VAC (Vacation)

Remote Design Sprint

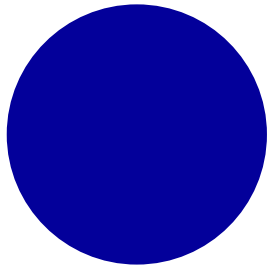
2020

Intro

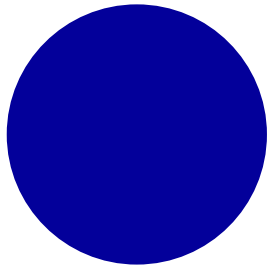
Over the last 12 months working on machine learning driven experiences I realised that there's a lot of value in synthesizing my learnings to create a set of design principles to help guide ML driven experience design across the organisation.

What's machine learning?

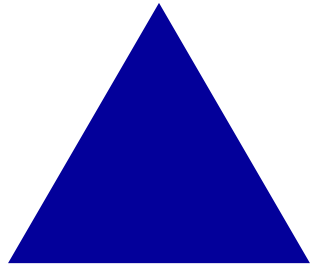
Supervised learning



Input
(Data)



Input
(Data)

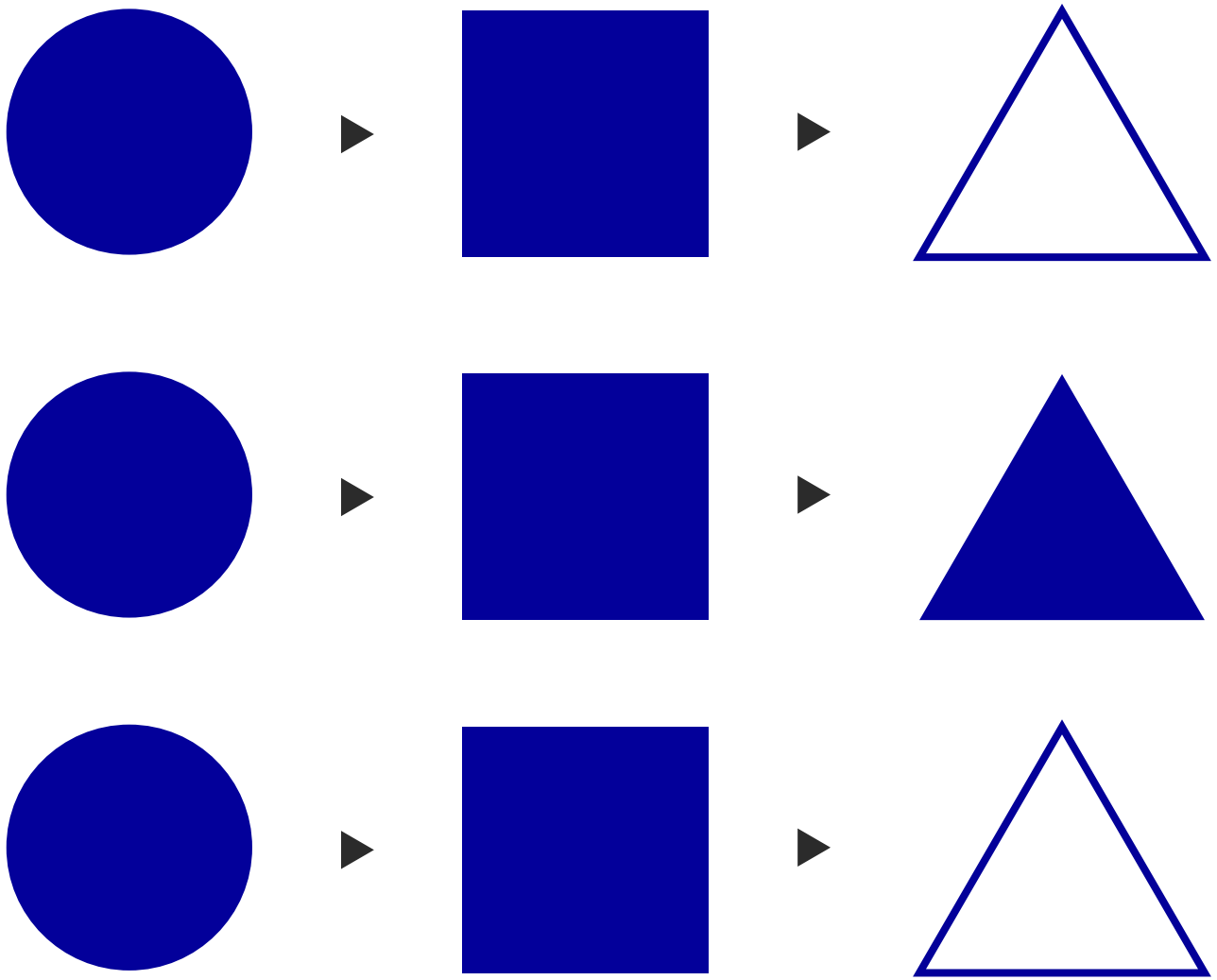


Output
(Prediction)

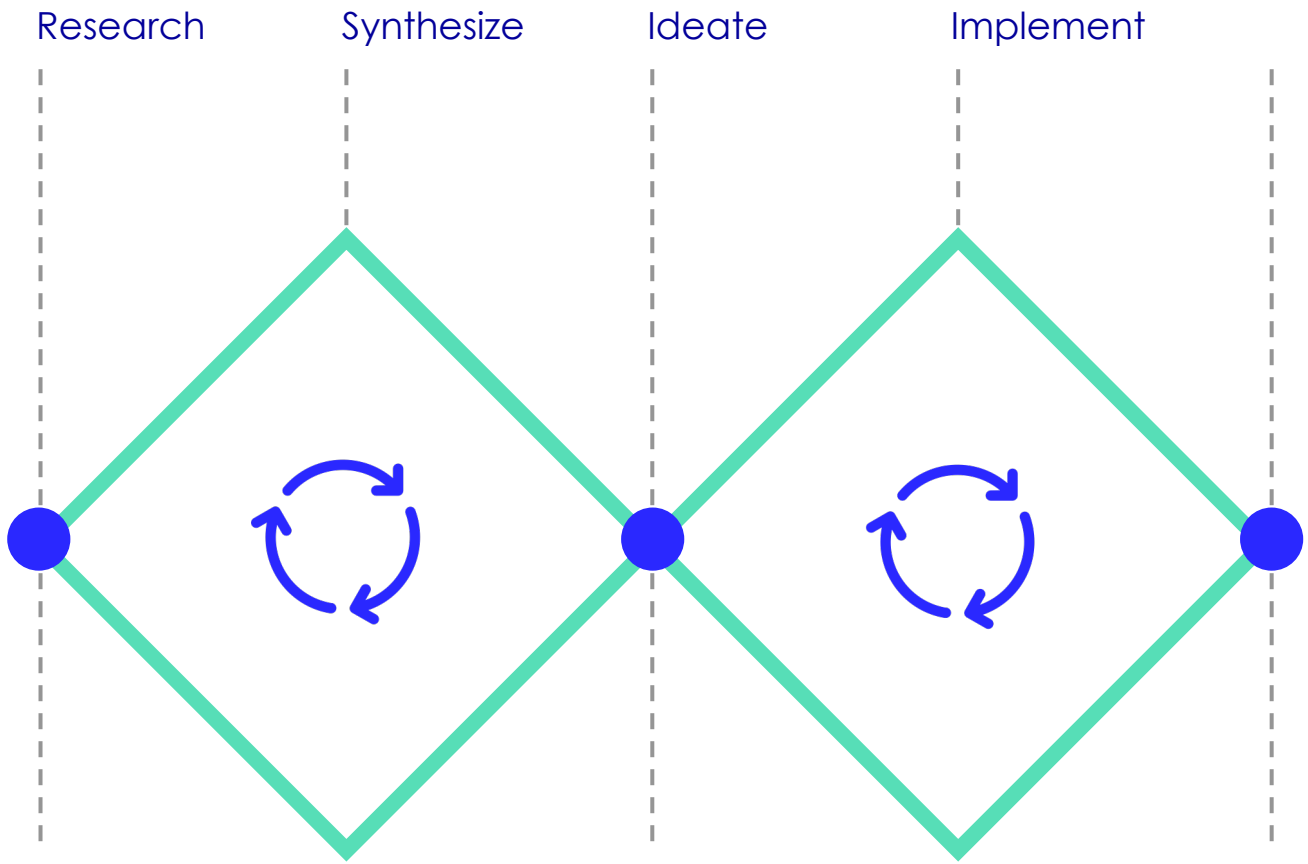
Input
(Data)

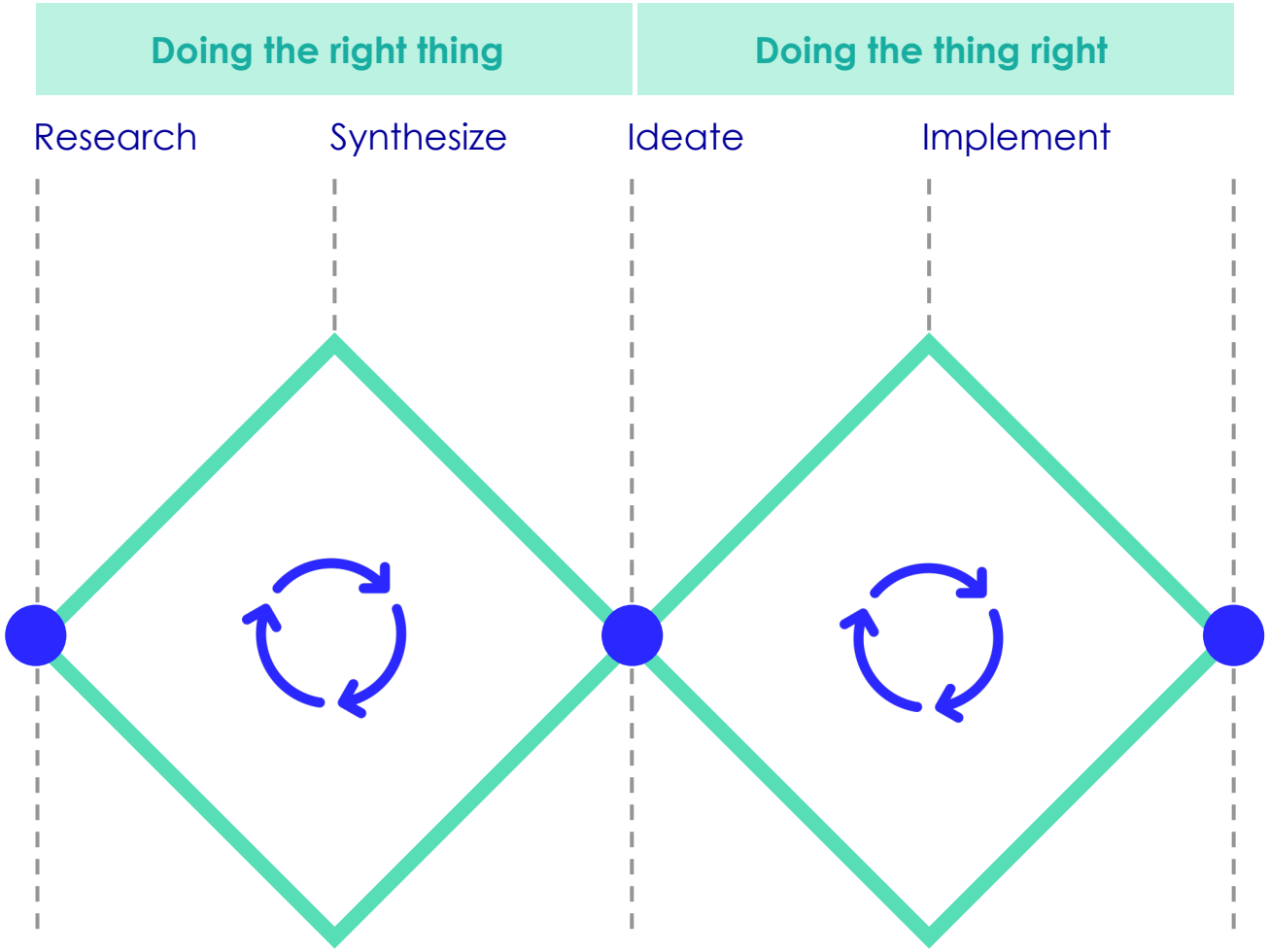
Machine Learning
(Algorithm)

Output
(Prediction)



What’s design?


