

BSDS-204: Advanced Machine Learning

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TIME SERIES STOCHASTIC MODELS

Time Series Forecasting

REINFORCEMENT LEARNING

Neural Networks

Projects

Reference

THANK YOU

# BSDS-204: ADVANCED MACHINE LEARNING COURSE INSTRUCTOR - Ms. MANPREET KAUR BHATIA

Gauri Sharan - BSc Data Science, Semester 4

June 11, 2024



# Table of Contents

BSDS-204: MACHINE Learning

REINFORCEMENT

THANK YOU

Time Series: Stochastic Models TIME SERIES FORECASTING

REINFORCEMENT LEARNING

NEURAL NETWORKS

Projects



#### Introduction to Time Series

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Introduction to Time Series

Components of

TIME SERIES

DATE-TIME
INDEXING

CONCEPT OF HOLIDAYS

ROLLING STATISTIC

ROLLING STATISTI
CONCEPT OF
STATIONARITY
TEST FOR
STATIONARITY

ACF AND PAC

DECOMPOSITION

DATA EXPLORATIO

AND CLEANING

WHAT IS A TIME SERIES?

A time series is a sequence of data points measured at regular time intervals.

Components of a Time Series

- Trend
- Seasonality
- Cyclical
- Irregular



### Components of Time Series

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Components of Time Series

DATE-TIME INDEXING CONCEPT OF HOLIDAYS RESAMPLING ROLLING STATISTIC

STATIONARITY
TEST FOR
STATIONARITY
ACF AND PACF
DECOMPOSITION

Trend

A trend is a long-term pattern or direction in the data.

SEASONALITY

Seasonality refers to the periodic fluctuations in the data which are seasonal in nature.

Cyclical

Cyclical fluctuations refer to the periodic fluctuations in the data which are cyclic in nature.

IRREGULAR

Irregular fluctuations refer to the random or unpredictable fluctuations in the data.



#### Date-Time Indexing

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TIME SERIES
STOCHASTIC
MODELS
Introduction to

INTRODUCTION TO TIME SERIES COMPONENTS OF TIME SERIES

DATE-TIME INDEXING

RESAMPLING
ROLLING STATISTIC
CONCEPT OF
STATIONARITY
TEST FOR
STATIONARITY
ACE AND PACE

STATIONARITY
ACF AND PACF
DECOMPOSITION
DATA EXPLORATION
AND CLEANING

WHAT IS DATE-TIME INDEXING?

Date-time indexing is the process of assigning a unique identifier to each data point based on the date and time it was recorded.

Why is Date-Time Indexing Important?

Date-time indexing is important because it allows us to easily identify and manipulate specific data points based on their date and time.



## CONCEPT OF HOLIDAYS

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What are Holidays?

Holidays are special days that are not included in the data.

Why are Holidays Important?

Holidays are important because they can affect the data and need to be accounted for in the analysis.



#### RESAMPLING

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INTRODUCTION TO TIME SERIES COMPONENTS OF TIME SERIES DATE-TIME INDEXING CONCEPT OF

RESAMPLING

Stationarity Test for Stationarity ACF and PACF Decomposition WHAT IS RESAMPLING?

Resampling is the process of reducing the frequency of the data.

Why is Resampling Important?

Resampling is important because it can help to reduce the noise in the data and make it easier to analyze.



#### ROLLING STATISTICS

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TIME SERIES STOCHASTIC MODELS

INTRODUCTION TO TIME SERIES COMPONENTS OF TIME SERIES DATE-TIME INDEXING CONCEPT OF HOLIDAYS

ROLLING STATISTICS

CONCEPT OF STATIONARITY TEST FOR STATIONARITY ACF AND PA DECOMPOSITION WHAT ARE ROLLING STATISTICS?

Rolling statistics are statistics that are calculated over a moving window of data.

WHY ARE ROLLING STATISTICS IMPORTANT?

