Assessing Mental Health Issues on College Campuses: Preliminary Findings from a Pilot Study

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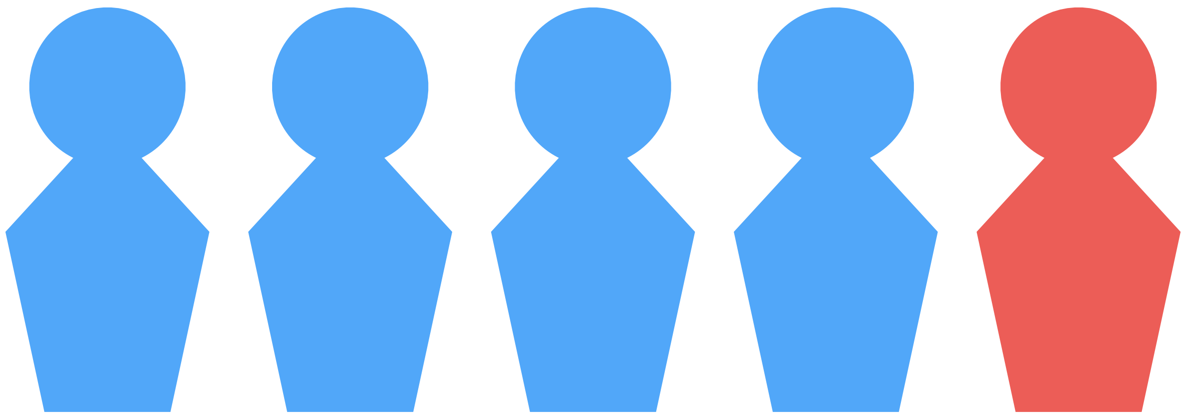
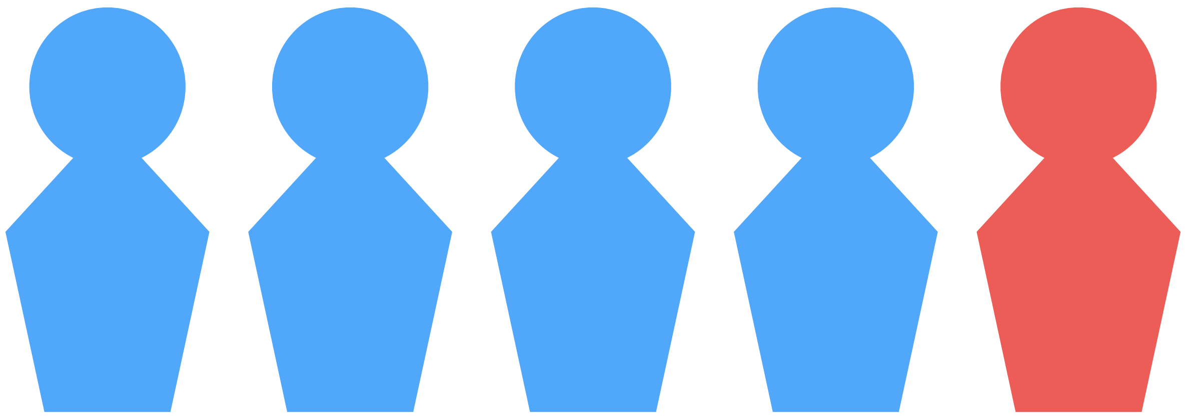
Cornell University



1 in 5 adults in the U.S.
has mental illness in a year



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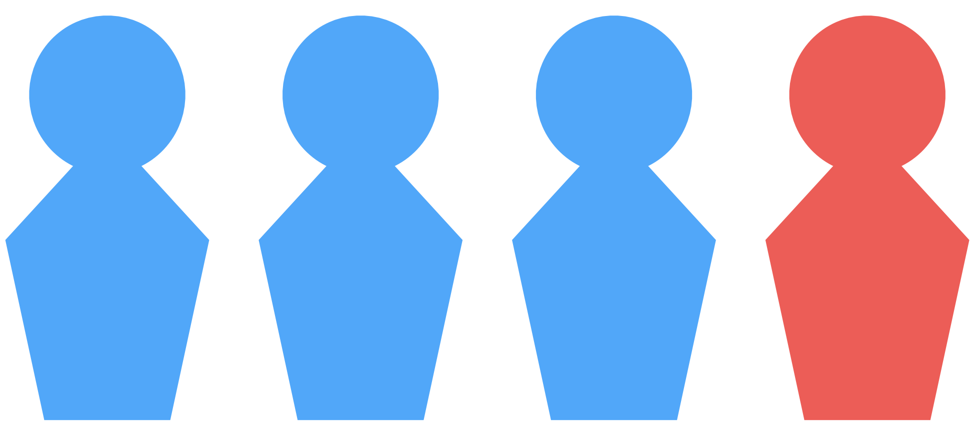

1 in 4 college students in the U.S.
has mental illness in a year

Based on 19,681 students over 40 schools,

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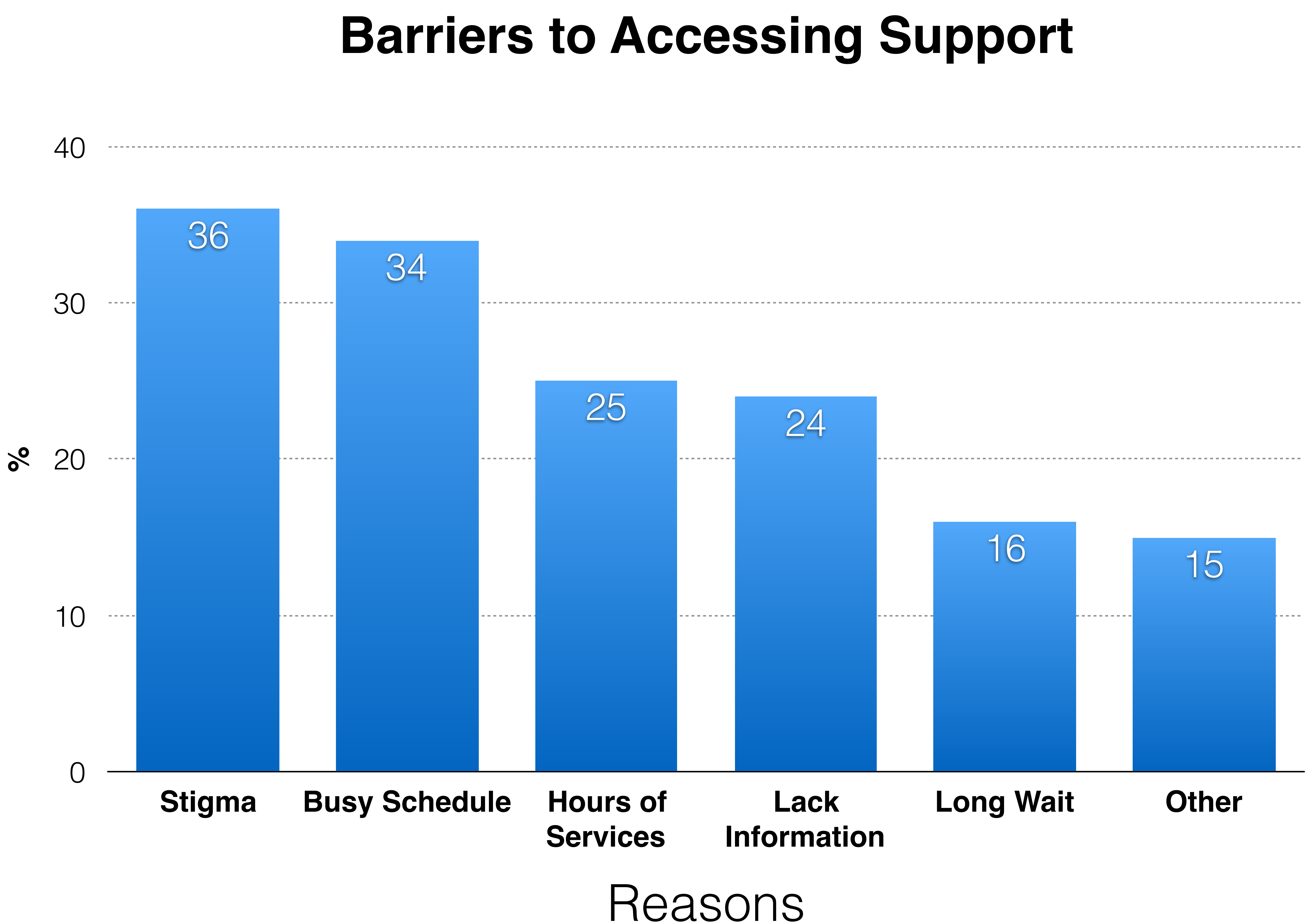
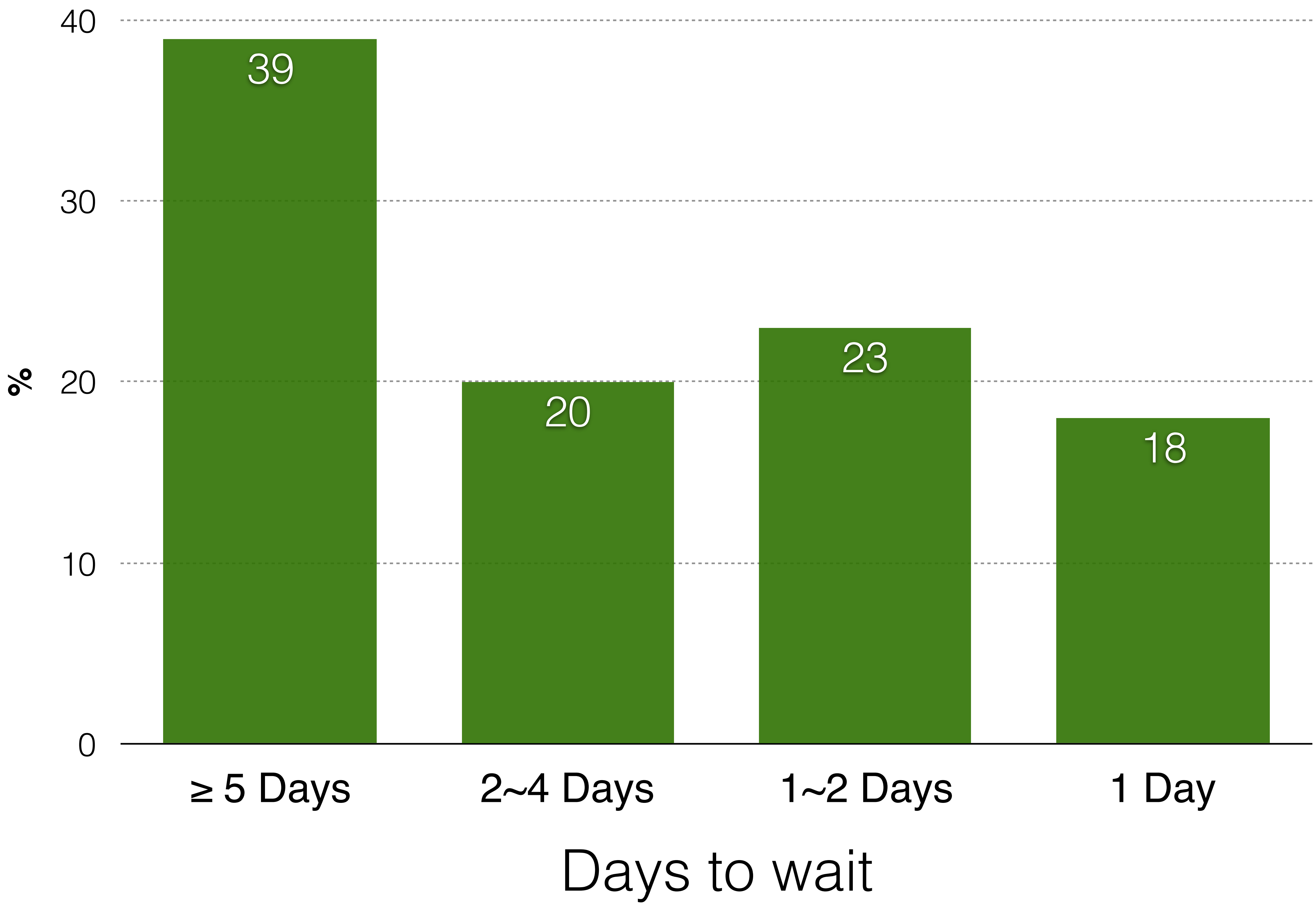
However, 40% of them did not seek help.


