Selected Topics Communications and Mobile Computing
(Smart Health)

TU Graz
University of Notre Dame
What is a Biomarker?

- A **biological marker**, better known as a "biomarker", is a characteristic that is objectively measured and evaluated as an indicator of normal biological processes, pathogenic processes, or pharmacological responses to a therapeutic intervention.
What is a Biomarker?

• Term biomarker first coined in the 1980s.
• Biomarkers were developed as a response to understand the relationship between environmental factors and disease.
• Biomarkers include tools and technologies that can aid in understanding the
  – Prediction
  – Cause
  – Diagnosis
  – Progression
  – Regression
  – Outcome
of various diseases.
What is a Biomarker?

• Biomarker variety
  – Each body system has specific biomarkers (e.g., cardiovascular, respiratory, neurological, psychological, ...).
  – Each biomarker is relatively easy to measure.
  – Each biomarker forms a piece of routine medical examinations (e.g., weight and BMI measurements to predict obesity).
What is a Biomarker?

• Ideal biomarker characteristics:
  – Safe and easy to measure.
    • Should create as little discomfort for patient as possible (e.g., blood sample).
  – Cost-effective.
  – Rapid return of results for early initiation of treatment and monitoring effectiveness.
  – Consistent across gender and ethnic groups.
    • Highly reproducible among various clinical laboratories.
Biomarker Types

• **Biomarkers of exposure:**
  – Reconstruct and predict past exposure to risk factors.

• **Biomarkers of risk or susceptibility:**
  – Identify individuals at increased risk for development of a disease.

• **Biomarkers of disease:**
  – Used for screening or diagnosis, progression, or regression assessment, etc.
Etiology (causes of a disease or condition)

Pathogenesis (the manner of development of a disease)

Detection

Biomarkers

Alzheimer’s Disease

Risk factors

Screening & diagnosis

Prognosis
Digital Biomarker

- “Digital biomarkers are consumer-generated physiological and behavioral measures collected through connected digital tools that can be used to explain, influence and/or predict health-related outcomes.” [Wang et al. 2019]
Digital Biomarkers

- Novel measurement, known insight
- Novel measurement, novel insight
- Known measurement, known insight
- Known measurement, novel insight
- Continuous blood pressure is used to predict the risk of a heart attack
- Continuous blood pressure is used to predict depression
- Discrete blood pressure data is used to predict the risk of a heart attack
- Discrete blood pressure data is used to predict depression
Digital Biomarkers

**PROSPECTIVE METHOD**
- Identify dataset of interest
- Identify method of acquisition
- Hypothesize
- Collect and analyze data

**RETROSPECTIVE METHOD**
- Extract and clean data
- Plan and conduct analysis on dataset of interest
- Conduct hypothesis-driven exploratory analysis
- Identify and confirm relationship(s) of interest

**Relationship established between data and a health-related outcome**
- Diagnosis
- Prognosis
- Prediction
Digital Biomarkers

• n of 1
  – Longitudinal individual-level data
  – Personalized baselines
• Population subgroups
  – Longitudinal population-level data
  – Control for previous/existing disease states
  – More likely to find evidence of causality
Digital Biomarkers

- Individual composite score (proprietary combination of steps, sleep, and # of Facebook posts)
- Composite scores of population
- Disease risk
- Phenotypic signature
- High risk individuals
Digital Biomarkers

**DIGITAL TOOLS**
Consumers will play an increasingly important role in generating digital data.

**CONSUMER**
As consumers begin to collect a wealth of data, they will be responsible for provisioning access to end-users who provide a meaningful use case.

**USE CASES**
The longitudinal, objective data collected from digital tools can be used to inform discovery of digital biomarkers.

- Chronic disease management
- Disease progression
- Mental health
- Preventive health

- Disease diagnosis
- Fitness / wellness
- Treatment monitoring

Data collection

Provisioning access
Digital Biomarkers
Types of Research

- **Descriptive**: describe a group of individuals on a set of variables or characteristics (understanding and classification).
  - Case study
  - Cross-sectional study
  - Qualitative study

- **Exploratory**: examine a phenomenon of interest and explores its dimensions, including how it relates to other factors (relationships can lead to predictive models).
  - Cohort study
  - Case control study

- **Experimental**: basis for comparing two or more conditions; controls or accounts for the effects of extraneous factors; draw meaningful conclusions about observed differences.
  - True experimental designs
  - Quasi-experimental designs
Case Study Design

