Future of Mental Health Sensing on College Campuses

Andrew T. Campbell, Dartmouth College HotMobile, February 12, 2018





what happens if life throws you a googly?

















why do students burn out, drop classes, do poorly, even drop out of college when others excel?

what is the impact of stress, mood, workload, sociability, sleep and mental health on academic performance?

is there a set of behavioral trends or signature to the semester?

can mobile sensing and predictive modeling assess student mental wellbeing?



most faculty are unaware that their students are struggling beyond grades

Instructor Date: Dean Liss Them Please return to Himman Box 6064 by February 9, 2015 .	Instructor Date: Dean Larissa Hopkins Please return to Hinman Box 6064 by February 9, 2015.	Instructor Date: Dean Lariusa Hopkins Please return to Hinman Box 6064 by February 9, 2015.
REPORT OF MEDTERM STANDING The Office of the Deam of Undergraduate Students is in the process of assessing the current academic progress for the student listed below. An estimated grade from you, along with any relevant comments, would be especially helpful. NOTE: Requests of this sort are made for a variety of reasons, and do not necessarily imply any deficiency in the student's current or past academic work.	REPORT OF MIDTERM STANDING The Office of the Dean of Undergraduate Students is in the process of assessing this student's current academic progress. An estimated grade from you, along with any relevant comments, would be especially helpful. NOTE: Requests of this sort are made for a variety of reasons, and do not more any deficiency in the student's current or past academic work.	REPORT OF MEDTERM STANDING The Office of the Dean of Undergraduate Students is in the process of assessing this student's current academic progress. An estimated grade fiven you, along with any relevant comments, would be especially helpful. NOTE: Requests of this sort are made for a variety of reasons, and do not necessarily imply my deficiency in the student's current or past academic work. Student name:
Professor: Campbell, Andrew T.	Course	Professor: Campbell, Andrew
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		Enstructor



but there is no objective data



48 students over 10 week Spring 2013 term

- •10 female, 38 male CS students
- •30 undergraduates, 18 graduates
- 8 seniors, 14 juniors, 6 sophomores, 2 freshmen, 3 Ph.D students, 1 second-year Masters student, and 13 first-year Masters students
- •23 Caucasians, 23 Asians and 2 African-Americans.
- Gave out Androids to students in my Android programming class
- •No feedback to students, only collection.
- •No funding so begged and borrowed and just did it you have believe.

sensing system













around conversation

face-to-face conservation: duration and frequency



we also computed

- activity duration
- outdoor mobility
- indoor mobility
- location and co-location
- phone usage (apps, lock/unlock)



ecological momentary assessment (EMA)





32,000 EMAs >9000 facelog images



mental health surveys

PATIENT HEALTH QUESTIONNAIRE (PHQ-9)

DATE:				_				
Not at a	II Several days	More than half the days	Nearly every day					
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0	1	2	3					
0	1	2	3					
0	1	2	3					
0	4	2	2					
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pre-post questionnaires

- depression scale
- perceived stress scale
- Ioneliness scale
- flourishing scale
- Big 5

study design

recruiting participants





recruiting participants orientation








Dataset size

53 GB of data, 32,000 EMAs, 48 pre-post surveys, interviews **Passive sensor data from phone**

activity, sleep, face-to-face conversation frequency/duration, indoor and outdoor mobility, location, distance travelled, colocation, light, app usage, calendar, call logs **Experience sampling**

pam (affect), behavioral, class, campus events, social events, sleep quality, exercise, comments, mood

Pre-post surveys from Survey Monkey

stress, personality, mental and physical health, loneliness, mood, sleep

Transcripts: educational stats

Other: Facebook (not released), face log images (not released), dining details, seating data

Entry-exit interviews (not released)

social net in class, classes information (deadlines for all classes), group review, study specific questions.





StudentLife

StudentLife is the first study that uses passive and automatic sensing data from the phones of a class of 48 Dartmout term to assess their mental health (e.g., depression, loneliness, stress), academic performance (grades across all the cumulative GPA) and behavioral trends (e.g., how stress, sleep, visits to the gym, etc. change in response to college





Fri	8	9 L	95	10	11	11		12		2				
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Mon	8	9 L	95	10	11		12			2	3	A	3Ax/Bx	
08	3	09	09 10 11 12		2	01		02	2 03 0		94 (05 0		
	time of the day (8 am - 6 pm)													





evening: 6 pm-12 am









loneliness



stress



*p≤0.05, **p≤0.01





face-to-face conversation











class attendance







- look at individual differences between high and low peformers
- define higher level behaviors for studying and partying
- track behavior changes using time series analysis

capturing behavioral change



behavioral slope and breakpoints









attending classes and studying











when do students study?



partying trends across the term


GPA













why no signal? it has to be there

somewhere, no?



College age young adults 18-25 are more likely to have major depressive episodes than any other age groups.

Vast majority of college students who screen positively for depression never seek mental health services.

Suicide is the second leading cause of death among people ages 15-24.