Research
Synthesize
Ideate
Implement


Doing the right thing
Doing the thing right
Research
Synthesize
Ideate
Implement

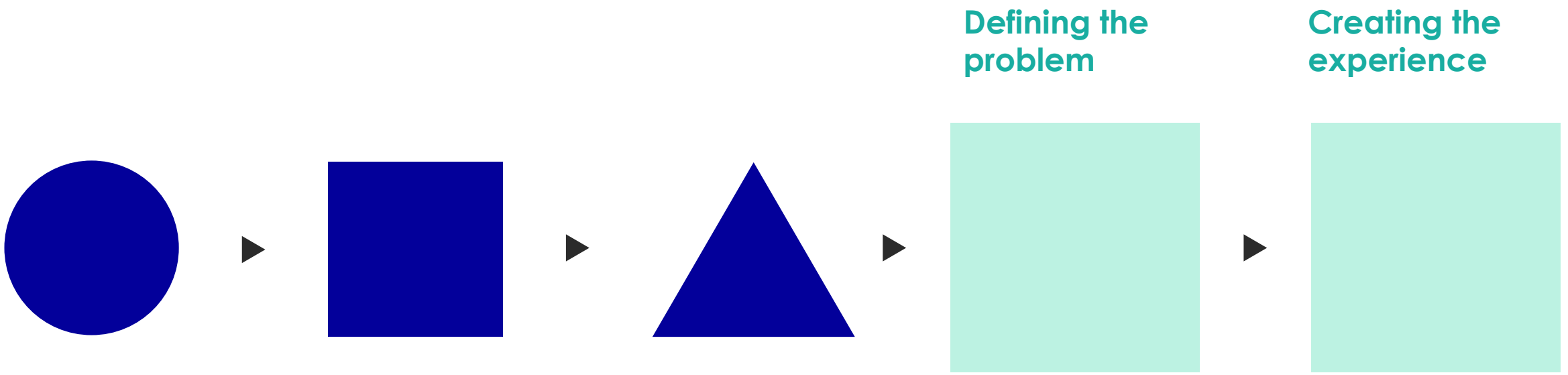
Defining the problem

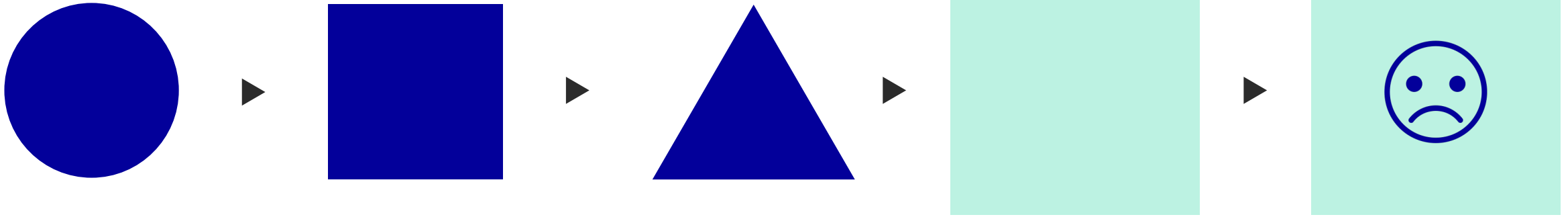
Creating the experience

Input
(Data)

Machine Learning
(Algorithm)

Output
(Prediction)


Defining the problem
Creating the experience
Input
(Data)
Machine Learning
(Algorithm)
Output
(Prediction)

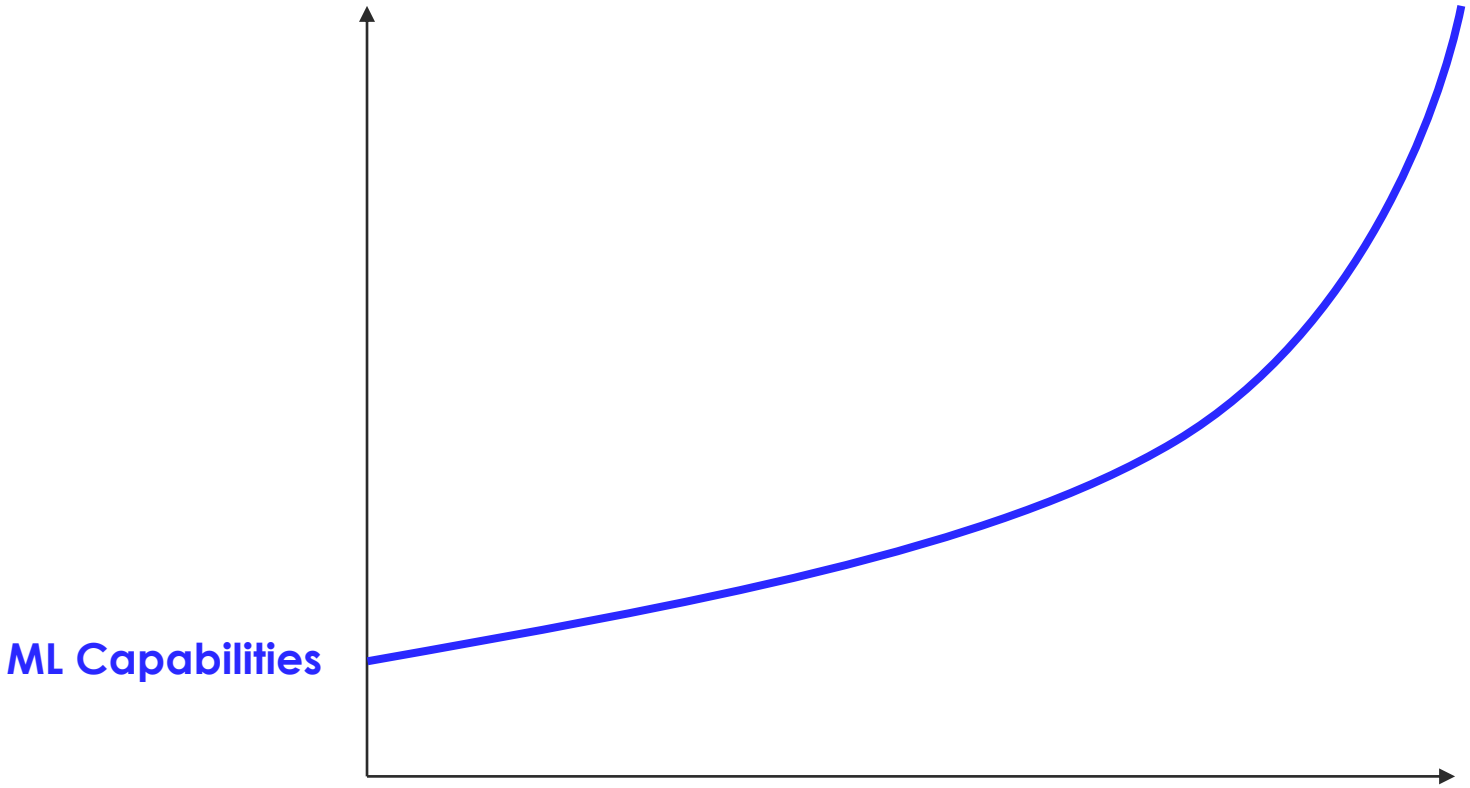


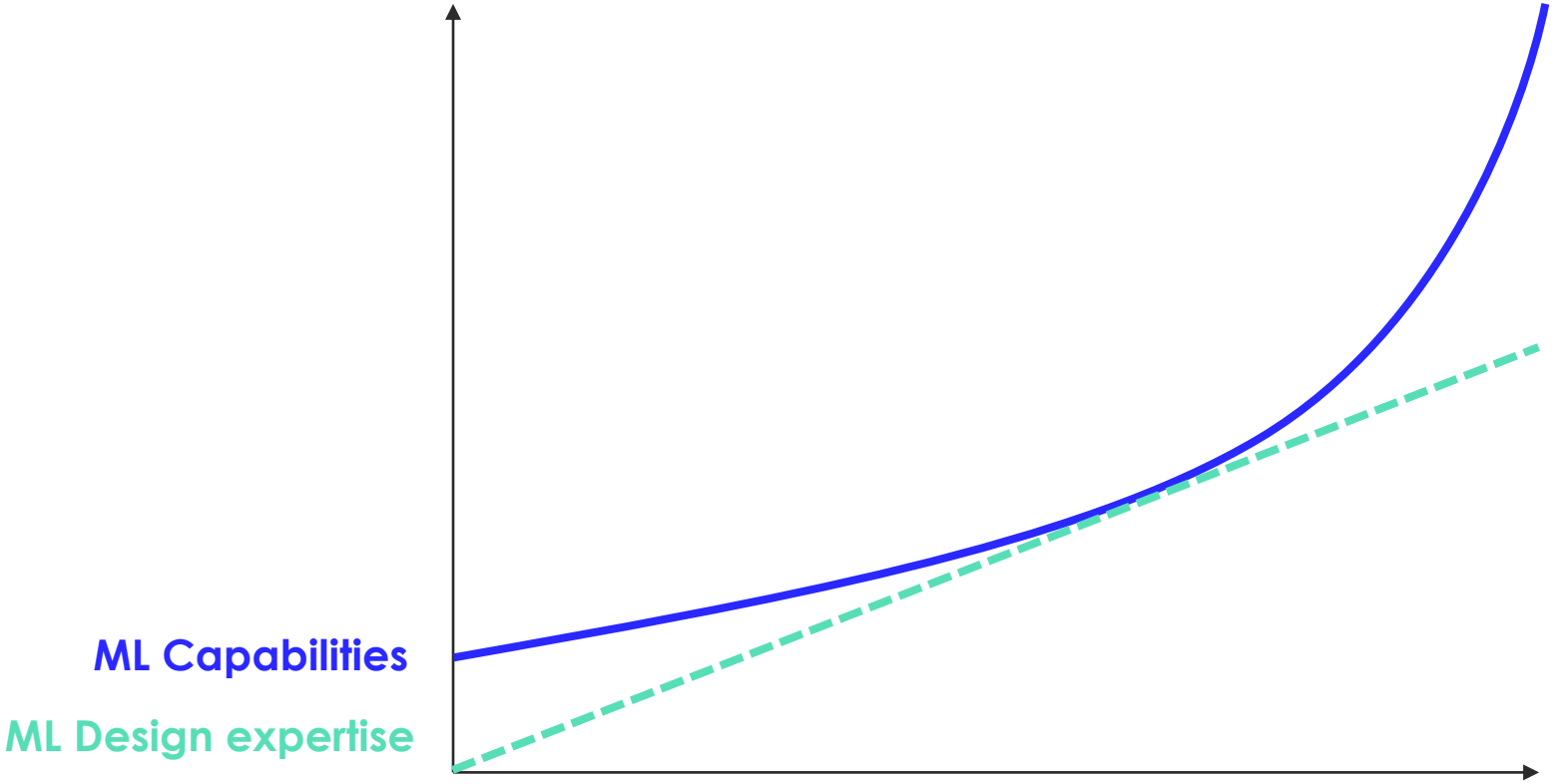
Input
(Data)

