and ML Objectives
  - Requirements of Data-Driven Products
  - Iterative Process
  - Framing ML Problems

Agenda

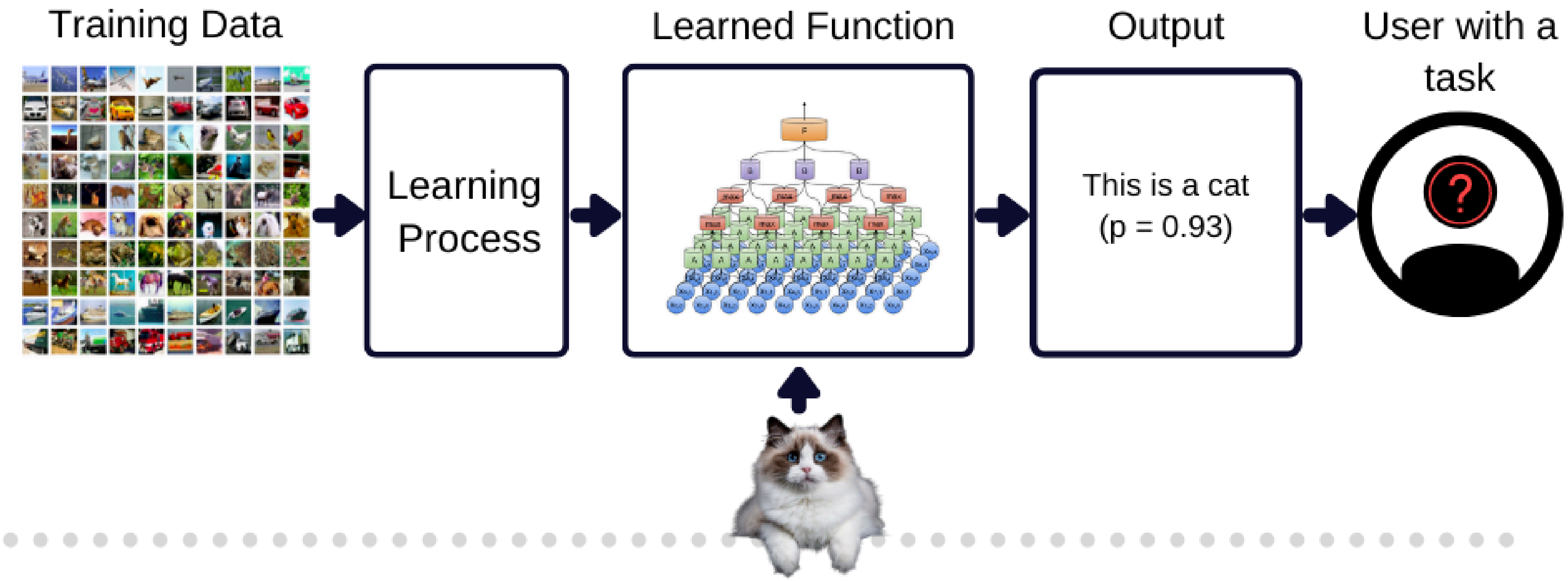
- **1.3 Project Setup**
  - Introduction.
  - Repo File Structure.
  - Git, authorization, and production pipelines.
  - VS Code and Git.
  - Python virtual environments.
  - Branching Strategies.
  - Commit Messages.

