Emotion recognition with mobile phone & wearable sensor data

- Replication paper
  - Bogomolov, Andrey, et al. "*Daily stress recognition from mobile phone data, weather conditions and individual traits*." Proceedings of the 22nd ACM international conference on Multimedia. 2014.

Yongshin Kim

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C O N T E N T S

Problem Statement

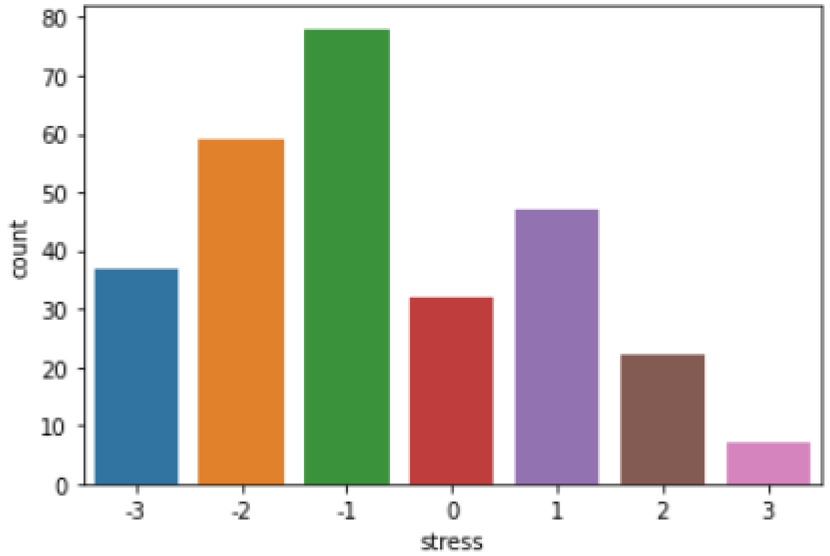
- Stress lowers the quality of life and causes various diseases. Research was actively conducted to analyze stress through physiological approaches. (Bogomolov, Andrey, et al. [1])
- **What I want to predict? “Stress”**
  - Using wearable devices and smartphones to track people's physical, physiological status so that we can understand the relationship between physical activities and stress level.
- **What others did in the past?**
  - Research on stress detection based on **voice analysis** considered different speech characteristics such as pitch, glottal pulse, spectral slope and phonetic variations. (Lu and colleagues. [2])
  - Other studies focused on the **video analysis** of behavioural correlates of psychological stress. (D. Giakoumis et al. [4])
    - ✓ These systems, despite providing an unobtrusive method for stress monitoring, cannot be employed in a large variety of real world and mobile environments and pose privacy concerns related to the recording of people’s behaviour.

Overview

- Dataset: K-Emophone
- Data preprocessing
  - eliminate missing values.
  - convert timestamp variable to a date.
  - set the time window three hours before and after ESM received.
  - combine ESM data with physical activity data.
  - devide stress data into two parts(non-stressed, stressed).
  - scale unification.
  - Outlier detection.
- Feature extraction
  - mean, median, min, max, variance, standard deviation.
  - use SHAP values to select important feature(feature selection).
- Classification
  - daily stress as a 2-class(binary) classification problem(non-stressed vs stressed).
  - decision tree(baseline model), support vector machines, **random forest**, Xgboost.
- Evaluation
  - K-fold cross validation (k = 10).

Approach

- Dependent variable



1. Stress level
    - Negative skew
    - To address the imbalance in stress data, the stress level was changed from 7 point likert scale to binary scale
        - ✓ -3, -2, -1 → -1 and 0, 1, 2, 3 → 1
    - stressed vs non-stressed (Bogomolov, Andrey, et al. [1])

