Personalized Diabetes Management Using Electronic Medical Records

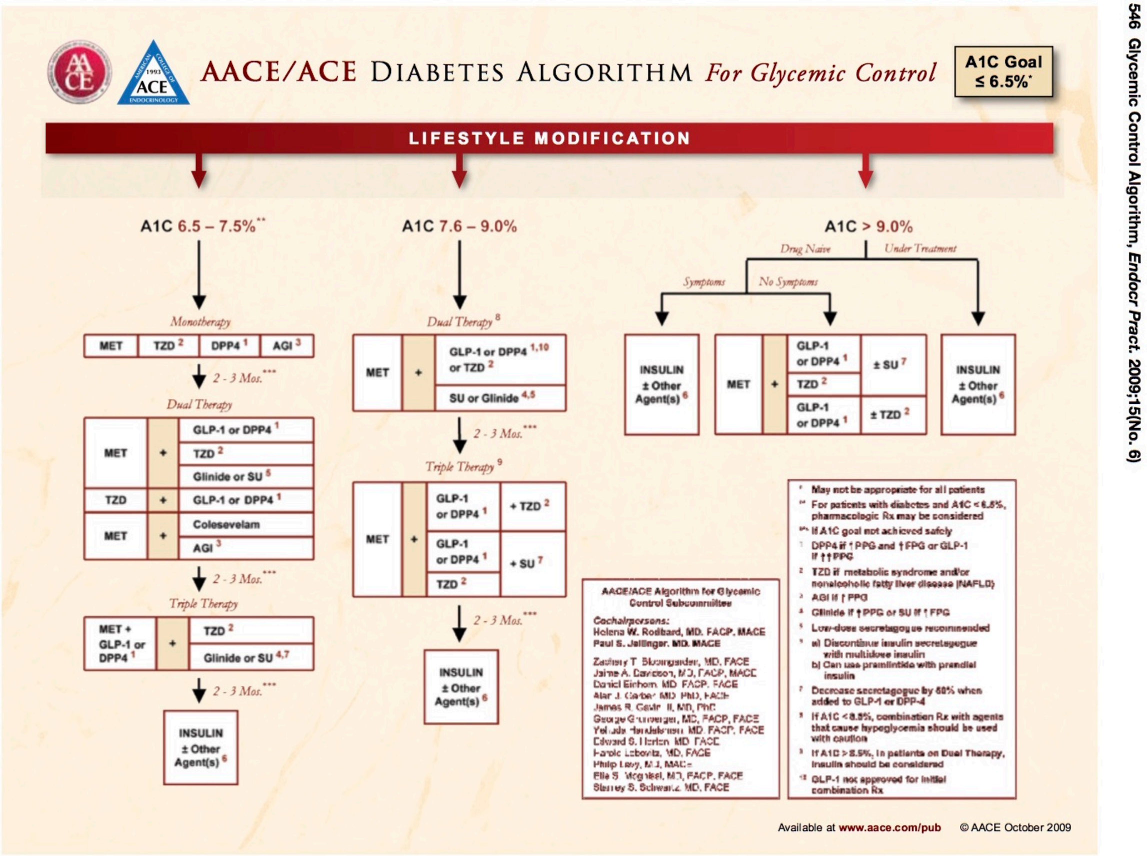
DIMITRIS BERTSIMAS, NATHAN KALLUS, ALEX WEINSTEIN, DAISY ZHUO

OPERATIONS RESEARCH CENTER, MIT

SEPTEMBER 8, 2016

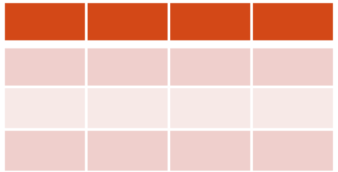
Current practice

- Clinical guidelines for managing type 2 diabetes do not differentiate based on patient-specific factors.
- This is despite evidence that response to blood glucose regulation agents can differ among population subgroups.

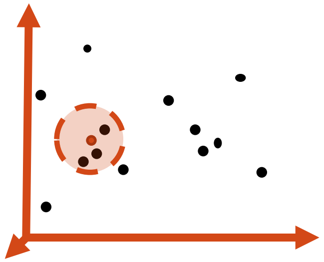


Solution

Data



Algorithms



Clinical Expertise

Our aspirations

We developed a **data-driven** algorithm for **personalized** diabetes management using **electronic medical records** (EMR).

- For any given patient, the algorithm generates a personalized treatment recommendation based on evidence from the historical records in a hospital EMR system.
- Our approach yields substantial improvements in HbA1c relative to standard of care.
- Our prototyped dashboard visualizes the recommendation algorithm and can be used by providers to inform decisions related to diabetes care.