About

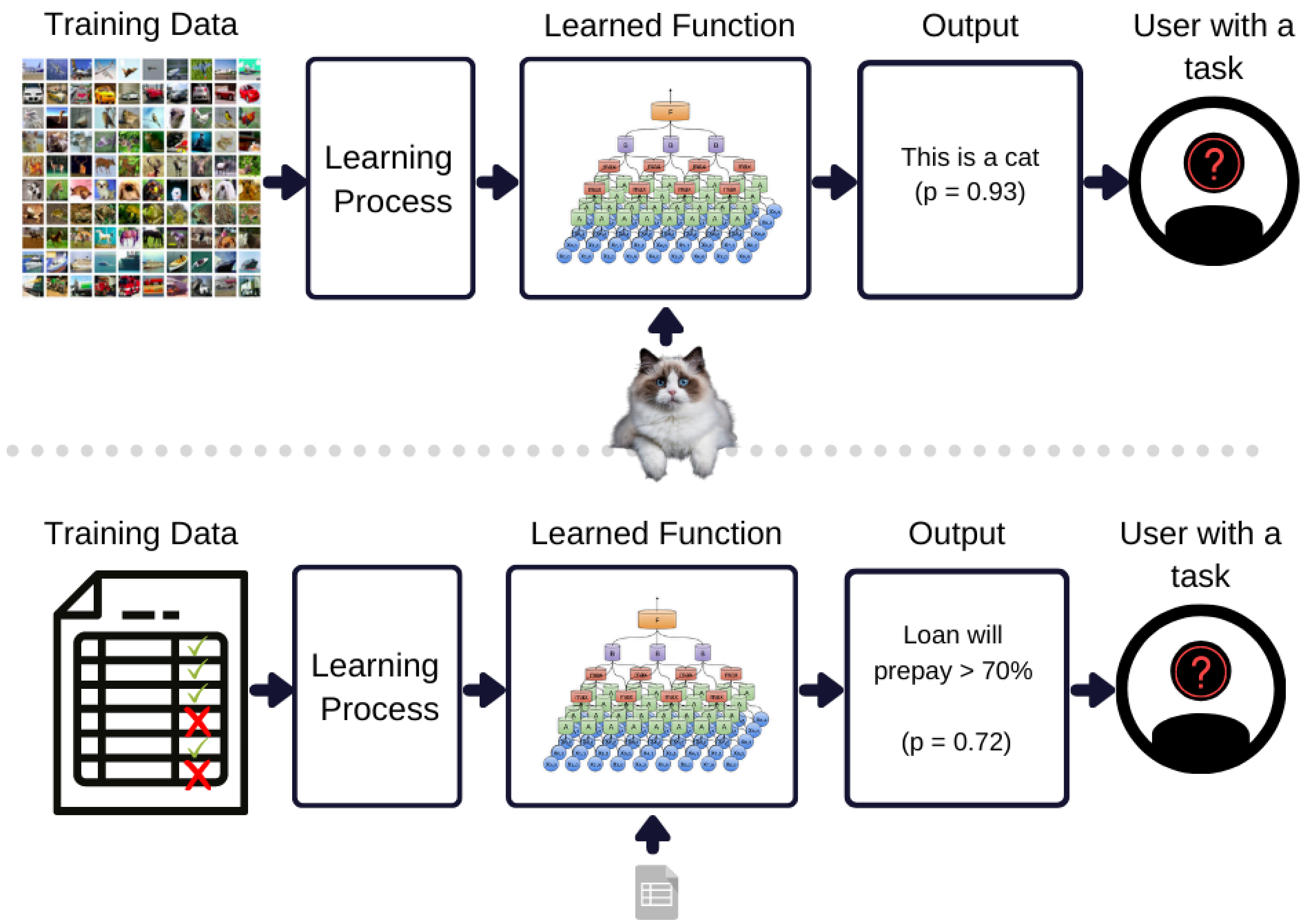
- These notes are based on Chapters 1 and 2 of *Designing Machine Learning Systems*, by Chip Huyen.

Machine Learning

ML: An Illustration



ML: An Illustration



What is Machine Learning (ML)?

> “A computer program is said to learn from experience *E* with respect to some class of tasks *T* and performance measure *P*, if its performance at tasks in *T*, as measured by *P*, improves with experience *E*.” (Mitchel, 1997)

> "Machine learning is an approach to (1) learn (2) complex patterns from (3) existing data and use these patterns to make (4) predictions on (5) unseen data." (Huyen, 2022)

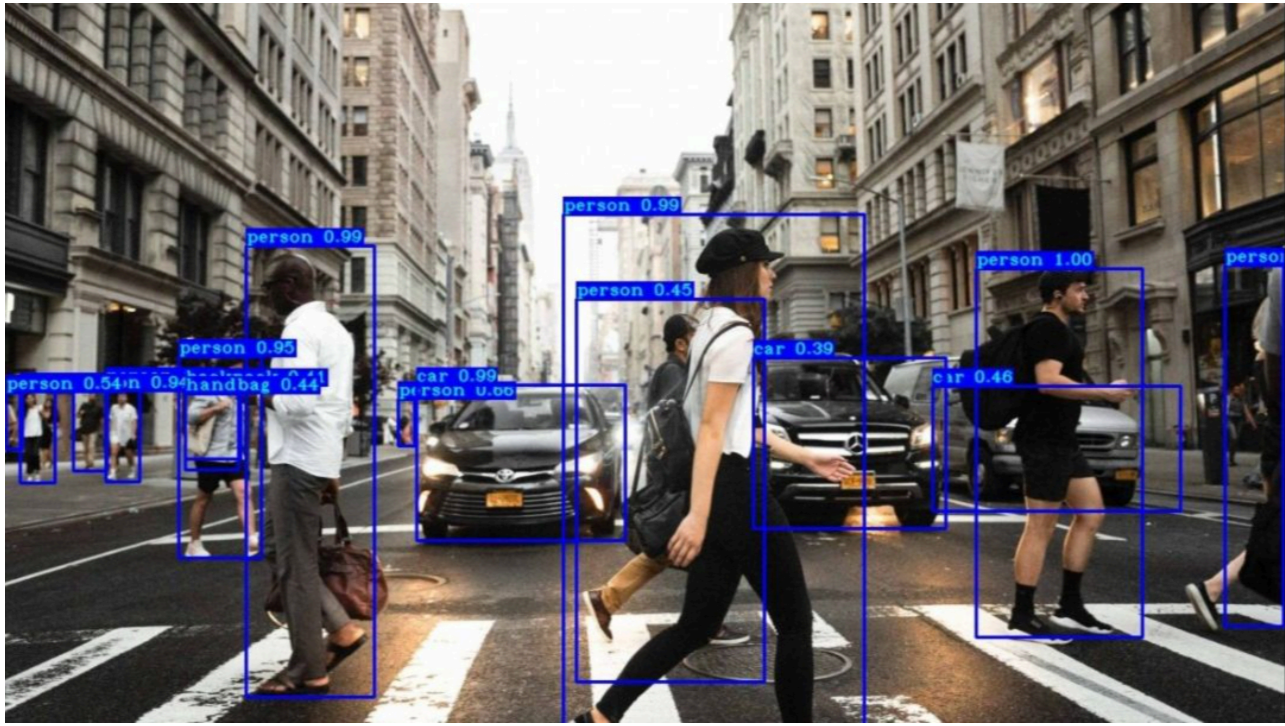
What is Machine Learning (ML)?

