Ubiquitous and Mobile Computing
CS 528: Mobile Sensing

Abigail Albuquerque, Zaher Bunni,

Huibin Cui, Justin Luce, Justin Weintraub

Computer Science Dept.

Worcester Polytechnic Institute (WPI)

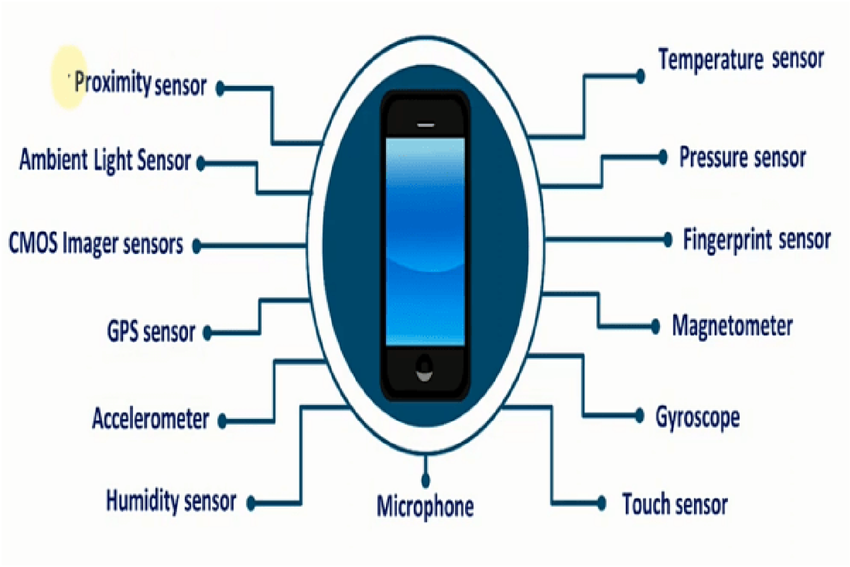
Presenting on: ***Predicting Job Performance Using Mobile Sensing***

S. Mirjafari et al.

Introduction

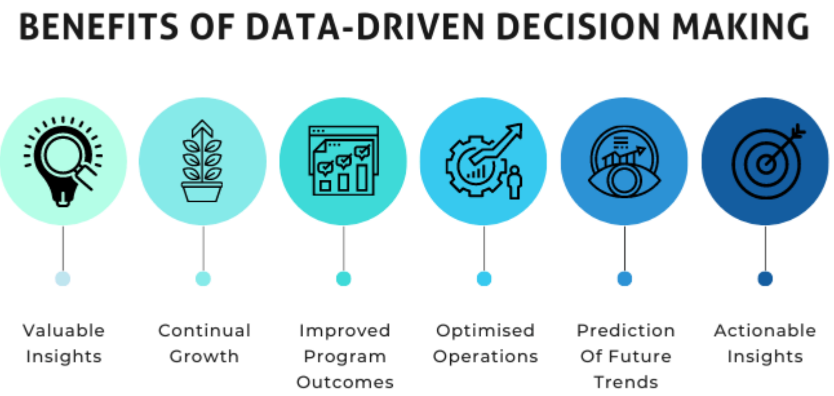
- With the advent of mobile devices, we're able to **inexpensively and continuously collect sensor data**

- The paper **hypothesizes** that **sensor data** collected from phones and wearables **can predict job performance**



Motivations and Vision

- Provide **data-driven insights** into job factors that lead to a high-performing day



- The vision is to provide a **scalable way to predict performance**
  - Users can improve their performance at job, no matter the job type

Related Work and Novel Approaches

- **Sensor data has been used in** the past
  - To predict cognitive load and human behavior
  - To explain worker's performance or predict worker's getting promoted

- **Novel approaches proposed in paper:**
  - Framework to extract meaningful features from sensing data
    - No longer need hand-crafted features
  - Gradient techniques to predict job performance

Prediction Types

The following surveys were given out:

- ITP (Individual task proficiency)
- IRB (In-role behavior)
- OCB (Organizational citizenship behavior)
  - (Organization culture)
- CWB (Counterproductive work behavior)

Changes in performance in relation to these categories were monitored.

