Artificial Intelligence for Project Managers Are You Ready?

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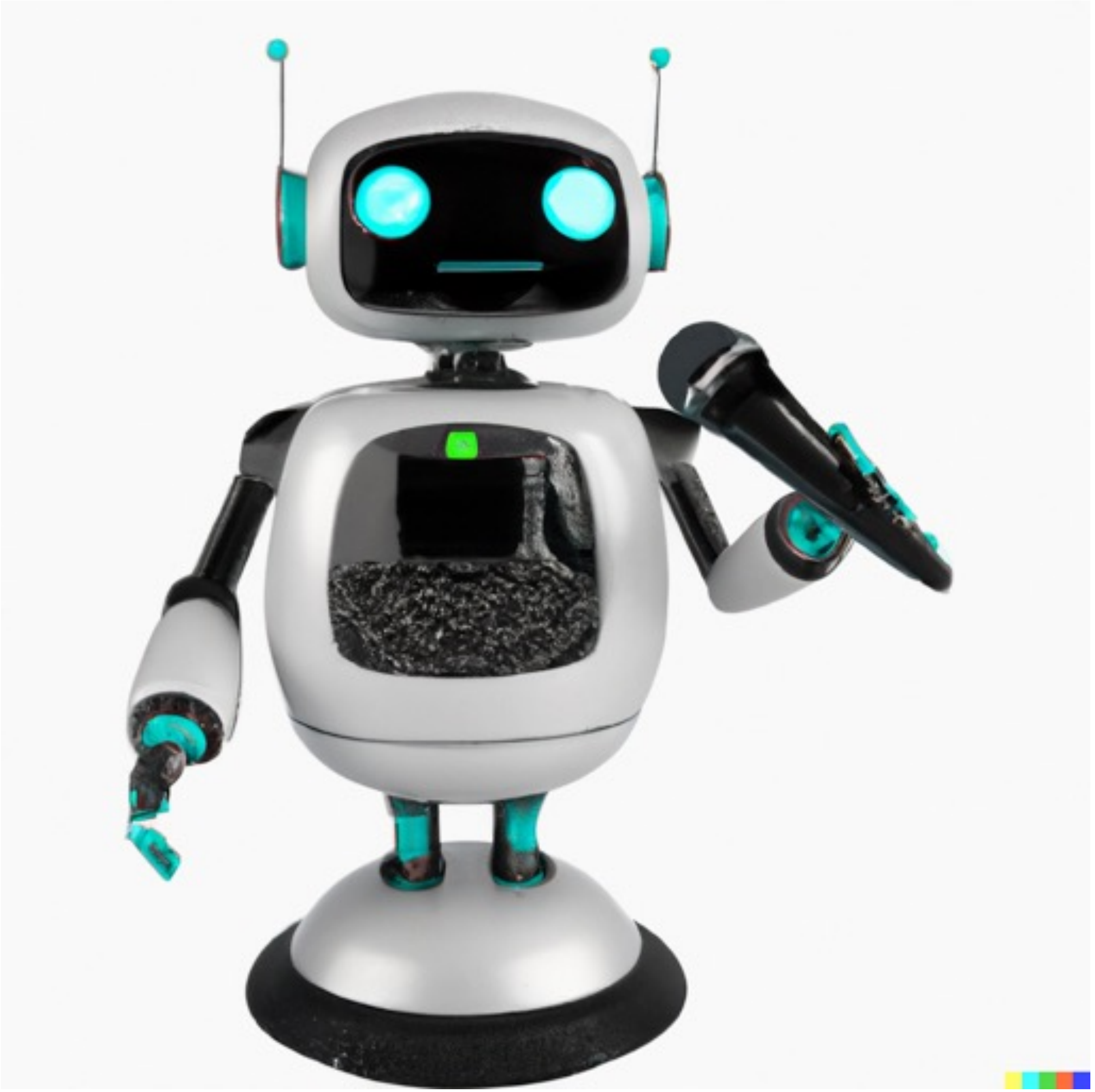


Agenda

1. What is(n't) AI?
2. Are you ready for AI?
3. The lifecycle of an AI/ML initiative
4. Overcoming the data quality challenge
5. Ethical considerations with AI
6. Business implications of AI
7. Success and failure factors for AI initiatives

What Is(n't) AI?

Artificial intelligence is software, not magic

Defining Artificial Intelligence

Artificial Intelligence (AI)

Computer systems able to perform tasks normally requiring human intelligence.

Machine Learning (ML)

Computer systems with the ability to learn without being explicitly programmed. Training of ML models often involve significant data curation, sometimes including data labeling.

