Using Artificial Intelligence to Classify Activities Captured in Smart Homes

Master’s Thesis
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TU Graz

Outline

- Introduction
- State of the Art Solutions
- Data Set
- Chosen Classification Algorithms
- Evaluation
- Conclusion

Introduction

SmartLab in the University of Jaén

Binary sensor

proximity sensor

UJAmI SmartLab photos taken from Espinilla, Medina, and Nugent, 2018 (CC BY-NC 4.0).

Problem Statement

Recognise human activities based on sensor data in order to automate assistance in a smart home

Example Use Case:

- Assistance with coordination and scheduling
  - Economic heat management

Research Question

To which extent can artificial intelligence help to classify activities captured in smart environments?

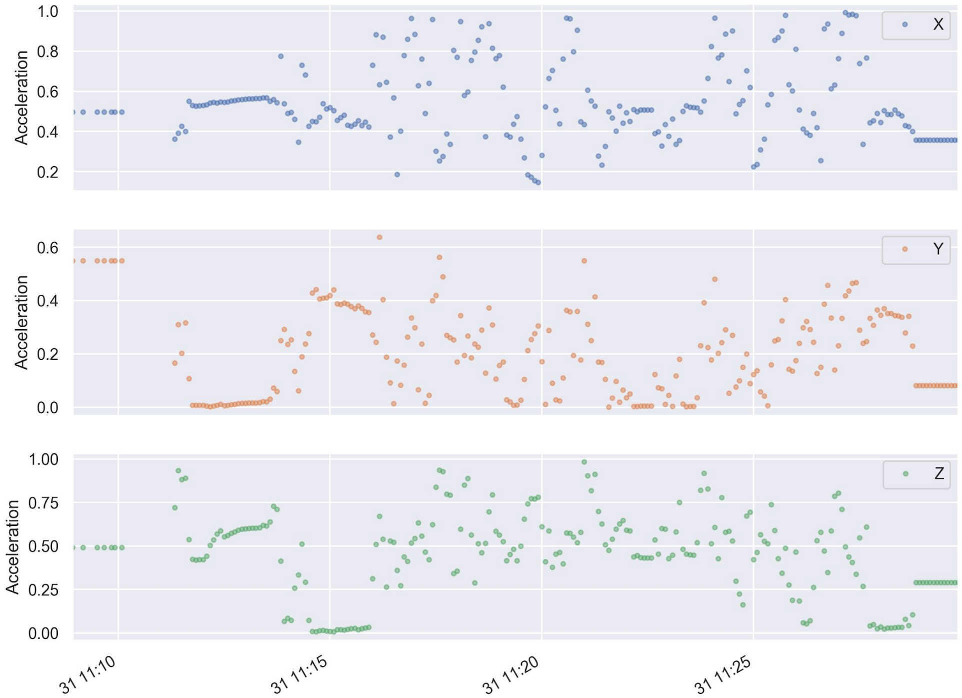
Time Series Data

Definition: series of ordered observations collected sequentially over time

Univariate: 1 random variable

Multivariate: multiple random variables

Acceleration Data of Smart Watch
(Morning Segment 2017-20-31)



Multivariate Time Series Classification

- Supervised learning
  - **Labelled data set:** N samples $\{(x_1, y_1), \ldots, (x_N, y_N)\}$, $x \in X$ (inputs), $y \in Y$ (output data)
  - **Goal:** find $f : X \mapsto Y$
  - **Training:** learn how to predict the class label from viewing labelled data points

- Input data subsets
  - **Training set**
  - **Validation set** (optional)
  - **Testing set**

State of the Art Solutions

Solutions by Scientists using the same Data Set

Author(s)	Algorithm	Testing Accuracy
Salomón and Tîrnăucă, 2018	weighted finite automata	91%
Karvonen and Kleyko, 2018	expert system similar to a finite state machine	81%
Ceron, López and Eskofier, 2018	J48, Ib1, support vector machines, random forest, AdaBoostM1, bagging	63% (AdaBoostM1)
Jiménez and Seco, 2018	multi-event naive Bayes classifier	61%
Razzaq et al., 2018	filtered classifier (Weka tool)	47%
Lago and Inoue, 2018	hybrid model (hidden markov chain and logic model)	45%

Solutions for Sensor-based Human Activity Recognition

- Hammerla and Plötz, 2016: explored several deep learning algorithms: feedforward networks, CNNs, LSTMs
    - Best performance: LSTMs

Data Set

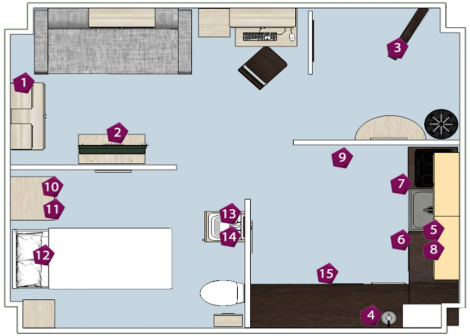
UCAmI Cup 2018 Data Set

- **Location:** SmartLab of the University of Jaén
- **Classes:** 24 human activities of daily living
  - Mutually exclusive
  - Single resident
- **Training data set:** 7 days of recordings
- **Testing data set:** 3 days of recordings

Features

1. **Event streams** of binary sensors
2. **Spatial data** from intelligent floor
3. **Proximity data** between smart watch and bluetooth beacons
4. **Acceleration data** from smart watch

Proximity sensors



1-Book
2-TV Controller
3-Entrance door
4-Medicine box
5-Food cupboard
6-Fridge
7-Pot drawer
8-Water bottle
9-Garbage can
10-Wardrobe door
11-Pyjamas drawer
12-Bed
13-Bathroom tap
14-Toothbrush
15-Laundry basket

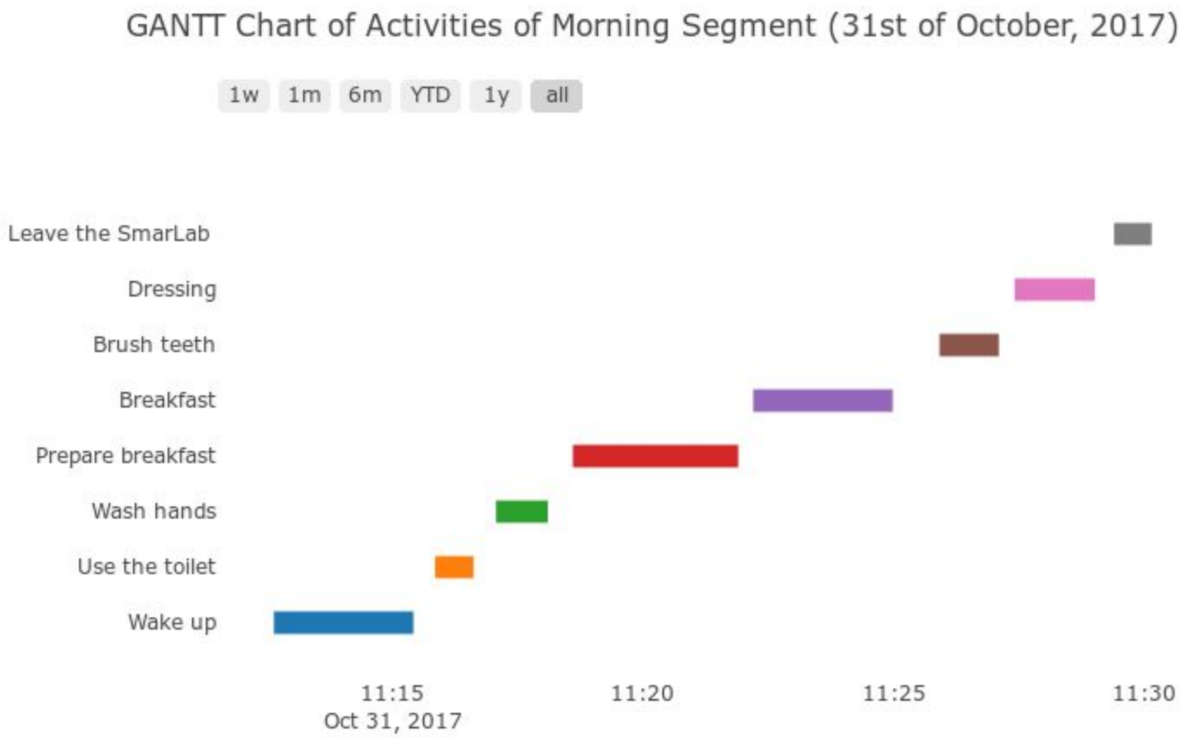
Intelligent floor tiles

UJAmI SmartLab layout images taken from Espinilla, Medina, and Nugent, 2018 (CC BY-NC 4.0).