• Often a description of an individual case’s condition or response to an intervention
  – Can focus on a group, institution, school, community, family, etc.
  – Data may be qualitative, quantitative, or both.
  – **Case series**: observations of several similar cases are reported.
Case Study

Example

• In 1848, young railroad worker, Phineas Gage, was forcing gun powder into a rock with a long iron rod when the gun powder exploded. The iron rod shot through his cheek and out the top of his head, resulting in substantial damage to the frontal lobe of his brain. Incredibly, he did not appear to be seriously injured. His memory and mental abilities were intact, and he could speak and work. However, his personality was markedly changed. Before the accident, he had been a kind and friendly person, but afterward he became ill-tempered and dishonest.

• Phineas Gage’s injury served as a case study for the effects of frontal lobe damage. He did not lose a specific mental ability, such as the ability to speak or follow directions. However, his personality and moral sense were altered. It is now known that parts of the cortex (called the association areas) are involved in general mental processes, and damage to those areas can greatly change a person’s personality.
Cross-Sectional Study

- Researcher studies a stratified group of subjects at one point in time.
- Draws conclusions by comparing the characteristics of the stratified groups.
- Well-suited to describing variables and their distribution patterns.
• Example:

Let’s say we want to investigate the relationship between daily walking and cholesterol levels in the body. We recruit walkers and non-walkers at the same time and compare cholesterol levels among these different populations.
Qualitative Study

• Seeks to describe how individuals perceive their own experiences within a social context.

• Emphasizes in-depth, nuanced understanding of human experience and interactions.

• Methods include in-depth interviews, direct observations, examining documents, focus groups.

• Data are often participants’ own words and narrative summaries of observed behavior.
Example

- A researcher wants to understand how provision of healthcare to undocumented persons affects the people and institutions involved.
- In multiple communities, information is gathered from undocumented patients, primary care clinicians, specialists, and hospital administrators.
- Methods: in-depth interviews, key informant interviews, participant observations, case studies, focus groups.
Cohort Study

- A group of individuals who do not yet have the outcome of interest are followed together over time to see who develops the condition.
- Participants are interviewed or observed to determine the presence or absence of certain exposures, risks, or characteristics.
- May identify risk by comparing the incidence of specific outcomes in exposed and not exposed participants.
Cohort Study

• Example
  – To determine whether exercise protects against coronary heart disease (CHD).
    • Assemble the cohort: 16,936 Harvard alumni were enrolled.
    • Measure predictor variables: administer a questionnaire about activity and other potential risk factors, collected data from college records.
    • 10 years later, sent a follow-up questionnaire about CHD and collected data about CHD from death certificates.
Cohort Study

• **Strengths**
  – Powerful strategy for defining incidence and investigating potential causes of an outcome before it occurs.
  – Time sequence strengthens inference that the factor may cause the outcome.

• **Weaknesses**
  – Expensive – many subjects must be studied to observe outcome of interest.
  – Potential **confounders**: e.g., cigarette smoking might confound the association between exercise and CHD.
Case-Control Study

• Generally retrospective.
• Identify groups with or without the condition.
• Look backward in time to find differences in predictor variables that may explain why the cases got the condition and the controls did not.
• Assumption is that differences in exposure histories should explain why the cases have the condition.
• Data collection via direct interview, mailed questionnaire, chart review.
Case-Control Study

• Strengths
  – Useful for studying rare conditions.
  – Short duration & relatively inexpensive.
  – High yield of information from relatively few participants.
  – Useful for generating hypotheses.

• Weaknesses
  – Increased susceptibility to bias:
    • Separate sampling of cases and controls.
    • Retrospective measurement of predictor variables.
  – Only one outcome can be studied.
Case-Control Study

• Example
  – Purpose: To determine whether there is an association between the use of aspirin and the development of Reye’s syndrome in children.
    • Draw the sample of cases – 30 patients who have had Reye’s syndrome.
    • Draw the sample of controls – 60 patients from the much larger population who have had minor viral illnesses without Reye’s syndrome.
    • Measure the predictor variable: ask patients in both groups about their use of aspirin.
Longitudinal Studies

• A **longitudinal** study is a **research** design that involves repeated observations of the same variables over longer periods of time (i.e., uses **longitudinal** data).

• Example:
  – How do friendships change from freshman to senior year on a college campus?
  – How do friendships impact wellness and health?
Statistical Power Analysis

• Prior to conducting a study, it is advisable to conduct a statistical power analysis.

