OSN Mood Tracking: Exploring the Use of Online Social Network Activity as an Indicator of Mood Changes

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Psychological State & Online Social Networks

Existing research:

- Long-term studies (months to years)
- Emotional trends of groups
- Single OSN

Our Research - OSN Mood Tracking

Analyse the user’s online activity on Facebook and Twitter

Identify features that can be exploited to detect the user’s **mood** changes

Short time frame (7 day sliding window)

Ground truth data via experience sampling

Aim: Find correlations between mood and online activity

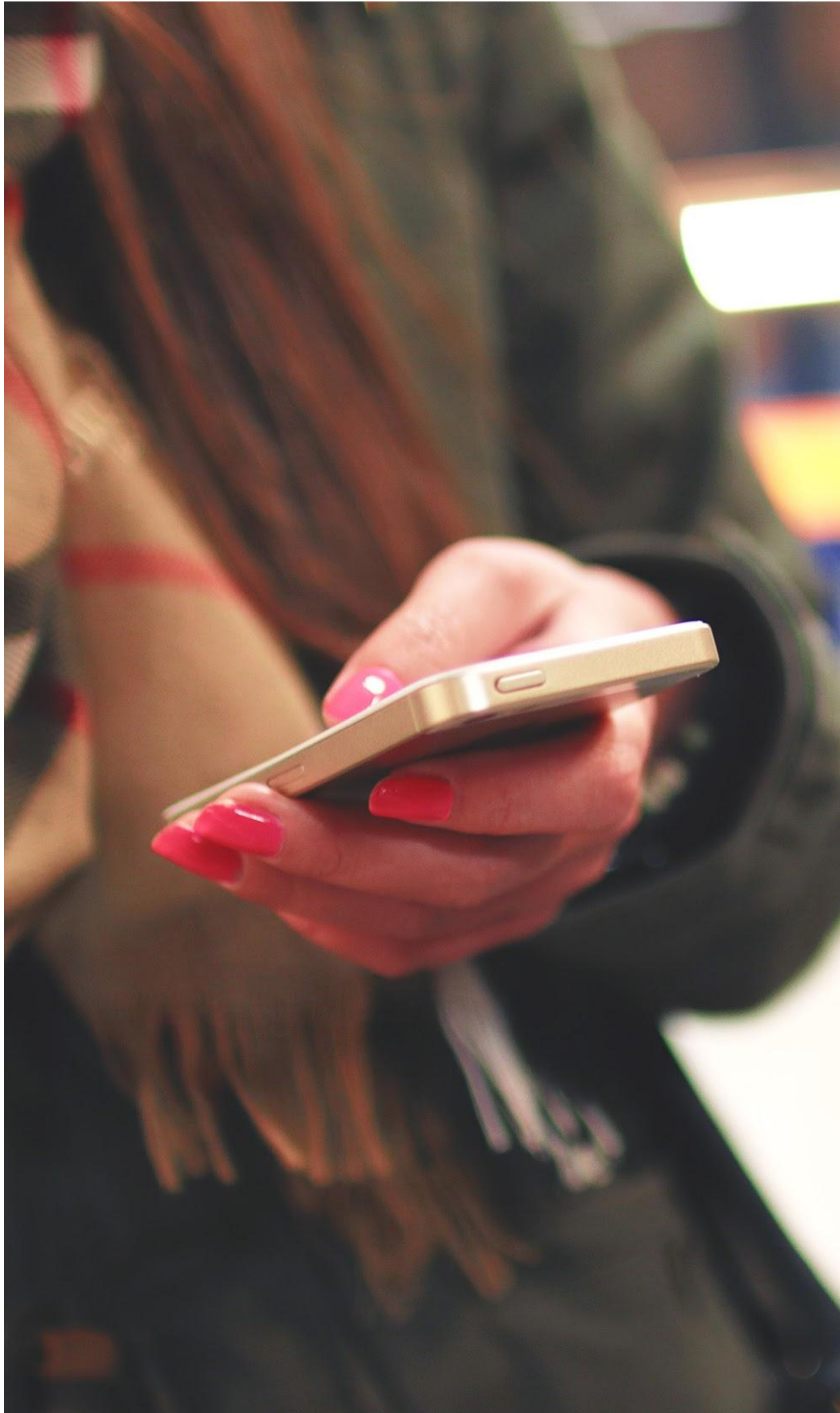
Recruitment

Aimed at OSN users who maintain a relatively frequent interaction with Facebook and Twitter

Advertised at a British university (18 - 25 years old)