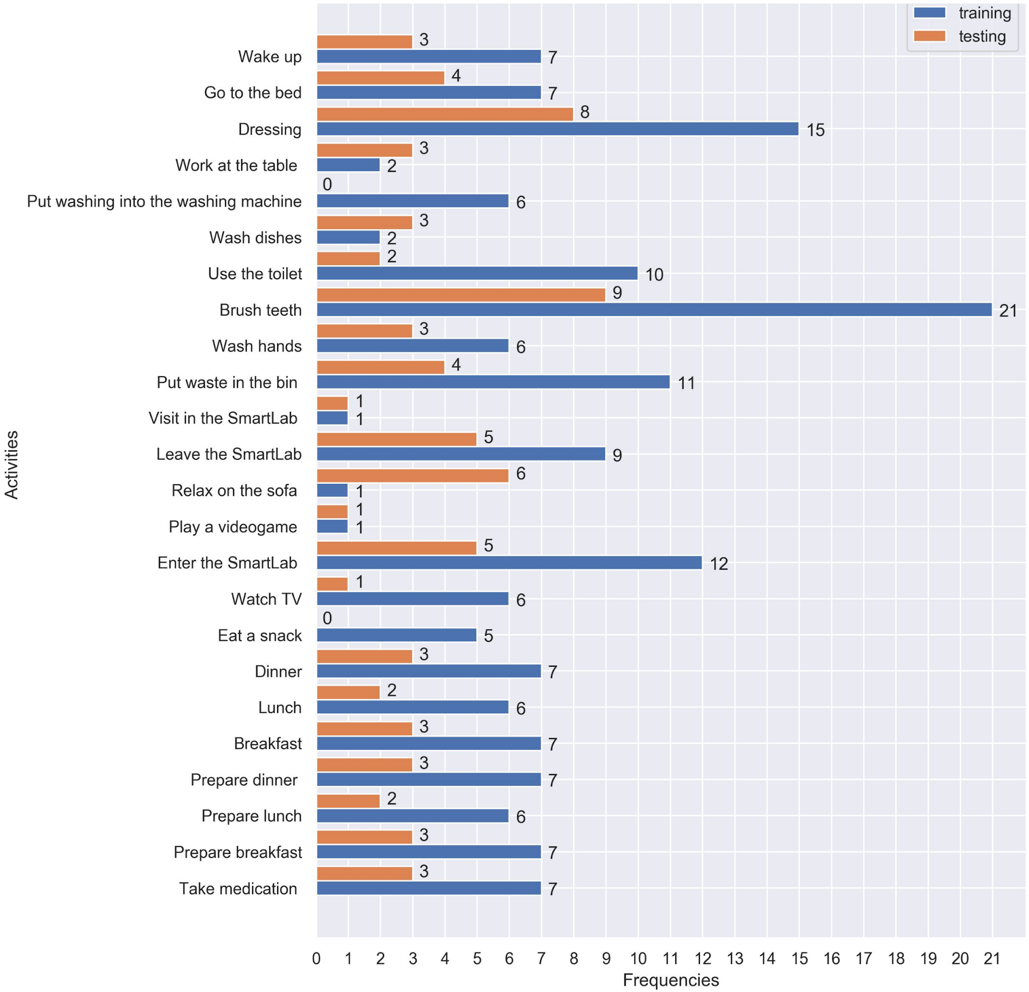
Preprocessing

- Aggregation of sensor data into 5 second slots as samples
- **Training samples:** 5.344
- **Testing samples:** 2.920

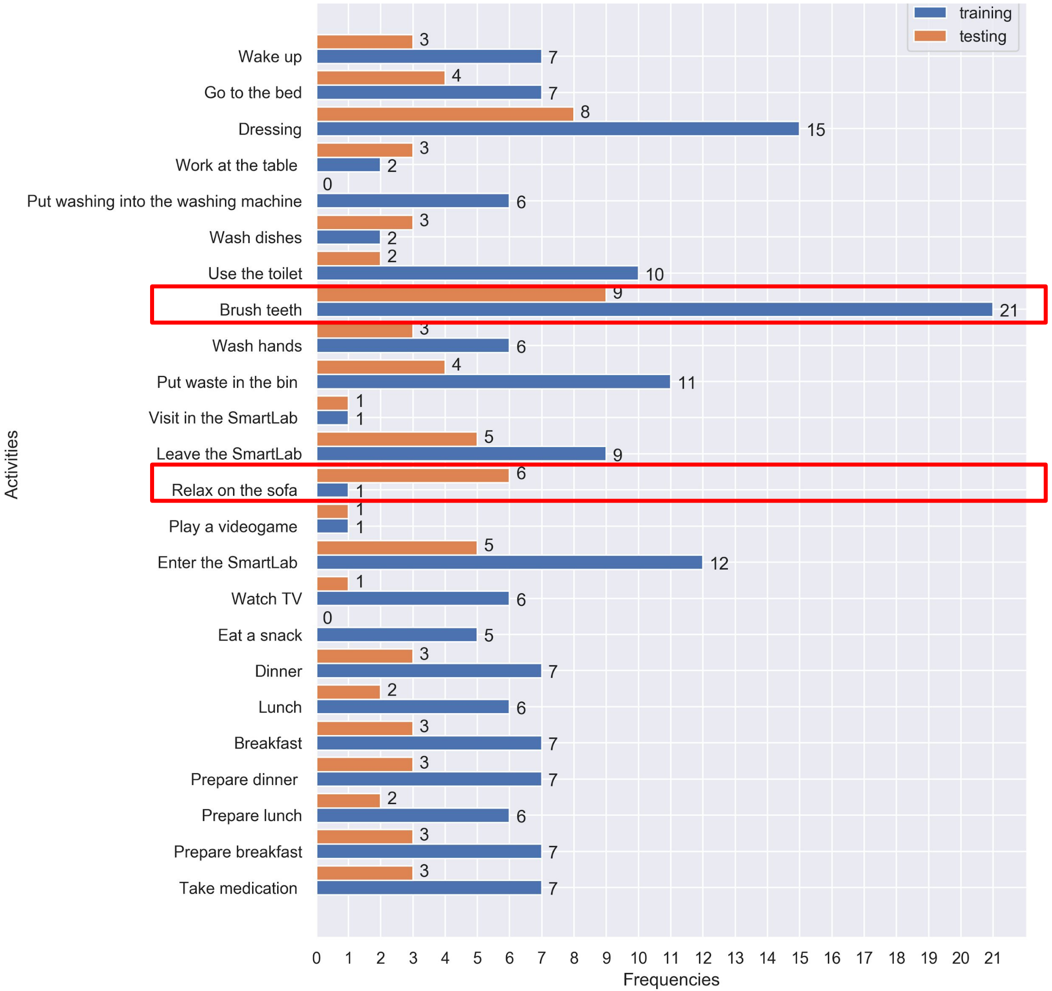
24 Classes: Human Activities of Daily Living



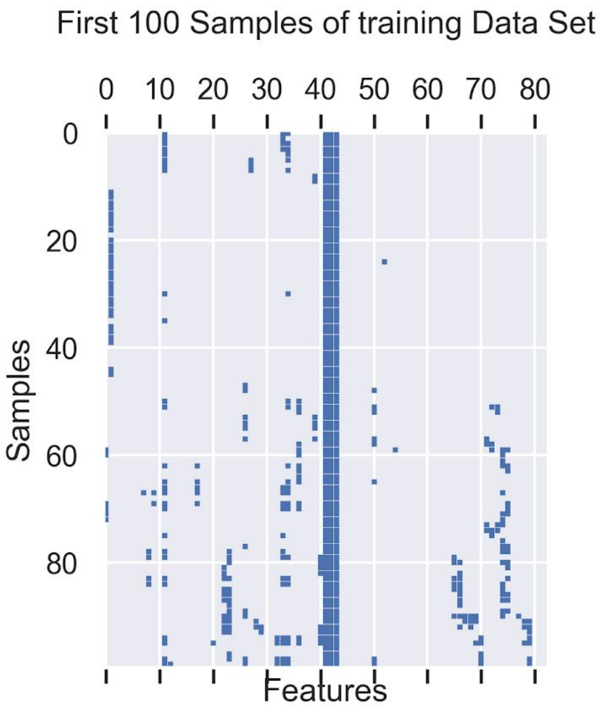
Frequencies of Activities in Data Set



Frequencies of Activities in Data Set



Sparseness of Input Data Set



Chosen Classification Algorithms

Chosen Classification Algorithms

- Standard Classification Algorithms (scikit-learn)
  - Non-linear classifiers
    - Logistic Regression
    - Gaussian Naive Bayes
    - Decision Tree
    - Support Vector Machine
    - K-Nearest Neighbors
  - Ensemble algorithms
    - Random Forest
    - Bagging
    - Extra Tree
    - Gradient Boosting
- Deep Learning Algorithms
  - Multilayer Perceptron (MLP from scikit-learn)
  - Long Short-Term Memory Neural Network (LSTM from Keras)
  - Convolutional Neural Network (CNN from Keras)

