INFERRING MOOD INSTABILITY ON SOCIAL MEDIA BY LEVERAGING ECOLOGICAL MOMENTARY ASSESSMENTS

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Background

Quantifying attributes of mental well-being

Survey Instruments

- Self-Report Questionnaires

Active Sensing

- Ecological Momentary Assessments (EMAs)

Passive Sensing

- Smartphones and Wearables
- Social Media

SOCIAL MEDIA AS PASSIVE SENSOR!

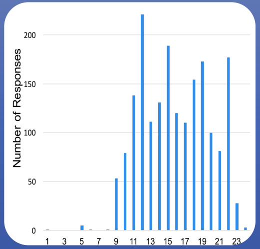
Challenge

Ground-truth Data

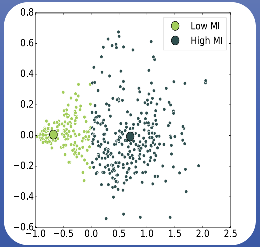
Mood Instability

Goals & Contributions

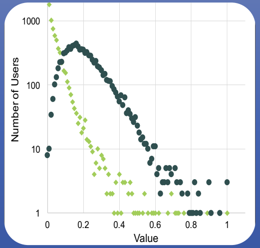
Broad tasks



Combination of Active and Passive Sensing

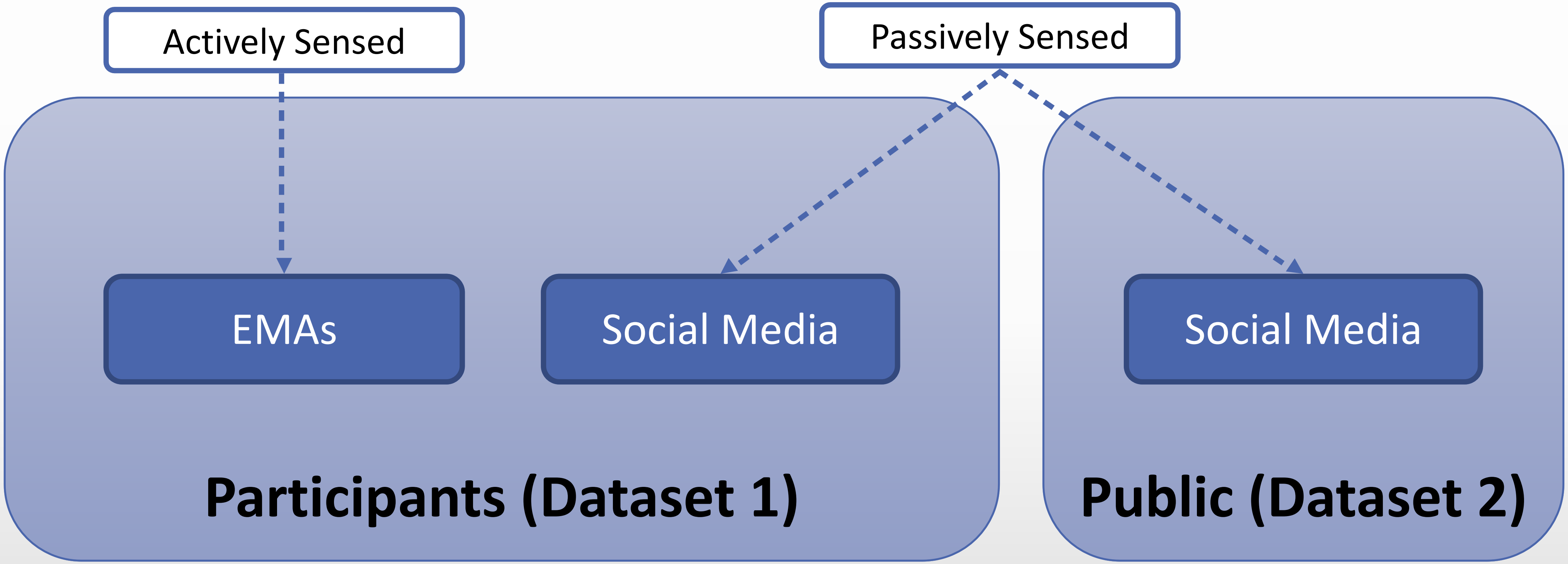


A machine learning framework identifying mood instability for a larger population