• Power is the probability that a statistical test will detect a significant effect that exists.

• The power analysis will suggest an adequate sample size for the study.
Statistical Power Analysis

- Four parameters:
  - Significance level ($\alpha$)
    - Difference ($p$-value) between two groups or more based on some variable
  - Sample size ($n$)
    - Number of participants in study
  - Effect size (ES)
    - Magnitude of the difference between populations or the relationship between explanatory and response variable
  - Power ($1 - \beta$)

\[
\text{Power } \propto \frac{\text{Sample size }(n)}{\text{Effect size } (\Delta), \text{Alpha}(\alpha)}
\]
### Statistical Power Analysis

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Significance level ($\alpha$):</td>
<td>.05 *</td>
</tr>
<tr>
<td></td>
<td>.01</td>
</tr>
<tr>
<td></td>
<td>.001</td>
</tr>
<tr>
<td>Effect size:</td>
<td>“small”</td>
</tr>
<tr>
<td></td>
<td>“medium” *</td>
</tr>
<tr>
<td></td>
<td>“large”</td>
</tr>
<tr>
<td>Power:</td>
<td>.80 *</td>
</tr>
<tr>
<td></td>
<td>.90</td>
</tr>
</tbody>
</table>

* Typical values for social/behavioral/health sciences
Relationship Between Alpha ($\alpha$), Sample Size ($n$), and Power ($1-\beta$)

Two group t-test of equal means (equal n's)

- $\alpha = 0.025$ (2) $\beta = 0.500$
- $\alpha = 0.050$ (2) $\beta = 0.500$
- $\alpha = 0.100$ (2) $\beta = 0.500$
Bias

- **Bias**: Deviation of results or inference from truth, or processes leading to such deviations. Any trend in the collection, analysis, interpretation, publication, or review of data that can lead to conclusions that are systematically different from the truth.

- Bias is an **error**.

- Two types of errors:
  - **Random**: use of invalid outcome measure that equally misclassifies cases and controls.
  - **Systematic**: use of invalid measures that misclassify cases in one direction and controls in another.
Random Error (Chance)
Systematic Error (Bias)
Chance vs. Bias

• Chance is caused by random error.
• Bias is caused by systematic error.

• Errors from chance will cancel each other out in the long run (large sample size).
• Errors from bias will not cancel each other out whatever the sample size.

• Chance leads to imprecise results.
• Bias leads to inaccurate results.
Examples

- Selection Bias: errors in the process of identifying the study population.
- Recall Bias: differences in the accuracy or completeness of the recollections retrieved by study participants.
- Confirmation Bias: often unconscious act of referencing only those perspectives that fuel our pre-existing views.
Example of Sensing/Processing Pipeline

- **Kinesis**: collect real-time, streaming data.
- **Lambda**: event-driven server-less computing platform.
- **Machine Learning**: ML models and predictions.
- **Amazon SNS**: Simple Notification Service.
Machine Learning Options

• **Supervised learning**: classification is seen as supervised learning from examples.
  – Supervision: The data (observations, measurements, etc.) are labeled with pre-defined classes. It is like that a “teacher” gives the classes (supervision).
  – Test data are classified into these classes too.

• **Unsupervised learning** (clustering)
  – Class labels of the data are unknown.
  – Given a set of data, the task is to establish the existence of classes or clusters in the data.
Supervised Learning

• Learning (training): Learn a model using the training data.
• Testing: Test the model using unseen test data to assess the model accuracy

\[
Accuracy = \frac{\text{Number of correct classifications}}{\text{Total number of test cases}},
\]

![Diagram showing the process of supervised learning:]

Step 1: Training
Step 2: Testing
Supervised Learning

• Given
  – a data set $D$,
  – a task $T$, and
  – a performance measure $M$,

a computer system is said to **learn** from $D$ to perform the task $T$ if after learning the system’s performance on $T$ improves as measured by $M$.

• In other words, the learned model helps the system to perform $T$ better as compared to no learning.
Supervised Learning

Assumption: The distribution of training examples is identical to the distribution of test examples (including future unseen examples).

• In practice, this assumption is often violated to a certain degree.
• Strong violations will clearly result in poor classification accuracy.
• To achieve good accuracy on the test data, training examples must be sufficiently representative of the test data.
Labels (Annotations)

Walking
00:19:02
Stop

Tap to Start

Happy
00:00:28
Stop

Sitting
Standing
Walking
Lying
Running
Biking

Home
Work
School
Store
Dining
Gym

Happy
Sad
Angry
Annoyed
Shocked
Stressed

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Validating Biomarkers

- Select candidates relevant to disease pathway.
- Identify and quantitate the association between the marker and the disease.