Rolling statistics are important because they can help to identify trends and patterns in the data.



#### CONCEPT OF STATIONARITY

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INTRODUCTION T TIME SERIES COMPONENTS OF TIME SERIES DATE-TIME INDEXING CONCEPT OF HOLIDAYS RESAMPLING

CONCEPT OF

STATIONARITY

ACF AND PAC

DECOMPOSITION

DATA EXPLORATIO

WHAT IS STATIONARITY?

Stationarity refers to the property of a time series that its statistical properties remain constant over time.

Why is Stationarity Important?

Stationarity is important because it is a necessary preprocessing condition for many time series analysis techniques.



### Test for Stationarity

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TIME SERIES STOCHASTIC MODELS

INTRODUCTION T TIME SERIES
COMPONENTS OF TIME SERIES
DATE-TIME
INDEXING
CONCEPT OF
HOLIDAYS
RESAMPLING
ROLLING STATIS:

CONCEPT OF STATIONARITY

STATIONARITY

DECOMPOSITION

DATA EXPLORATION

AND CLEANING

WHAT IS A TEST FOR STATIONARITY?

A test for stationarity is a statistical test that is used to determine whether a time series is stationary or not.

Why is a Test for Stationarity Important?

A test for stationarity is important because it can help to identify whether a time series is suitable for analysis.



## ACF AND PACF

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What are ACF and PACF?

ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) are statistical measures that are used to analyze the autocorrelation of a time series.

WHY ARE ACF AND PACF IMPORTANT?

ACF and PACF are important because they can help to identify the underlying structure of a time series.



## DECOMPOSITION

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#### What is Decomposition?

Decomposition is the process of breaking down a time series into its component parts.

#### Why is Decomposition Important?

Decomposition is important because it can help to identify the underlying structure of a time series.

#### Data Exploration and Cleaning

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TIME SERIES STOCHASTIC MODELS

INTRODUCTION TO TIME SERIES COMPONENTS OF TIME SERIES DATE-TIME INDEXING CONCEPT OF HOLIDAYS RESAMPLING ROLLING STATIST

ROLLING STATISTIC
CONCEPT OF
STATIONARITY
TEST FOR
STATIONARITY
ACF AND PACF
DECOMPOSITION

Data Exploration and Cleaning

#### WHAT IS DATA EXPLORATION?

Data exploration is the process of analyzing and summarizing the data to gain insights.

#### Why is Data Exploration Important?

Data exploration is important because it can help to identify trends and patterns in the data.



# EXAMPLE CODE

# Import necessary libraries

```
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MACHINE
Learning
```

```
CONCEPT OF
HOLIDAYS
RESAMPLING
ROLLING STATISTI
CONCEPT OF
STATIONARITY
TEST FOR
```

DATA EXPLORATION



#### EDA OF TIME SERIES

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Time Series Forecasting

EDA OF TIME SERIES

GRAPHICAL
REPRESENTATIONS
TRADITIONAL
MODELS FOR TIME
SERIES
FORECASTING
SES, DES, AND

REINFORCEMENT LEARNING

Neural Networks WHAT IS EDA OF TIME SERIES?

EDA (Exploratory Data Analysis) of time series is the process of analyzing and summarizing the data to gain insights.

Why is EDA of Time Series Important?

Through EDA, we can identify significant variables, detect outliers and anomalies, and test foundational assumptions. This approach helps in developing models and determining the best parameters for future predictions.



#### GRAPHICAL REPRESENTATIONS

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TIME SERIES FORECASTING EDA OF TIME

Graphical Representations

TRADITIONAL
MODELS FOR TIME
SERIES
FORECASTING
SES, DES, AND
TES

REINFORCEMENT LEARNING

Neural Networks WHAT ARE GRAPHICAL REPRESENTATIONS?

Graphical representations are visualizations of the data that can help to identify trends and patterns.

Why are Graphical Representations Important?