Psycholinguistic cues and Mood Instability Lexicon

Objective: Inferring Mood Instability



- **Small-scale**
- **Actively sensed data as Ground-truth**

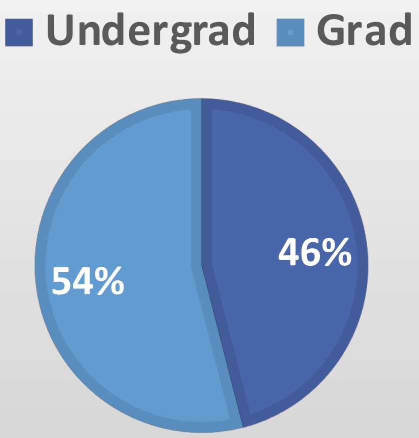
- **Large-scale**
- **Unlabeled**

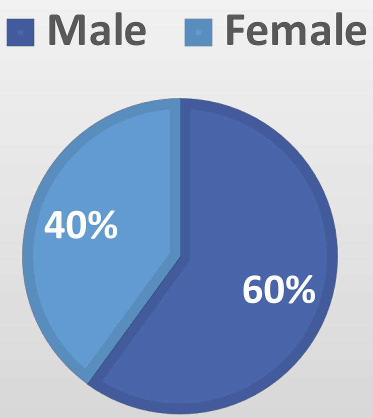
Study and Data

CampusLife, Georgia Tech

Recruitment

- 51 participants
- Mean age: 22 Years
- Incentives: $40-$120
- 5 weeks (Spring 2016)





Data

- Survey Questionnaire (Entry and Exit)
- Active Sensing: EMAs (Daily)
- Smartphone sensors (Barometer, Call, Accelerometer, App usage..)
- Social Media (Facebook, Twitter)

Privacy & Ethics

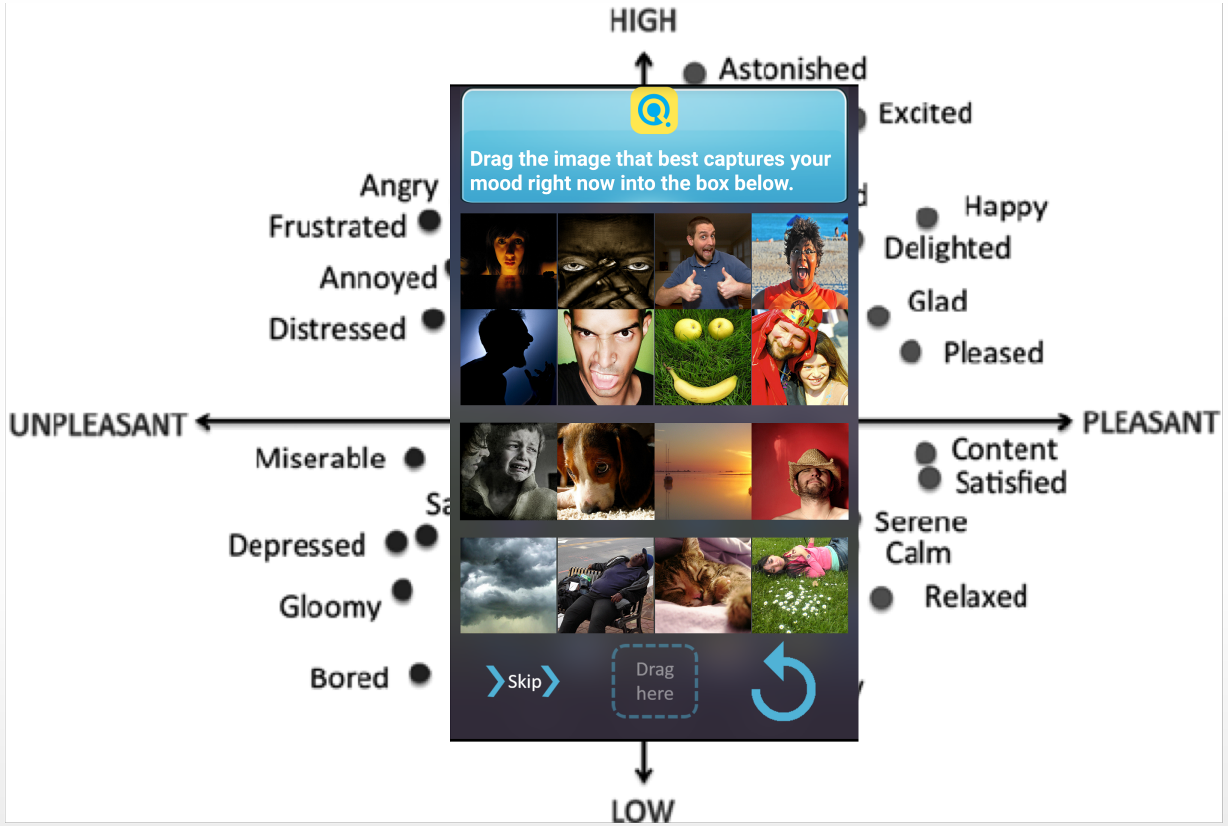
- IRB approval
- Data sharing consent
- Secure servers
- De-identification