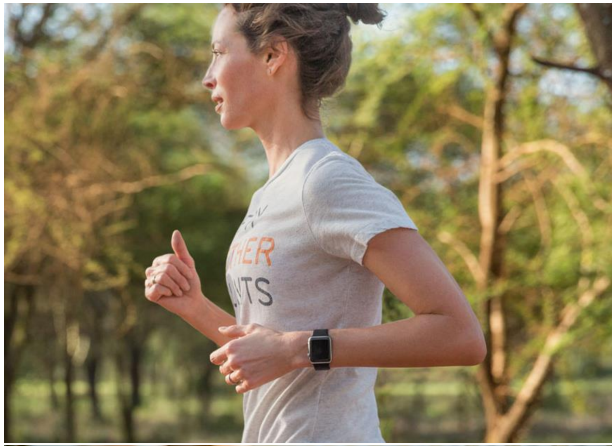
Dataset

- 298 Workers from various industries were given wristbands and an app to monitor them.
- Industries
  - Tech (44%)
  - Consulting (13%)
  - University (17%)
  - Misc (26%)
- 82% of participants under 40
- 48% women

Feature Set – Low Level Features

Low level features are raw/simple aggregations of sensor data.

- **Physical Activity**
- **Mobility**
- **Phone Usage**
- **Heart Rate**
- **Stress**
- **Sleep quality** (timing/duration)
- **Weather**



Feature Set – High Level Features

High level features in this domain require knowledge on different worker's circumstances and expertise in their domain.

- Generated from an unsupervised autoencoder
  - Deals with noise effectively and has high prediction performance

Model Design - Overview

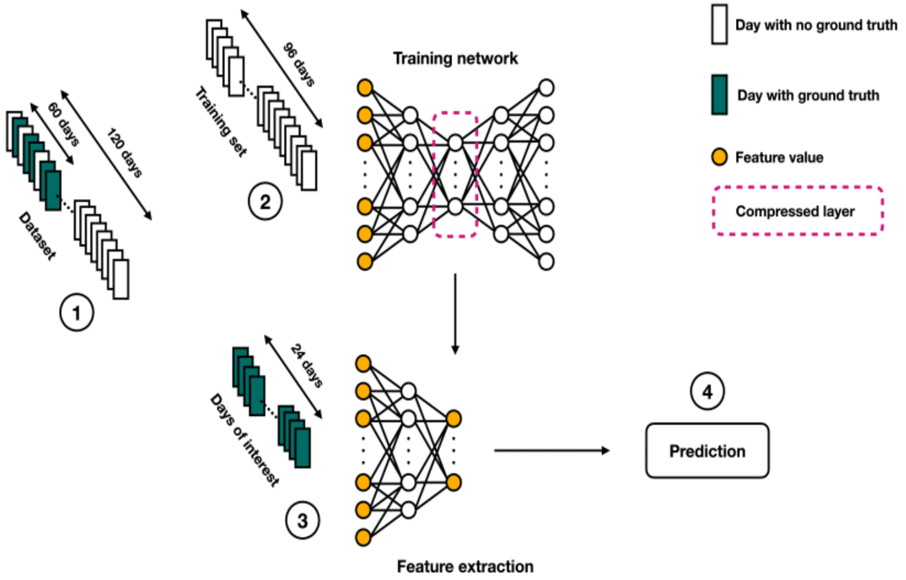
- Auto Encoder
  - To generate high level features to augment the lower level features for better prediction performance
  - The autoencoder is trained using different network architectures
  - The best architecture which gives the lowest MSE on the validation set is selected.
  - Lower level data are normalized to remove outliers
- XGBoost ML model
  - Trained and evaluated using the output of the auto encoder set to obtain final job performance prediction

Model Design – Auto Encoder

- Total data is 120 days of mobile sensing data per worker split into 80/20%

- An autoencoder is trained on the lower level features of 96 days (80%) with no job performance ground truth.

- Lower level features of 24 days with ground truth (20%) are fed into the trained encoder to generate higher level features.