ML is a collection of methods that allow a computer to:

- **Learn autonomously** to perform a task based on a set of examples and without being explicitly programmed to perform the task.
- **Gain from experience** such that the method performs better in the measure that it observes additional examples.
- **Generalize results** beyond the data used for training the method.

Why Use Machine Learning?

- ML is used when a task is too complex or impractical to program explicitly.
- When applied successfully, ML will enable
  - Greater scale: automation.
  - Better performance.
  - Doing things that were not possible before.
- (Image Source)



When to Use ML?

- A business problem is not the same as an ML problem.

- Generally, a business will be concerned with profit maximization (directly or indirectly): increasing sales, cutting costs, enhancing customer satisfaction, reducing churn, increasing time on the website, etc.

    - The objective of an ML method is to enhance the performance of the task, given more data.

    - Optimising ML performance metrics does not automatically translate to optimizing business performance.

- Some of the most popular business applications of ML are in areas where business and ML performance overlap: fraud detection, recommender systems, etc.

ML System Design

Characteristics of ML Use Cases (1/4)

Learning is involved

- The system can learn autonomously.
- Given a series of inputs, the system learns how to produce outputs.
- Not every ML model can learn any hypothesis; more complex models will tend to be more flexible.

Complex patterns

- There are patterns to learn, and they are complex.
- ML solutions are only helpful if there are patterns.
- An ML model can learn simple patterns, but the cost of applying ML may be unreasonable.

Characteristics of ML Use Cases (2/4)

Existing data

- Data is available, or it is possible to collect data.
- Out-of-domain predictions may fail because of a lack of training data.
- Online (real-time) learning systems could be deployed and trained using production data.

Predictions

- ML algorithms will generate predictions. Therefore, the problem to solve should be predictive.
- A prediction could be about a future event (forecast) or an event that is difficult to observe (e.g., fraud detection or clustering).

Characteristics of ML Use Cases (3/4)

Unseen data

- Unseen data shares patterns with the training data.
- The learning method generalizes reasonably well on testing data.

It is repetitive

- ML algorithms perform better with experience: repetitive tasks afford such experience.

The cost of incorrect predictions is low

- Achieving perfect performance may not be possible.
- Human-level performance or better could be achieved.

Characteristics of ML Use Cases (4/4)

It is at scale

- Upfront costs are involved: infrastructure, staff, DevOps.
- Setting up an ML system that caters to many ML models concurrently.

