Additional Neural Network Concepts

Advanced Optimization

Adam optimization algorithm, which improves the training process of neural networks compared to traditional gradient descent.

Adam Algorithm Intuition

- Adam: Adaptive Moment Estimation and adjusts the learning rate automatically based on the behavior of the parameters during training.
- It uses different learning rates for each parameter, allowing for more efficient convergence to the minimum of the cost function.
- If w_i (or b) keeps moving in the same direction, increase α_i .
- If w_i (or b) keeps oscillating, reduce α_i .

MINIST Adam

• It is more robust to the choice of initial learning rate, making it a preferred option among practitioners for training neural networks.

Additional Layer Types

Recap: Dense Layer

Every neuron in the layer gets its inputs all the activations from the previous layer.

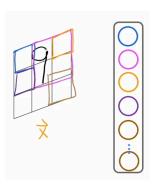
$$a_j^{[l]} = g(\vec{w}_j^{[l]} \cdot \vec{a}^{[l-1]} + b_j^{[l]})$$

Convolutional Layer

If each neuron (unit) in a layer only looks at a subset (part) of the outputs from the previous layer, this approach can offer certain advantages.

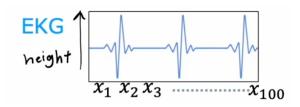
- · Faster computations.
- Less training data (Less prone to overfitting).

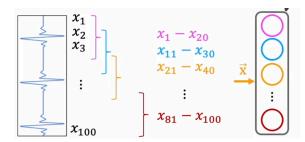
The example illustrates how a convolutional layer processes a handwritten digit image by having each neuron look at a limited rectangular area of the image.



Convolutional Neural Network

In a different context, the convolutional layer can be applied to **EKG signals (electrocardiograms)**, where neurons analyze small windows of the signal to classify heart conditions. (it is 1D array not 2D array example)



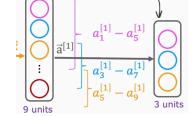


- Each neuron in the convolutional layer examines a small window of the EKG signal:
 - For example, the first neuron might analyze the first 20 data points, while the second

neuron looks at points 11 to 30.

Second Convolutional Layer:

- The second layer takes the activations from the first layer as its input.
- Each neuron in this layer also looks at a limited number of activations from the previous layer, rather than all of them.
- For example:
 - The first neuron in the second layer might look at the first 5 activations from the first layer.



- The second neuron might analyze activations 3 to 7.
- The third neuron might focus on activations
 5 to 9.
- This method allows the network to identify patterns in the EKG signal that can indicate heart conditions, improving classification accuracy.

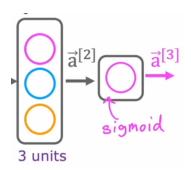


Purpose of the Second Layer:

- This structure allows the network to learn more complex features by combining the information from the first layer's activations.
- By focusing on different subsets of activations, the second layer can capture higher-level patterns in the EKG signal that may be indicative of specific heart conditions.

Final Output Layer

- The final output layer (often a sigmoid layer) takes the activations from the last convolutional layer.
- This output layer typically makes a binary classification decision, such as determining whether the patient has a heart disease or not, based on the combined information from the previous layers.





QUES: The Adam optimizer is the recommended optimizer for finding the optimal parameters of the model. How do you use the Adam optimizer in TensorFlow?

- The call to model.compile() will automatically pick the best optimizer, whether it is gradient descent, Adam or something else. So there's no need to pick an optimizer manually.
- When calling model.compile , set
 optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3) .
- The Adam optimizer works only with Softmax outputs. So if a neural network has a Softmax output layer, TensorFlow will automatically pick the Adam optimizer.
- The call to model.compile() uses the Adam optimizer by default

Explain: Correct. Set the optimizer to Adam.

model = Sequential([
 Dense(units=25, activation='relu'),

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Dense(units=15, activation='relu'),
Dense(units=20, activation='linear'),

])
# it has some initial learning rate
model.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=1e-3),
loss=SparseCategoricalCrossEntropy(from_logits=True))

model.fit(X, Y,epochs=100)
```