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

Our Methodology

Phase 1 - Design Research

Addressing the Human Factor

Continued →

BUSINESS CONTEXT ANALYSIS

CONTEXTUAL INTERVIEWS

ETHNOGRAPHY

DEFINING PERSONAS

USER JOURNEY MAPPING

IDENTIFYING JOBS TO BE DONE (JTBD)

USE CASE - BRIEF

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

Continued →

- USE CASE - BRIEF
- DESIGNING **HUMAN MACHINE FEEDBACK LOOP**
- IDENTIFYING **DATA SOURCES THAT ARE REPRESENTATIVE** OF THE PROBLEM TO BE SOLVED
- DESIGNING DATA COLLECTION **MECHANISMS TO EFFECTIVELY CAPTURE USER GENERATED DATA**
- ESTABLISHING **GUIDELINES TO FILTER THE DATA** -HOW A THEORETICAL HUMAN EXPERT WOULD PRIORITIZE DATA?
- DESIGN **FILTERS TO ELIMINATE BIASES** (CULTURAL, SOCIAL, ECONOMIC, SKILL RELATED)

BASED INSIGHTS FROM RESEARCH & ETHNOGRAPHIC STUDIES IN PHASE 1

Phase 2 - Continued

PRIORITIZING FEATURES
USING INSIGHTS & DOMAIN KNOWLEDGE FROM PHASE 1
+
ASSISTING DATA SCIENTISTS IN THE SAME

MAPPING PREDICTIONS TO DECISIONS
THAT PROVIDE VALUE TO END USERS

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?

ML TASK

Input, output to predict,type of problem

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

PREDICTIONS

When to use new inputs and how long to featurize?

OFFLINE EVALUATION

Methods and checks to evaluate before deployment

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
FIRST TIME USER EXPERIENCE

DEFINING
TRIGGERS FOR CONTEXTUAL ASSISTANCE

EXPLICIT OR IMPLICIT MECHANISMS TO REWARD GOOD RESPONSES AND INFORM ON BAD ONES

VISUALISING DECISION MAKING

DESIGNING CONVERSATIONS
(If required)

Phase 3 - The experience

DESIGNING GUIDELINES TO **MITIGATE ERRORS**

DESIGNING GUIDELINES TO **MITIGATE ERRORS**

SETTING CRITERIA AND METRICS FOR LIVE EVALUATION

Machine Human Feedback loop