Deep Learning (DL)

Computer systems with ”brain-like” logically structured algorithms called artificial neural networks (ANNs).

Categories of Artificial Intelligence

We are here →

Artificial Narrow Intelligence (ANI)

- Specializes in one area and solves one problem.

We are afraid of this →

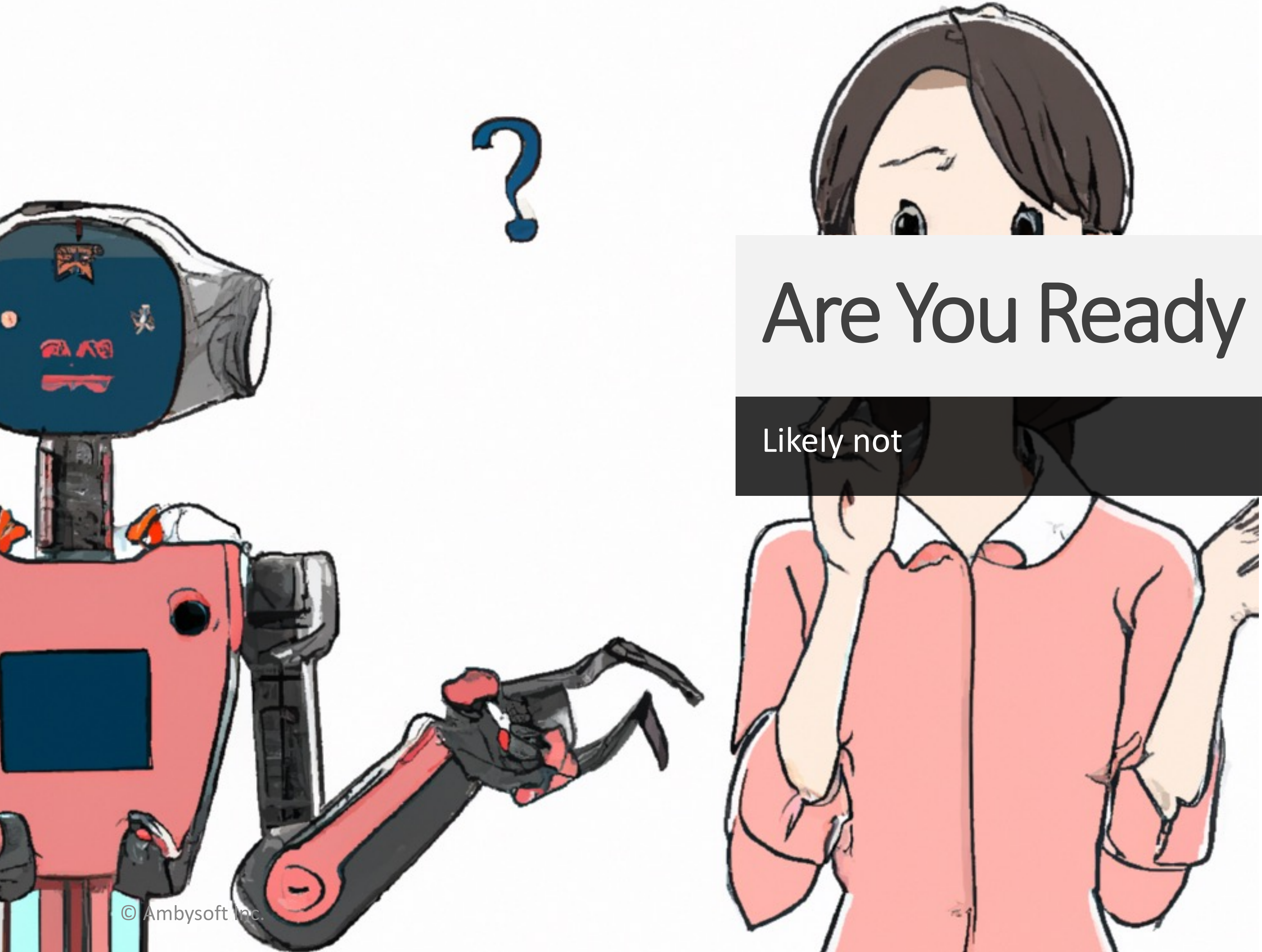
Artificial General Intelligence (AGI)

- As smart, or smarter, than a human with a wide range of abilities.

And really afraid of this →

Artificial Super Intelligence (ASI)

- An intellect that is much smarter than the best human in practically every field.



Are You Ready For AI?

Likely not

Does your leadership understand AI?

