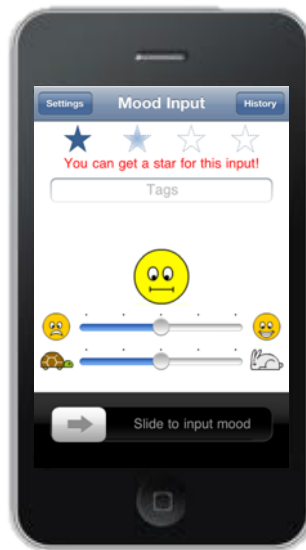


MoodScope:

Sensing mood from smartphone usage patterns



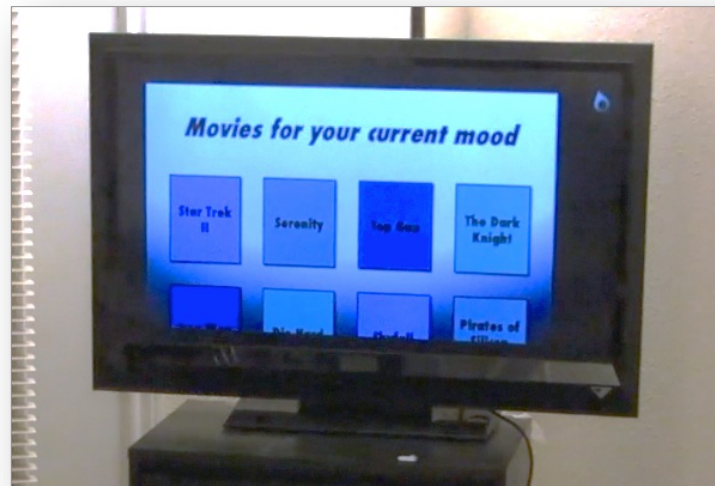
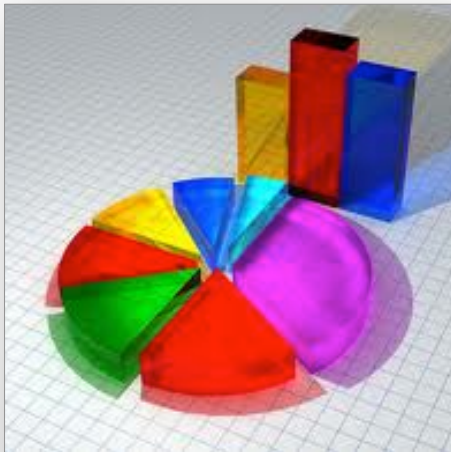
Robert Likamwa
Lin Zhong



Yunxin Liu
Nicholas D. Lane

Mood-Enhanced Apps

Personal analytics



Media recommendation

Social ecosystems



Affective Computing

(Mood and Emotion)

```
graph TD; A["Affective Computing  
(Mood and Emotion)"] --> B["Biometric-based  
(Skin conductivity,  
Temperature, Pulse rate)"]; A --> C["Audio/Video-based  
(AffectAura, EmotionSense)"]; B --- D["Highly temporal"]; B --- E["High cost of deployment"]; B --- F["Hassle"]; C --- G["Captures expressions"]; C --- H["Power hungry"]; C --- I["Slightly invasive"];
```

Biometric-based
(Skin conductivity,
Temperature, Pulse rate)

Highly temporal
High cost of deployment
Hassle

Audio/Video-based
(AffectAura, EmotionSense)

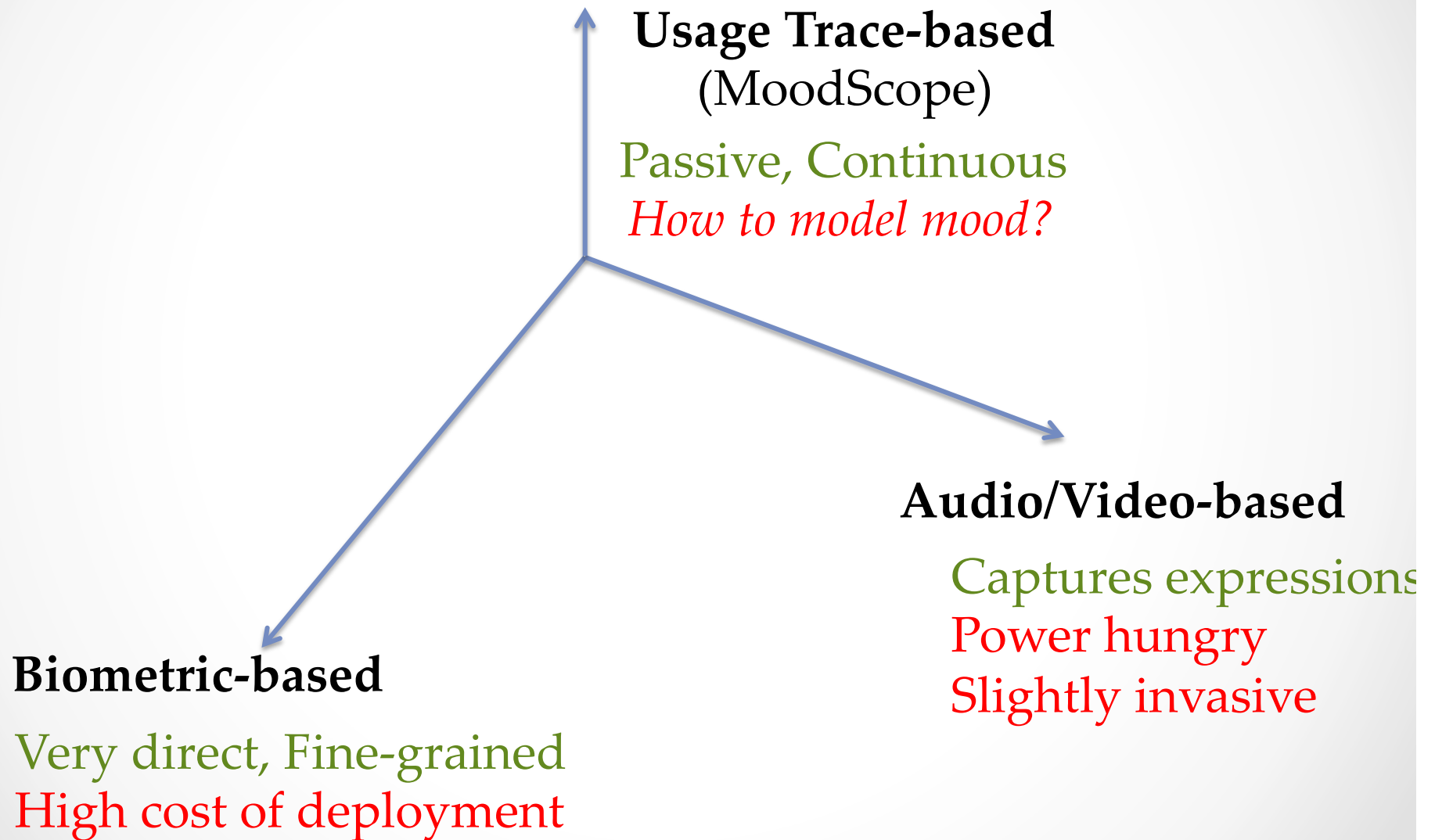
Captures expressions
Power hungry
Slightly invasive