Machine Learning
(Algorithm)

Output
(Prediction)

Why design principles?


ML Capabilities


ML Capabilities
ML Design expertise

Democratization

Evangelism

Adoption

Democratization

Evangelism

Adoption

Democratization

Evangelism

Adoption

Differentiation

Focus on travel context and organisational domain with relatable examples.

Designers

Best practices when designing ML driven experiences with relatable examples and personal commentary.

Stakeholders

Overview of design process and preview of main things to consider when designing ML driven experiences.

What's has been done?

Methodology

Q3

- Defining scope with stakeholders
- Surveying designers
- Gathering learnings in ML acceleration team (personalisation research)
- Refining with data science
- Drafting principles and refining examples
- Gathering feedback

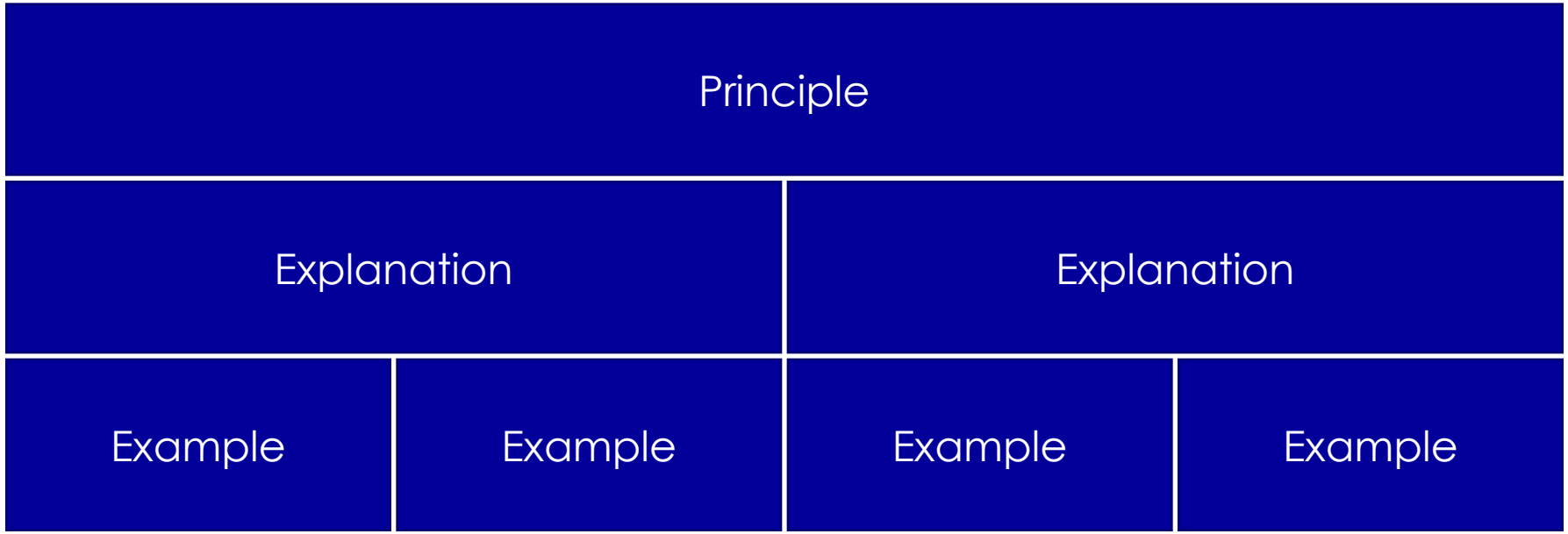
Thank you

- Humiun Miah – product management
- Alessio Petrozziello – data science

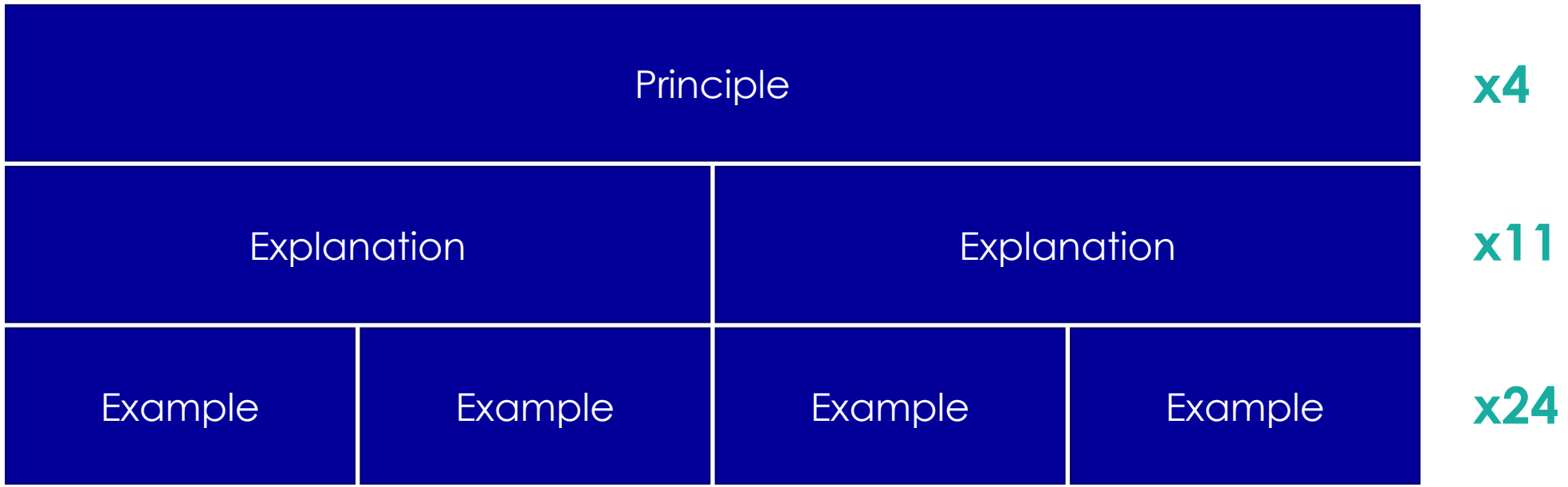
Design principles

Overview

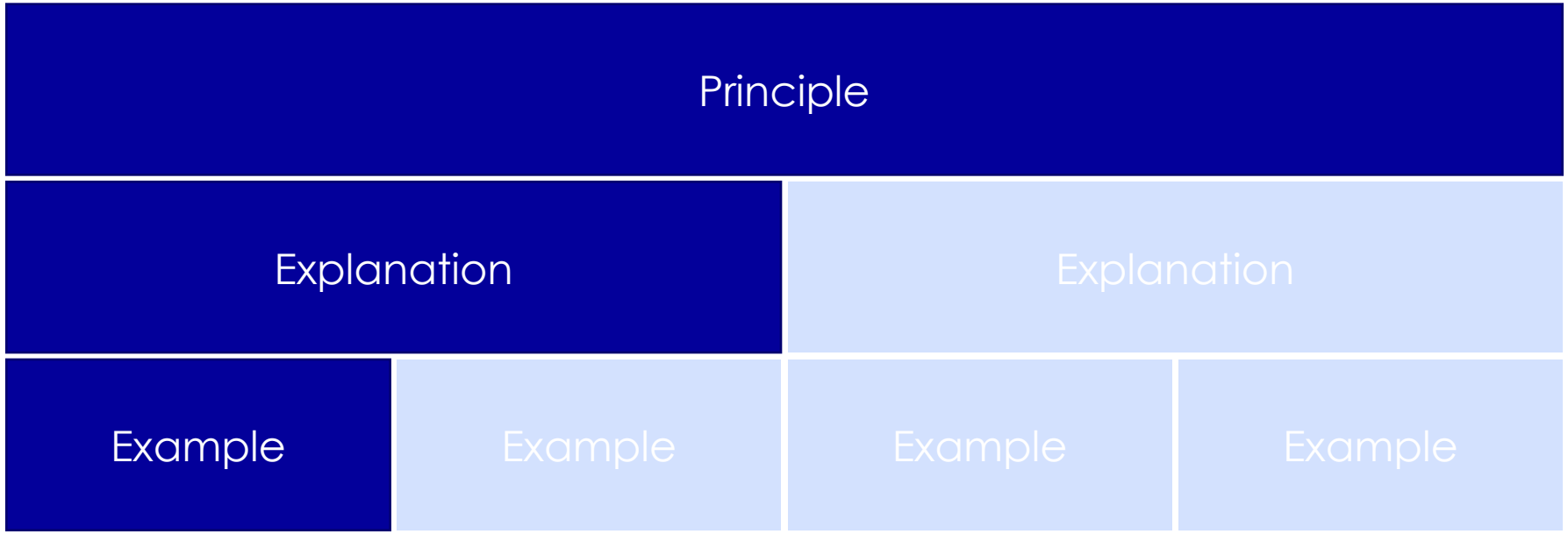
Overview


Principle
Explanation
Explanation
Example
Example
Example
Example

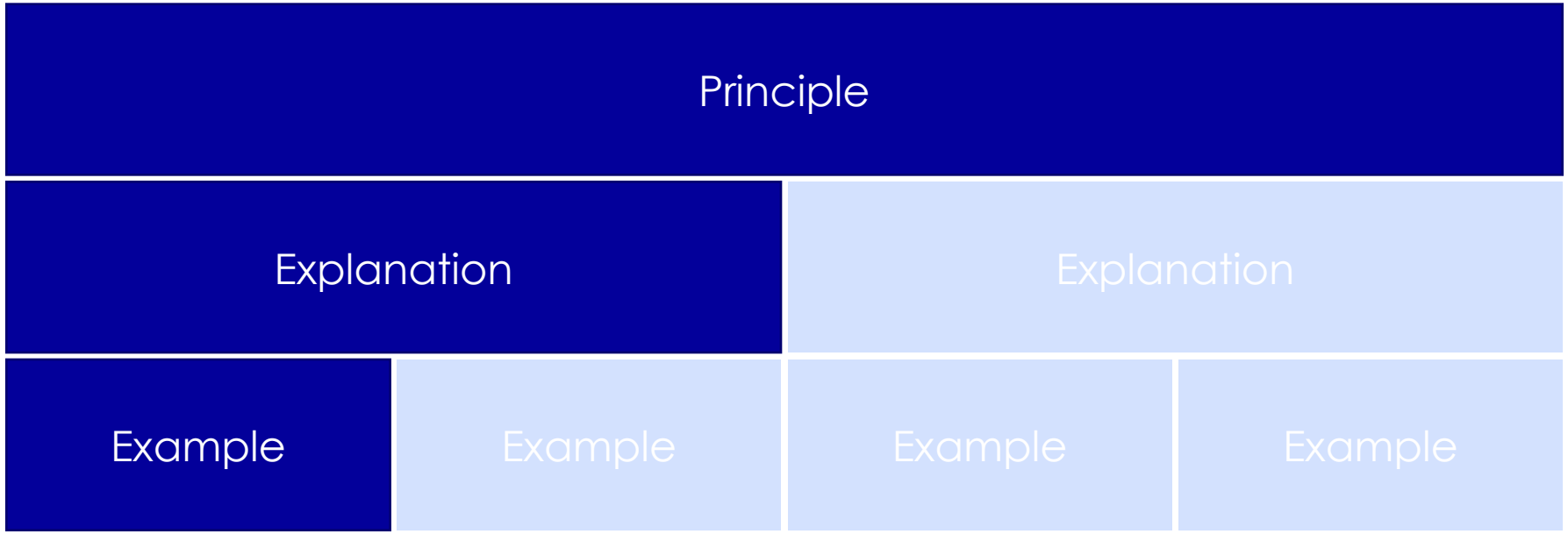
Overview


Principle
x4
Explanation
Explanation
x11
Example
Example
Example
Example
x24

Overview


Principle
Explanation
Explanation
Example
Example
Example
Example

Overview



Full content will be available on Confluence soon!

Design principles

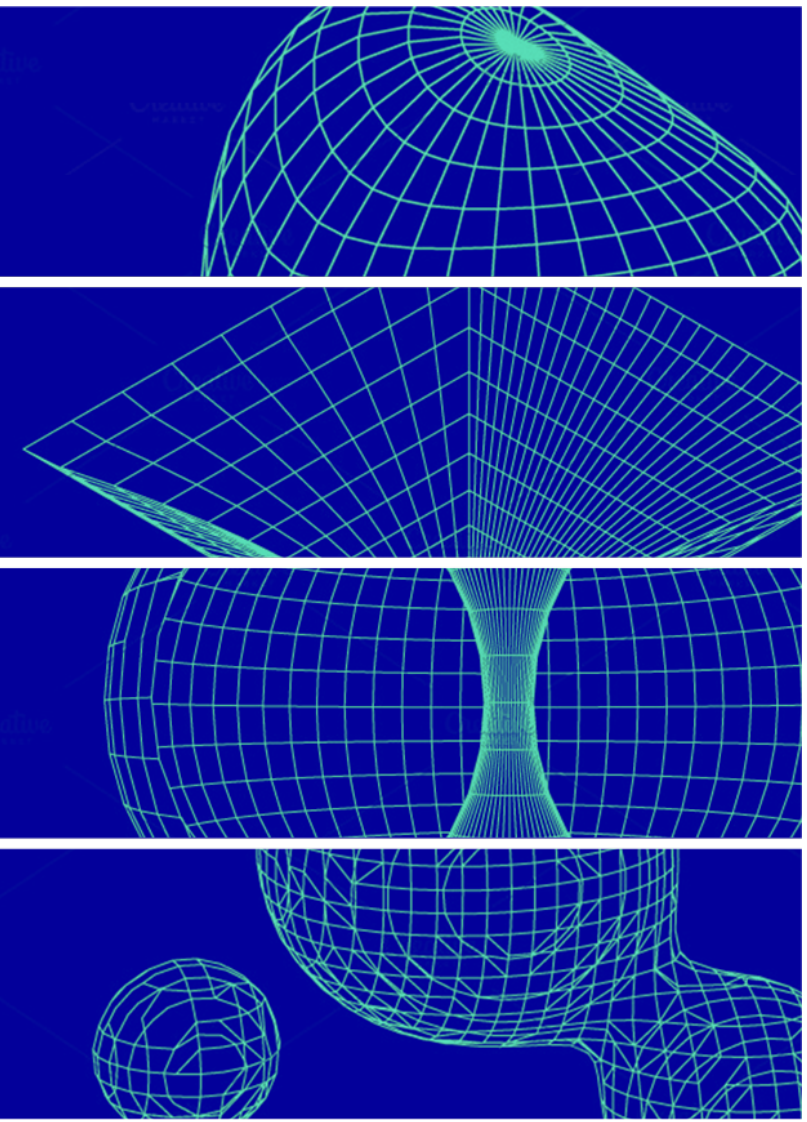
Feedback

Adaptable

Pragmatic

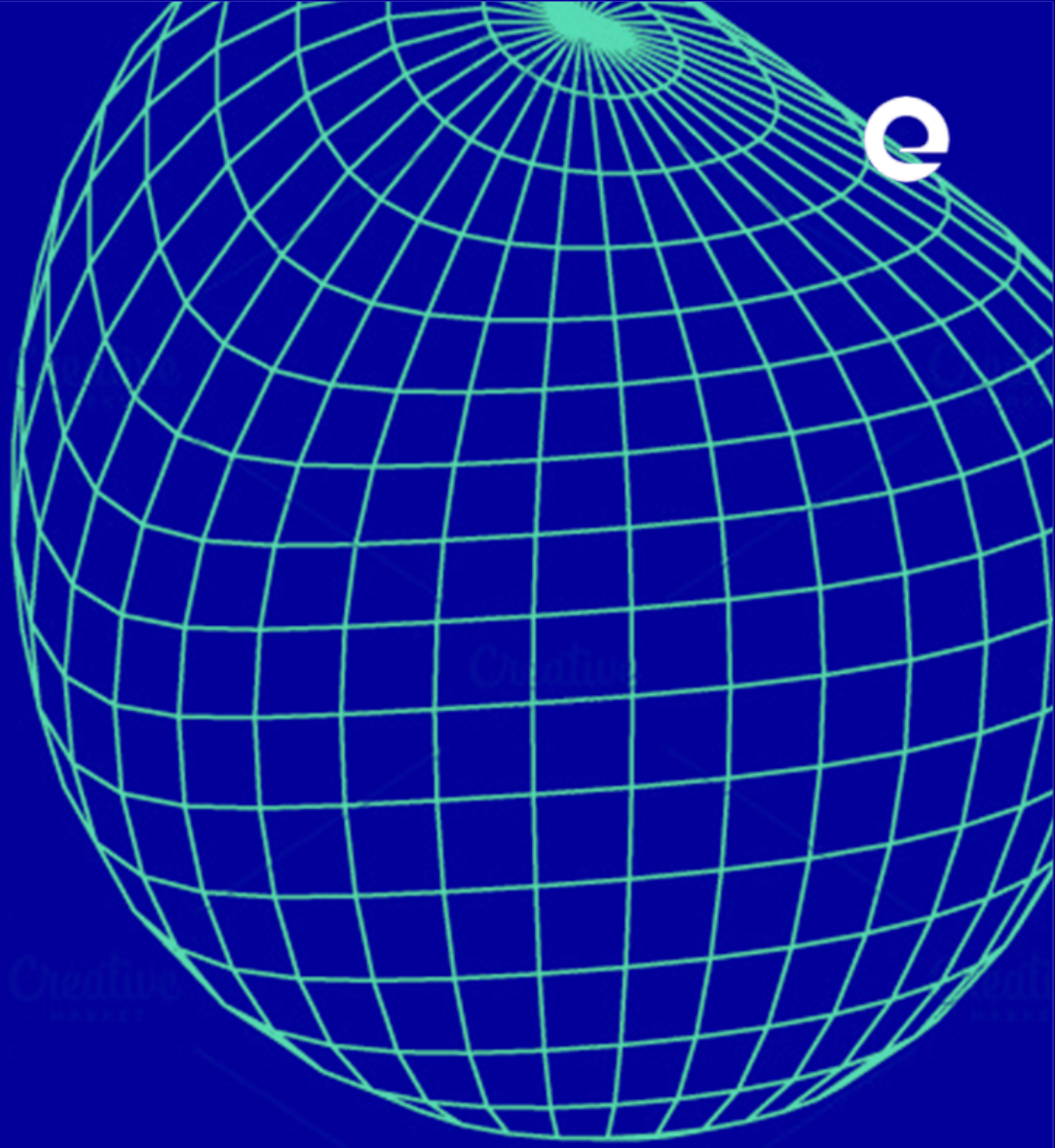
Transparent

Collaborative



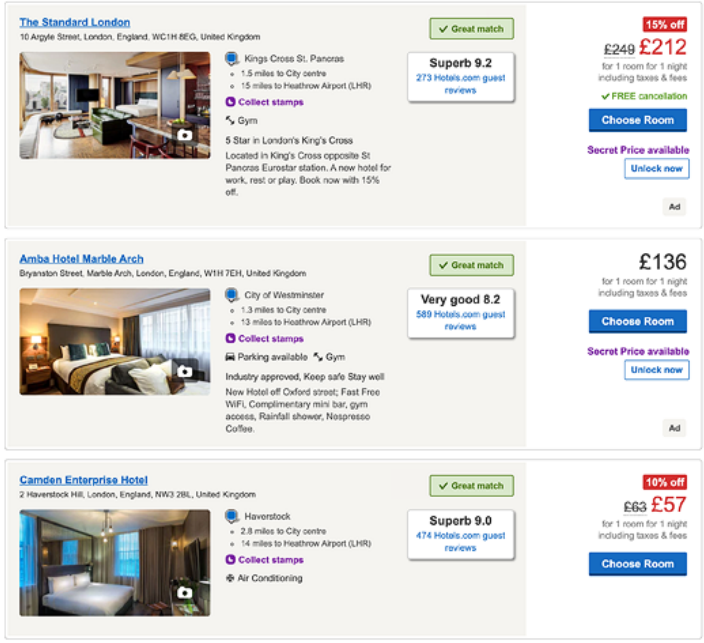
Adaptable

Adapt the experience to the ML model output.

