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Generating context graphs using human activity recognition models

September 2016

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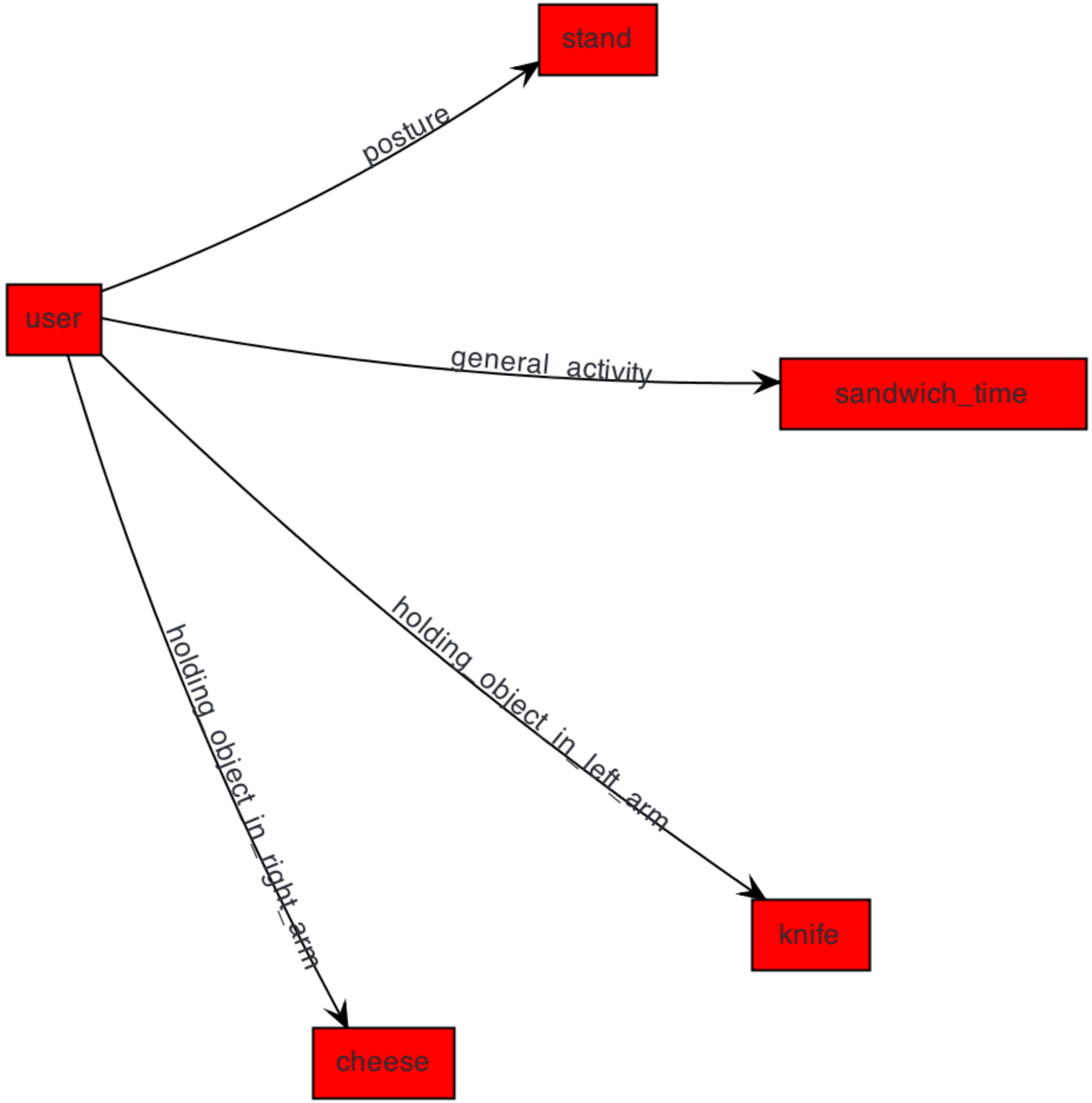
Overview

- Method for generating context graphs by extracting a set of predefined attributes from sensor data
- these attributes can then be mapped to a context graph directly or using a rule-based system

Introduction: context graphs

- graph representation of user context
- nodes represent concepts
- edges represent associations between concepts
- can be used to store and operate on data in Ambient Intelligent Applications



Context graph generated from the Opportunity dataset

Problem statement

- Having available low-level sensor data, the goal is to obtain a corresponding high-level representation in the form of a context graph which can later be used for high level reasoning using context graphs and patterns.

- E.g. for the Opportunity dataset, 113 sensor inputs are mapped to 6 high-level attributes.

