Implications of Regularization on Human Activity Learning Approaches

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Overall Project Goals

- Deep learning based Human Activity Recognition relies heavily on large datasets for generalization
- Unfair class dependent bias can be a result of the regularization effect explodes while adopting transfer learning to perform arbitrary downstream tasks
- The goal of the project is to understand the impact of regularization and data augmentation on human activity recognition class accuracies
- Understand the possible bias introduced by regularization hidden by overall accuracy

Specific Aims

- Across 3 popular open source HAR datasets we aim to understand the effect of augmentation and regularizations on class accuracies
- Moreover we can understand the biases that these techniques induce and through which we can make make better decisions for the techniques that are to be picked for various use cases

Deliverables

- Tensorflow models of 3 different deep learning architectures on the datasets
- Each model architecture has 7 different weight parameters : Baseline, weight decay and 5 augmentation techniques

Related Work - Current State of the Art

- The main inspiration for our work is some recent work out of FAIR[2]
- The authors did a study on the effects of weight decay and augmentation on per class accuracy of RESNET models trained on Imagenet
- The work shows that there can be a massive risk of bias being introduced with many classes having a stark reduction in accuracy after augmentation in large image recognition models
- The study noted that even in data agnostic techniques like weight decay, there is imbalance in the change of class accuracies

Technical Approach

Our Technical Approach is as follows:

- Identify 3 popular open source HAR datasets to perform our study
- Identify state of the art different models that provide good results on the datasets
- Perform 5 augmentation techniques, along with weight decay and compare against our baseline model

Technical Approach - Datasets

We consider the following 3 popular open source datasets.

UCIHAR [4]

Human Activity Recognition database built from the recordings of 30 subjects performing activities of daily living while carrying a waist-mounted smartphone with embedded inertial sensors

USC-HAD [8]

The focus of the dataset is healthcare related applications such as physical fitness monitoring The activity data is captured by a high-performance inertial sensing device and includes 12 activities and collected data from 14 subjects

PAMAP2 [7]

The PAMAP2 Physical Activity Monitoring dataset contains data of 18 different physical activities, performed by 9 subjects wearing 3 inertial measurement units and a heart rate monitor.

Technical Approach - Augmentations

We perform these 5 augmentations:

Rotation

A method for simulating different sensor positions by plotting a uniformly distributed 3D random axis and a random rotation angle and applying the corresponding rotation to the sample

Scaling

Multiply by a random scalar to scale the size of the data in the window to simulate the motion of weaker magnitudes

Magnify

Multiply by a random scalar to magnify the size of the data in the window to simulate stronger amplitude motion

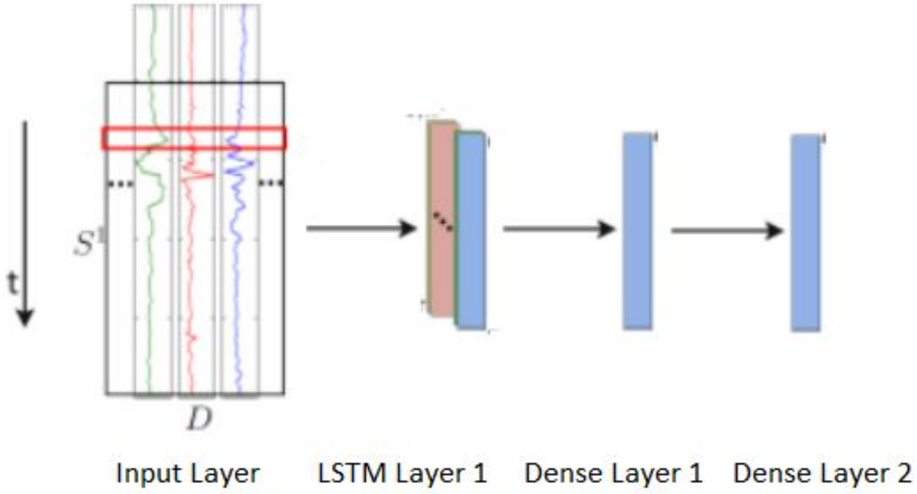
Resampling

Simulates multiple disturbances by varying the sampling frequency of sensor data

Noise Addition

A method for simulating additional sensor noise by multiplying the raw sample values with values that match uniform distribution