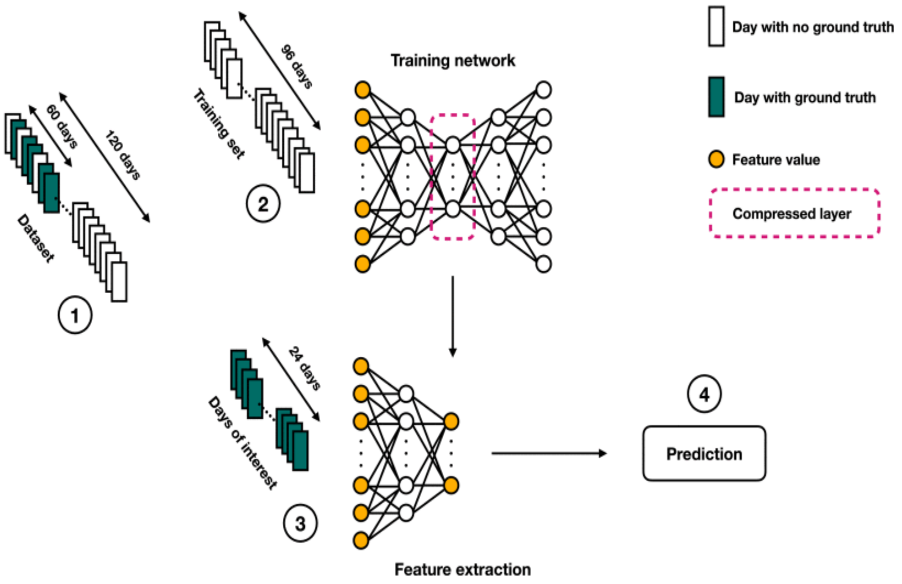


Model Design – Final classification

- Higher level feature values are extracted from the compressed layer for the final prediction task of job performance.

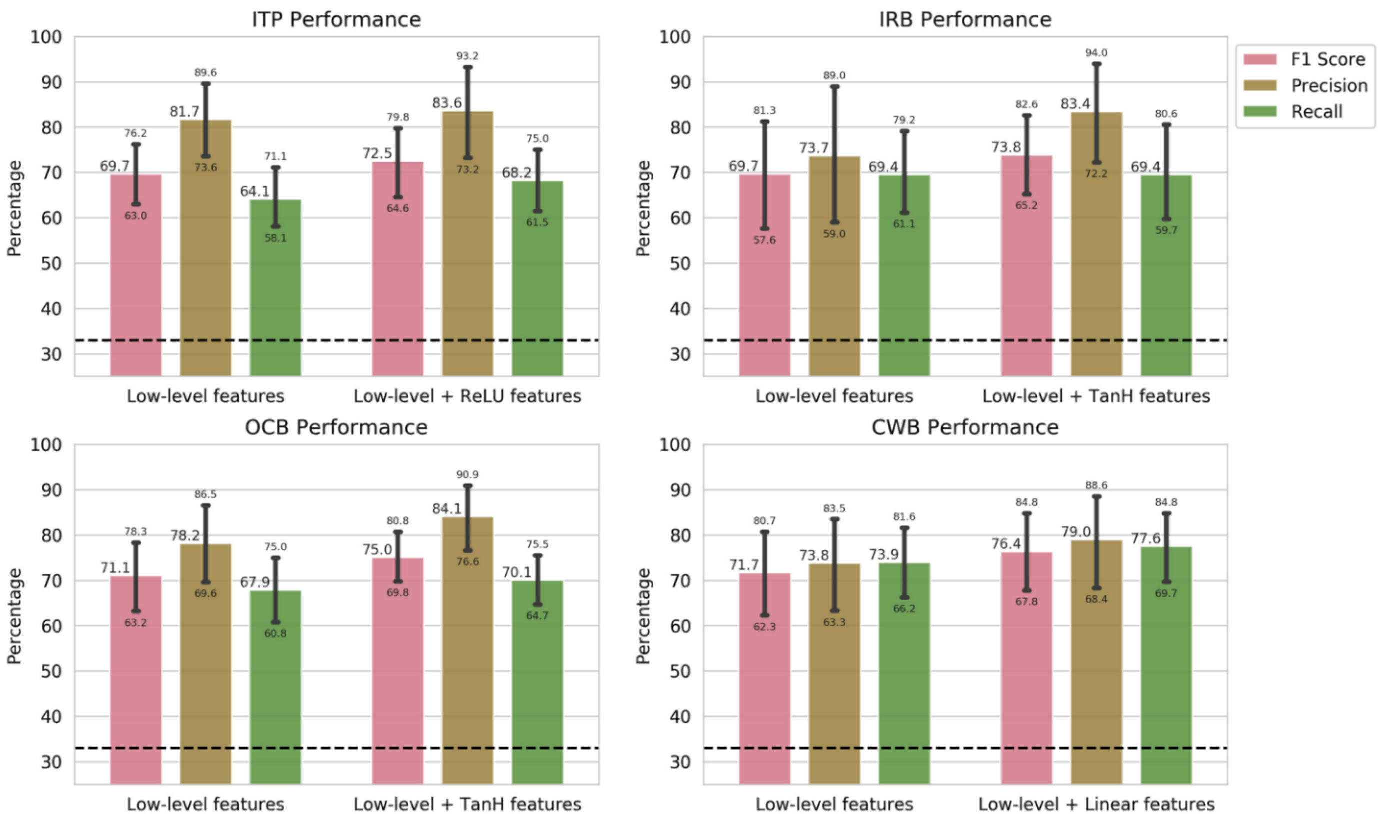
- Finally, split the prediction dataset with augmented feature set into the training and test sets.