EMA Data

Photographic Affect Meter (PAM)

(Pollak et al., 2011)

Pollak, J. P., Adams, P., & Gay, G. (2011, May). PAM: a photographic affect meter for frequent, in situ measurement of affect. In *Proceedings of the SIGCHI conference on Human factors in computing systems* (pp. 725-734). ACM.



1,606 EMA Responses
(Mean responses/participant: 32)

Social Media Data-I

CampusLife Population

23 Participants

13k+ status updates

10 Participants

1.5k tweets

One-time collection

Social Media Data-II

Unlabeled Twitter data with self-disclosure

(Coppersmith et al., 2014)

Coppersmith, G., Dredze, M., & Harman, C. (2014). Quantifying mental health signals in Twitter. In *Proceedings of the Workshop on CLPsych: From Linguistic Signal to Clinical Reality*.

Bipolar

- Self-Disclosure of Bipolar Disorder
- Eg: *I have been diagnosed with Bipolar Disorder*

Borderline

- Self-Disclosure of Borderline Personality Disorder
- Eg: I suffer from bpd

Control

- Random Twitter Stream
- Excludes *Bipolar* and *Borderline*

37m+ tweets, 19k+ unique users

Linguistic Equivalence

Cross-platform & Cross-population

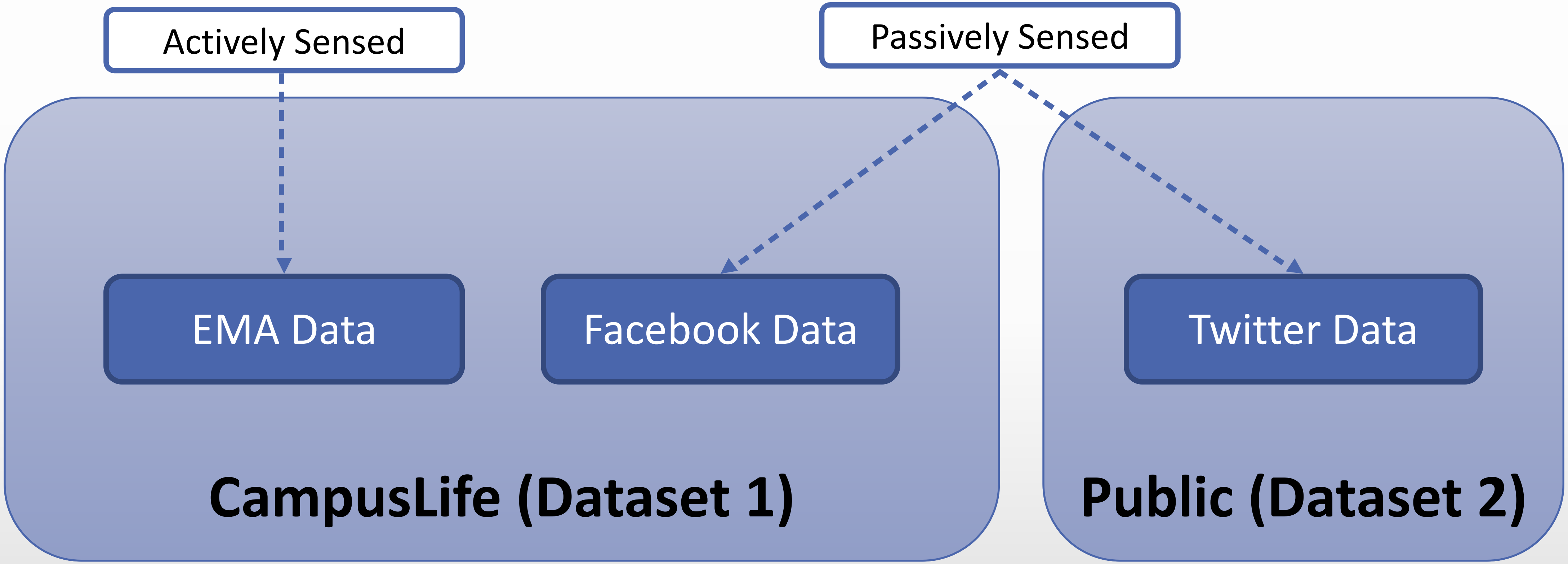
(Baldwin et al., 2013)

Baldwin, T., Cook, P., Lui, M., MacKinlay, A., & Wang, L. (2013, October). How noisy social media text, how diffrnt social media sources?. In IJCNLP(pp. 356-364).

Pair-wise comparison of word-vectors (cosine similarities)

Cross-platform Linguistic Equivalence (*Facebook and Twitter*)	**0.90**
Cross-population Linguistic Equivalence (*College and General population*)	**0.95**

