From personal informatics to personal analytics

data science-driven solutions for personal health

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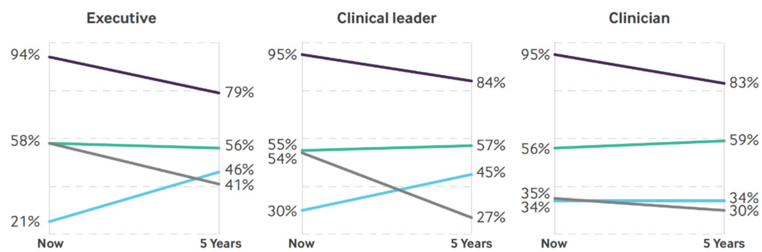
Data and Data Science in Health

- Increasing volume of health data
  - Electronic Health Record
  - Health Information Exchange
  - Patient-generated data
- Concerns regarding information overload and disruptions to work

Data and Data Science in Health



https://catalyst.nejm.org/about/news/nejm-catalyst-insights-report-finds-patient-generated-data-genomic-data-expected-among-useful-sources-health-care-data-next-five-years/

Data and Data Science in Health

- Exciting advances in data science
  - Data mining and machine learning
  - Natural language processing
  - Mechanistic models
  - Predictive analytics
- How to make data science work for humans and inform human decisions and choices?

Nutrition in type 2 diabetes

- Lack of clear behavioral goals
  - Healthy diet ≠ blood glucose management
  - Individual differences
- Need to balance multiple priorities
  - Cost, taste, culture, family…
- Diverse populations
  - Low literacy and numeracy
- Clear need for easy to understand decision support

Personal analytics

- Descriptive
  - Identifying important trends
- Predictive
  - Anticipating consequences
- Prescriptive
  - Recommending solutions

Personal analytics

- Descriptive
  - Identifying important trends – Glucolyzer
- Predictive
  - Anticipating consequences – Glucoracle
- Prescriptive
  - Recommending solutions – Glucotype

Personal analytics

- *Descriptive*
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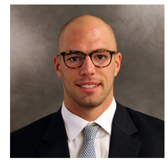
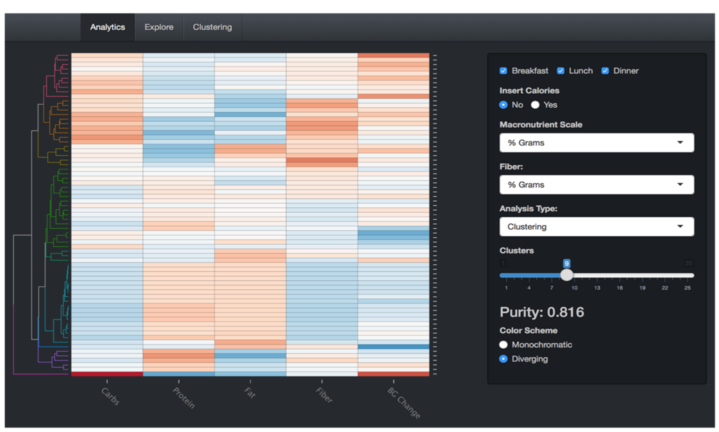
Discovery with visual analytics



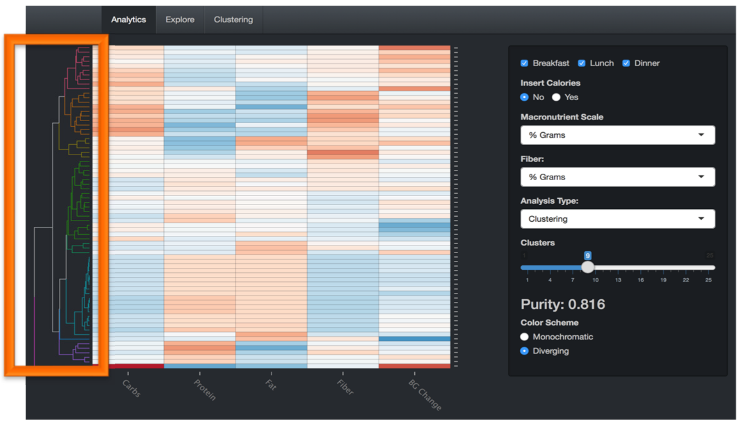
Daniel Feller

- Data:
  - Meals (nutritional composition assigned by expert dietitians)
  - Blood glucose before/after meals
- Analytics
  - Hierarchical clustering for grouping of meals
- Interactive visualization:
  - Identify nutritional profiles of meals that have a particular glycemic impact (what’s a good meal for this person?)