73 people registered their interest

36 were chosen to participate - self-reported most active online



Study Duration

Study ran during exam period into summer break

Wider variability of mood changes: exam pressure vs. relaxed summer break

Expected participation: **30 days**

Average participation: **28 days**

Data Collection - Online

Two crawlers developed to collect activity data from the personal timelines and home feeds on Facebook and Twitter every 15 mins

Facebook

- Statuses
- Posts by friends
- Shares
- Likes
- Comments

Twitter

- Tweets
- Replies
- Retweets

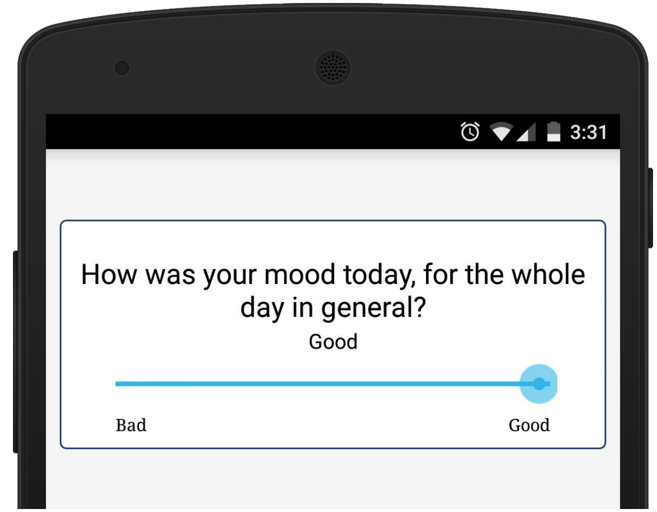
Data Collection - Ground Truth

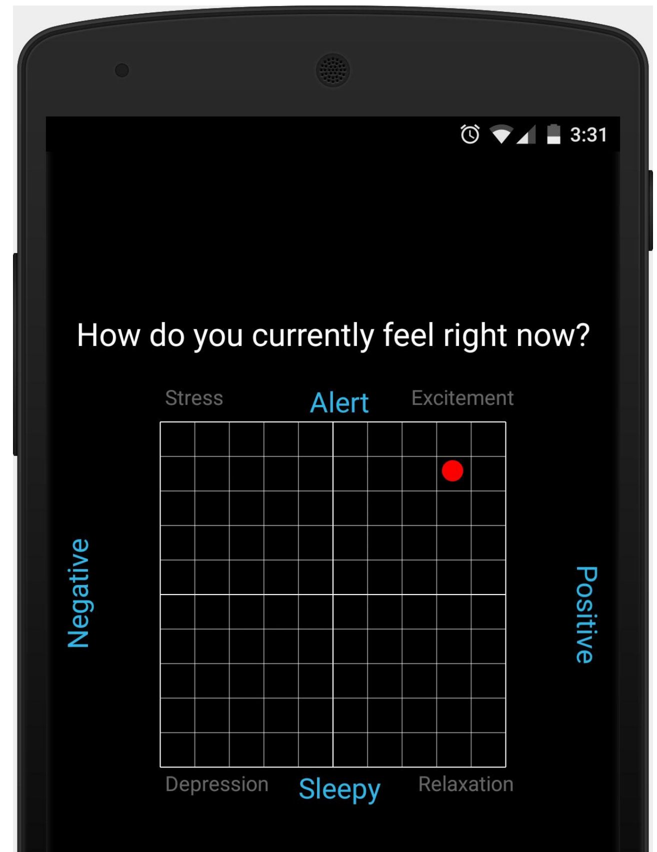
Participants installed the smartphone applications Easy M for Android or PACO for iOS

Daily prompts at 10pm to answer two questions:

1. How was your mood today, for the whole day in general?
2. How do you currently feel right now?

Overall response rate: 88%





Data Cleaning

Following data collection, both datasets were cleaned

- User reported multiple moods in a single day - later time was used

- Participants were removed completely if:
    - The same mood was reported every day
    - Final dataset was less than 15 days long

Final Dataset

16 participants

406 days of individual data (avg. 25 days per participant)

1,760 online actions (posts, likes, etc.) performed by the participants

Methodology

- Which online features best represent mood?
- Normalise mood across participants using z-score
- Extracted online features calculated over 7d sliding window, 6d overlap
- Pearson’s correlation between each online activity feature and each participants’ mood changes
- % of participants with significant correlations with that feature ($p < 0.05$)

Statistical Features

Counts of online actions:

- Status updates
- Likes
- Comments
- Posted links / photos / videos
- Tweets
- Retweets
- Hashtags (#)
- Mentions (@)

- Character length of statuses / tweets
- Activity during morning / afternoon / evening / night

Statistical Features

Aggregate features:

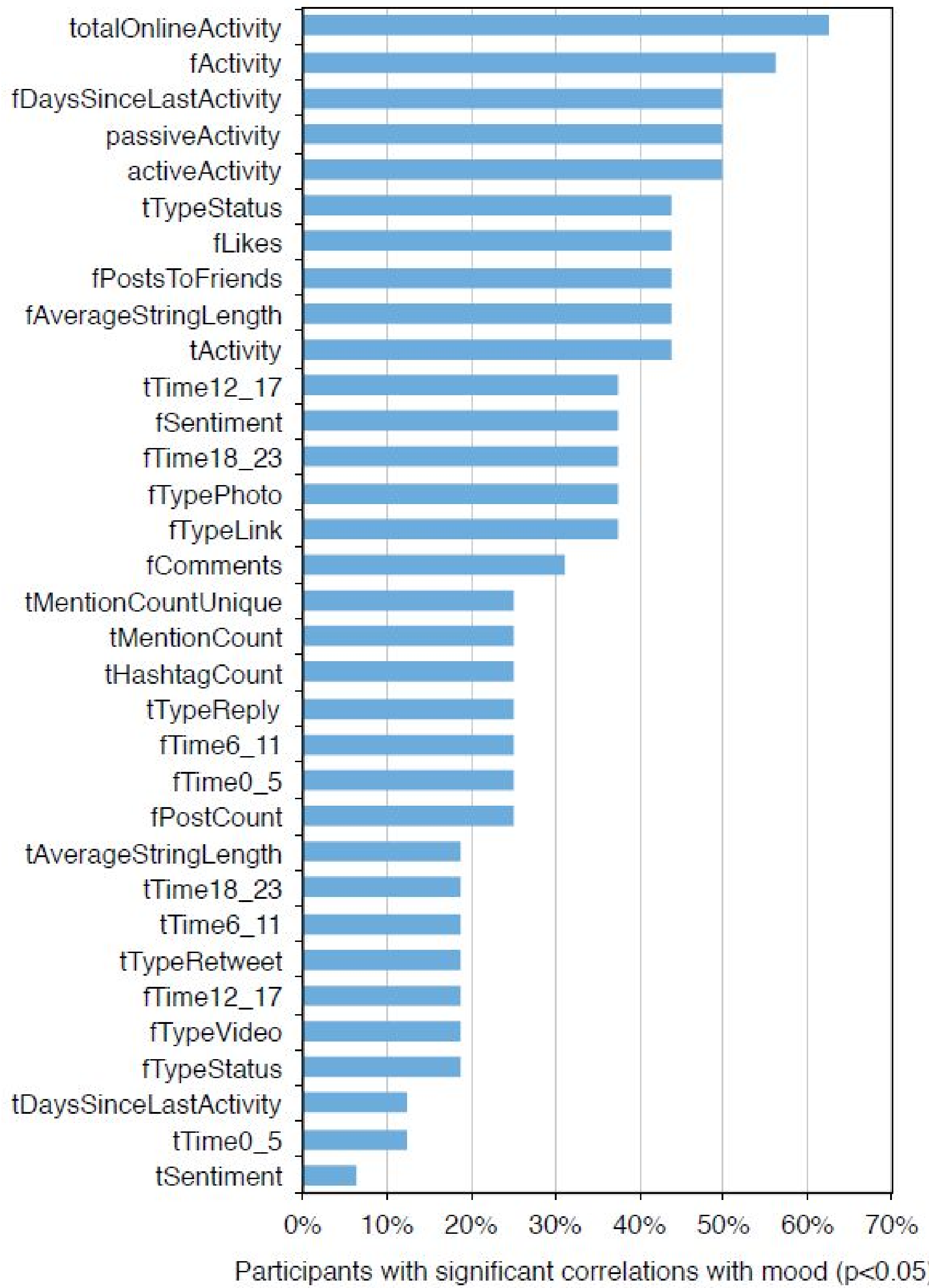
- Total Facebook activity
- Total Twitter activity
- Total online activity
- Active activities
  - Posts
  - Comments
  - Tweets
  - Replies
- Passive activities
  - Likes
  - Retweets
- Sentiment analysis

Results

Total Online Activity

61% of participants demonstrating statistically significant correlation with mood ($p < 0.05$)