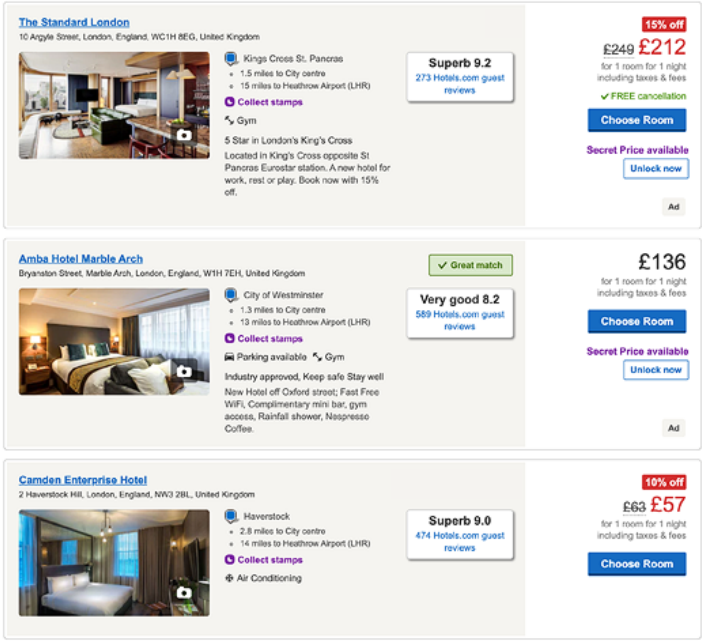


Work with data science to understand ML model output and adapt it to the user problem you're trying to solve.

Consider whether you're optimising for precision (less but more accurate results) or recall (more but less accurate results).



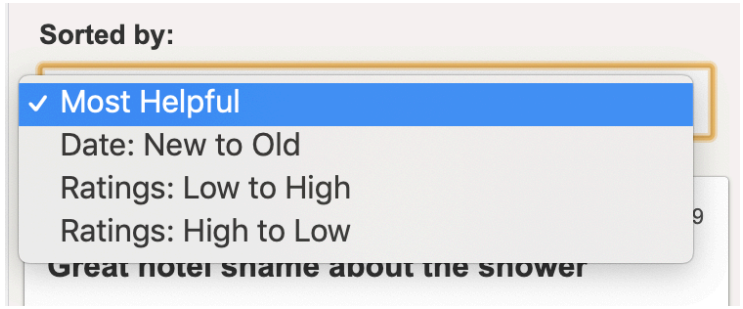
Recall



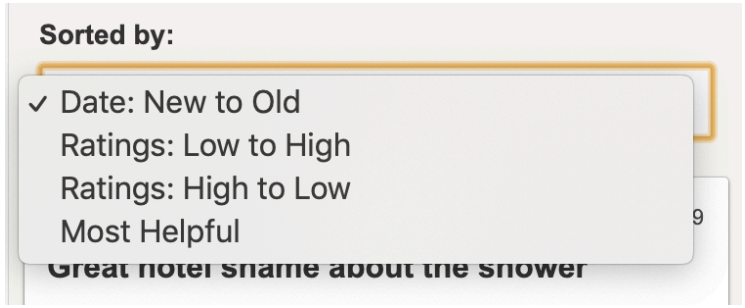
Precision

Consider how the experience will adapt to the ML model output.

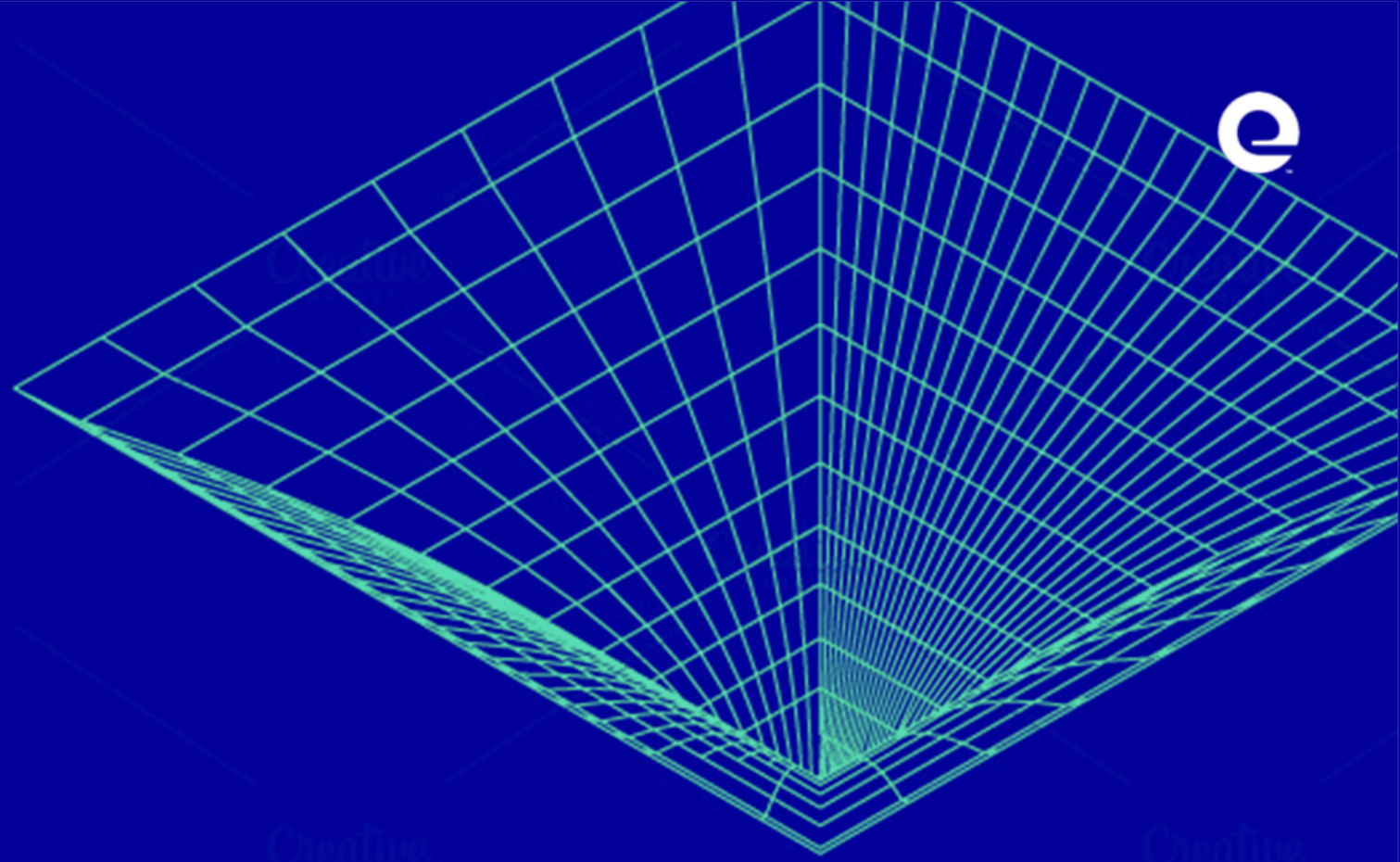
ML platforms can time out returning no output, consider fall back scenarios for users if that happens.



Default



Fallback

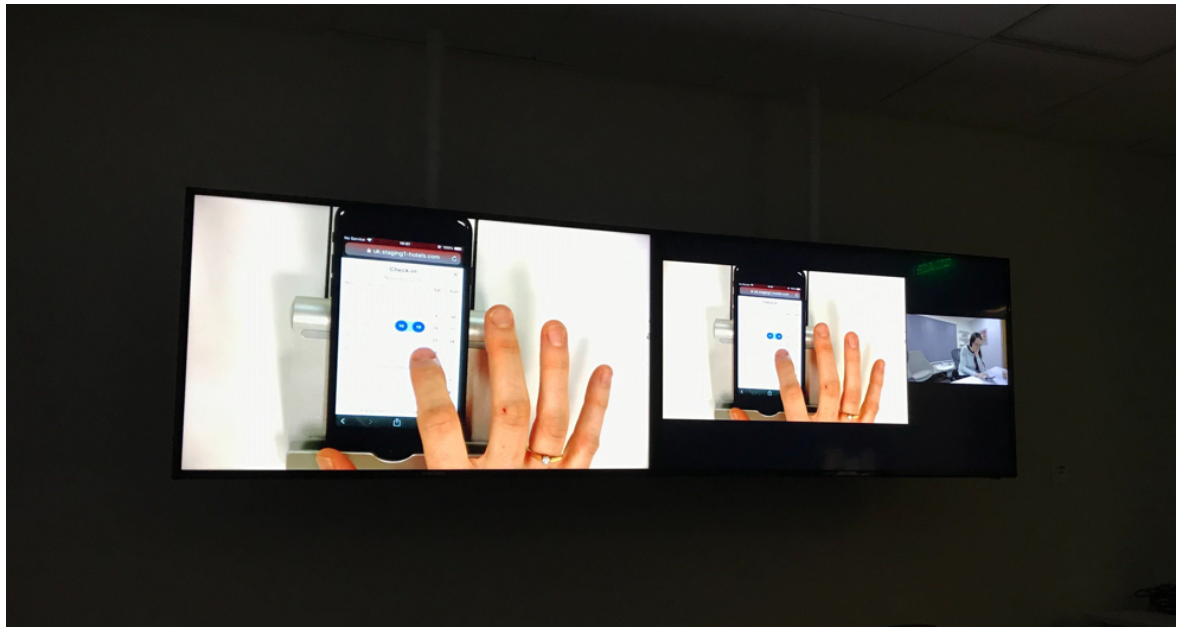


Pragmatic

Take a pragmatic approach to ML problems.

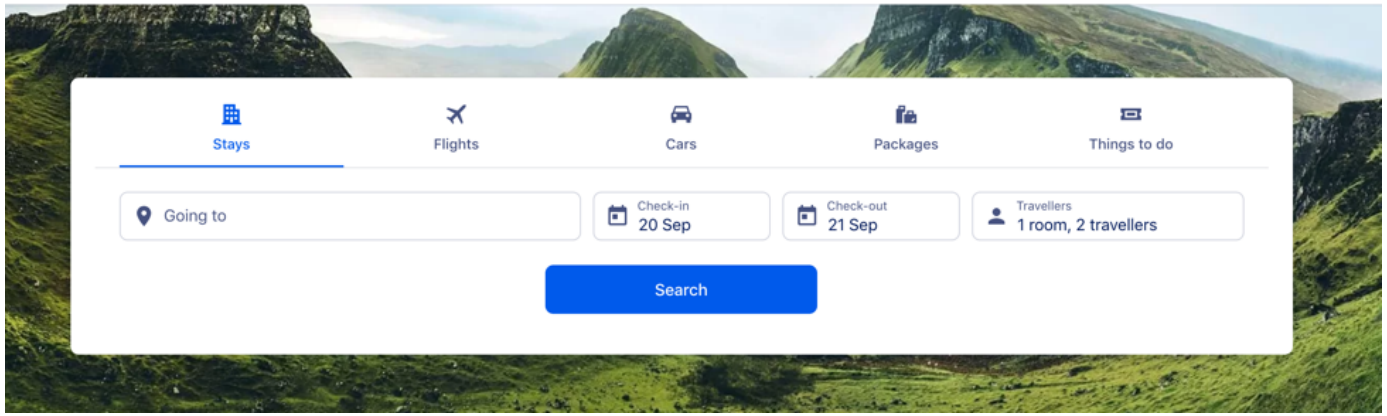
Machine learning is not always necessary to test a machine learning hypothesis, consider less complicated ways.

