0+| NJL model from an ANN framework

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What is an ANN?



- An Artificial Newral Network (ANN) is a computer system modeled after the human brain's network of neurons
- It consists in interconnected nodes (neurons) organized into layers: input layer, hidden layers, and output layer
- ANNs are used to recognize patterns, make predictions, and solve complex problems

How does an ANN



- Input Layer: Receives data. Each neuron represents an input feature
- **Hidden Layers:** Process the input data. Neurons apply mathematical functions to the inputs.
- **Output Layer:** Produces the final prediction or classification.
- **Example:** Predicting Rainfall

Inputs: Temperature, humidity, wind speed, atmospheric pressure

Output: Probability of rain (Yes/No).

Steps to create an ANN framework

- 1. Define the Problem
- 2. Collect and Prepare Data
- 3. Design the Network Architecture
- 4. Initialize the Network
- 5. Choose Activation Functions
- 6. Define the Loss Function and Optimizer
- 7. Train the Network
- 8. Evaluate the Network
- 9. **Deploy the Network**

Step I: Define the problem



- We want to predict whether it will rain based on weather conditions
- Our goal is to create an ANN that can accurately make this prediction
- Example:

Inputs: Temperature, humidity, wind speed, atmospheric pressure

Output: Probability of rain (Yes/No)

Step 2: **Collect and** Prepare Data

- Gather historical weather data
- Preprocess the data:
 - Normalize the data (e.g., scale temperature between 0 and 1)
 Split the data into training and testing sets
- Example:

Historical data for temperature, humidity, wind speed, and atmospheric pressure along with whether it rained or not.

Step 3: **Design the** Network Architecture

- Decide on the number of layers and neurons in each layer
- Simple architecture for our example:
 - Input Layer: 4 neurons (one for each weather parameter)
 - Hidden Layer: 5 neurons
 - Output Layer: 1 neuron (probability of rain)

Step 4: Initialize the Network

- Randomly initialize the weights and biases
- Weights are adjusted during training to minimize prediction errors
- Example:

Initial weights are random values that will be fine-tuned



Step 5: Choose Activation **Functions**

- Activation functions introduce non-linearity to the network
- Common choices:
 - Hidden layers: ReLU (Rectified Linear Unit)
 - Output layer: Sigmoid (for binary classification)
- Example:

Use ReLU for hidden layer and Sigmoid for output layer

Step 6: **Define the Loss Function** and Optimizer

- Loss function measures the error in predictions
 - Use binary cross-entropy for our example
- Optimizer updates the weights to minimize the loss
 - Use Adam optimizer

Step 7: Train the Network

- Feed the training data into the network
- Adjust the weights based on the error in predictions
- Iterate over multiple epochs to improve accuracy
- Example:
 - Train the network with historical weather data to learn the patterns



Step 8: Evaluate the Network

- Test the network on the testing set
- Calculate accuracy, precision, and recall to evaluate performance
- Example:
 - Test with new weather data and check if the predictions match actual rainfall



Step 9: Deploy the Network



- Integrate the ANN into a weather prediction system
- Example:
 - Use the ANN to predict if it will rain based on current weather conditions



What did we learn?



- ANNs are powerful tools for making predictions based on complex patterns in data
- Following the step-by-step process, we created an ANN to predict rainfall using weather data
- This framework can be adapted to solve various problems
- Example:
 - Beyond predicting rain, similar methods can be used for tasks like predicting stock prices, diagnosing medical conditions, and more

Example: Water polluted with solids



d) High

e) Medium

f) Low

Example: Water polluted with solids Q

ImageNe Big Data





I Luviano, Y Concha, AR, work in progress

Example: Water polluted with solids



0+l dimensional NJL model

Lagrangian



R Pioquinto, S Hernández-Ortiz, AR, work in progress



0+l dimensional NJL model

Lagrangian

$$\mathcal{L} = \psi^{\dagger} \left(i\gamma_4 D^4 + im + i\mu\gamma_4 \right) \psi + \frac{g^2}{2} \left[(\psi^{\dagger}\psi)^2 + (\psi^{\dagger}i\gamma_5\psi)^2 \right]$$
Gap equation (chiral limit)
$$m^0 = 2G$$
Finite temperature and density
$$m = \frac{1}{2} \left[\tanh\left(\frac{m+\mu}{2t}\right) + \tanh\left(\frac{m-\mu}{2t}\right) \right]$$

R Pioquinto, S Hernández-Ortiz, AR, work in progress

Step I: **Define the** pro Q

• We want to solve a transcendental equation (gap equation) that depends on the coupling G and the temperature T to start with

$$1=G anhrac{m}{2t}$$

Step 2: **Collect and** Prepare . Data

• We give several values of G and T and solve the gap equation even if solutions are unphysical



Step 3: **Design the** Network Architecture

- Simple architecture for our problem:
 - Input Layer: 2 neurons, G and T
 - Hidden Layer: 2 layers, 64 neurons each
 - Output Layer: 1 neuron, the dynamical mass

Step 4: Initialize the Network

- Randomly initialize the weights and biases
- Weights are adjusted during training to minimize prediction errors

Define the neural network model model = Sequential([Input(shape=(2,)), # Input layer with 2 features (T and G) Dense(64, activation='relu'), Dense(64, activation='relu'), Dense(1) # Output layer with 1 neuron (x)])

model.compile(optimizer='adam', loss='mse')

Train the model

model.fit(np.column_stack((T_flat, G_flat)), X_flat, epochs=100, batch_size=32, validation_split=0.2)

Step 5: Choose Activation **Functions**

- We select:
 - Hidden layers: ReLU
 - Output layer

Define the neural network model model = Sequential([Input(shape=(2,)), # Input layer with 2 features (T and G) Dense(64, activation='relu'), Dense(64, activation='relu'), Dense(1) # Output layer with 1 neuron (x)])

model.compile(optimizer='adam', loss='mse')

Train the model

model.fit(np.column_stack((T_flat, G_flat)), X_flat, epochs=100, batch_size=32, validation_split=0.2)

Step 6: **Define the Loss Function** and

Loss function

MSE 0

Optimizer

Adam 0

Define the neural network model model = Sequential([Input(shape=(2,)), # Input layer with 2 features (T and G) Dense(64, activation='relu'), **Optimizer** Dense(64, activation='relu'), Dense(1) # Output layer with 1 neuron (x)

model.compile(optimizer='adam', loss='mse')

Train the model model.fit(np.column stack((T flat, G flat)), X flat, epochs=100, batch size=32, validation split=0.2)

Step 7: Train the Network

- Feed the training data into the network (Sols of the gap eq. with several G's and T's
- Adjust the weights based on the error in predictions (MSE)
- Iterate up to 100 epochs

_loss: 5.5604e-06
_loss: 9.8271e-06
_loss: 9.8643e-06
_loss: 2.0244e-04
_loss: 3.1287e-05
_loss: 8.1444e-06

Step 8: Evaluate the Network



- Test the network on the testing set
- Calculate accuracy, precision, and evaluate performance



Step 8: Evaluate the Network

Q

- Test the network on the testing set
- Calculate accuracy, precision, and evaluate performance



Step 9: Deploy the Network

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• **Predictions**



Future Endeavors

Q



- Work in higher dimensions
- Introduce additional parameters (magnetic fields, etc)
- Feed the ANN with physical information
- Compute other physical observables
- Develop a similar framework for other problems in QCD
 - LSMq
 - FESR
 - **Etc**

GRACIAS