Classifying EEG Spectrograms by Phalangeal Articulation using LRC Neural Networks

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EE 4OJ4/EE 4OH4 Research Project

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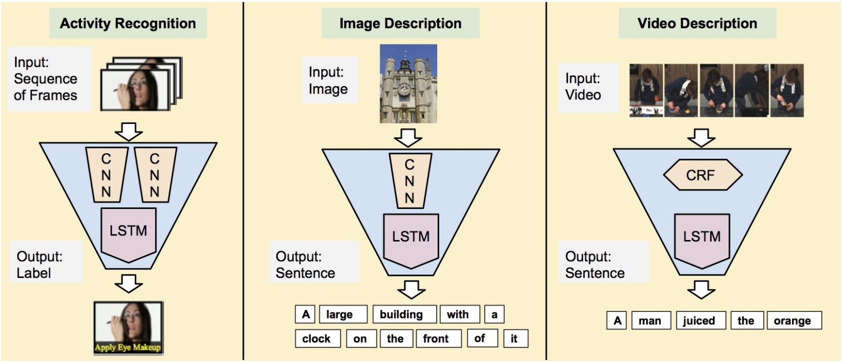
Problem and Approach

- Problem:
  - Given EEG data, determine which phalanges were articulated
- Approach:
  - What information can be used?
    - EEG data contains both time and frequency information
    - Spectrograms can capture frequency information over time
  - How can the data be classified?
    - Multiple machine learning algorithms exist for classification
    - Neural networks provide automated feature detection and universal approximation

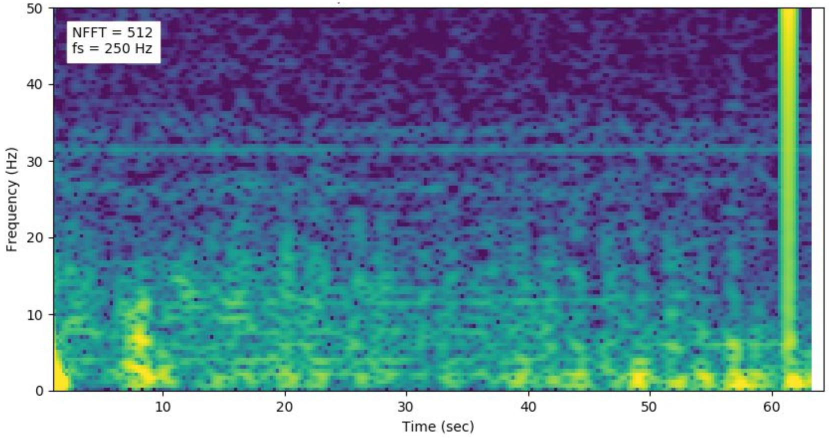
Approach (cont.)

- Various classes of neural networks
- Data involves a sequence of spectrograms
- Spectrograms similar in dimensionality as images
- Long-term Recurrent Convolutional (LRC) neural networks:
    - A class of neural networks for visual and sequence learning
    - Utilizes convolutional neural networks and long short-term memory