Do you have a realistic vision for what you want to achieve with AI?

Do you have AI expertise available, including data scientists?

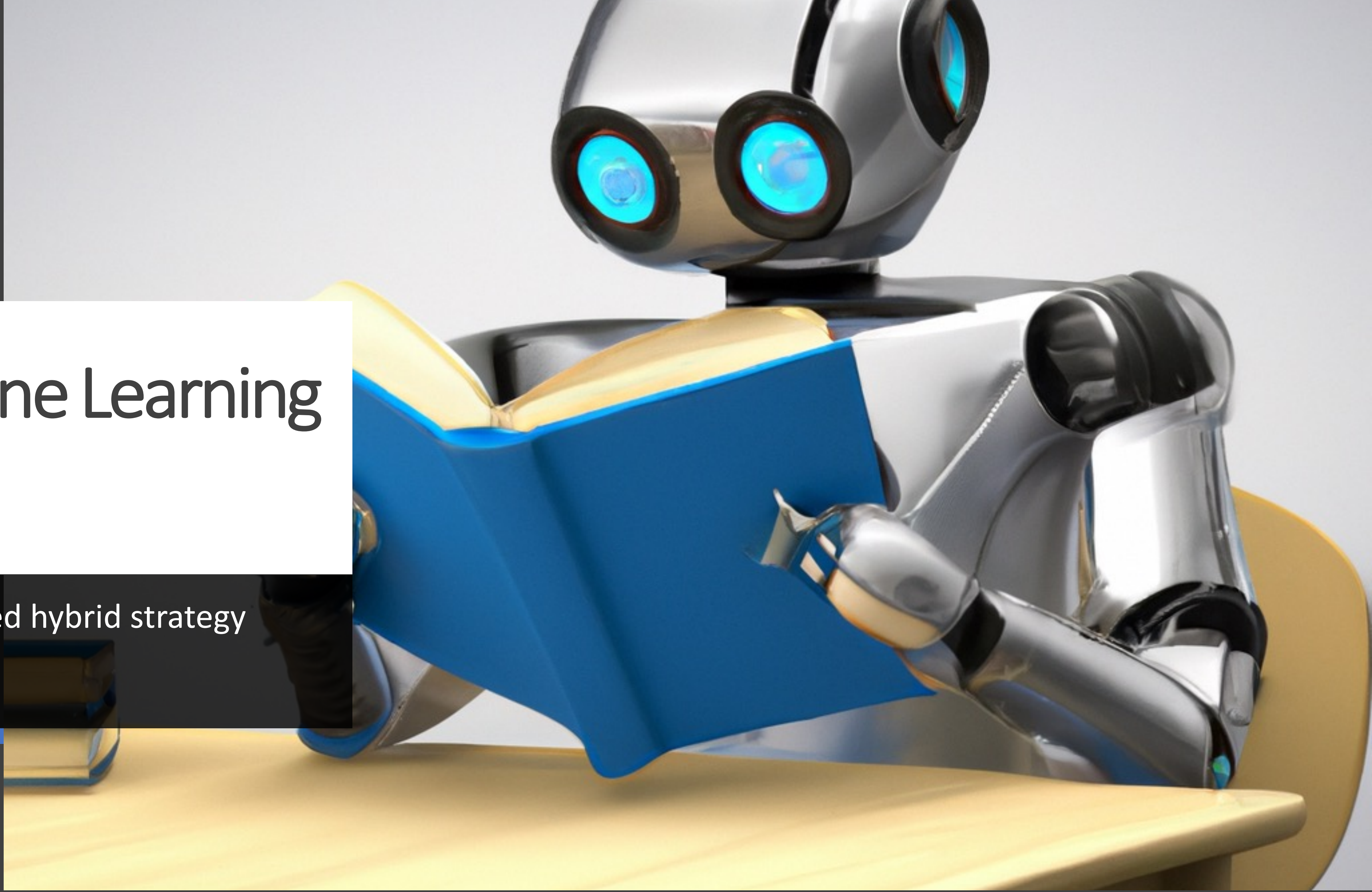
Can you staff teams with dedicated, diverse, and interdisciplinary people?

Do you understand your current level of data technical debt?

Does your organization have a clear AI strategy?

The Machine Learning Lifecycle

You need a disciplined hybrid strategy



Four Uncomfortable Observations and a Claim

This isn’t a project. Treating this as a series of projects MIGHT work, but it’s most likely just going to inject needless cost, risk, and time into your initiative.