83 undergraduate students across two 10 week term in the winter and spring terms 2016
•44 female, 40 male students
•26 Asians, 5 African-Americans, 24 Caucasians, 1 multiracial, 26 not specified

- average age 20.33, std=2.31
- Users' Android, iPhone, microsoft band 2



we hypothesize that mobile sensor data from phones and wearables represent proxies for the DSM-5 depression symptoms in college students; that is, we design a set of behavioral features to capture the characteristics of the depression symptoms that **"take into account lifestyles of students"** (e.g., going to class, working in study areas, socializing on campus)

symptoms to phone behavioral features

change in sleep

- sleep onset, sleep wakeup, sleep duration
 decreased interest in activities
 - number of places visited, physical activity, time spent in study places and dorms, and social engagement

loss of concentration

lock/unlock during the day, at study places and at dorms

depressed mood/fatigue

• heart rate/ heart rate variability



self-reported pre-post PHQ8 and weekly PHQ4

PATIENT HEALTH QUESTIONNAIRE (PHQ-9)



(Healthcare professional: For interpretation please refer to accompanying scoring card) (c) The distribution of PHQ-4 depression subscale scores (d) The distribution of mean PHQ-4 depression subscale scores

correlation matrix of symptom features and PHQ-8 item scores



PHQ-8 score: sleep changes; and diminished ability to concentrate



*p≤0.05, **p≤0.01

PHQ-8 score: diminished interest in activities; and depressed mood, fatigue



*p≤0.05, **p≤0.01

study places



We use ANOVA to determine whether or not the mean of the two groups (non-depressed and depressed) significantly differ.

sleep



predicting weekly PHQ-4

We use lasso regularized logistic regression to determine if a student is depressed or not; selected features are:

- sleep end
- unlock duration at study places
- •stationary time, number of conversations
- •number of places visited, time at dorm, time at study places
- •median heart rate



false positive rate ROC curve of logistic regression model obtained from 10-fold cross validation for binary classification of depression





24/7 passive sensing is here!

we have a mountain to climb

•validity of sensors and diagnostic predictive models
•flaky signals, real-world noise
•interventions
•over burdened clinicians
•privacy, privacy, privacy



new forms of intervention



friends

family

student dean the toctor

student

personalized mental health sensing and intervention models are essential

People may experience:

Mood: mood swings, sadness, elevated mood, anger, anxiety, apathy, apprehension, euphoria, general discontent, guilt, hopelessness, loss of interest, or loss of interest or pleasure in activities

Behavioral: irritability, risk taking behaviors, disorganized behavior, aggression, agitation, crying, excess desire for sex, hyperactivity, impulsivity, restlessness, or self-harm

Cognitive: unwanted thoughts, delusion, lack of concentration, racing thoughts, slowness in activity, or false belief of superiority

Psychological: depression, manic episode, agitated depression, or paranoia

Sleep: difficulty falling asleep or excess sleepiness

Weight: weight gain or weight loss

Also common: fatigue or rapid and frenzied speaking





Predicting relapse in schizophrenia

schizophrenic






200 x 4 study

follow 200 first years undergraduate students over their four years of college

- behavioral sensing all year
- brain imagine 2 per year
- focus: anxiety and depression
- User's phones
- largest and longest campus life study

depression is associated with network differences in the medial prefrontal cortex





0.275 0.300 0.325 0.350 RSFC similarity to depression template

initial analysis of the resting state functional connectivity (RSFC) data shows a relationship between RSFC and depression scale (PHQ)



Dror Ben-Zeev and Rachel Brian (UW), Tanzeem Choudhury and Hane Aung (Cornell), Ethan Berke (was DHMC), Randy Colvin and Stefanie Tignor (Northeastern), Sam Gosling (UT Austin), Gabriella Harari (Stanford), Catherine Norris (Swarthmore), **Rui Wang**, Kizito Masaba, Shayan Mirjafari, Weichen Wang, and Xia Zhou, Emily Scherer (Dartmouth)



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"StudentLife", UbiComp, 2014 "SmartGPA", UbjComp, 2015 "CrossCheck", UbiComp 2016 "Predicting Symptoms", UbiComp 2017 "Depression Tracking", UbiComp 2018





No major leaps forward yet

- Lots of small scale studies (N=100, T=20 weeks) with differing features/models and results
- No generalizable results , no repeated studies, and no randomized control trials (RCTs)
- Things are inconclusive but progress is being made and there is commercial activity always a good sign
- Significant challenges remain



Widely accepted feature set/models will emerge

Breakthrough in personalized depression models and interventions proven out

Advances in deep learning and wearables for mobile mental health — the phone will be a step toward that

Multiple large scale RCT studies will confirm clinical validity of depression sensing across the general population

 Clinician acceptance of mobile PHQ9 prediction. Biz models emerge for payers/providers



- Depression sensing driven intervention (e.g., next gen Cognitive behavioral therapy) is common
- Personalized depression and intervention models embedded not only mobile — maybe everything you touch (from social media, future wearables, your car)
- Mental health assistant mental health sensing based Al
 - reactive model start the move:
 - "Hey Siri how am I doing today?"
 - proactive model will dominate:
 - "Andrew, go for a long run today your open between 1-2 pm"
 - "I've booked an appointment for you to see Mark Tuesday"
 - "You didn't take your meds yesterday call Mark"



silent tsunami

44 million Americans live with mental health disorders

ACCESS

55% of the US counties have no MH provider – 45% of psychiatrists do not accept insurance – 57% do not accept medicaid









what happens if life throws you a googly?

Mobile will detect it.







StudentLife

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