Applications of LRC Neural Networks
Source: http://jeffdonahue.com/lrcn/

Data - Input



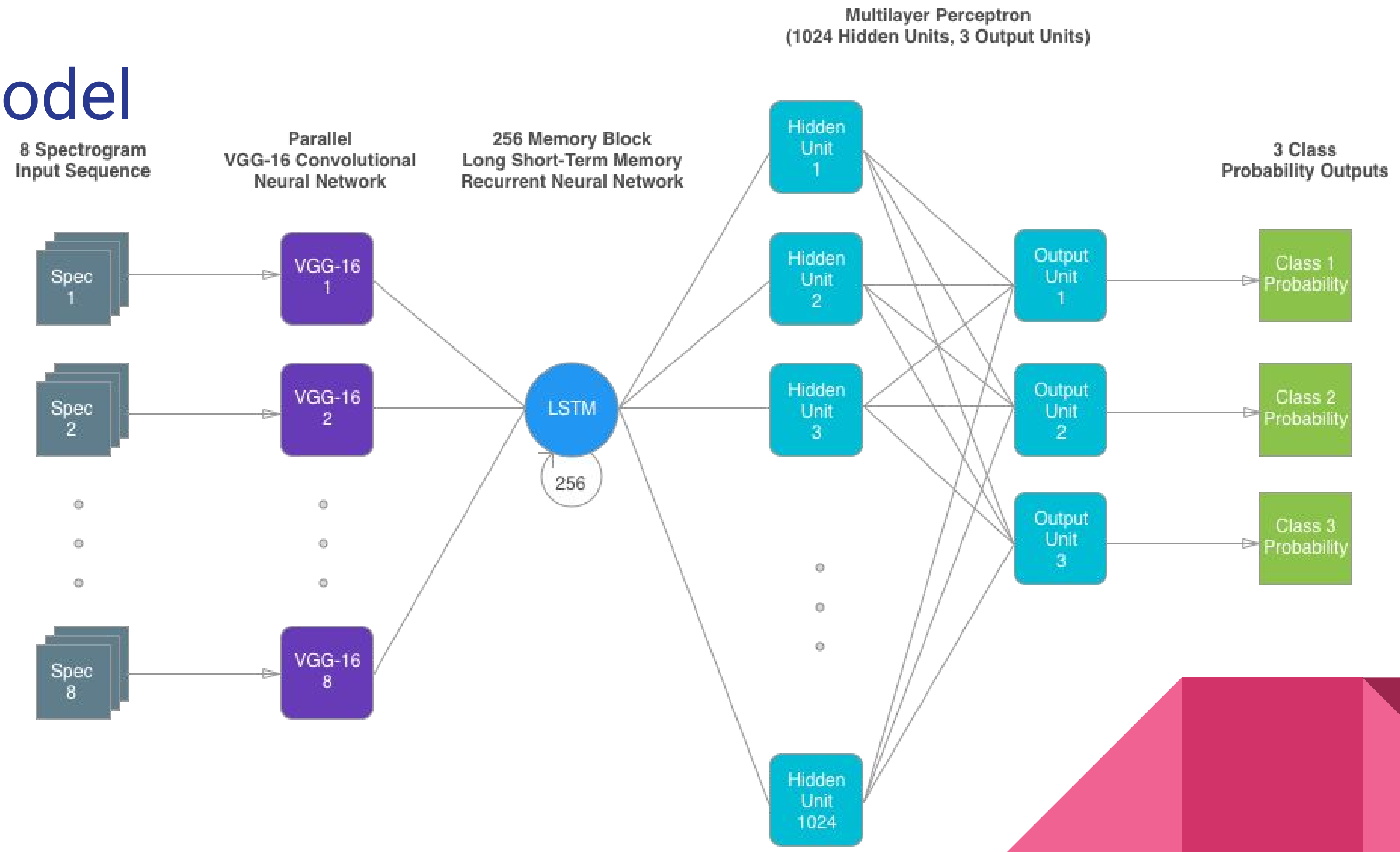
Sample spectrogram for sustained left middle finger flexion from 1 channel

- 8 EEG channels
- For each channel:
  - Set-up and teardown data trimmed
  - DC offset removed
  - Mains interference notched
  - 1-50 Hz bandpass filtered
  - Spectrograms generated
  - Spectrograms partitioned into multiple samples with dimensionality of 250 freq. points x 50 time points
- Depending on the training run configuration, samples were either replicated or augmented to increase sample size

Data - Labels and Output

- Labels:
  - One-hot encoded representation of each class
  - 3 classes: left index, left middle, and left ring finger flexion
  - e.g. [1., 0., 0.], [0., 1., 0.], [0., 0., 1.]
- Outputs:
  - Array of probabilities for each class
  - e.g. [0.50, 0.25, 0.25] would mean 50% probability for class 1, 25% probability for class 2 and 3

Model



Multilayer Perceptron
(1024 Hidden Units, 3 Output Units)
8 Spectrogram Input Sequence
Parallel VGG-16 Convolutional Neural Network
256 Memory Block Long Short-Term Memory Recurrent Neural Network
3 Class Probability Outputs
Spec 1
Spec 2
Spec 8
VGG-16 1
VGG-16 2
VGG-16 8
LSTM
256
Hidden Unit 1
Hidden Unit 2
Hidden Unit 3
Hidden Unit 1024
Output Unit 1
Output Unit 2
Output Unit 3
Class 1 Probability
Class 2 Probability
Class 3 Probability

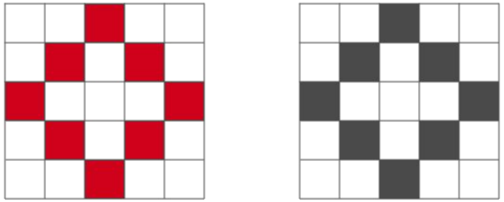
Convolutional Neural Network (CNN)

- Biologically-inspired multilayer perceptrons (MLPs)
- Mimic visual cortex:
  - Complex cell arrangement sensitive to stimuli within a restricted region (receptive field)
  - Region tiled across entire visual field
  - Cells act as localized filters for detecting spatial patterns
  - Response can be approximated by a convolution operation:

$$(f * g)[n] \stackrel{\text{def}}{=} \sum_{m=-\infty}^{\infty} f[m]\, g[n-m]$$
$$= \sum_{m=-\infty}^{\infty} f[n-m]\, g[m].$$

