

Machine Learning as a Design Material

Imagining Beyond Automation, Reminders and Recommenders



Qian Yang (HCII)

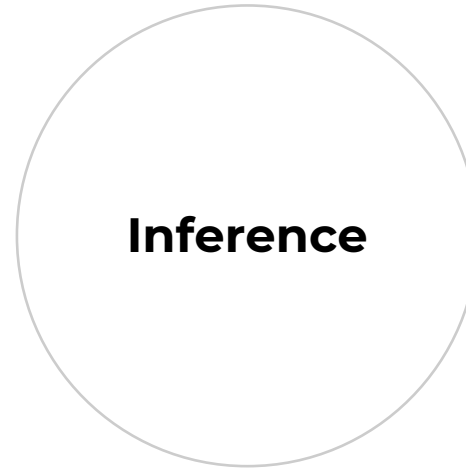
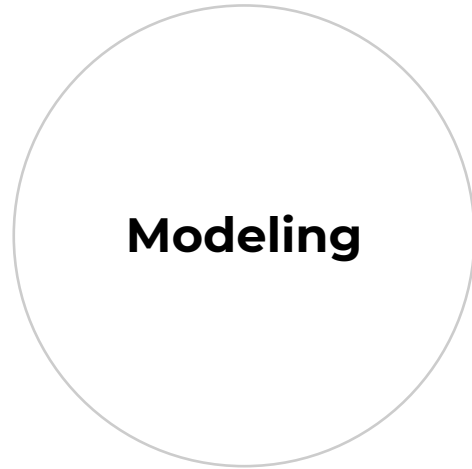
Joint work with John Zimmerman (HCII)

Aaron Steinfeld (RI)

