Ubiquitous and Mobile Computing CS 528:MoodScope: Building a Mood Sensor from Smartphone Usage Patterns

Yu Tian

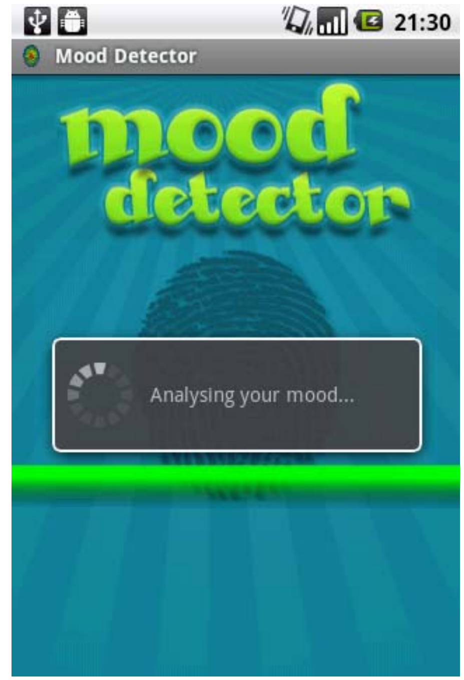
Qianyun Yang

Computer Science Dept.

Worcester Polytechnic Institute (WPI)

Motivation

- Mood plays a significant role in our lives, influencing our behavior, driving social communication, and shifting our consumer Preferences.
- In digital realm of mobile devices, there is a distinct lack of knowledge about mood unless manually provided.
- The implementation of a mood sensor may be a key step to enhance the context-awareness of mobile devices.



- **Motivational Applications:** Mood logger and browser, Mood sharing and Mood-enhanced application.

Introduction

- **Benefits of mood sensing:**

(1) Can be used by Netflix or Spotify to recommend movies based on user's current mood.

(2) Build an interesting digital social ecosystem as users' devices automatically share their moods with friends.

- **MoodScope System**
- A system that recognizes users' mood from their smartphone usage patterns. It can peer into usage data and infer a user's mood.
- This system is lightweight and power efficient, application-independent, doesn't require users to carry any extra hardware sensors or rely on the use of the microphone or camera.

Main Contributions

- Demonstrate the feasibility of inferring mood from smartphone usage, paving the way for energy-efficient, privacy-preserving systems that automatically infer user mood.
- How mood affects smartphone usage is personal, a general model performs significantly worse than personalized model.
- Design a user-friendly mood journaling tool to effectively collect user mood data.
- Describe a lightweight, power-efficient, and easy-to-deploy realization of MoodScope.

Related Work

- **Recognizing emotions from voice and video:** Facial or spoken expressions of people may not reflect their true feelings.
- **Alternative physiological signal:** It requires additional hardware.
- **Leveraging signals from smartphones:**
- **MoodScope:** It exploits pre-existing usage patterns of an individual, avoids invasive image and audio data, can run continuously in the background without compromising phone battery life.
- **Science of Mood:**

  Circumplex mood model,

  Ekman's six basic categories,

  Positive and Negative Affect Schedule (PANAS)

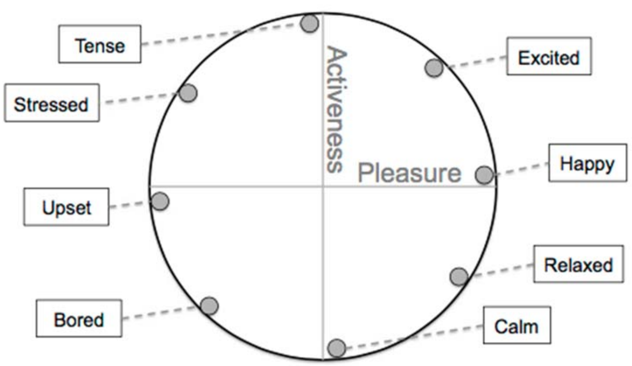


Figure 1: The circumplex mood model

User Study

- **Participants:** 32 existing iphone users from both America and China, cover several professions, several different ages and sex.
- **Pre-Study Focus Group:** The first part dealt with the impact of mood changes on smartphone usage habits. The second part asked for the participants' opinions on mood sharing.
- **Field Study:** Mood Journaling Application and Smartphone Interaction Logger.