Data: Recap



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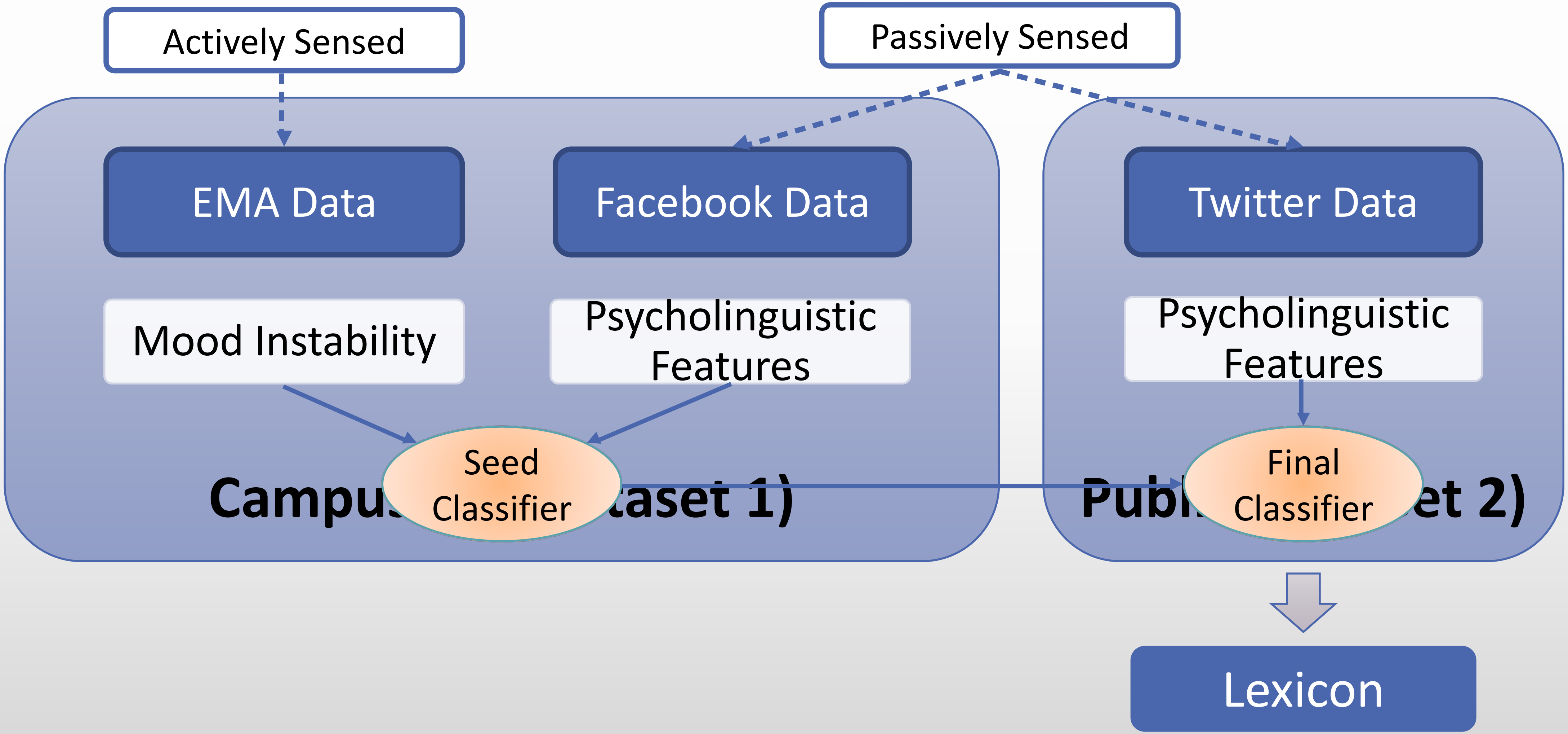
Methods and Results