And Others

Backstories

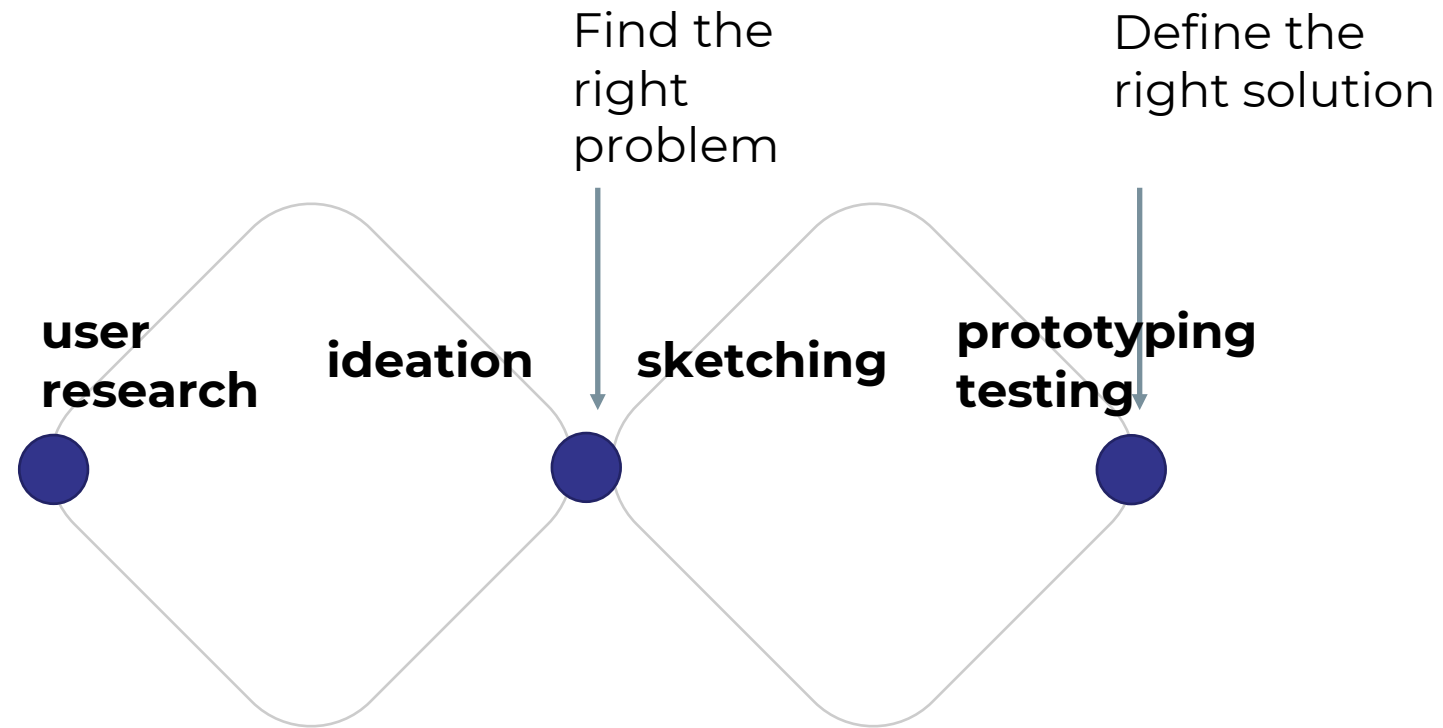
Machine
Learning
Pipeline



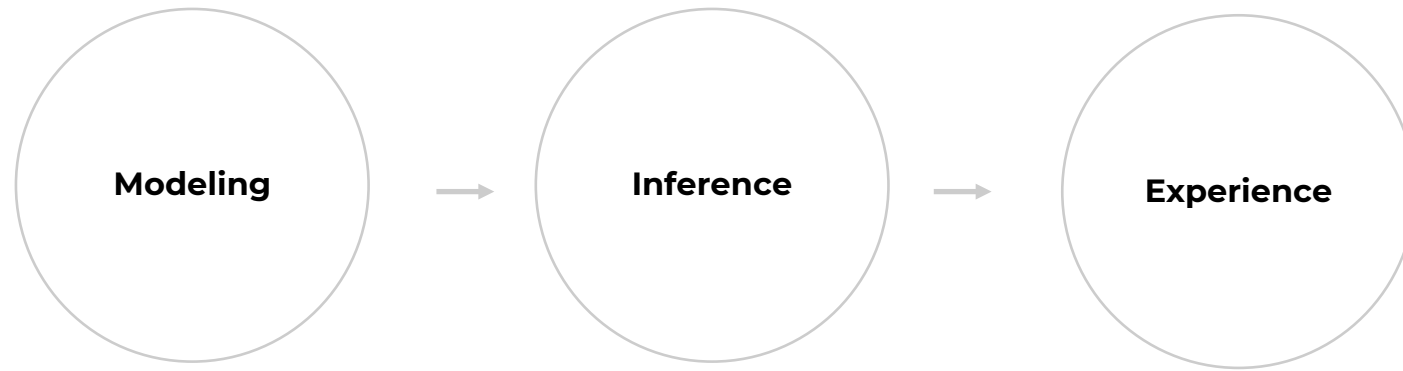
predictability / explainability
trust / transparency
UX cost of inference errors
feeling of control / agency