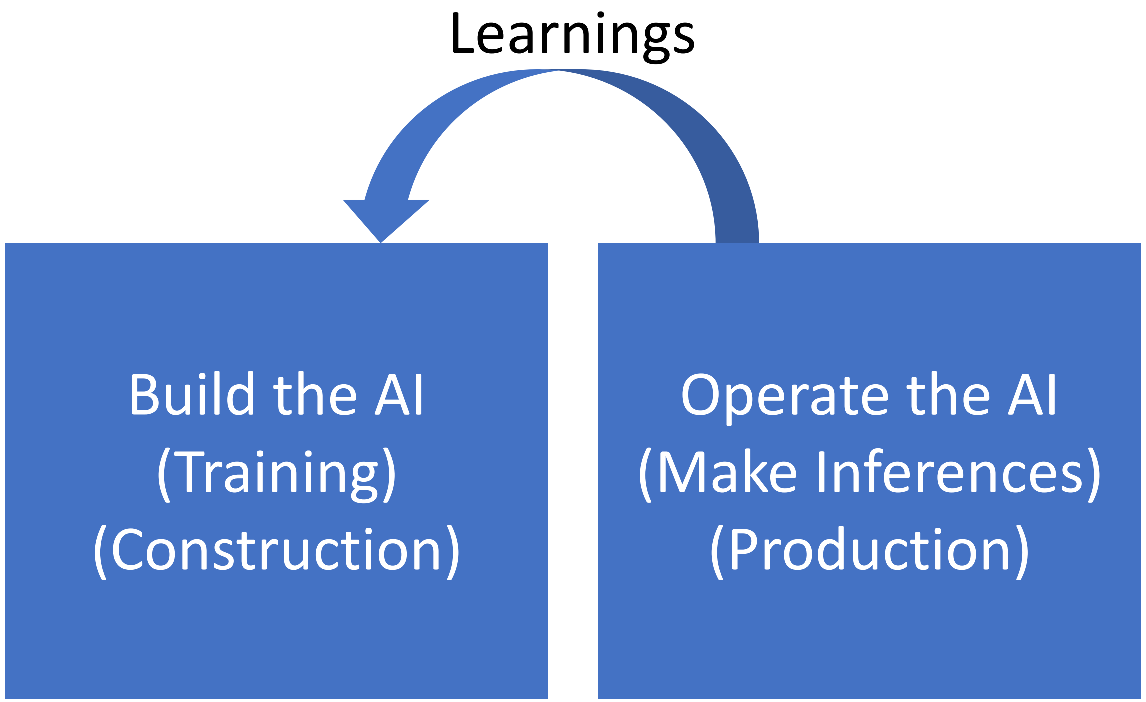
A “predictive” approach to an ML initiative has exactly zero chance of success.

A “pure agile” approach to an ML initiative has very little chance of success.