Barriers to Accessing Support
40
30
20
10
0
%
36
34
25
24
16
15
Stigma
Busy Schedule
Hours of Services
Lack Information
Long Wait
Other
Reasons

Appointment Wait Times



Ratio of student to psychological counselors is 1900 : 1

A new tool to monitor students' behavior and assess their mental well-being continuously and unobtrusively is needed.


86% of US college student regularly use a smartphone.

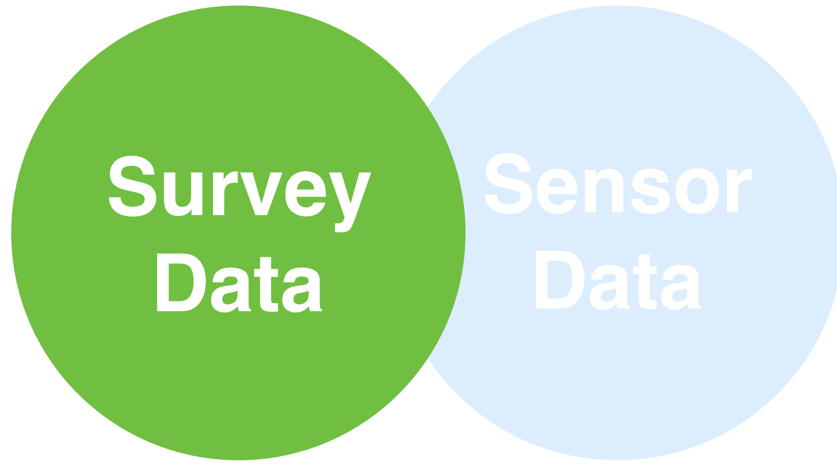
Pilot Study - Smartphone Based Mental Health Assessment Tool

- Conducted in an Ubicomp class in the Spring term (4 months) at Cornell University.
- Cornell health center was involved.
- 22 participants (12 females and 10 males) participated.

Pilot Study - Smartphone Based Mental Health Assessment Tool

- App was run on iOS and Android devices.

- Both self-assessment survey and passive sensing data were collected.



