

Identifying College Students with Depression Using Passive Sensing

Communication Qualifier Talk

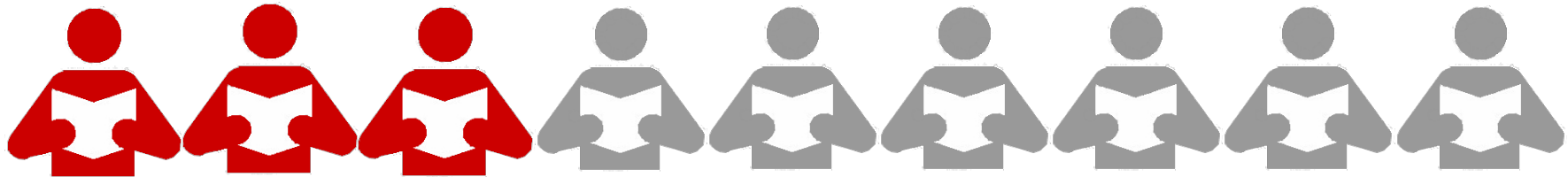
By Prerna Chikersal

Anind Dey (Advisor)

Mayank Goel (Advisor)

Depression in College Students

Difficulty functioning due to depression (33%)



Most common disorder among people with suicidal behaviors!

Depression in College Students

Difficulty functioning due to depression (33%)



Considered suicide (11.2%) [2015-16]



Attempted suicide (2.1%) [2015-16]

Current treatments for depression are effective and reduce the risk of suicide...

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...BUT...

Research Problem

- Students face many **barriers to seeking treatment**
 - Most common - “Stress is a normal part of student life”
- Detecting and monitoring depression is **necessary**

Research Problem

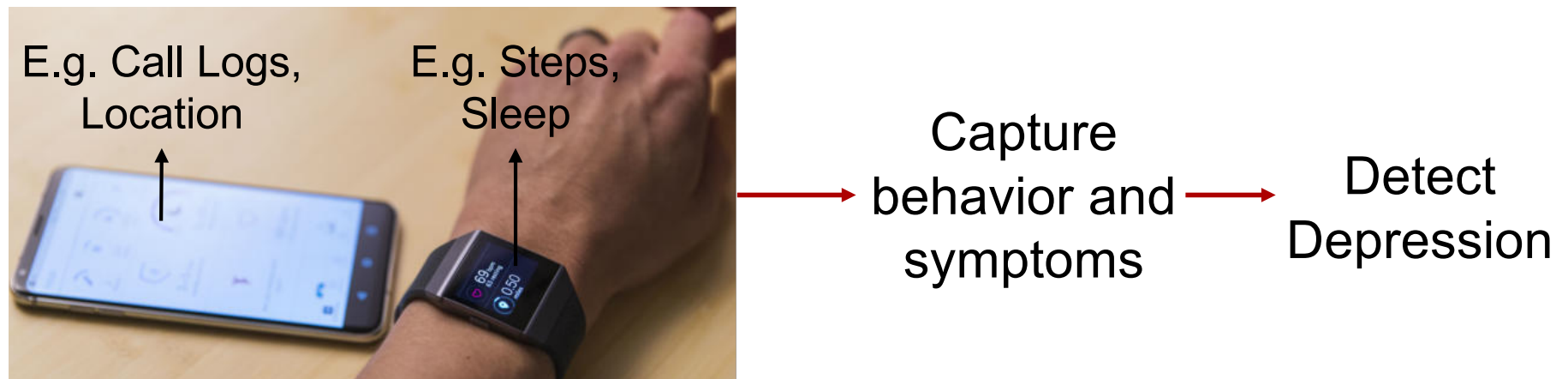
- Students face many **barriers to seeking treatment**
 - Most common - “Stress is a normal part of student life”
 - Detecting and monitoring depression is **necessary**
 - **Current state:**
 - Periodic psychometric tests → Reduce compliance.
- Need more efficient tools to detect depression.**

Research Goals

1. To detect depression as early as possible.
2. To enable interventions.
3. To further the understanding of depression.

Solution

Our Work:



• Detect:

1. Post-semester Depression (85.7%)
2. Change in Depression (84.3%)
3. Change in Levels of Depression (72.4%)

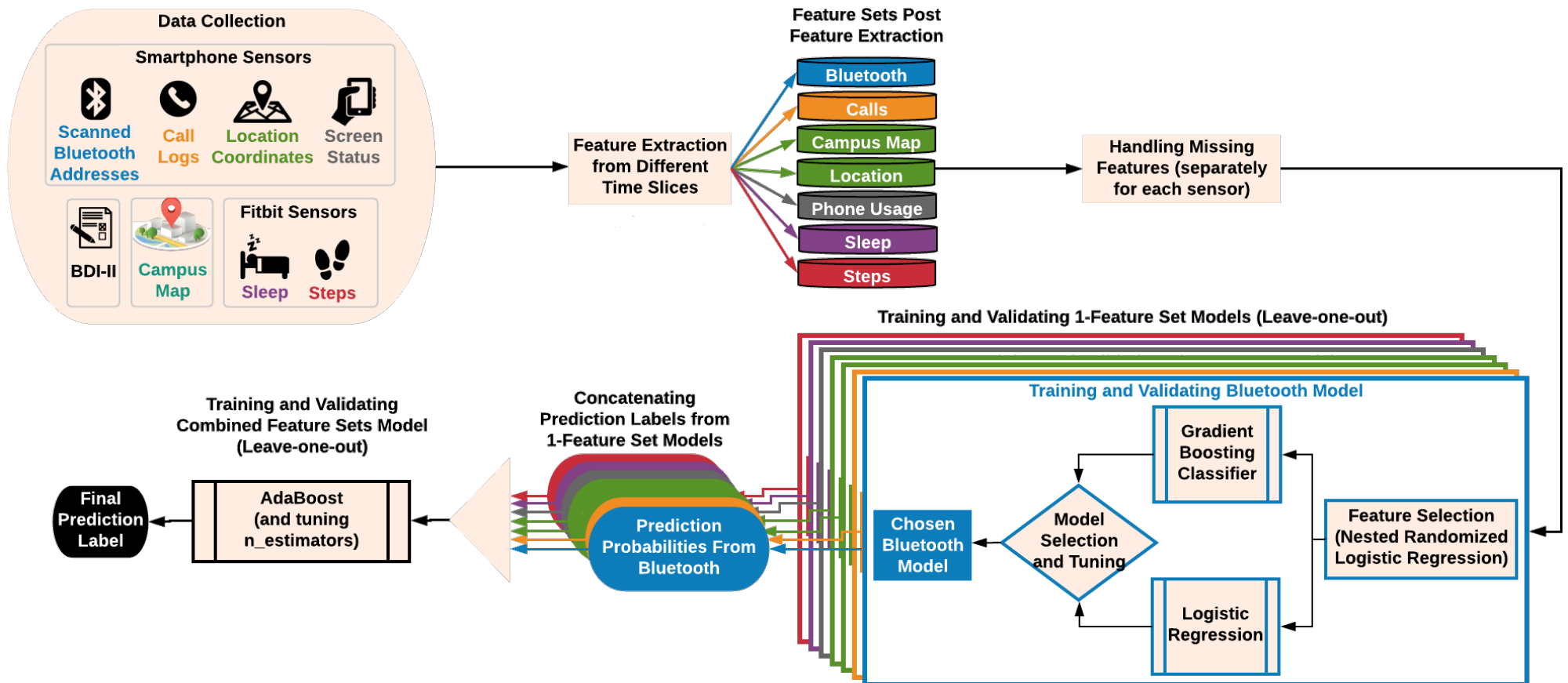
Previous Work

- Relationship between depression and:
 - Location variance, regularity in movement patterns across days, and evenness in time spent across locations.
 - Phone usage and frequency
 - Sleep duration
 - Speech and conversation duration

