Toward End-to-end Prediction of Future Wellbeing using Deep Sensor Representation Learning

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interventions
Background

• Sensors capture high-resolutional body signals.

• Well-established methods are based on hand-crafted features.

• Deep learning performed well w/o feature engineering.
Dataset facts

• 2013 – 2017, New England
• 252 undergrads
• 6981 days
• 6 ~ 90 days each
Sensor data: “X”

- Q-sensor
- 8 Hz
- 3 channels

- Skin conductance
- Skin temperature
- Acceleration
Survey labels: “y”

- Email survey
- Twice a day
- 5 self-report scores
Old method: Prediction with hand-crafted features
Old method: Prediction with hand-crafted features
Representation learning (RL) framework: learn features from raw data

Methods
RL framework: train feature extractor
RL framework: predict end-to-end

Raw sensor data -> Auto-feature -> Inference model -> Prediction

Methods
Settings

• Wellbeing prediction: regression
• Today’s 24-hour data --> tomorrow evening’s wellbeing
• Evaluation: mean absolute error (MAE)
• Cross validation
Fig. 3. Wellbeing Prediction Performance Comparison: 8 Hz vs 1 Hz raw data with 8-dimensional features. The shaded areas are ± corresponding standard deviation.
Auto vs crafted features

<table>
<thead>
<tr>
<th>Feature method</th>
<th>Auto-Learned features (8Hz, dim=8)</th>
<th>Crafted features (dim=172)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alertness±(SD)</td>
<td>15.5 (0.5)</td>
<td>16.8 (0.4)</td>
</tr>
<tr>
<td>Happiness±(SD)</td>
<td>14.6 (0.3)</td>
<td>16.4 (0.3)</td>
</tr>
<tr>
<td>Energy±(SD)</td>
<td>14.8 (0.2)</td>
<td>16.1 (0.2)</td>
</tr>
<tr>
<td>Health±(SD)</td>
<td>14.3 (0.5)</td>
<td>15.8 (0.3)</td>
</tr>
<tr>
<td>Calmness±(SD)</td>
<td>15.7 (0.3)</td>
<td>16.7 (0.3)</td>
</tr>
</tbody>
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Auto features: smaller dimension & errors!
Conclusions

• Feature dimensionality does not have a strong impact on prediction performance;
• Raw data resolution has significant influence on prediction performance;
• Using auto features can produce higher prediction accuracy than using crafted features.
Moving forward

• Other AE structures: temporal information
• Relaxed personalization strategy: predict unseen participants
• Interpretability of auto features: correlation, localization, activation map, etc.
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References