User research study in a controlled environment using sample data to simulate ML model output.



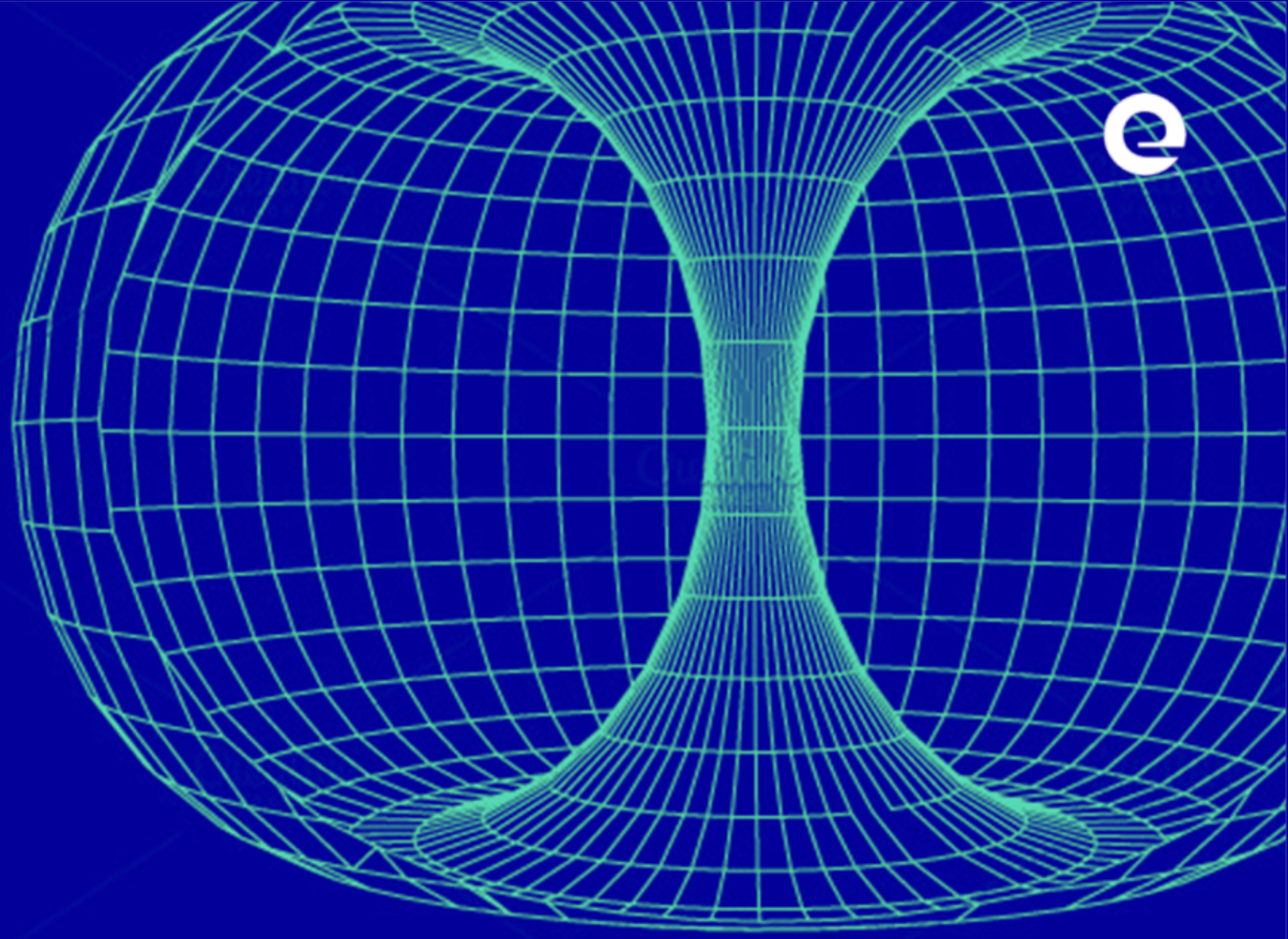
Understand the complications that come from our limitations and capabilities.

As a travel platform we have a cold start problem, meaning it takes time before we collect data about a user behaviour. As a result majority of ML models we have use historic data and user's context to provide valuable predictions.



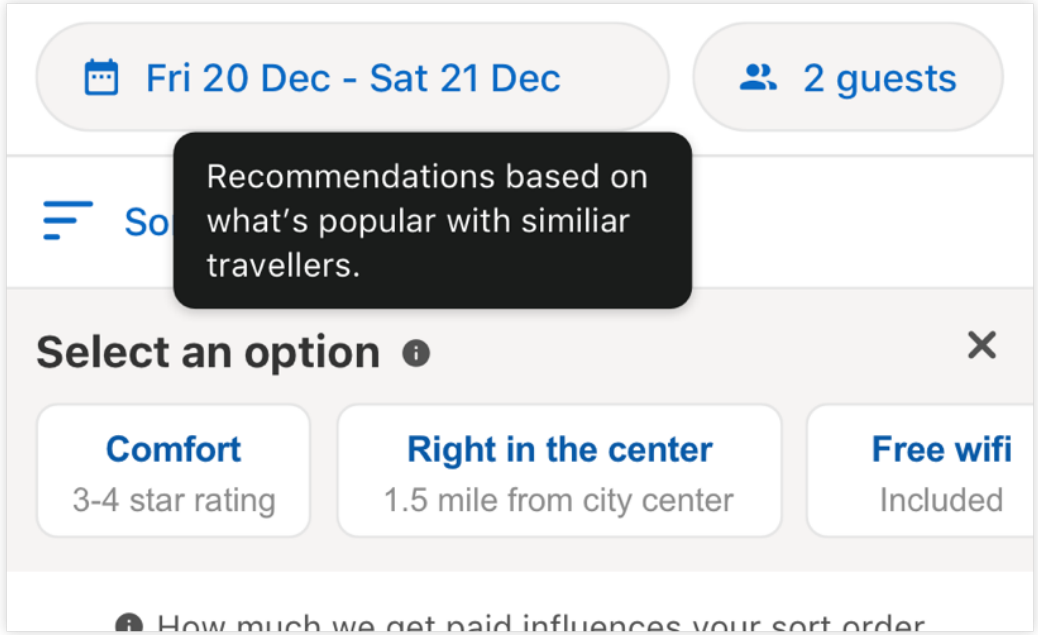
Transparent

Make sure to be transparent to end users and stakeholders.



Consider how to introduce ML driven features that challenge existing user mental models.

Consider explaining ML features with clear and explicit language. Having confusing or unclear language can cause mistrust.

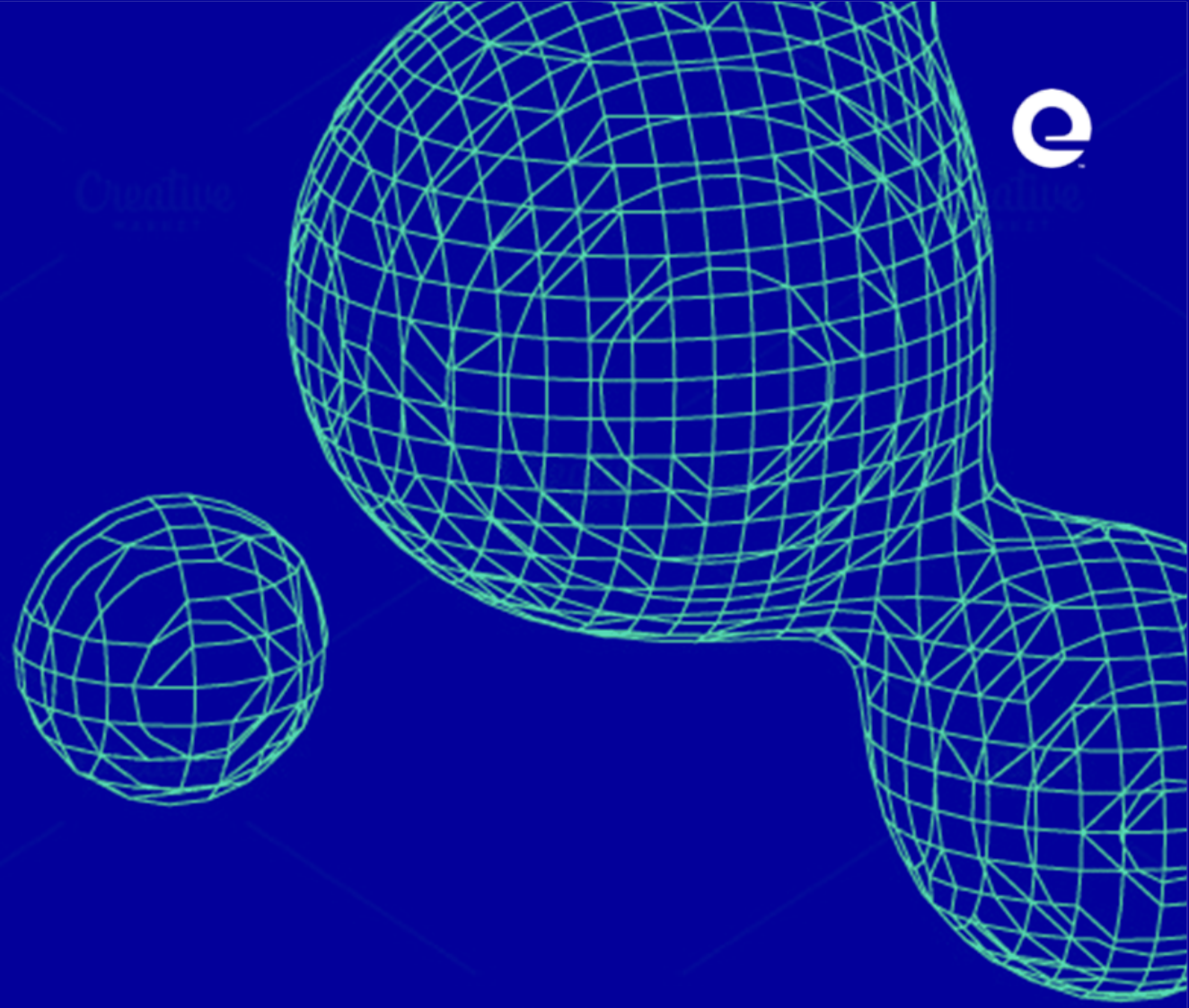


Work with data science to make sure there's no bias in the data you're collecting for the ML model.