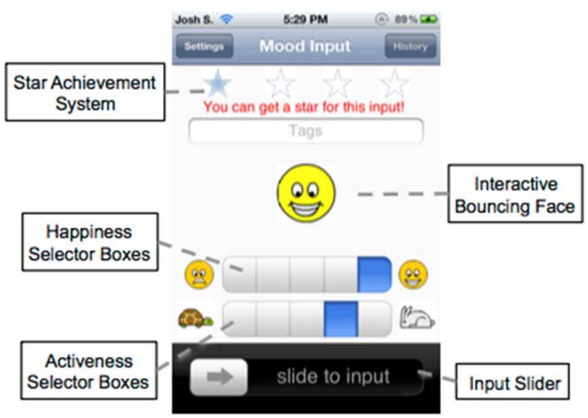


Figure 2: Mood journaling application view

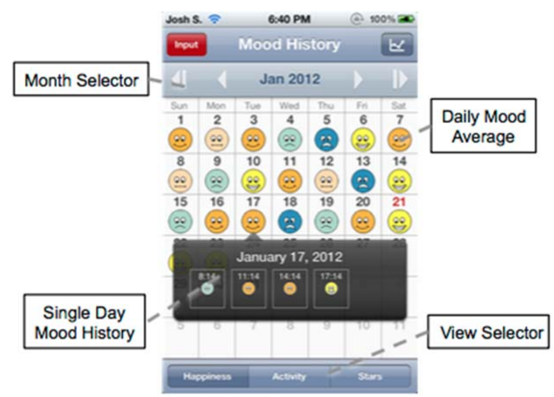


Figure 3: Mood calendar application view

User Study

- **Post-Study Focus Group:** Ask for Beijing participants for their opinions regarding the usability and effectiveness of mood journaling application.
- **Characteristic of User Mood Entries:** They consider mood as a two-dimensional vector with 25 possible values (P#, A#).
- The response rate, mood persistence, and distribution of the entered moods show MoodScope's efficacy in collecting a wide variety of moods from the users, and provide insight into the design of MoodScope.

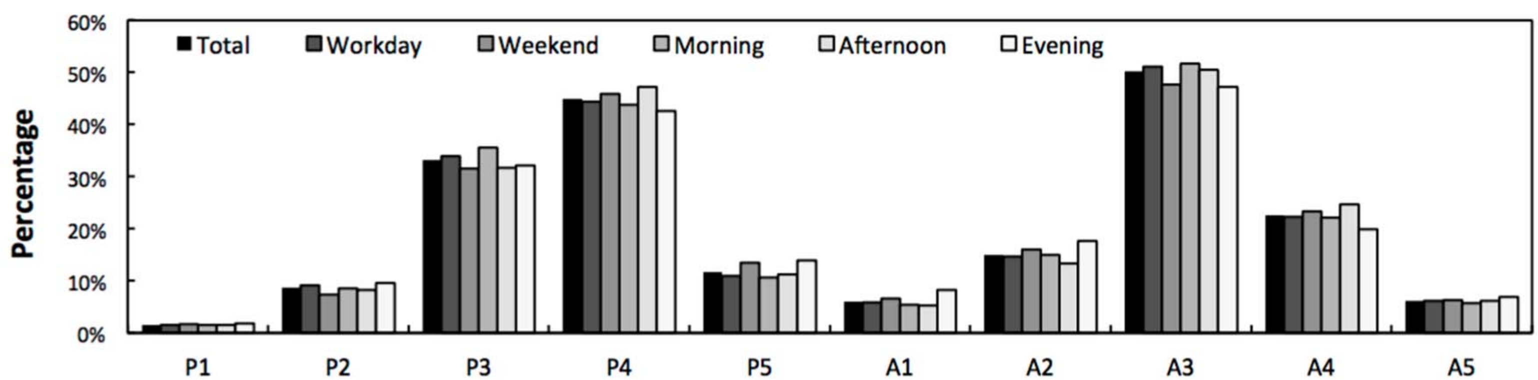


Figure 4: Distribution of user mood entries, grouped by different times-of-day. P1-P5 are moods entered as "very displeased" to "very pleased", while A1-A5 signify "very inactive" to "very active."