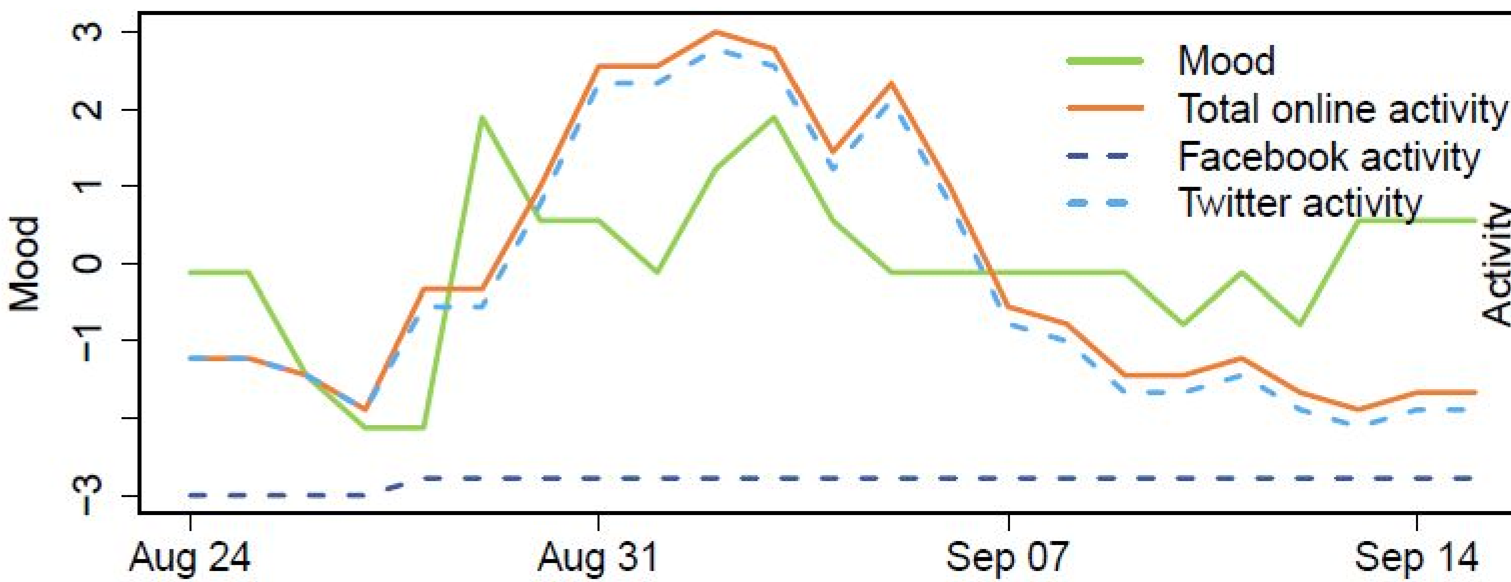
Count of all actions on both Facebook and Twitter