This includes ethical considerations and historical biases of the data, as well as, any bias that comes from existing user behaviour.

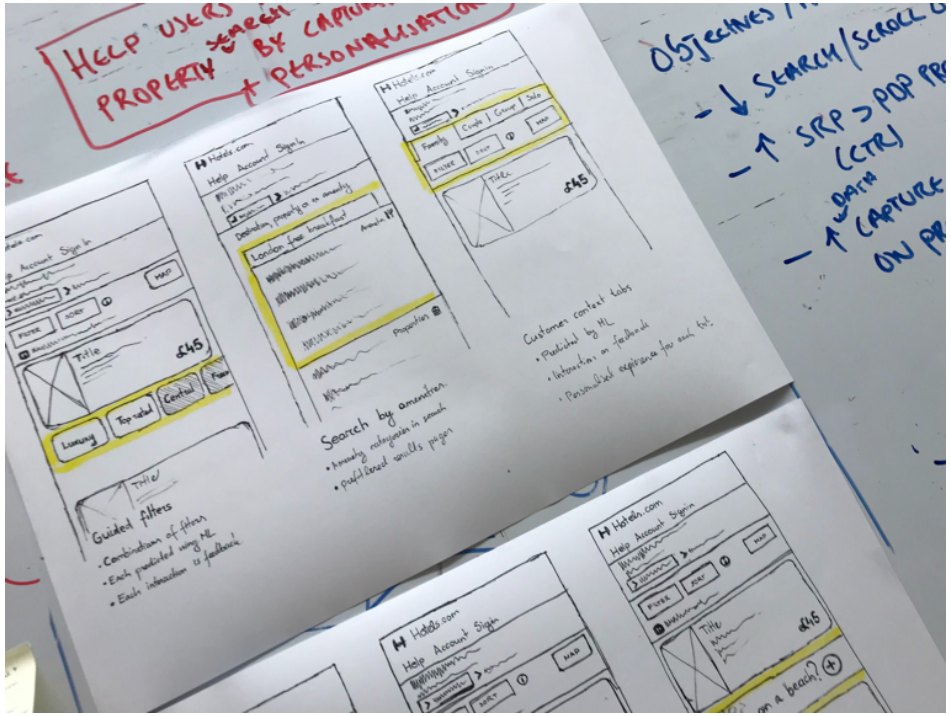
Collaborative

Facilitate collaboration between product, data science and end users.

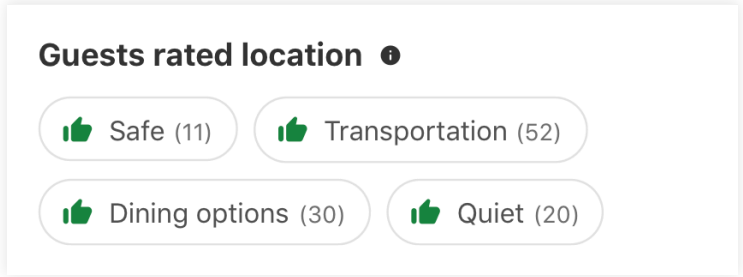


Lead the collaboration between data science and product. Co-creating from discovery to delivery.

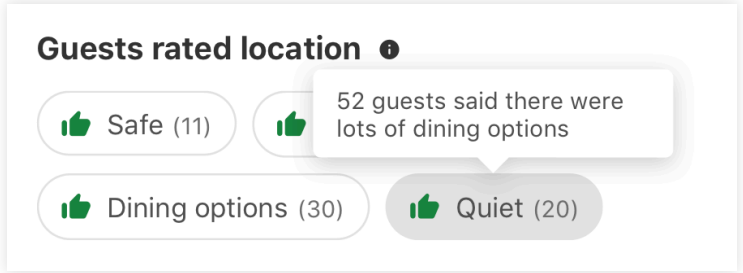
Visualise feature ideas early in the process to influence algorithm choices and to facilitate conversations between product and data science.



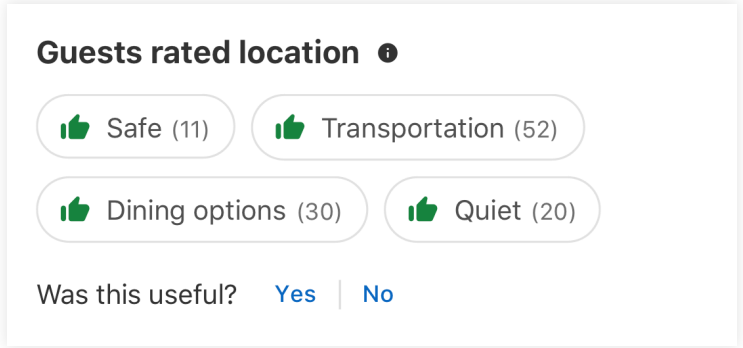
Capture data signals for data science and for end users to ensure the model predictions are accurate.



Implicit



Explicit (Soft)



Explicit (Hard)

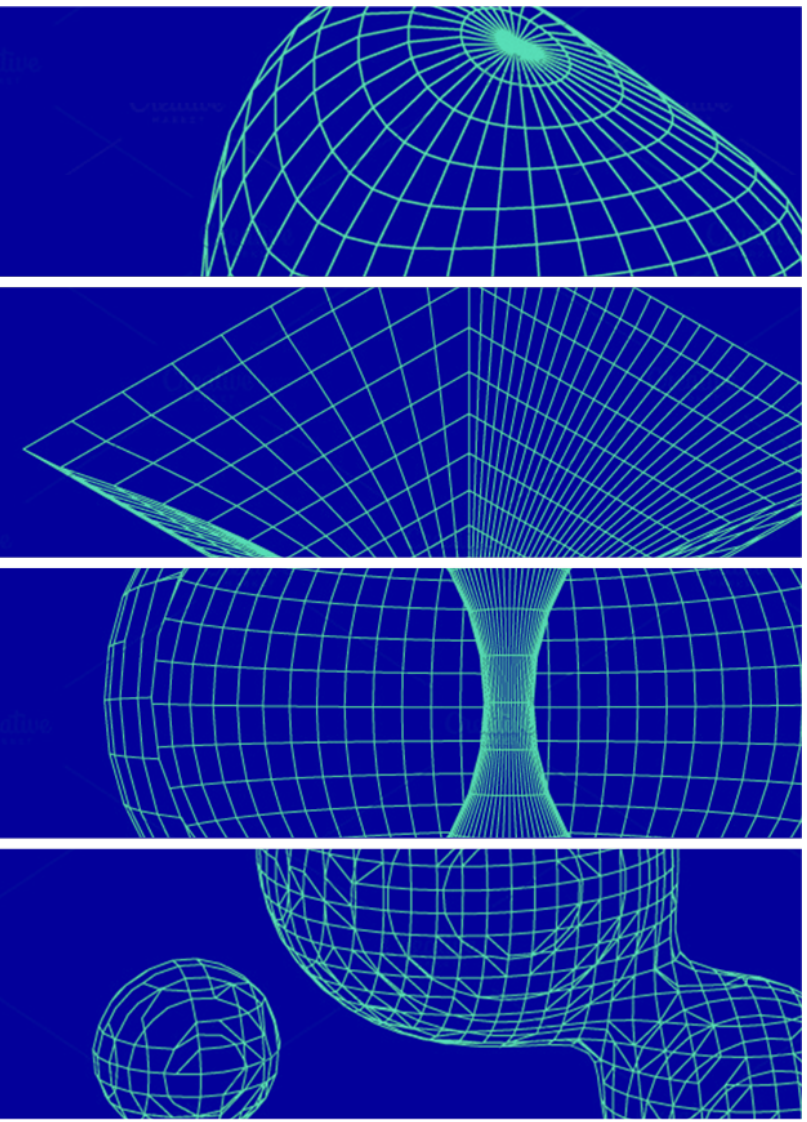
Take time to understand the value of different levels of data capture signals - explicit and implicit.

Adaptable

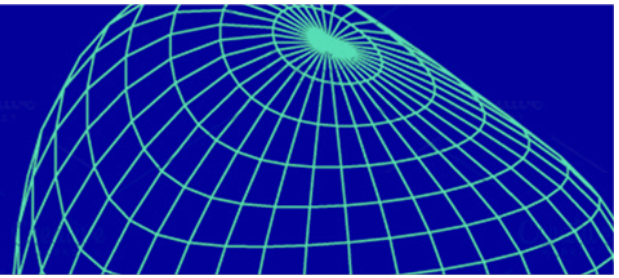
Pragmatic

Transparent

Collaborative

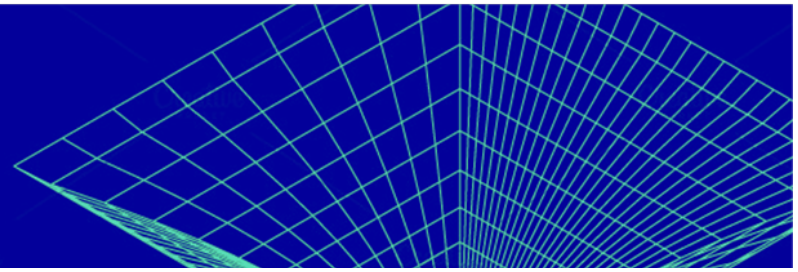


Adaptable



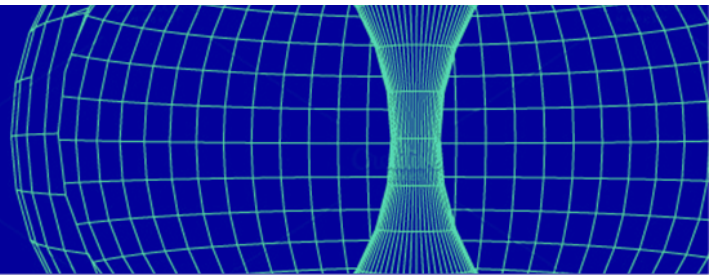
- Work with data science to understand ML model output and adapt it to the user problem you're trying to solve.
- Consider how the experience will adapt to the ML model output.

Pragmatic



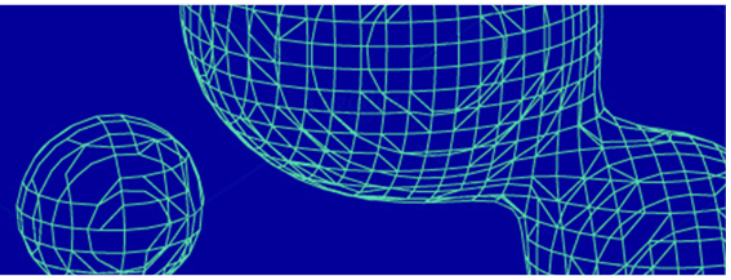
- Machine learning is not always necessary to test a machine learning hypothesis, consider less complicated ways.
- Understand the complications that come from our limitations and capabilities.