CNN (cont.): Simplified Illustration

- Sample 5x5 image
- Converted to grayscale
- Simplified digital representation



Sample Image

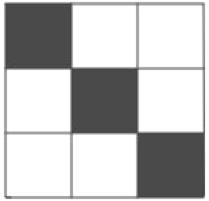
Grayscale Representation

0	0	1	0	0
0	1	0	1	0
1	0	0	0	1
0	1	0	1	0
0	0	1	0	0

Simplified Digital Representation

CNN (cont.): Simplified Illustration

- Sample 3x3 filter
- Simplified digital representation



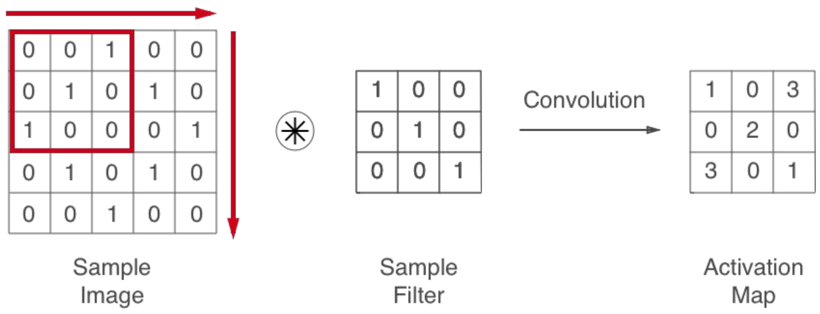
Sample
Filter

1	0	0
0	1	0
0	0	1

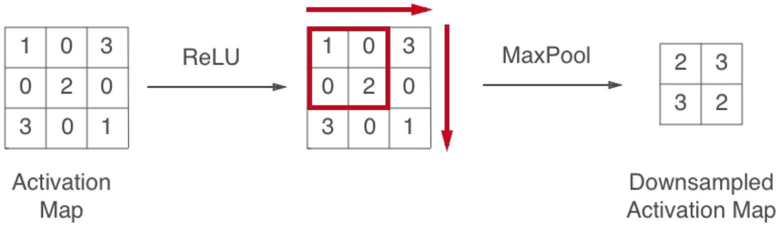
Simplified
Digital Representation

CNN (cont.): Simplified Illustration

- Convolutional filters tiled across an image
- Receptive fields convolved with visual field regions, generating an activation map
- Activation map:
    - Regions with spatial patterns with a high correlation with the filter pattern have high activation values, and vice versa
- Filter stride of 1 pixel, generating a 3x3 activation map



CNN (cont.): Simplified Illustration



$$f(x) = \max(0, x)$$

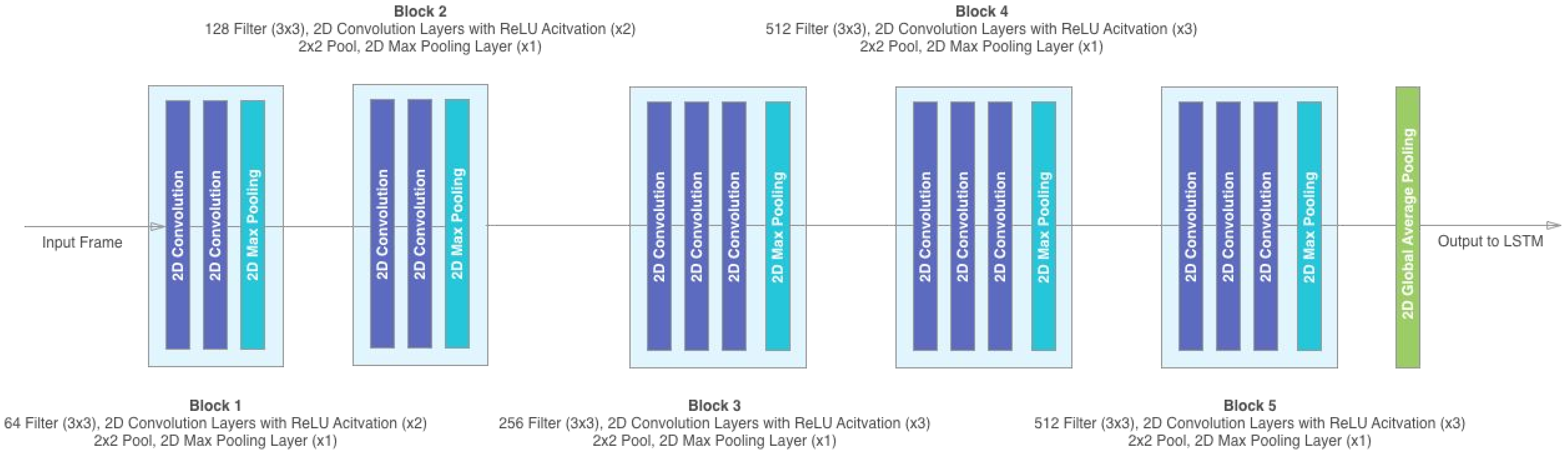
Rectified Linear Unit (ReLU)