Can your mobile phone
infer your mood?

From already-available,
low-power information?*

* No audio/video sensing, no body-instrumentation

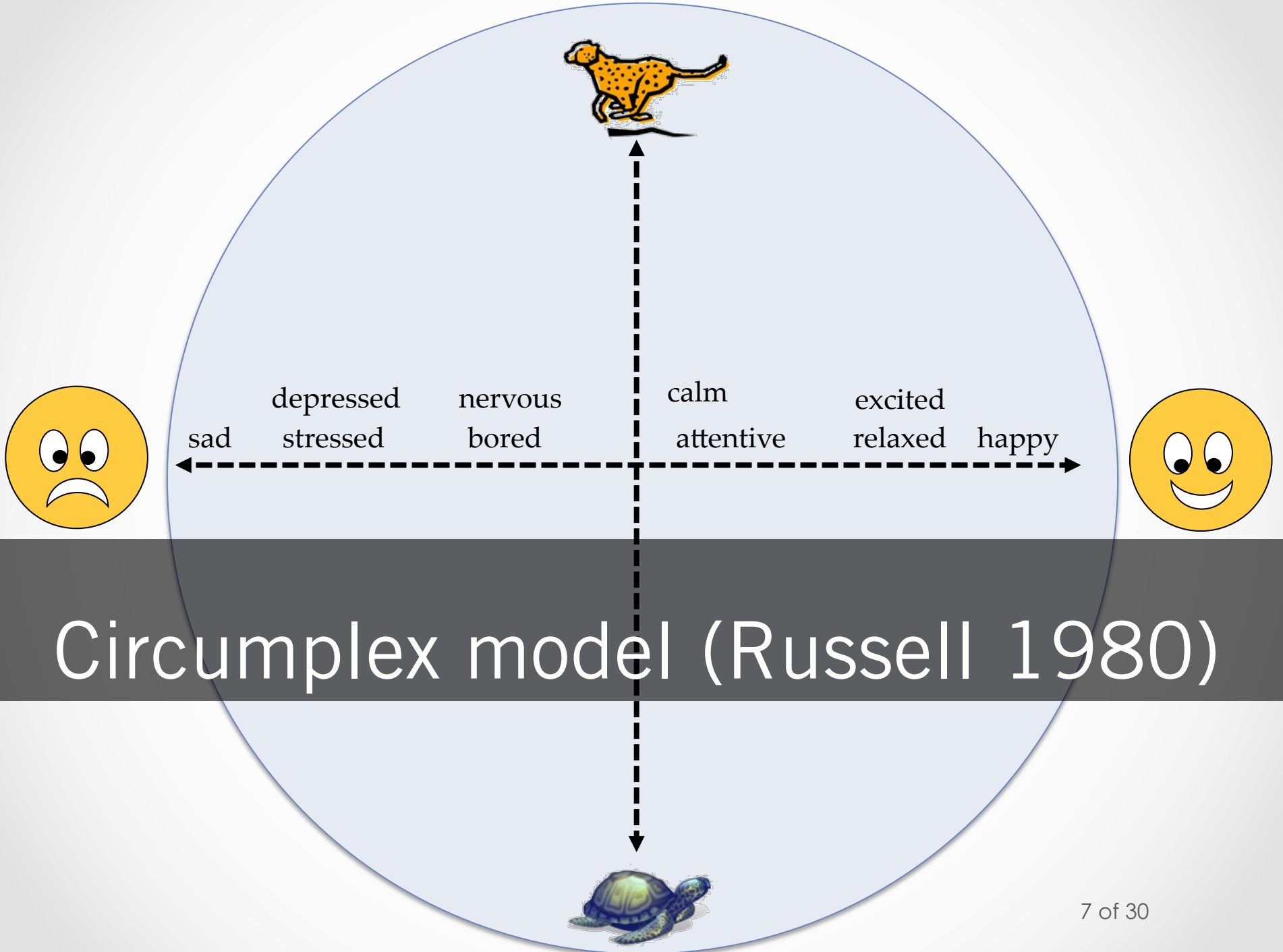
MoodScope \in Affective Computing



Mood is...