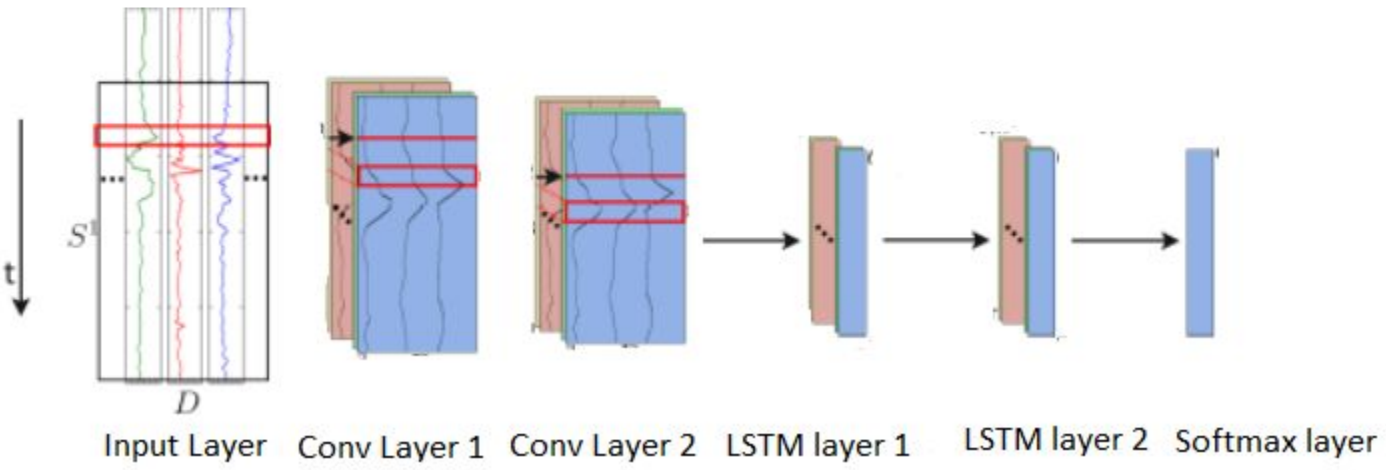
Technical Approach - Model 1: LSTM



Model 1: LSTM

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 128, 9)]          0

 lstm (LSTM)                 (None, 100)               44000

 dropout (Dropout)           (None, 100)               0

 dense (Dense)               (None, 100)               10100

 dense_1 (Dense)             (None, 6)                 606

=================================================================
Total params: 54,706
Trainable params: 54,706
Non-trainable params: 0
_________________________________________________________________
```

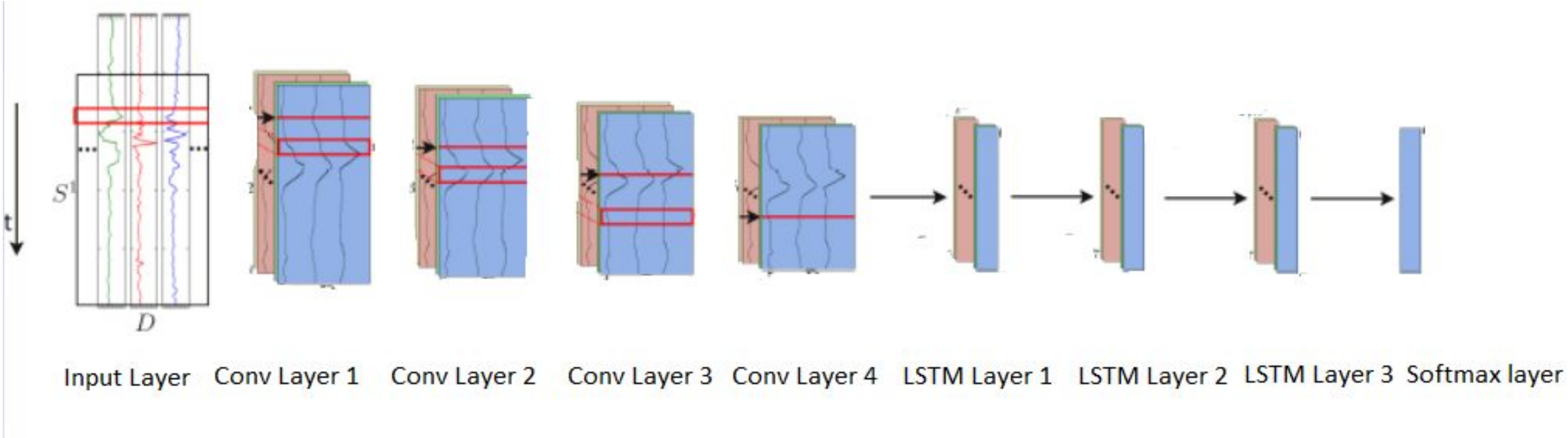
Technical Approach - Model 2: DeepConvLSTM Medium



Model 2: DeepConvLSTM Medium

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 128, 6, 1)]       0

 conv2d (Conv2D)             (None, 124, 6, 64)        384

 conv2d_1 (Conv2D)           (None, 120, 6, 64)        20544

 reshape (Reshape)           (None, 120, 384)          0

 lstm (LSTM)                 (None, 120, 128)          262656

 dropout (Dropout)           (None, 120, 128)          0

 lstm_1 (LSTM)               (None, 128)               131584

 dropout_1 (Dropout)         (None, 128)               0

 dense (Dense)               (None, 12)                1548

=================================================================
Total params: 416,716
Trainable params: 416,716
Non-trainable params: 0
_________________________________________________________________
```