- Train an XGBoost model on the training set and evaluate its performance on the test set.



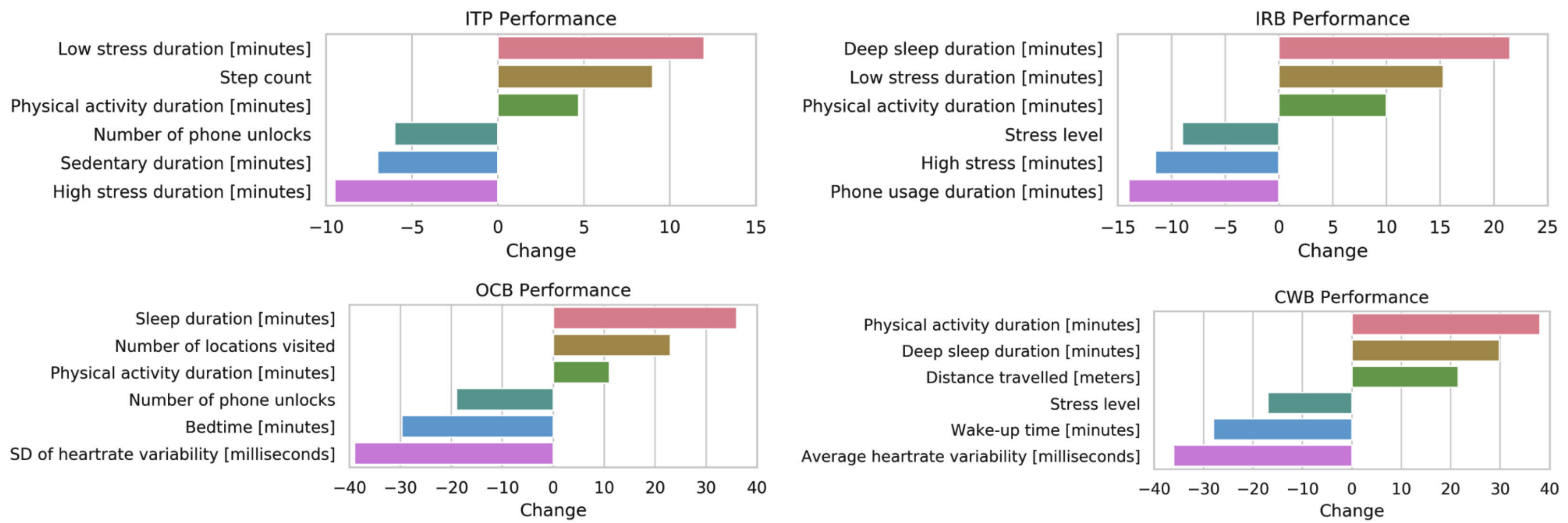
Results – Predictive Power

F1 has statistically significant results with predicted job performance in each metric



Results – Gradient Analysis

Probability gradients were used to see how variables need to change for higher work performance



Assumptions/Limitations

- The suggestions derived from model was not validated in empirical trials
- The model is not good for personalization
- Ethical and privacy concerns

Summary

- Context: Mobile sensing predict job performance.
- Approach:
  Collected mobile and wearable sensor data.
  Extracted lower-level features and transformed them using an autoencoder.
- Model: XGBoost used for prediction; achieved a 75% F1 score.
- Conclusion: Mobile sensing can effectively forecast job performance.

What did we learn?

- Efficacy of mobile sensing in performance analysis
- Autoencoder's role in scalable feature engineering
- Ethical implications of/in workplace sensing
- Practical use of machine learning in occupational settings

Future Work

- Investigate the broader capability of gradient analysis for mobile sensing problems
- Validate behavioral change suggestions through empirical trials and feedback
- Explore worker's data governance and ownership in workplace applications
- Implement and run models locally on smartphones to preserve user privacy

References

- S. Mirjafari et al., "Predicting Job Performance Using Mobile Sensing," in IEEE Pervasive Computing, vol. 20, no. 4, pp. 43-51, 1 Oct.-Dec. 2021