

# How to Trust, but Verify, in Healthcare

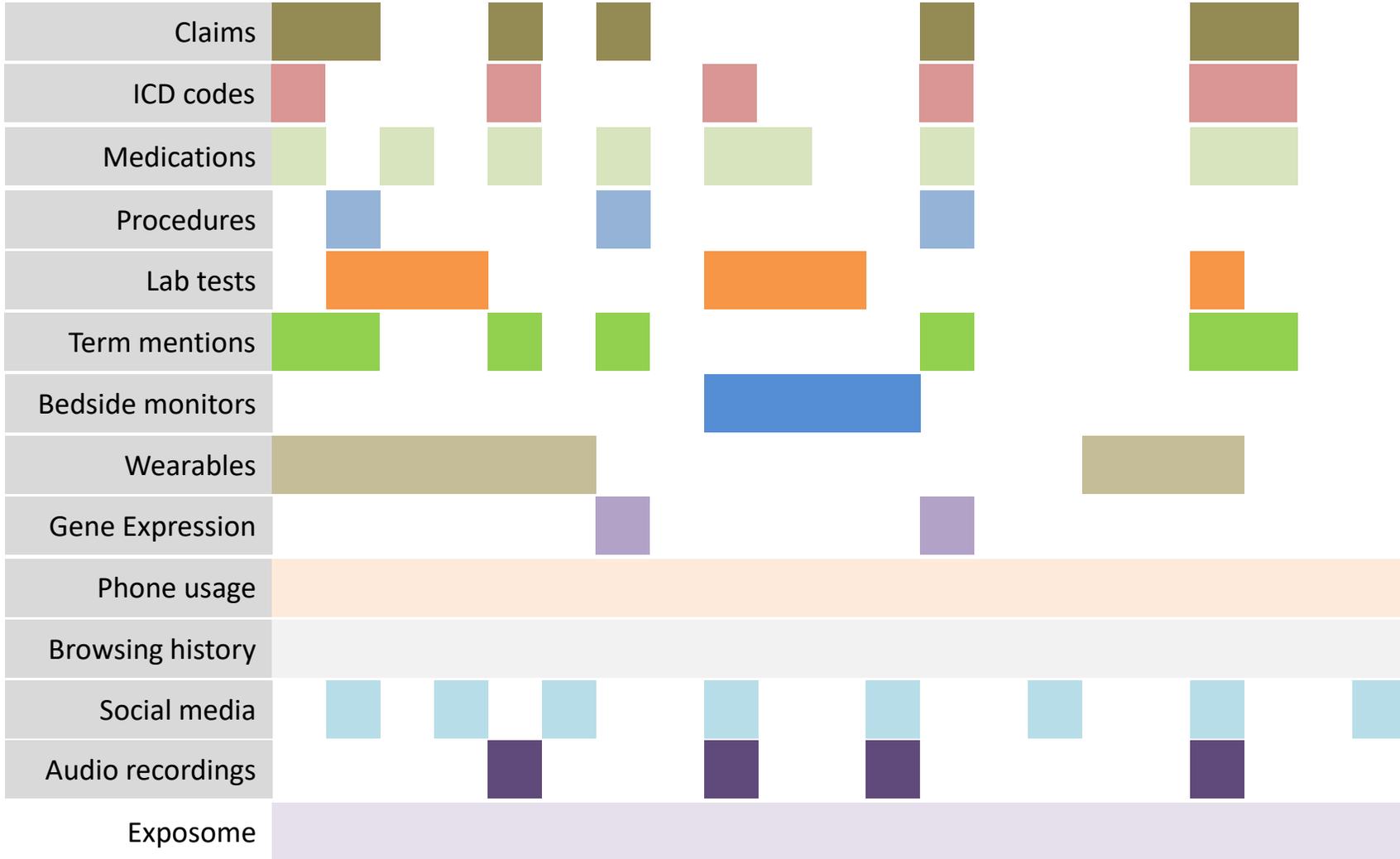
Nigam Shah, MBBS, PhD

[nigam@stanford.edu](mailto:nigam@stanford.edu)



**STANFORD**  
SCHOOL OF MEDICINE

# Patient Journey



:

Based on:

1. Genetic markers
2. Demographics & SES
3. Prior medical record
4. Wearables (digital biomarkers)
5. Behavioral and social data

Decide who  
to treat

If (**Risk** > Th.)