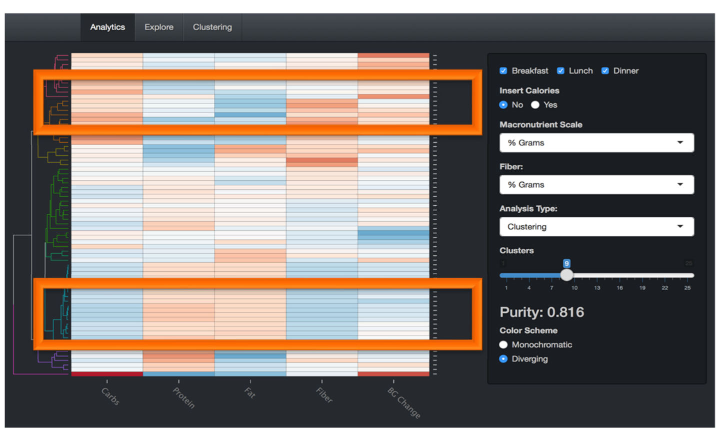
Glucolyzer



Glucolyzer

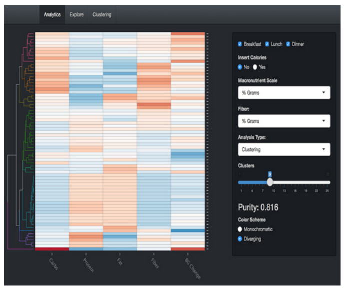


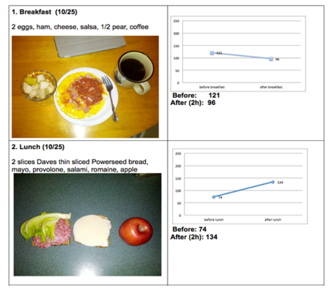
Glucolyzer



Glucolyzer evaluation

- Study with 10 Registered Dietitians
  - Compare Glucolyaer with tabular presentation





(60-120 meals)

Glucolyzer evaluation

- Results:
  - Using Glucolyzer: more patterns, similar accuracy
  - More non-carbohydrate patterns
- Challenges:
  - Cognitive complexity
  - Limited time
  - Apophenia

Feller D., Burgermaster, M., Davidson, P.D., Smaldone, A., Levine, M., Albers, D.J., Mamykina, L., Supporting Clinical Decision Making with Patient-Generated Data, *JAMIA* 2018

Personal analytics

- Descriptive
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- *Predictive*
  - *Anticipating consequences – Glucoracle*
- Prescriptive
  - Recommending solutions – Glucotype

Predictive analytics

- Data:
  - Meals (nutritional composition assigned by
    expert dietitians)
  - Blood glucose before/after meals
- Analytics
  - Data Assimilation with Mechanistic Physiological Models
- Decision support
  - Personalized forecasts for post-meal changes in blood glucose levels

Maria Hwang

Matt Levine

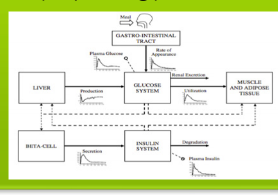
Pooja Desai

Personalized forecasts

Individualized post-meal forecast

Data Assimilation:
- Forecasts glucose trajectory
- Personalize model via parameter estimation
- Correct model states trajectory given new parameter measurement