- Activation map passed through a layer of rectified linear units (ReLUs), an activation function to improve network nonlinearity:

$$f(x) = \max(0, x)$$

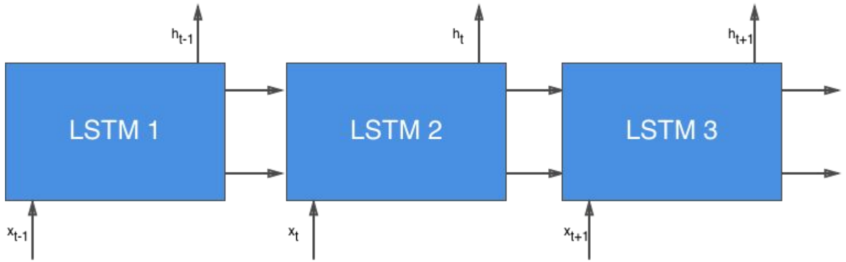
- Pooling layer downsamples activation map, reducing number of parameters
- MaxPool layer used, replacing a pool of values with its maximum value
- 2x2 pool size, stride of 1 pixel

CNN (cont.): VGG-16 Architecture

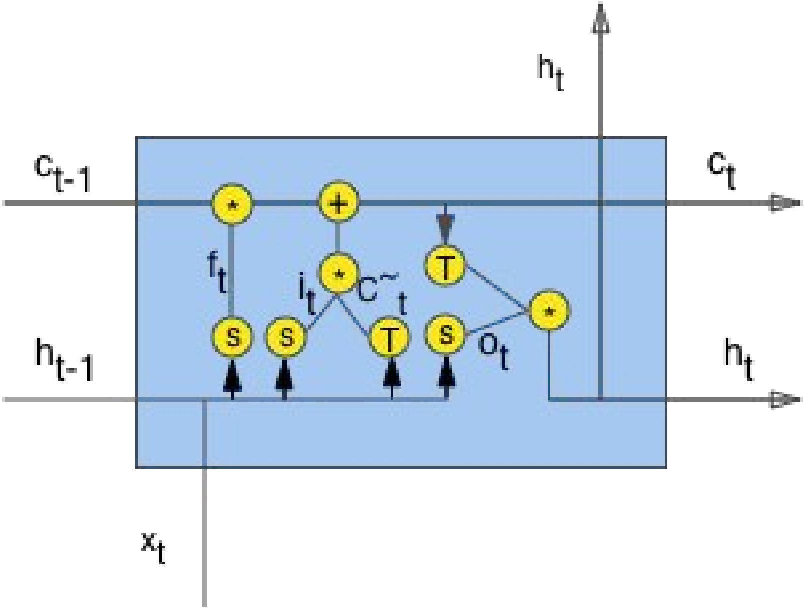


Long short-term Memory (LSTM)

- A type of recurrent neural networks (RNNs)
  - Artificial neural networks
  - Consists of stateful memory units that are cyclically connected
  - Detect sequential patterns
- LSTMs, unlike regular RNNs, are well suited for data with variable gaps between events
  - E.g. variations observed in speech due to demographic and biological variability
- LSTMs consist of chains of repeated LSTM units



LSTM (cont.)



- Within each LSTM unit, a series of operations occur:
  - S, logistic sigmoid:

$$S(t) = \frac{1}{1 + e^{-t}}$$

  - T, hyperbolic tangent:

$$T(t) = \frac{e^{2t} - 1}{e^{2t} + 1}$$

  - +, element-wise addition
  - *, element-wise multiplication
- Also utilizes weight matrices W, U, and V, and bias vector b

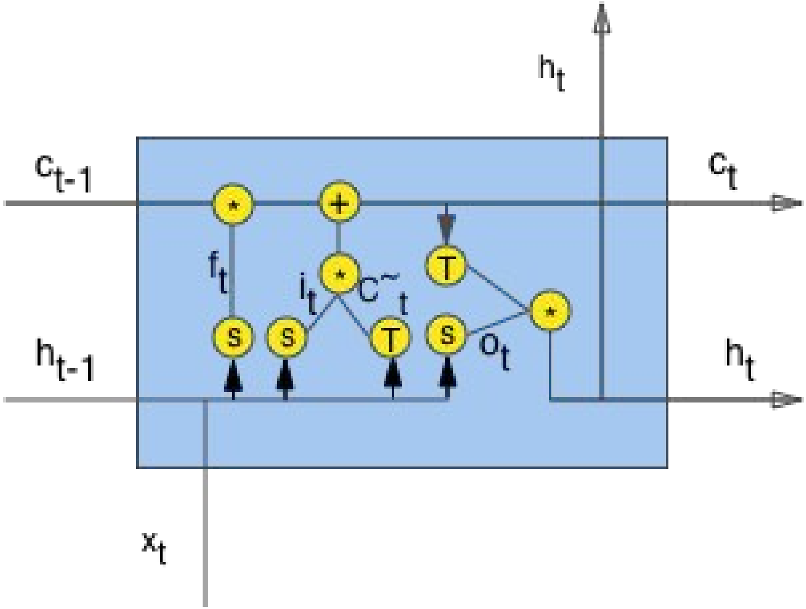
LSTM (cont.)