Technical Approach - Model 3: DeepConvLSTM Large



Model 3: DeepConvLSTM Large

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 128, 6, 1)]       0

 conv2d (Conv2D)             (None, 124, 6, 64)        384

 conv2d_1 (Conv2D)           (None, 120, 6, 64)        20544

 conv2d_2 (Conv2D)           (None, 116, 6, 64)        20544

 conv2d_3 (Conv2D)           (None, 112, 6, 64)        20544

 reshape (Reshape)           (None, 112, 384)          0

 lstm (LSTM)                 (None, 112, 128)          262656

 dropout (Dropout)           (None, 112, 128)          0

 lstm_1 (LSTM)               (None, 112, 128)          131584

 dropout_1 (Dropout)         (None, 112, 128)          0

 lstm_2 (LSTM)               (None, 128)               131584

 dropout_2 (Dropout)         (None, 128)               0

 dense (Dense)               (None, 12)                1548

=================================================================
Total params: 589,388
Trainable params: 589,388
Non-trainable params: 0
_________________________________________________________________
```

Technical Approach - Regularization

- Here we add a penalty to our loss function that penalises the complexity of the model
- Penalizing these weights helps the model generalize better to new data and prevents underfitting
- Weight Decay performed using L1 and L2 Regularization
- Coefficient for L1 Reg : 10^{-5}
- Coefficient for L2 Reg: 10^{-4}

Results - UCIHAR LSTM Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
Walking	0.94	0.95	0.96	0.96	0.95	0.94	0.97
Stairs-Up	0.96	0.97	0.97	0.98	0.95	0.96	0.98
Stairs-Down	.99	0.99	0.99	0.99	0.99	1.0	0.99
Sitting	0.80	0.77	0.8	0.82	0.79	0.79	0.81
Standing	0.83	0.86	0.79	0.9	0.81	0.83	0.94
Lying	1	0.99	0.94	1	1	1	1
Overall Accuracy	0.92	0.92	0.9	0.94	0.91	0.92	0.95

Results - UCIHAR DeepConvLSTM Medium Model

Activity	Baseline	Weight Decay	Resampling	Scaling	Noise	Rotation	Magnify
Walking	0.96	0.96	0.97	0.96	0.95	0.98	0.983
Stairs-Up	0.96	0.97	0.968	0.97	0.96	0.97	0.987
Stairs-Down	0.96	0.985	0.97	0.98	0.97	0.97	0.965
Sitting	0.86	0.84	0.85	0.87	0.84	0.81	0.81
Standing	0.86	0.86	0.92	0.9	0.86	0.88	0.92
Lying	0.97	0.99	0.94	0.94	0.93	0.98	0.97
Overall Accuracy	0.93	0.933	0.94	0.94	0.92	0.93	0.942

Results - UCIHAR DeepConvLSTM Large Model

Activity	Baseline	Weight Decay	Resampling	Scaling	Noise	Rotation	Magnify
Walking	0.97	0.97	0.98	0.97	0.96	0.95	0.983
Stairs-Up	0.98	0.98	0.97	0.98	0.97	0.97	0.97
Stairs-Down	0.97	0.987	0.98	0.97	0.97	0.96	0.98
Sitting	0.86	0.87	0.88	0.88	0.85	0.83	0.89
Standing	0.88	0.87	0.94	0.95	0.86	0.87	0.94
Lying	0.97	0.99	0.98	0.97	0.95	0.97	0.98
Overall Accuracy	0.94	0.95	0.96	0.96	0.93	0.93	0.96