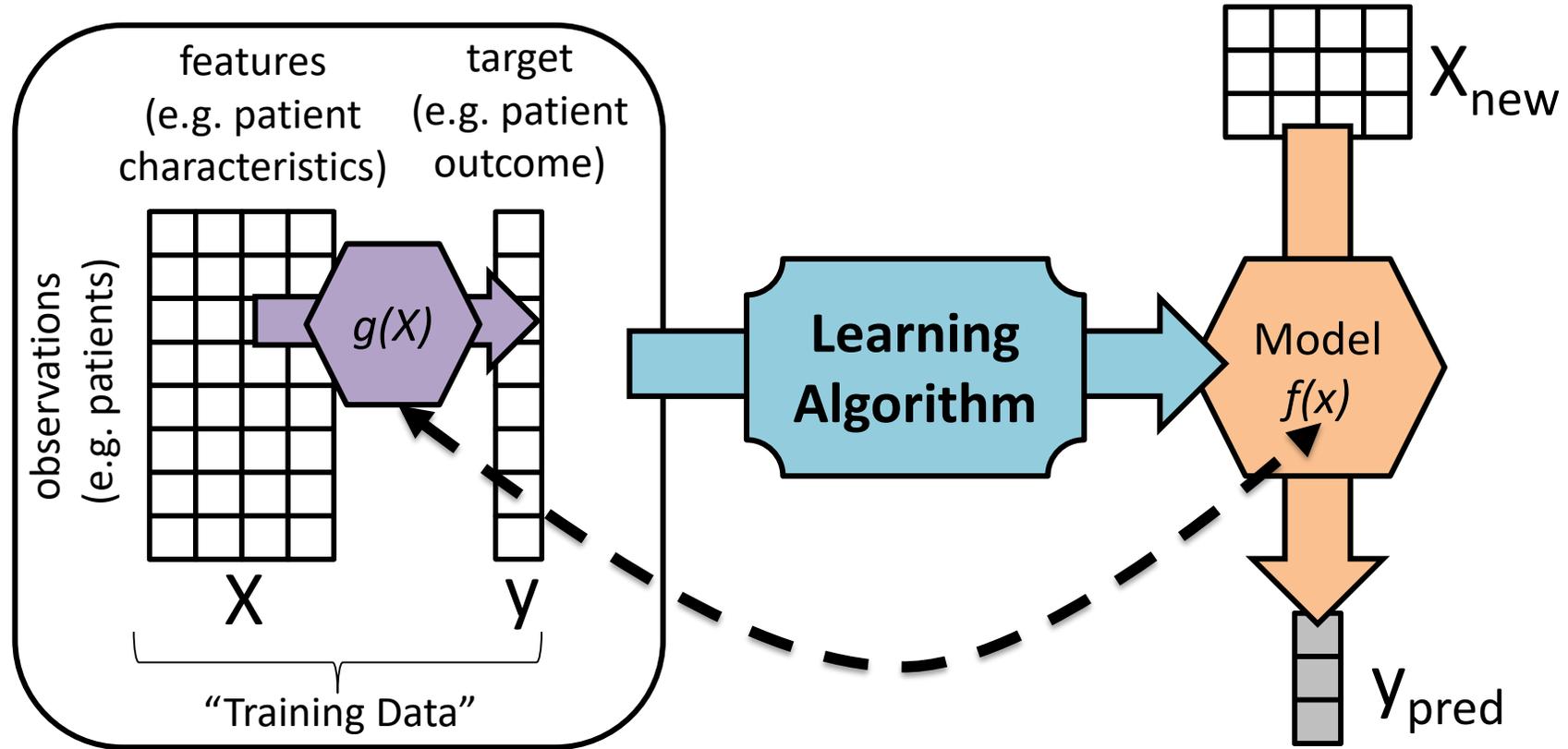
then (do = **X**)