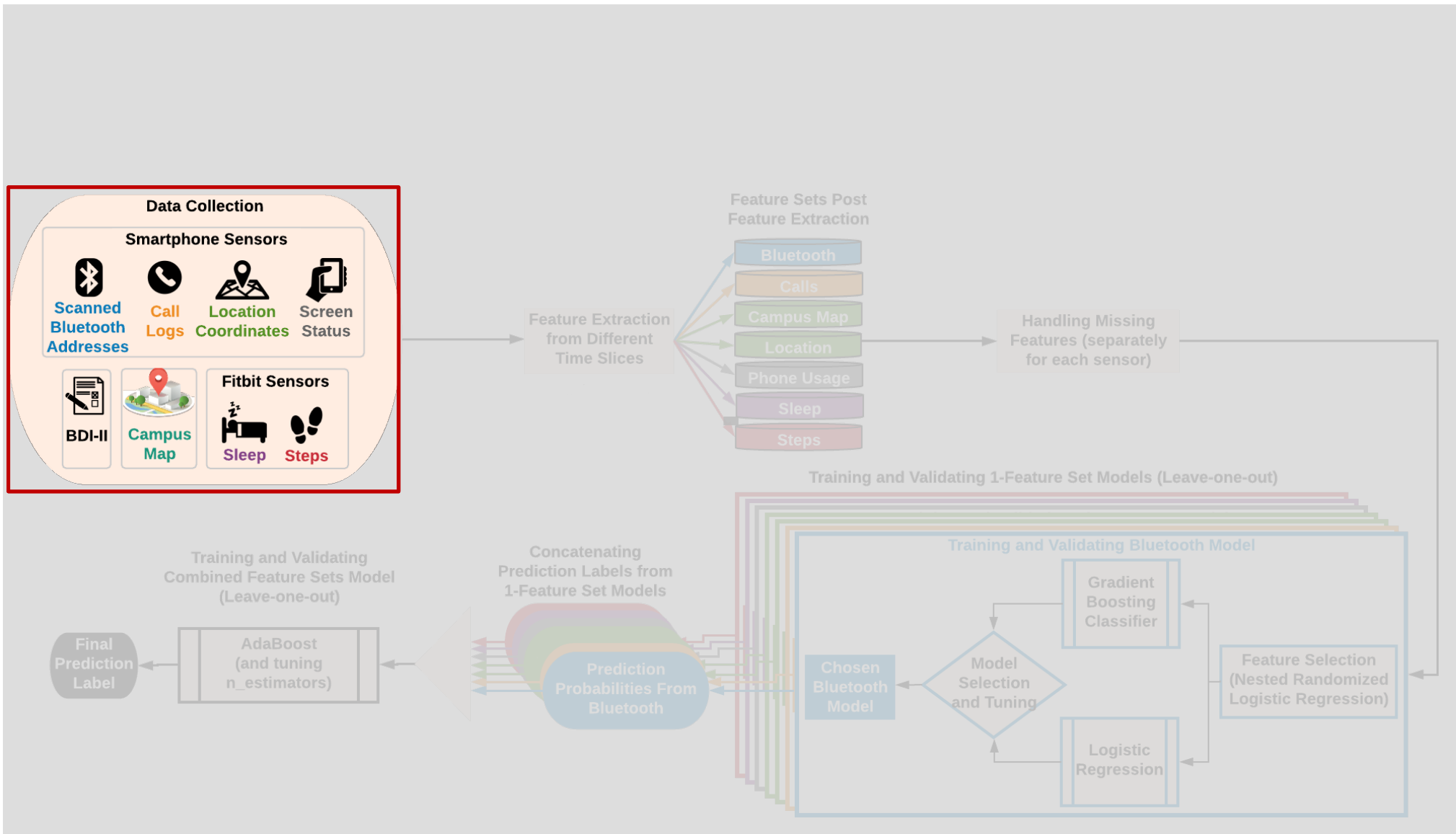
Previous Work

- Used to detect depression using Machine Learning.
- Limitations:
 - Small sample size.
 - Short duration.
 - Limited number and type of sensors.
 - Don't look at our three outcomes.

Methodology



Methodology

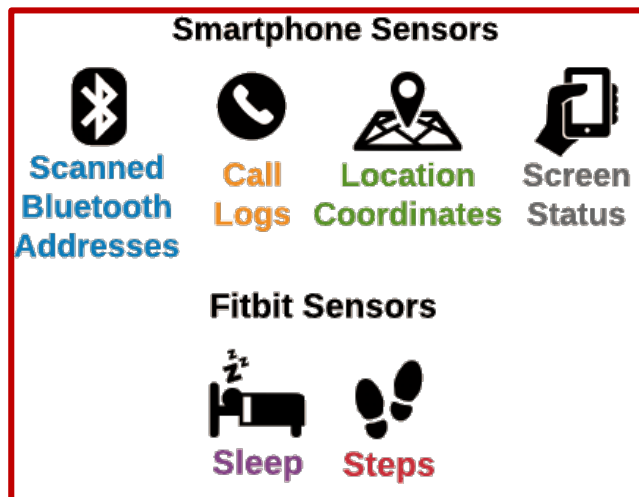


Data Collection

- **Participants**
 - 138 first-year college students.
 - Provided Fitbit Flex 2 and adequately compensated.
- **System for Passive Data Collection**
 - AWARE app for Android/ iOS.
 - Fitbit API.

Data Collection

Passively collected data



One Semester

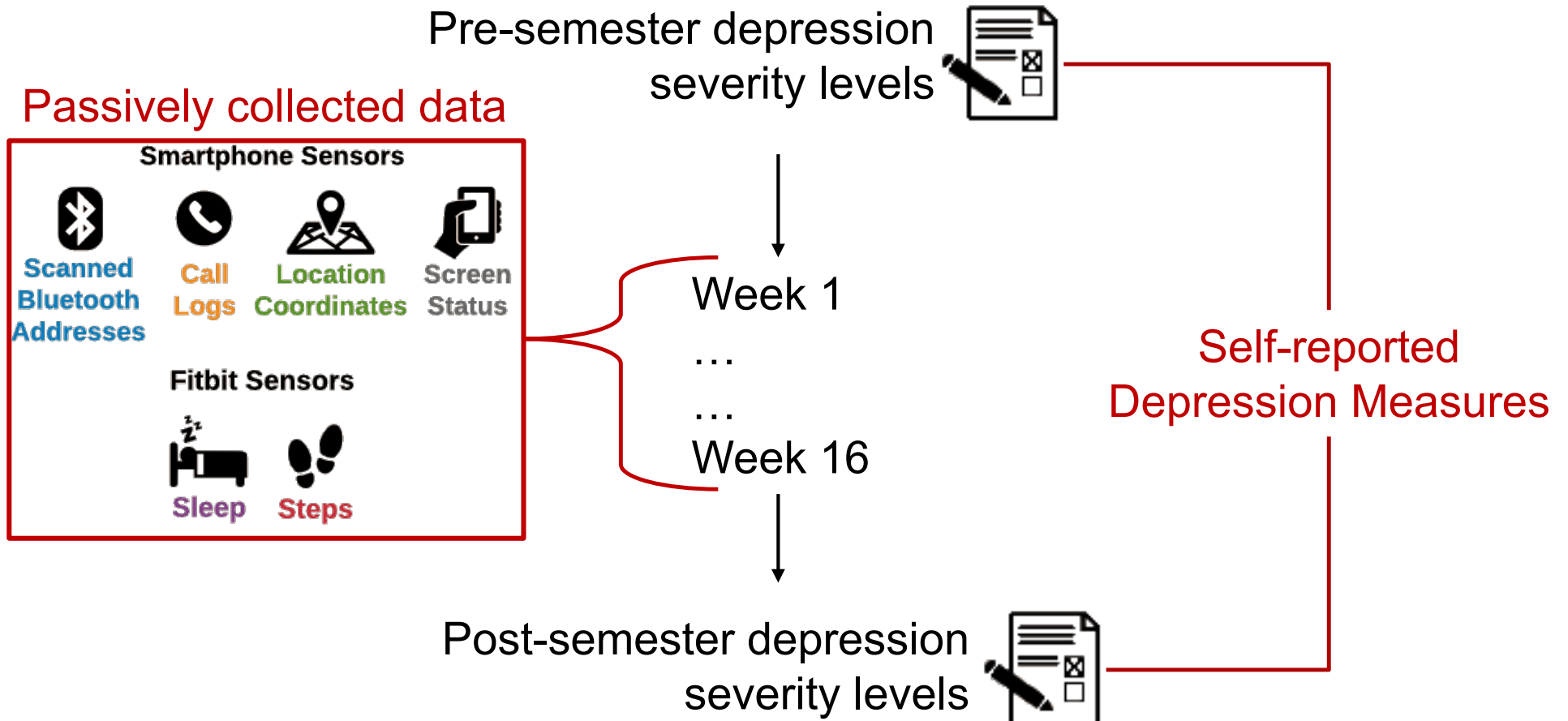
Week 1

...

...