Data

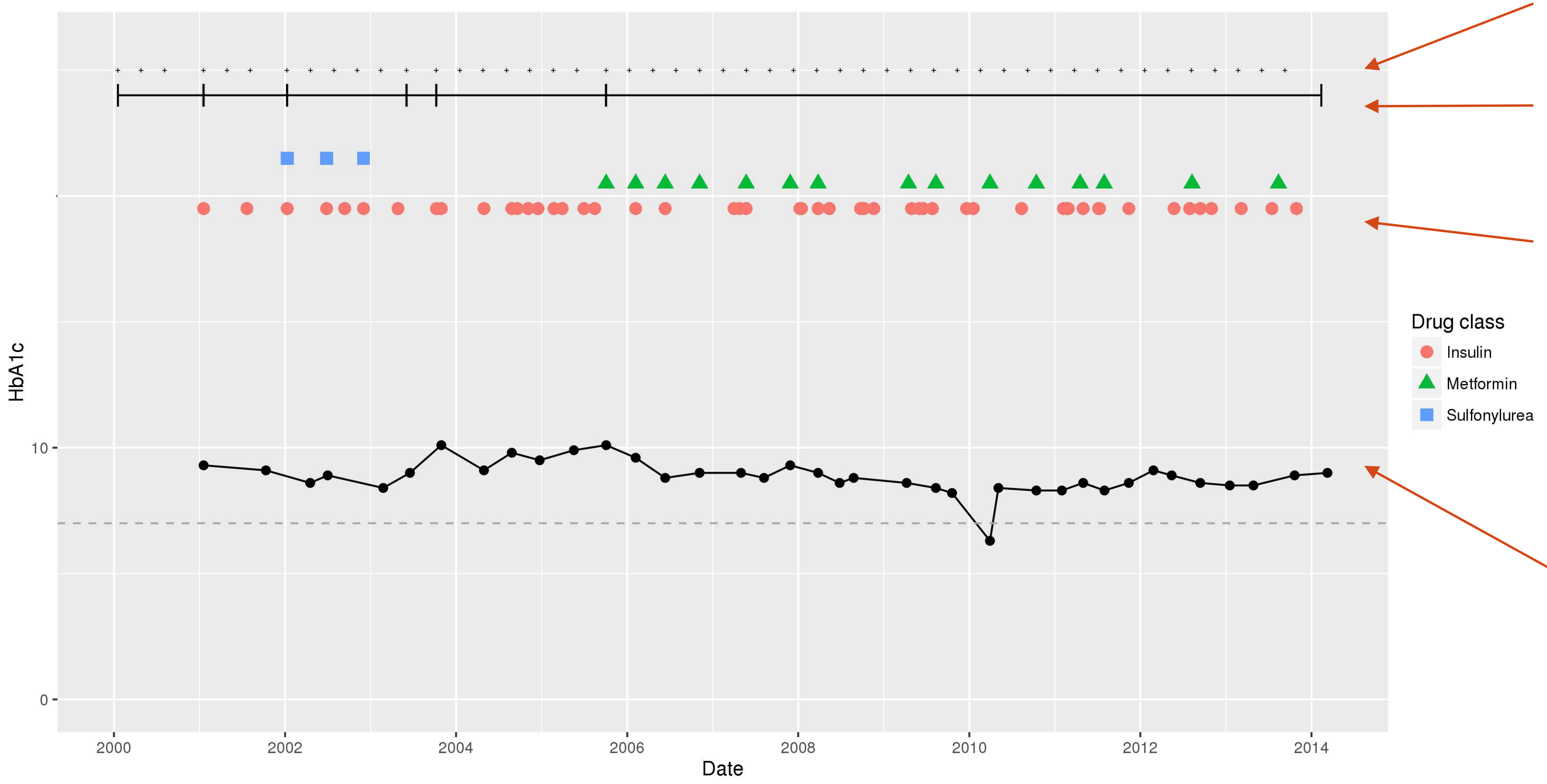
EMR for > 1.1 million patients from Boston Medical Center

- We defined inclusion criteria based on presence of medication records for blood glucose regulation agents (metformin, insulin, sulfonylureas, etc.) and sufficient HbA1c observations and medical history.
- 10,086 patients met inclusion criteria.

Patient characteristics

- *Demographic*: age, sex, race/ethnicity, language, religion, marital status.
- *Medical history*: records for BMI, HbA1c, serum creatinine levels.
- *Treatment history*: medication records.

Modeling lines of therapy and visits



Patient visits every 100 days

New line of therapy each time drug combo changes

Treatment history

HbA1c history

Decisions and outcomes

Decisions and outcomes are defined relative to each patient visit:
- 52,842 unique patient visits.

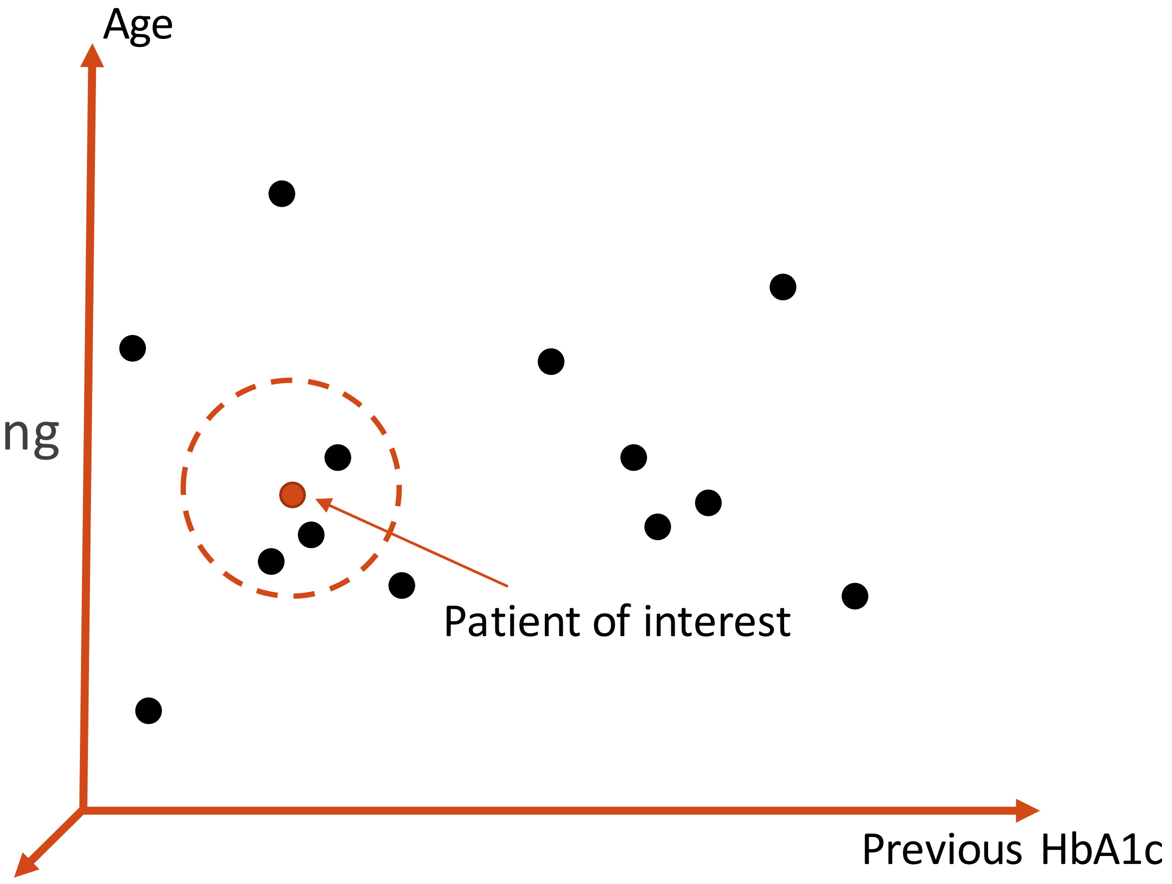
Outcome of interest:
- Average post-treatment HbA1c in period 75-200 days after each visit.