Results - USC HAD LSTM Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
Walking Forward	0.94	0.93	0.92	0.92	0.9	0.91	0.94
Walking Left	0.88	0.90	0.88	0.89	0.88	0.85	0.89
Walking Right	0.89	0.93	0.93	0.93	0.91	0.89	0.93
Walking Upstairs	0.83	0.89	0.88	0.9	0.83	0.78	0.89
Walking Downstairs	0.85	0.88	0.82	0.9	0.85	0.72	0.92
Running Forward	0.93	0.92	0.95	0.96	0.95	0.95	0.94
Jumping	0.77	0.78	0.84	0.89	0.85	0.74	0.93
Sitting	0.93	0.92	0.91	0.95	0.95	0.93	0.96
Standing	0.84	0.87	0.83	0.85	0.85	0.84	0.82
Sleeping	0.99	0.99	0.95	1.0	1.0	0.99	1.0
Elevator Up	0.48	0.39	0.32	0.38	0.59	0.5	0.47
Elevator Down	0.27	0.45	0.51	0.52	0.43	0.41	0.47
Overall Accuracy	0.84	0.86	0.84	0.87	0.86	0.83	0.87

Results - USC HAD DeepConvLSTM Medium Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
Walking Forward	0.95	0.96	0.94	0.94	0.96	0.96	0.95
Walking Left	0.92	0.94	0.92	0.93	0.94	0.94	0.94
Walking Right	0.96	0.93	0.94	0.95	0.94	0.95	0.94
Walking Upstairs	0.96	0.95	0.92	0.96	0.95	0.96	0.95
Walking Downstairs	0.96	0.95	0.94	0.94	0.95	0.96	0.96
Running Forward	0.97	0.97	0.97	0.97	0.95	0.97	0.97
Jumping	0.96	0.97	0.96	0.94	0.97	0.96	0.97
Sitting	0.97	0.97	0.95	0.97	0.98	0.96	0.96
Standing	0.87	0.88	0.88	0.87	0.87	0.88	0.89
Sleeping	0.99	0.99	0.96	1.0	1.0	1.0	1.0
Elevator Up	0.57	0.48	0.51	0.44	0.5	0.53	0.51
Elevator Down	0.34	0.44	0.46	0.54	0.51	0.47	0.47
Overall Accuracy	0.89	0.9	0.89	0.9	0.91	0.91	0.9

Results - USC HAD DeepConvLSTM Large Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
Walking Forward	0.96	0.97	0.94	0.95	0.95	0.91	0.94
Walking Left	0.96	0.98	0.95	0.95	0.94	0.91	0.92
Walking Right	0.94	0.97	0.94	0.95	0.95	0.92	0.94
Walking Upstairs	0.97	0.98	0.95	0.98	0.95	0.89	0.95
Walking Downstairs	0.97	0.97	0.95	0.96	0.89	0.85	0.91
Running Forward	0.98	0.99	0.99	0.99	0.97	0.96	0.98
Jumping	0.99	0.99	0.98	0.97	0.88	0.85	0.93
Sitting	0.98	0.98	0.96	0.97	0.95	0.87	0.96
Standing	0.91	0.92	0.92	0.89	0.83	0.8	0.85
Sleeping	0.99	1.0	0.97	1.0	0.99	1.0	1.0
Elevator Up	0.47	0.64	0.37	0.37	0.34	0.41	0.49
Elevator Down	0.49	0.4	0.56	0.64	0.69	0.51	0.51
Overall Accuracy	0.88	0.92	0.9	0.91	0.89	0.85	0.89

Results - Pamap2 LSTM Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
lying	1.	1	0.96	1	0.95	1	1
sitting	0.97	0.98	0.98	0.98	0.95	0.97	0.98
Standing	0.95	0.94	0.96	0.96	0.95	0.94	0.97
walking	0.94	0.95	0.97	0.98	0.95	1	0.98
Running	0.96	0.97	0.98	0.97	0.99	0.94	0.95
Cycling	0.93	0.94	0.93	0.96	0.79	0.79	0.95
Nordic-Walking	1	0.94	0.7	0.99	0.81	0.83	0.96
Watchig_TV	0.94	0.98	0.99	0.96	1	1	0.98
Computer Networks	0.92	0.93	0.91	0.95	0.91	0.93	0.96
Car Driving	0.88	0.877	0.9	0.92	0.89	0.92	0.93
Ascending Stairs	0.86	0.89	0.87	0.94	0.88	0.95	0.93
Descending Stairs	0.93	0.94	0.91	0.96	0.92	0.94	0.92