- First, select new data to store:
  - Logistic sigmoid (input gate) layer selects which values to update:

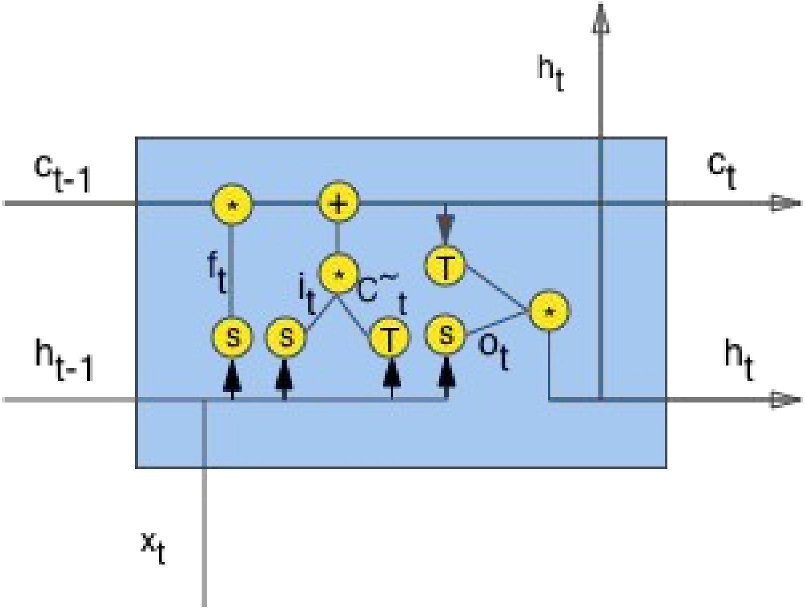
$$i_t = s(W_i x_t + U_i h_{t-1} + b_i)$$

  - Hyperbolic tangent layer generates new candidate values:

$$C^{\sim}_t = t(W_c x_t + U_c h_{t-1} + b_c)$$



LSTM (cont.)



- Next, another logistic sigmoid layer selects data to forget:

$$f_t = s(W_f x_t + U_f h_{t-1} + b_f)$$

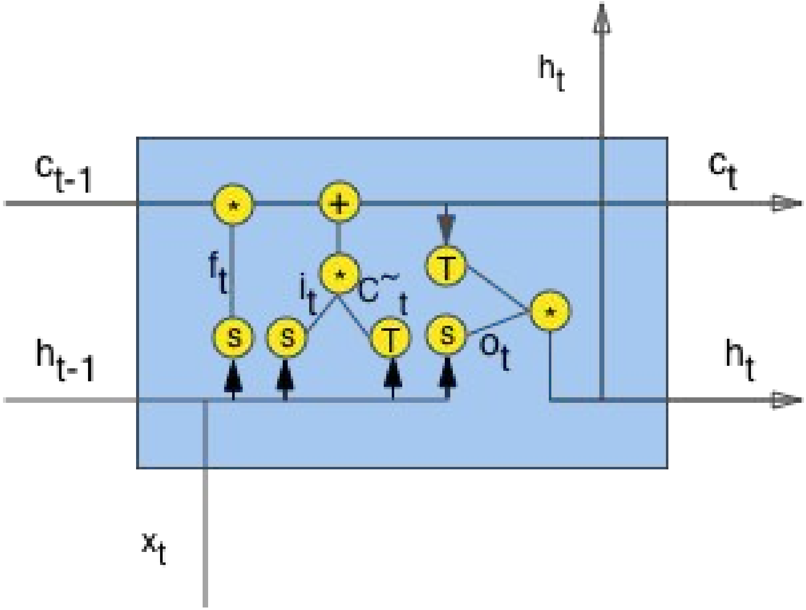
- Takes h_{t-1} and x_t, then returns either 0 or 1 for each value in cell state c_{t-1}:
  - 0 for “forget”
  - 1 for “remember”

LSTM (cont.)