Well-being
Survey

Beginning,midterm,
end of semester

Sleep
Survey

10:30 AM

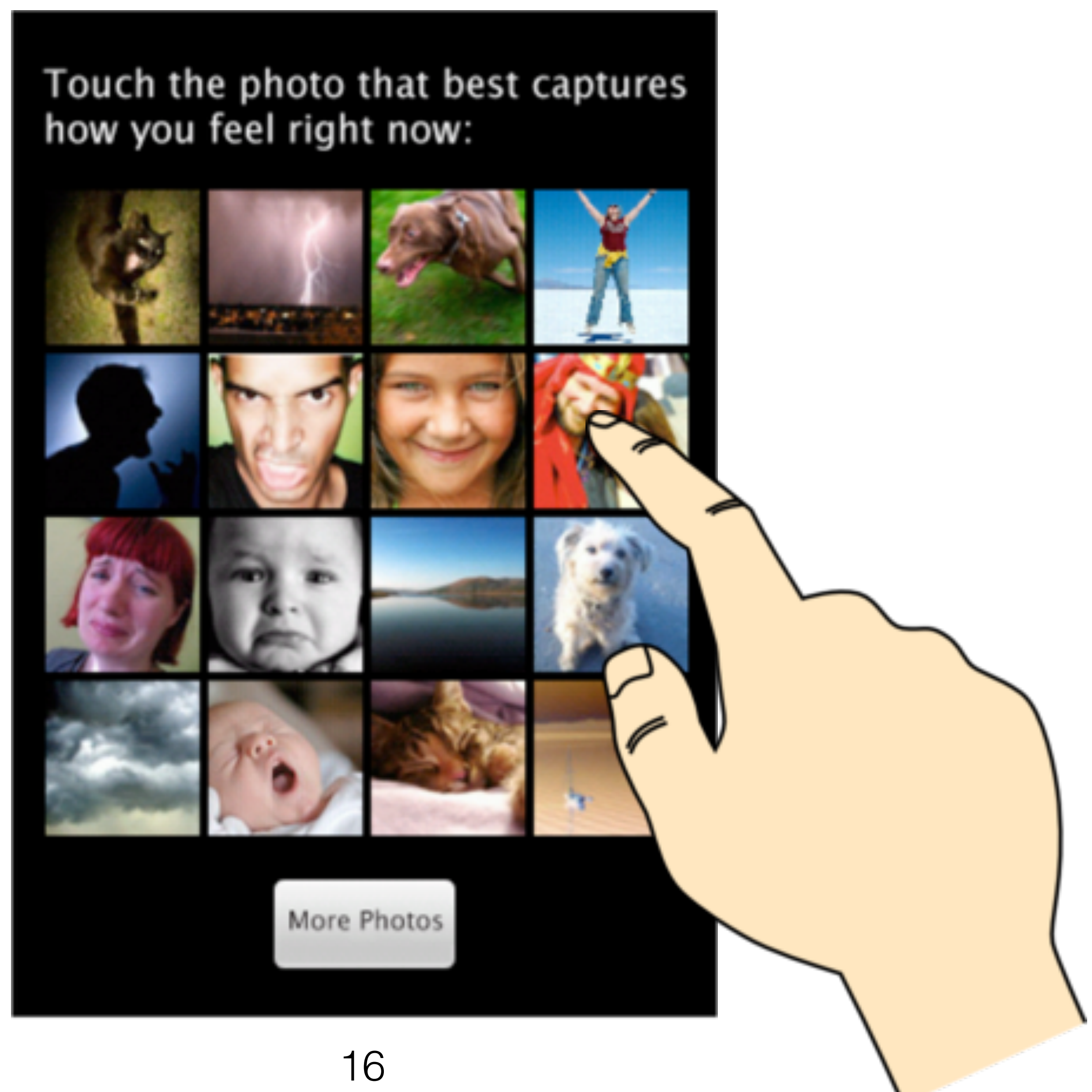
Photographic Affect Meter
(PAM) Survey

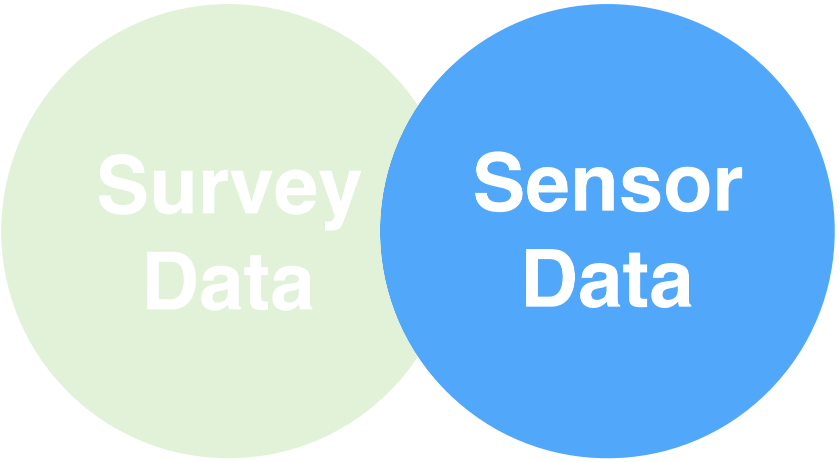
10:30 AM
4:30 PM

Survey Data

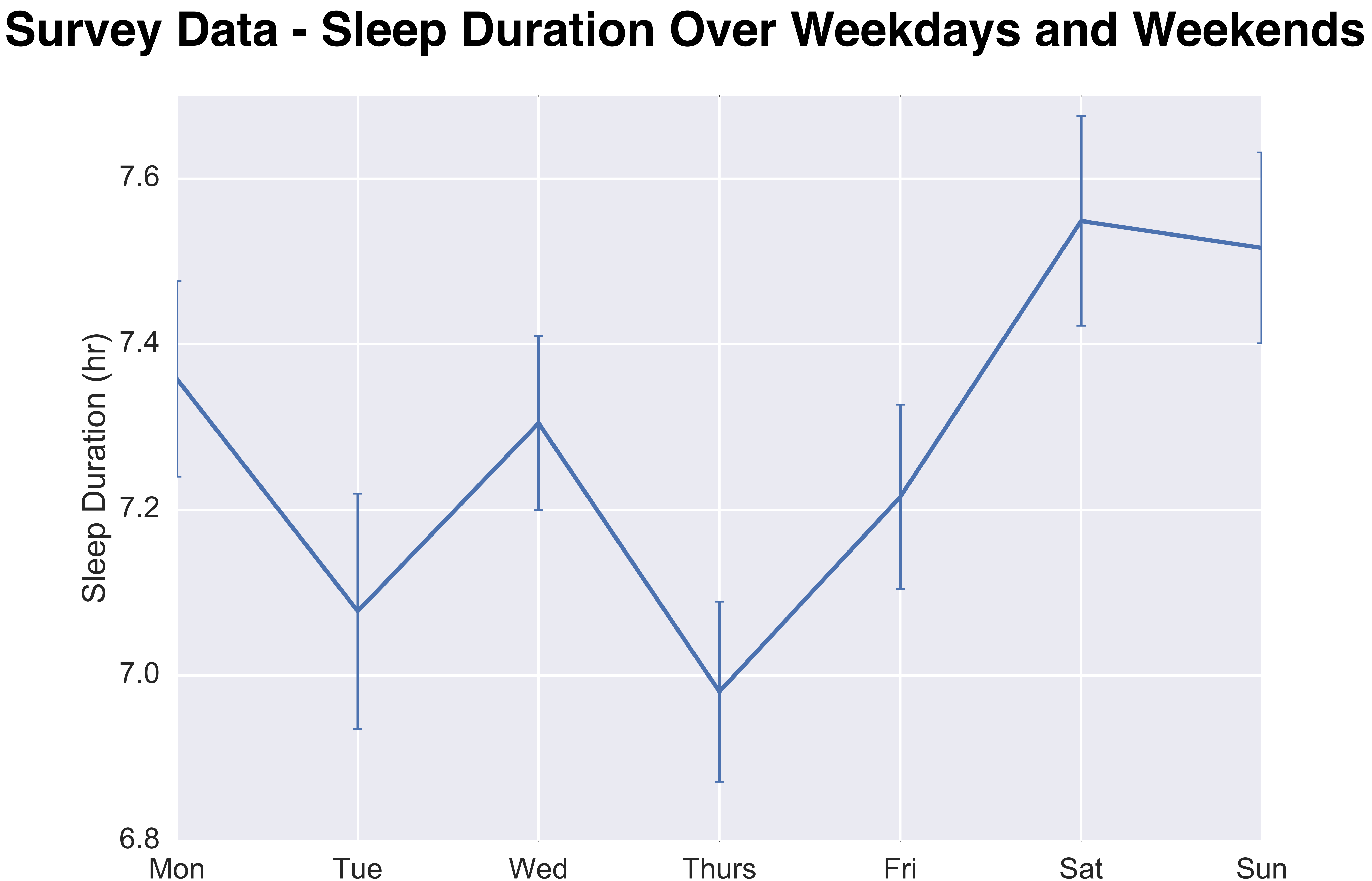
Sensor Data

Photographic Affect Meter (PAM) Survey

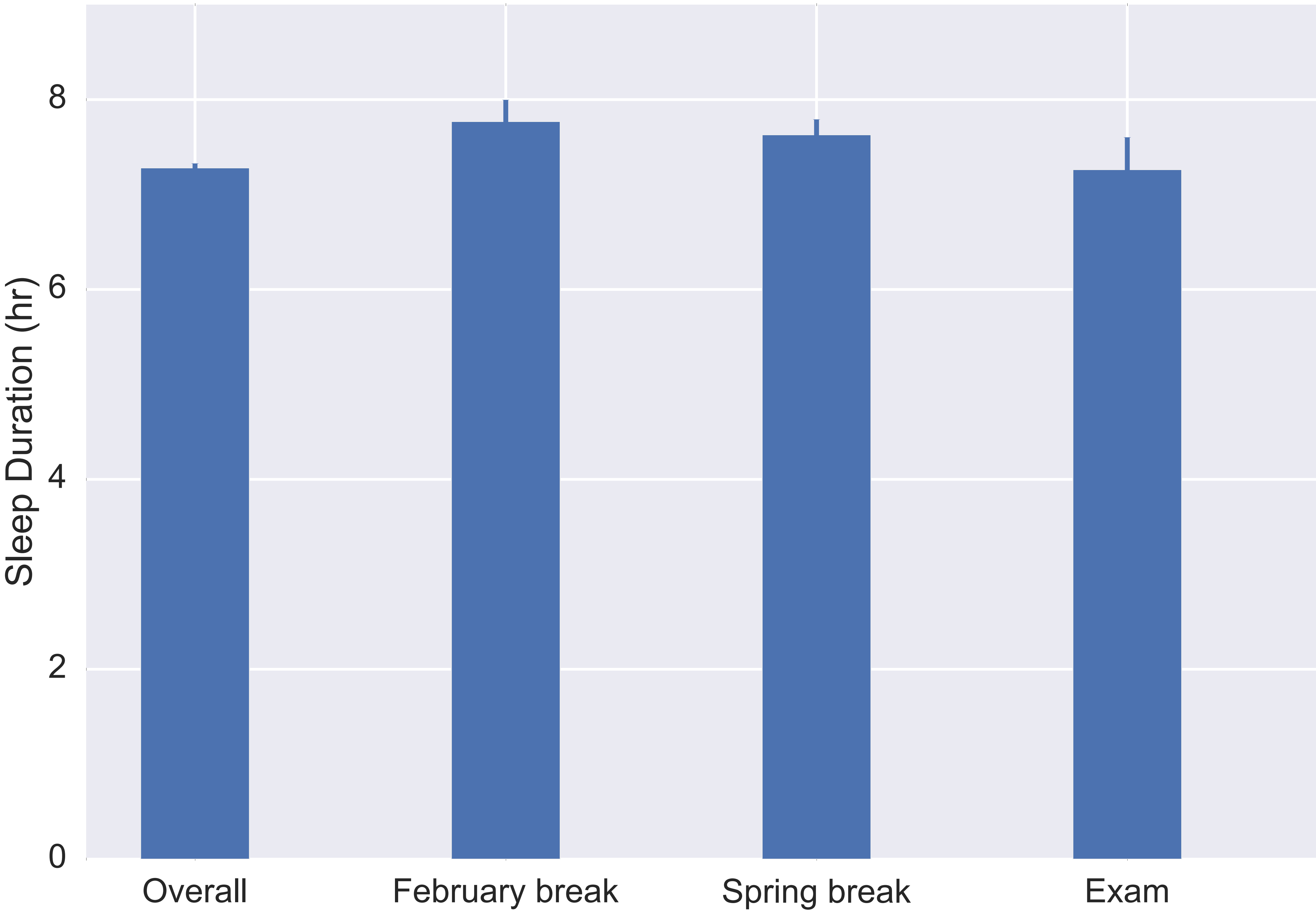




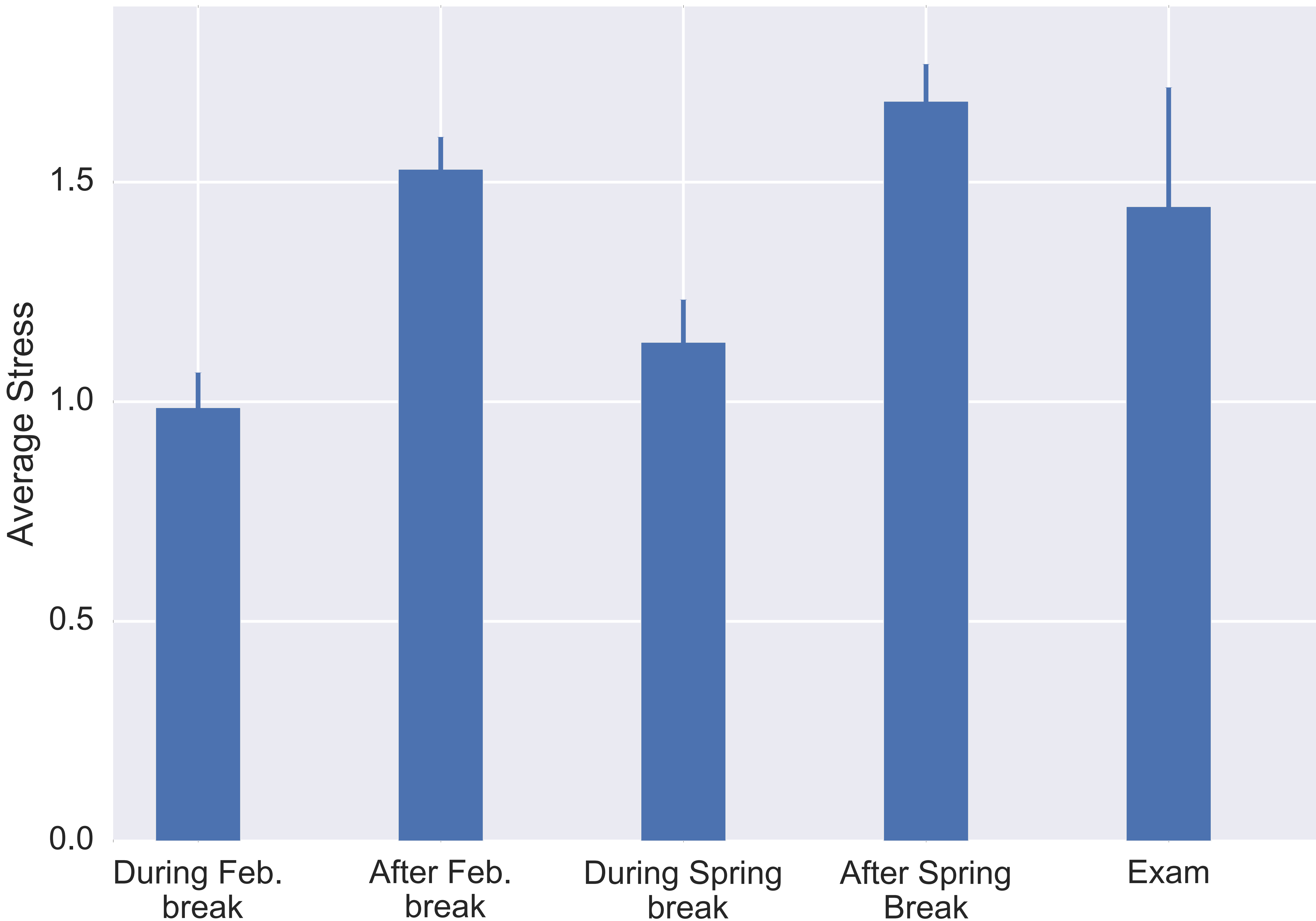
Activity Call Audio Location Charging


Survey Data - Sleep Duration Over Weekdays and Weekends
Sleep Duration (hr)
7.6
7.4
7.2
7.0
6.8
Mon
Tue
Wed
Thurs
Fri
Sat
Sun

Survey Data - Sleep Duration During Study and Exam Period



Survey Data - Average Stress Level Over the Semester



The low-dimension structures of students' sensor data might be indicative of the underlying pattern of their daily behavior.