Backstories

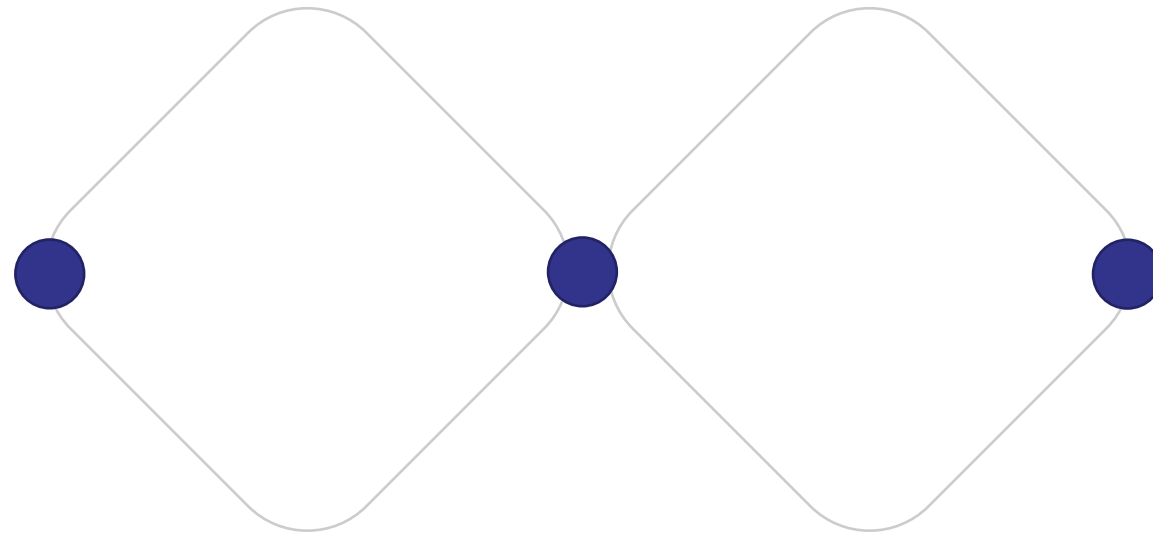
User-Centered Design Pipeline



Machine Learning Pipeline



User-Centered Design Pipeline





Designing Context-Aware UI

DIS'16

Designing Clinical Decision Support

CHI'16

UX-ML Design Workshops

unpublished

Synthesis of HCI Literature

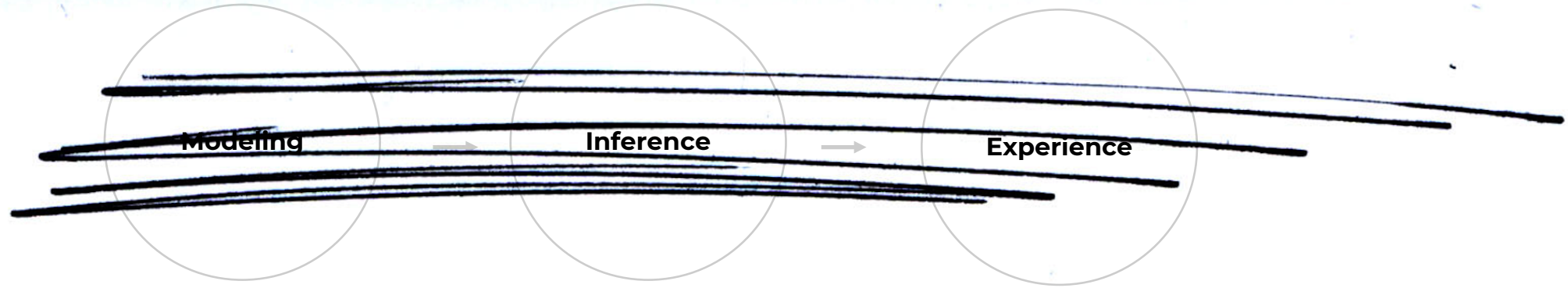
CHI'18

Investigating Best Practice in Industry

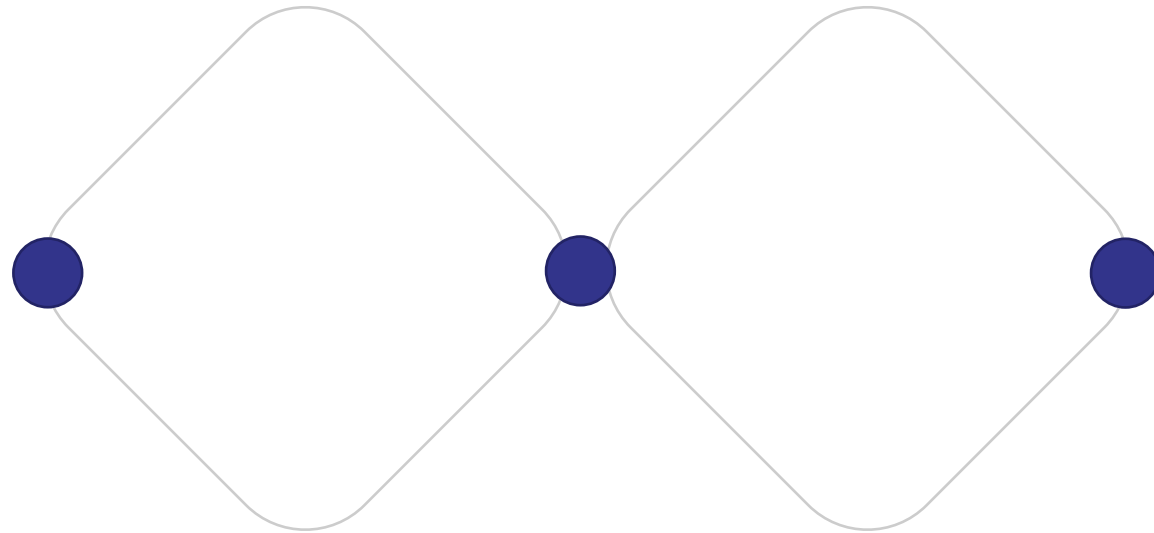
DIS'18

My Starting Point

Machine
Learning
Pipeline



User-
Centered
Design
Pipeline

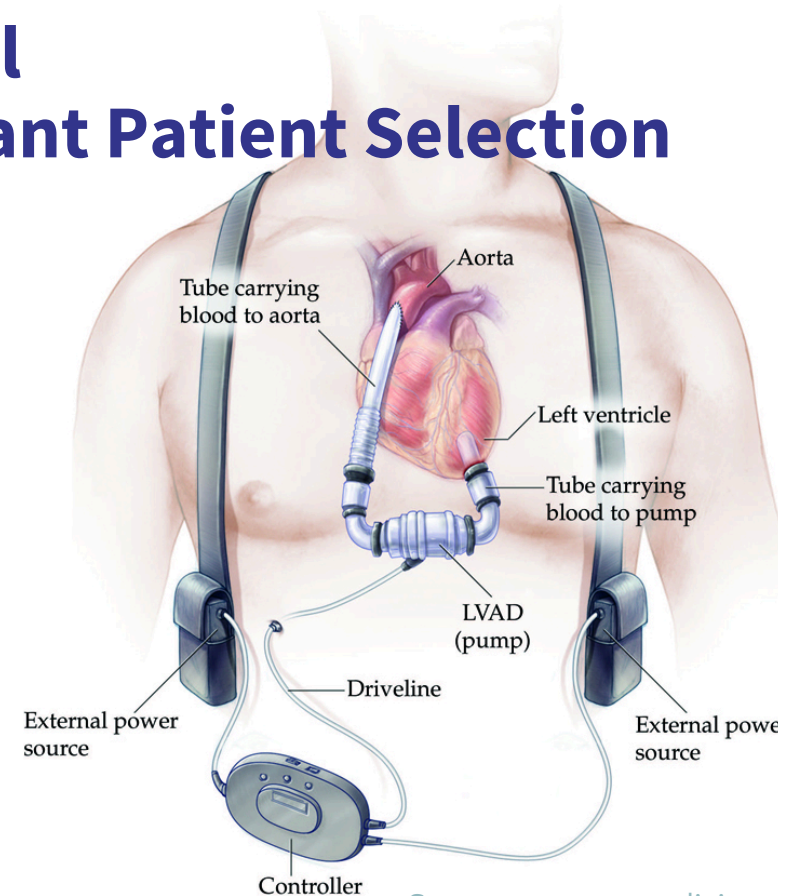


Designing a Machine Learning Tool In Support of Artificial Heart Implant Patient Selection

A difficult end-of-life decision

- High-risk surgery and recovery
- Lifestyle change
- Critical implant window

Available data and learning algorithms that predict likely outcome of a patient's implant



Source: www.mayoclinic.org