Week 16

Data Collection

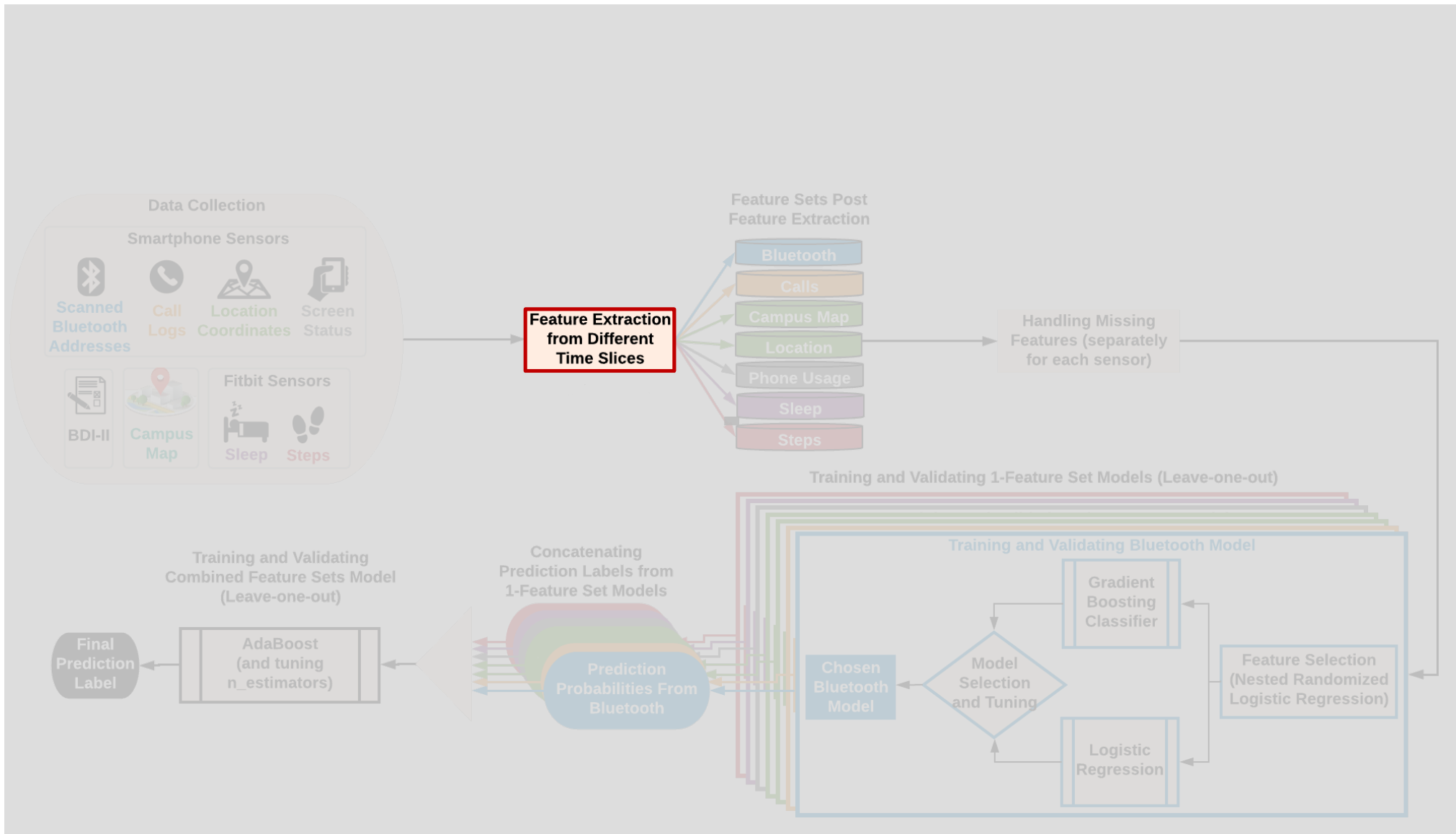


Data Collection

Outcomes (Ground Truth)

- **Post-semester Depression**
 - Binary: *“no depression”* vs. *“mild/ moderate/ severe depression”*
- **Change in Depression**
 - Binary: *“severity level remains the same”* vs. *“severity level worsens”*
- **Change in Levels of Depression**
 - 4-class: By how much does severity level worsen?
“By 0 (same)” vs. *“by 1”* vs. *“by 2”* vs. *“by 3”*

Methodology



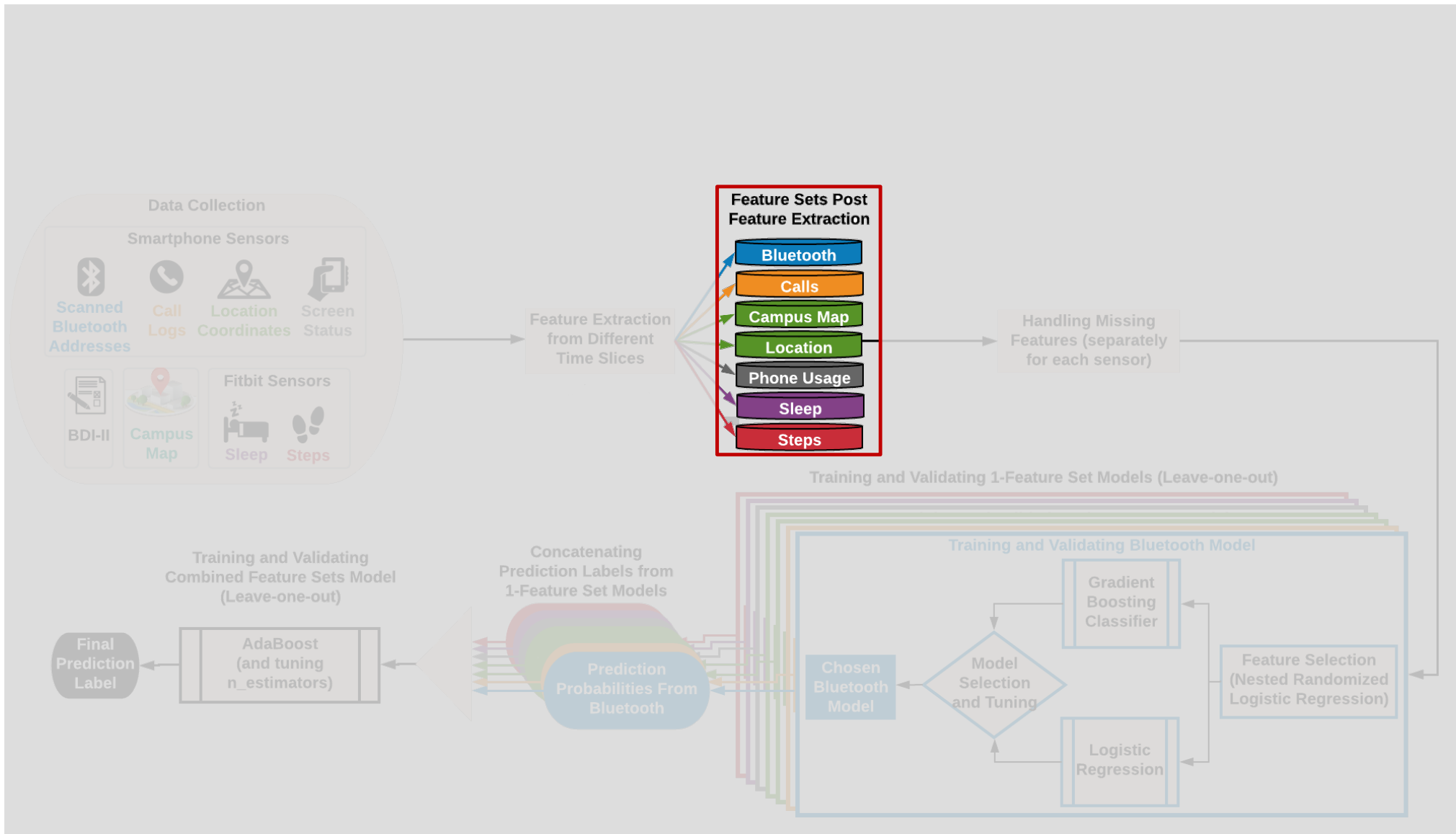
Feature Extraction: Temporal Slicing

- Features are aggregated over different temporal slices instead of the whole semester.
- Why?

Feature Extraction: Temporal Slicing

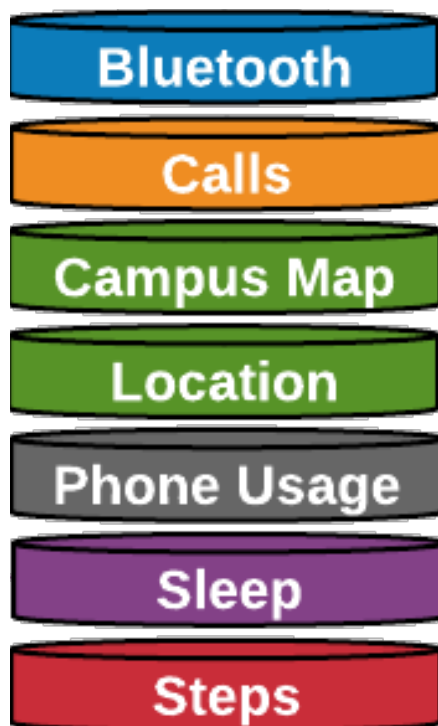
- Features are aggregated over different temporal slices instead of the whole semester.
- Why?
- → There are 45 such temporal slices.