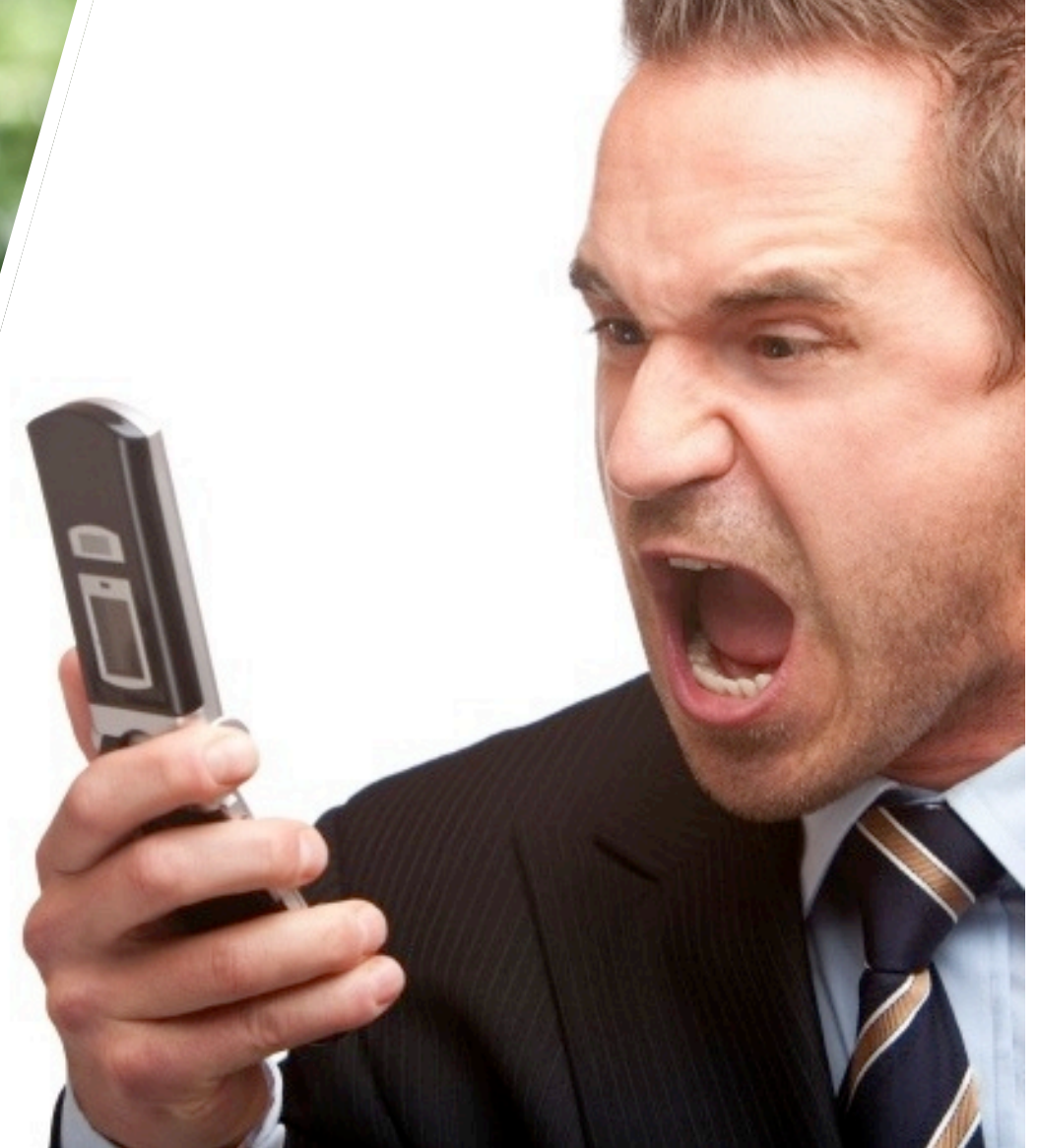
- ... a persistent long-lasting state
 - Lasts hours or days
 - Emotion lasts seconds or minutes
- ... a strong social signal
 - Drives communications
 - Drives interactions
 - Drives activity patterns






Circumplex model (Russell 1980)

How is the user communicating?



What apps is the user using?

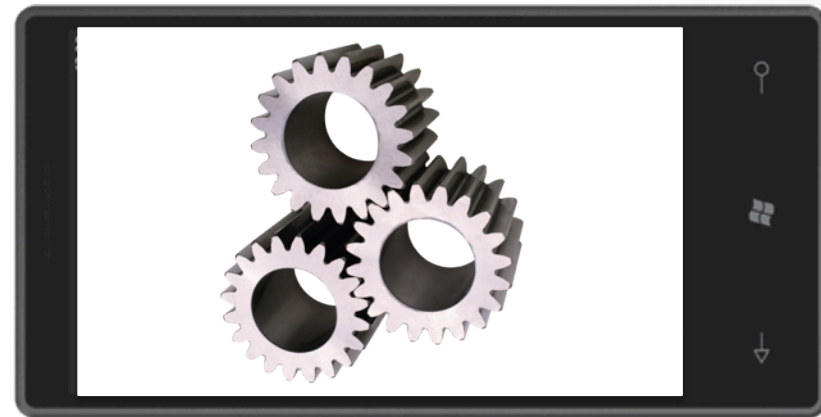


$$f \left(\text{usage} \right) = \text{mood}$$


iPhone Livelab Logger

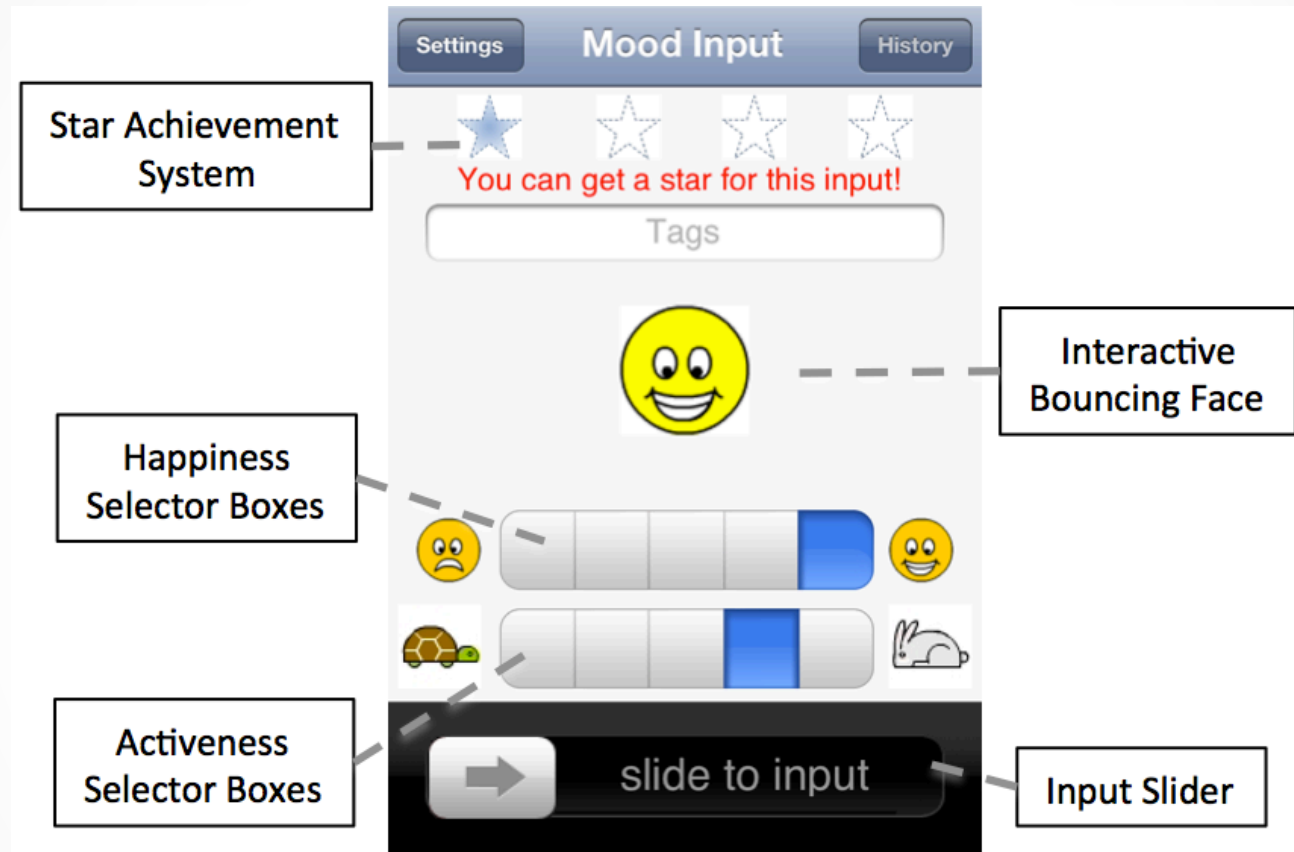
- Web history
- Phone call history
- Sms history
- Email history
- Location history
- App usage