Patterns are constantly changing

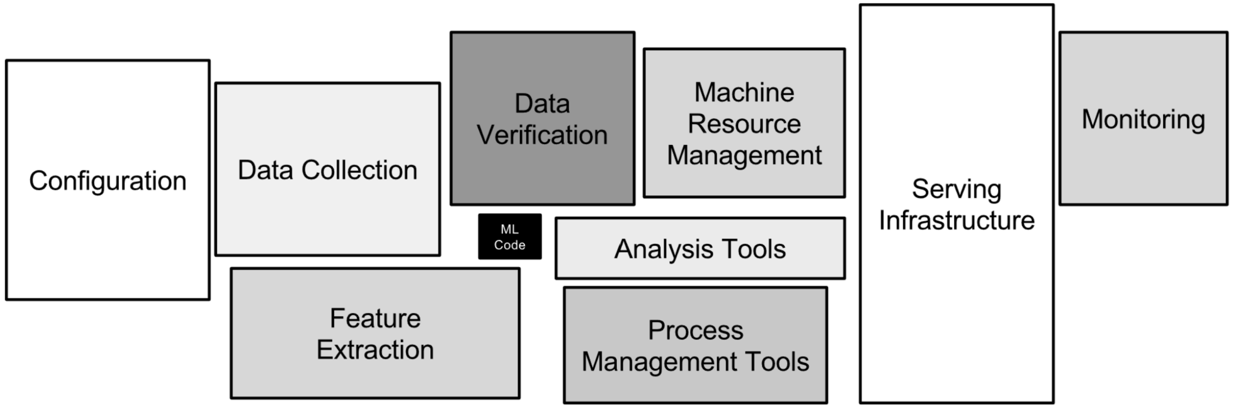
- Hard-coded solutions can become stale and outdated.
- The ML system's environment changes: economics, social behaviour, trends, etc.
- Feedback: the ML system informs a company's actions, affecting, in turn, the company's interactions with the external environment.

ML Systems Design

- ML methods are not ML systems: the learning method needs to be applied to data, assessed, tuned, deployed, governed, and so on.
- ML system design is a system approach to MLOps, i.e., we will consider the system holistically, including
    - Business requirements.
    - Data stack.
    - Infrastructure.
    - Deployment.
    - Monitoring.

ML Systems Design

- MLOps: a set of tools and best practices for bringing ML into production.
- Image: (Sculley, 2015)



How is ML in Production Different?

ML in Research vs Production

Dimension	Research	Production
Requirements	State-of-the-art model performance on benchmark datasets	Different stakeholders have different requirements
Computational priority	Fast training, high throughput	Fast inference, low latency
Data	Static	Constantly shifting
Fairness	Often not a focus	Must be considered
Interpretability	Often not a focus	Must be considered

Business and ML Objectives (1/5)

Different stakeholders require different things

- ML engineers: increase performance or efficiency of recommender system.
- Sales: recommend more profitable options.
- Product: reduce latency.
- Platform: stability.
- Manager: control costs.

Business and ML Objectives (2/5)

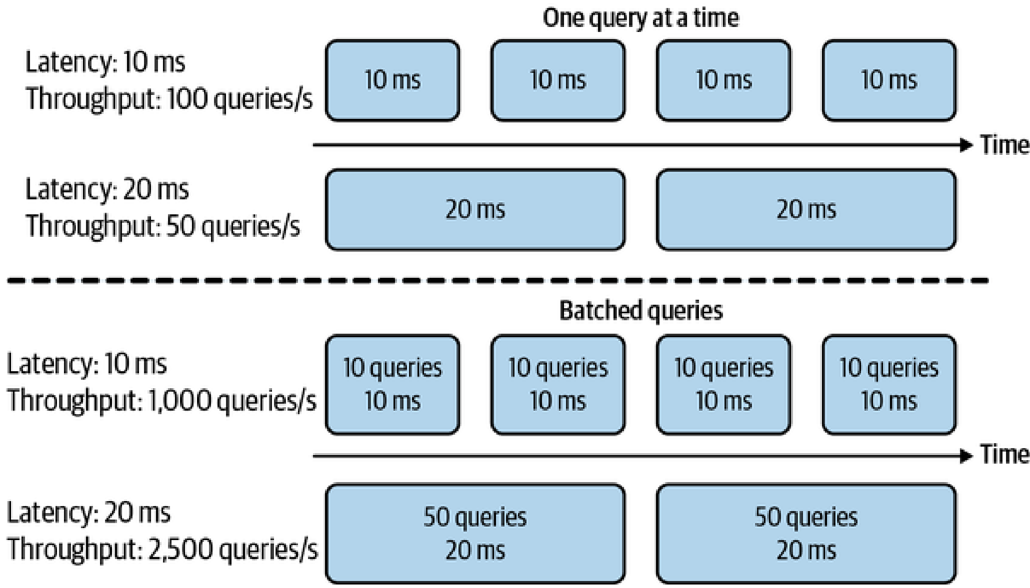
Computational priorities during model development

- Training is the bottleneck.
- Throughput, the number of cases processed, should be maximized.

Business and ML Objectives (3/5)

Computational priorities in production

- Fast inference is desirable.
- Latency, the time between when a query is received and when it is addressed, should be minimized.
- Latency is usually measured using percentiles of time elapsed (e.g., 99th percentile should be below X ms.)



Business and ML Objectives (4/5)

Data

- Data quality.
- Historical vs constantly generated data.