Semantic attributes

- The semantic attributes represent a list of characteristics or descriptions of the activities performed by the subject.
- can be mapped to edges in a context graph directly or using specific rules.
- E.g. the activity of making a sandwich is described by:
  - `posture=stand`
  - `left_arm_object=knife`
  - `right_arm_object=cheese`

Generating context graphs

- Select a list of semantic attributes that are relevant to the context graph representation
- identify these attributes in sensor data using machine learning
- generate context graphs using the identified attributes.
- E.g. for a given sensor output sample, the identified attribute may be `holding_object_in_right_arm` with the value `knife`, thus we can add the edge `user-holding_object_in_right_arm->knife` to the graph.

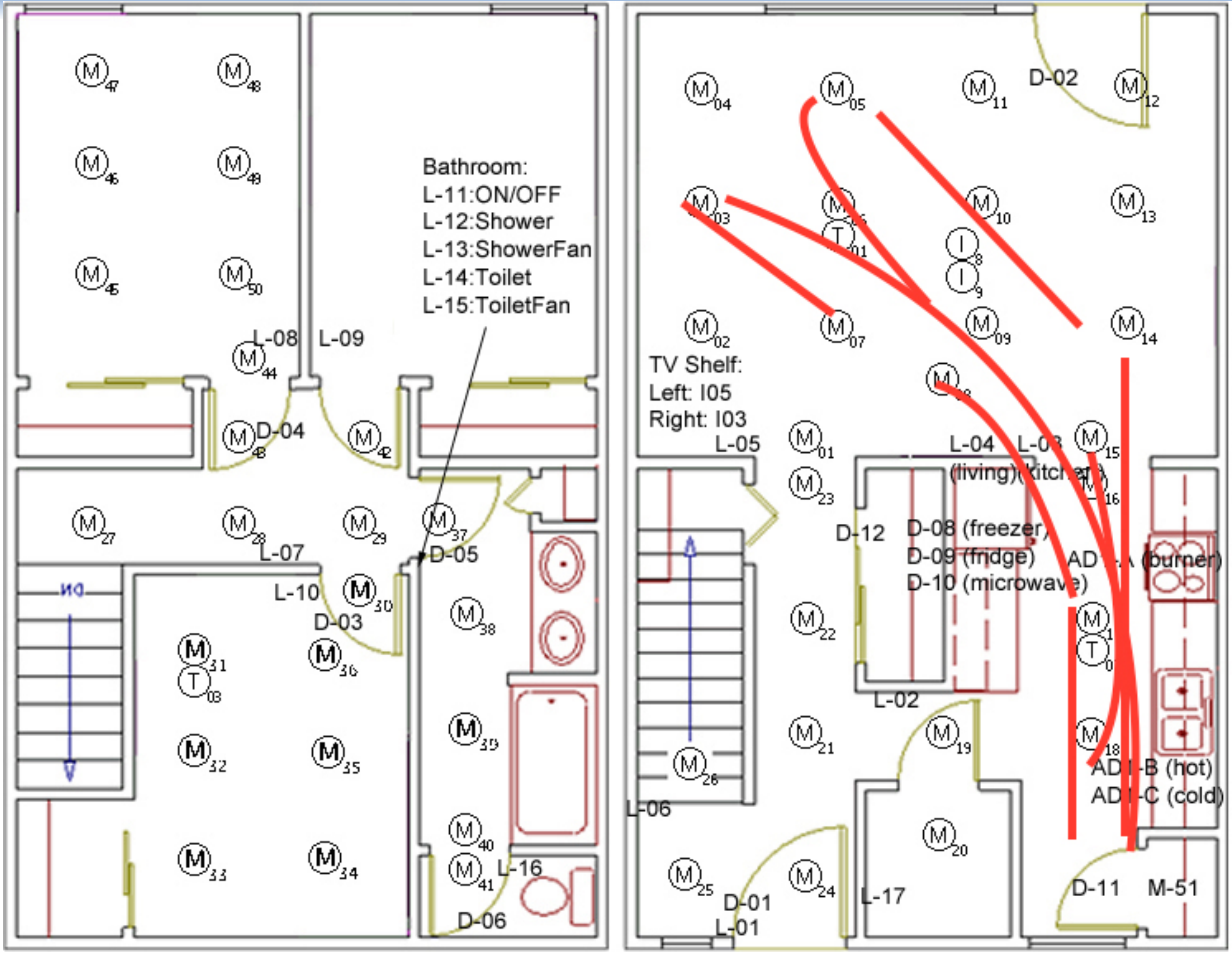
Datasets

- Experiments were carried on two datasets:
  - WSU CASAS - ambient sensors
  - Opportunity - on-body sensors
- For each dataset, we selected a list of semantic attributes, trained classifiers that identify individual attributes and measured performance

WSU CASAS

- smart home environment
- Data was recorded using ambient sensors installed inside the house
- 8 daily life activities
- small number of training features

WSU CASAS sensors layout



Cupboard:
Middle Shelf:
Left: I06
Right: I04
Bottom Shelf:
Left: I01
Right: I02
Counter: I07

Door: D07

WSU CASAS: training

- sensor readings were generated as timestamped events whenever a sensor would activate
- 16000 samples
- sliding window mechanism with K=15.
- used SVM and logistic regression. SVM proved slightly better overall.