Runs as shell
Hash private data
Nightly uploads



Adapted From C. Shepard, A. Rahmati, C. Tossel, L. Zhong, And P. Kortum, "Livelab: Measuring Wireless Networks And Smartphone Users In The Field," In Hotmetrics, 2010.

Mood Journaling App



User-base

32 users aged between 18 and 29

11 females

Inference

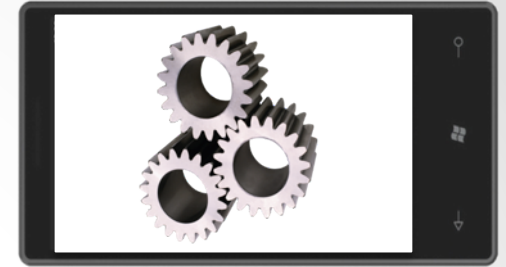
- Detect a mood pattern
- Validate with only 60 days of data
- Wide range of candidate usage data
- Low computational resources

Daily Mood Averages

- Separate pleasure, activeness dimension
- Take the average over a day

$$\frac{\Sigma \left(\begin{array}{cc} \text{😊} & \text{😞} \\ \text{😊} & \text{😊} \end{array} \right)}{4}$$

Exploring Features

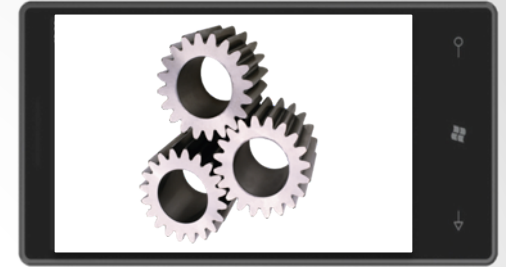


- Communication
 - SMS
 - Email
 - Phone Calls
- To whom?
 - # messages
 - Length/Duration

Consider “Top 10” Histograms

- ? How **many** phone calls were made to #1? #2? ... #10?
- ? How **much time** was spent on calls to #1? #2? ... #10?

Exploring Features



- Communication
 - SMS
 - Email
 - Phone Calls
- To whom?
 - # messages
 - Length/Duration
- Usage Activity
 - Applications
 - Websites visited
 - Location History
- Which (app/site/location)?
 - # instances

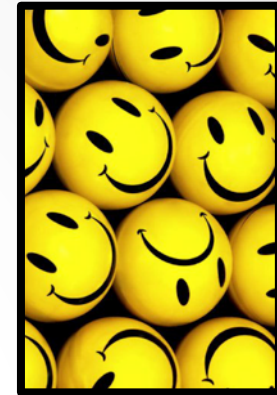
Previous Mood

- Use previous 2 pairs of mood labels



Data Type	Histogram by:	Dimensions
Email contacts	# Messages	10
	# Characters	10
SMS contacts	# Messages	10
	# Characters	10
Phone call contacts	# Calls	10
	Call Duration	10
Website domains	# Visits	10
Location Clusters	# Visits	10
Apps	# App launches	10
	App Duration	10
Categories of Apps	# App launches	12
	App Duration	12
Previous Pleasure and Activeness Averages	N/A	4