Approach

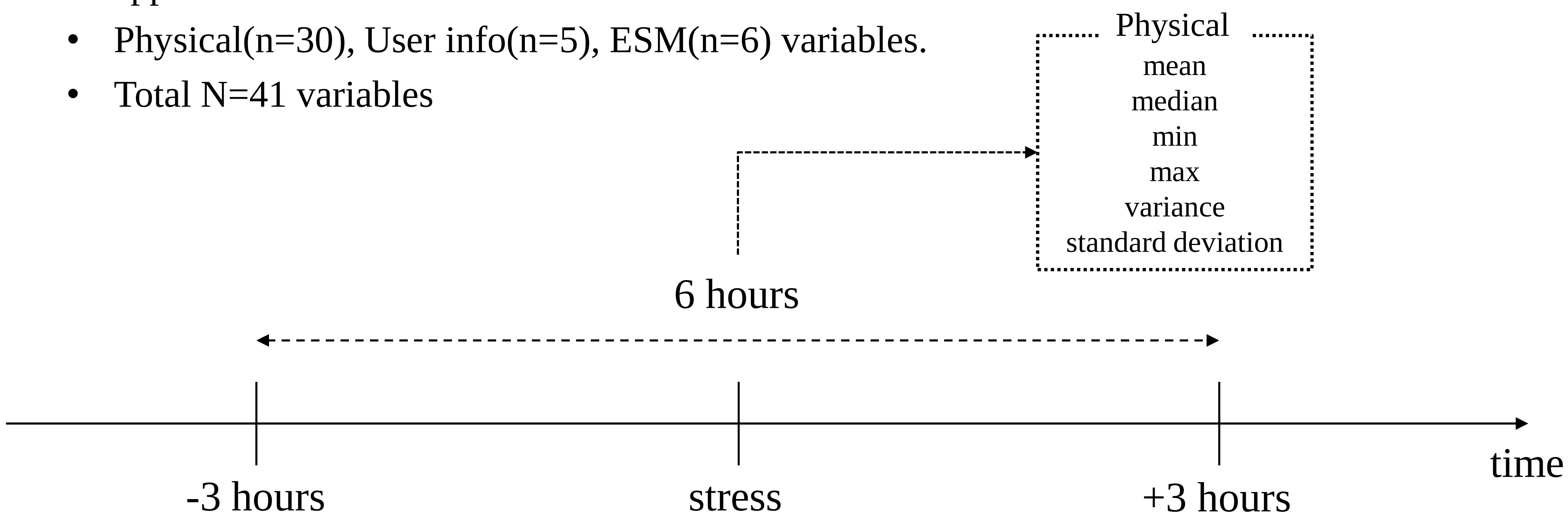
- Independent variables
  1. Physical data
     - heart rate, gsr, accelerometer-x, y, z
  2. User info data
     - openness, conscientiousness, neuroticism, extraversion, agreeableness
     - Researchers showed significant associations between person’s stress and personality. (Duggan et al. [5])
  3. ESM data
     - valence, arousal, attention_level, emotion_duration, disturbance, emotion_change

Approach

- Preprocessing
  - Eliminate missing values.
  - Convert timestamp variable to a date.
  - Set the time window three hours before and after ESM received.
  - Combine ESM data with physical data.
  - Devide stress data into two parts(non-stressed, stressed).
  - Scale unification.
  - Outlier detection.

Approach

- Feature extraction
  - Because stress data is significantly less than physical data, features are extracted based on the time at which stress data is collected.
  - Feature will be extracted 3 hours before and after stress data is collected.
  - Mean, median, min, max, variance, standard deviation collected in a given time zone are applied to the stress data.
  - Physical(n=30), User info(n=5), ESM(n=6) variables.
  - Total N=41 variables