Fairness

- Fair and ethical decision-making is a key requirement.
- ML algorithms make predictions based on encodings of past observations: they can perpetuate the biases in the data and more.

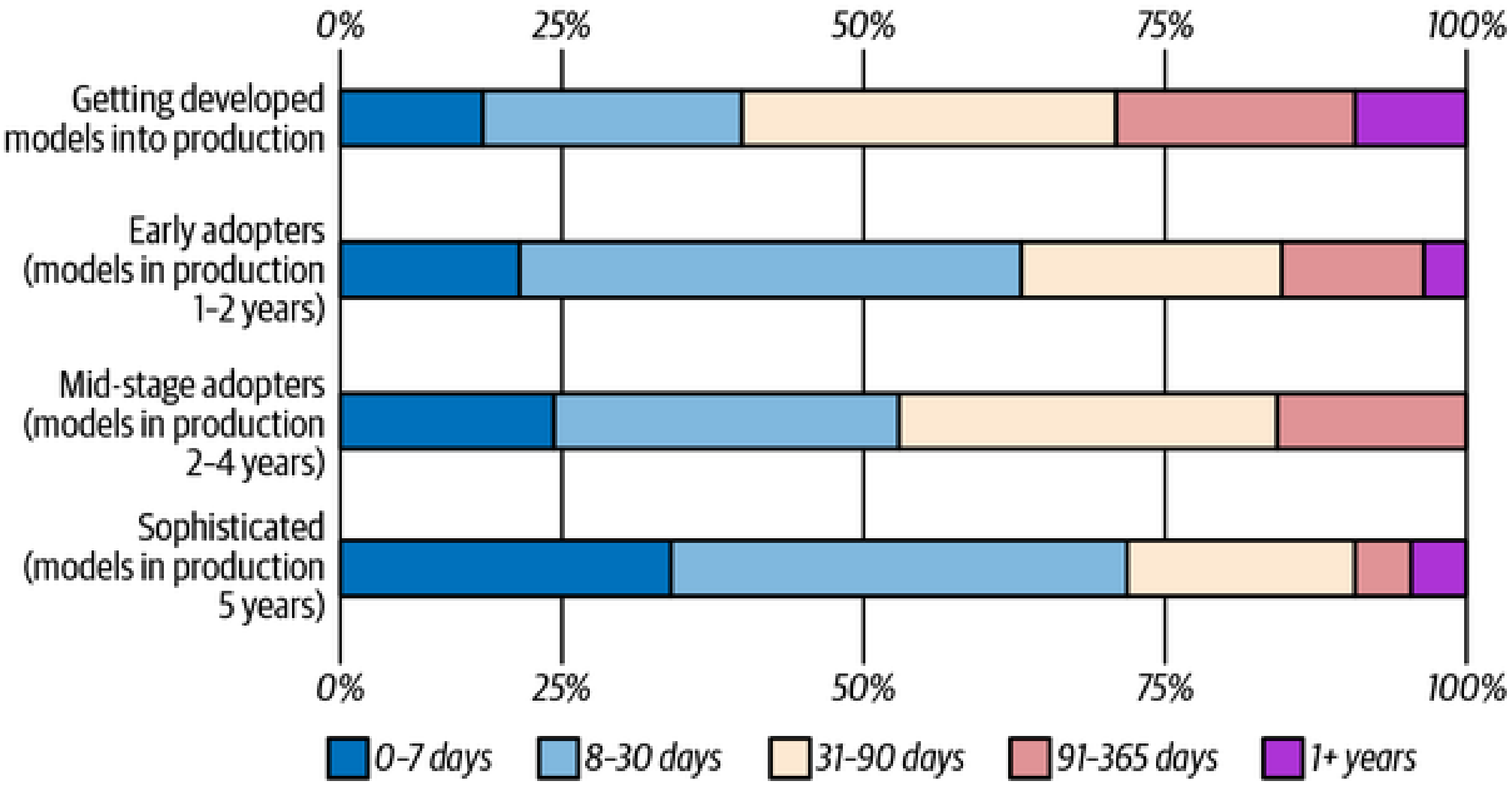
Business and ML Objectives (5/5)

Explainability

- Trust.
- Legal requirements.
- Informativeness: Besides predictions, we require feature importance and other information about our results.
- Transferrability: Can learning from a scenario be applied to other scenarios?