Methodology



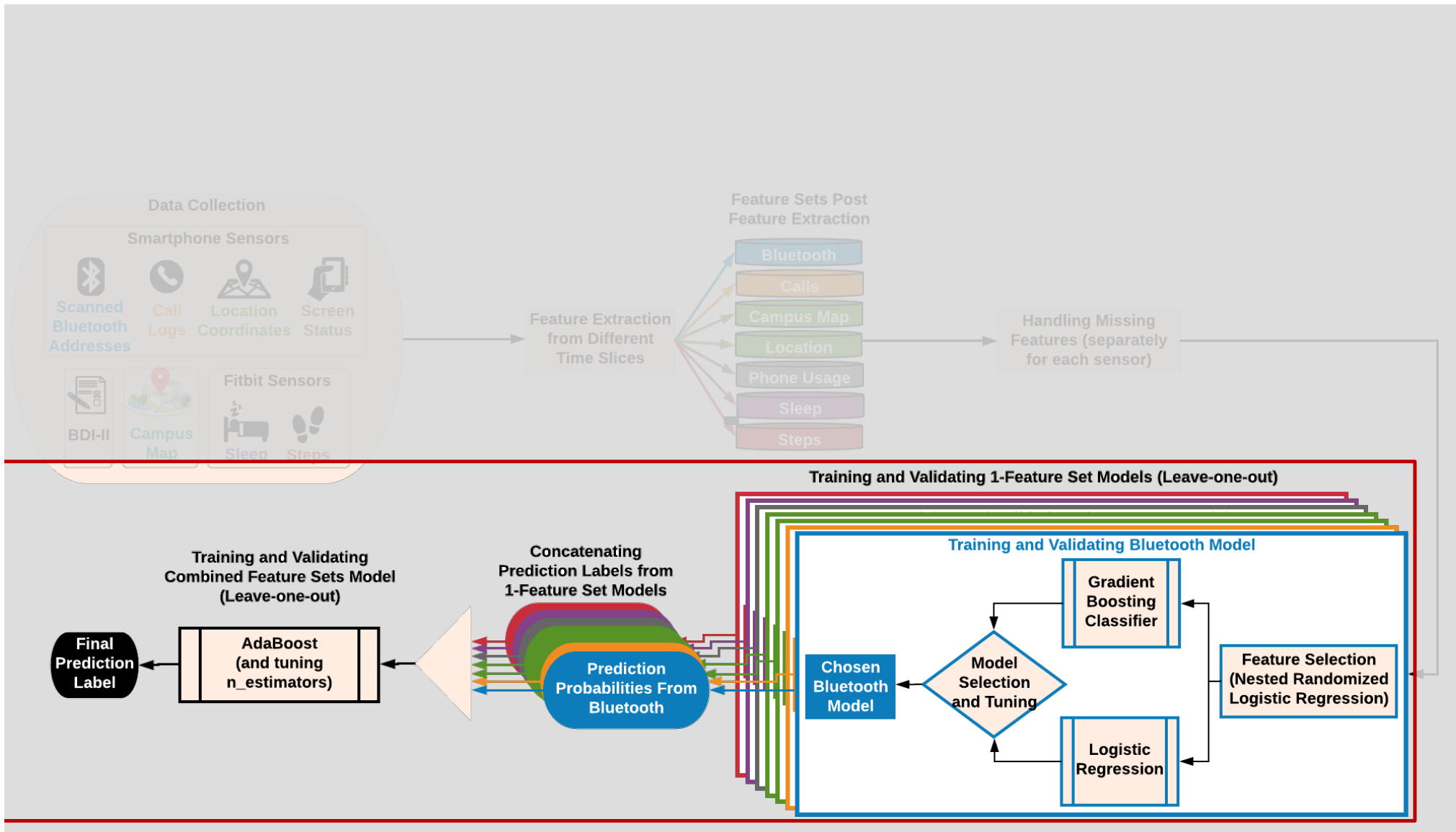
Feature Extraction: Feature Sets

- 7 feature sets



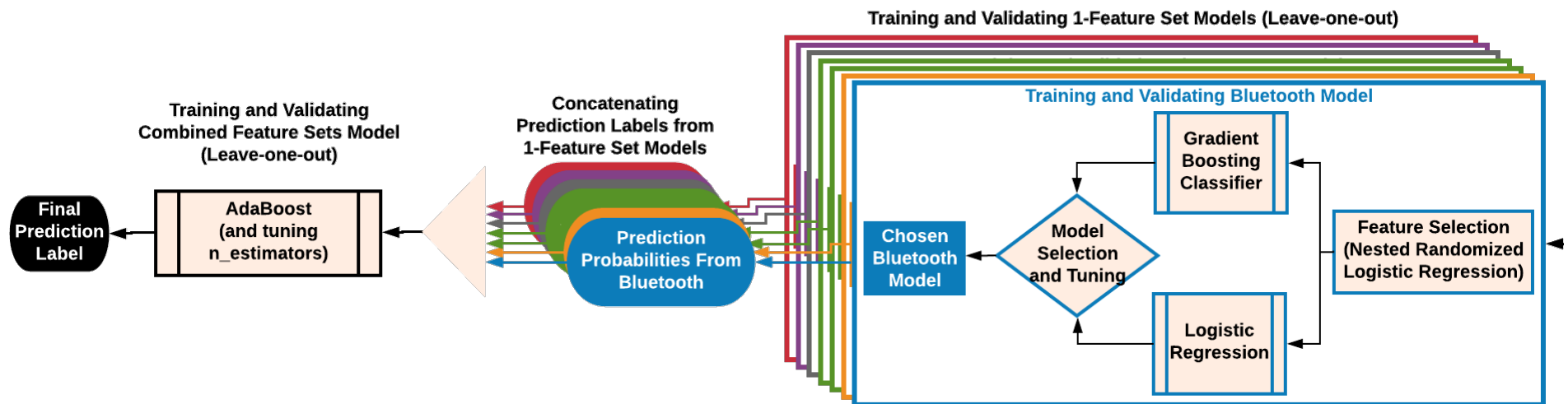
- Each contains behavioral features calculated over 45 temporal slices.
- Understandable
 - E.g. Location → “circadian movement” (regularity in a person’s movement patterns).