Data Type	Histogram by:	Dimensions
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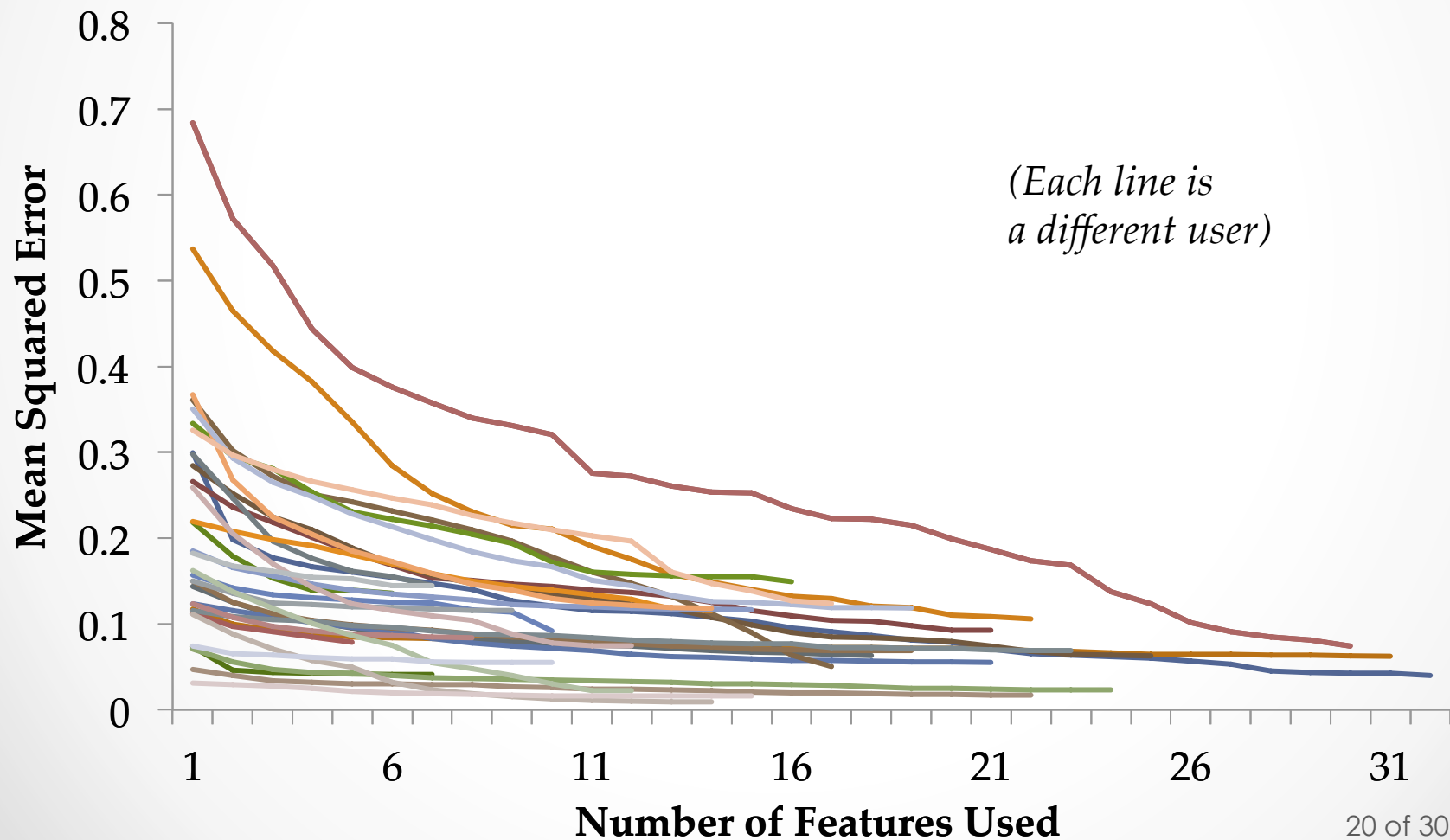


Model Design

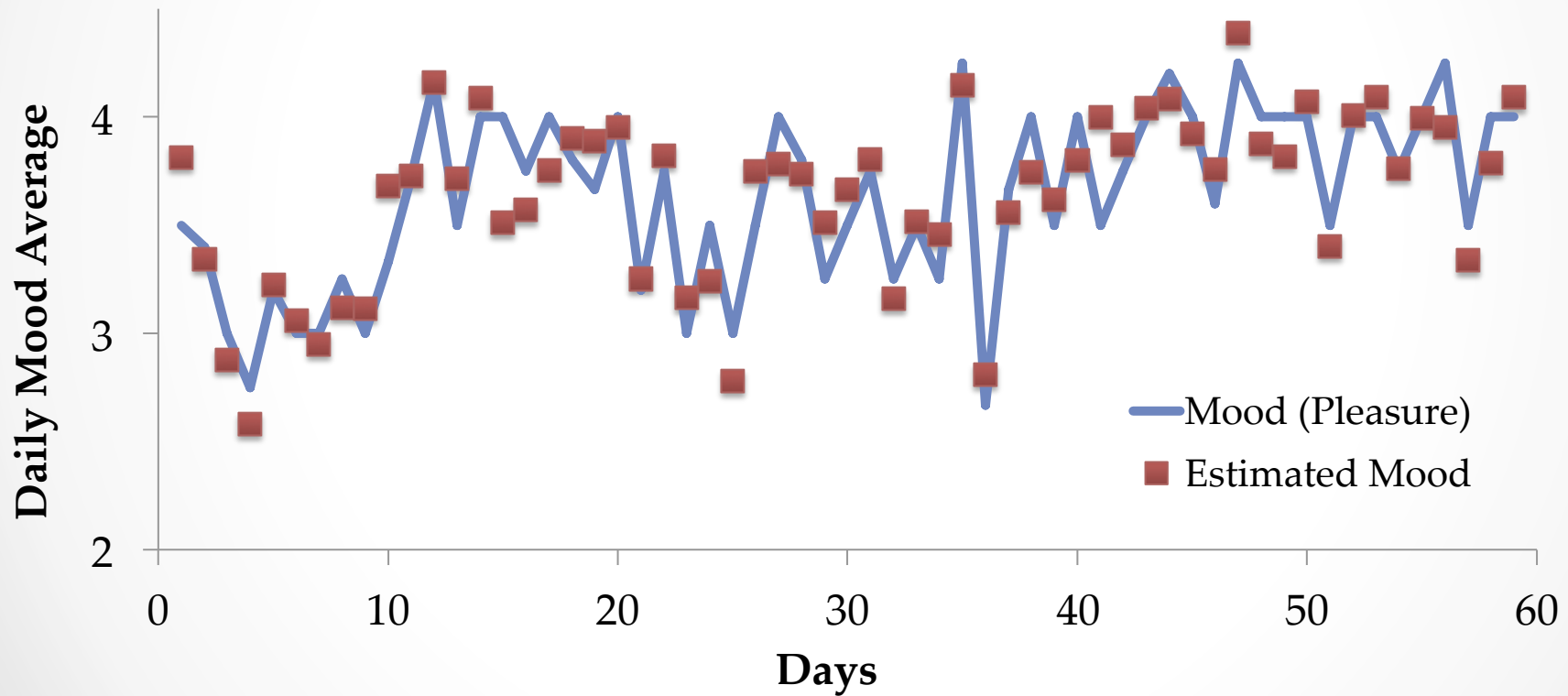
- Multi-Linear Regression
 - Minimize Mean Squared Error
- Leave-One-Out Cross-Validation
- Sequential Forward Feature Selection during training