Requirements of ML Systems

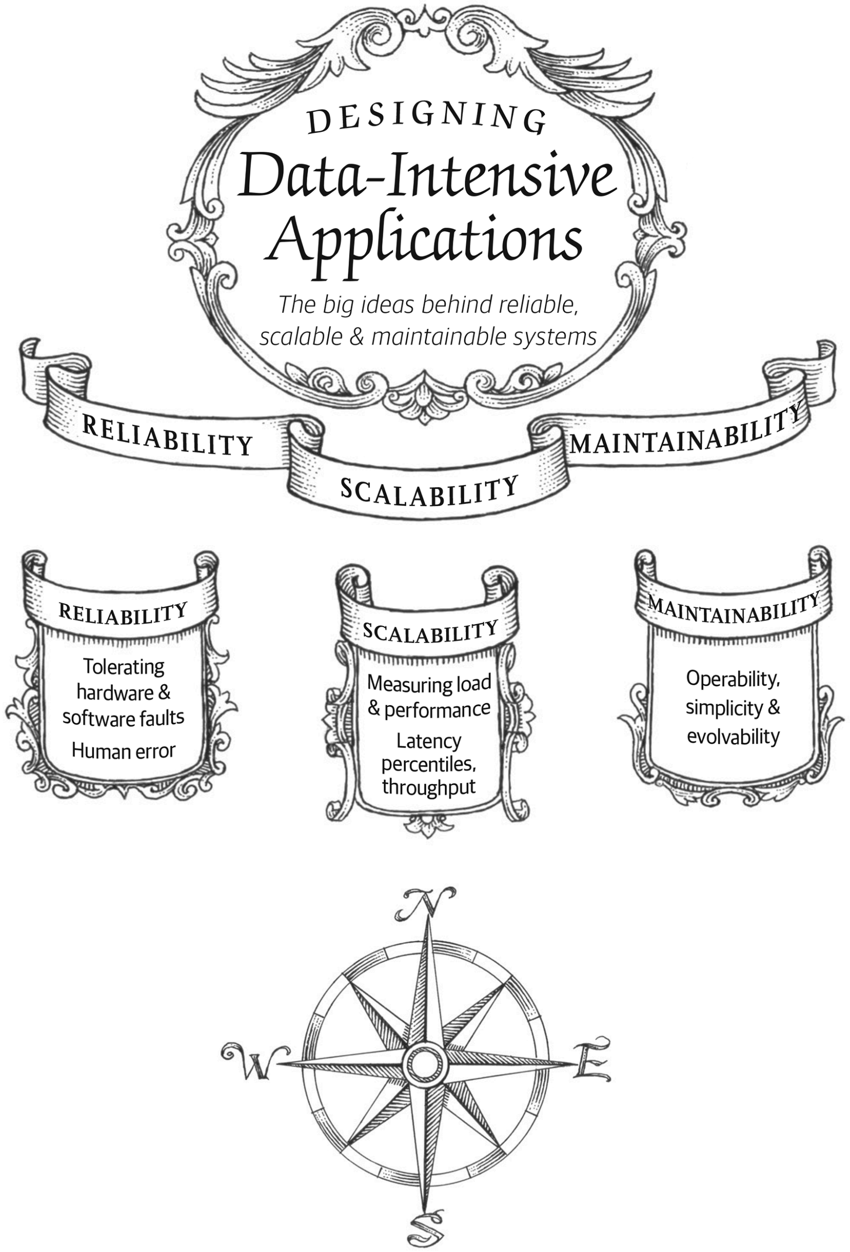
Lead Time to Production



(Huyen, 2022)

Designing Data-Intensive Applications

- Many applications today are data-intensive instead of compute-intensive.
  - The limit factor is data and not computation.
  - Concerns: the amount of data, the complexity of data, and the speed at which it changes.
- ML Systems tend to be embedded in data-intensive applications.
- (Kleppmann, 2017)



Fundamental Requirements of ML Systems (1/2)

- **Reliability**: The system should continue to perform the correct function at the desired level of performance, even in the face of adversity.

- May require reporting uncertainty of results.
    - Remove "silent failures": The system should alert the users to unexpected conditions.
    - If all else fails, shut down gracefully (e.g., close connections, log errors, alert downstream processes, etc.)