Human physiology



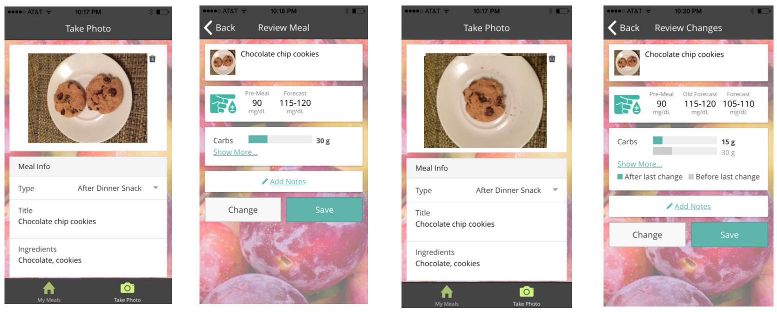
Personal data

Validating the model

- Initial studies showed that DA model can perform as well or sometimes better than experts in forecasting glycemic impact of meals
- Model accuracy varies greatly between individuals

Albers DJ, Levine M, Gluckman B, Ginsberg H, Hripcsak G, Mamykina L. Personalized glucose forecasting for type 2 diabetes using data assimilation. PLOS Computational Biology. 2017 Apr 27;13(4):e1005232

Glucoracle



Glucoracle study

- Qualitative perceptions
  - Individuals with type 2 diabetes recruited from TuDiabetes (n=5)
  - Individual from economically disadvantaged community (n=5)
  - Used for 4 weeks
  - Qualitative interviews
- Large scale deployment
  - glucoracle.com

Glucoracle study

- Overall positive perceptions
  - Forecasts are perceived as insightful and revealing, at time even game-like
  - Intuitive and relatively easy to understand
  - Forecasts can be used to make decisions
    - Adjust the planned meal
    - Adjust similar meals in the future
    - Other ways to compensate for meals (exercise, drink water)

Desai, P., Levine, M., Albers, D., Mamykina, L., Pictures Worth a Thousand Words: understanding elements of effective health visualizations for low numeracy patients with type 2 diabetes, in in the *Proceedings of the ACM Conference on Human-Factors in Computing Systems, CHI 2018*

Design challenges

- When to forecast
  - When meal is ready – too late
  - When grocery shopping – too uncertain
- Time horizon of impact
  - Immediate impact, or long-term impact
- Habits and outliers
  - Impact of one meal, or impact of a habit
- Need for recommendations
  - How to react to a undesired forecast

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Prescriptive analytics

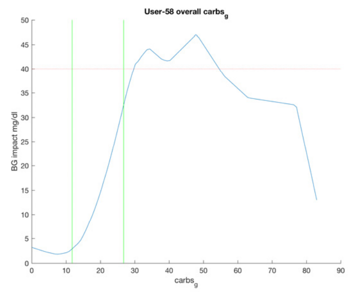
- Data:
  - Meals (nutritional composition assigned by expert dietitians)
  - Blood glucose before/after meals
- Analytics
  - Attributable Component Analysis (collaboration with Esteban Tabak, NYU)
- Recommendations
  - Personalized nutritional goals formulated in natural language (including in-the-moment decision support)

Elliot Mitchell

Matt Levine

Beth Heitkemper

Computational discovery



Attributable Component Analysis: identifying ranges of macronutrients that are systematically associated with high glycemic impact (DJ Albers, Esteban Tabak)

Personalized goals

- Expert system
  - A set of heuristics for translating computational discoveries into personal goals formulated in natural language
- Based on interviews with diabetes educators and dietitians
  - Increase/reduce macronutrient X
  - Replace macronutrient X with macronutrient Y
  - Replace X servings of carbohydrates with "free food"

Personalized goals

- Example goal:
  - For high carbohydrate breakfasts, reduce your carbs to be about 1 carb choice. Examples of 1 carb choice are 1 slice of whole wheat toast, 1 cup of oatmeal, or 1 apple