Robust PCA - Method for Recovering Corrupted Low-Rank Matrices

Given high-dimension data $\boldsymbol{D}$, decompose $\boldsymbol{D}$ into $\boldsymbol{A}$ and $\boldsymbol{E}$.

where $\boldsymbol{D} = \underbrace{\boldsymbol{A}}_{\text{Low-rank component}} + \underbrace{\boldsymbol{E}}_{\text{Sparse component (gross errors)}}$.

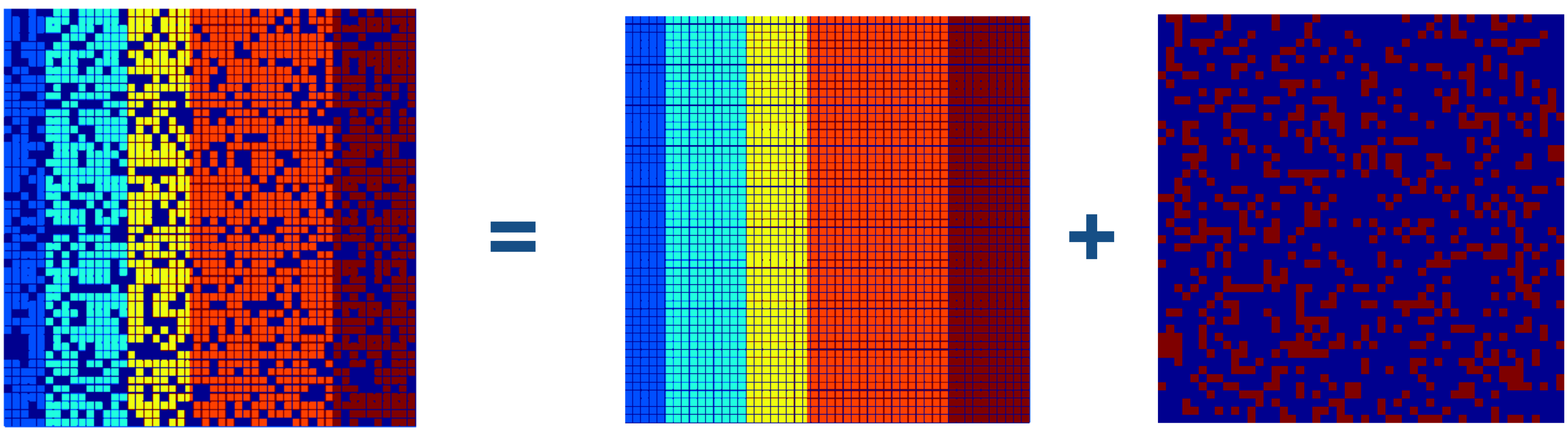
Zhouchen Lin, Minming Chen, and Yi Ma. 2010. The augmented lagrange multiplier method for exact recovery of corrupted low-rank matrices. *arXiv preprint arXiv:1009.5055* (2010).

Robust PCA - Method for Recovering Corrupted Low-Rank Matrices

Given high-dimension data ***D***, decompose ***D*** into ***A*** and ***E***.

where $D = A + E$.