The Design of MoodScope Output

- To estimate a user's mood

  Output: Daily Averages

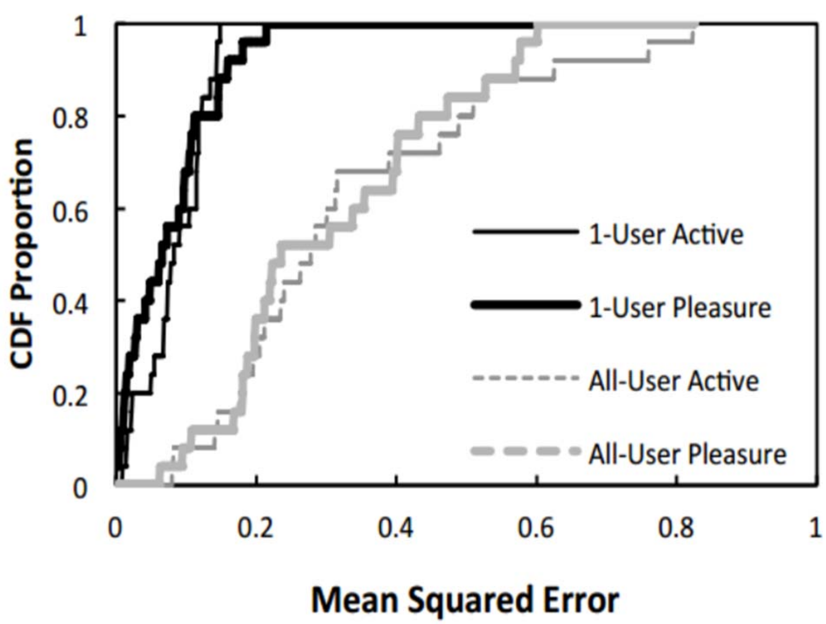
  Input: Usage Records(Social Interaction; Routine Activity)

Table 1: Feature table of usage histograms (and previous mood averages)

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 2 Pleasure and Activeness Averages	N/A	4

Internal Model of MoodScope

- **Multi-Linear Regression:** discern an inference mode
- **Sequential Forward Selection of Features:** choose relevant features, reducing the dimensionality
- **Personalized Mood Model and All-User Mood Model**



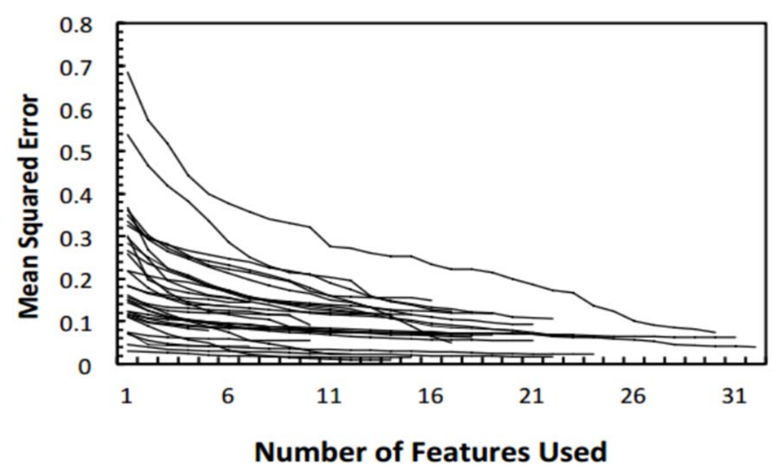


Figure 8: Decrease of Mean Squared Error of pleasure model as features are added. Each line represents a different user. A user's line ends when SFS terminates.

