Human Activity Recognition

Deep Learning Lab

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02.08.2021

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Input Pipeline

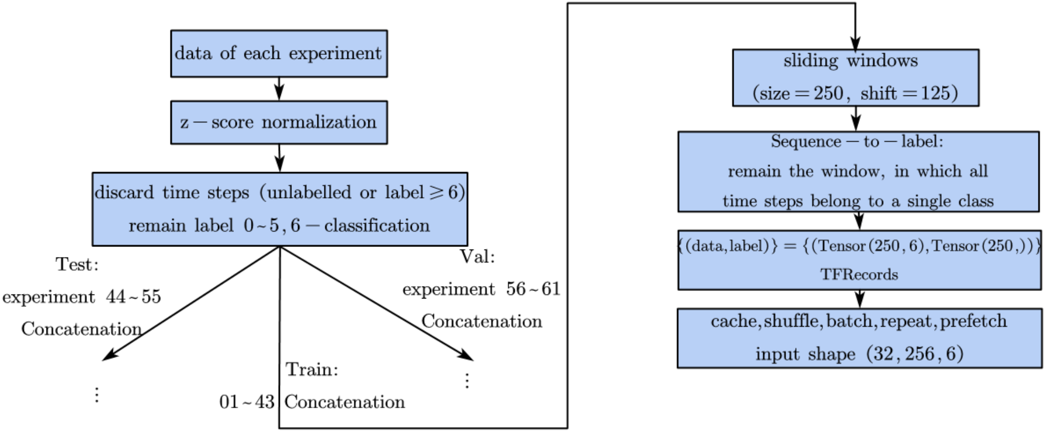

Figure: Input Pipeline

Model

- Selection of classification tasks
  - Sequence-to-Label (S2L) classification tasks
- LSTM
  - LSTM blocks: which include one LSTM layer, one BN layer to avoid overfitting, and use tanh as the activation function
  - Each LSTM Block returns a sequence result
  - Dropout layer
  - Pooling layer and dense layer to get a certain label
- GRU
  - GRU blocks: which include one GRU layer, one BN layer to avoid overfitting, and use tanh as the activation function
  - Each GRU Block returns a sequence result
  - Dropout layer
  - Pooling layer and dense layer to get a certain label

Model

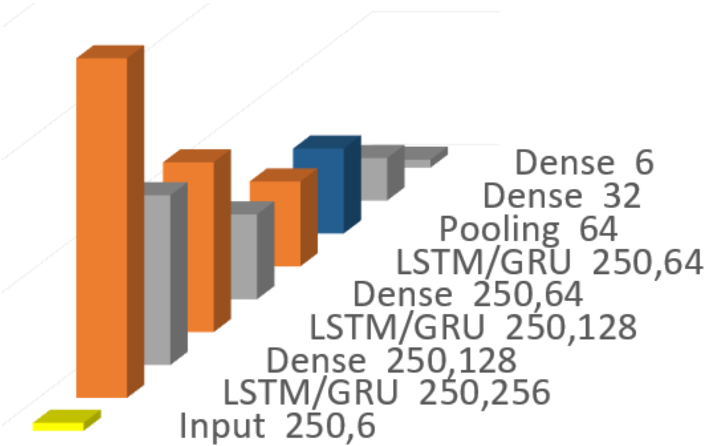

Figure: Model architecture

Training and hyperparameter optimization

- Training
  - Loss function: sparse categorical cross entropy
  - Optimizer: Adam
- Hyperparameter optimization
  - Hyperparameter tuning for LSTM/GRU

Table: Some results of hyperparameter tuning

Trial	**1**	**2**
Block type	GRU	LSTM
Pooling type	GlobalMax	GlobalMax
Total steps	7500	4000
Learning rate	6.58e-5	5.40e-5
Dropout rate	0.44	0.31
Val accuracy	94.05%	93.83%

Evaluation and Visualization

- Feed the sliding windows without overlap into the model
- The predict part is thinner than the ground truth
- The prediction fits well with the ground truth

Evaluation and Visualization

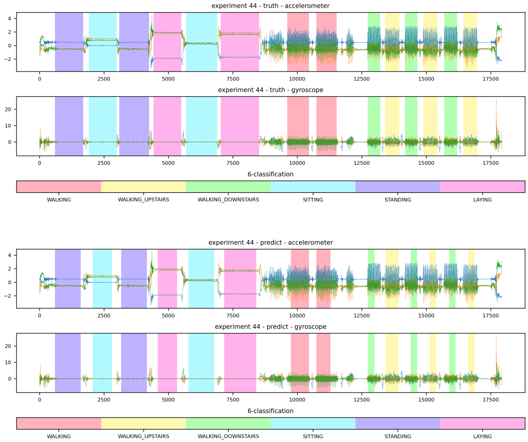

Figure: Ground Truth and Prediction

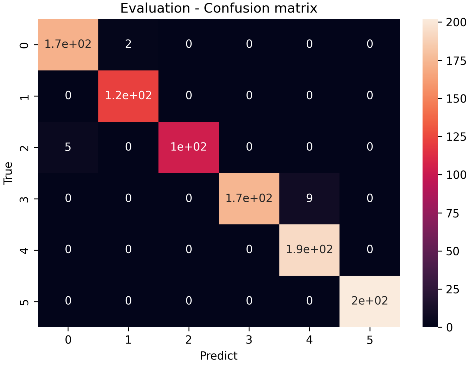

Figure: Confusion Matrix

Conclusions

- At the end, we choose GRU model, we can see that the prediction fits well with the ground truth

Table: Final result

Model	Test accuracy
GRU	98.3%

- The original dataset is highly imbalanced. After we drop out the data of postural transitions, we can get a good result of the human activity recognition task