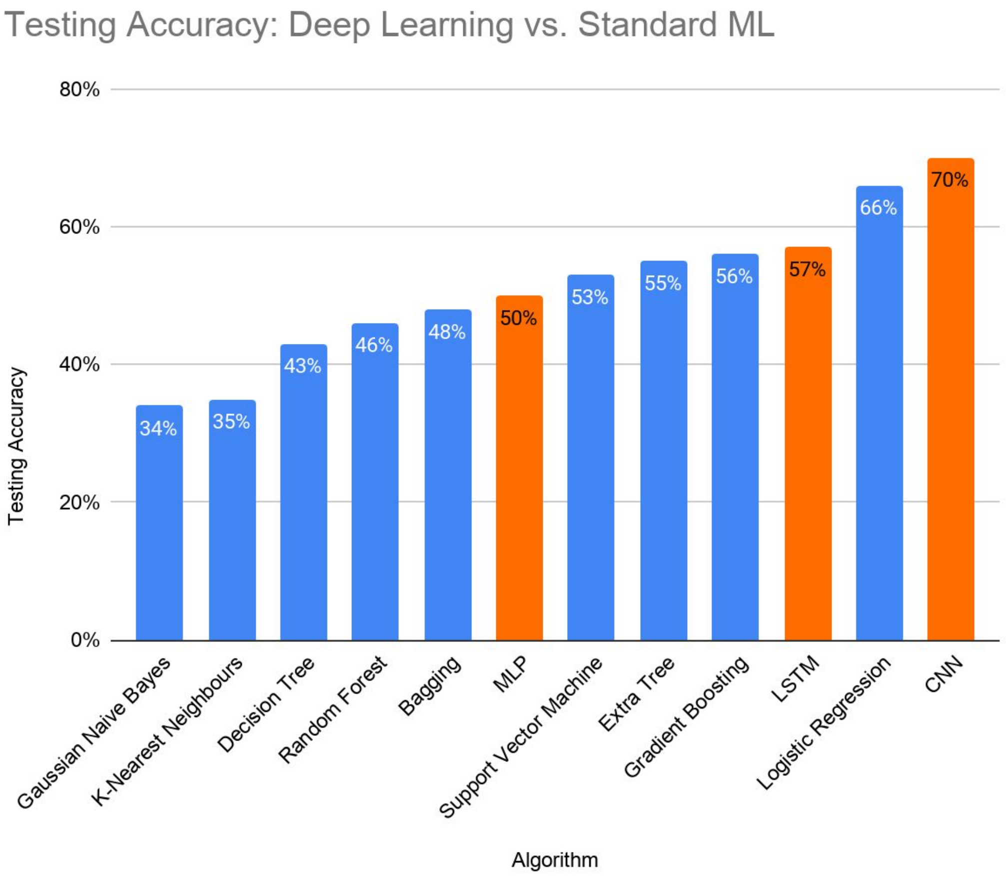
Hyperparameter Tuning

- Hyperparameter optimisation
  - Logistic Regression: grid search
  - CNN: Talos (automated hyperparameter tuning tool)

- Battling Overfitting
  - Architecture changes (number of layers and neurons)
  - Regularisation
    - Dropout
    - L2
  - Early stopping

Evaluation

Results


Testing Accuracy: Deep Learning vs. Standard ML
Testing Accuracy
Algorithm
80%
60%
40%
20%
0%
34%
35%
43%
46%
48%
50%
53%
55%
56%
57%
66%
70%
Gaussian Naive Bayes
K-Nearest Neighbours
Decision Tree
Random Forest
Bagging
MLP
Support Vector Machine
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Gradient Boosting
LSTM
Logistic Regression
CNN

Solutions by Scientists using the same Data Set

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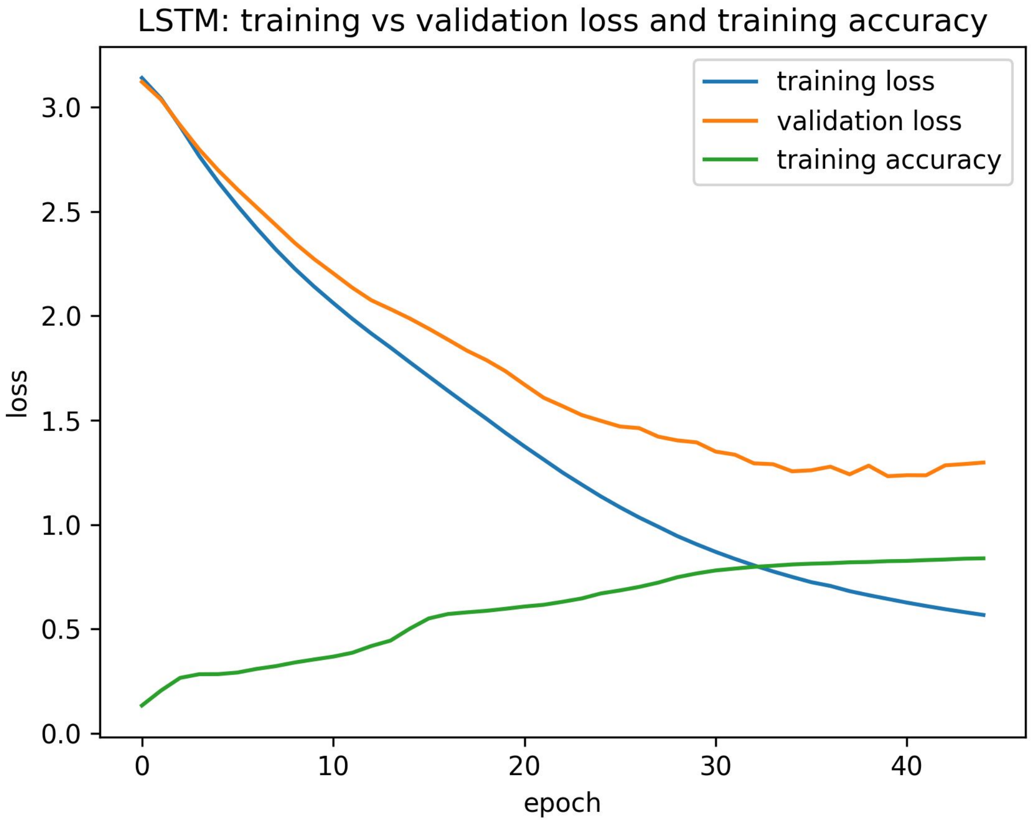
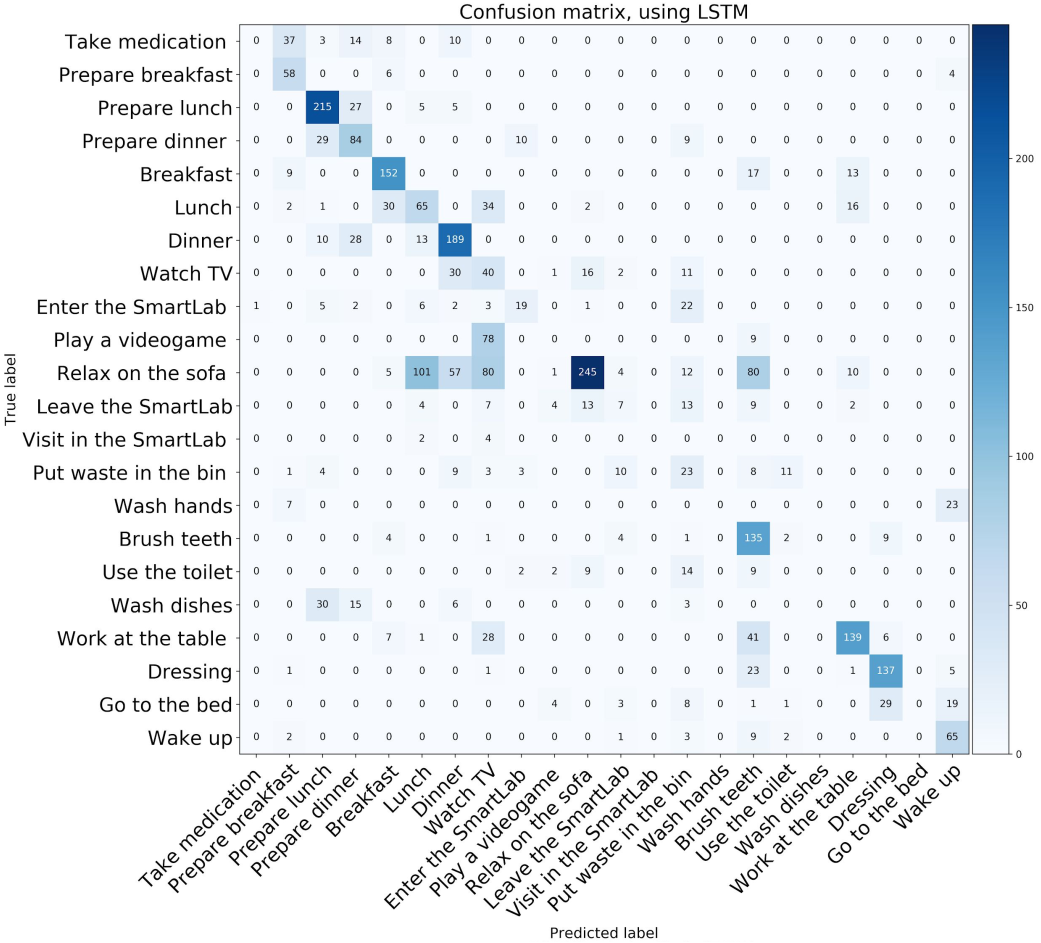
LSTM