Participant 1: Positive

Coefficient: 0.45

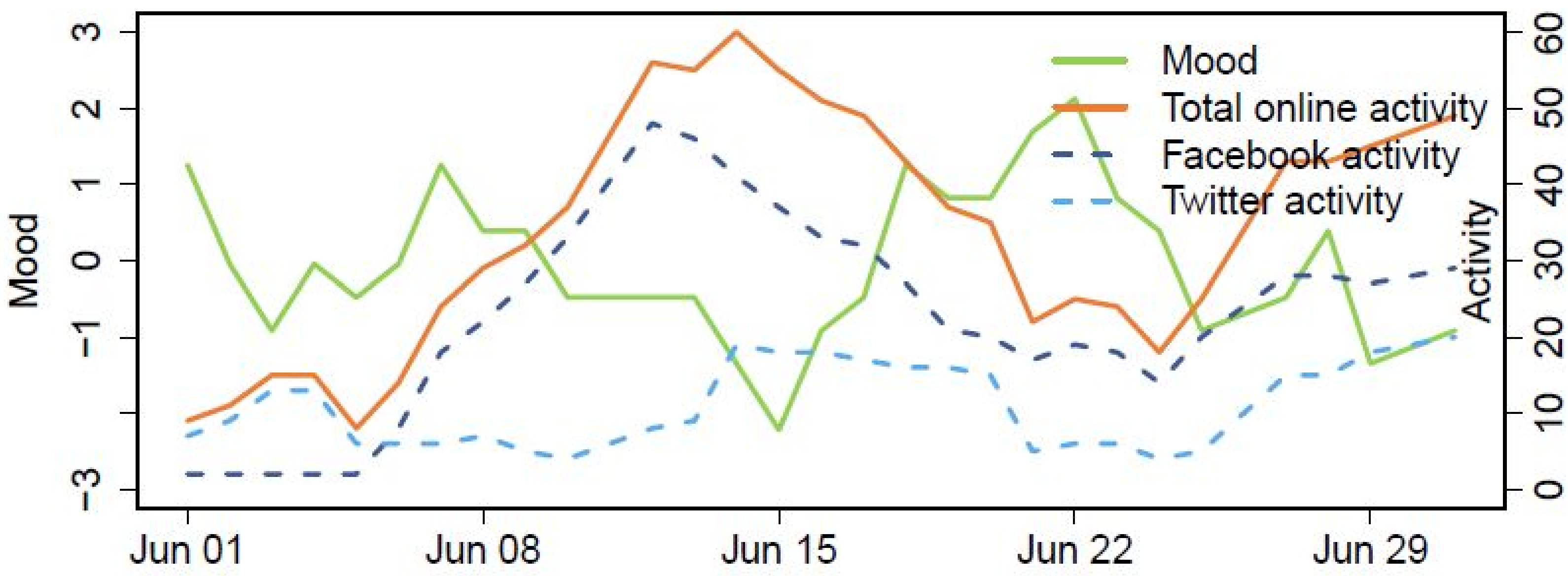
P-value: 0.03



Participant 2: Negative

Coefficient: -0.46

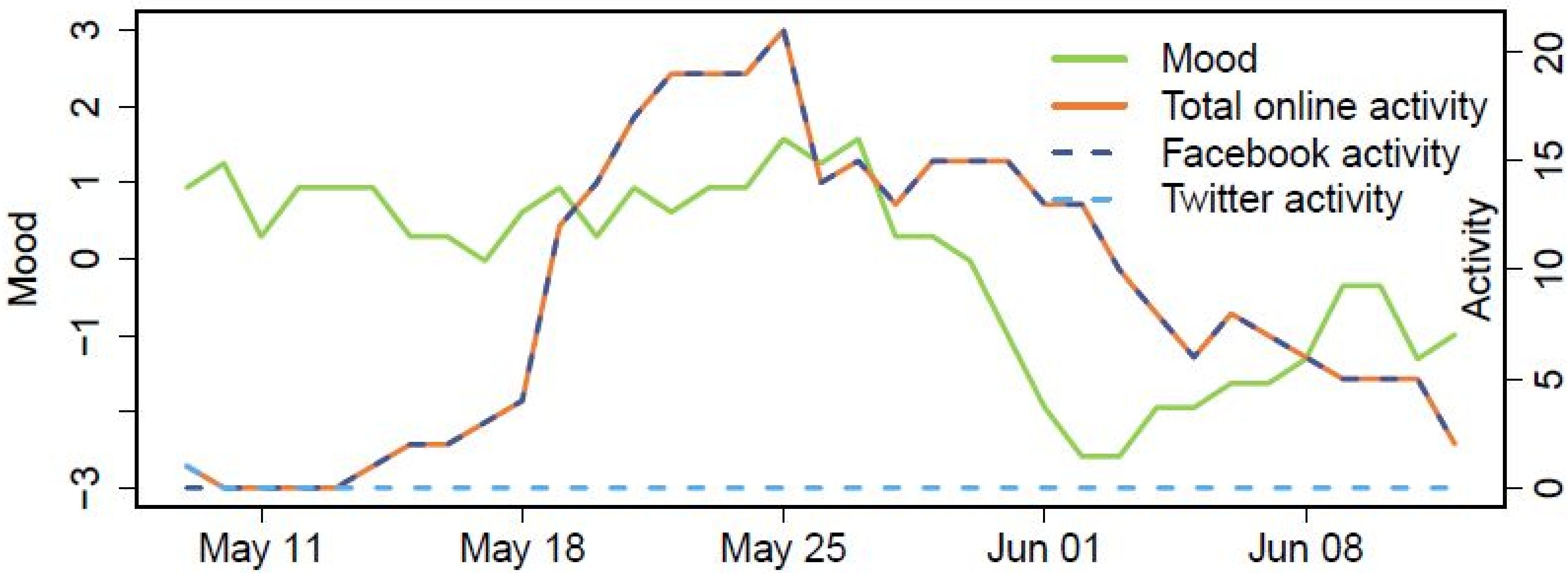
P-value: 0.01



Participant 3: Weak

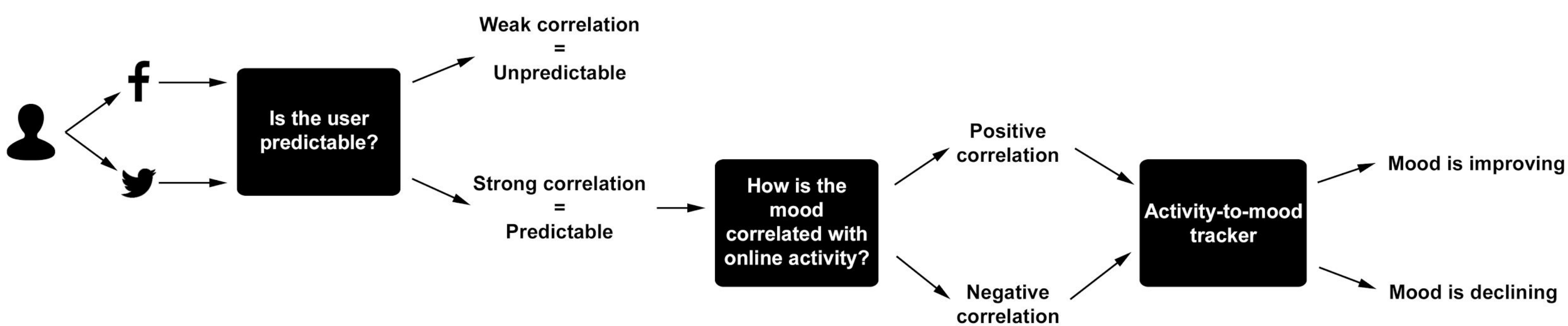