Personalized goals

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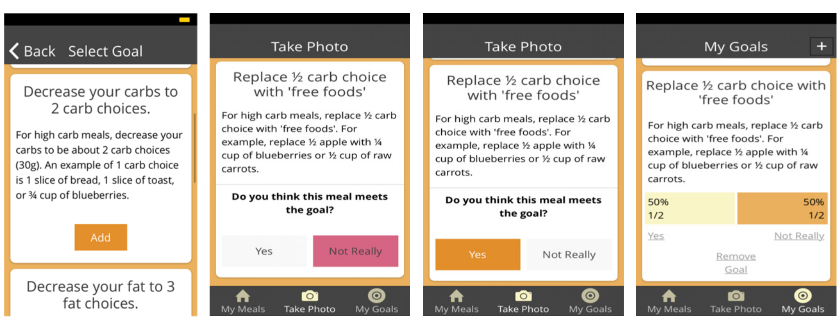
In-the-moment decision support

- For new meals: assess how well the meal fits personal goals
  - Does this mean fit your goal?
- Change meals that don't fit goals

GlucoType



Validating personalized goals

- Controlled lab study
  - Individuals from low income communities (n=14)
  - Composing meals using printed food models
  - Choosing meal photographs

Validating personalized goals

- Goal comprehension
  - Can individuals understand goals if they are given all nutritional information?
- Goal assessment
  - Can they recognize what meals meet goals without nutritional information?
- Goal adherence
  - Can they follow goals (in controlled setting)?

Personalized goals

Results

- Individuals can understand and follow personalized nutritional goals, but nutritional assessment presents challenges
  - Goal comprehension: 86% accuracy (with nutritional labels)
  - Goal assessment: 52% accuracy (pictures without labels)
  - Goal adherence: 62% met the goal; 86% moved towards the goal

Pilot feasibility study

- Methods:
  - Participants recruited from low income communities (n=20)
  - Use GlucoType for 4 weeks (option to continue)
  - Cold start problem
    - Generic goals, personalized goals

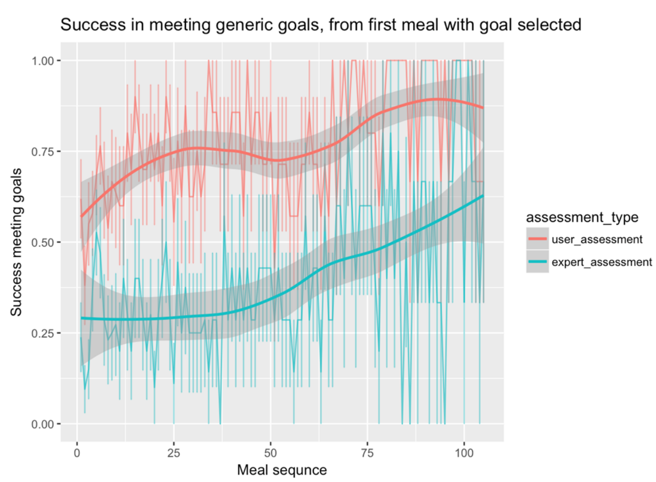
Research questions

- Engagement (usage logs)
- Goal achievement (user-reported and expert-reported)
- Acceptability (qualitative interviews)
  - Subjective perceptions
  - Perceived benefit
  - Barriers

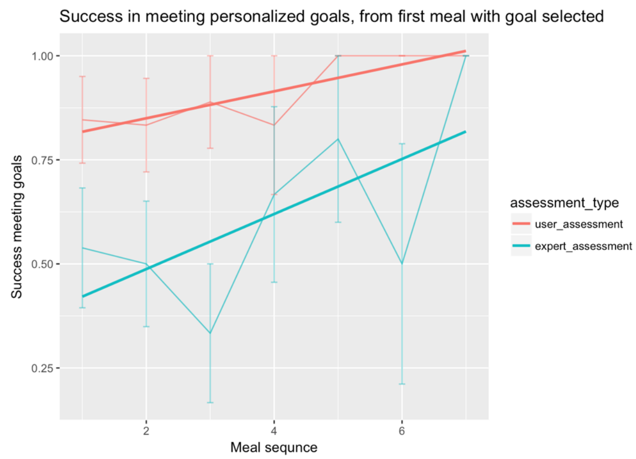
Results: Engagement

- Moderate levels of engagement (3 to 12 meals per week)
- Personalized goals generated after 8 meals with pre/post readings (3-5 days)
- Range of goals (covering all macronutrients)
- Various degrees of goal stability