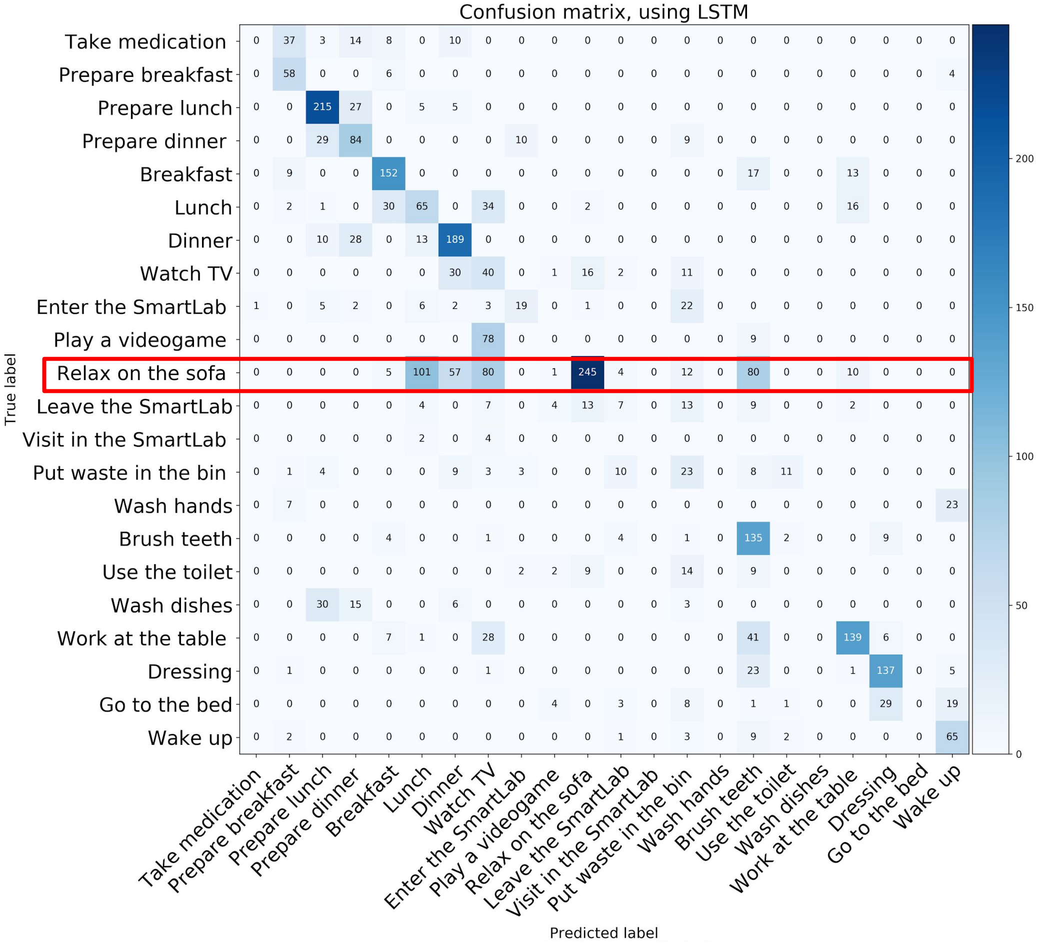
Testing accuracy: 57%



LSTM Confusion Matrix



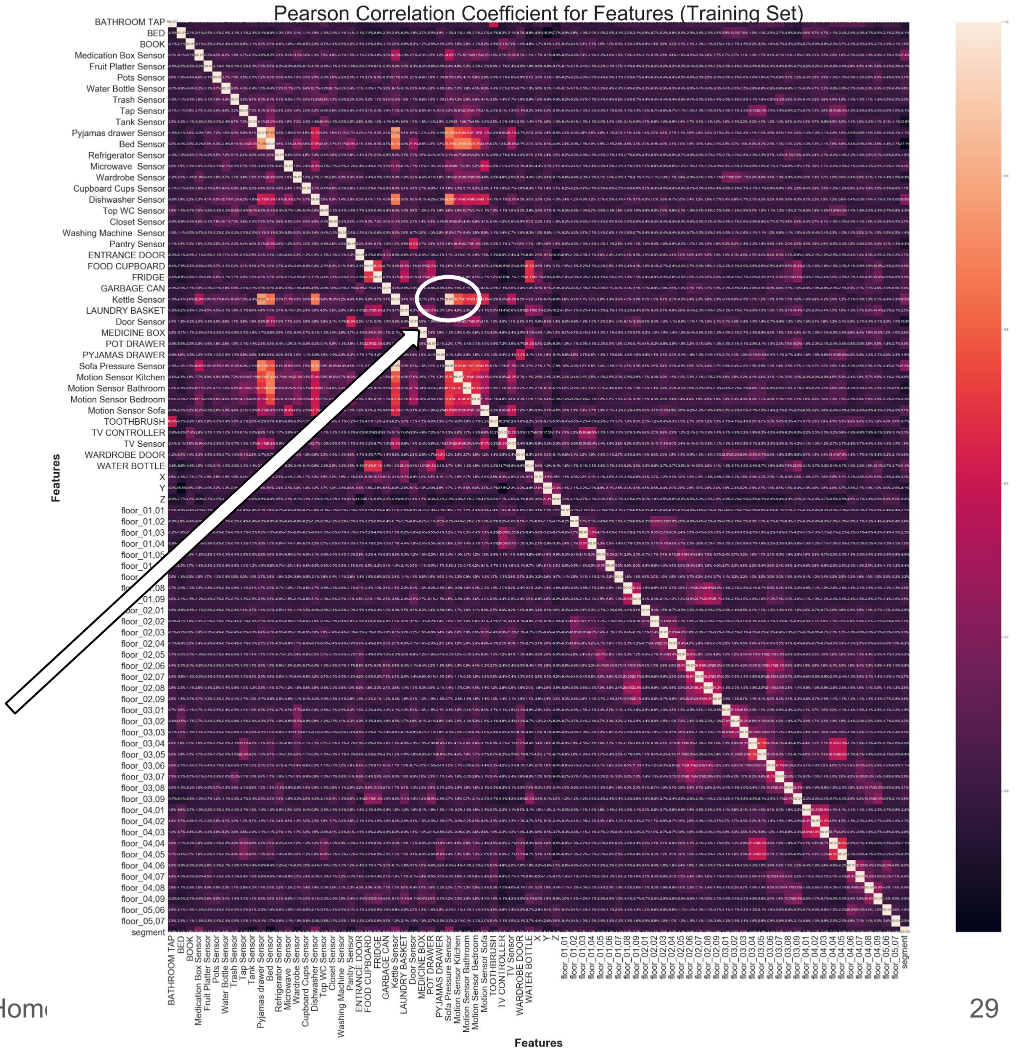
LSTM Confusion Matrix



Pearson Correlation

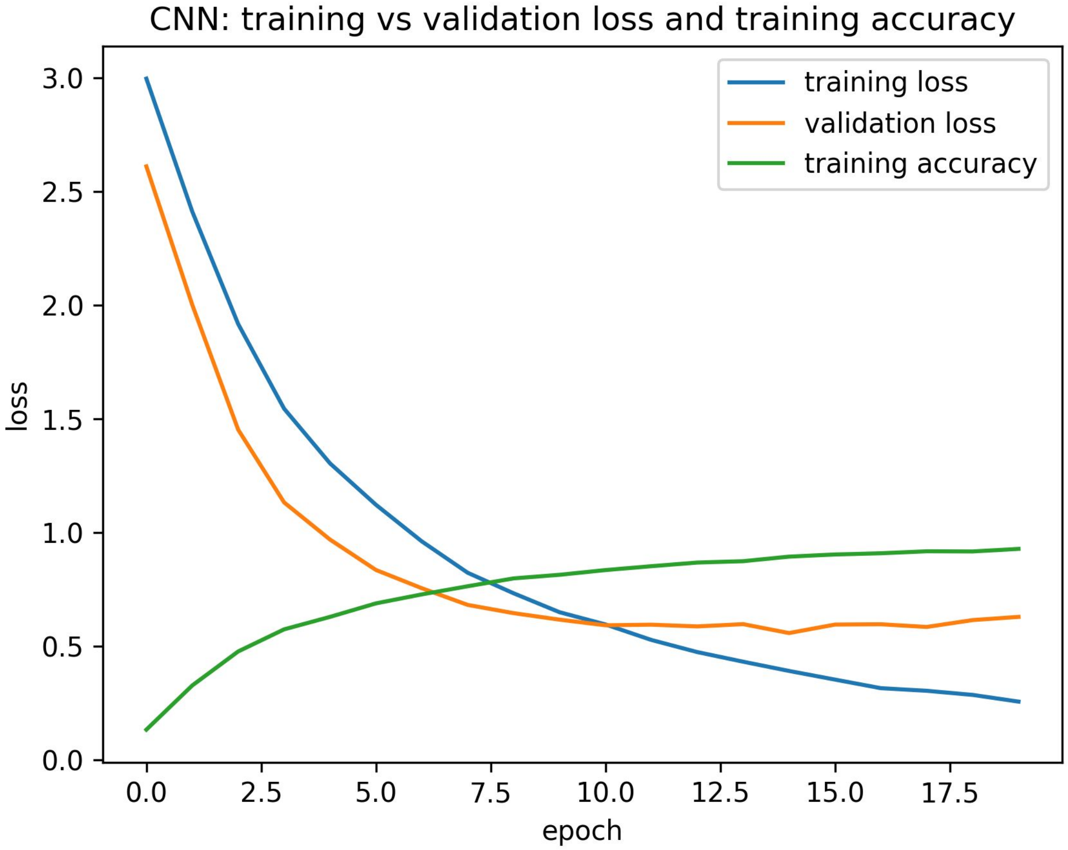
Definition: quantifies the relationship between two features (correlation or linear independence)

High association of **92.6%** between **sofa pressure sensor** and **proximity sensor of the kettle**