Coefficient: 0.09

P-value: 0.60

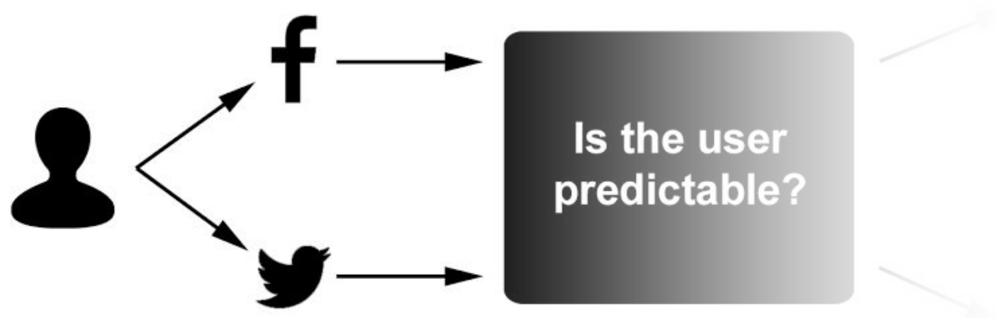


Mood Tracking System

1. Strong vs. weak classifier (correlation coefficient)
2. Positive vs. negative classifier (signage of coefficient)
3. Total Online Activity feature