Yang et al. *Investigating the Heart Pump Implant Decision Process: Opportunities for Decision Support Tools to Help*. CHI '16

Reframing the Problem of Designing Human-Centered ML

Technology in Searching for a Purpose

Machine Learning Technical Advances in Searching for a Purpose

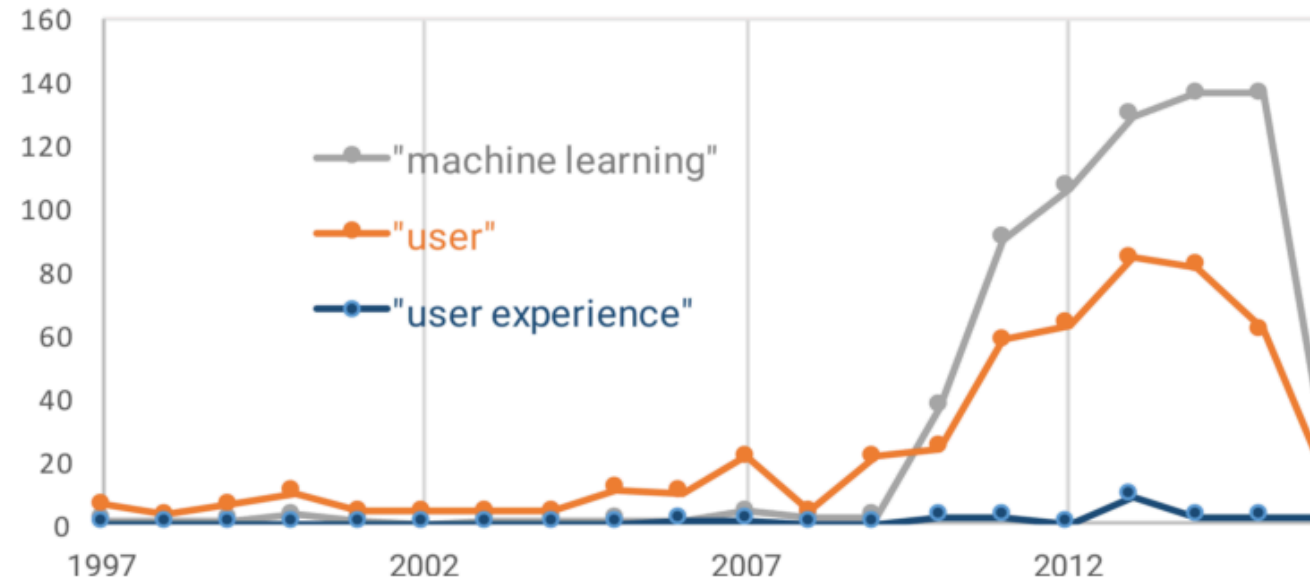


Figure 1. The numbers of HCI publications that mentioned “machine learning”, “machine learning” and “user”, and “machine learning” and “user experience” over the years.

Qian Yang, Nikola Banovic, and John Zimmerman. **Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Research.** CHI '18.

Reframing the Problem of Designing Human-Centered ML

Technology in Searching for a Purpose

Machine Learning Technical Advances in Searching for a Purpose

Match-Making

S. Bly and E. F. Churchill. 1999. **Design through matchmaking: technology in search of users.** *interactions* 6, 2 (March 1999), 23-31.