At each visit, we observe ground-truth “standard of care” treatment:
- For most visits, provider prescribed continuation of current line of therapy.

We need a method to estimate the *counterfactual* outcomes; i.e. what the patient’s outcome would have been under other treatments.

k-nearest neighbors regression

- To estimate a patient's potential outcome under treatment *T*, we search the EMR database for the *k* most similar patient visits receiving treatment *T*.
- Then take average of neighbors' outcomes.
- Similarity defined as weighted distance among patient demographic, medical history, and treatment history characteristics.
  - Relative weights of features determined by separate linear regression model used to identify most predictive factors.



*k*NN yields accurate predictions

Calculate out-of-sample R^2 of *k*NN HbA1c predictions

- For patients who *actually received* each treatment.
- R^2 differs by model but fairly predictive for all treatments.

Compare with lasso and random forest predictive models

- Similar accuracy, but more interpretable

	***k*NN**	**Lasso**	**Random forest**
Average R^2	0.40	0.39	0.41
Min. R^2	0.20	0.33	0.24
Max. R^2	0.54	0.53	0.53

Personalized recommendation algorithm

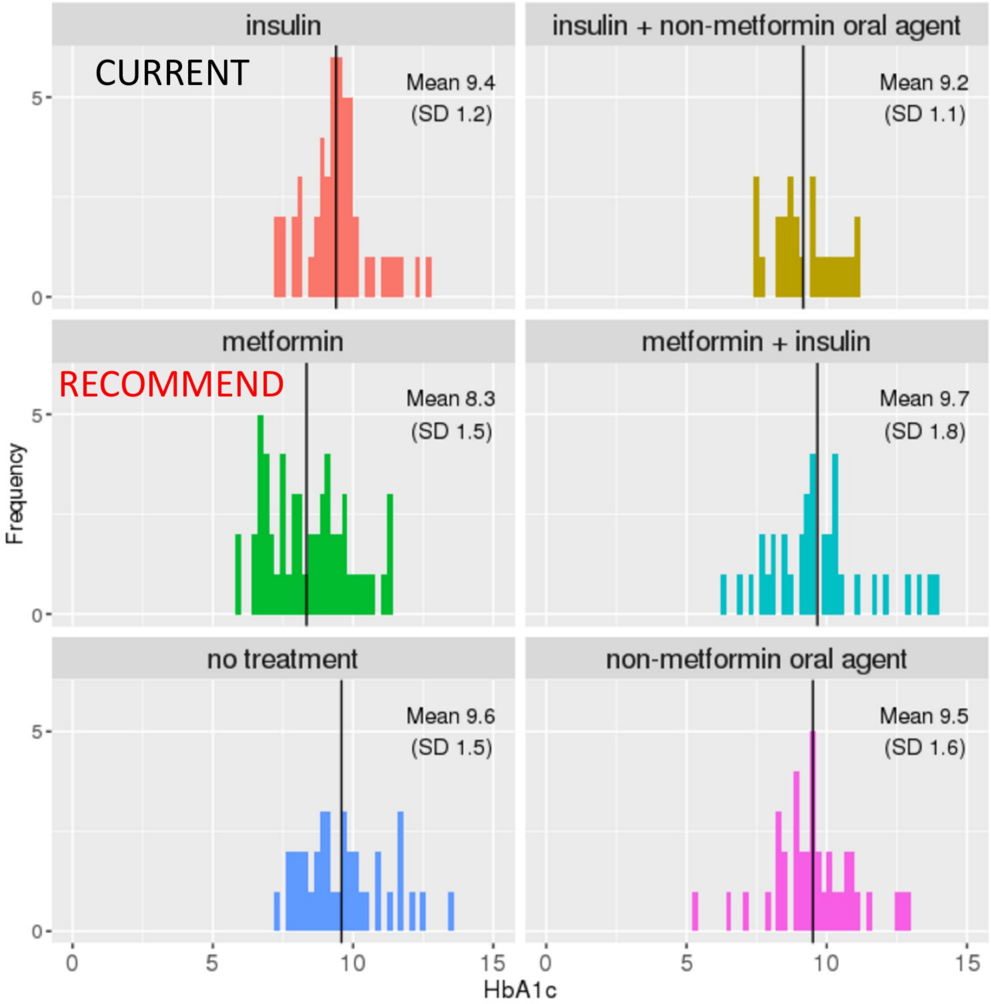
For any given patient at any given visit:

1. Generate menu of available treatment options.
   - Menu includes current treatment and natural deviations from current treatment; incorporates contraindications to metformin.
2. Use *k* nearest neighbor regression to predict potential outcome under each treatment option.
3. Reject any non-current treatment option with predicted outcome above pre-specified HbA1c threshold.
   - Threshold: HbA1c at least **0.8%** better than continuing current treatment.
4. Recommend remaining option with best predicted outcome.