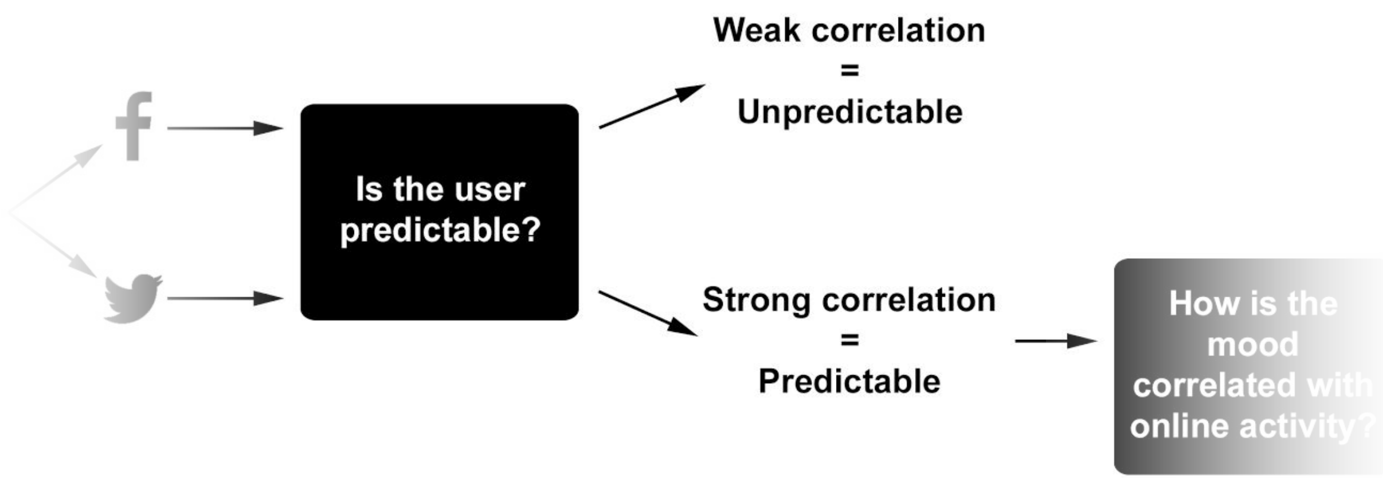


Mood Tracking System



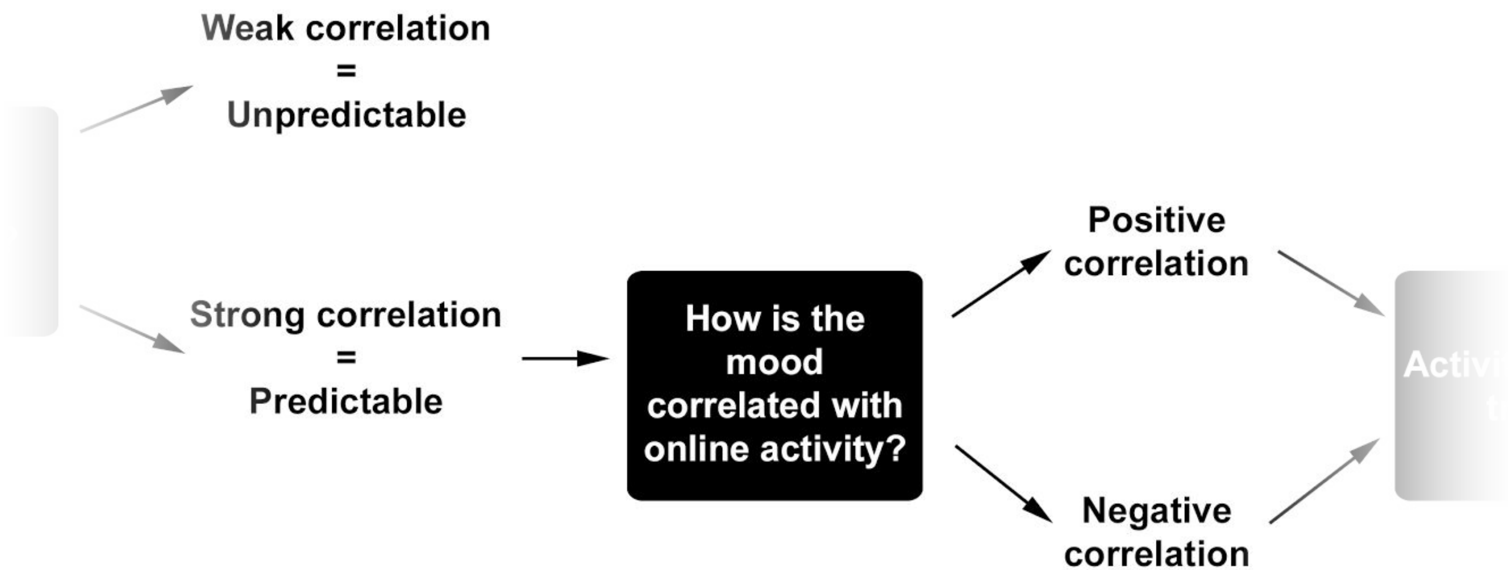
1. The user's activity on Facebook and Twitter is passively tracked

Mood Tracking System



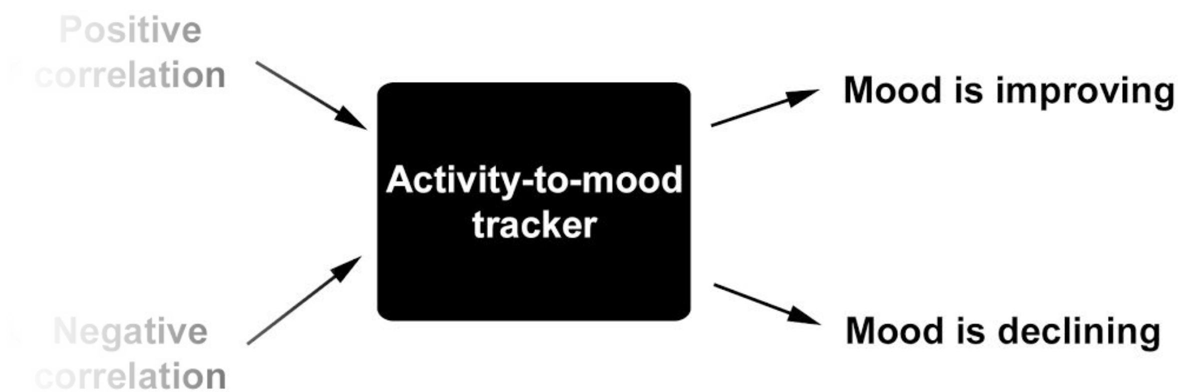
2. The user's mood is classified as predictable or unpredictable