Methods: Overview



Quantifying Mood Instability

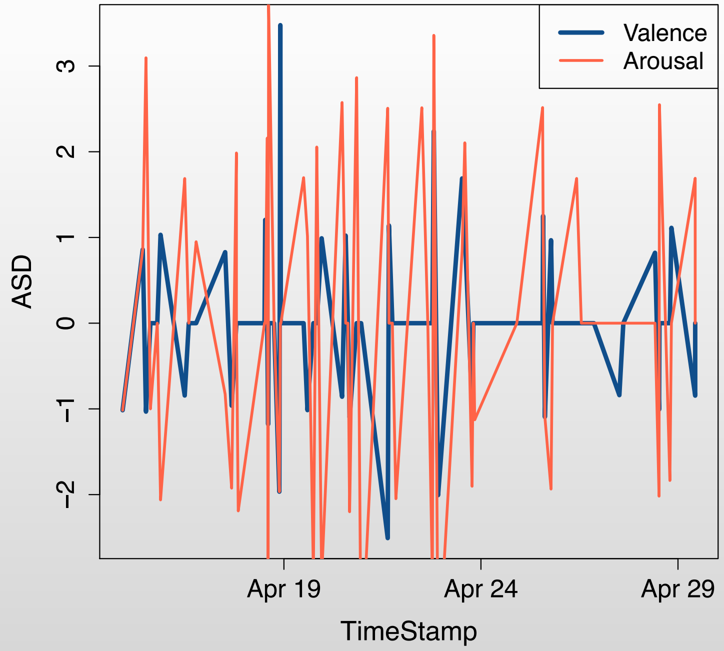
Adjusted Successive Differences (ASDs)