Internal Model of MoodScope

- **Hybrid Mood Model Approaches:** combine a small amount of user-specific training data with large amounts of training data collected from the general user population
- **Comparison to Strawman Models**

Table 2: Strawman model performance comparison

Model	Pleas. MSE	Pleas. Acc.	Activ. MSE	Activ. Acc
Model A: average mood	0.242	73%	0.229	74%
Model B: slow-varying mood	0.354	61%	0.318	65%
Model C: no phone features	0.258	70%	0.277	71%
All-user Model	0.296	66%	0.289	67%
Personalized Model	0.075	93%	0.085	93%

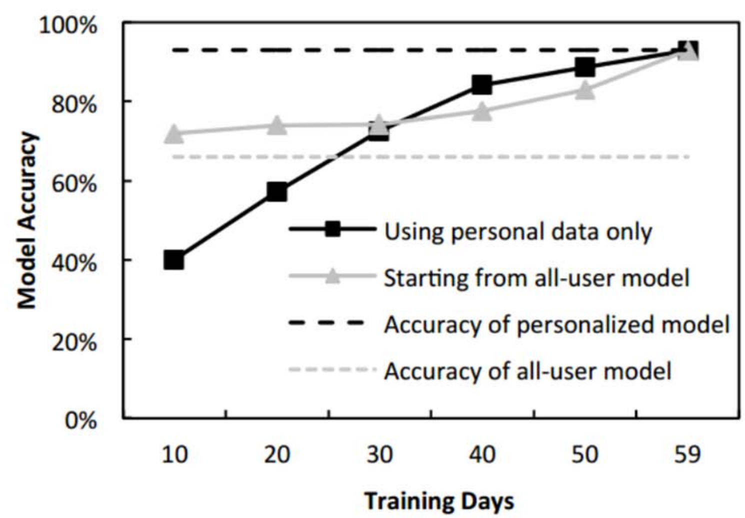


Figure 9: Pleasure training accuracy vs. training data size

Feature Table Characteristics

- **Discriminative Features:**
  - Count number of occurrences in reduced feature table
  - Count number of statistically significant features
  - Count number of most discriminative features

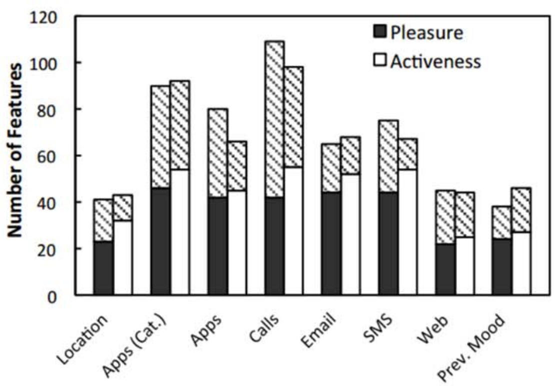


Figure 10: Number of features in SFS-reduced tables. So
bars represent statistically significant features ($p < 0.05$).