Technology



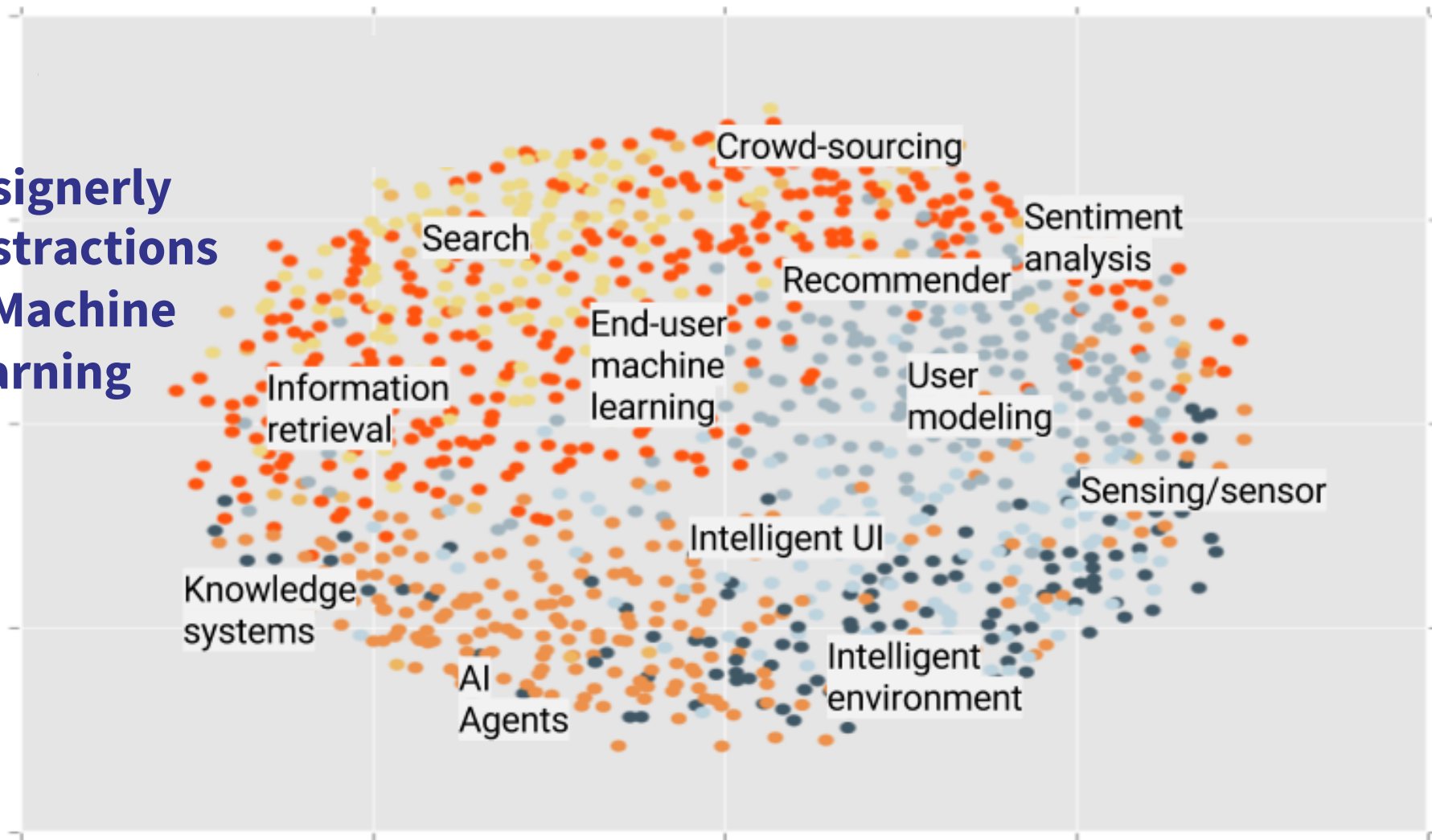
Match-Making

S. Bly and E. F. Churchill. 1999. **Design through matchmaking: technology in search of users.** *interactions* 6, 2 (March 1999), 23-31.