(a) **Recommendation:** Switch from insulin monotherapy to metformin monotherapy

Predicted HbA1c (%): 8.3

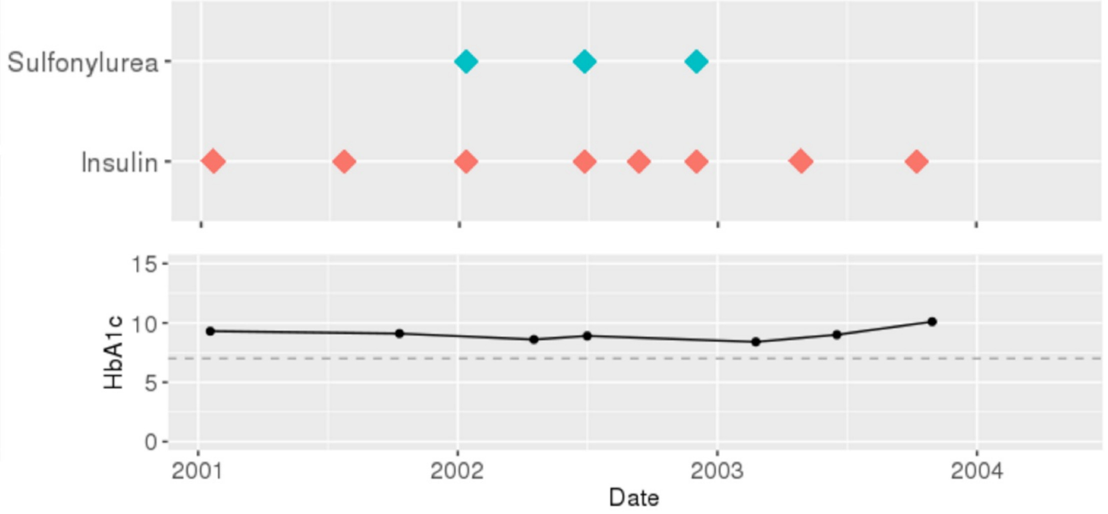
(b) **Outcomes for similar patients who were prescribed…**



(c)

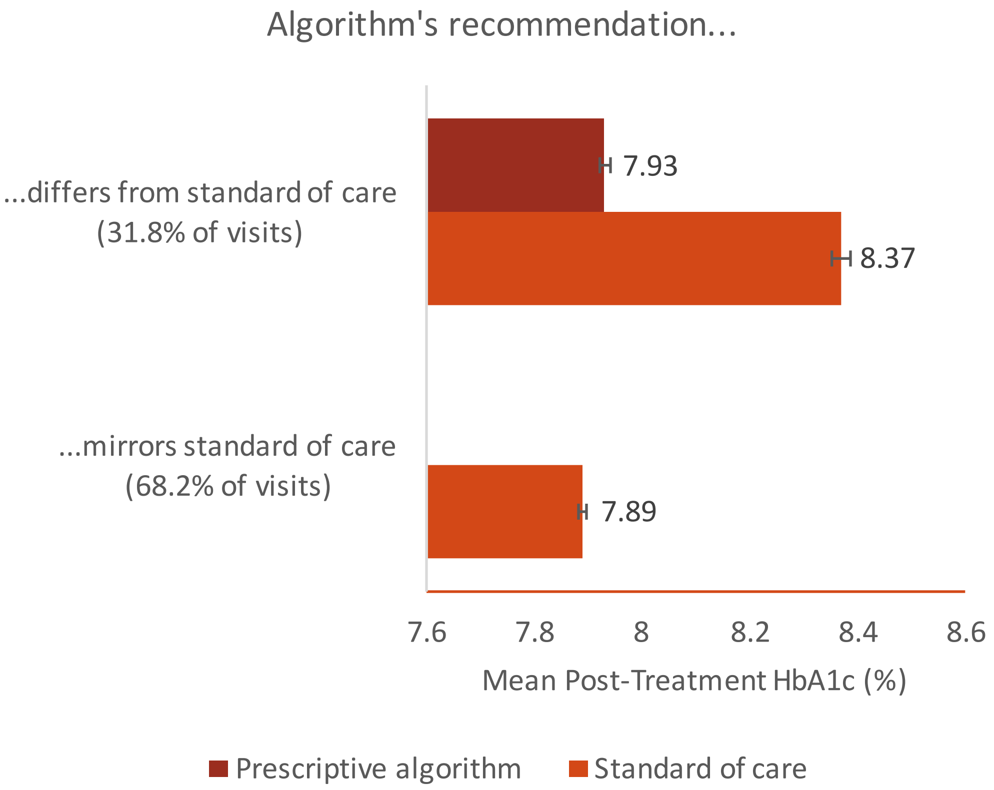
PATIENT ID	12XXXXX
AGE (Years)	61.9
SEX	F
RACE/ETHNICITY	Black
CURRENT HbA1c (%)	10.1
CURRENT REGIMEN	Insulin

(d) **Patient Treatment & HbA1c History**



Effectiveness of algorithm

- The algorithm is tuned to be conservative; it only recommends a change if the predicted benefit is large
  - In 31.8% of patient visits, the algorithm recommends a treatment different from standard of care
  - Among those visits, mean HbA1c % under algorithm was lower than SOC by **0.44** ($p<0.001$)



