Camera On

How do you feel? Type in the chat!

AI for Product Managers

Operationalizing AI

- Welcome and Introduction
- AI: Unpacked
- **Operationalizing AI**
- Data Privacy & Ethics
- Beyond Production
- Bring it Home

Trivia

By one estimate, a supervised deep-learning algorithm will generally achieve acceptable performance with around how many labeled examples per category?

Source: McKinsey

Type your answers in the Chat Box!

A. 1,000
B. 5,000
C. 50,000
D. 100,000

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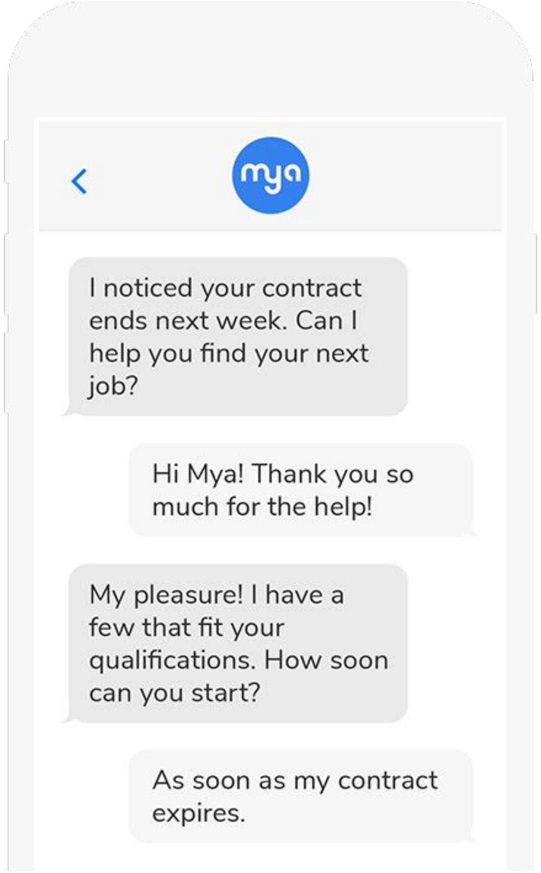
Real Cases:
Mya

What the user sees: An AI-powered chatbot that manages their job application process.

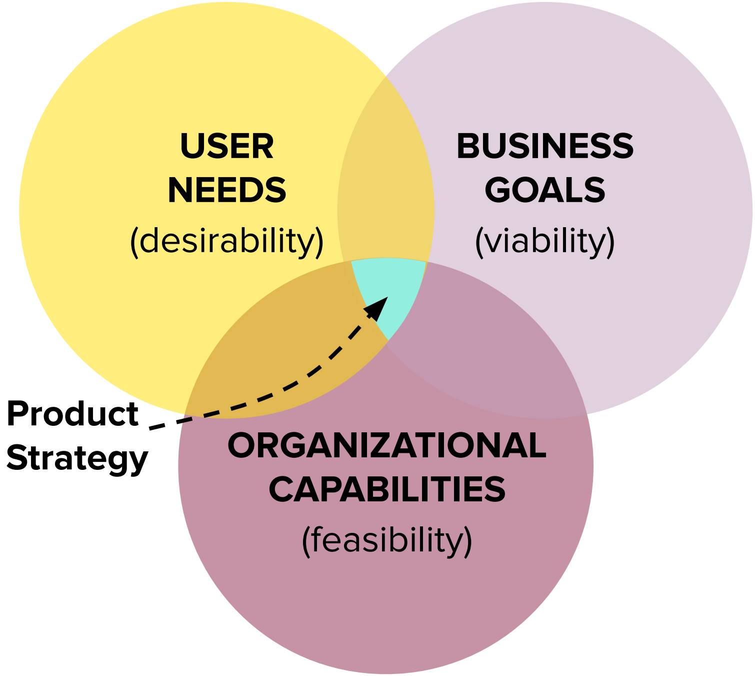
Under the hood:

- ML Frameworks: Python Machine Learning and Natural Language processing Models.
- High-level languages: Python and Ruby.
- High-level languages: HTML, CSS, JavaScript to present the front-end.
- Data ingestion pipelines: AWS.
- &, more!



The PM Lens

1. What problems do users have? What "job" are they looking to accomplish? (**Desirability**)
2. How does the business benefit from solving the user problem? (**Viability**)
3. How can we build the solution to leverage our strengths? (**Feasibility**)



Barriers to AI Implementation

Enterprise Maturity

56% of respondents said that acquiring new skills will be required to do both existing and newly created jobs, according to a Gartner Research Circle survey

Fear of the Unknown

42% of respondents don't understanding AI benefits and use in the workplace. Success depends on considering both tangible and intangible benefits, and determining how to meaningfully quantify them.

Full data scope + data quality

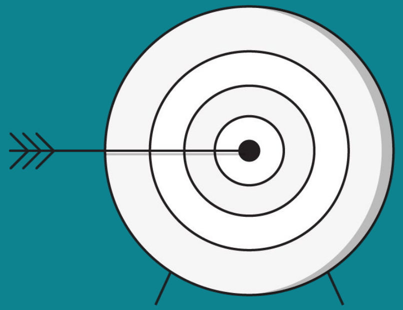
Successful AI initiatives depend on a large volume of data from which organizations can draw insights. The more complex the situation, the more likely the situation will not match the AI's existing data, leading to AI failures.

A Good ML Problem

A machine learning algorithm can be trained to do one thing well. Complex questions require the use of multiple machine learning algorithms to work together.