Decide how  
to treat

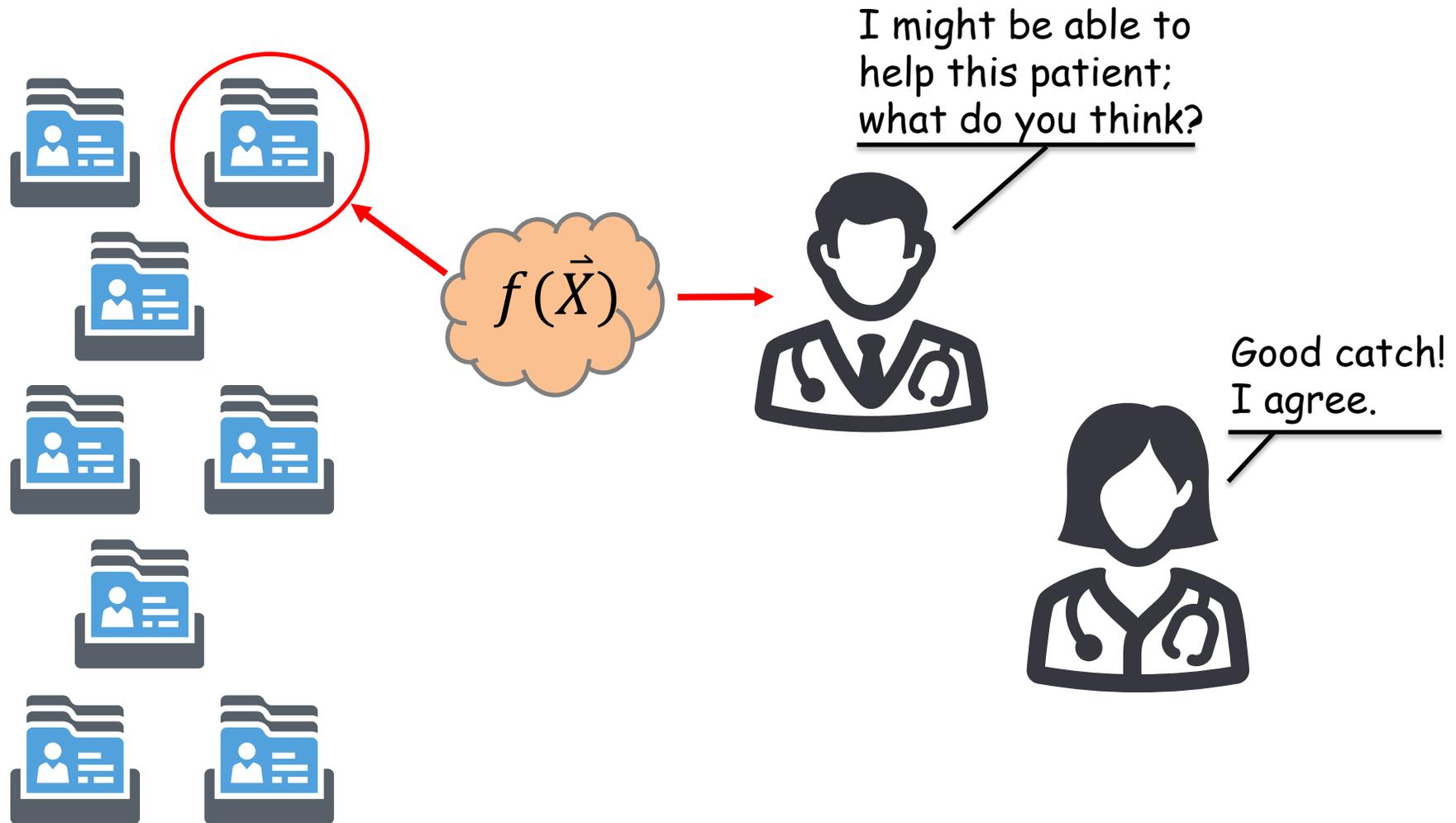
Based on:

1. Biomarker measurements
2. Mechanistic understanding of disease
3. Similar patients' outcomes
4. What's covered, and available
5. How much time we have on hand

