How can design help?

BRINGING IN THE HUMAN FACTOR.

if not aligned with human needs we might end up building a powerful system to solve a very small or perhaps a non-existent problem

if this is not the case it might still fail as the system may not be prepared to handle the entire range of user behaviours.

GUIDING THE INTELLIGENCE

A major challenge with developing ML systems arise from data collection, filtering and labelling.

Understanding how a theoretical human expert might perform the task can help in establishing guidelines to perform the above activities

BUILDING TRUST & TRANSPARENCY

Design can help in rendering the complexities of an ML system comprehendable to its users, enabling better trust and confidence.

Trust and transparency is necessary to make the users more tolerant to any unexpected or undesirable outcomes.

Our Methodology

Phase 1 -

Design

Research

Design Team Stakeholders End Users Phase 2 -

Enhancing

Learning &

Prediction

Quality

Design Team
Development Team

Phase 3 -

Designing

for User

Experience

Design Team

Phase 4 -

Evaluation (post release)

Design Team

Development Team

ENGAGEMENT

MODEL PHASE 1 PHASE 3 PHASE 4 PHASE 2 (SUPPORT) Understanding the Designing the user Design mechanics to Collecting feedbacks from Description business context and acquire quality data and experience and interface real users and iterating to conducting in depth user designing filters to with emphasis on creating improve the user remove bias arising from trust and transparency. research to identify right experience. problems to focus on human factors. Engagement **Business / Customers** Product / Platform Product / Platform Data Scope Customers Duration Developers 000 Users **Business Unit** Data Scientists 000 Stakeholder Developers 00 Users Developers Involvement **Notes**

Our Methodology

Phase 1 - Design Research

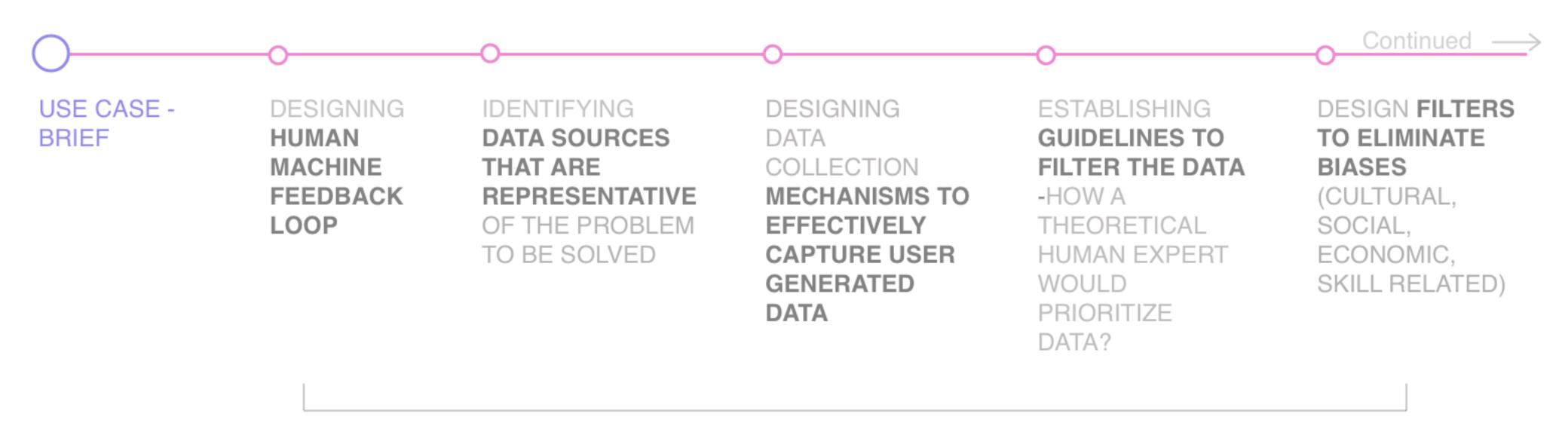
Addressing the Human Factor



Who is the end user of the predictive system?What are we trying to do for the end user of the system?What objectives are we serving?Why is it important?

Understanding the wide range of possible behaviours, expectations, responses and inhibitions due to the diversity of target users.

Phase 2 - Learning & Predictions



BASED INSIGHTS FROM RESEARCH & ETHNOGRAPHIC STUDIES IN PHASE 1

Phase 2 - Continued

PRIORITIZING FEATURES

USING **INSIGHTS &** DOMAIN KNOWLEDGE FROM PHASE 1 USERS

ASSISTING DATA SCIENTISTS IN THE SAME

MAPPING PREDICTIONS TO **DECISIONS** THAT PROVIDE VALUE TO END

SETTING **CRITERIA FOR** OFFLINE **EVALUATION**

Phase 2 Artefact - ML Canvas

DECISIONS

How are predictions used to make decisions that provide the proposed value to end users?

Input, output to predict, type of

predict,type of problem

ML TASK

PREDICTIONS

When to use new inputs and how long to featurize?

OFFLINE EVALUATION

Methods and checks to evaluate before deployment

VALUE PROPOSITIONS

What are the problems being solved and the objectives being served.

What can the end users expect from the ML system?

DATA SOURCES

Possible data sources that are representative of the problem being solved

DATA COLLECTION

Methods to generate/ collect data

FEATURES

Possible data sources that are representative of the problem being solved

BUILDING MODELS

When and how frequently models should be created/ updated with new data?

LIVE EVALUATION & MONITORING

Methods and checks to evaluate after deployment

Phase 3 - The experience

Continued -> DESIGNING **VISUALISING** DEFINING **EXPLICIT OR DESIGNING** TRIGGERS FOR CONVERSATIONS FIRST TIME USER **IMPLICIT DECISION MAKING EXPERIENCE** CONTEXTUAL **MECHANISMS** (If required) ASSISTANCE TO REWARD GOOD RESPONSES AND INFORM ON BAD ONES

Phase 3 - The experience

DESIGNING
GUIDELINES
TO MITIGATE
ERRORS

DESIGNING
GUIDELINES
GUIDELINES
TO MITIGATE
ERRORS

DESIGNING
CRITERIA AND
METRICS FOR
LIVE
EVALUATION

Machine Human Feedback loop