Graphical representations are important because they can help to communicate insights to stakeholders.



#### Traditional Models for Time Series Forecasting

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TRADITIONAL MODELS FOR TIME SERIES

SES, DI TES

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Traditional models are statistical models that are used to forecast time series data.

Why are Traditional Models Important?

Traditional models are important because they can provide a baseline for comparison with more advanced models.



# SES, DES, AND TES

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FORECASTING
EDA OF TIME
SERIES
GRAPHICAL
REPRESENTATIONS
TRADITIONAL
MODELS FOR TIME
SERIES
FORECASTING
SES DES AND

REINFORCEMENT

Neural Networks WHAT ARE SES, DES, AND TES?

SES (Simple Exponential Smoothing), DES (Double Exponential Smoothing), and TES (Triple Exponential Smoothing) are traditional models for time series forecasting.

WHY ARE SES, DES, AND TES IMPORTANT?

SES, DES, and TES are important because they are widely used methods for forecasting time series data, particularly for modeling trends and seasonality, and are effective in capturing underlying patterns and making accurate predictions.



#### EXAMPLE CODE

```
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Learning
```

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TIME SERIES

FORECASTING

GRAPHICAL REPRESENTATIONS TRADITIONAL MODELS FOR TIME SERIES

SES, DES, AND TES

REINFORCEMENT LEARNING

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```
data = pd read_csv('data.csv')
print(data head())
print(data.info())
print(data.describe())
data = data.dropna()
data = data.drop_duplicates()
model = SES(data)
forecast = model.forecast()
plt.plot(data)
plt.plot(forecast)
plt.show()
```



### Introduction to Reinforcement Learning

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Introduction to Reinforcement Learning

SELECTION OF RL
ALGORITHM
ALPPROACHES TO
IMPLEMENT
REINFORCEMENT
LEARNING
ELEMENTS OF
REINFORCEMENT
LEARNING
MARKOV DECISION
MARKOV DECISION

WHAT IS REINFORCEMENT LEARNING?

Reinforcement learning is a type of machine learning that involves training an agent to make decisions in an environment.

Why is Reinforcement Learning Important?

Reinforcement learning is important because it can be used to solve complex problems that involve making decisions in an uncertain environment.



## SELECTION OF RL ALGORITHM

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Time Series Forecasting

REINFORCEMENT LEARNING INTRODUCTION TO REINFORCEMENT LEARNING

SELECTION OF RL ALGORITHM

Approaches to
Implement
Reinforcement
Learning
Elements of
REINFORCEMENT
LEARNING

WHAT IS THE SELECTION OF RL ALGORITHM?

The selection of RL algorithm is the process of choosing the appropriate algorithm for a given problem.

Why is the Selection of RL Algorithm Important?

The selection of RL algorithm is important because it can affect the performance of the agent.



# Approaches to Implement Reinforcement Learning

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TIME SERIES FORECASTIN

REINFORCEMENT LEARNING

INTRODUCTION TO REINFORCEMENT LEARNING SELECTION OF RI

Approaches to Implement Reinforcemen' Learning

ELEMENTS OF REINFORCEMEN' LEARNING MARKOV DECIS WHAT ARE APPROACHES TO IMPLEMENT REINFORCEMENT LEARNING? Approaches to implement reinforcement learning include model-based and model-free methods.



#### Elements of Reinforcement Learning

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ELEMENTS OF

What are Elements of Reinforcement Learning? Elements of reinforcement learning include the agent, environment, and actions.



# Markov Decision Process

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TIME SERIES
FORECASTING
REINFORCEMENT

LEARNING INTRODUCTION TO REINFORCEMENT LEARNING

GENFORCEMENT
JEARNING
BELECTION OF RL
ALGORITHM
APPROACHES TO
MPLEABENT
REINFORCEMENT
JEANNING
ELEMENTS OF
REINFORCEMENT
JEANNING

Markov Decision

WHAT IS MARKOV DECISION PROCESS?

Markov decision process is a mathematical framework for modeling decision-making problems.

WHY IS MARKOV DECISION PROCESS IMPORTANT?

Markov decision process is important because it can be used to model complex decision-making problems.



### OPTIMAL POLICY

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FORECASTING