WSU CASAS results

Attribute - Value pair	Precision	Accuracy	Recall	F1 score
using(can-of-water)	0.57	0.88	0.55	0.55
action(watering)	0.56	0.87	0.55	0.55
using(closet)	0.75	0.96	0.6	0.66
watching(dvd)	0.74	0.91	0.47	0.57
using(tv)	0.73	0.91	0.47	0.57
using(microwave)	0.62	0.89	0.68	0.64
location(living-room)	0.94	0.9	0.96	0.94
action(clean-kitchen)	0.68	0.84	0.64	0.65
using(cleaning-supplies)	0.68	0.84	0.63	0.65
location(kitchen)	0.83	0.85	0.55	0.66
action(prepare-birthday-card)	0.8	0.94	0.67	0.72
using(phone)	0.59	0.94	0.28	0.37
action(clean-living-room)	0.68	0.83	0.64	0.65
action(filling-medication-dispenser)	0.54	0.94	0.51	0.52
location(hallway)	0.74	0.96	0.59	0.656
action(choose-outfit)	0.75	0.96	0.59	0.66
action(asnwering-phone)	0.61	0.94	0.29	0.39
using(pot)	0.62	0.88	0.67	0.64
action(prepare-soup)	0.62	0.89	0.68	0.64
using(phone-agenda	0.8	0.94	0.67	0.72
using(pill-dispenser)	0.54	0.94	0.51	0.524