Conclusions

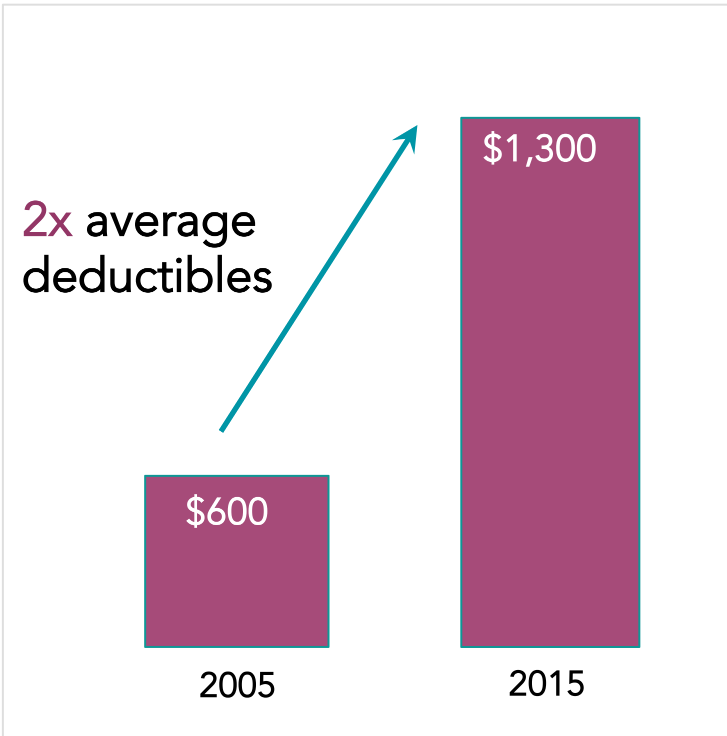
- We developed a data-driven, personalized prescriptive algorithm for type 2 diabetes.
- When the algorithm is sufficiently confident to reject continuing current treatment, post-treatment HbA1c % is lower than standard of care by **0.44** on average.
- The intuitive dashboard prototype can support medical decision making by providing evidence-based treatment recommendations.

Personalized Healthcare Management

DIMITRIS BERTSIMAS, STEPHEN SOFOUL, **NATALY YOUSSEF**

myAHealth

The Landscape



Shift of financial risk to health users

23.5M

Americans served by Accountable Care Organizations (ACOs)

Shift to value based healthcare

Traditionally…

Katy

50 years old
Diabetic
Overweight
Lives in Boston

Ashley

50 years old
Diabetic
Overweight
Lives in Boston

- ? Progression of diabetes?
- ? Treatment personalized?
- ? Engagement in wellness?
- ? Perception of risk & health?

From "one size fits all" to a multidimensional view

Holistic View

Katy

50 years old
Diabetic
Overweight
Lives in Boston

Single-family home
Shops Trader Joe's
Voted in election
Invests in stocks

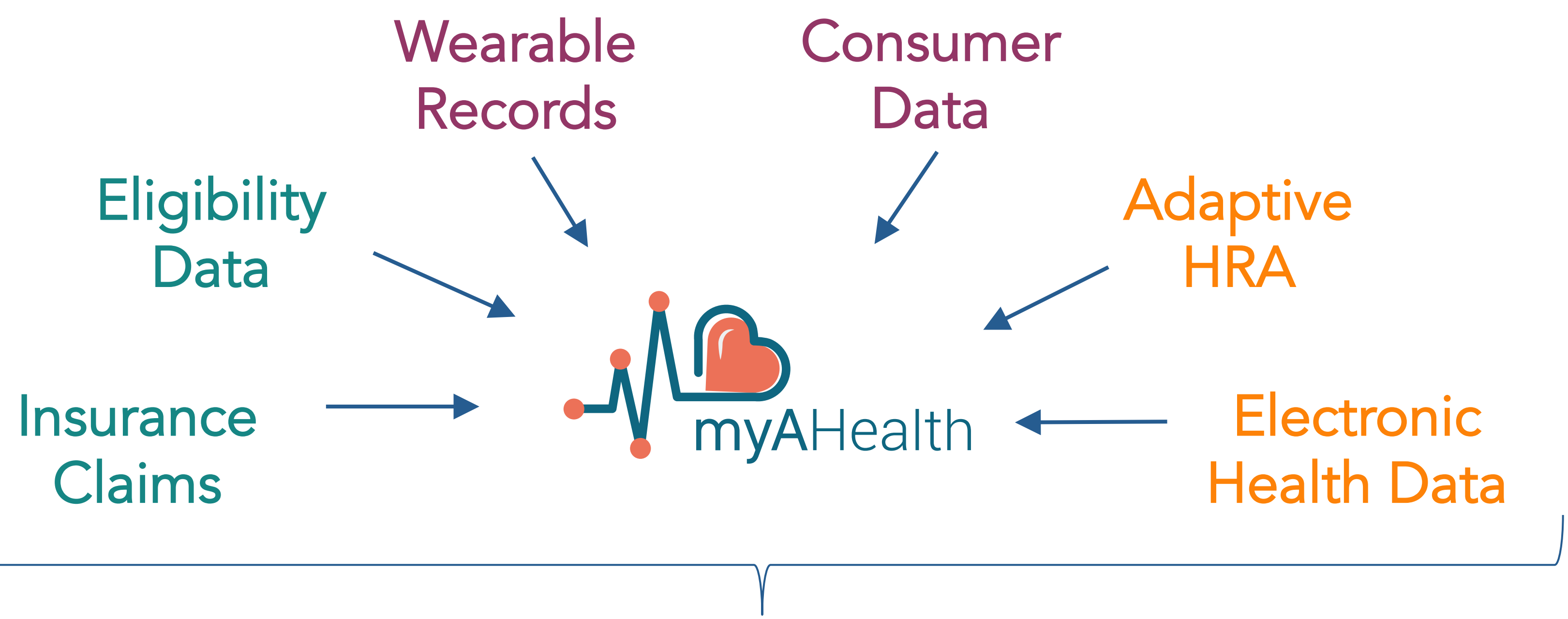
Can we personalize healthcare to better manage outcomes?

