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

- 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
Discovery with visual analytics

- **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?)

Daniel Feller

Glucolyzer
Glucolyzer evaluation

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

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
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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
Personalized forecasts

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

Individualized post-meal forecast

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

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 times 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)

- 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)
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.
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

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

Results
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

Success in meeting personalized goals, from first meal with goal selected

Meal sequence

Results: Goal Achievement

User-expert agreement by weeks since selecting goal, across all goals

Filtering weeks with two or fewer meals logged; R56 participants only

Weeks since first selecting goal
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

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
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