<table>
<thead>
<tr>
<th></th>
<th>Diseased (TD)</th>
<th>Healthy (TH)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Test Positive</strong></td>
<td>True positive (TP)</td>
<td>False Positive (FP)</td>
<td>$\text{PPV} = \frac{\text{TP}}{(\text{TP})+(\text{FP})}$</td>
<td></td>
</tr>
<tr>
<td><strong>Test Negative</strong></td>
<td>False Negative (FN)</td>
<td>True negative (TN)</td>
<td>$\text{NPV} = \frac{\text{TN}}{(\text{FN})+(\text{TN})}$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sensitivity = $\frac{\text{TP}}{(\text{TP})+(\text{FN})}$</td>
<td>Specificity = $\frac{\text{TN}}{(\text{FP})+(\text{TN})}$</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
TP, FP, TN, FN

- True Positives (TP)
- False Positives (FP)
- True Negatives (TN)
- False Negatives (FN)

**Sensitivity**
\[
\text{Sensitivity} = \frac{TP}{TP + FN}
\]

**Specificity**
\[
\text{Specificity} = \frac{TN}{TN + FP}
\]

**Diagram**
- Selected elements
- True positives
- False positives
- False negatives
- True negatives

**Graph**
- Cutoff Value
- Negative
- Positive
- Healthy
- Disease
- True Negatives
- True Positives
- FN= False Negative
- FP= False Positive

**Lab Value or Clinical Measure**

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## PPV, NPV

<table>
<thead>
<tr>
<th>Definition</th>
<th>PPV</th>
<th>NPV</th>
</tr>
</thead>
<tbody>
<tr>
<td>% that a person with positive test is actually diseased.</td>
<td>% change that a person with negative test is actually disease free.</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Use</th>
<th>Proceed with a patient with positive test</th>
<th>Proceed with a patient with negative test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relation to prevalence</td>
<td>Low prevalence low PPV</td>
<td>High prevalence low NPV</td>
</tr>
<tr>
<td></td>
<td>High prevalence high PPV</td>
<td>Low prevalence High NPV</td>
</tr>
</tbody>
</table>
Sensitivity & Specificity

- Sensitivity: true positive rate; tests pick all diseased plus some without, i.e., they won’t miss the disease.
- Specificity: true negative rate; tests pick only the diseased ones, but may miss some.
Sensitivity & Specificity
Receiver Operating Characteristics

A ROC curve of a random classifier

A ROC curve of a perfect classifier

Two ROC curves
Receiver Operating Characteristics

- Area under the ROC curve: AUC score
• Convenient & popular summaries of experimental results.
• P-value measures a sample’s compatibility with a hypothesis.
• Example:
  – Does a disease affect a biomarker?
  – Take mean biomarker levels in healthy versus diseased samples and compute p value.
  – Indicates the probability that a difference in means at least as large as the one observed can be generated from random samples if the disease does not affect the mean biomarker level.
P-values

• Null hypothesis: “no association between a biomarker and a disease”.
  – A small $p$-value (typically $\leq 0.05$) indicates strong evidence against the null hypothesis, so you reject the null hypothesis.
  – A large $p$-value ($> 0.05$) indicates weak evidence against the null hypothesis, so you fail to reject the null hypothesis.
  – $p$-values very close to the cutoff (0.05) are considered to be marginal (could go either way). Always report the $p$-value so your readers can draw their own conclusions.
P-values
# Statistical Tests

<table>
<thead>
<tr>
<th>Number of groups</th>
<th>Level of Measurement</th>
<th>Nominal</th>
<th>Ordinal</th>
<th>Interval/Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 group</td>
<td></td>
<td>$\chi^2$ test</td>
<td>Kolmogorov-Smirnoff 1 sample test</td>
<td>t-test of sample mean vs. known population value</td>
</tr>
<tr>
<td>2 independent groups</td>
<td></td>
<td>$\chi^2$ test</td>
<td>Mann-Whitney U test</td>
<td>Independent samples t-test</td>
</tr>
<tr>
<td>2 dependent groups</td>
<td></td>
<td>McNemar test</td>
<td>Wilcoxon test</td>
<td>Paired t-test</td>
</tr>
<tr>
<td>&gt;2 independent groups</td>
<td></td>
<td>$\chi^2$ test</td>
<td>Kruskal-Wallis ANOVA</td>
<td>ANOVA</td>
</tr>
<tr>
<td>&gt;2 dependent groups</td>
<td></td>
<td>Cochran Q test</td>
<td>Friedman ANOVA by ranks</td>
<td>Repeated measures ANOVA</td>
</tr>
</tbody>
</table>
Independent Samples t-Test

Males and females are asked a question that is measured on a five-point Likert scale:

To what extent do you feel that regular exercise contributes to your overall health?