Methodology

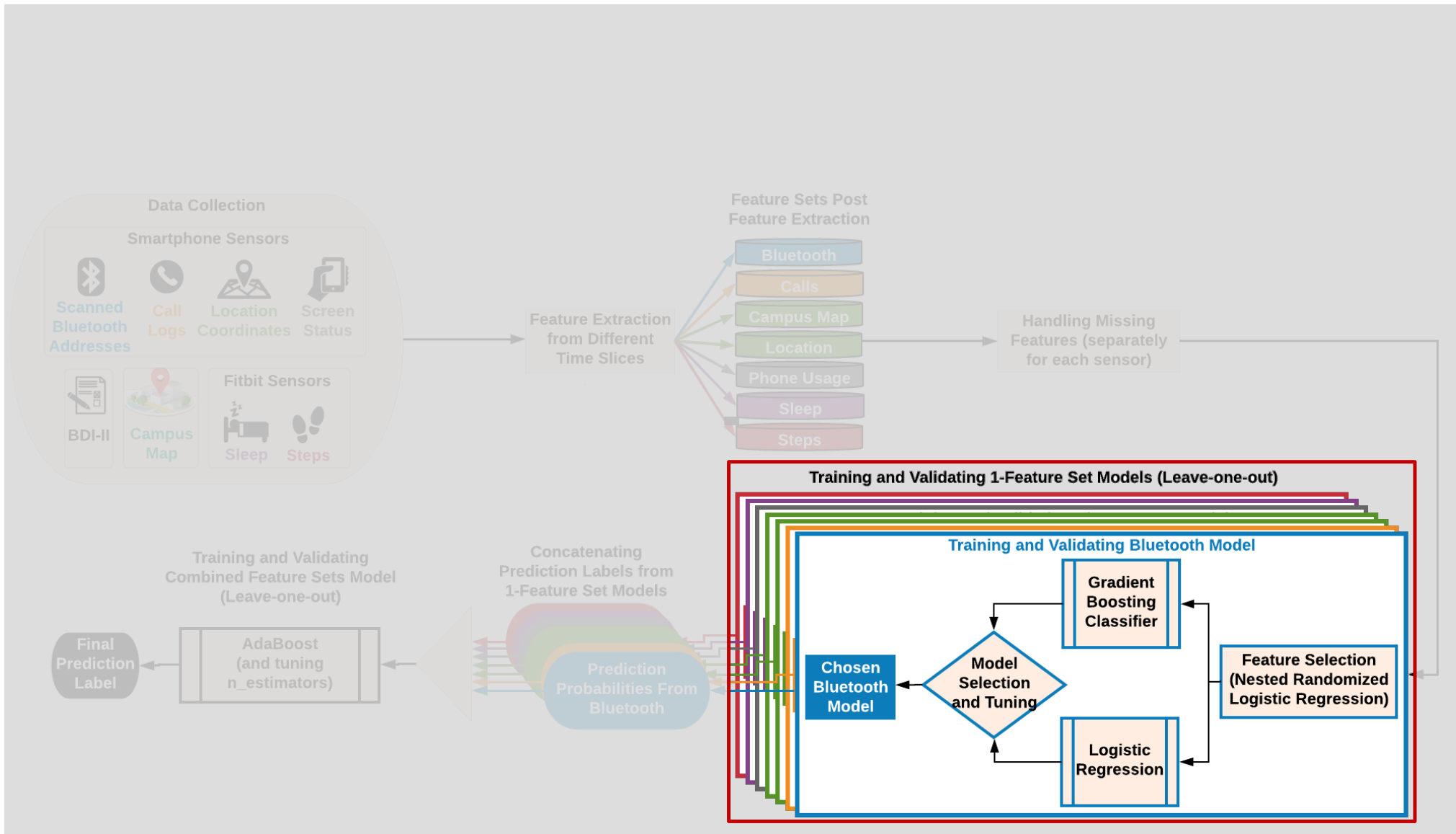


Modeling

- > **50K features** and only **79 people** from **all** feature sets!
- Feature selection very challenging!

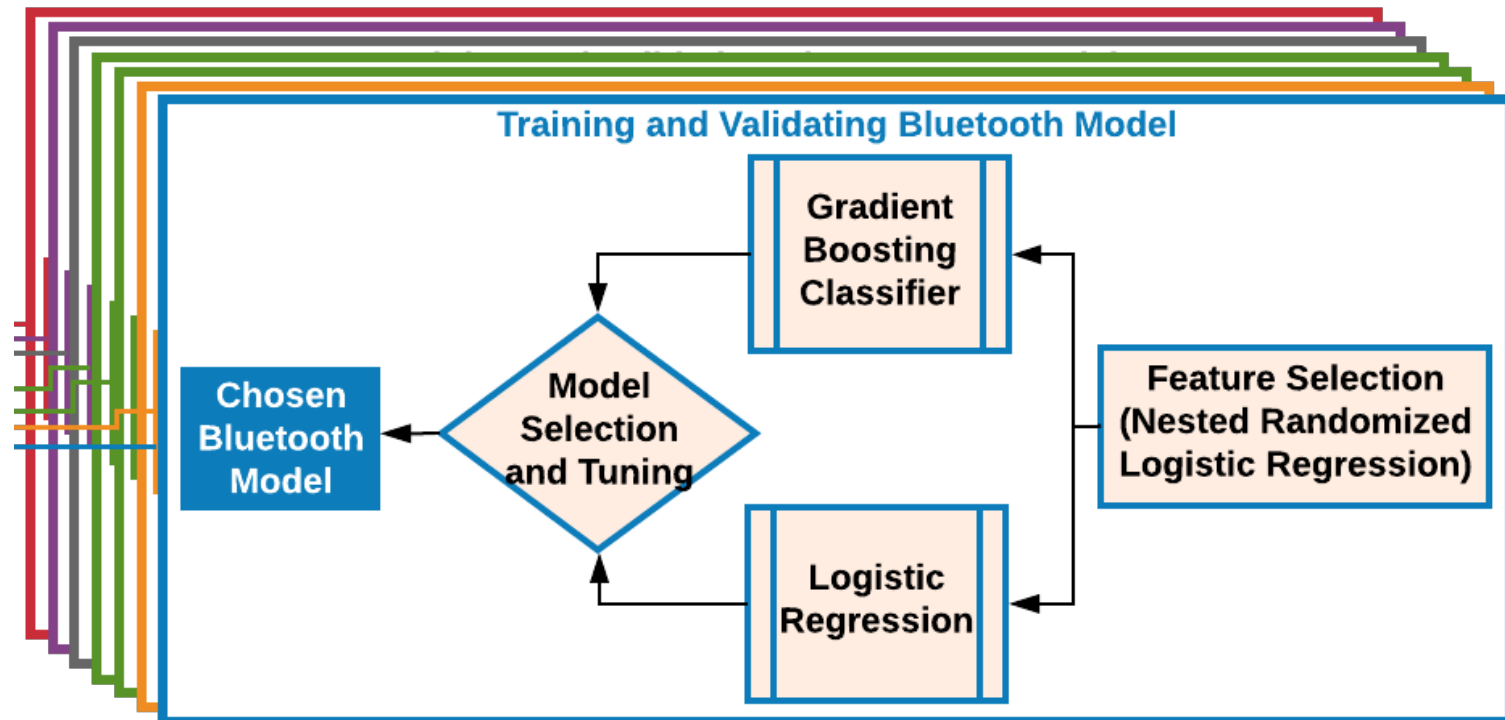


Methodology



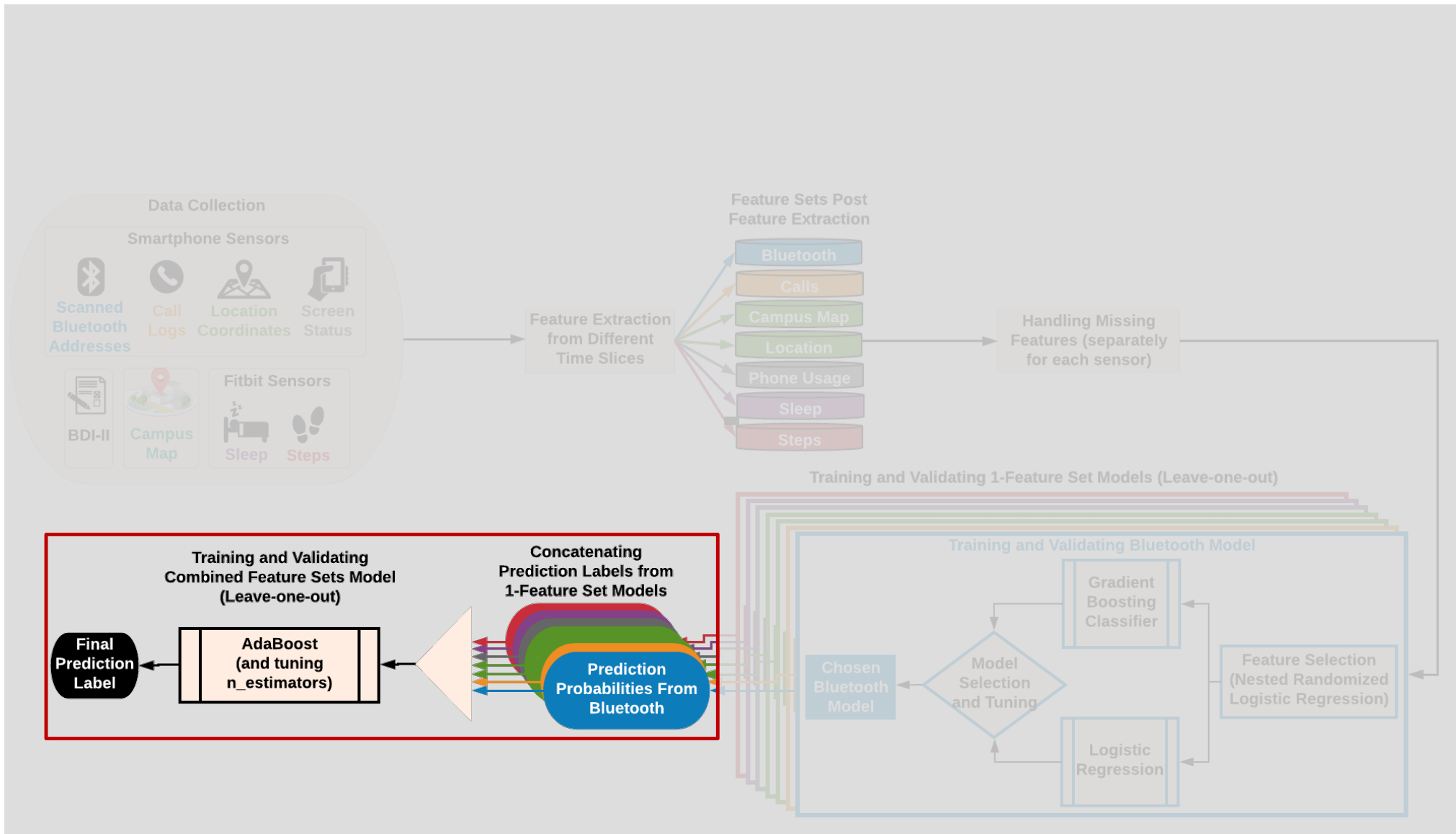
Training and Validating 1 Feature-Set Models