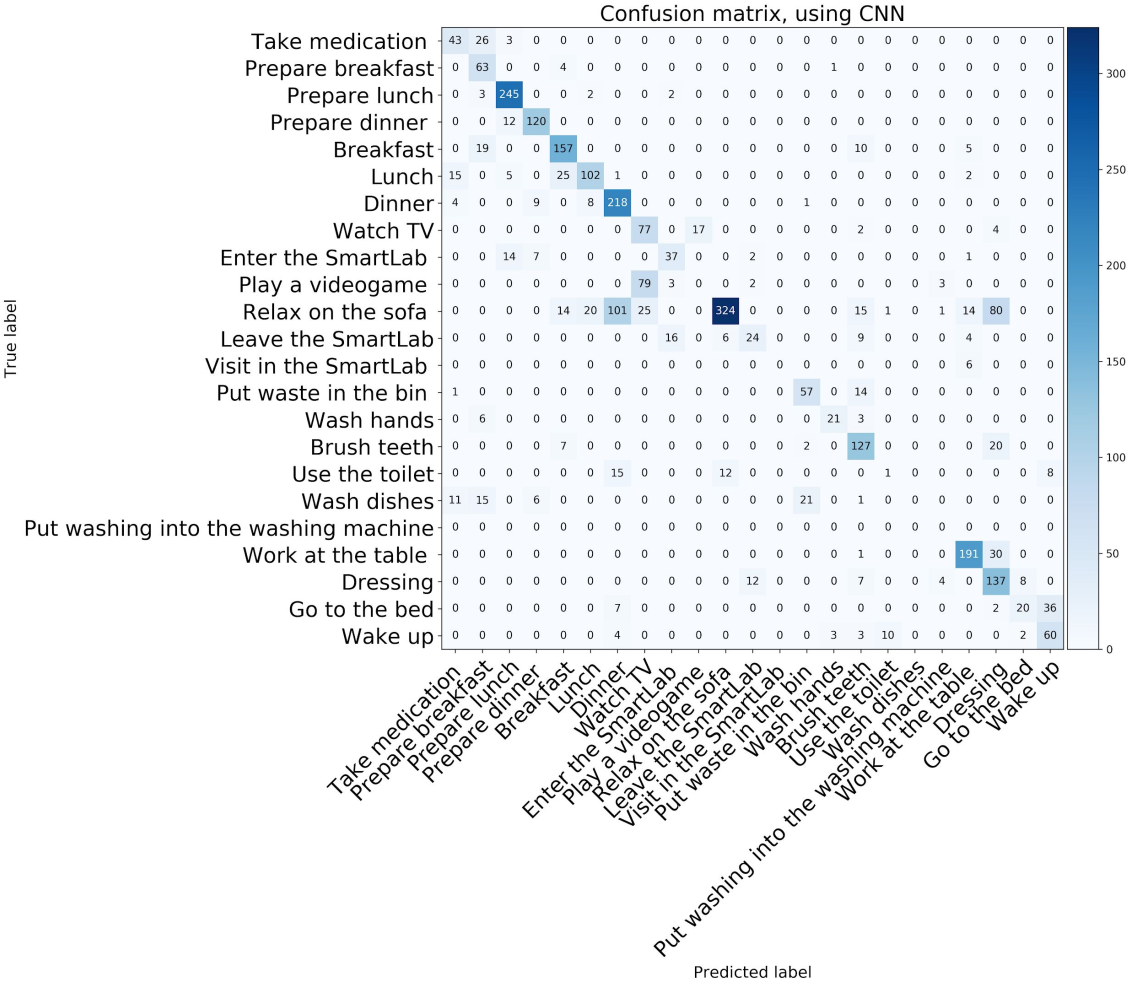


CNN

Testing accuracy: 70%

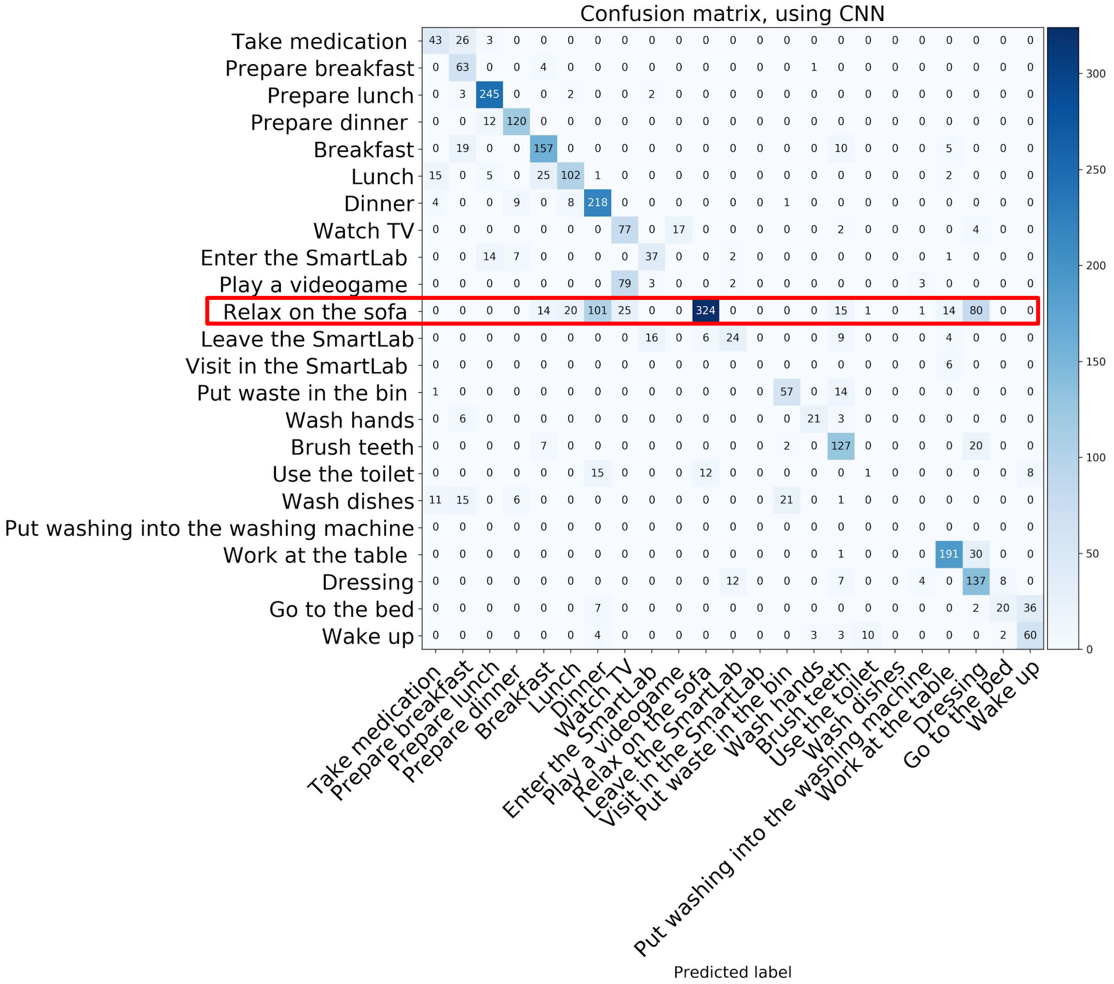


CNN Confusion Matrix



True label \ Predicted label	Take medication	Prepare breakfast	Prepare lunch	Prepare dinner	Breakfast	Lunch	Dinner	Watch TV	Enter the SmartLab	Play a videogame	Relax on the sofa	Leave the SmartLab	Visit in the SmartLab	Put waste in the bin	Wash hands	Brush teeth	Use the toilet	Wash dishes	Put washing into the washing machine	Work at the table	Dressing	Go to the bed	Wake up
Take medication	43	26	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Prepare breakfast	0	63	0	0	4	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
Prepare lunch	0	3	245	0	0	2	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Prepare dinner	0	0	12	120	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Breakfast	0	19	0	0	157	0	0	0	0	0	0	0	0	0	0	10	0	0	0	5	0	0	0
Lunch	15	0	5	0	25	102	1	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Dinner	4	0	0	9	0	8	218	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
Watch TV	0	0	0	0	0	0	0	77	0	17	0	0	0	0	0	2	0	0	0	0	4	0	0
Enter the SmartLab	0	0	14	7	0	0	0	0	37	0	0	2	0	0	0	0	0	0	0	1	0	0	0
Play a videogame	0	0	0	0	0	0	0	79	3	0	0	2	0	0	0	0	0	0	3	0	0	0	0
Relax on the sofa	0	0	0	0	14	20	101	25	0	0	324	0	0	0	0	15	1	0	1	14	80	0	0
Leave the SmartLab	0	0	0	0	0	0	0	0	16	0	6	24	0	0	0	9	0	0	0	4	0	0	0
Visit in the SmartLab	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0
Put waste in the bin	1	0	0	0	0	0	0	0	0	0	0	0	0	57	0	14	0	0	0	0	0	0	0
Wash hands	0	6	0	0	0	0	0	0	0	0	0	0	0	0	21	3	0	0	0	0	0	0	0
Brush teeth	0	0	0	0	7	0	0	0	0	0	0	0	0	2	0	127	0	0	0	0	20	0	0
Use the toilet	0	0	0	0	0	0	15	0	0	0	12	0	0	0	0	0	1	0	0	0	0	0	8