REINFORCEMENT

INTRODUCTION TO REINFORCEMENT LEARNING

ALGORITHM
APPROACHES TO
MPLEMENT
REINFORCEMENT
LEARNING
ELEMENTS OF
REINFORCEMENT
LEARNING

WHAT IS OPTIMAL POLICY?

Optimal policy is a policy that maximizes the expected cumulative reward.

WHY IS OPTIMAL POLICY IMPORTANT?

Optimal policy is important because it maximizes the expected discounted return, ensuring that the policy chosen is the best possible given the constraints and objectives of the system being managed.



# Bellman Equation

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APPROACHES TO IMPLEMENT REINFORCEMENT LEARNING ELEMENTS OF REINFORCEMENT LEARNING

WHAT IS BELLMAN EQUATION?

Bellman equation is a mathematical equation that is used to calculate the optimal policy.

Why is Bellman Equation Important?

it provides a necessary condition for optimality in dynamic programming, allowing for the calculation of the optimal value function and policy in Markov decision processes (MDPs).



#### Temporal Differencing

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REINFORCEMENT LEARNING SELECTION OF RL ALGORITHM

REINFORCEMENT LEARNING ELEMENTS OF REINFORCEMENT LEARNING WHAT IS TEMPORAL DIFFERENCING?

Temporal differencing is a technique that is used to estimate the value function.

WHY IS TEMPORAL DIFFERENCING IMPORTANT?

Temporal differencing is important because it can be used to estimate the value function.



# Q-LEARNING

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Time Series Forecasting

REINFORCEMENT
LEARNING
INTRODUCTION TO
RESINFORCEMENT
LEARNING
SELECTION OF RL
ALGORITHM
APPERACUES TO
IMPLEMENT
REINFORCEMENT
LEARNING
ELEMENTS OF
REINFORCEMENT
LEARNING

#### WHAT IS Q-LEARNING?

Q-learning is a type of reinforcement learning that is used to learn the optimal policy.

#### Why is Q-Learning Important?

Q-learning is important because it provides a model-free approach to reinforcement learning, allowing agents to learn optimal policies without prior knowledge of the environment. This flexibility and adaptability make Q-learning a valuable tool for optimizing decision-making processes in various fields



#### EXPLORATION VS. EXPLOITATION

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Time Series Forecasting

#### REINFORCEMENT LEARNING

Introduction to Reinforcement Learning Selection of RL

Algorithm

Approaches to
Implement
Reinforcement

LEARNING

ELEMENTS OF
REINFORCEMENT
LEARNING

WHAT IS EXPLORATION VS. EXPLOITATION?

Exploration vs. exploitation is a trade-off that is used to balance the exploration of new actions and the exploitation of known actions.



# SARSA

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REINFORCEMENT
LEARNING
INTRODUCTION TO
REINFORCEMENT
LEARNING
SELECTION OF RL
ALGORITHM
APPROACHES TO
IMPLEMENT
LEARNING

WHAT IS SARSA?

SARSA is a type of reinforcement learning that is used to learn the optimal policy.

WHY IS SARSA IMPORTANT?

SARSA is important because it can handle stochastic and dynamic environments. SARSA is also simple to implement and can be used with different exploration strategies, making it a versatile tool for solving sequential decision-making problems.

## FROZEN GYM LAKE ENVIRONMENT

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Time Series Forecasting

REINFORCEMENT LEARNING

REINFORCEMENT
LEARNING
SELECTION OF RL
ALGORITHM
APPROACHES TO
IMPLEMENT

REINFORCEMENT
LEARNING
ELEMENTS OF
REINFORCEMENT
LEARNING

Overview

The Frozen Gym Lake Environment is a classic problem in reinforcement learning.

Goal

The goal is to navigate from the starting point to the goal point.



#### Gym Library

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Time Series Forecasting

REINFORCEMENT LEARNING

Introduction to Reinforcement Learning Selection of RL

Selection of RL Algorithm Approaches to Implement Reinforcement

LEARNING

ELEMENTS OF

REINFORCEMENT

LEARNING

#### Overview

The Gym library is a collection of environments for reinforcement learning.

#### KEY FEATURES

- Provides a variety of environments.
- Supports multiple reinforcement learning algorithms.



#### SOLVING FROZEN GYM LAKE ENVIRONMENT

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LEARNING
SELECTION OF RL
ALGORITHM
APPROACHES TO
IMPLEMENT
REINFORCEMENT

LEARNING
ELEMENTS OF
REINFORCEMENT
LEARNING

APPROACH
Use SARSA to learn the optimal policy.