Training and Validating 1-Feature Set Models (Leave-one-out)

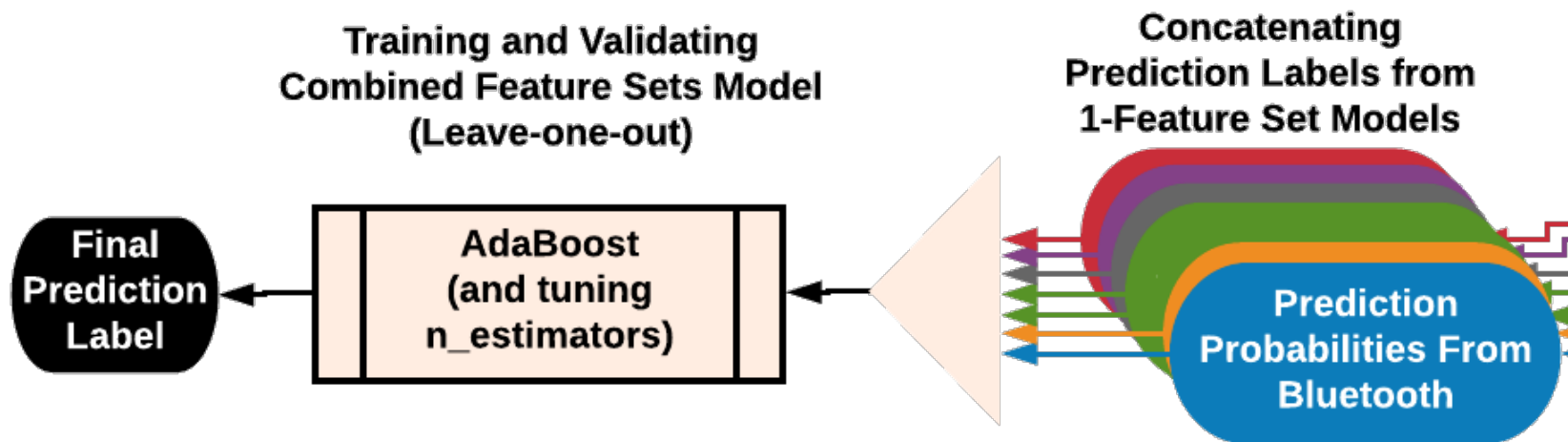


- Leave-one-out cross-validation

Methodology



Training and Validating Combined Feature-Sets Model



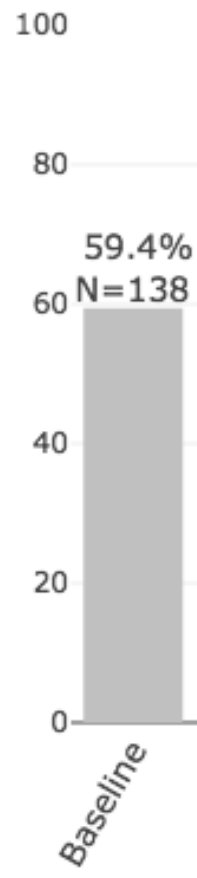
- Leave-one-out cross-validation

Descriptive Statistics

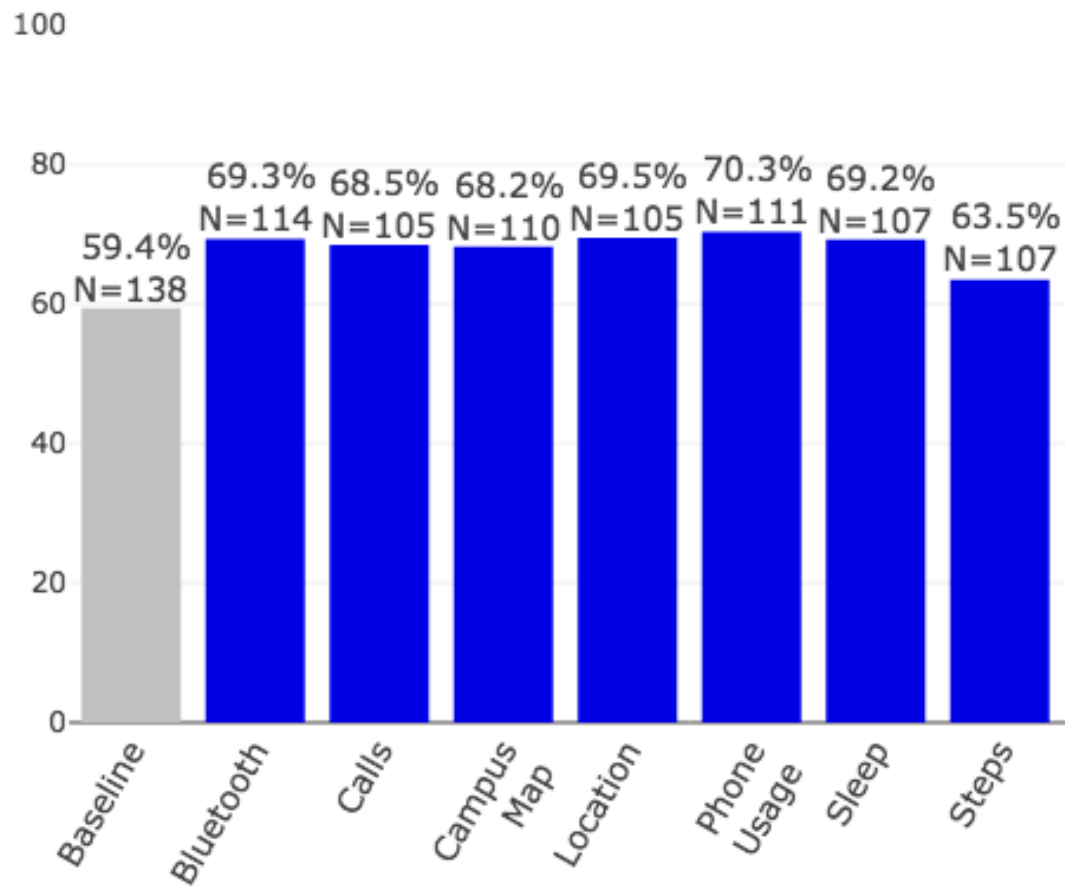
- Depression
 - Pre-semester, 14.5% students had depressive symptoms.
 - Post-semester, this increased to 40.6%.
- Change in Depression
 - Depression severity levels remained the same for 63.8% people.
 - Only 3 people got better (and were excluded).
 - Everyone else got worse.
- Change in Levels of Depression
 - 55.3% got worse by 1 severity level.
 - 34.1% got worse by 2 severity levels.
 - 10.6% got worse by 3 severity levels.

Results

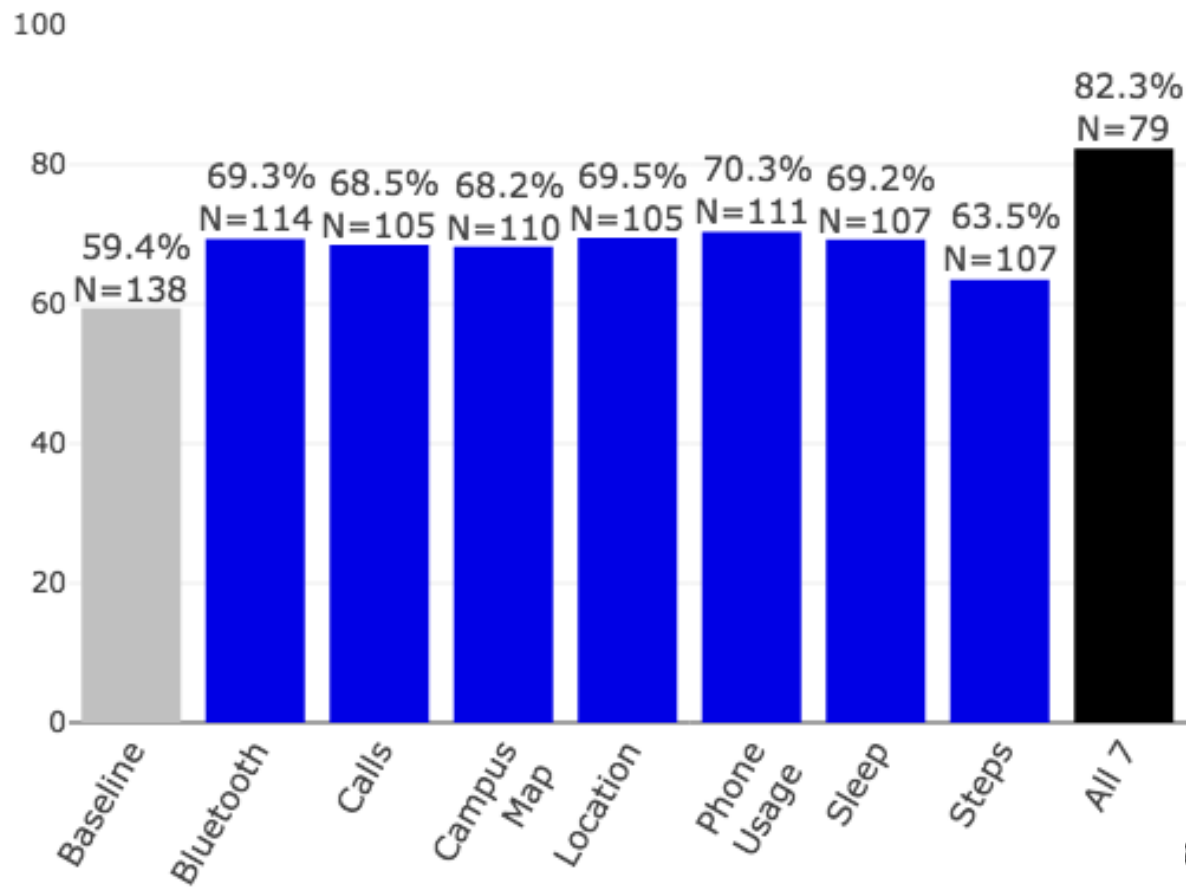
Results: Detecting Post-Semester Depression