1  Strongly agree
2  Agree
3  Neither agree nor disagree
4  Disagree
5  Strongly disagree

Do males and females differ in their response to this question?
Independent Samples t-Test

$\text{mean}_{\text{males}} = 2.5$

$\text{mean}_{\text{females}} = 3.2$
Independent Samples t-Test

- Use tools like SPSS, R, SAS, Excel, Matlab, Minitab, ...

**Group Statistics**

<table>
<thead>
<tr>
<th>GENDER</th>
<th>N</th>
<th>Mean</th>
<th>Std. Deviation</th>
<th>Std. Error Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXERCISE 1 male</td>
<td>25</td>
<td>2.56</td>
<td>1.158</td>
<td>.232</td>
</tr>
<tr>
<td>2 female</td>
<td>25</td>
<td>3.24</td>
<td>1.012</td>
<td>.202</td>
</tr>
</tbody>
</table>

**Independent Samples Test**

<table>
<thead>
<tr>
<th>EXERCISE</th>
<th>t</th>
<th>df</th>
<th>Sig. (2-tailed)</th>
<th>Mean Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>EXERCISE</td>
<td>-2.212</td>
<td>48</td>
<td>.032</td>
<td>-.68</td>
</tr>
</tbody>
</table>
Mann-Whitney U Test

<table>
<thead>
<tr>
<th>Level</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>9</td>
<td>A graduate degree</td>
</tr>
<tr>
<td>8</td>
<td>Some graduate work</td>
</tr>
<tr>
<td>7</td>
<td>Completed college</td>
</tr>
<tr>
<td>6</td>
<td>Some college</td>
</tr>
<tr>
<td>5</td>
<td>Completed high school</td>
</tr>
<tr>
<td>4</td>
<td>Some high school</td>
</tr>
<tr>
<td>3</td>
<td>Completed grade school</td>
</tr>
<tr>
<td>2</td>
<td>Some grade school</td>
</tr>
<tr>
<td>1</td>
<td>No formal education</td>
</tr>
</tbody>
</table>

Gender

N = 14  
Female  
N = 10  
Male

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Mann-Whitney U Test

For each group, the Sum and mean of ranks Is computed.

The test statistics suggest that males’ and females’ education levels do not differ in this population.

Test Statistics

<table>
<thead>
<tr>
<th>EDUC Education level</th>
<th>Mann-Whitney U</th>
<th>Wilcoxon W</th>
<th>Z</th>
<th>Asymp. Sig. (2-tailed)</th>
<th>Exact Sig. [2*(1-tailed Sig.)]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>56.500</td>
<td>111.500</td>
<td>-.807</td>
<td>.420</td>
<td>.437^a</td>
</tr>
</tbody>
</table>

^a. Not corrected for ties.
^b. Grouping Variable: GENDER
MCS (Smart Devices + Sensors)
Many Sensors + Big Data
Stroke Death Rates, 2011-2013
Adults, Ages 35+, by County

Rates are spatially smoothed to enhance the stability of rates in counties with small populations.

Data Source:
National Vital Statistics System
National Center for Health Statistics
Social media is playing a critical role in detecting disease outbreaks. By continuously analyzing data from patients, discussion forums and the social media, HealthMap software flagged Ebola 9 days before outbreak was announced. Metadata like the patient identifier and other location attributes in social media posts would help pinpoint the relative location of the incidence. Data gathered is clustered on a daily basis using the location attributes. Dense clusters are identified possibly through a visualization system.
– Position Health
  • Use smartphone geopositioning technology to recognize when a patient is entering an acute care facility anywhere in the US connecting provider teams
Geo-Social Information

- Echosec is a location-based search platform that provides actionable knowledge based on social media and other information.
Healthcare Applications

Today in Calgary
The average activity for people in Calgary Today at 9:58 PM local time.