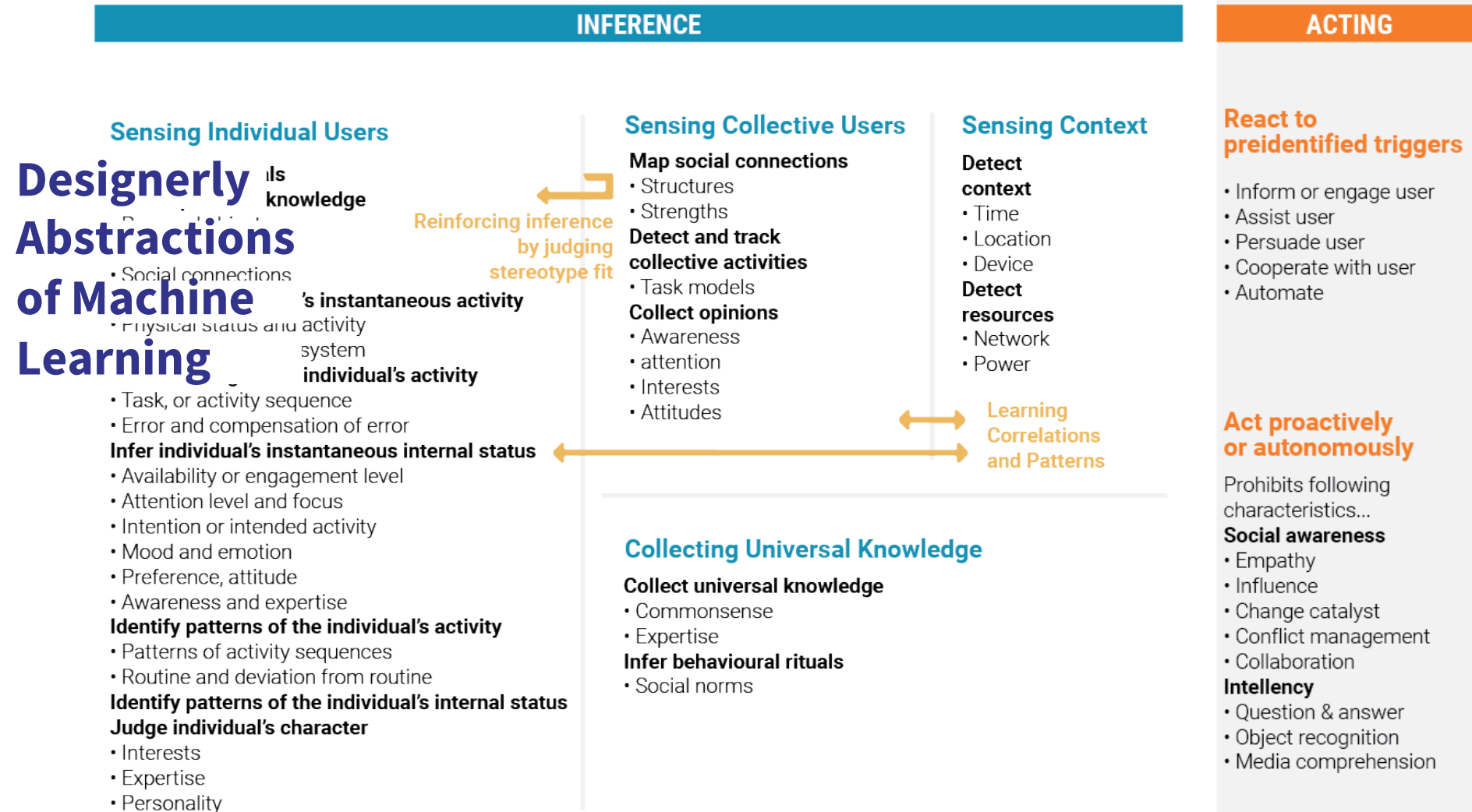
Machine Learning



Designerly Abstractions of Machine Learning



Qian Yang, Nikola Banovic, and John Zimmerman. **Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Research.** CHI '18.



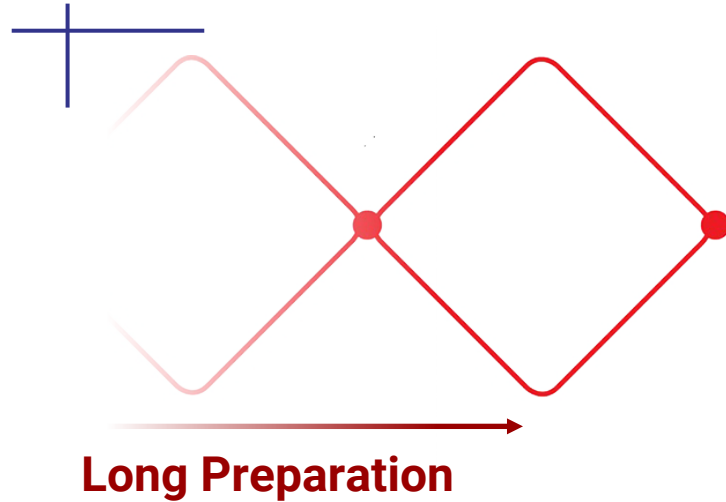
Qian Yang, Nikola Banovic, and John Zimmerman. **Mapping Machine Learning Advances from HCI Research to Reveal Starting Places for Design Research.** CHI '18.

Machine Learning Technical Advances in Searching for a Purpose

Investigating the Best Practice in Industry

Qian Yang, Alex Scuito, John Zimmerman, Jodi Forlizzi, and Aaron Steinfeld. 2018. Investigating How Experienced UX Designers Effectively Work with Machine Learning. In *Proceedings of DIS '18*