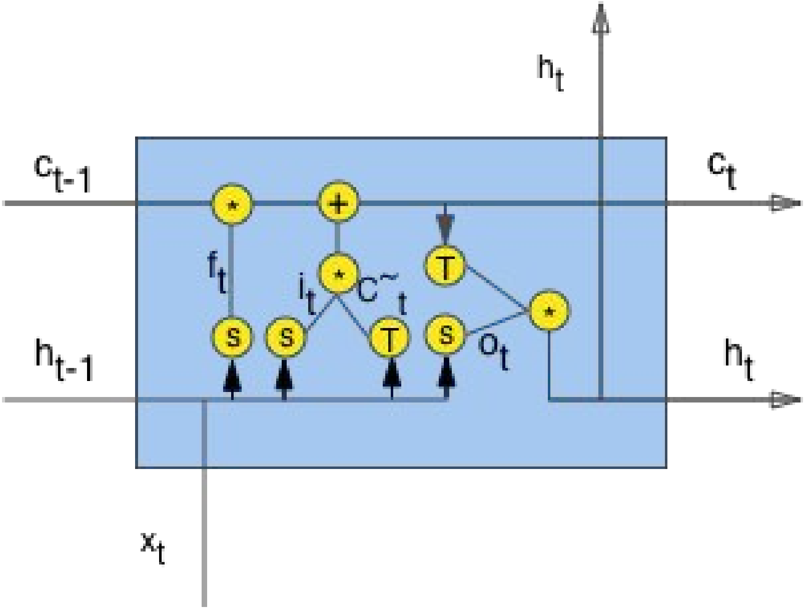
- Then, the cell state is updated from the old state C_{t-1} to the new state C_t:

$$C_t = i_t * C^{\sim}_t + f_t * C^{\sim}_{t-1}$$

- Forgets what has to be forgotten by multiplying the old state C_{t-1} with the output of the forget gate f_t
- Adds new candidate values scaled by update weights by multiplying the new state C_t with the output of the input gate i_t



LSTM (cont.)



- Finally, the output is generated:

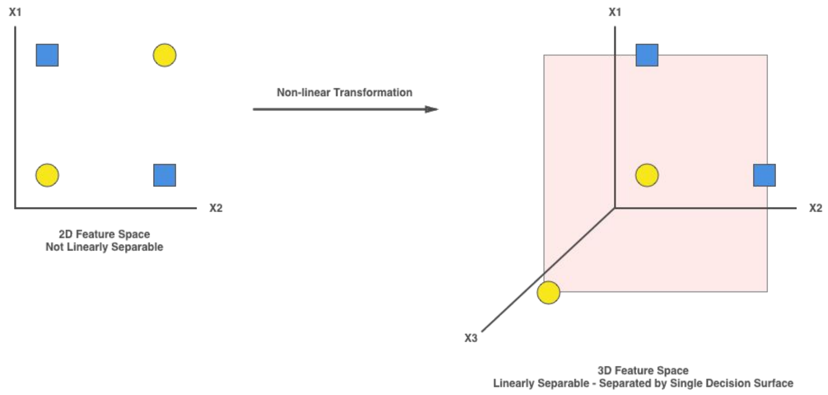
$$o_t = s(W_o x_t + U_o h_{t-1} + V_o C_t + b_o)$$

$$h_t = o_t * t(C_t)$$

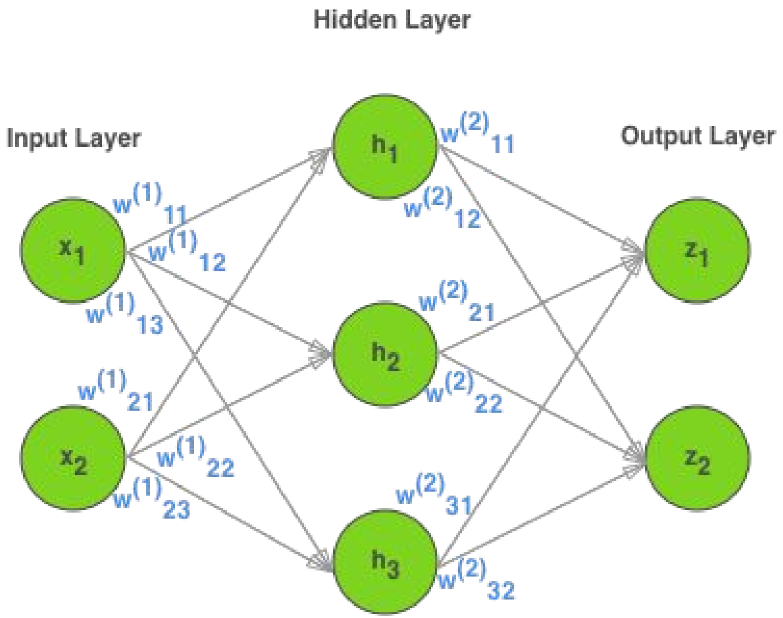
- First, a logistic sigmoid layer selects which values of the cell state to output
- Next, the cell state values pass through a hyperbolic tangent layer, scaling it to values between -1 and 1
- Finally, the outputs of the first and second steps are multiplied, resulting in a filtered cell state

Multilayer Perceptron (MLP)

- Artificial neural networks
- Consists of fully connected layers of nodes
- Map input data into outputs via a learned non-linear transformation
    - Projects input data into a space where they become linearly separable, enabling classification



MLP (cont.)