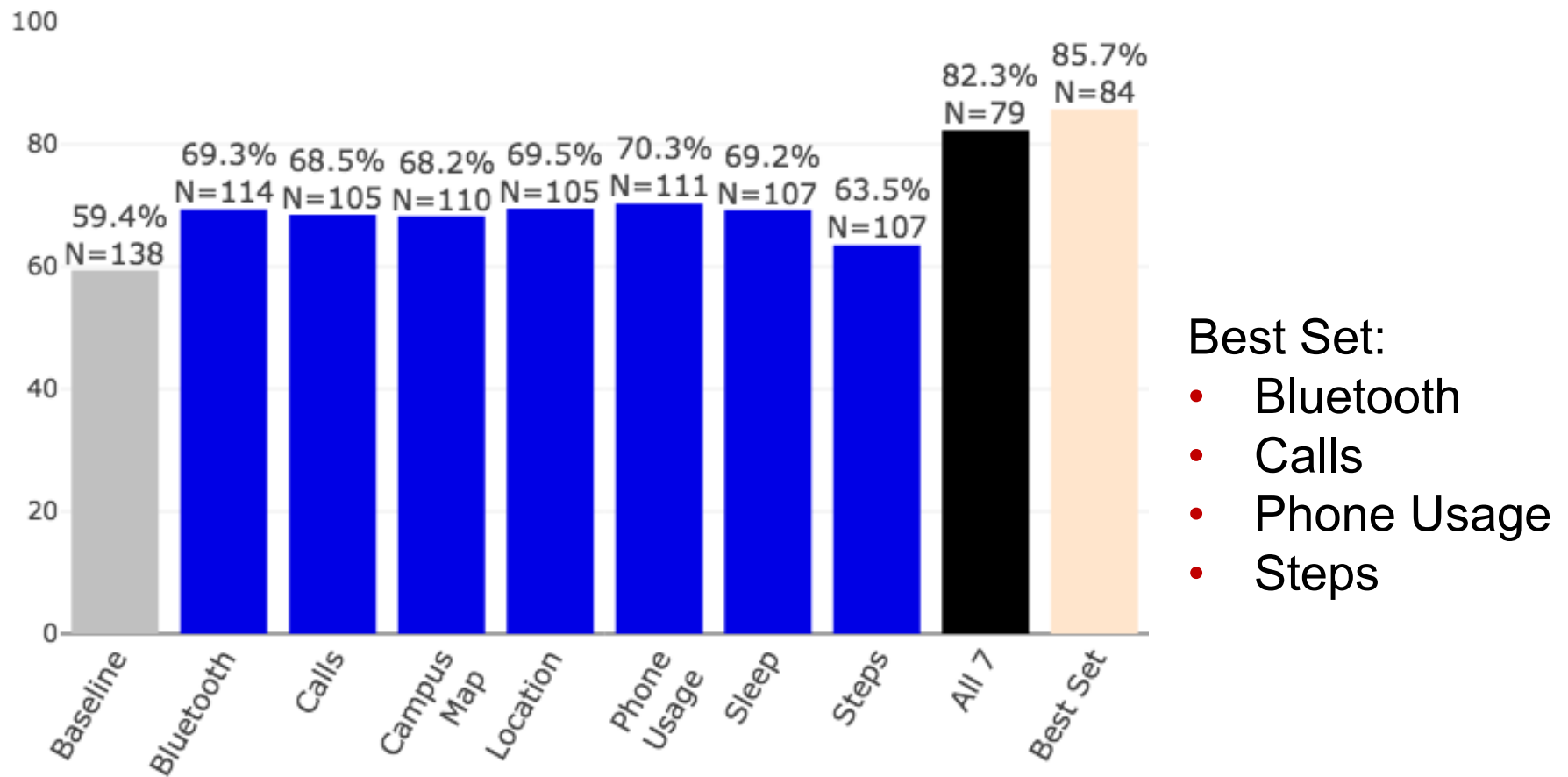
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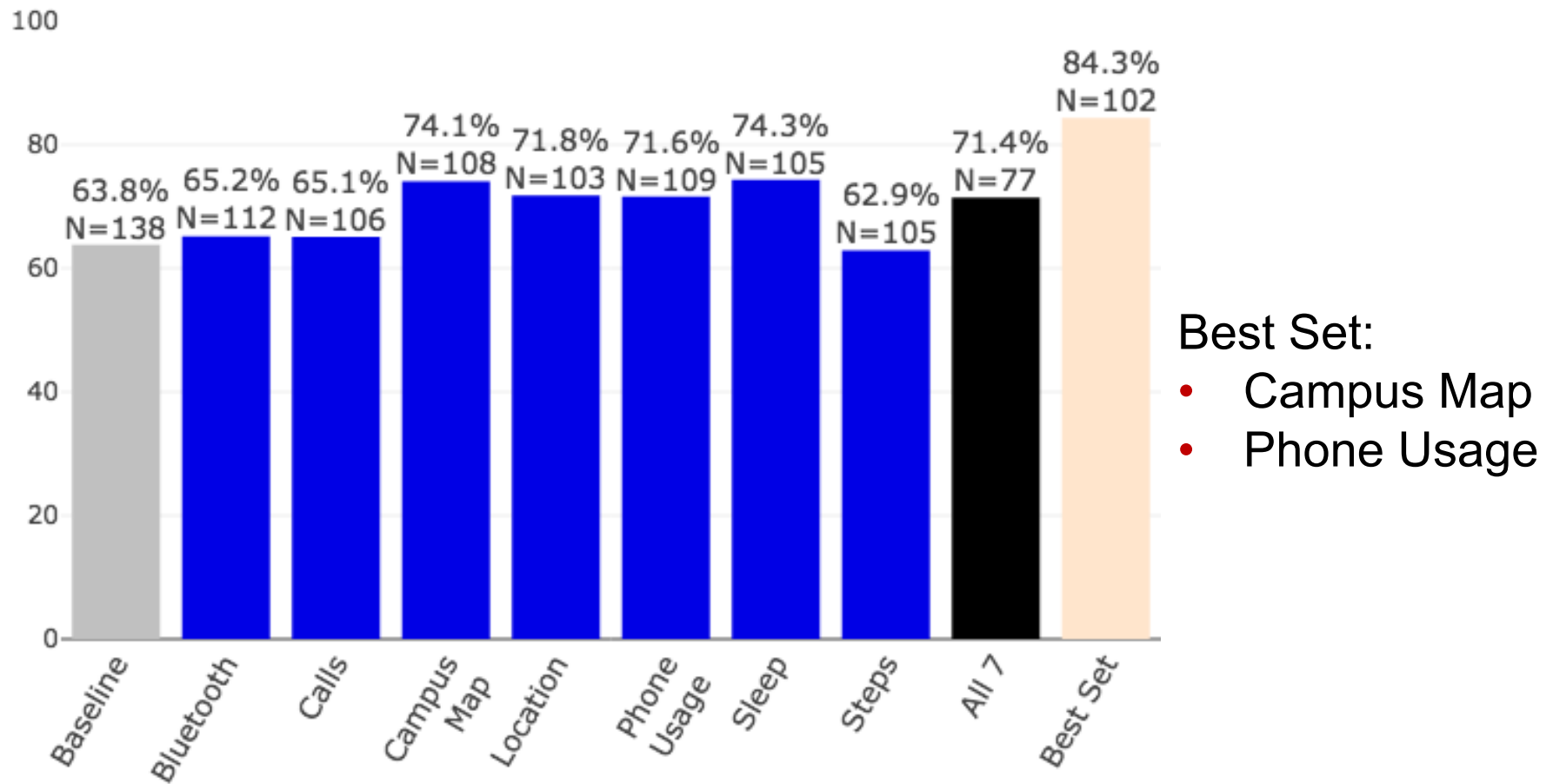
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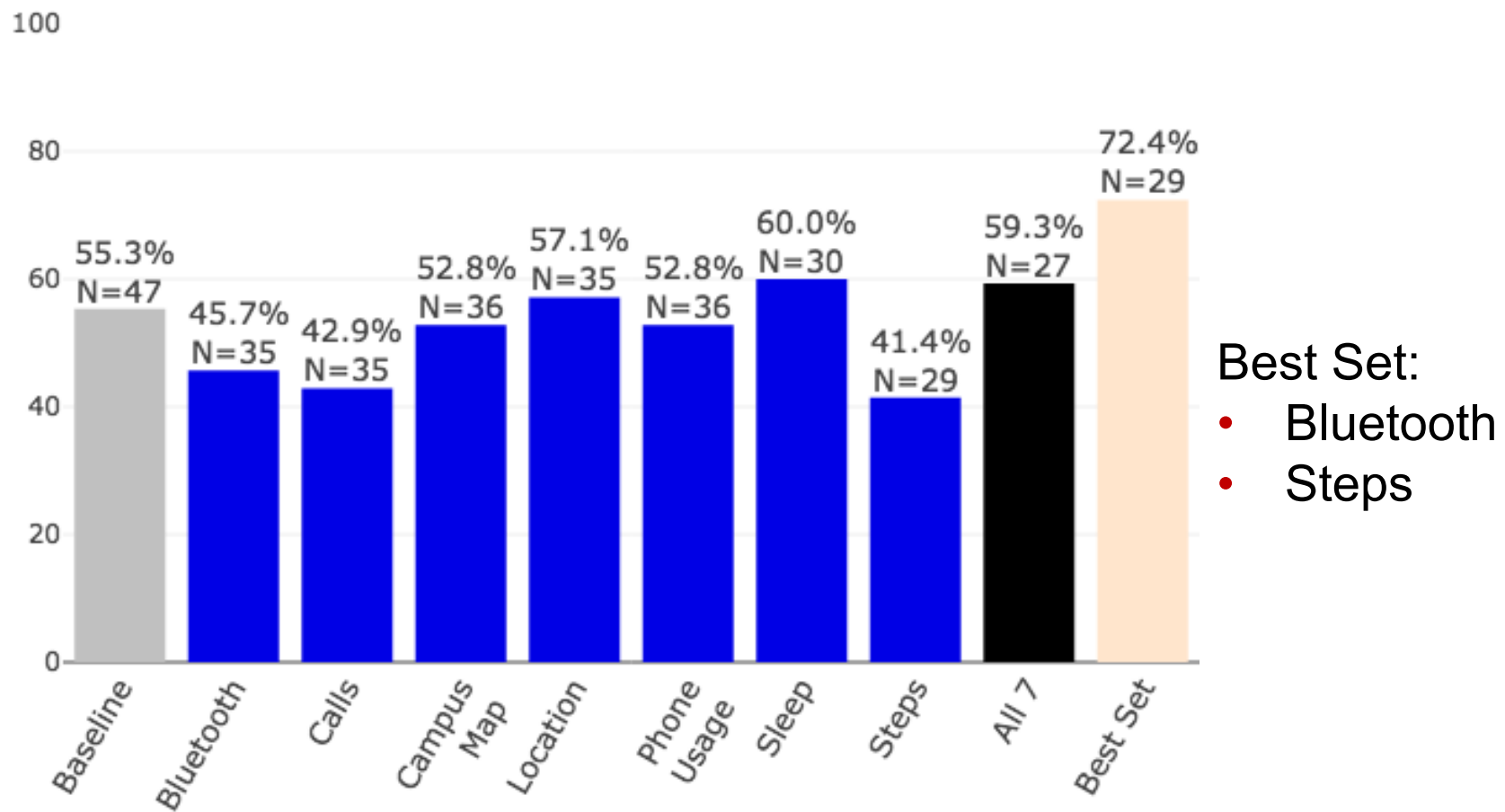
Results: Detecting Post-Semester Depression