# A model

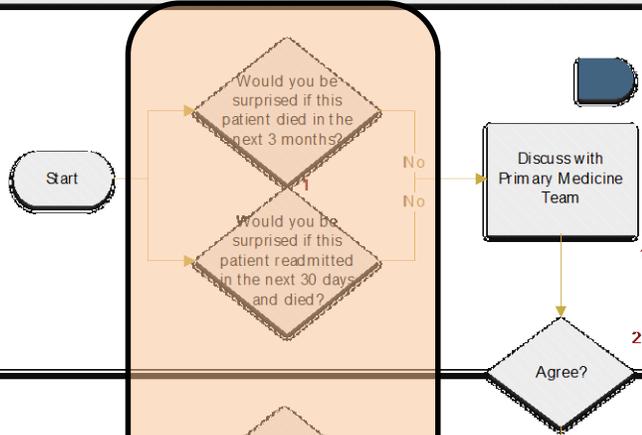


# A workflow



# Inpatient Hospital Medicine Initiated Workflow – Goals of Care Workflow

CNS



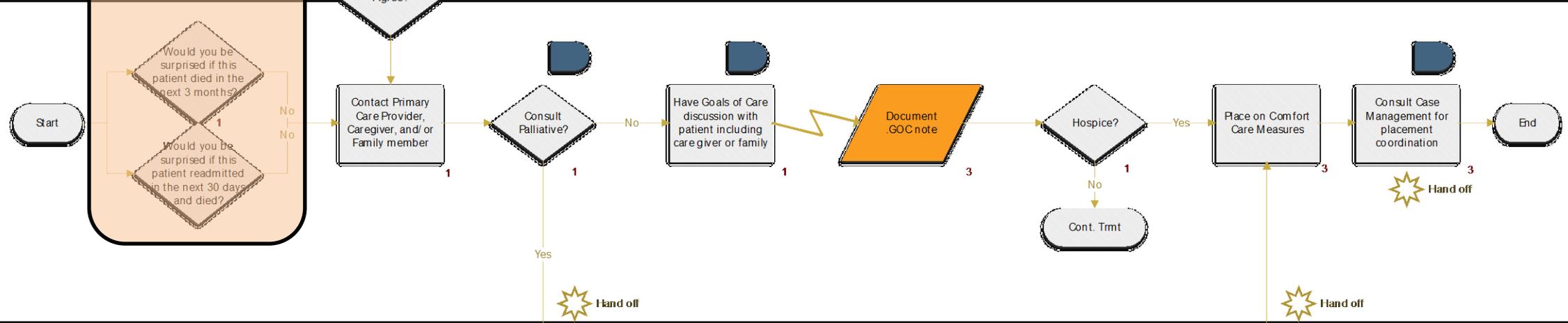
## Summary Stats

Total Steps: 21  
Level 1: 7  
Level 2: 7  
Level 3: 7

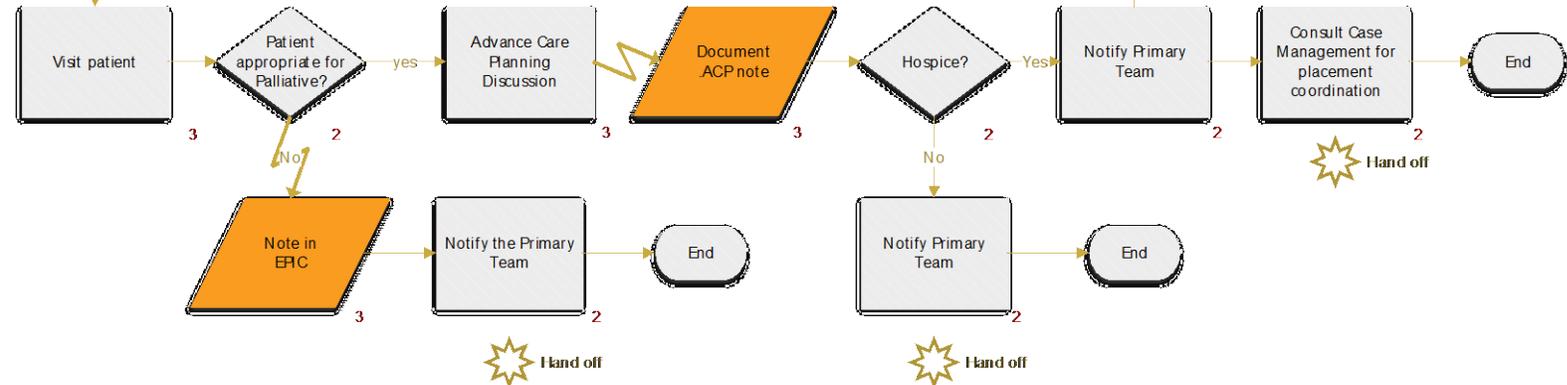
Handoffs: 7

Total Cycle Time: 48 hours

Hospital Med Attending



Palliative Medicine



### Reliability Level:

- (1) Individuals: Feedback, checklists, training, basic standards
- (2) Procedures: Embedded standard work, reminders, constraints
- (3) Systems: fail safes, physical layout, built-in feedback, automated systems, concentration of responsibility