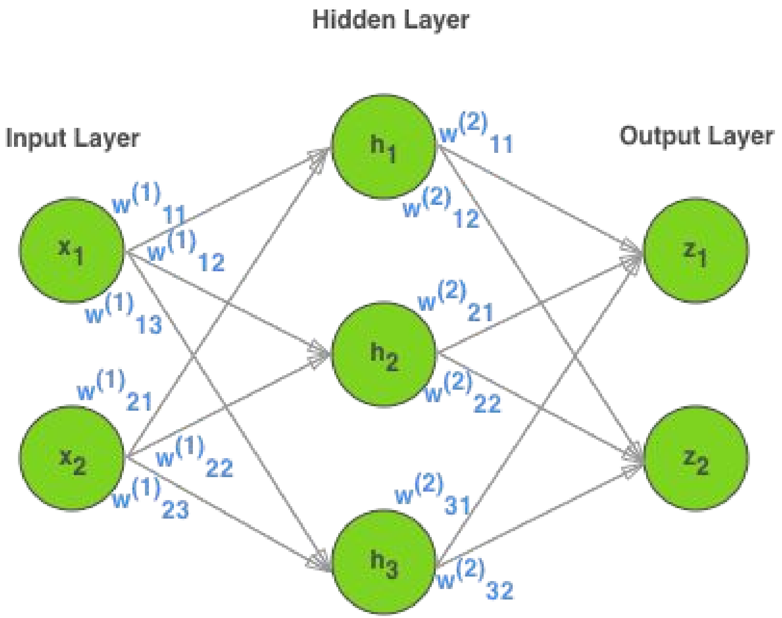
- MLPs consist of 3 primary stages:
  - Input layer
  - Hidden layer/s
  - Output layer
- With at least 1 hidden layer, MLP becomes a universal approximator
- Sample MLP with a 2-node input layer, 3-node hidden layer, and 2-node output layer
- In practical deep learning applications, multiple hidden layers are utilized to generate more features

MLP (cont.)

- Input nodes represent input features
- Hidden nodes represent generated features
- Output nodes represent class probabilities
- To make predictions, forward propagation is performed:

$$h(x) = s(b^{(1)} + w^{(1)}x)$$

$$z(h(x)) = G(b^{(2)} + w^{(2)}h(x))$$



MLP (cont.)

$$h(x) = s(b^{(1)} + w^{(1)}x)$$

$$z(h(x)) = G(b^{(2)} + w^{(2)}h(x))$$

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

Softmax function

- **x** is the input layer vector, which contains input features
- **h** is the hidden layer vector, which contains generated features
- **z** is the output layer vector, which contains class probabilities
- **b** are bias vectors, **w** are weight matrices, which are learned parameters
- **s** is the hidden layer activation function , set to ReLU for this model
- **G** is the output layer activation function, set to the softmax function for multi-class classification

MLP (cont.)

- Initially, parameters are randomized, resulting in low prediction accuracies
- To improve accuracies, parameters are learned via the backpropagation algorithm:
  - Trains the model on labelled data
  - Updates parameters until a cost function is minimized