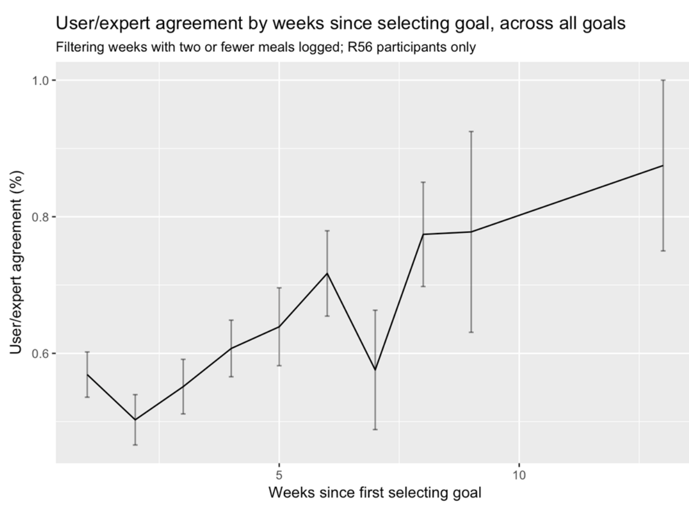
Results: Goal Achievement



Results: Goal Achievement



Results: Goal Achievement



Acceptability

- Viewing goals at the time of meal presents opportunity for reflection
- Many challenges with formulation of goals
  - Macronutrients/portion sizes
- Need to translate goals into concrete action plans
  - What does a meal with 3 carb choices look like?
- Need to incorporate personal preferences?
  - What does a meal with 3 carb choices that I would like look like?

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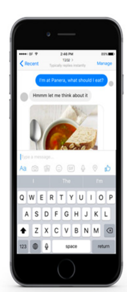
Future work

- Limitations of current approaches
  - Expectation for user-initiated interactions
  - Limited interactivity
  - Reliance on visual displays
- Dialog systems
  - Using conversational interfaces to help individuals engage in a dialog with data and data science

Future work

- Dialog systems as an interaction paradigm
- Responding to natural user questions

T2D2

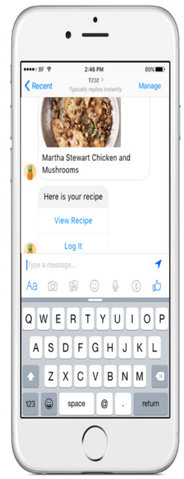


Elliot Mitchell

T2D2

What can I make with chicken and mushrooms?

Searching for GreatPlate recipe recommendations



Conclusion

- Interacting with data science
  - Personal analytics as an interaction paradigm for data-science driven solutions
  - Many interaction paradigms, need better understanding of trade-offs
  - New interaction paradigms for engaging humans with data science

Acknowledgements

Collaborators:

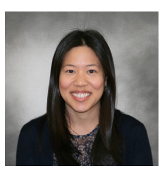
- David Albers, PhD
- George Hripcsak, PhD
- Noemie Elhadad, PhD
- Arlene Smaldone, PhD, CPNP, CDE
- Patricia Davidson, DCN, MS, RD, CDE

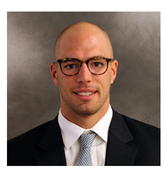
Funding:

- NIDDK, R01DK090372
- NiDDK, R56DK113189
- NLM, R01 LM06910
- RWJF, 73070

ARCH lab


Drashko Nakikj


Michelle Chau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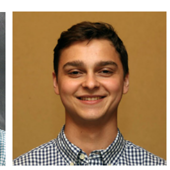
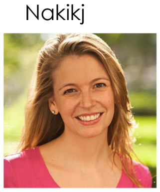
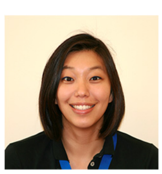

Matt Levine


Marissa Burgermaster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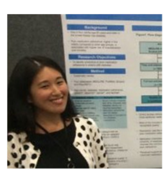
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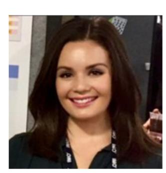
Meghan Reeding


Pooja Desai