# Definitions and Clarifications

- Trustworthiness: of the model, or the workflow around it, or both?
- Trust = proof over time that a thing does what it claims to do. Trust is earned [over time].
- HOW = interpretability
- WHY = explainability

# When predicting 24 hr. mortality ...

- Interpretability is a poor surrogate for trust
  - Knowing ‘how’ does not help you decide what action to take
- Explainability is a poor surrogate for trust
  - Knowing ‘why’ does not help you decide what action to take
- Knowing that the model’s prediction has helped make good decisions in the past 2 years.

# Building trustworthy (and useful!) models

## How do we get the best $f: X \rightarrow Y$ ?

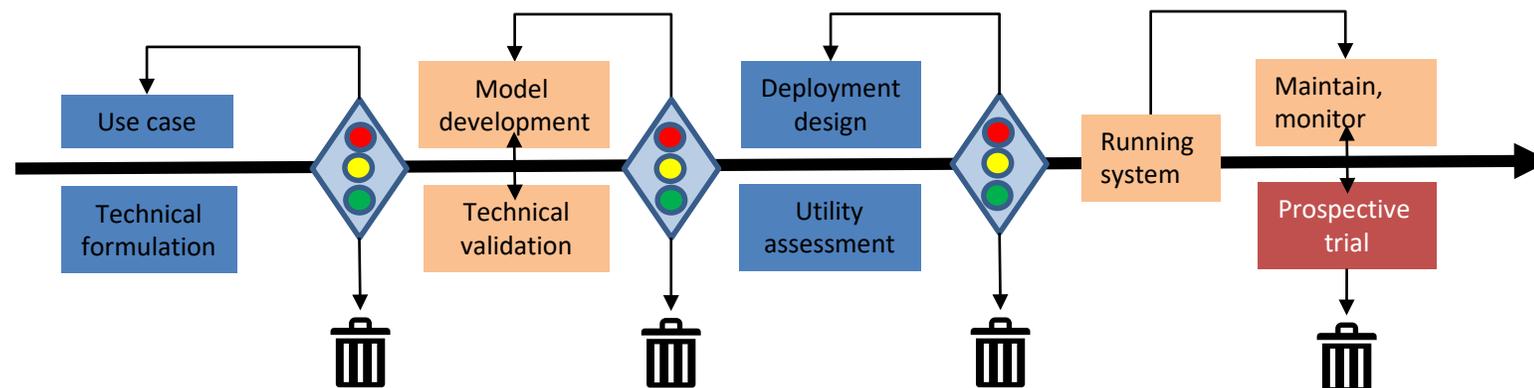
- Does representation learning help?
- Does multi-task learning help?
- Does using textual content help?
- How do we train fair models?

## Can we use $f: X \rightarrow Y$ in the real world?

- Can we get the data by 5 am, to make prediction by 6 am?

## Running system = model applied to each case + execution of workflow.

- Evaluate the impact of the *running system* on the outcomes we care about
- Maintenance is huge liability – who will carry the pager?
- Monitoring is unexplored



## Use case

- What clinical outcome(s) are you trying to affect?
- Who is the target population?
- What action would you take?
- Who will take that action?

## $f: X \rightarrow Y$ subject to...

- use an existing equation vs. learn a new equation.

## Utility assessment

- Given the costs of the actions and its benefit, is there net utility?

## Deployment design

- Do we increase the efficiency of existing workflows
- Do we require entirely new workflows

# Acknowledgements

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- **Engineers:** Vladimir Polony, Jose Posada
- **BMI Students:** Stephen Pfohl, Sehj Kashyap, Minh Nguyen, Scotty Flemming, Erin Craig
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