Transparent

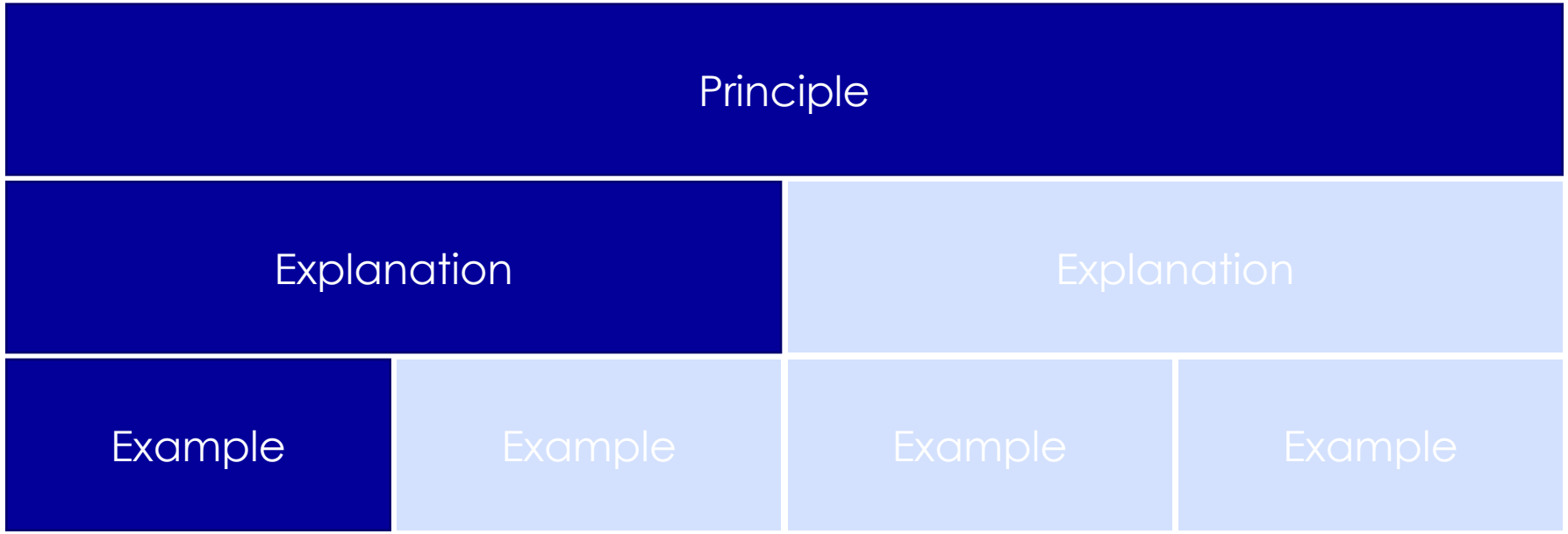


- Consider how to introduce ML driven features that challenge existing user mental models.
- Work with data science to make sure there's no bias in the data you're collecting for the ML model.

Collaborative



- Lead the collaboration between data science and product. Co-creating from discovery to delivery.
- Capture data signals for data science and for end users to ensure the model predictions are accurate.


Principle
Explanation
Explanation
Example
Example
Example
Example

What’s next?

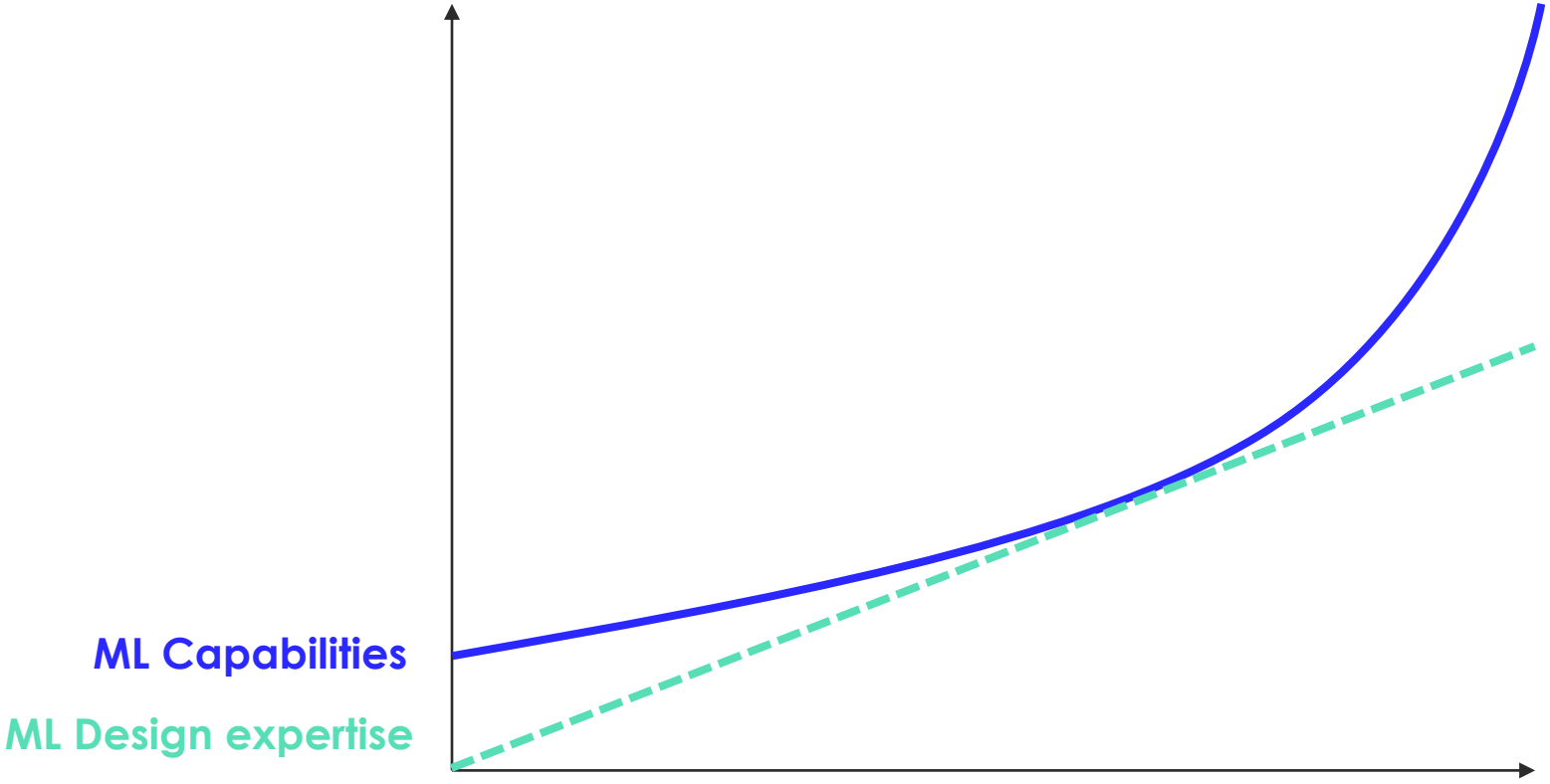
Opportunities

Next steps

- Principles documented in Confluence
- Promote and share documented principles

Opportunities

- Cross brand collaboration
- Extensive guidebook and L&D course
- Upskilling workshops and presentations


ML Capabilities
ML Design expertise

Resources

Designing for ML

Google - PAIR
https://pair.withgoogle.com/guidebook/

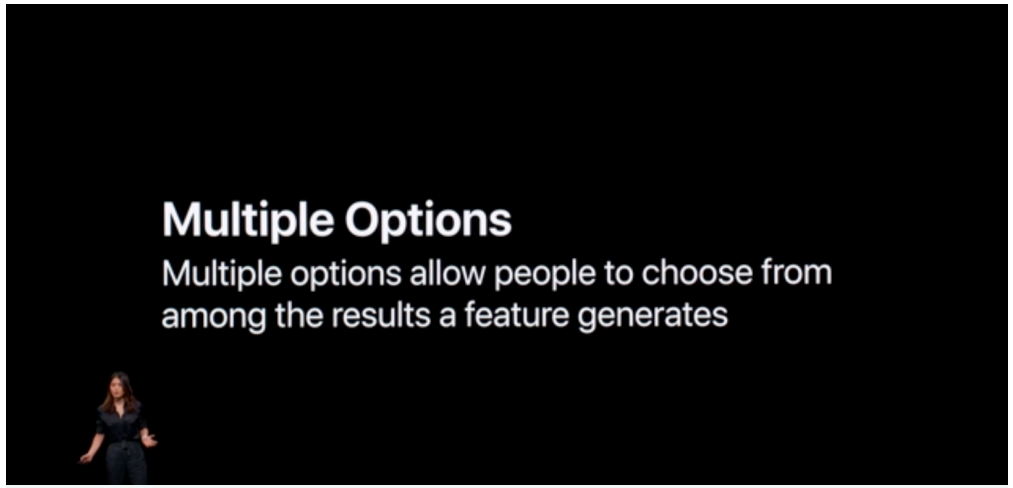
Microsoft - Human AI interaction design
https://www.microsoft.com/en-us/research/blog/guidelines-for-human-ai-interaction-design/

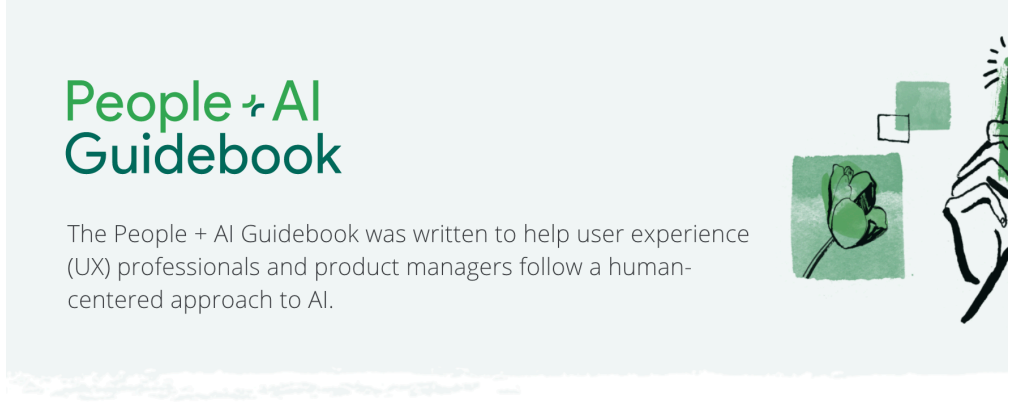
Apple - Designing Great ML Experiences
https://developer.apple.com/videos/play/wwdc2019/803/

Understanding ML

Google – A to Z of AI
https://atozofai.withgoogle.com/intl/en-GB/

Coursera – AI for everyone
https://www.coursera.org/learn/ai-for-everyone





Differentiation

Focus on travel context and organisational domain with relatable examples.

Thank You

Q&A


TM
expedia group™