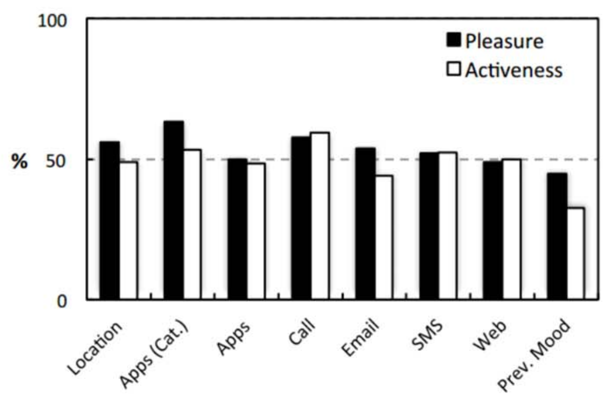


Figure 12: Percentage of features that positively correlat

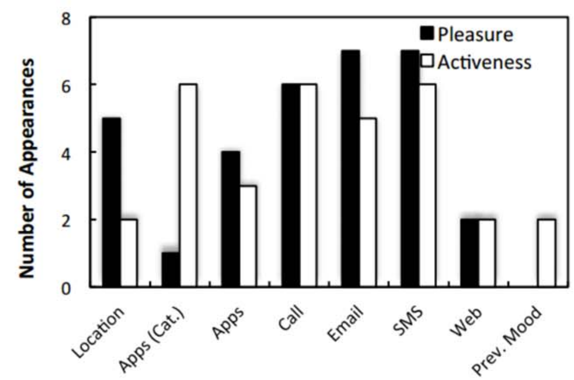


Figure 11: Number of times a category appears as a *most discriminative feature*

- **Positively and Negatively Correlated Features**

Mood Inference Engine

The mood inference engine consists of two software components, one residing in the phone and the other in the cloud.

- **Training in the Cloud**
- **Inference on the Phone**
  - Implementation and Performance
  - Communication Overhead
- **Application Programming Interface**

Table 4: Mood Inference Engine API specification

Interface	Description
`MoodState class`	Data structure containing two floats to represent pleasure and activeness.
`GetCurrentMood()`	Returns current `MoodState`.
`GetPastMood(time)`	Returns the `MoodState` at a given timestamp
`SetMood(mood)`	Sets the current `MoodState` to *moodstate*. Also updates the model on the cloud.

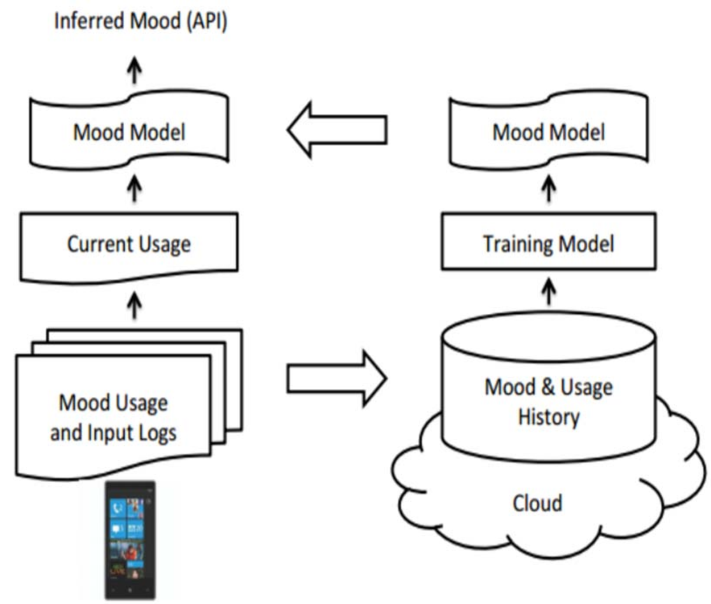


Figure 13: The Mood Inference Engine

Discussion and Result

- Design a MoodScope Social Sharing App on top of an iPhone Mood Inference Engine as and end to end demonstration of a fully functional mood-aware application.

- Deploy the application on three university students from the original 32 participants after their 2 months of training models in the field of study and received positive feedback.

- MoodScope is a promising and practical approach for inferring mood with smartphone.

Limitations and Future Work

- **Limitation:**
  - Evaluate MoodScope with a small-scale user population that fairly homogenous
  - Entering mood four times daily can be too burdensome for public adoption
  - Not every factor that impacts user mood van be captured by a smartphone
  - The privacy preserving mechanisms found within existing MoodScope design are insufficient for a release to the general public
- **Future Work:**
  - Large-scale validation of results and large-scale longitudinal user study
  - Determine if user behavior change is driven by mood or some other confounding factor
  - Explore how mood models can be trained using data from multiple people while still providing sufficient guarantees of privacy to each user.

Conclusion

- Recognize the importance of mood inference in application context-awareness
- Study the possibility of mood inference from smartphone usage analysis. Collect 2 months of usage data and self-reported mood from 32 users
- Use statistical regression technique and further work to robustly regress the daily average of mood and find the phone calls and categorized applications strongly predict mood
- Build a Mood Inference Engine that apply mood models to smartphone user data in real life
- Design a MoodScope API for application developers to use the outputs of our mood inference system to build and enhance their own custom mood-enable application.

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