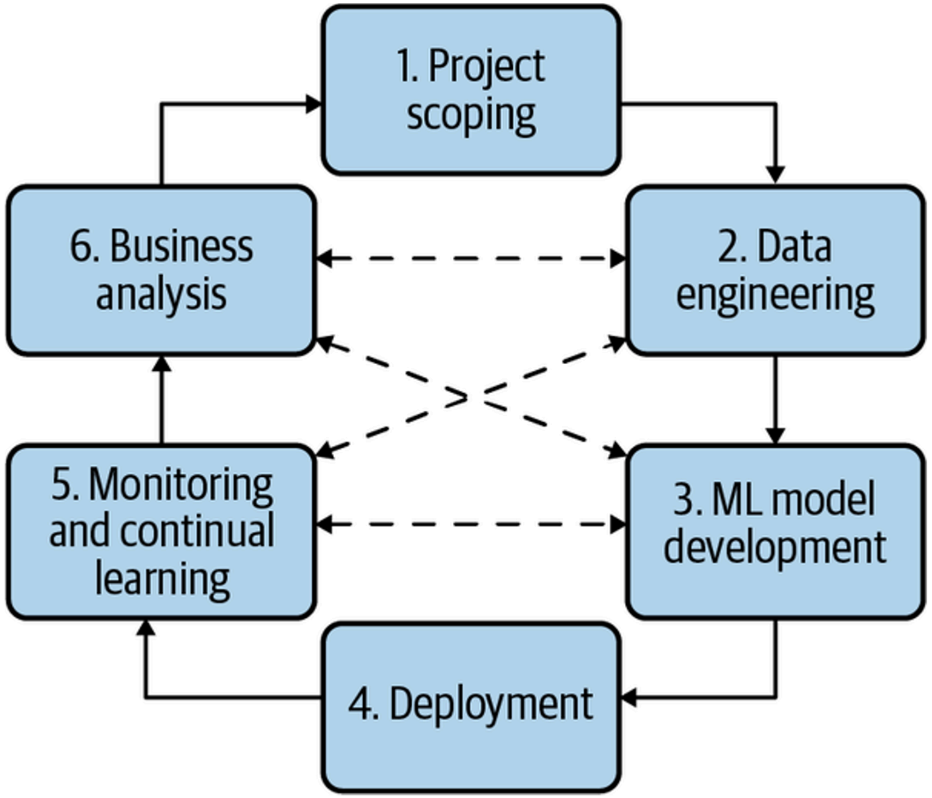
- **Scalability**: To ensure the possibility of growth.
    - Increase complexity.
    - Traffic volume or throughput.
    - Model count.

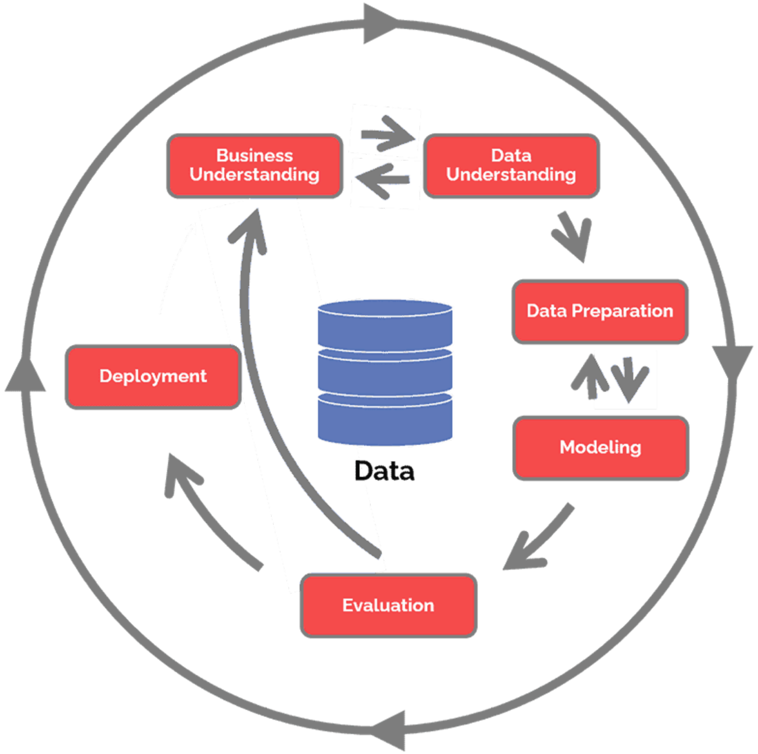
Fundamental Requirements of ML Systems (2/2)

- **Maintainability**: To allow different contributors to work productively on the same system.
    - Maintain existing capacities.
    - Expand to new use cases.
- **Adaptability**: To shifting data distributions and business requirements.
    - The system should allow for the discovery of aspects for performance improvements.
    - Allow updates without service interruptions.

ML System Design: An Iterative Process

Developing ML Systems





Have things changed that much? (Huyen, 2022) and CRISP-DM (c. 1999)

Framing ML Problems

- The output of an ML model dictates the type of ML problem.
- In general, there are two types of ML tasks
  - Classification.
  - Regression.
- A regression model can be framed as a classification model and vice versa.
  - Regression to classification: apply quantization.
  - Classification to regression: predict the likelihood of class.

Framing ML Problems (1/2)

Binary Classification

- Two classes.
- Simplest classification problems

Multiclass Classification

- More than two (mutually exclusive) classes.
- High cardinality (number of classes) problems will be more complex than low cardinality problems.
- High cardinality can be addressed with a hierarchical classification approach: first, classify into large groups, then classify into specific labels.