Ashley

50 years old
Diabetic
Overweight
Lives in Boston

Apartment rental
Shops at Walmart
Not registered to vote
Works two shifts

Personalized Healthcare Tool



Personalized Healthcare Decision Support

1. Supervised machine learning
2. Unsupervised learning & clustering
3. Robust optimization under risk

Personalized Healthcare Tool

myAHealth

1 **DATA**

Connects healthcare users with their data

2 **ANALYTICS**

Understands healthcare users as consumers

3 **OPTIMIZATION**

Personalizes healthcare decisions to individuals

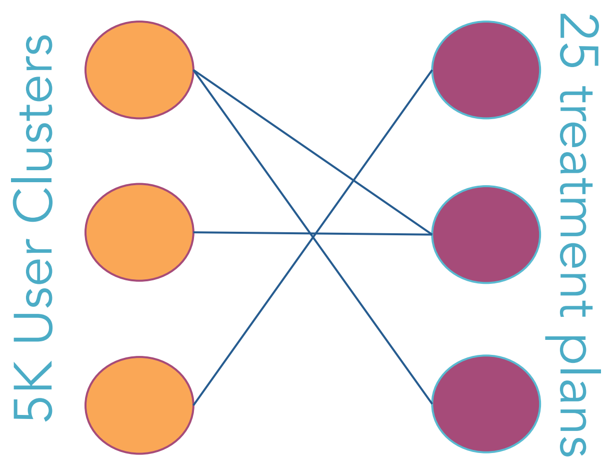
Financial decisions (choice of insurance)
+
Seeking personalized care (treatments, disease management)

Analytics Backend

Robust Optimization Framework

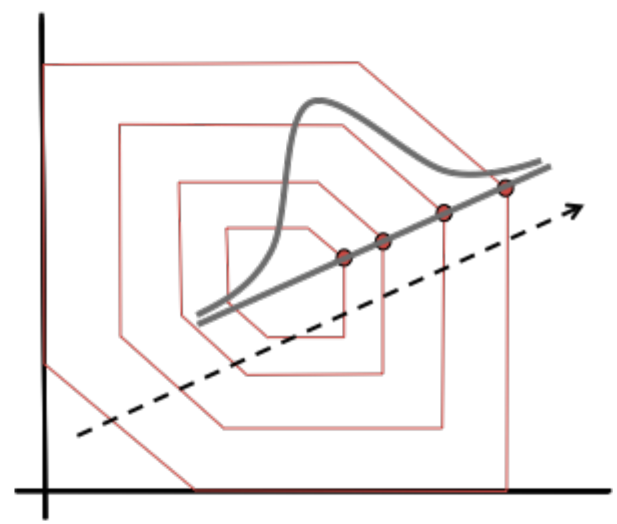
Through a data-driven approach, we model matching problem as a mathematical optimization under uncertainty