Wash dishes	11	15	0	6	0	0	0	0	0	0	0	0	0	21	0	1	0	0	0	0	0	0	0
Put washing into the washing machine	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Work at the table	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	191	30	0	0
Dressing	0	0	0	0	0	0	0	0	0	0	0	12	0	0	0	7	0	0	4	0	137	8	0
Go to the bed	0	0	0	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	2	20	36
Wake up	0	0	0	0	0	0	4	0	0	0	0	0	0	0	3	3	10	0	0	0	0	2	60

CNN Confusion Matrix



Conclusion

Research Question

To which extend can artificial intelligence help to classify activities captured in smart environments?

Conclusion

- **LSTM** not as performant as suggested in literature
- **CNN** and **logistic regression** highest accuracy, but outperformed by **finite state machines**

- Possible reasons for weak performance
  - Sensor data set problematic
    - Small and unbalanced
    - Noise and errors
    - Extreme sparseness

Conclusion

- Finite state machine solution
  - **Advantage:** can classify without having seen a training sample
  - **Disadvantage:** faulty sensors lead to long periods of misclassification

Thanks for listening!

References

Ceron, Jesus, Diego López, and Bjoern Eskofier (Dec. 2018). "Human Activity Recognition Using Binary Sensors, BLE Beacons, an Intelligent Floor and Acceleration Data: A Machine Learning Approach." In: The 12th International Conference on Ubiquitous Computing and Ambient Intelligence (UCAmI 2018). Vol. 2. 19 1265. Punta Cana, Dominican Republic: MDPI. doi: 10.3390/proceedings2191265

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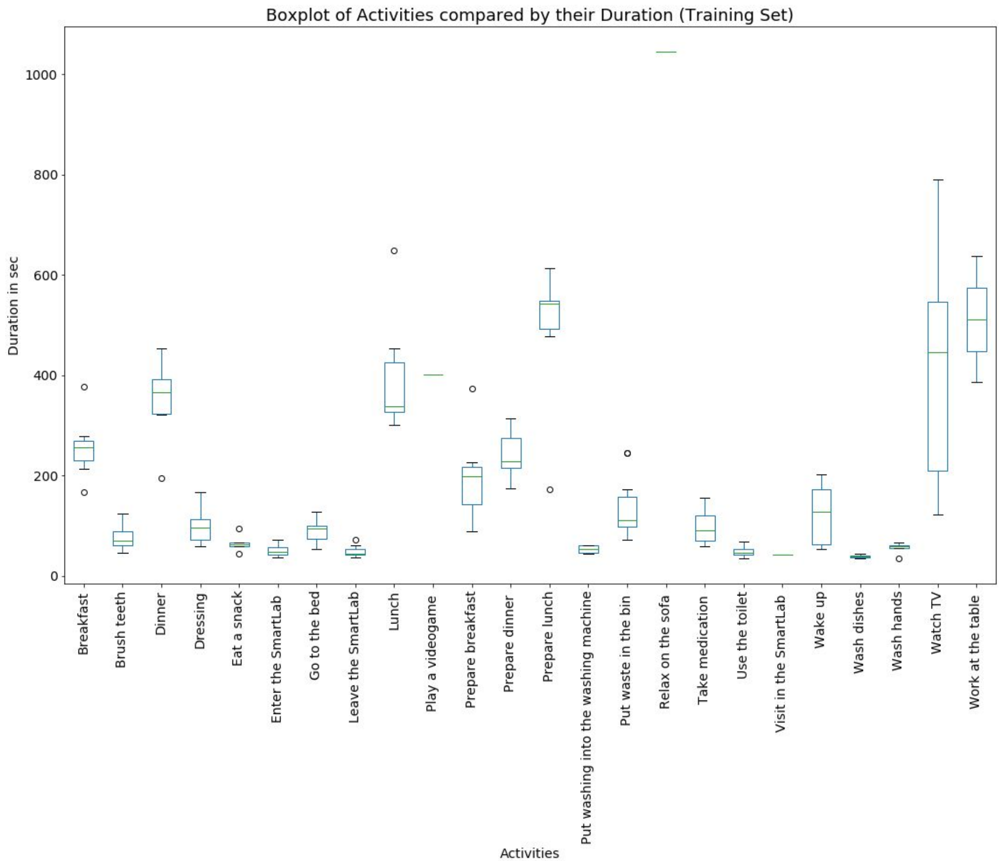
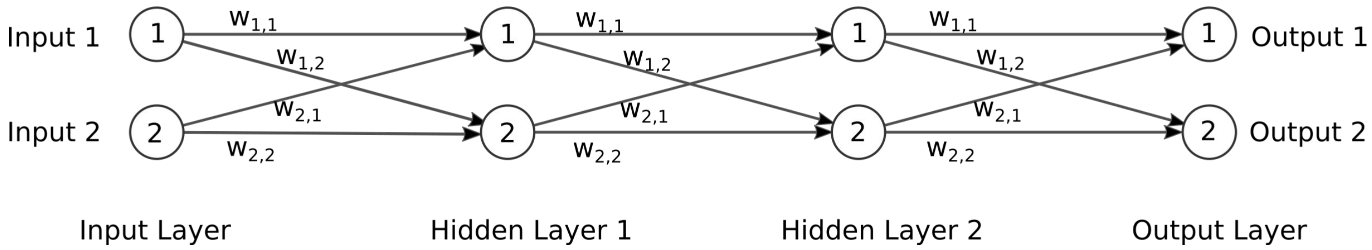
Appendix