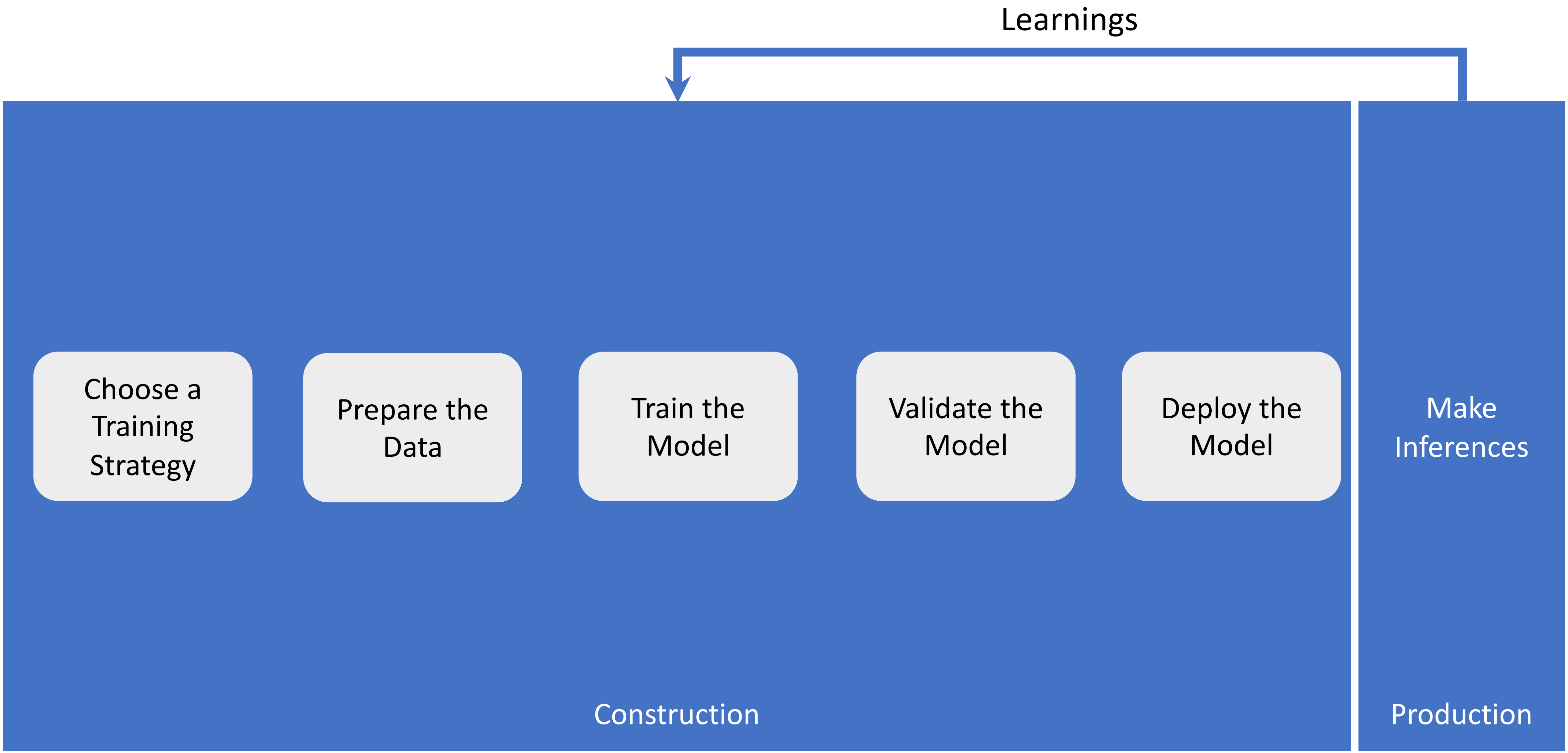
A “pure lean” approach has a better chance of success, but still isn’t ideal.

Claim: A disciplined hybrid