Sequential Feature Selection

Improvement of model as SFS adds more features



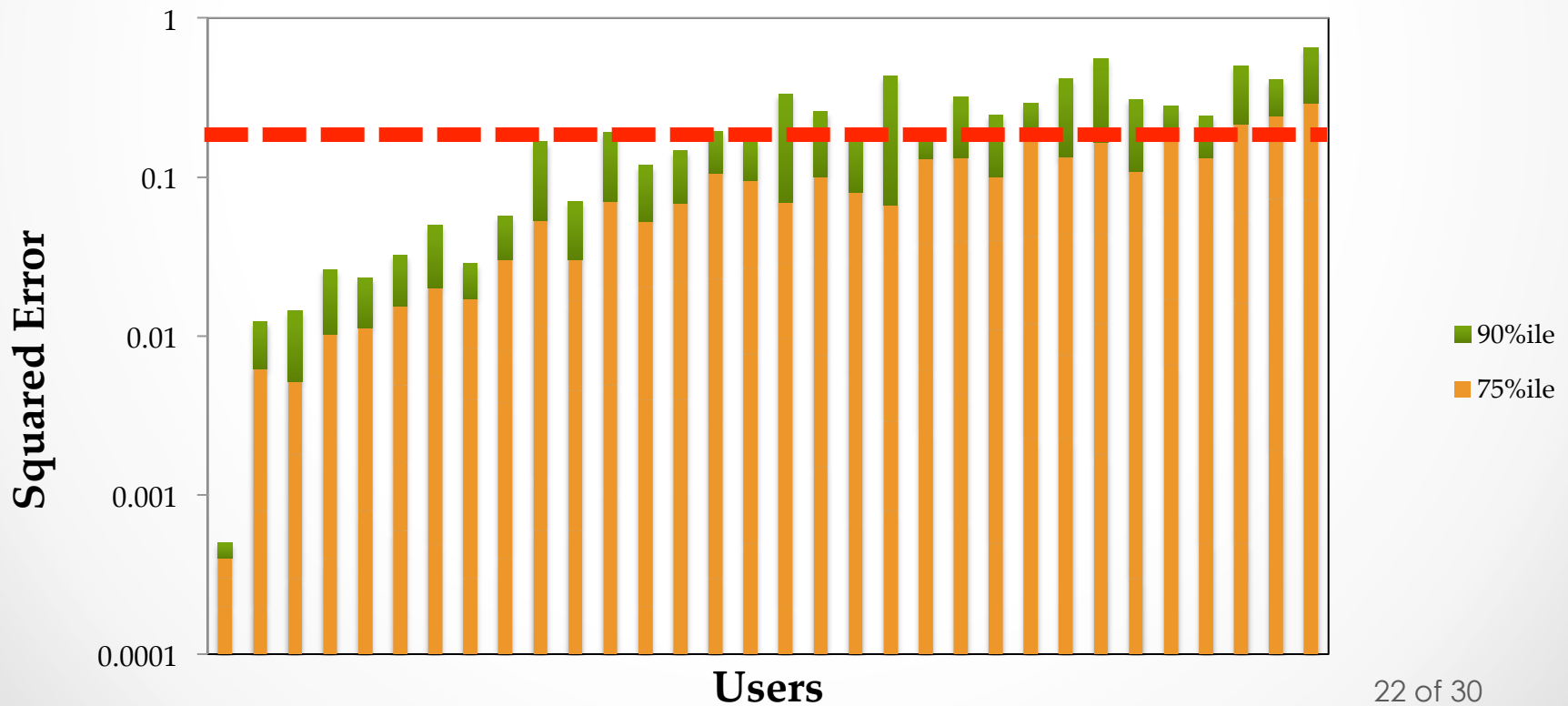
Sample Prediction



Error distributions

- Error² of > 0.25 will misclassify a mood label

93% < 0.25 error²



vs. Strawman Models