Vacuum Cleaning	0.95	0.93	0.94	0.97	0.95	0.94	0.98
Ironing	0.94	0.96	0.93	0.92	0.94	0.98	0.93
Folding Laundry	0.94	0.96	0.92	0.93	0.93	0.94	0.95
House Cleaning	0.95	0.94	0.91	0.97	0.94	0.96	0.93
Playing Soccer	0.91	0.92	0.93	0.94	0.93	0.93	0.95
Overall Accuracy	0.94	0.95	0.92	0.96	0.93	0.95	0.96

Results - Pamap2 - ConvLSTM Medium Model

Activity	Baseline	Weight Decay	Rotation	Scaling	Noise	Resampling	Magnify
lying	1.	1	0.96	1	0.95	1	1
sitting	0.98	0.97	0.98	0.98	0.95	0.97	0.97
Standing	0.94	0.96	0.96	0.96	0.95	0.94	0.98
walking	0.96	0.98	0.97	0.98	0.95	1	0.98
Running	0.97	0.95	0.98	0.97	0.99	0.94	0.92
Cycling	0.95	0.96	0.93	0.98	0.96	0.93	0.92
Nordic-Walking	1	0.96	0.94	1	1	0.97	0.96
Watchig_TV	0.96	0.97	0.99	0.98	1	1	0.97
Computer Networks	0.91	0.92	0.91	0.96	0.91	0.93	0.93
Car Driving	0.87	0.90	0.9	0.92	0.86	0.91	0.92
Ascending Stairs	0.88	0.91	0.87	0.94	0.88	0.96	0.93
Descending Stairs	0.94	0.93	0.91	0.97	0.92	0.95	0.91
Vacuum Cleaning	0.97	0.98	0.94	0.99	0.95	0.93	0.98
Ironing	0.94	0.95	0.93	0.92	0.94	0.98	0.94
Folding Laundry	0.95	0.97	0.92	0.95	0.93	0.95	0.93
House Cleaning	0.97	0.96	0.91	0.97	0.94	0.97	0.95
Playing Soccer	0.93	0.94	0.93	0.94	0.93	0.93	0.94
Overall Accuracy	0.95	0.953	0.94	0.97	0.93	0.95	0.96

Conclusion and Future Direction

Conclusion

- The best regularization and data augmentation seems to vary across models and datasets
- A significant difference is not noticed in class accuracies in human activity recognition when compared to image classification [2]

Future Direction

Conduct analysis on

1) On a combination of data augmentation techniques
2) Other Techniques
    - Contrastive Learning[1]
    - Augmentation techniques using generative models [5] [6]
3) Exploring impact on other Datasets
    - Opportunity Activity Recognition
    - WISDM dataset

Contribution

Arunachalam Chidambaram

- Preprocessed datasets
- Implemented DeepConv LSTM
- Built platform for training runs
- Literature review

Hariram

- Implemented Augmentation Techniques
- Preprocessed PAMAP2 dataset for ML access pattern
- Identified the Label Preserving Limit for applying DA
- Worked for results in UCI HAR- DeepConv LSTM, Conv LSTM models
- Worked for results in PAMAP- LSTM Model
- Literature review

Shreyas Rajesh

- Preprocessed USC HAD dataset
- Worked for results in UCI HAR- LSTM Model, DeepConv LSTM Model, ConvLSTM Model
- Worked for results in USC HAD- DeepConvLSTM Model, ConvLSTM
- Worked on adding the weight decay
- Literature review

References

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[7] https://archive.ics.uci.edu/ml/datasets/PAMAP2+Physical+Activity+Monitoring

[9] https://sipi.usc.edu/had/

[10] To Explore More Datasets from : NESL's Model-Dataset-Platform Zoo - Datasets