strategy will provide your highest chance of success.

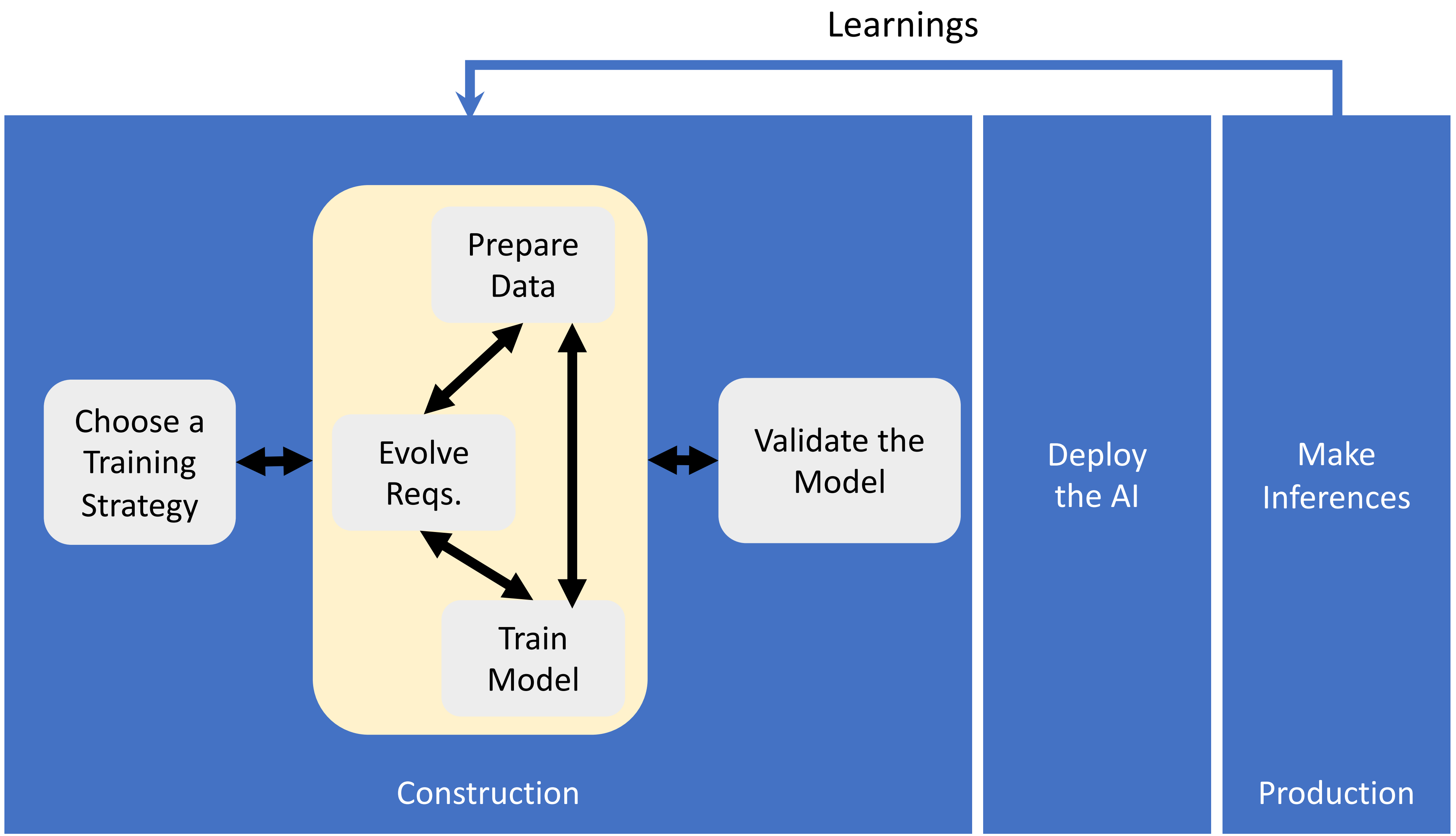
A Very High-Level View of the ML Lifecycle