Results: Detecting Change in Depression



Results: Detecting Change in Levels of Depression



Results: Prediction

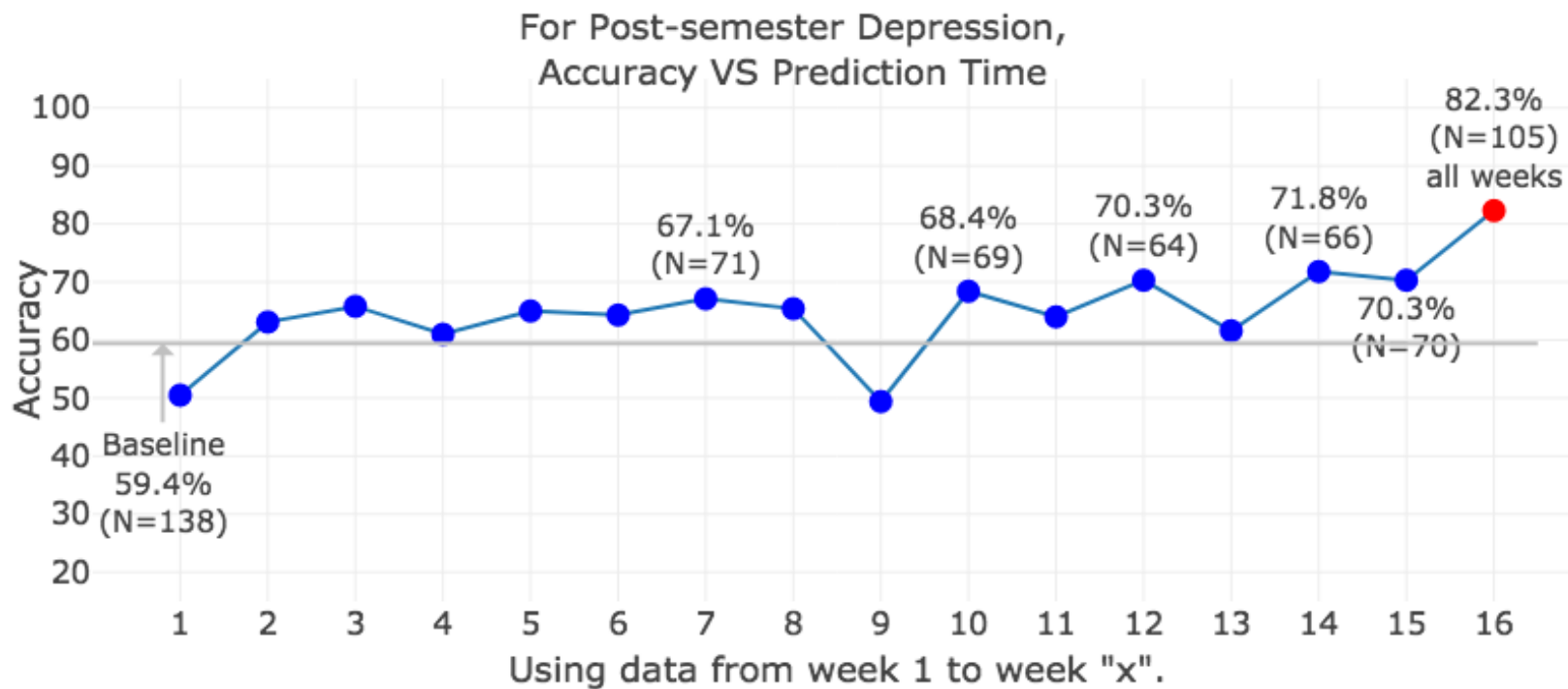
- Detection vs Prediction

Results: Prediction

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- How early can we predict these outcomes?
- Use data from week 1 to week x .

Results: Prediction

- Detection vs Prediction
- How early can we predict these outcomes?
- Use data from week 1 to week x.



Implications

Implications - Examples

- Early Prediction models
→ Preemptive interventions in future studies



Predicted risk for
depression is high!



Implications - Examples

- Understandable model
→ Inform Treatment and self-guided reflection



Implications - Examples

- Our Feature Extraction Library
 - Tens of thousands of behavioral features!
 - Can contribute to:
 - Longitudinal and Inter-University
 - Large initiatives that combine passive sensing with the participants' medical history, biological data, etc.

UCLA Grand Challenges

Depression

(100,000 participants)



THE PRECISION MEDICINE INITIATIVE

(long-term, NIH)

Thank you!

- Questions?
- Contact:
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