(Jahng et al., 2008)

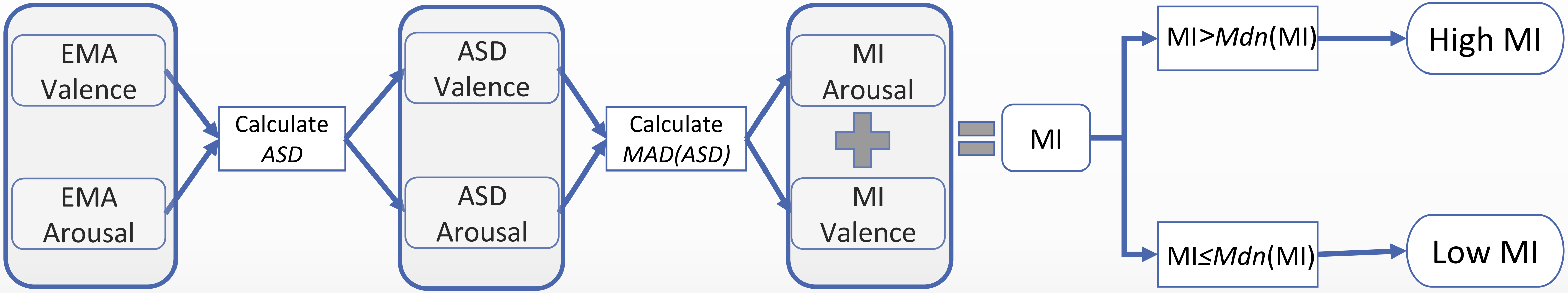
Jahng, S., Wood, P. K., & Trull, T. J. (2008). Analysis of affective instability in ecological momentary assessment: Indices using successive difference and group comparison via multilevel modeling. *Psychological methods*.

Non-uniform time differences in EMA responses

$$ASD_{i+1} = \frac{x_{i+1} - x_i}{[(t_{i+1} - t_i)/Mdn(t_{i+1} - t_i)]^{\lambda}}$$



Labeling Mood Instability



- ASD: Adjusted Successive Differences
- MAD: Mean Absolute Deviation
- MI: Mood Instability

Machine Learning Classifier

Seed Classifier

Linguistic Inquiry and Word Count (Pennebaker et al., 2003)

Pennebaker, J. W., Mehl, M. R., & Niederhoffer, K. G. (2003). Psychological aspects of natural language use: Our words, our selves. *Annual review of psychology*.

- Psycholinguistic Lexicon: Linguistic Inquiry and Word Count (LIWC)
- Supervised machine learning classifier
  - 23 CampusLife participants
  - k-fold cross-validation (k=5) for parameter tuning
  - Naïve Bayes, Logistic Regression, Random Forest, **Support Vector Machine**

Seed Classifier: Accuracy Metrics

Metric	mean	stdev.	max.
Naïve Bayes	0.58	0.54	0.83
Logistic Regression	0.51	0.35	0.80
Random Forest	0.48	0.64	0.83
SVM (Knl.=Poly.)	0.56	0.24	0.80
SVM (Knl.=RBF)	0.51	0.35	0.80
SVM (Knl.=Linear)	**0.68**	**0.29**	**0.83**

Challenge

Unstable Classification?