Low-rank component **Sparse component (gross errors)**



D **Observation** ***A*** **Low-rank** ***E*** **Sparse**

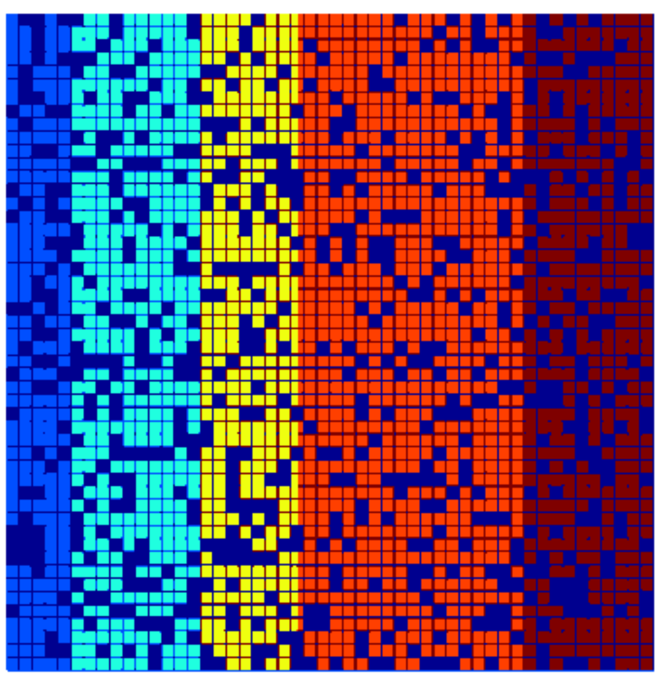
Zhouchen Lin, Minming Chen, and Yi Ma. 2010. The augmented lagrange multiplier method for exact recovery of corrupted low-rank matrices. *arXiv preprint arXiv:1009.5055* (2010).

Robust PCA - Finding Underlying Behavioral Pattern

Given high-dimension data ***D***, decompose ***D*** into ***A*** and ***E***.

where ***D*** = ***A*** + ***E***.

Low-rank component **Sparse component (gross errors)**



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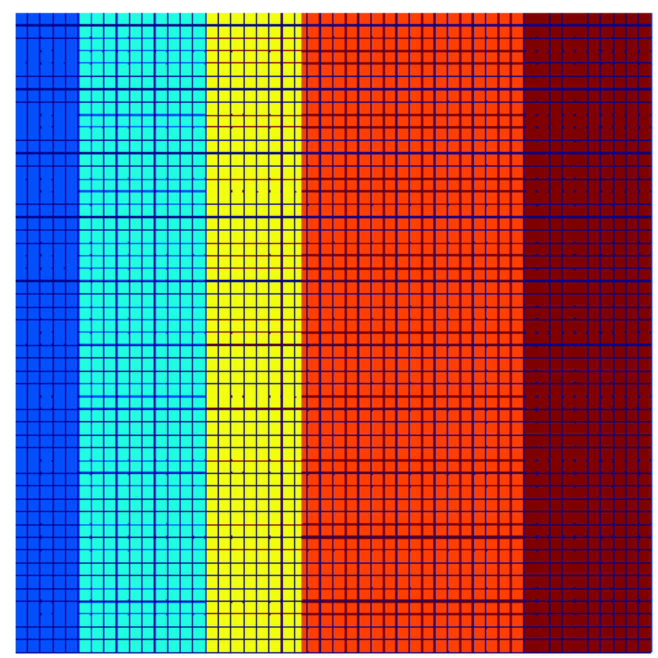

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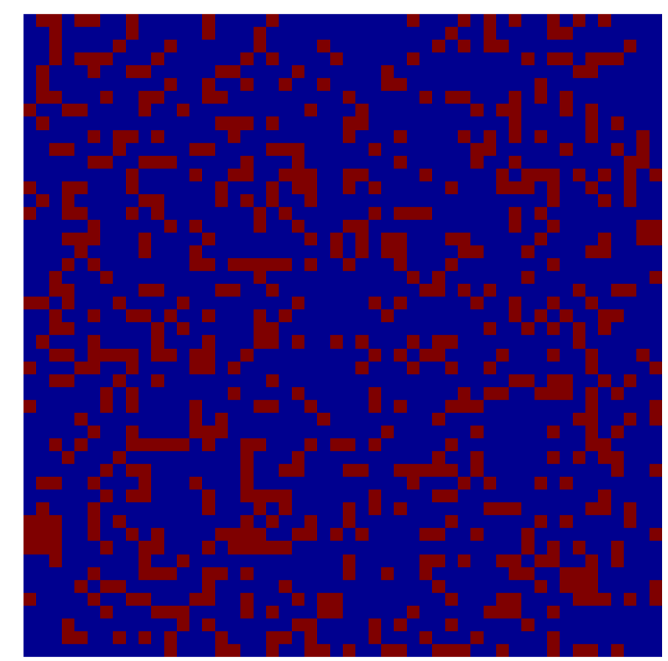
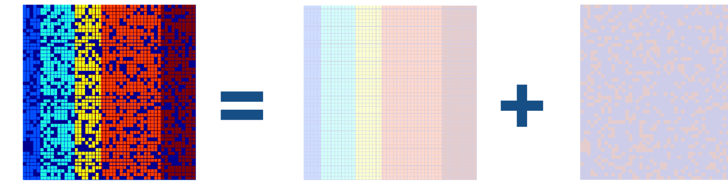
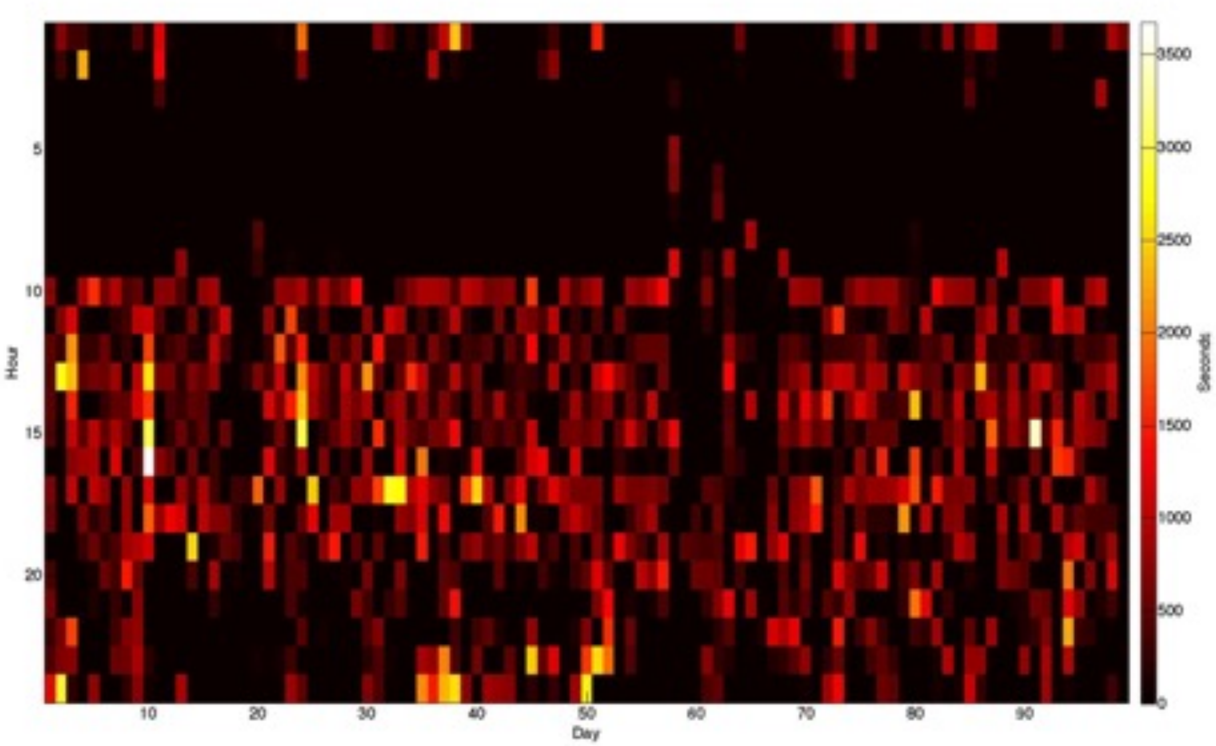