Best Practice in Industry: Match-Making

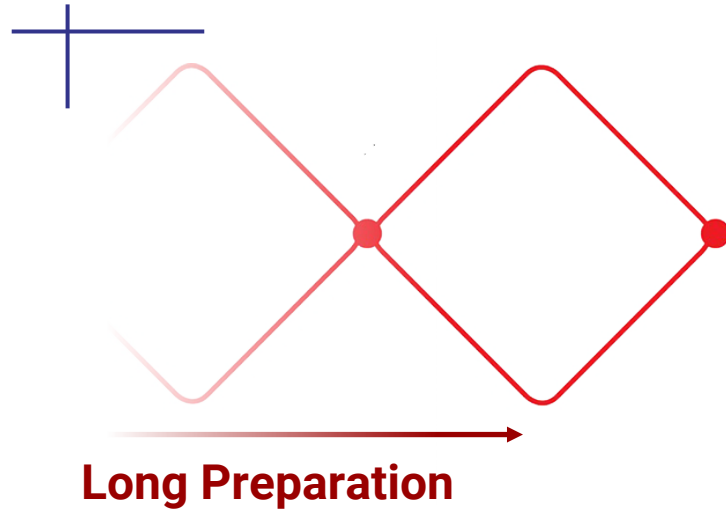


Stage1: Long Preparation

- Design and visualize/analyze telemetry data.
- Observe and monitor user behavioral patterns.
- Imagining what user behavior might be worth learning and what learned interactions might be valuable for users.
- *(I) framed the questions not as do you (data scientist) know what would work, but in your gut, do you think this would be possible. Possible on a scale of 1-10. (P8)*

** Design and implement baseline interactions at the same time.

Best Practice in Industry: Match-Making



Stage1: Long Preparation

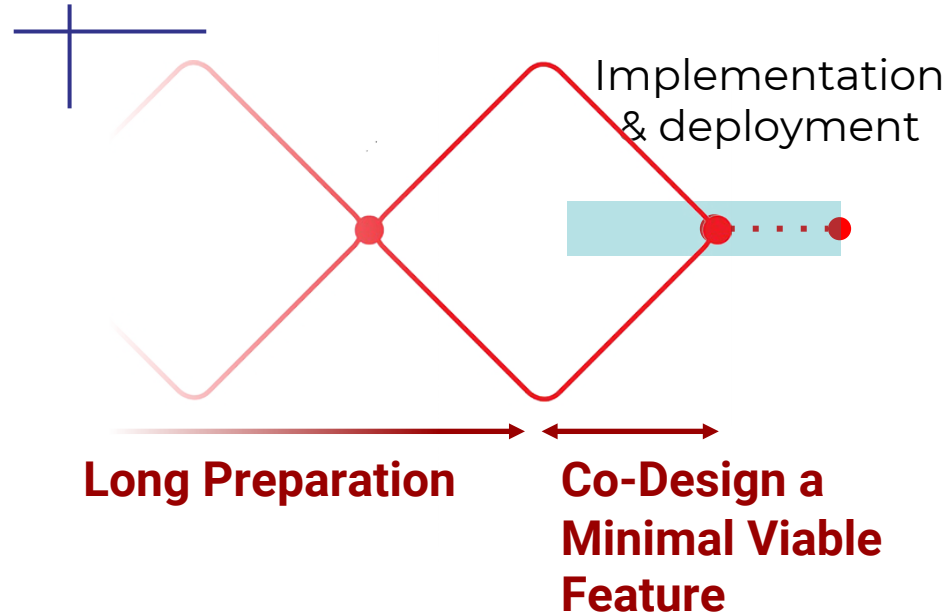
Arriving on a design goal shared between designers and data scientists, i.e.:

We use machine learning so that we can build something that **can personalize for a lot of people.** (P3)

In consumer tech, we try to **raise the level of abstraction** [of user commands] rather than doing everything manually. (P7)

[I want users] **foreseeing our relationship improve**, where the relationship is the recommendations we are giving them. :ater there is a kind of an acknowledgment when we talk about “personalization”... An acknowledgment that a more personalized experience is a better experience that one is less likely to walk away from. (P14)