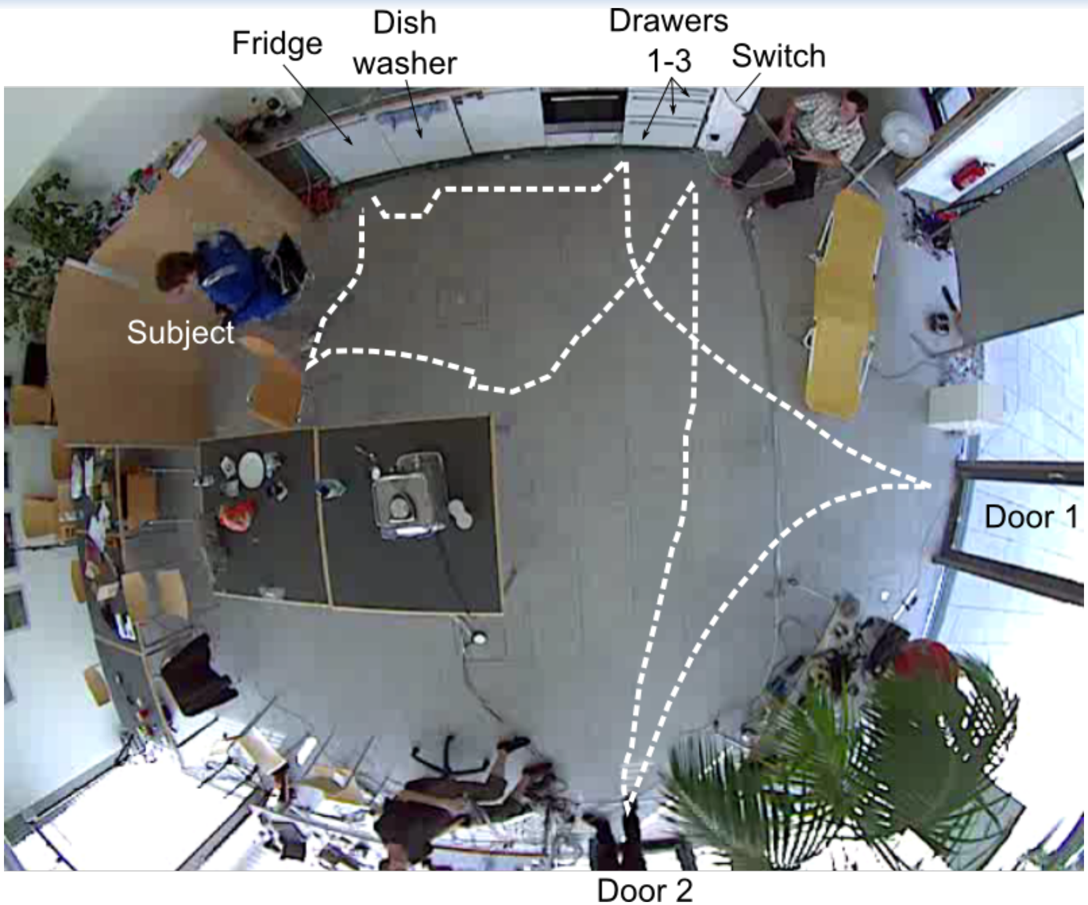
WSU CASAS results

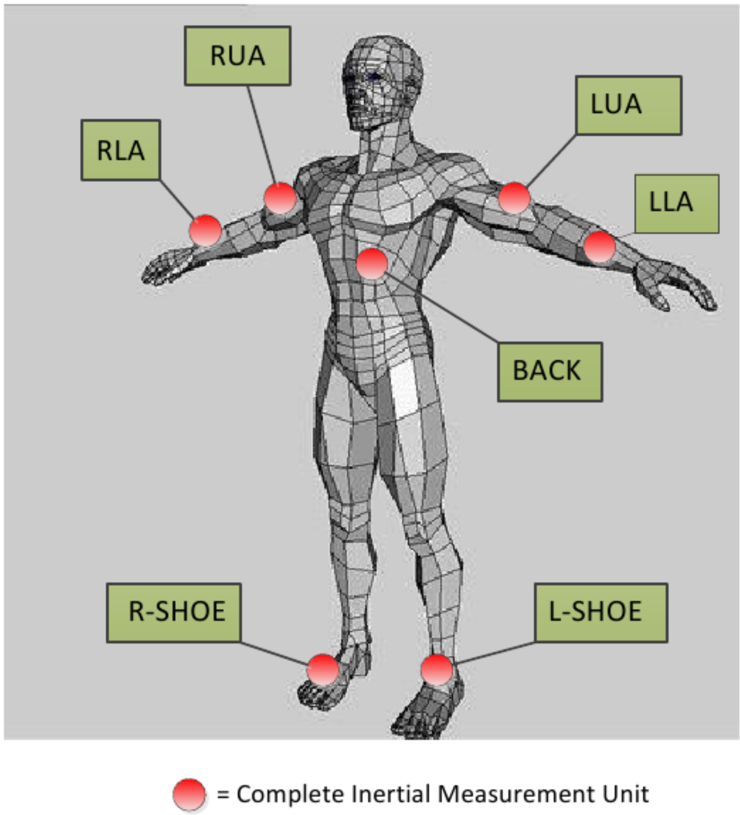
- average F1 score greater than 0.5
- Reference state-of-the-art on the activity recognition task(Krishnan, 2012): 0.54

The Opportunity Challenge

- The Opportunity dataset consists of a large number of annotated sensor data recorded while subjects performed daily life activities
- The data was recorded using 113 wearable sensors on 17 daily life activities, with 6 hours of recorded activities. E.g. cleaning the table, drinking water, etc.
- Sensors include accelerometers and gyroscopes

Opportunity dataset: sensors





Subject's trajectory while performing an activity

Sensors' position

Opportunity: ML model

- Used a deep neural network architecture which we optimized on the Opportunity Challenge gesture recognition task
- We then tested this architecture on identifying semantic attributes in the dataset

Opportunity: network layers

- 4 convolutional layers with 6 [4x1]
  - filters are applied among the time dimension
  - act as feature extractors
- 2 LSTM layers with 64 units each
  - model the temporal dynamics of the dataset
- Fully connected layer with Softmax activation

Opportunity: preprocessing

- We segmented the training samples using a sliding window mechanism of 800ms with 50% overlap
    - this resulted in 60000 samples
- feature scaling
- linear interpolation for missing values
- The input to the network is a [24 x 113] matrix

Opportunity:baseline models

- Baseline CNN with no recurrent layers
- Baseline LSTM model with recurrent layers applied directly on the raw sensor data
- Models submitted to the Opportunity challenge