D **Raw Sensor Data** ***A*** **Underlying Pattern** ***E*** **Noise**

Example - The Raw Sensor Data from One User

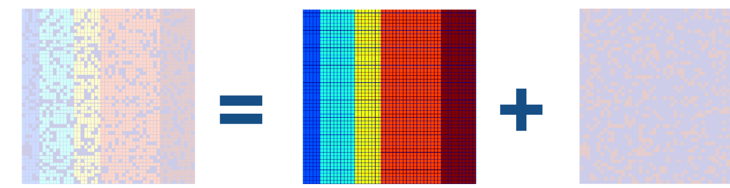


#seconds user being active
during an hour

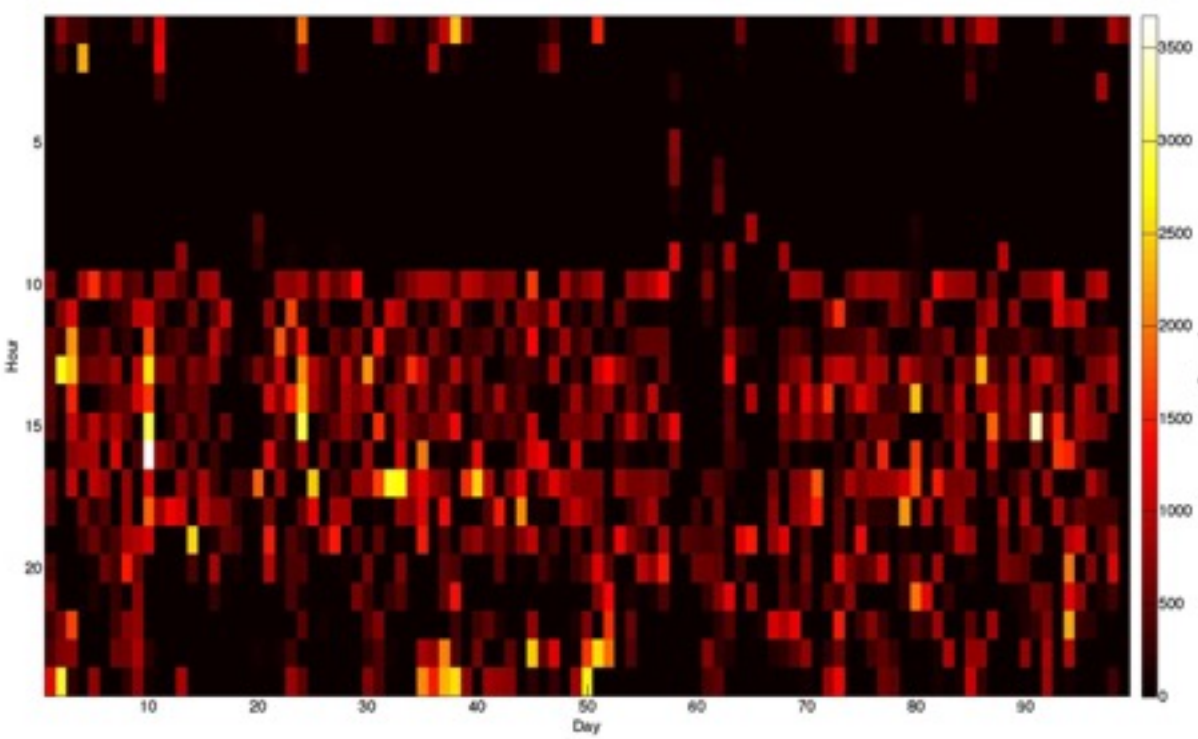


Raw Activity Data

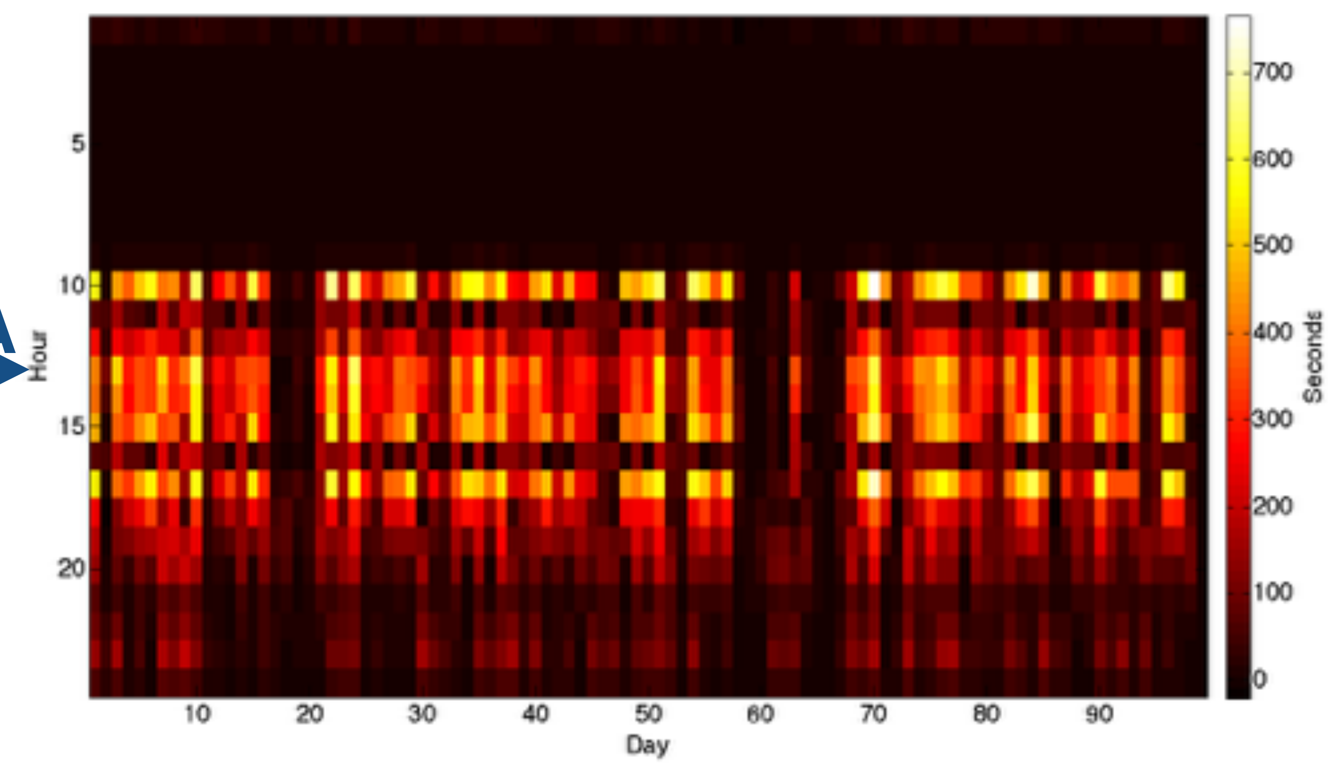
Example - The Low-rank Matrix from the User's Sensor Data



Low-rank matrix
after decomposition



RPCA



Raw Activity Data

Underlying Activity Pattern

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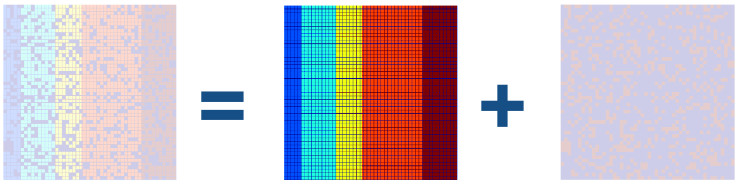