Models using **full-knowledge** of a user's data with LOOCV

Model A: *Assume User's Average Mood*

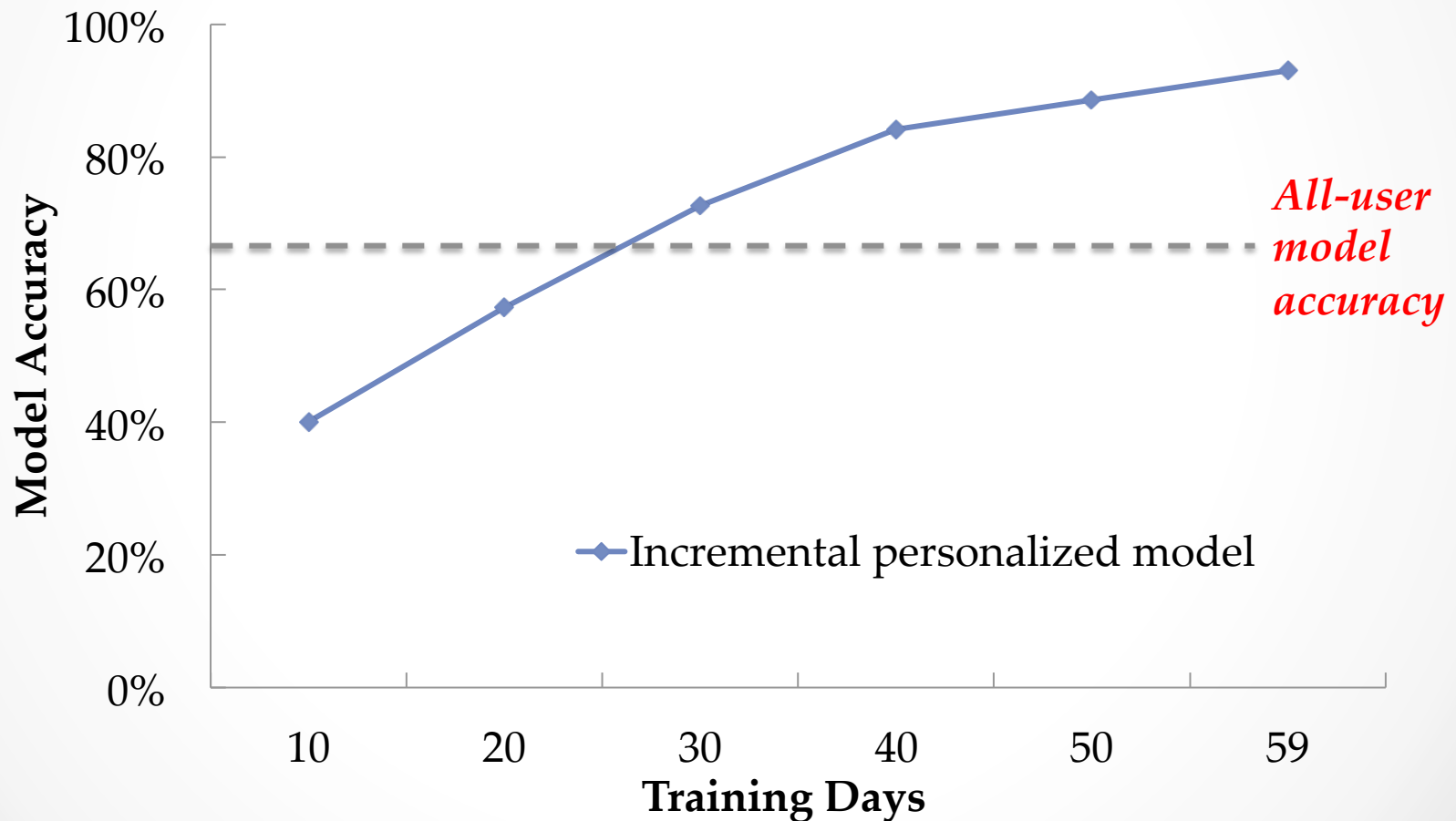
73% Accuracy

Model B: *Assume User's Previous Mood*

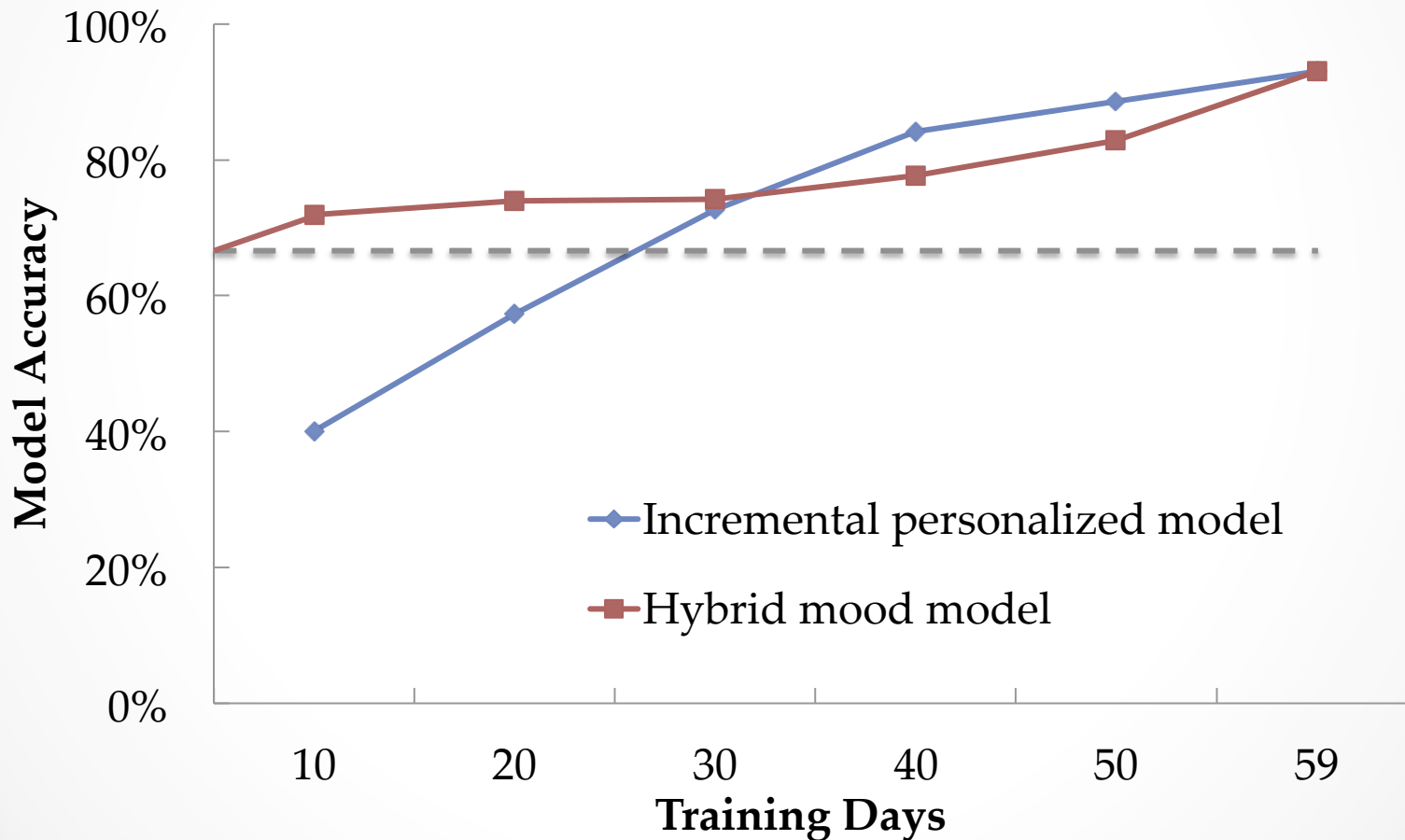
61% Accuracy

MoodScope Training: 93% Accuracy.

