

HUMAN ACTIVITY RECOGNITION USING DEEP

LEARNING TECHNIQUES



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1. Network architectures

Net((conv): Conv1d(in=561, out=256, kernel_size=3, stride=1, padding=1) (inp): Linear(in_features=561, out_features=256 / 64, bias=True) (rnn): LSTM(nodes=256, nodes=256, num_layers=2, batch_first=True) !! (act): Tanh() !! (d): Dropout(p=0.0, inplace=False) (out): Linear(in_features=256 / 64, out_features=12, bias=True))

Notes:

- RNN and layers do not require the *activation and dropout* layers, because of the RNN's internal structure
- input layers are used either Linear / Convolutional
- sequence length choices are: RNN (1, 5, 20), CRNN (5, 20)
- padding = kernel_size // 2

2. Training process

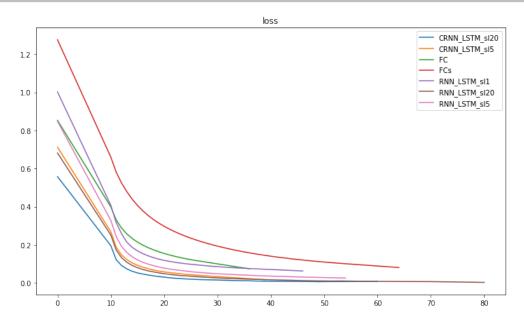
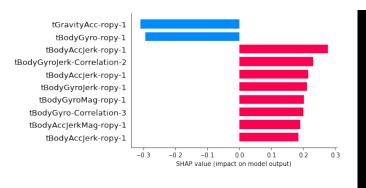


Figure 1: Comparison of network training losses during training

3. Feature analysis - using FCs

Utilizing SHAP (SHapley Additive exPlanations)



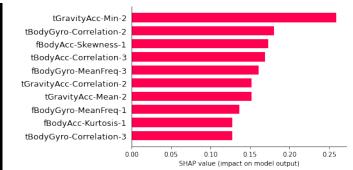


Figure 2: GT: WALKING == Pred

Figure 3: *GT: SIT_TO_STAND != Pred: STAND_TO_SIT*

4. Discussion

Count/label: [90 76 70 71 83 78 4 3 5 6 11 3] length: 500

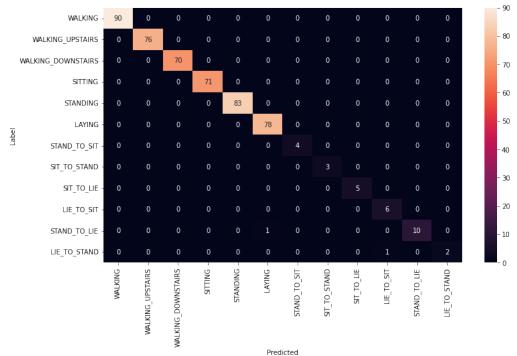


Figure 4: Confusion matrix of LSTM network with sequence length of 20

(Optional) Feature analysis for every class - using FCs

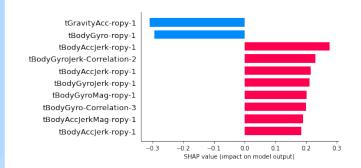


Figure 5: GT: WALKING == Pred

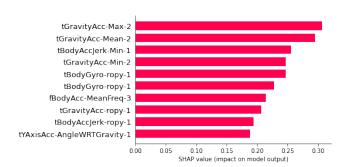


Figure 6: GT: WALKING_UPSTAIRS == Pred

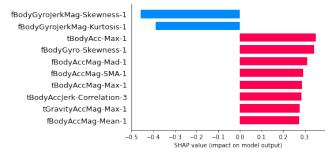


Figure 7: *GT: WALKING_DOWNSTAIRS* == *Pred*

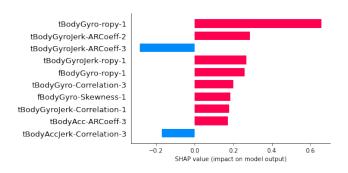


Figure 8: GT: SITTING == Pred

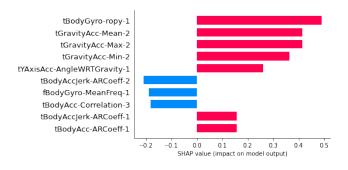


Figure 9: *GT: STANDING == Pred*

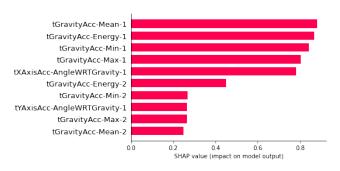


Figure 10: GT: LAYING == Pred

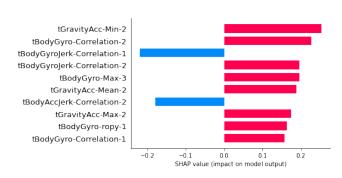


Figure 11: GT: STAND_TO_SIT == Pred

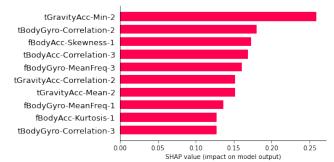


Figure 12: *GT: SIT_TO_STAND* != *Pred: STAND_TO_SIT*

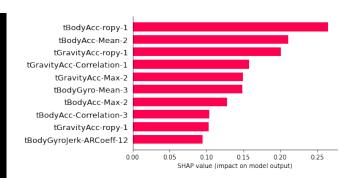


Figure 13: *GT: SIT_TO_LIE == Pred*

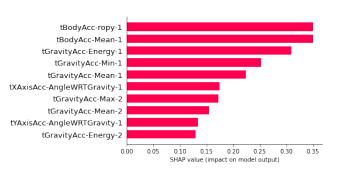


Figure 14: GT: LIE_TO_SIT == Pred

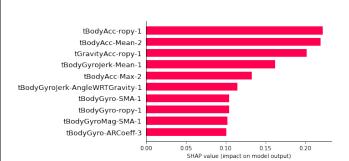


Figure 15: GT: STAND_TO_LIE == Pred

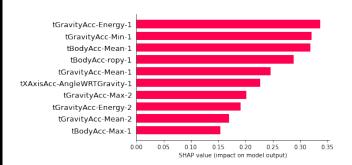


Figure 16: *GT: LIE_TO_STAND == Pred*