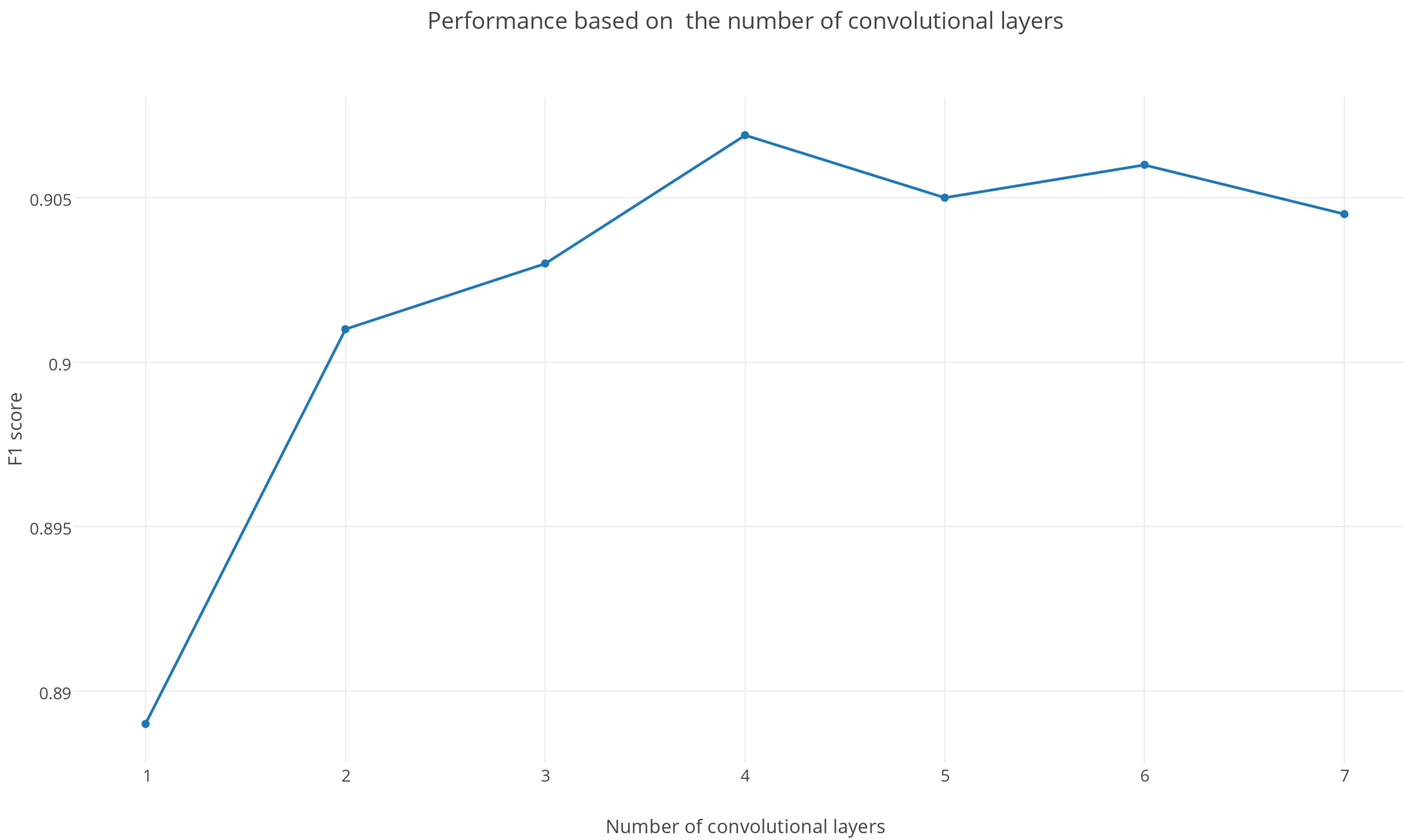
Opportunity: gesture task

Opportunity challenge submissions[4]	
Model	F1 score
LDA	0.69
QDA	0.53
NCC	0.51
1NN	0.87
3NN	0.85
UP	0.64
NStar	0.84
SStar	0.86
CStar	0.88
Deep learning approaches	
CNN[Yang et. al. 2015]	0.851
LSTM[Hammerla et. al. 2016]	**0.92**
Baseline CNN	0.876
Baseline LSTM	0.881
CNN_LSTM	**0.9096**

Opportunity: semantic attributes

Attribute	F1 score
posture	0.8916
general_activity	0.7688
left_arm_action	0.763
holding_object_in_left_arm	0.745
right_arm_action	0.748
holding_object_in_right_arm	0.701
performing_activity	0.905

Using deeper networks



Summary

- Presented a method for generating context graphs using semantic attributes extracted from low level sensor data
- We evaluated the performance of ML models for identifying semantic attributes on two relevant datasets
- For the Opportunity dataset, our neural network architecture achieves high scores on the open challenge associated with the dataset

Future work

- unsupervised learning approaches
- on-body sensor experiments closer to real world scenarios. E.g. only using two sensors (smart phone and wristband)

Thank you!

Questions__?