Walking 45,298,495 min
Biking 4,312,254 min
Running 0:45,506 min
Other activity 11:30,292 min

So far, 143 people in Calgary tracked 8,829 minutes of activity in total today, an average of 62 minutes per user. Yesterday 146 people clocked 6,194 minutes of total activity in Calgary, an average of 46 minutes per active user.

Calgary vs the world
Compare an average day in Calgary to the average of all other cities on Human.
Activity Recognition

[Images of various activities]
Activity Recognition

• Activity recognition identifies user actions
  – May also attempt to recognize goals

• Examples
  – Walking, jogging, running, jumping, washing dishes, playing basketball, reading, partying, studying

• Context may matter
  – Studying is more likely in a library
  – Partying occurs in a social environment
Activity Recognition

• Context-sensitive applications
  – Handle phone calls differently depending on context
  – Play music to suit your activity
  – Fuse with other info (GPS) for better results
    • Can confirm you are on subway vs. traveling in a car
  – New & innovative apps to make phones smarter

• Tracking & Health applications
  – Track overall activity; detect dangerous activity (falling)

• Social applications
  – Link users with similar behaviors (joggers, hunters)
Activity Recognition

- Smartphones, smartwatches, and combination
- A single accelerometer but custom hardware
  - Pedometers (limited function); Fitbit
- Dedicated accelerometers placed on various body parts
- Multi-sensor solutions
  - eWatch: accelerometer + light sensor, multiple locations
  - Smartbuckle: accelerometer + image sensor on belt
- Use Phone, but not a central component
  - Motionbands multi-sensor/location transmits data to smartphone for storage
Activity Recognition

1. Collect labeled raw time series sensor data (training data)
2. Prepare data for mining
   – Preprocess and transform data
3. Build classifier using classification algorithms
4. Deploy and use classifier
Activity Recognition

• Laboratory approach
  – Sequence through a specific set of activities
  – Insert label into data stream (via app) and then collect sensor data while subject performs activity

• Natural approach
  – Have subject perform activities “in the wild” and label manually afterwards using video capture (or equivalent) or let subjects label themselves

• Both methods require time and effort

• Natural approach more likely to generate more data and more realistic data, but also more errors
Activity Recognition

- Sensor data is time-series data
- Common classification algorithms expect “examples”
- Typical approach: extract higher level features using a sliding window (size depends on sensor, sampling rate, etc.) and generate fixed length records
Two Types of Predictive Models

- **Personal model**
  - Acquire training data for user & then generate model
  - Places data collection requirement on user, but may sometimes by easily automated

- **Universal/impersonal model**
  - Built on one set of users and applied to everyone else
    - No requirement on new user – no run-time training

- **Personal models almost always do significantly better, even using much less training data**
Deploying Classifiers

• Classifier may run on server
  – Data must be sent to it

• Classifier may run on client device
  – Must be able to handle computational requirements
  – Models can be exported as code and do not need to run under the data mining system
Location of Smartphone

• The location of the smart phone will impact activity recognition
  – Smartphone in pocket, in hand, at ear, belt clip, backpack, ...

• Phone orientation can have impact
  – Can correct for orientation using orientation info
Accelerometer Data for Six Activities

- Accelerometer data from Android phone
  - Walking
  - Jogging
  - Climbing Stairs
  - Lying Down
  - Sitting
  - Standing
“Walking”
“Jogging”
“Climbing Stairs Up”
“Lying Down”

![Graph showing acceleration over time with X, Y, and Z axes labeled.](image)
"Sitting"

![Graph showing acceleration over time for different axes (Z, X, Y). The graph illustrates a comparison between sitting and running, with running showing significant acceleration changes.](image-url)
"Standing"

![Graph showing acceleration over time for Y, Z, and X axes.](image)