Mood Tracking System



3. The user’s mood is classified as having a positive or negative correlation with online activity

Mood Tracking System



4. User is now classified as *positive* or *negative* - we can now use this grouping to infer the user's mood by simply observing their online activity

Feature Selection for Classifier

- Select a minimum set of features that maximised performance of classifier

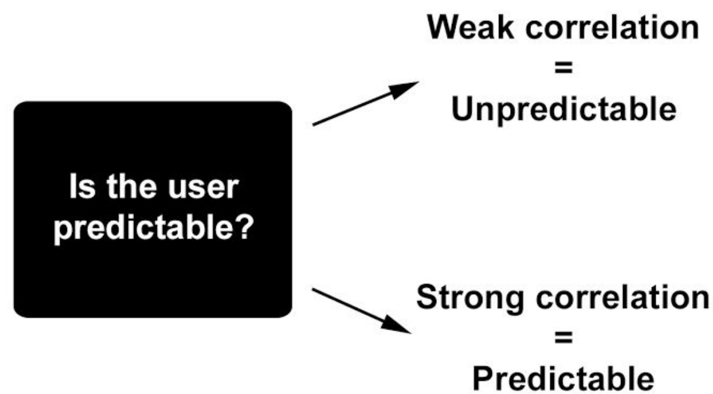
- Hill climbing iterative approach

- Features:
  - Average length of the Facebook posts (lengthFAvg)
  - Average length of the Twitter posts (lengthTAvg)
  - Ratio of “active” actions over “passive” actions (activePassiveRatio)
  - Ratio of Twitter actions over Facebook actions (twitterFacebookRatio)

- Features capture the level of commitment when interacting with the OSNs

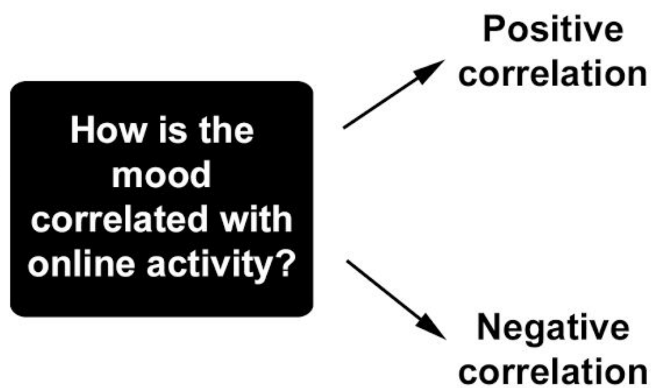
Strong vs. Weak

- Classifier: Random Forest
- Precision: **95.2%**
- Recall: **94.7%**
- F_1 score: **0.947**

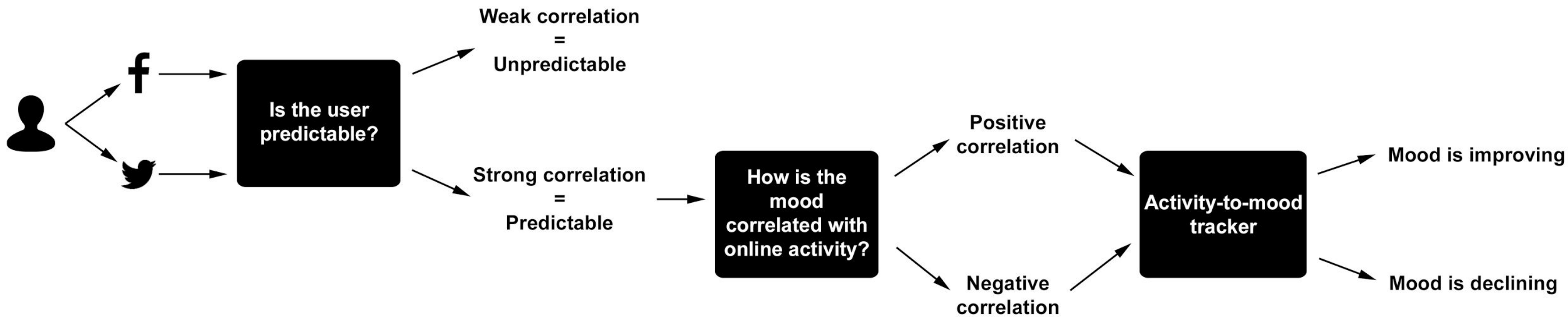


Positive vs. Negative

- Classifier: Voted Perceptron
- Precision: **84.4%**
- Recall: **80.0%**
- F_1 score: **0.763**



Conclusions



First case of exploring correlations between activities over multiple OSNs and real-world mood data captured through experience sampling

Shown it is feasible to track user's mood changes by analysing their online activity

Can we track our friends' mood too?

THANK YOU

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