The key to a good ML problem is:

- Breaking the business question down into a system of related questions & processes
- Thoroughly brief the team on the problem, metrics & what success looks like
- Building the appropriate data to support each ML process
- Determining exactly WHAT you need the output to do e.g. *provide insight or automate a decision*



Business Questions → Data Questions

Goal: Predict daily cloud usage within a Mean Absolute Percentage Error (MAPE) of 5%.

Data questions:

- What drives cloud usage?
- At what level of granularity should we investigate usage?

What other questions might we want to answer to allow us to best make our prediction?

Make Better Requests of Data Scientists

1. **Share the whole story.** What is the objective? What problem are you trying to understand? Why do you need the product?

2. **More is more.** Share the specific parts of the objective that are important to learn about (channel, region, time period, customer segment, etc.).

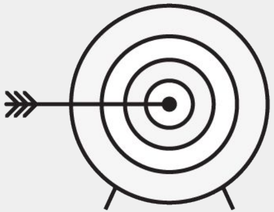
3. **What actions are enabled?** Explain what you hope to do with the product once built.

4. **Comparison is context.** How do we know if the output is “good” or not? Explain what the data should be compared against.

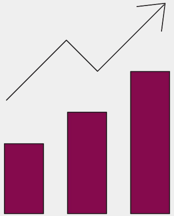
Established KPIs

Determine How You’ll Measure Success

Save Time & Money



Tactical or strategic



Revenue Growth

Established KPIs

Translate into ML metrics

Error Rate

Accuracy related metrics

Improvements over baseline & consistency

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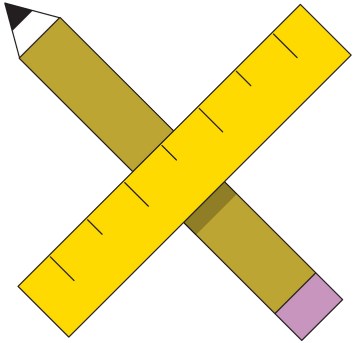
Building Strong Data for Success

Machine learning algorithms are often limited by a lack of good data. Before going down the ML path, **PMs must find and define what good data looks like**.



Ideal data: What would your ideal data look like? Does it exist or can it be created or accessed? Making a list of ideal data to reference with your peers, data teams and the data science team is a critical step!

Enough examples: Do you have enough examples of data to learn from? Some algorithms, while not as performant as truly advanced models, can be effective with as little as a few hundred examples. Others may require millions of examples.

Labeled data: Does your data align with your problem? A “Label” is the outcome you want your algorithm to learn from – good vs bad, class 1 vs class 2, etc.

Getting Labeled Data

One of the biggest challenges a team will experience is getting the right data. Some problems seem simple, and then become more complex as they are dissected.

Goal: Company A wants to be the best at image recognition

- What is a good image?
- Is it the same for all people?
- Good in a technical or aesthetic sense?

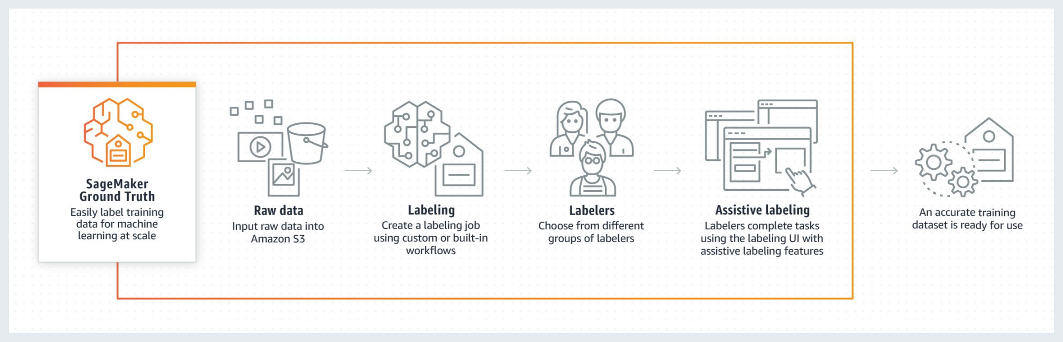
Operationalizing AI

Getting Labeled Data

A large part of the project, even before you can define feasibility with the data science team, will be getting good labeled data.

Approaches:

- Working with your data team to build a sample dataset
- Manually label data
- Shop for an available dataset in 2nd or 3rd party data
- Leverage a tool like AWS ground truth to create labels on your own data



What do you want your product to do?

Appropriate task: Are you automating many decisions/labels? Where you can't just look the answer up perfectly each time?

Expected outcome: The task should take no-more than a second to decide.

i.e. Is this a yellow line?

i.e. When should I merge?

Building Strong Data for Success

The term ”unicorn” is overused in data science to talk about the ideal candidate, peer, system, environment etc. **When data scientists are working with product managers, a ”unicorn” is someone who…**

- Clearly states the business problem with defined success
- Breaks the business problem into clear subproblems (ideally with assumptions and context added)
- Provides a set of available training data
- Understands the data science lifecycle

You cannot start the data science process until all of these are captured!

Discussion:

Design for Delight - Customer Benefit

10 minutes

Goal: Define a plan to deploy an AI solution that is customer-first and provides measurable benefit.

1. **What is the customer benefit**? We want a clear understanding of the customer problem we are solving based on D4D!
2. **How will you measure customer benefit**? The customer benefit must be measurable using data from the customer experience.
3. **Which team(s) need to be involved**? Identify the right partners in Product Development, Intuit AI, Data Engineering, Program Management, and Product Management. Define a DACI.
4. **Are there any ethical or privacy aspects to this business problem**? Check if the proposed use of data is compliant with our Data Stewardship Principles and our AI Governance Principles.

Define your proposal in your break out groups and prepare to share out!