Framing ML Problems (2/2)

Multilabel Classification

- An observation can have more than one label.
- One approach is to treat the problem as multiclass by creating unique labels out of combinations of individual labels.
- Another approach is one-vs-rest, where each label is treated with a different binary classification model.

Objective Functions (1/2)

- ML requires an objective function to guide the learning process through optimization.
- In the context of ML:

    - Regression tasks generally employ error or accuracy metrics: Root Mean Square Error (RMSE) or Mean Absolute Error (MAE).
    - Classification tasks are generally performed using log loss or cross-entropy.

Objective Functions (2/2)

- Log loss or cross-entropy loss is a performance metric that quantifies the difference between predicted and actual probabilities.
- In a two-class setting, it is given by

$$H(y,p) = -\frac{1}{N}\sum_{i=1}^{n}\big(y_i ln(\hat{p}_i) + (1-y_i)ln(1-\hat{p}_i)\big)$$

- Formulation is related to maximum likelihood: minimizing negative log-likelihood is the "same" as minimizing log loss.

Objective Functions

- Assume the actual value is 1.
- If the model is confident and correctly predicted 0.9, then

```
Loss = -(1*ln(0.9)) = 0.1054
```

- If the model is unsure and predicts 0.5, then

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Loss = -(1*ln(0.5)) = 0.6932
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- If the model is confident but incorrectly predicted 0.1, then

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Loss = -(1*ln(0.1)) = 2.3026
```

Our Reference Architecture

The Flock Reference Architecture

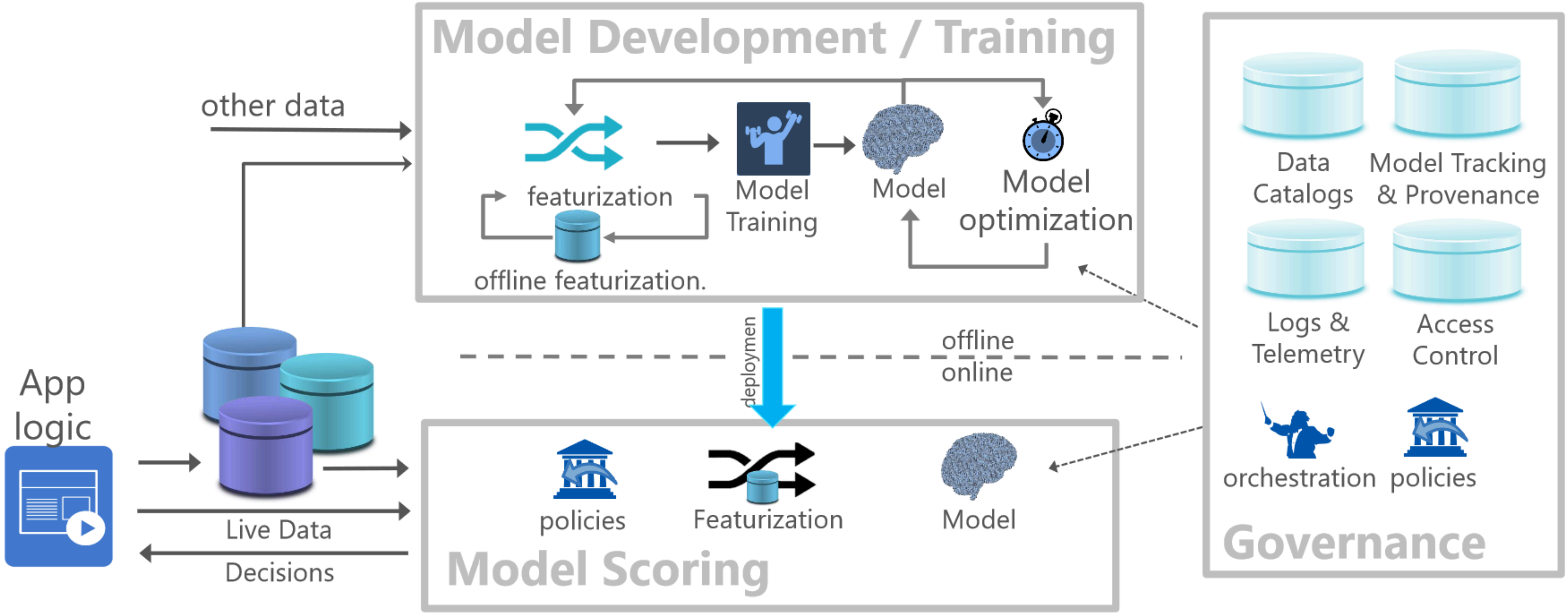

Figure 1: Flock reference architecture for a canonical data science lifecycle.

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