1 Multi-Dimensional



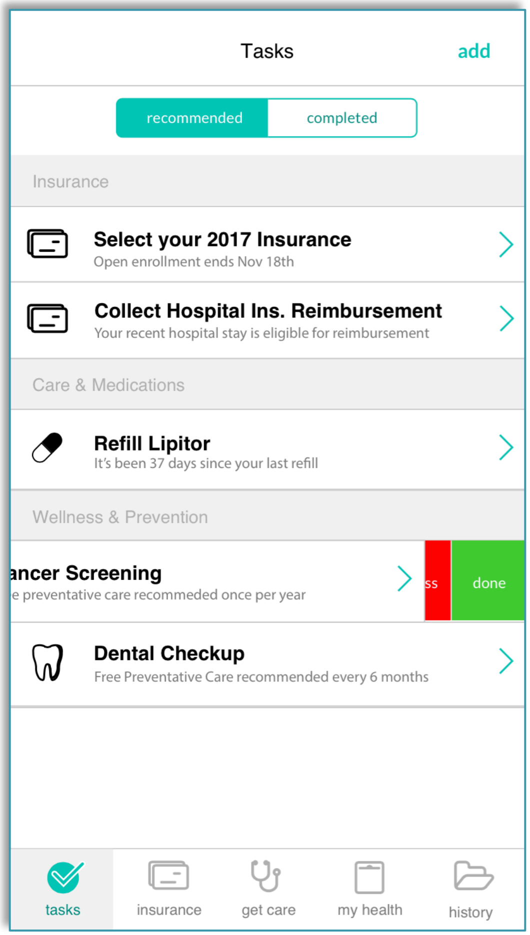
170 Billion
possibilities

2 Real-Time Execution

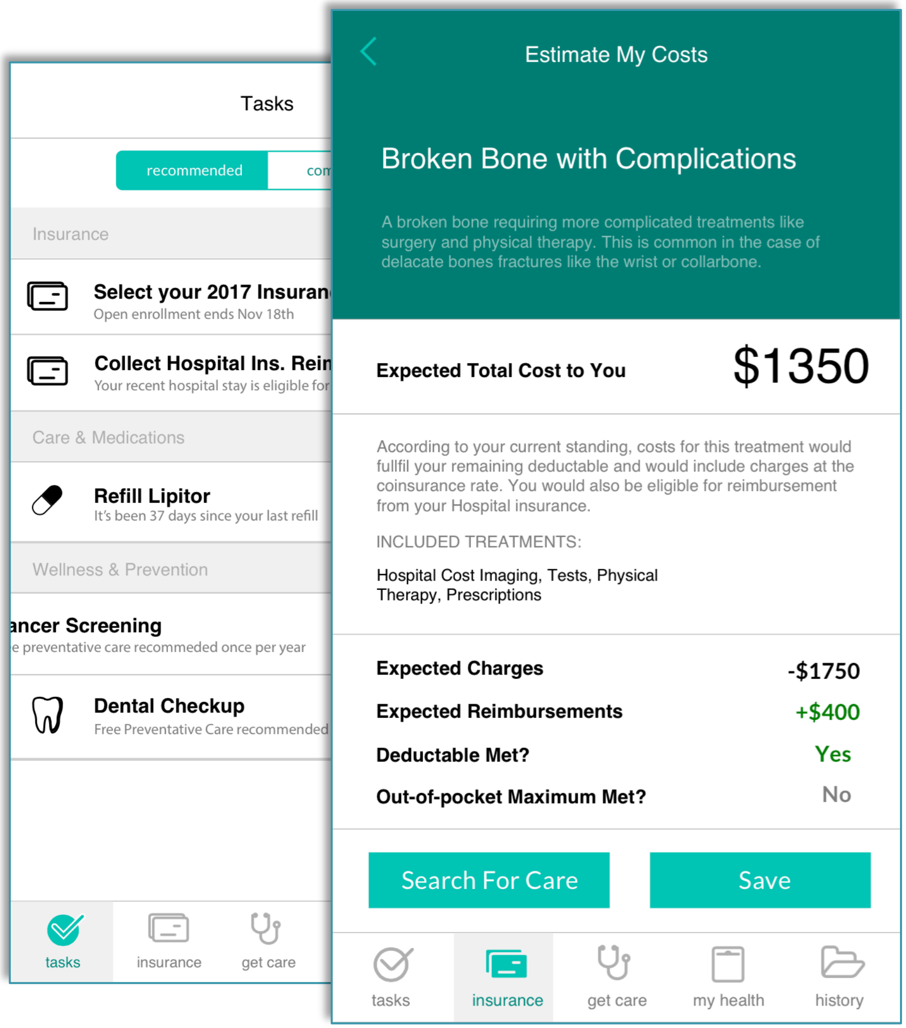


Risk simulation
in seconds

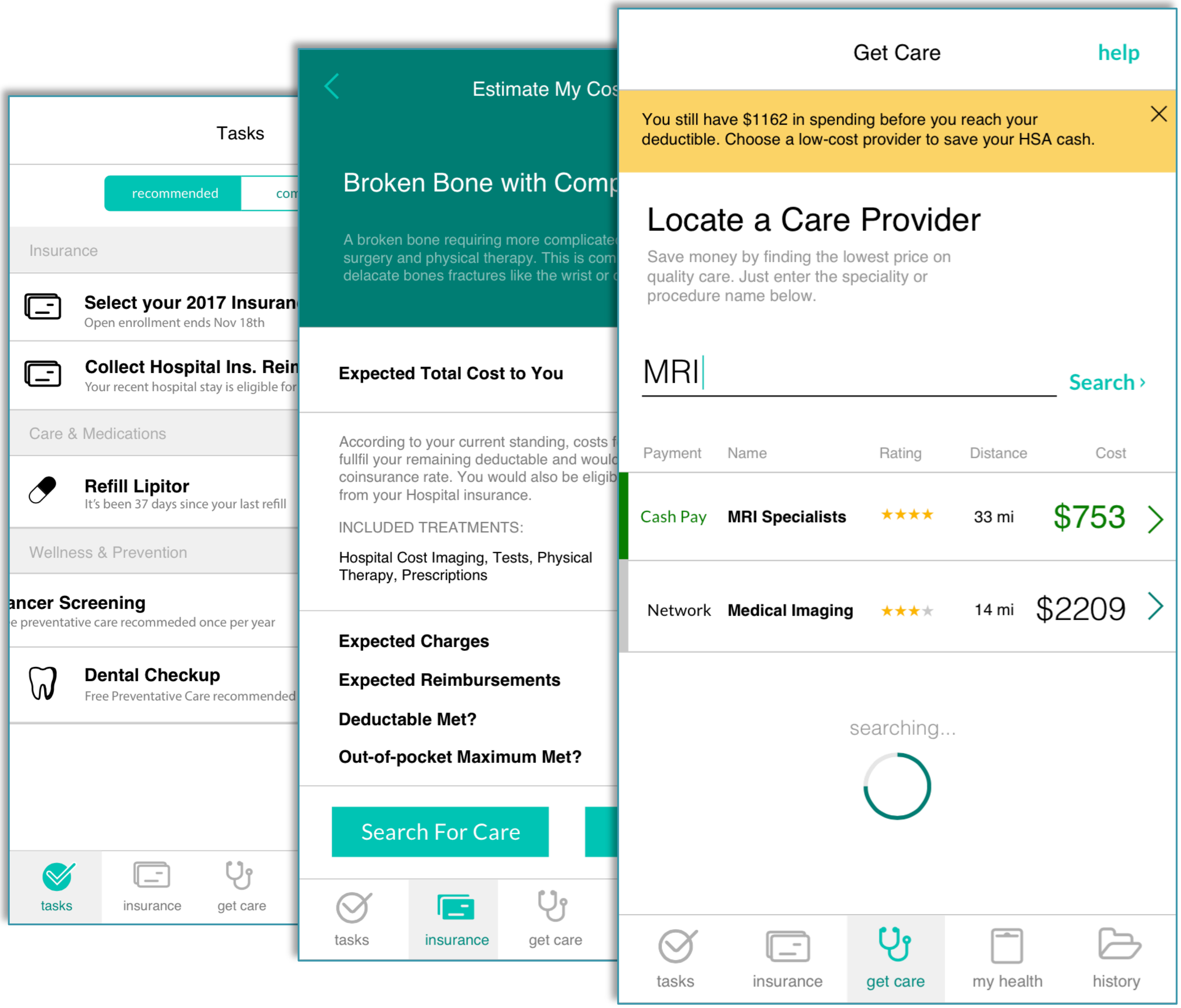
User Interaction



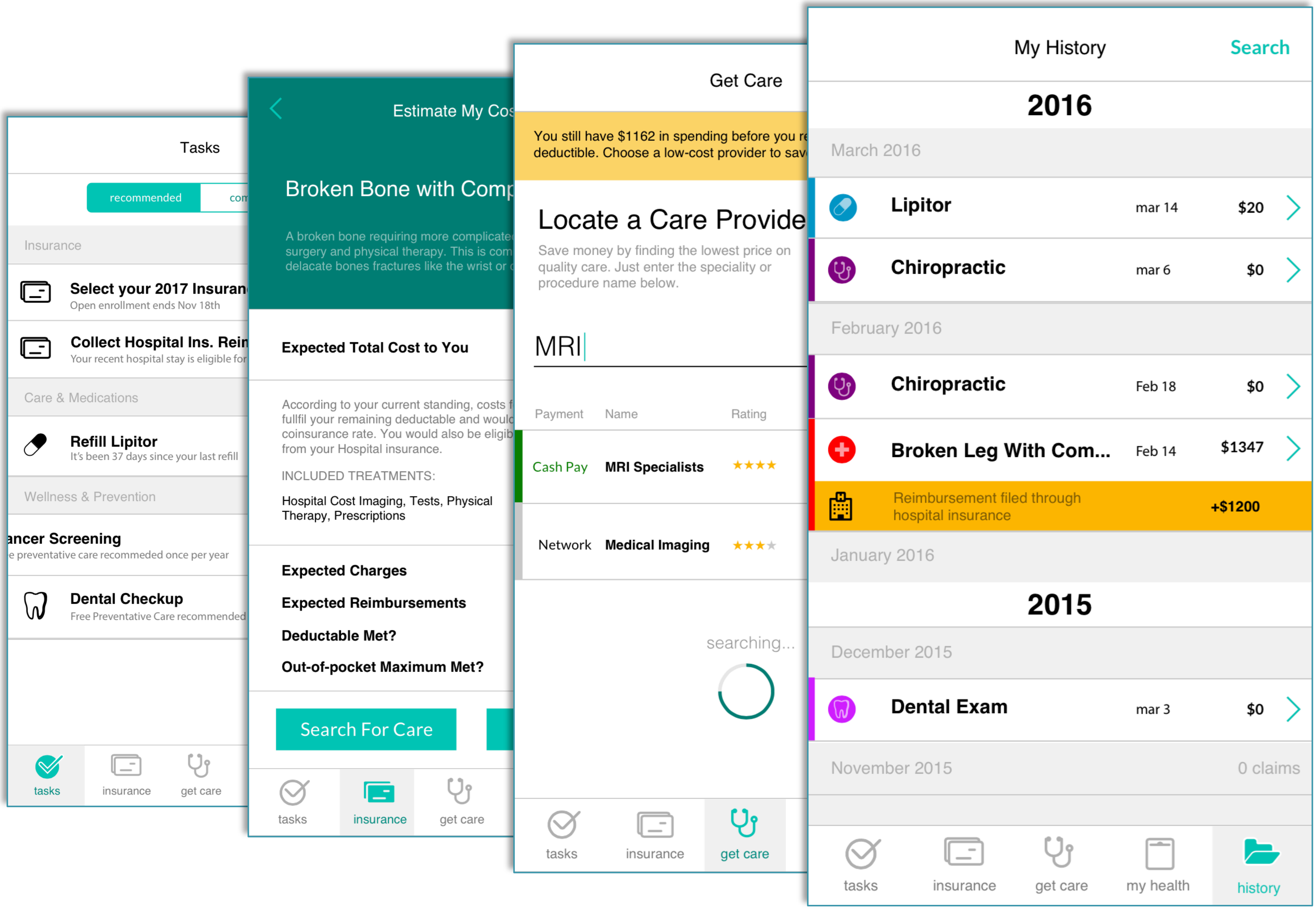
User Interaction