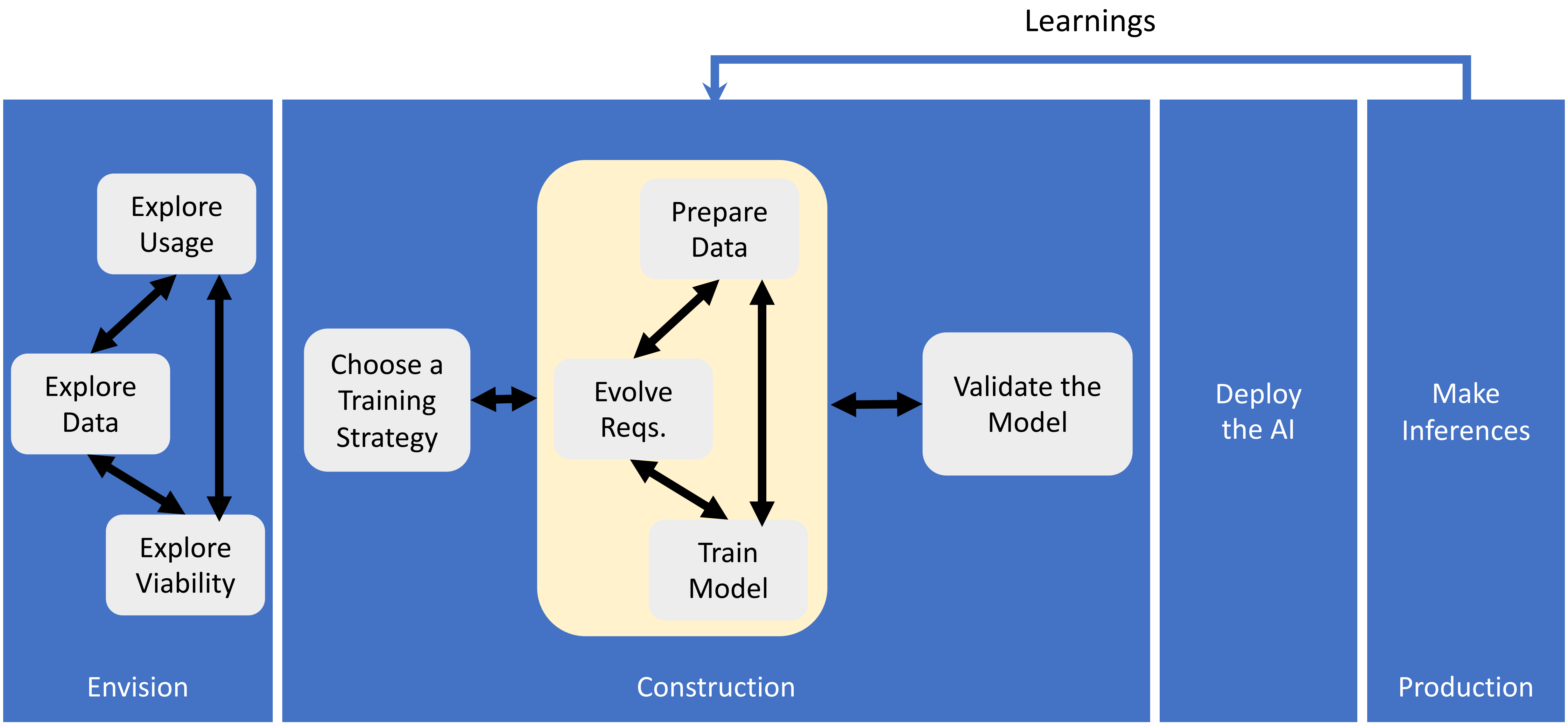
Adding Details to Construction



Construction is Iterative and Incremental



A Machine Learning Lifecycle



Common Lifecycle Risks

Learnings

- Model drift
- Function creep

Envision

- Misaligned stakeholders
- Inadequate data
- Biased data
- Difficult to create diverse, cross-disciplined team
- Non-viability
- Insufficient exploration
- “Detached” exploration

Construction

- Data technical debt proves worse than originally believed
- Creation of a biased model
- Creation of an inadequate model
- “Never-ending” edge cases ➔ Unpredictable timeline
- Non-viability

Deploy the AI

- Unprepared stakeholders

Make Inferences

- Biased usage
- Non-viability

Overcoming the Data Quality (DQ) Challenge

It is time to pay the data piper

Potential DQ Issues Faced by ML Teams

- Biased data
- Insufficient data
- Semantic differences across sources
- Missing data values
- Inconsistent data values
- Unclear/unknown sources of record
- Ownership limitations
- Privacy/security
- Data poisoning
- Data drift
- and many more…

Data Quality Techniques for ML Teams

Data cleansing

Database refactoring

Manual regression testing

Data masking

Synthetic training data

AI data cleansing (e.g. for MDM)

Automated regression testing

Data stewards

Data guidance (standards, guidelines, …)

Data labeling

Database modeling

Executable business rules (in the db)