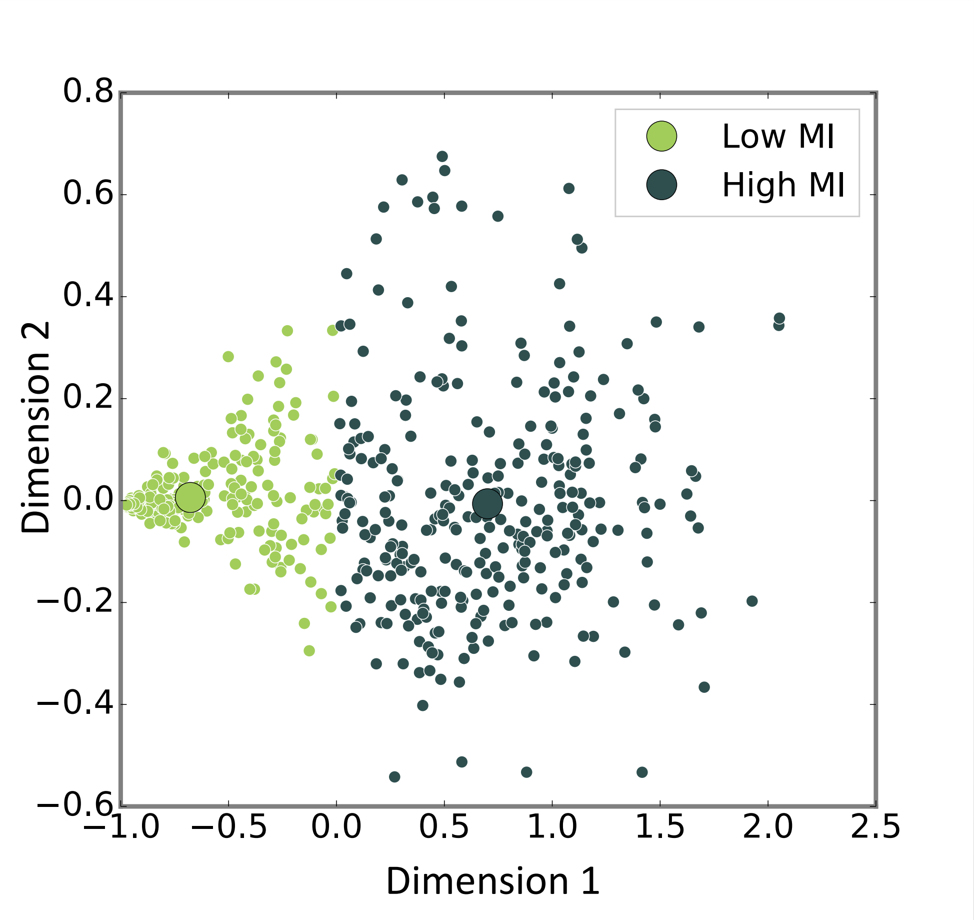
Semi-Supervised Classifier

Self-Training

(Dara et al., 2002)

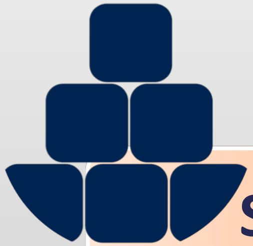
Dara, R., Kremer, S. C., & Stacey, D. A. (2002). Clustering unlabeled data with SOMs improves classification of labeled real-world data. *Proc. of the 2002 IJCNN*. IEEE.

- *K*-Means clustering (*K*=2)
- Classification of centroids using seed classifier



Semi-supervised Classifier: Stability

Data	k-fold CV accuracies of SS Classifier (%High MI)						
Folds	**1**	**2**	**3**	**4**	**5**	**mean**	**stdev.**
Bipolar	62.87	63.64	62.66	63.18	63.38	63.15	**0.39**
Borderline	61.06	61.81	62.44	62.84	62.31	62.09	**0.68**
Control	36.70	36.54	36.56	36.47	37.26	36.71	**0.32**