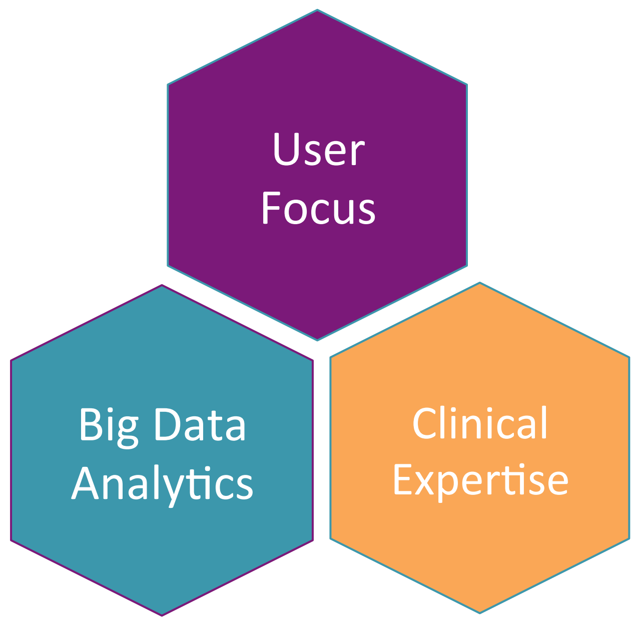
User Interaction



User Interaction

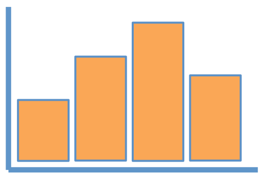


In Development



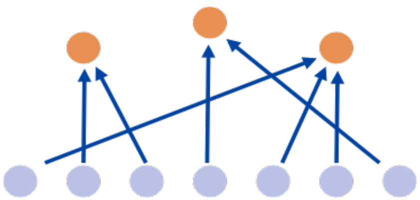
In Conclusion…

DESCRIPTIVE ANALYTICS



PREDICTIVE ANALYTICS

PRESCRIPTIVE ANALYTICS



OPERATIONS RESEARCH CENTER

myAHealth