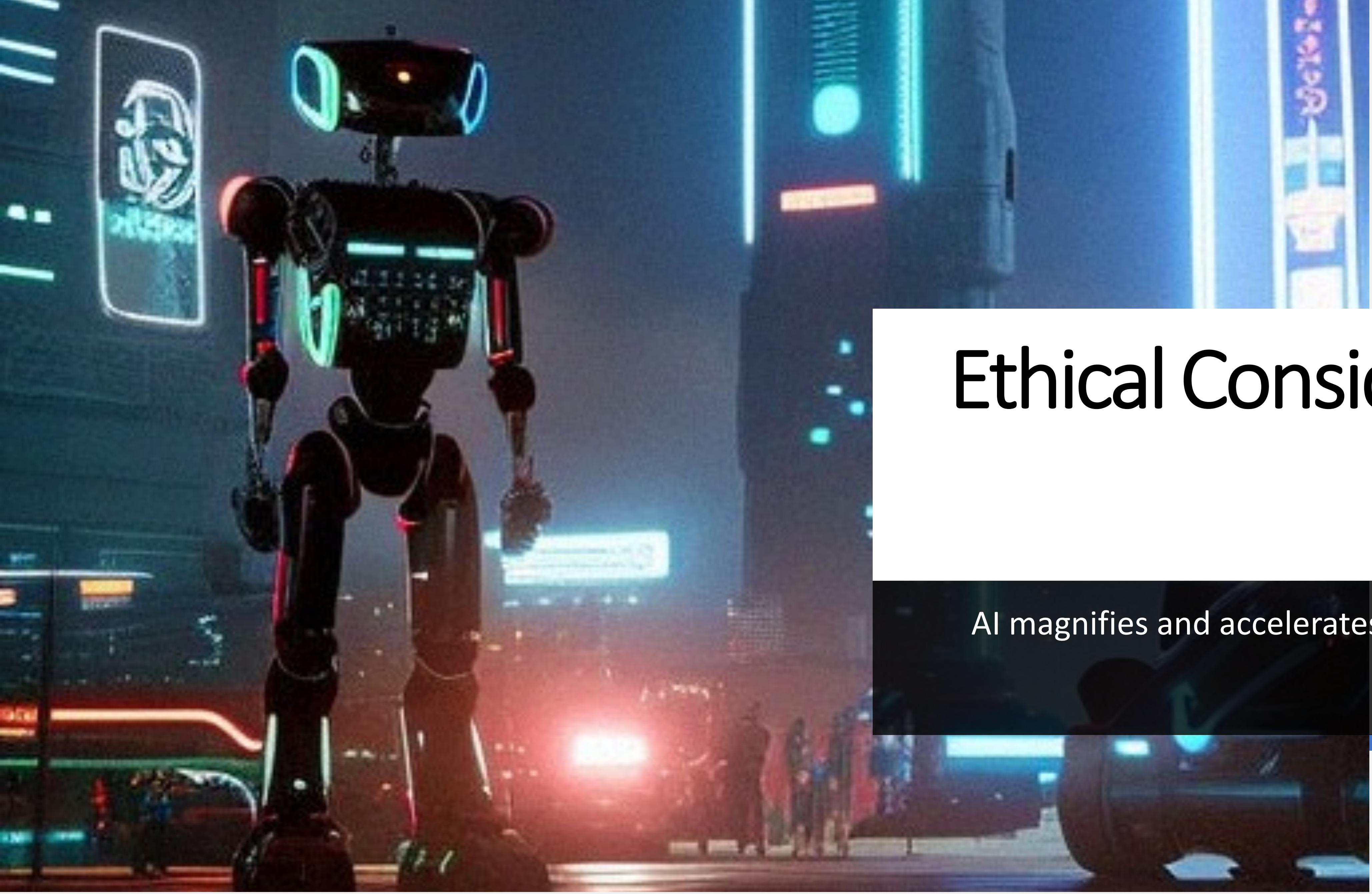
Defect logging

Transformation (as in ETL)

Reviews (design, architecture)

Data architecture

and more….



Ethical Considerations with AI

AI magnifies and accelerates your existing biases

Ethical Consideration: Safety

Have you considered the potential of harming people?

Have you considered physical harm, mental harm, financial harm, … ?

Ethical Consideration: Human Dignity

Do you understand the overall process that the AI is part of?

Does your model take societal values into account?

Does you model take multi-cultural considerations into account?

Ethical Consideration: Fairness

Have you actively considered bias in the development of your model?

Is your model appropriately gender/race/culture/age neutral?

How do you know?

Ethical Consideration: Accountability

If the AI makes a decision, who will be held responsible for it?

Can you explain how a decision was made?

Do you know the provenance of the data used to train your model?

Ethical Consideration: Trustworthiness

Can your model's inferences/predictions be challenged?

Are they explainable?

Are they fair?

Business Implications of AI

AI will force you to rethink everything

Potential Benefits of AI

- Augment the capabilities of your staff
- Provide new/improved offerings to your customers
- Enhance existing business processes
- Replace existing business processes
- Increase the reach and scale of your customer offerings
- Increased operational efficiency
- Increased consistency in decision making
- Improved governance

Potential Risks of AI

- Rapid, dramatic, and public failure
- Reputational risk
- Unwarranted trust in AI-generated results
- Unrealistic expectations of AI capability
- Biased decision making

Success and Failure Factors of AI Initiatives

Are you ready?

Are You Ready for an AI Initiative?

Do you have realistic expectations?

Do you understand the ethical issues surrounding AI?

Are your leaders capable?

Is your data ready?

Can you build diverse, cross-disciplinary teams of dedicated staff?

Have you defined your way of working (WoW) for the initiative?

Would you like this presentation
for your chapter, user group, or organization?

Reach out to me at ScottAmbler.com

Thank You!

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Additional Slides

The Agile Data Mission

To share proven agile and lean strategies for data initiatives.

Learn more at AgileData.org

The Agile Modeling Mission

To share proven and effective strategies for modeling/mapping and documentation.

Learn more at AgileModeling.com

(More) AI Terminology

It’s confusing at first, but you’ll get it

Additional AI Terms That I May Use Today

- **Data labeling**. The process of identifying raw data, such as images or text, and adding one or more meaningful labels to it to provide context so that a machine learning (ML) model can learn from it.
- **Foundational model**. An AI model trained on broad data at scale that can then be adapted to a wide range of downstream tasks. Can provide a basis from which to start your own model development. Examples: BloombergGPT and BioGPT.
- **Semi-supervised learning**. A model training approach that uses both labeled and unlabeled data, a hybrid technique between supervised and unsupervised learning. Typically only a small percentage of the data is labeled, as labeling tends to be expensive. Also called weak supervised learning.
- **Supervised learning**. A model training approach where the model is provided examples of inputs, it predicts outputs, and the model is corrected accordingly.
- **Unsupervised learning**. A model is trained without known outputs. The model is given data and the goal is to find interesting patterns in it. Since we don’t know what those patterns will be, there is no obvious way to provide corrections.