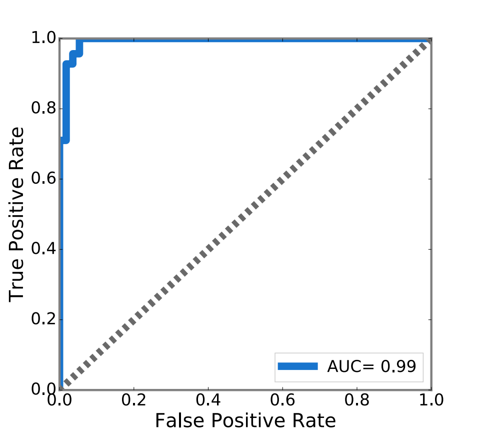
Addressed

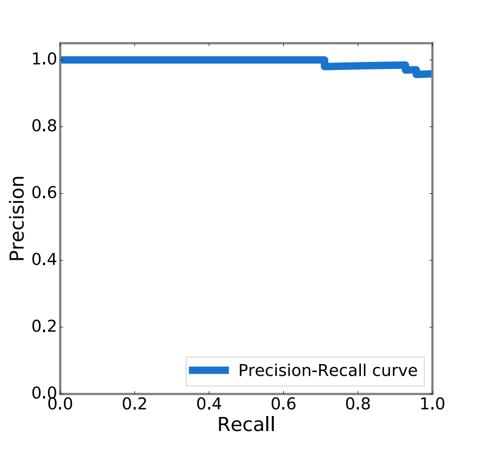
Stable Classification

Results

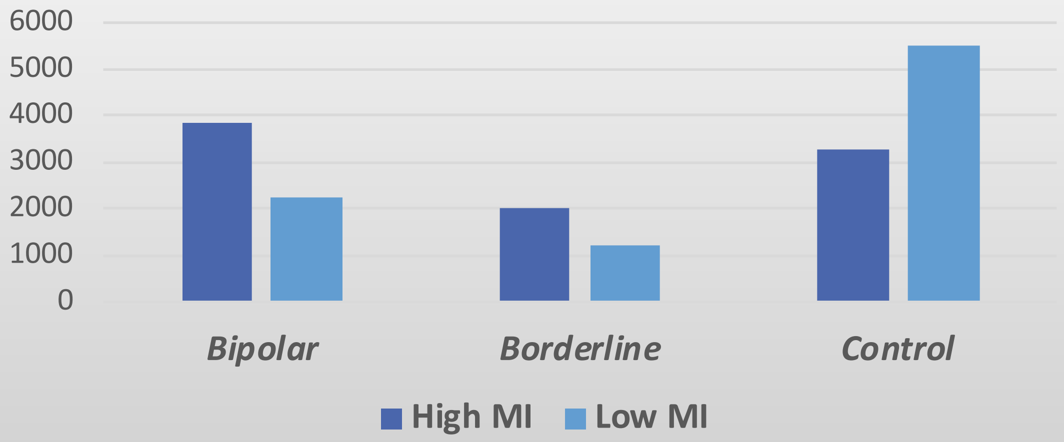
Machine Learning Classification

- High Accuracy





- Higher Occurrence of High MI in *Bipolar* and *Borderline* datasets as compared to *Control*



Analyzing the Language

Psycholinguistic Features

Mood Instability Lexicon

Psycholinguistic Features

Psycholinguistic Group	H. MI vs. L. MI
Affective Attributes	83%
Cognitive Attributes	521%
Interpersonal Focus	124%
Lexical Density and Awareness	195%
Social/Personal Concerns	90%

High MI

Low MI

Discussion

Implications

- Social media as a passive sensor
- Ability to detect Mood Instability
- Tackle the challenges of lack of labeled data
- Application in other health sensing problems
- Integrate multiple sensors

Limitations & Future Work

- Clinical Relevance
- Causal Claims
- Self-Reported and Social Media Data
- Multimodal Data

Acknowledgements

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University of Cambridge
University of Michigan
University of Notre Dame
Texas
The University of Texas at Austin
University of Virginia
University of Washington

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Thank You

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Folds	1	2	3	4	5	mean	stdev.
Bipolar	66.81	69.86	64.64	43.76	62.82	51.38	**10.30**
Borderline	61.37	63.81	54.41	34.04	56.13	45.06	**11.76**
Control	42.04	46.05	37.35	24.79	37.94	31.40	**7.99**