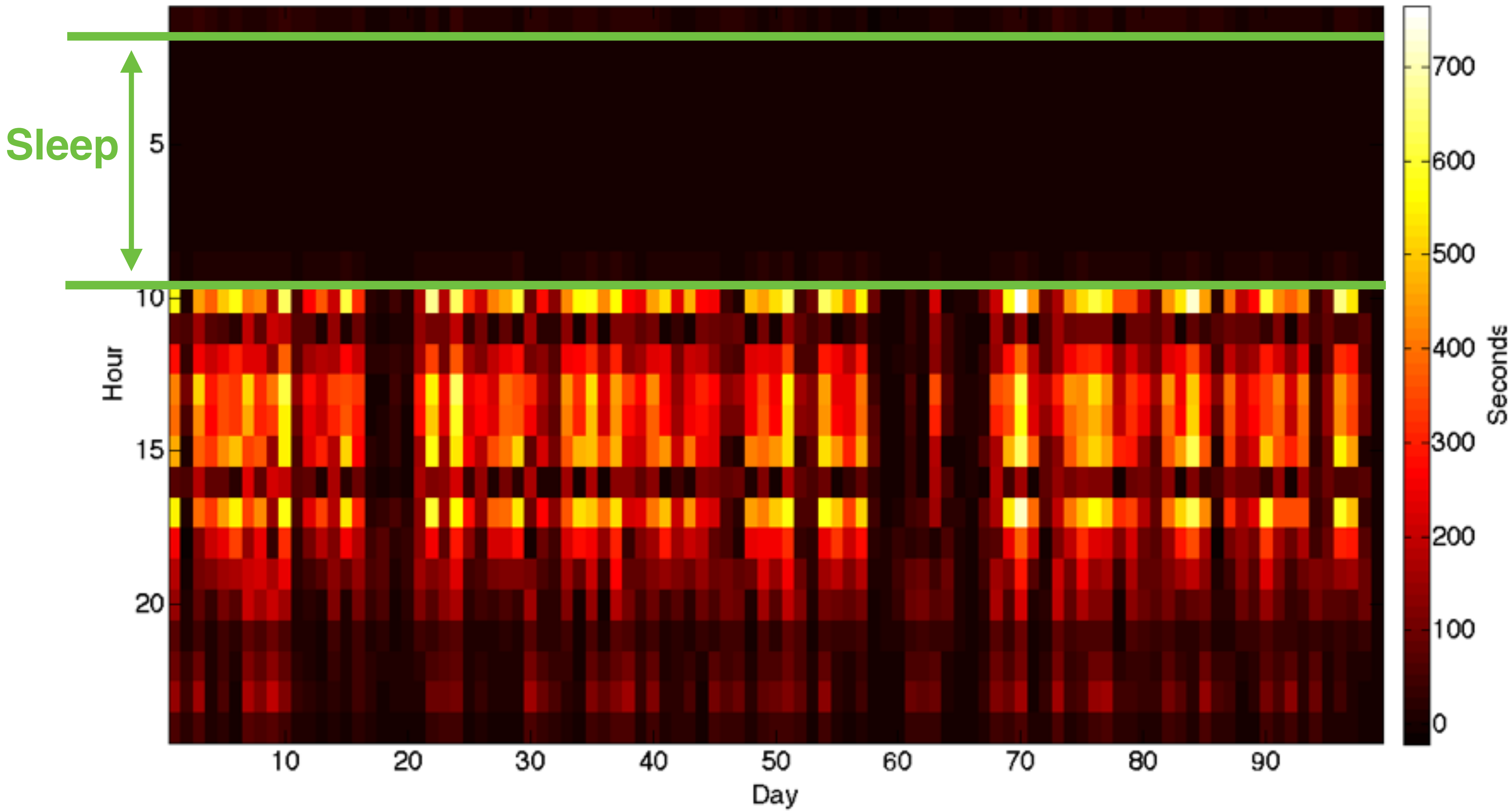

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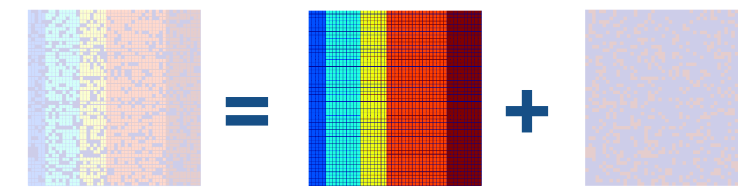
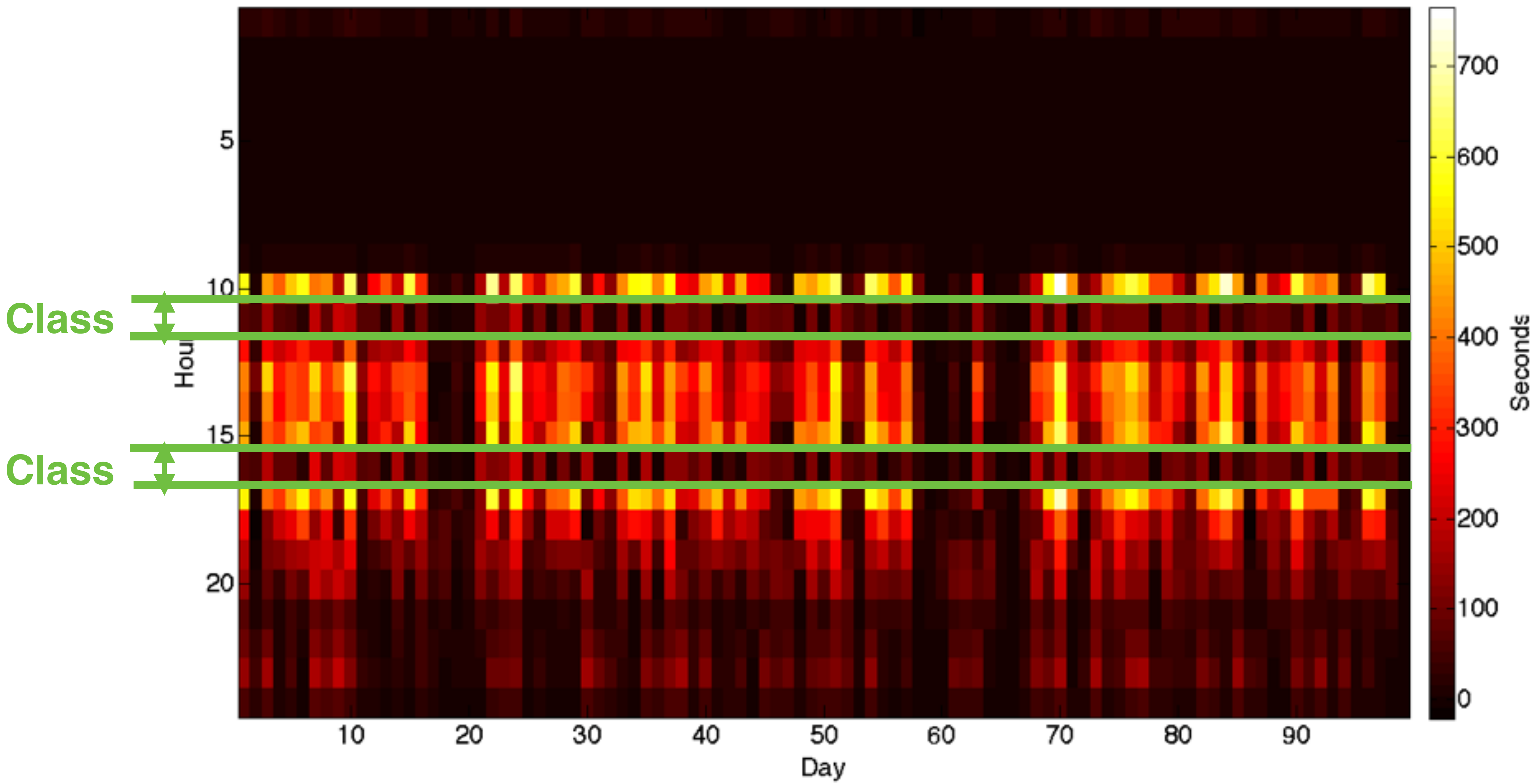
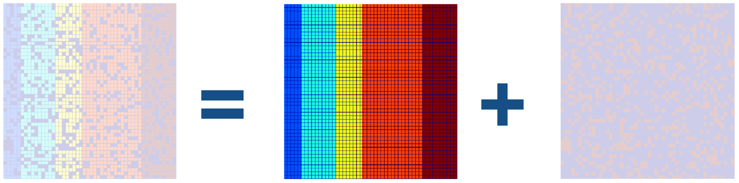
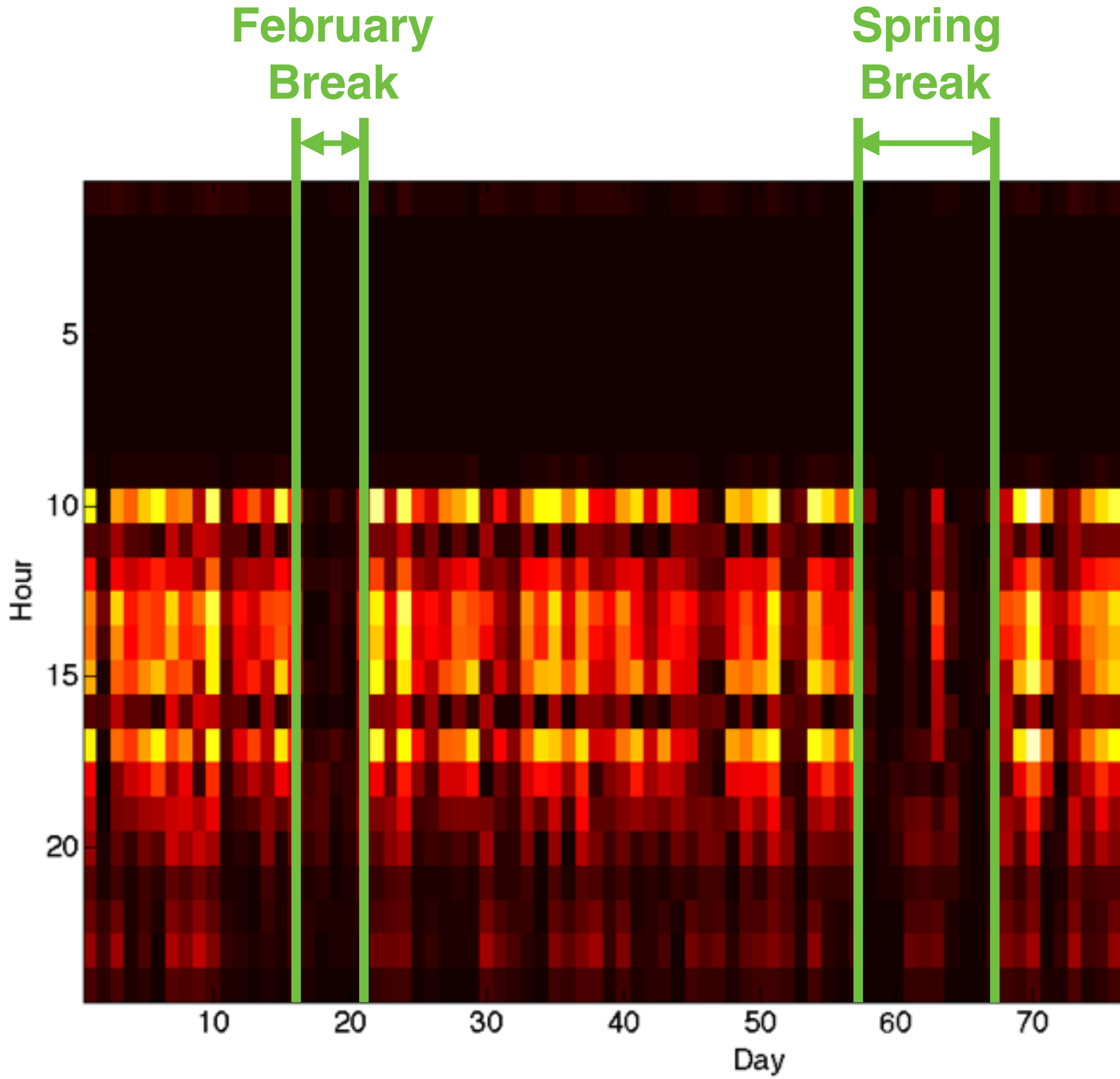