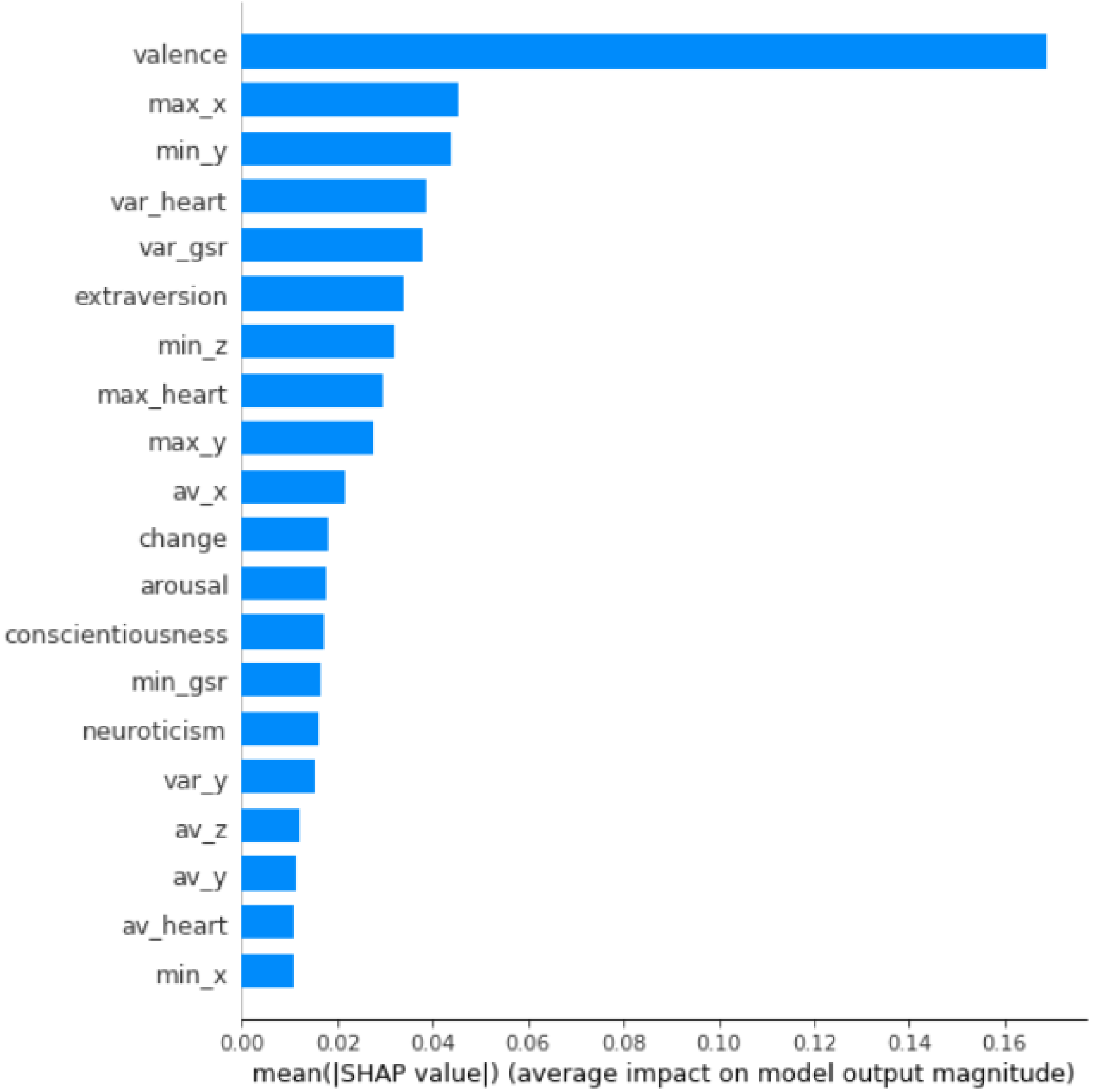


Approach

- Feature selection
  - Use SHAP values to select important features.
  - The top 20 variables(out of total 41) were selected.

- Model building
  - Decision tree (baseline model)
  - Support vector machines
  - Random forest
  - XGBoost

- K-fold cross validation (k = 10)
  - Referred to the replication paper.