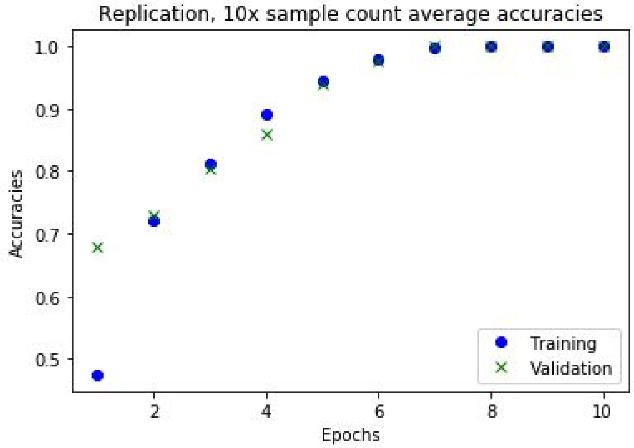
Training

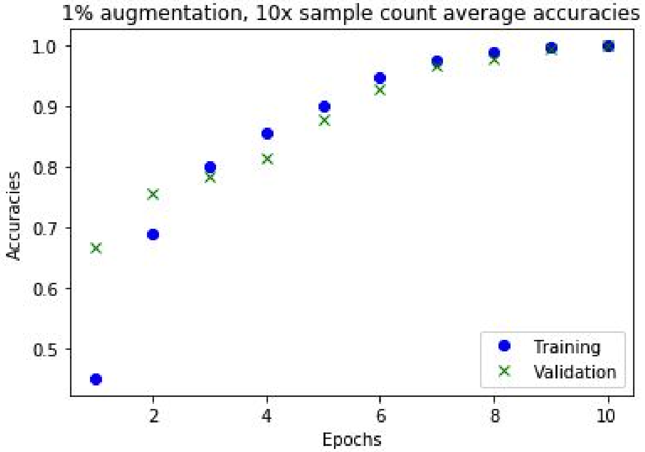
- Model was trained on 300 labelled samples
- Samples partitioned into training and validation sets
  - 70% (210) for training, 30% (90) for validation
- Training trials ran for 10 epochs
- Epochs processed 300 samples in 32-sample batches

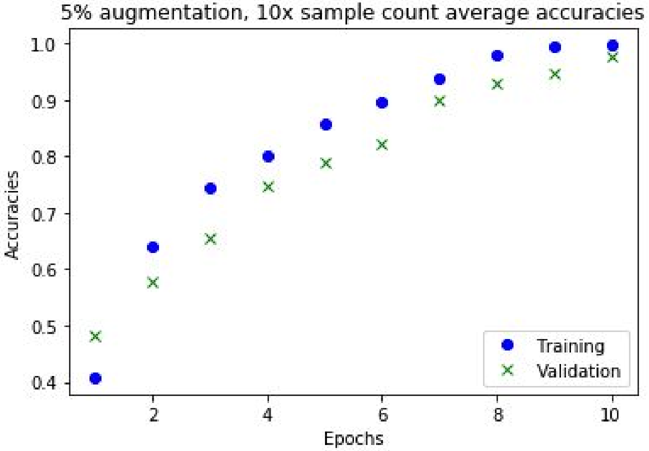
Training (cont.)

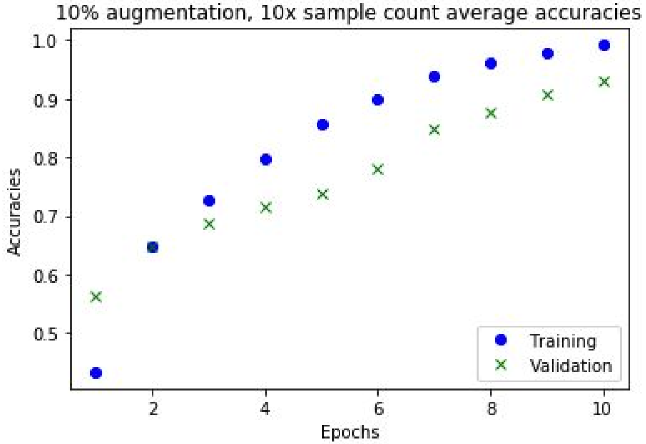
- Loss function was categorical cross entropy
- Optimizer was Adaptive Moment Estimation (Adam) with Nesterov Momentum:
  - Learning rate: 0.00015
  - Beta 1: 0.9
  - Beta 2: 0.999,
  - Epsilon: 1e-08,
  - Schedule Decay: 0.004
- 4 training set-ups, 3 trials each:
  - Replication, 10x sample count
  - 1% augmentation, 10x sample count
  - 5% augmentation, 10x sample count
  - 10% augmentation, 10x sample count

Results


Replication, 10x sample count average accuracies
Accuracies
Epochs
Training
Validation


1% augmentation, 10x sample count average accuracies
Accuracies
Epochs
Training
Validation


5% augmentation, 10x sample count average accuracies
Accuracies
Epochs
Training
Validation


10% augmentation, 10x sample count average accuracies
Accuracies
Epochs
Training
Validation

Recommendations

- Multiple changes can be implemented, which could improve the performance of the model
- Some potential changes:
  - Expand model to work with more classes: classify for finer phalangeal articulations
    - Requires more training data and more complex models
  - Use wider, deeper networks to improve performance
    - More computationally expensive and prone to overfitting
  - Use other CNN architectures:
    - ResNet, Inception
    - Apparently have higher accuracies and less expensive than VGG
  - Use other RNN architectures
    - Gated Recurrent Unit (GRU)
    - Unlike LSTMs, no memory unit, uses 2 gates (reset, update) instead of 3
    - On par performance, less complex, more efficient

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