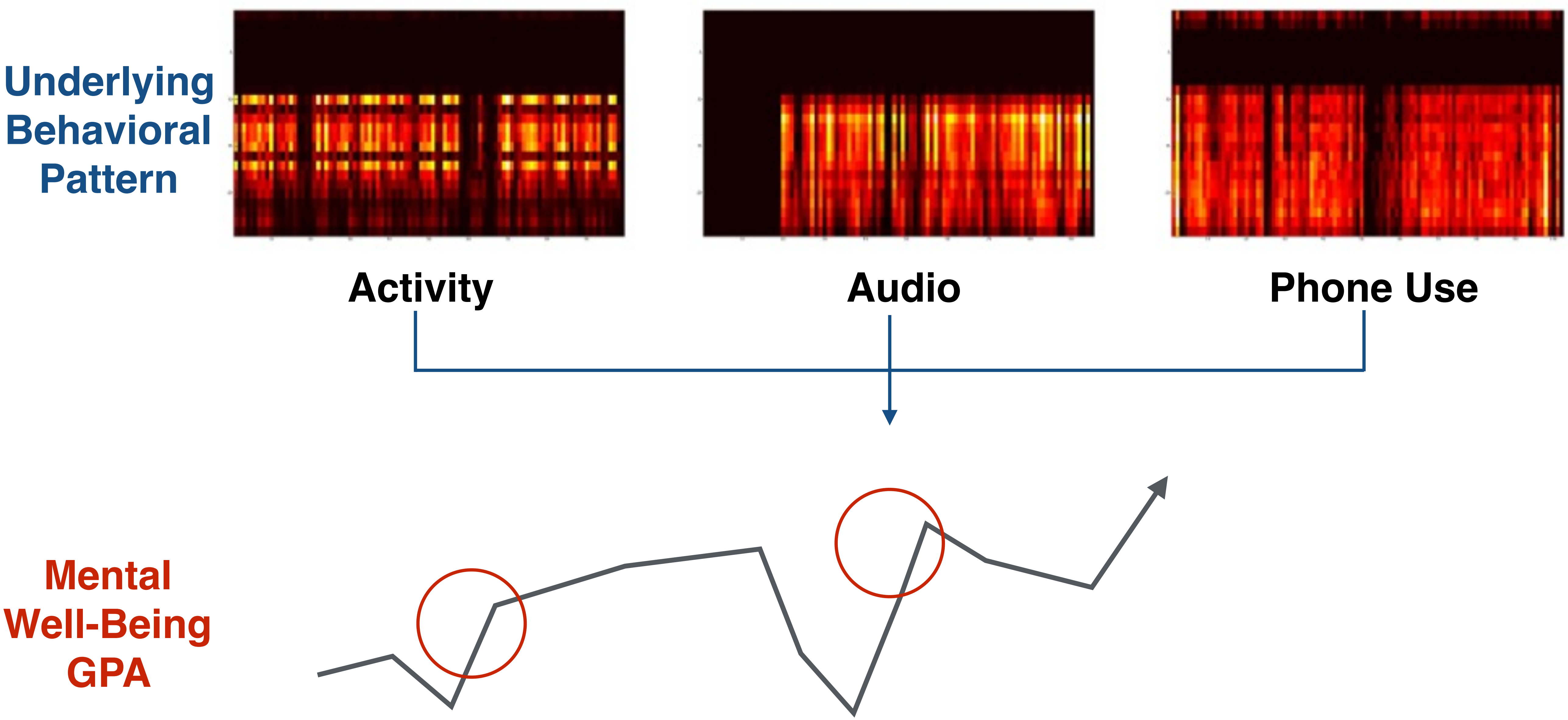


Example - The Low-rank matrix from the User's Sensor Data

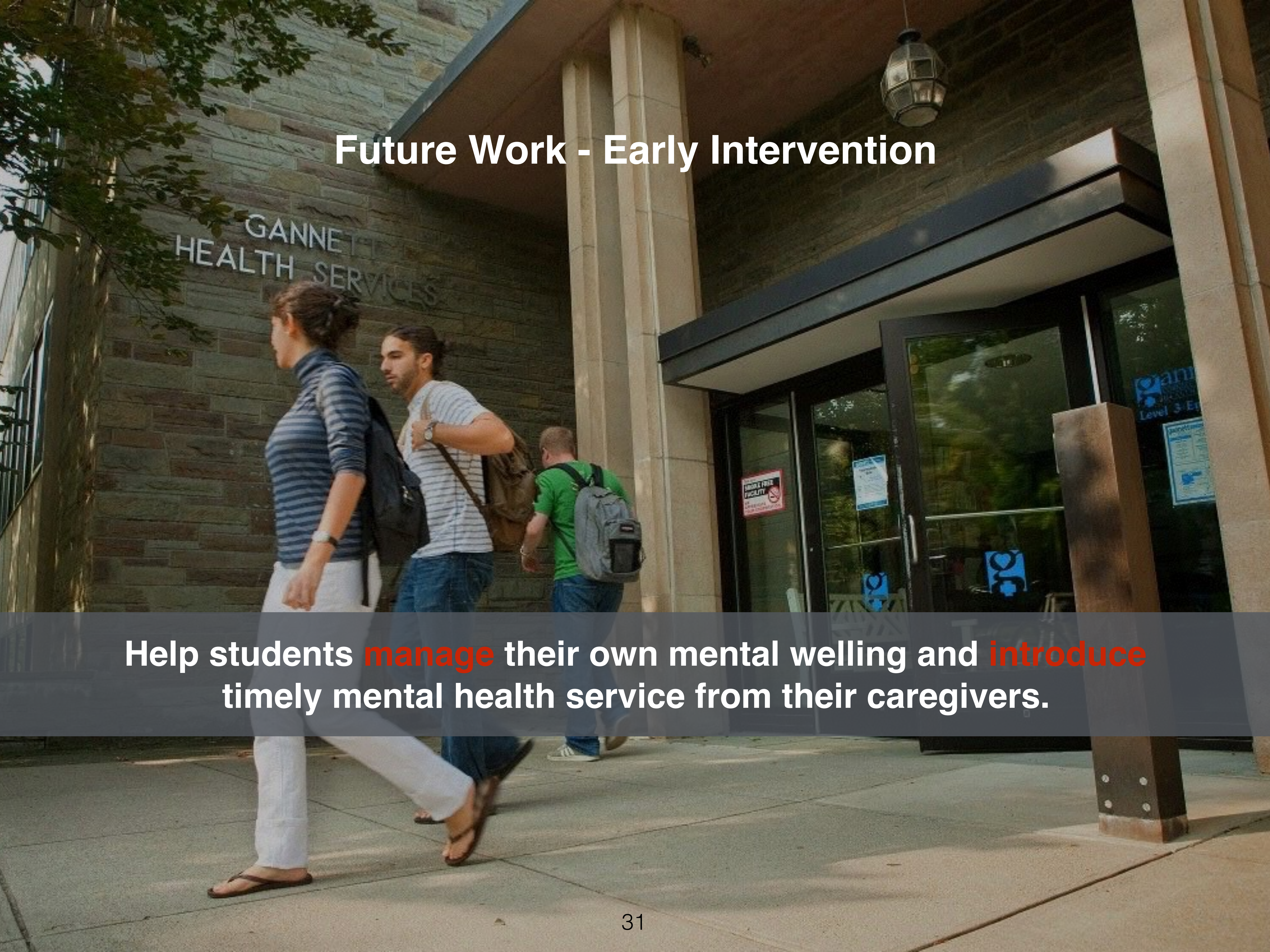




Next Step - Identifying the Change of Behavioral Pattern



Future Work - Early Intervention



Help students manage their own mental welling and introduce timely mental health service from their caregivers.


Thank you!