Evaluation

- Physical variables

	Precision	Recall	Accuracy	F1-score
Decision Tree(B)	0.545	0.546	0.564	0.545
SVM	0.296	0.500	0.592	0.372
Random Forest	0.491	0.493	0.550	0.483
XGBoost	0.532	0.529	0.571	0.528

- Physical variables + User info variables

	Precision	Recall	Accuracy	F1-score
Decision Tree(B)	0.518	0.517	0.550	0.517
SVM	0.296	0.500	0.592	0.372
Random Forest	0.498	0.499	0.557	0.489
XGBoost	0.502	0.502	0.539	0.501

Evaluation

- Physical variables + User info variables + ESM variables

	Precision	Recall	Accuracy	F1-score
Decision Tree(B)	0.583	0.586	0.599	0.583
SVM	0.824	0.712	0.761	0.716
Random Forest	0.686	0.660	0.702	0.665
XGBoost	0.730	0.667	0.723	0.672

- Selected variables (SHAP values)

	Precision	Recall	Accuracy	F1-score
Decision Tree(B)	0.608	0.606	0.631	0.607
SVM	0.806	0.678	0.732	0.674
Random Forest	0.701	0.682	0.716	0.687
XGBoost	0.740	0.674	0.730	0.680

Conclusion

- The goal of the research was to predict people’s daily stress level from three different sets of data: 1) physical data; 2) User info data; 3) ESM data.

- When only physical data was used, it seems to be a bit difficult to predict stress.(around 50%)

- However, by including user info data and ESM data, the results provide evidence that individual daily stress can be predicted with about 70 percent accuracy.

- Lastly, Among many features, SHAP values were used to find important features. As a result, it created the best performance model with around 70 percent accuracy.

Limitation

- Stress data was transformed to binary variables from 7 points likert scales. As a result, It’s hard to check how much stress the user’s have.

- Instead of using complex deep learning models, this work only used somewhat simple machine learning models.

Code review

- **Hansoo(TA)**

1. **Feature extraction and Evaluation**
    - The difference between feature extraction and feature selection, as well as evaluation and research goals, is not clear.
    - It is recommended to study how to grasp the feature importance by SHAP value for features extracted through SHAP values by rotating the entire model as taught in class.
2. **Why you use those models: decision tree, SVM, and XGboost**
    - There is no explanation as to why this model was used.
    - The baseline model doesn't exist in your code and explanation

- **Panyu(peer)**
    - recommend that more documentation about parameters are given.
    - for full dataset since it takes a lot of time, you may save it as a csv file.
    - compare with the baseline model

Reference

[1] Bogomolov, Andrey, et al. "Daily stress recognition from mobile phone data, weather conditions and individual traits." Proceedings of the 22nd ACM international conference on Multimedia. 2014.
[2] H. Lu, D. Frauendorfer, M. Rabbi, M. S. Mast, G. T. Chittaranjan, A. T. Campbell, D. Gatica-Perez, and T. Choudhury. Stresssense: detecting stress in unconstrained acoustic environments using smartphones. In Proceedings of the 2012 ACM Conference on Ubiquitous Computing, UbiComp ’12, pages 351–360, New York, NY, USA, 2012. ACM.
[3] K. R. Scherer, D. Grandjean, T. Johnstone, G. Klasmeyer, and T. B¨anziger. Acoustic correlates of task load and stress. In INTERSPEECH, 2002.
[4] D. Giakoumis, A. Drosou, P. Cipresso, D. Tzovaras, G. Hassapis, A. Gaggioli, and G. Riva. Real-time monitoring of behavioural parameters related to psychological stress. Studies in health technology and informatics, 181:287, 2012.
[5] C. Duggan, P. Sham, A. Lee, C. Minne, and R. Murray. Neuroticism: a vulnerability marker for depression evidence from a family study. Journal of Affective Disorders, 35(3):139 – 143, 1995.
[6] https://github.com/soyoungCf/shap
[7] https://colab.research.google.com/drive/1lwJC3S7On43OKuaECi1CS5pH8u9pPNJV

THANK YOU