- Y Axis
- Z Axis
- X Axis
# Results

<table>
<thead>
<tr>
<th>Activity</th>
<th>Accuracy</th>
<th>Activity</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking</td>
<td>89.71</td>
<td>Walking carrying items</td>
<td>82.10</td>
</tr>
<tr>
<td>Sitting &amp; Relaxing</td>
<td>94.78</td>
<td>Working on Computer</td>
<td>97.49</td>
</tr>
<tr>
<td>Standing Still</td>
<td>95.67</td>
<td>Eating or Drinking</td>
<td>88.67</td>
</tr>
<tr>
<td>Watching TV</td>
<td>77.29</td>
<td>Reading</td>
<td>91.79</td>
</tr>
<tr>
<td>Running</td>
<td>87.68</td>
<td>Bicycling</td>
<td>96.29</td>
</tr>
<tr>
<td>Stretching</td>
<td>41.42</td>
<td>Strength-training</td>
<td>82.51</td>
</tr>
<tr>
<td>Scrubbing</td>
<td>81.09</td>
<td>Vacuuming</td>
<td>96.41</td>
</tr>
<tr>
<td>Folding Laundry</td>
<td>95.14</td>
<td>Lying Down &amp; Relaxing</td>
<td>94.96</td>
</tr>
<tr>
<td>Brushing Teeth</td>
<td>85.27</td>
<td>Climbing Stairs</td>
<td>85.61</td>
</tr>
<tr>
<td>Riding Elevator</td>
<td>43.58</td>
<td>Riding Escalator</td>
<td>70.56</td>
</tr>
</tbody>
</table>
mCerebrum Overview

Smartphone

Biomarkers
- Stress
- Smoking
- Eating
- Lung Congestion
- Heart Motion
- Location
- Activity
- Driving
- Drug use

Encryption-based Privacy Filter

Privacy Controller

Data Quality
- Smartphone Sensors
  - GPS, Accel, Gyro

Machine Learning Models

Wireless Radios:
- Bluetooth, ANT+

High Data Rate Sensors
- Chestband
- Smart Watches
- UWB RF Sensor

70+ million samples/day
- 13 million
- 10+ million
- 38+ million

Low Data Rate Sensors
- Oral-B Toothbrush
- iCO Smokerlyzer
- Omron BP/Weight

1500
- 4
- 6

Secure Local Data Storage

Secure Cloud Data Storage

Data Recipients
Example

• Stroke survivor study
• Goal: detect differences in mobility compared to healthy subjects
• Focus on specific activities, e.g.: sitting down, standing up, walking up/down stairs, etc.
• Max. rate for accelerometer sensor is 200Hz.
Example

- Assume each sample requires 1 byte.
- Accelerometer: 3 axes, 200Hz: $3 \times 1 \text{byte} \times 200\text{Hz} = 600$ bytes per second
- Gyroscope: 600 bytes per second
- 1,200 bytes per second
- 72,000 bytes per minute
- About 100MB per day
- Assume a study of 1000 subjects:
  - 100GB per day!
  - 36.5TB per year!
mCerebrum Architecture
mCerebrum Architecture

- Communication interfaces
- Data sources
- Storage and routing interface
- Signal processing
- Participant interface
## mCerebrum Applications/Libraries

<table>
<thead>
<tr>
<th>Application</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>DataKit</td>
<td>Handles routing, privacy, and storage</td>
</tr>
<tr>
<td>DataKitAPI</td>
<td>API library for apps to use DataKit</td>
</tr>
<tr>
<td>Plotter</td>
<td>Real-time data visualizer</td>
</tr>
<tr>
<td>Privacy Controller</td>
<td>Allows the participant to suspend data collection and EMA prompting</td>
</tr>
<tr>
<td>Utilities</td>
<td>Common helper functions</td>
</tr>
<tr>
<td>Phone</td>
<td>Integrates the smartphone sensors</td>
</tr>
<tr>
<td>Chestband</td>
<td>Data collection from ANT+ sensor suite</td>
</tr>
<tr>
<td>Wrist</td>
<td>BLE wrist-worn motion capture device</td>
</tr>
<tr>
<td>iCO</td>
<td>Carbon Monoxide sensor support</td>
</tr>
<tr>
<td>Smartwatch</td>
<td>Bluetooth 4 connected watch</td>
</tr>
<tr>
<td>UWB RF</td>
<td>BLE chest sensor for measuring heart function and lung fluid</td>
</tr>
<tr>
<td>Blood Pressure</td>
<td>BLE-connected blood pressure cuff</td>
</tr>
<tr>
<td>Weight</td>
<td>BLE-connected weight scale</td>
</tr>
<tr>
<td>Smart Toothbrush</td>
<td>BLE-connected smart toothbrush</td>
</tr>
<tr>
<td>Stream Processor</td>
<td>Provides real-time computation of biomarkers (e.g. stress, smoking, etc.)</td>
</tr>
<tr>
<td>Mood Surfing</td>
<td>A custom built stress reduction app</td>
</tr>
<tr>
<td>Thought Shakeup</td>
<td>A custom built stress reduction app</td>
</tr>
<tr>
<td>Medication</td>
<td>Medication adherence compliance app and reminder system</td>
</tr>
<tr>
<td>Self Report</td>
<td>Customizable self-report prompts</td>
</tr>
<tr>
<td>EMA</td>
<td>Customizable EMA delivery application</td>
</tr>
<tr>
<td>Study</td>
<td>Main study interface; provides application management for all other apps</td>
</tr>
<tr>
<td>EMA/EMI Scheduler</td>
<td>Customizable scheduler for delivering user prompts based on biomarkers</td>
</tr>
<tr>
<td>Adherence Reminder</td>
<td>A scheduler for episodic data collection</td>
</tr>
<tr>
<td>Notification Manager</td>
<td>Gatekeeper for all user prompts</td>
</tr>
</tbody>
</table>