Durations of Activities

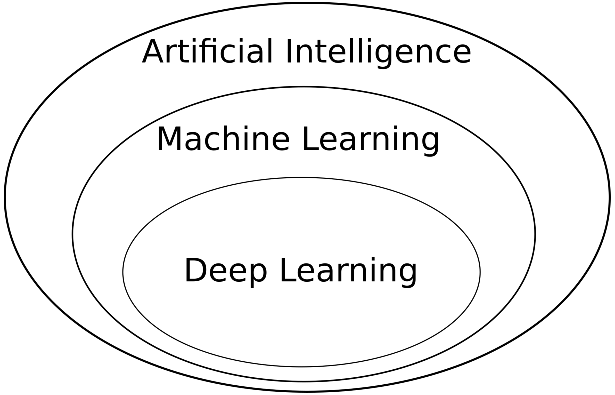


Deep Learning with Neural Networks



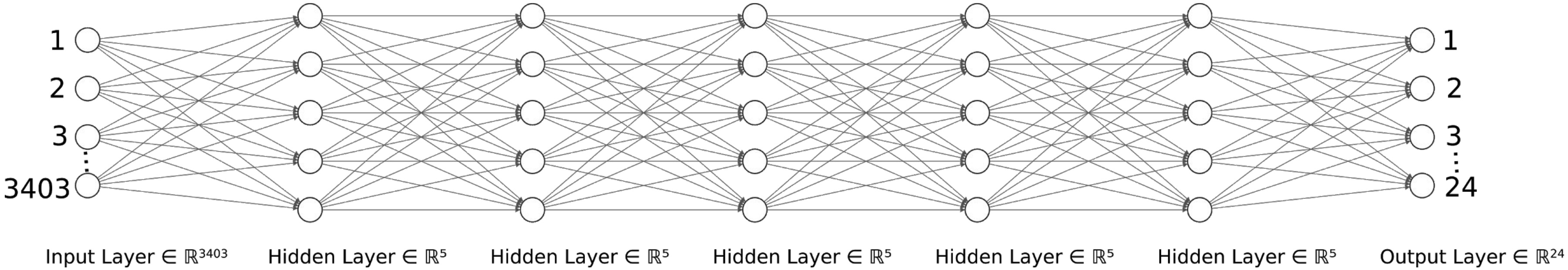
Deep Learning

- > 1 hidden layer
- complex ways of connecting layers
- automatic feature extraction

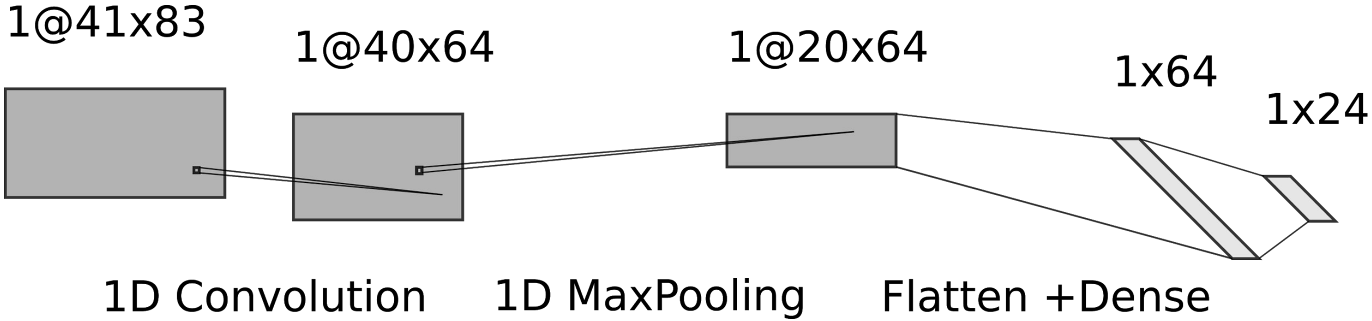


MLP Architecture

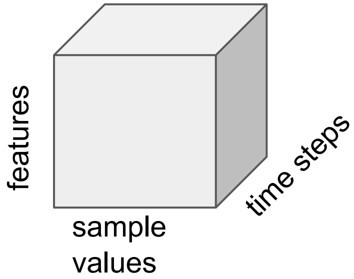
5 layers with each 5 neurons

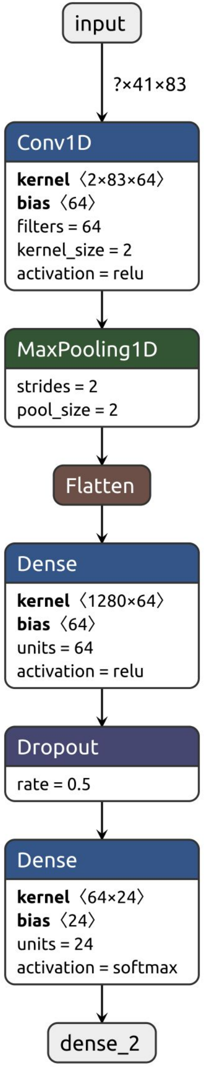


CNN Architecture

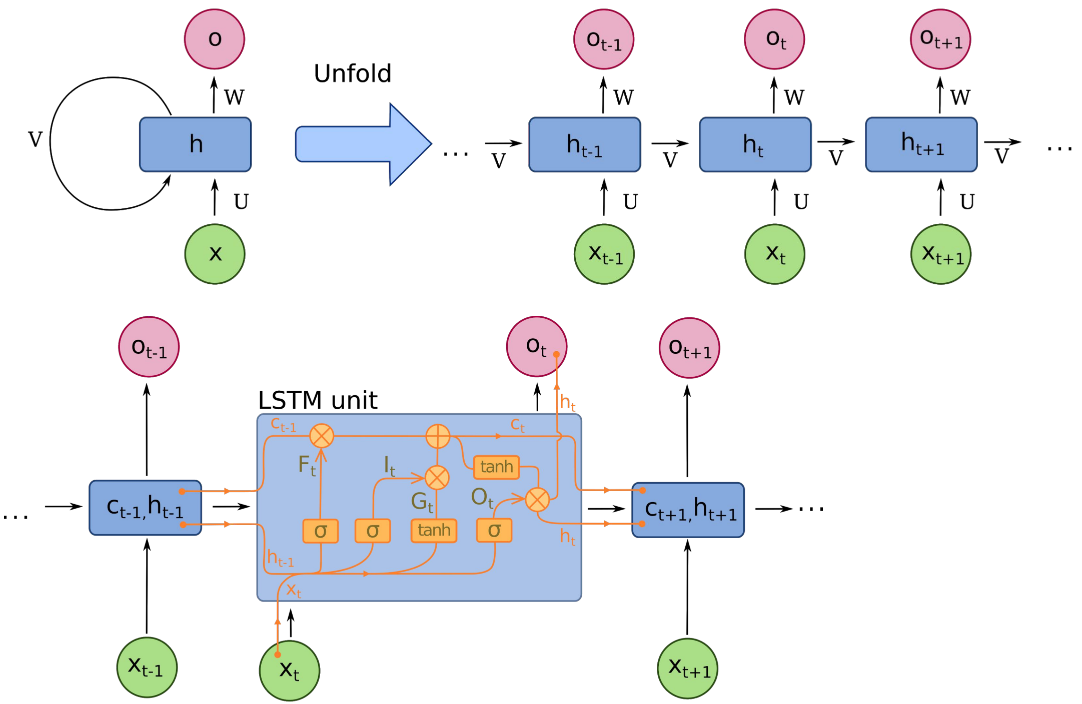


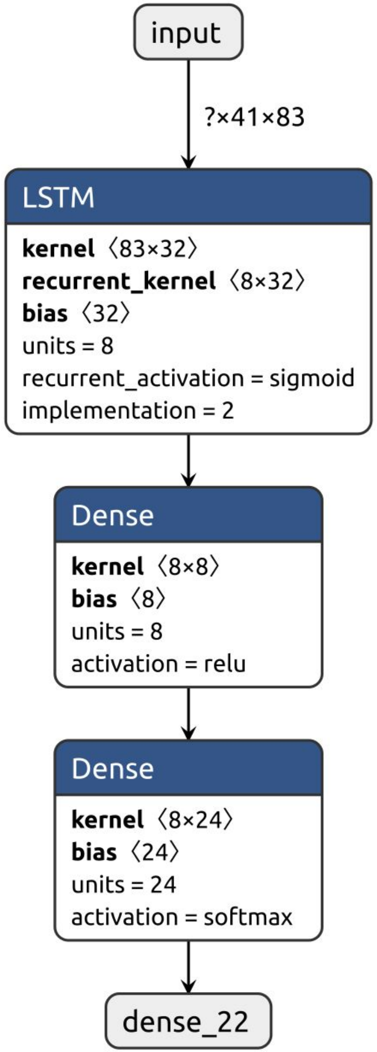
Input tensor:



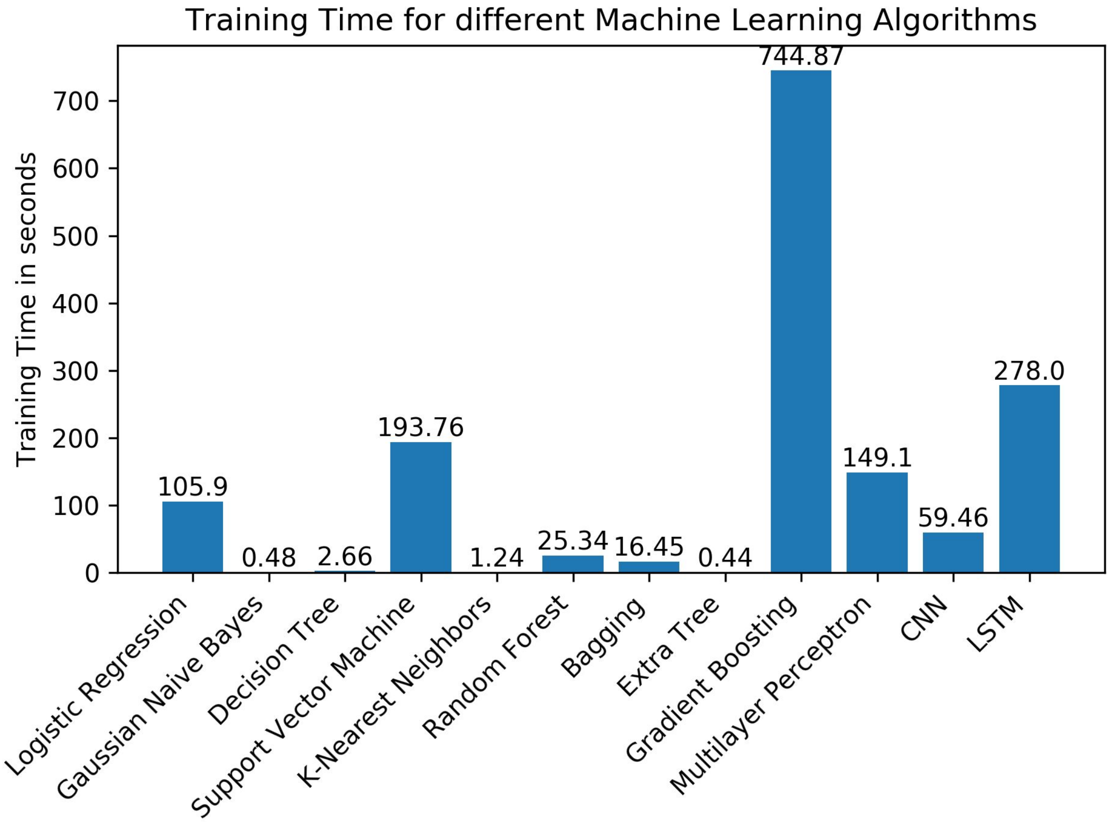


LSTM Architecture

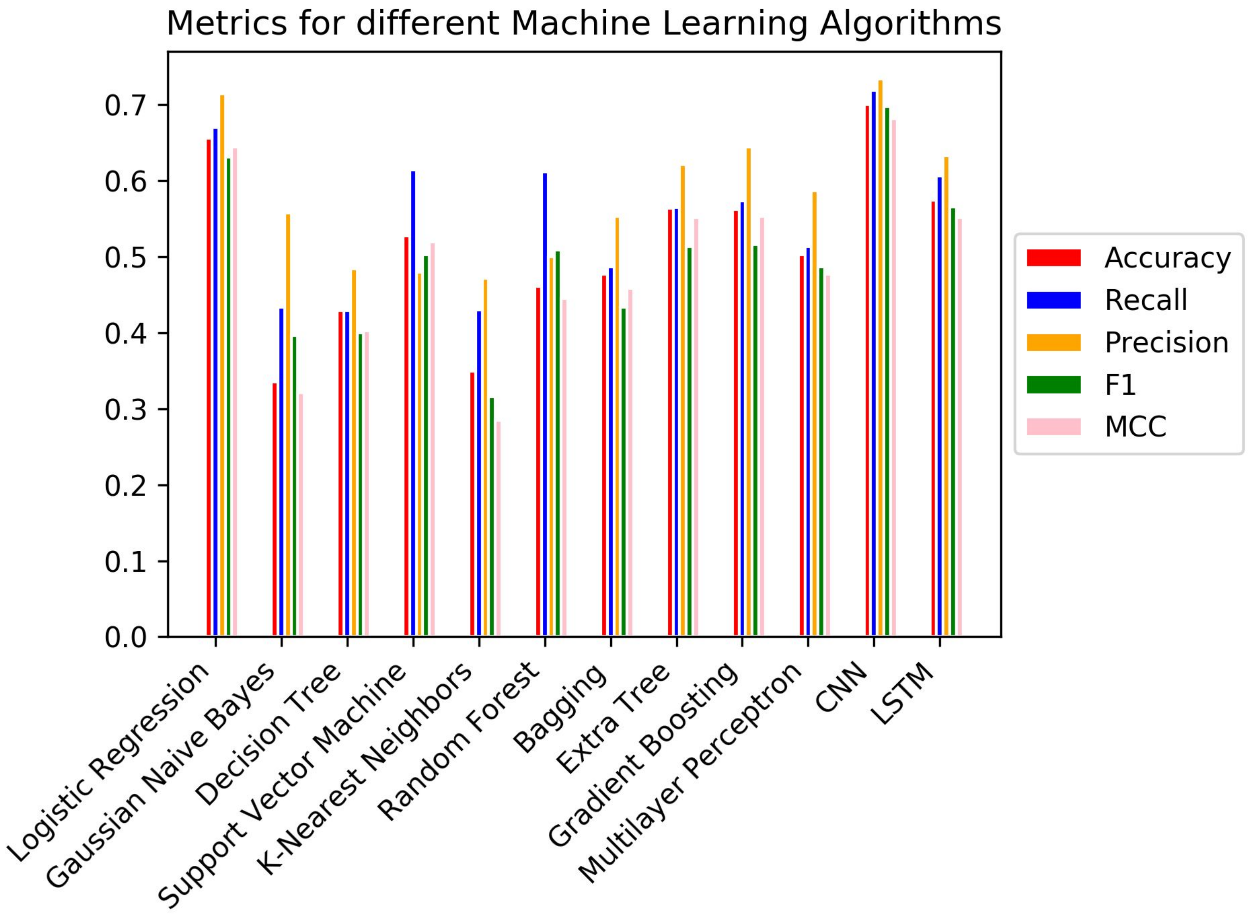




Training Times



Metrics


Metrics for different Machine Learning Algorithms
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
Accuracy
Recall
Precision
F1
MCC
Logistic Regression
Gaussian Naive Bayes
Decision Tree
Support Vector Machine
K-Nearest Neighbors
Random Forest
Bagging
Extra Tree
Gradient Boosting
Multilayer Perceptron
CNN
LSTM

Future Work

- CNN and LSTM with other (larger) human activity recognition data sets
- Improve preprocessing (feature selection, add statistical features...)
- Other deep learning architectures
  - Hybrid model using CNN mixed with LSTM layers
  - VGG, GoogLeNet...