Personalized Training

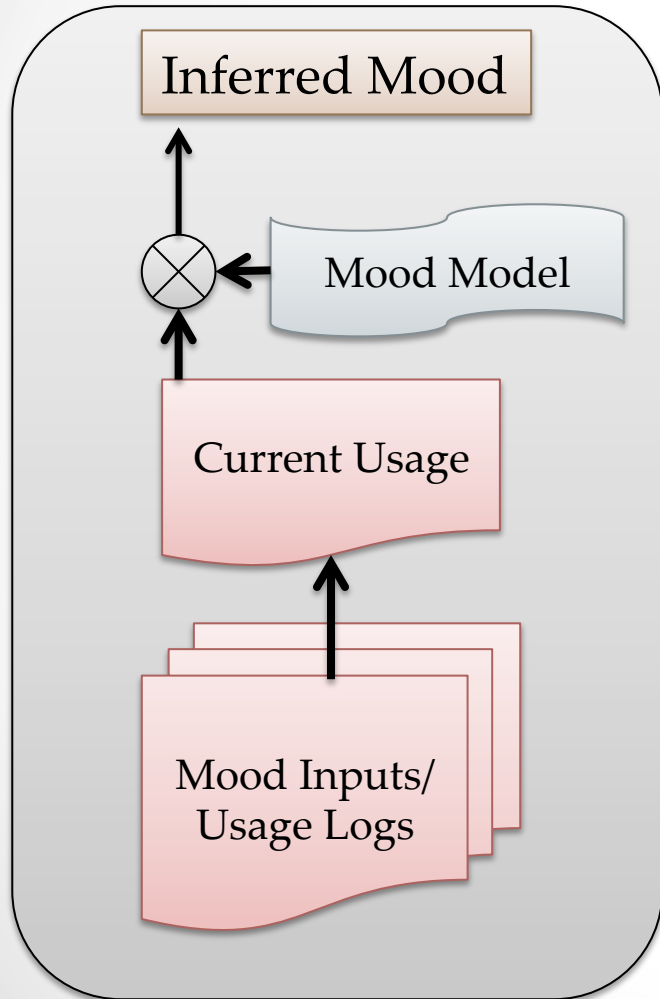


Personalized/All-user Hybrid Training

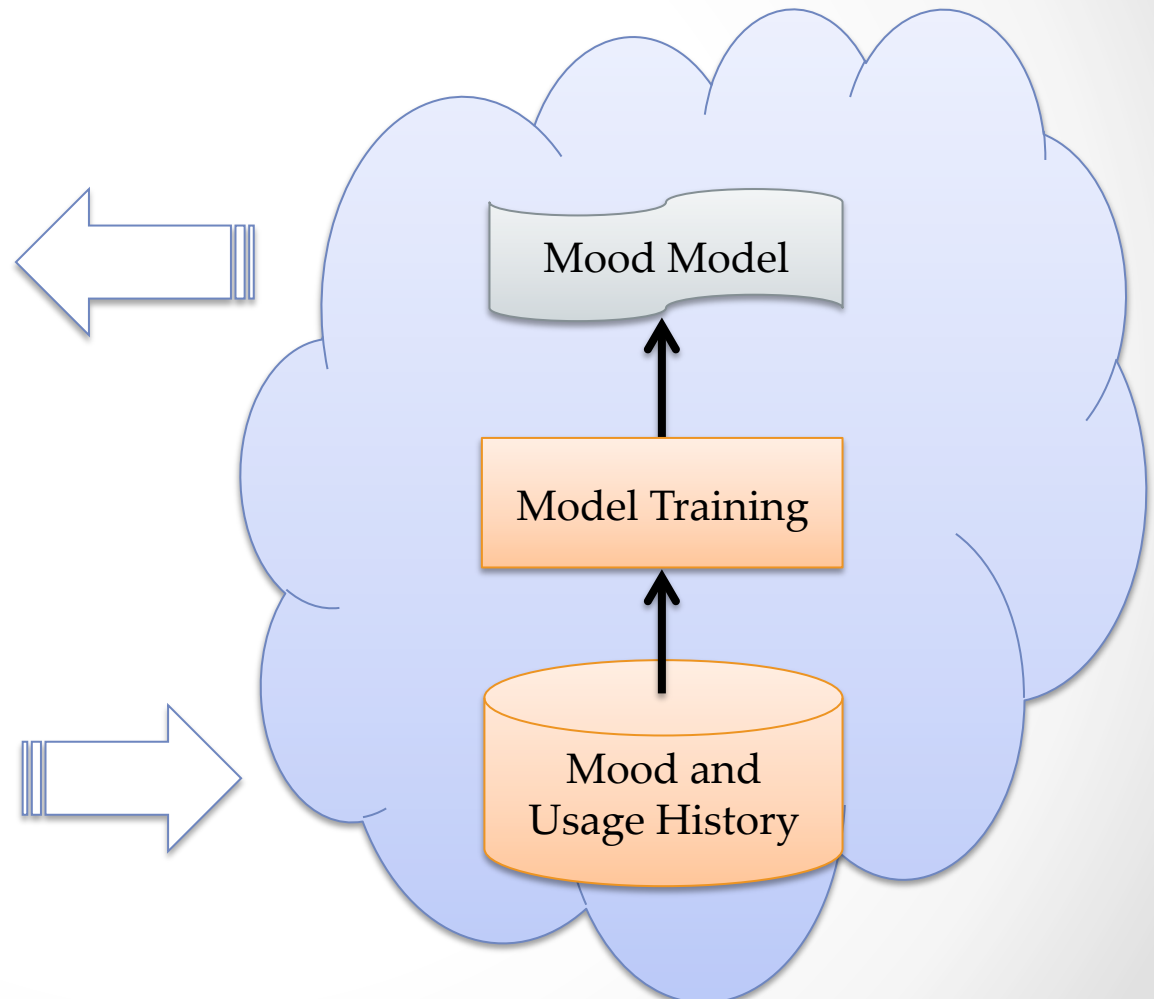


Resource-friendly Implementation

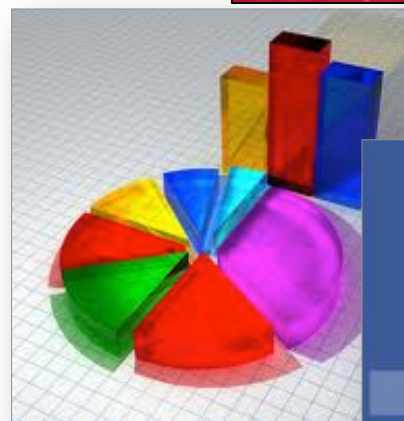
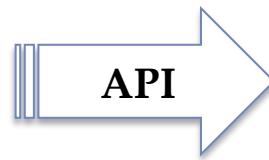
Phone



Cloud



Inferred
Mood



MoodScope:

Sensing mood from smartphone usage patterns

- Robustly (93%) detect each dimension of daily mood
 - On personalized models
 - Starts out with 66% on generalized models
- Validate with 32 users x 2 months worth of data
- Simple resource-friendly implementation