*Table 2: Overview of mCerebrum apps and libraries*
Figure 4: mCerebrum supports sensors ranging from 2 samples/day to 300 Hz per device including: BLE (green), Bluetooth 4.0 (red), ANT+ (orange), and internal (yellow). Additionally, it support short audio and video clips with a high data rate storage mechanism.
Participant Interaction

- Voluntary: self-report buttons
- Prompted:
  - Ecological momentary assessment (EMA) involves repeated sampling of subjects’ current behaviors and experiences in real time, in subjects’ natural environments.
  - Ecological momentary intervention (EMI) is a treatment that is provided to patients between sessions during their everyday lives.
  - Different types of triggers possible.
- Glance-able: updates to the graphical user interface (e.g., real-time step counter view).
Participant Interaction
Version 2.0

16+ hours battery life

MotionSense HRV
## mCerebrum Studies

<table>
<thead>
<tr>
<th>Site</th>
<th>Health Target(s)</th>
<th>Participants</th>
<th>Person-Days</th>
<th>Samples (Data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northwestern</td>
<td>Smoking and Eating</td>
<td>225</td>
<td>3,150</td>
<td>136 Billion (9 TB)</td>
</tr>
<tr>
<td>Rice</td>
<td>Smoking</td>
<td>300</td>
<td>4,200</td>
<td>182 Billion (12 TB)</td>
</tr>
<tr>
<td>Utah</td>
<td>Smoking</td>
<td>300</td>
<td>4,200</td>
<td>182 Billion (12 TB)</td>
</tr>
<tr>
<td>Vermont</td>
<td>Smoking and fMRI</td>
<td>90</td>
<td>1,260</td>
<td>55 Billion (3.5 TB)</td>
</tr>
<tr>
<td>Ohio State</td>
<td>CHF</td>
<td>225</td>
<td>6,750</td>
<td>224 Billion (15 TB)</td>
</tr>
<tr>
<td>UCLA</td>
<td>Oral Health</td>
<td>162</td>
<td>29,160</td>
<td>968 Billion (65 TB)</td>
</tr>
<tr>
<td>Johns Hopkins</td>
<td>Cocaine Use</td>
<td>25</td>
<td>350</td>
<td>18 Billion (1.5 TB)</td>
</tr>
<tr>
<td>Dartmouth</td>
<td>Behavior Change</td>
<td>100</td>
<td>1,400</td>
<td>58 Billion (4 TB)</td>
</tr>
<tr>
<td>Moffitt</td>
<td>Smoking and Stress</td>
<td>24</td>
<td>336</td>
<td>15 Billion (1 TB)</td>
</tr>
<tr>
<td>Minnesota</td>
<td>Workplace Performance</td>
<td>800</td>
<td>56,000</td>
<td>2,891 Billion (185 TB)</td>
</tr>
<tr>
<td><strong>Totals</strong></td>
<td></td>
<td><strong>2,251</strong></td>
<td><strong>106,806</strong></td>
<td><strong>4,729 Billion (300 TB)</strong></td>
</tr>
</tbody>
</table>
Student Presentations

- **Step 1:** Form a team if desired
  - Project is to be performed individually or as a team of two
- **Step 2:** Identify a topic of interest, e.g.,:
  - Identify a technology and explore its medical use
  - Identify a medical challenge and explore how technology is used to address it
- **Step 3:** Send an email to cpoellab@nd.edu by April 12th (midnight) that includes:
  - A meaningful title
  - Name of student (or team members if applicable; only one email per team)
  - Preferred presentation slots (1st and 2nd choice): May 13, May 20, June 3, June 17
- **Step 3:** Find 3-5 relevant papers for your project.
- **Step 4:** Prepare oral report in class, about 15 minute presentation
- **Step 5:** Submit written report by June 24th (midnight) to cpoellab@nd.edu