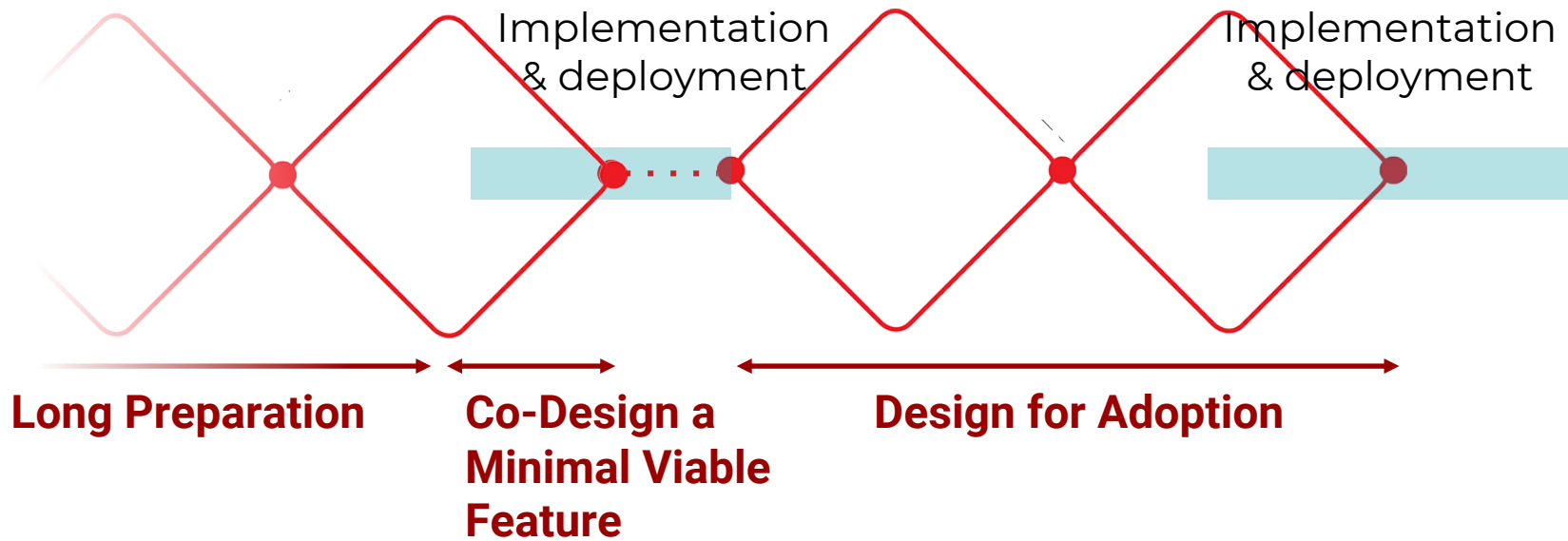
Best Practice in Industry



Stage2: Design, Develop and Deploy a Minimal Viable Product

- Develop a funnel of visions, a funnel of what exists and what is possible in the company (P8).
- Test basic dimensions of the design: i.e. Could users make sense of the ML interaction? Could users easily recover from ML inference errors.
- ** Always offer users the option to turn a new ML feature off.

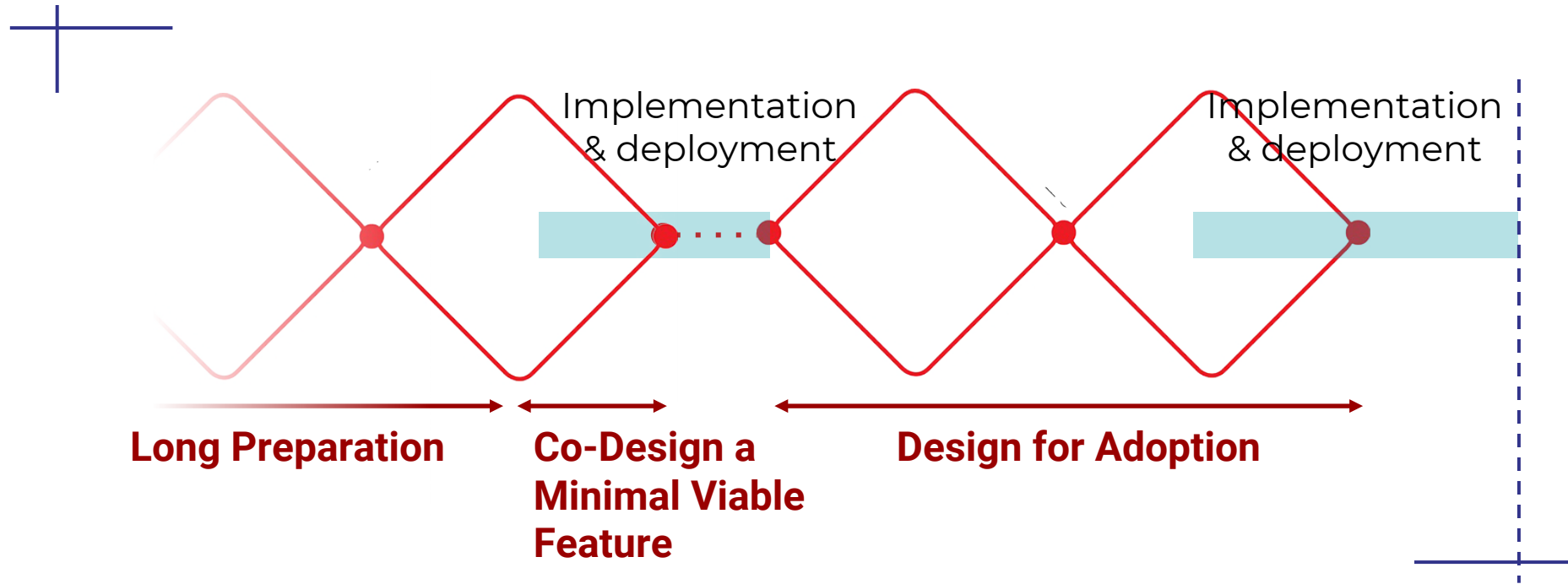
Best Practice in Industry



Stage3: Design for Adaptation

- Understand user mental models via field study and other traditional UCD methods;
- Re-design and potentially re-develop the system.

Best Practice of Designing Machine Learning in Industry



Thank you.

Qian Yang

yangqian@cmu.edu

yang-qian.github.io