```
env = gym.make('FrozenLake-v0')
# Initialize Q-table and policy
Q = np.zeros([env.observation_space.n, env.action_space.n])
policy = np.zeros([env.observation_space.n, env.action_space.n])
# Train using SARSA
for episode in range(1000):
    state = env.reset()
   done = False
    while not done:
        action = np.argmax(policy[state])
        next_state, reward, done, _ = env.step(action)
        Q[state, action] = Q[state, action] + 0.1 *
        (reward + 0.9 * np.max(Q[next_state]) - Q[state, action])
        policy[state] = np.argmax(Q[state])
```



#### Fundamentals of Artificial Neural Networks

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REINFORCEMENT LEARNING

Neural Networks

Fundamentals of Artificial Neural Networks

CONCEPTS IN ARTIFICIAL NEUR NETWORKS UNDERSTANDING ACTIVATION FUNCTIONS IN

#### DEFINITION

Artificial Neural Networks (ANNs) are computational models inspired by the structure and function of the human brain.

#### KEY COMPONENTS

- Neurons (nodes)
- Connections (edges)
- Weights
- Bias



# ADVANCED CONCEPTS IN ARTIFICIAL NEURAL NETWORKS

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Neural Networks

FUNDAMENTALS OF ARTIFICIAL NEURA

ADVANCED CONCEPTS IN ARTIFICIAL NEURAL NETWORKS

Understanding Activation Functions in

# REGULARIZATION

Techniques to prevent overfitting.

#### OPTIMIZATION ALGORITHMS

- Stochastic Gradient Descent (SGD)
- Adam
- RMSProp



# Understanding Activation Functions in Neural Networks

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Understanding Activation Functions in

#### DEFINITION

Activation functions introduce non-linearity into the neural network.

#### COMMON ACTIVATION FUNCTIONS

- Sigmoid
- ReLU (Rectified Linear Unit)
- Tanh (Hyperbolic Tangent)



### Loss Function

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#### DEFINITION

The loss function measures the difference between the predicted output and the actual output.

### COMMON LOSS FUNCTIONS

- Mean Squared Error (MSE)
- Cross-Entropy



## PERCEPTRON: - SINGLE LAYERED AND MULTIPLE LAYERED

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REINFORCEMENT LEARNING

Neural Networks

FUNDAMENTALS OF ARTIFICIAL NEURAL NETWORKS ADVANCED CONCEPTS IN ARTIFICIAL NEURAL NETWORKS UNDERSTANDING ACTIVATION

#### SINGLE LAYER PERCEPTRON

A single layer neural network with a linear activation function.

### Multi-Layer Perceptron

A neural network with multiple layers, allowing for more complex representations.



### STEPS TO FORMULATE ANN ALGORITHM

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REINFORCEMENT LEARNING

NEURAL NETWORKS
FUNDAMENTALS OF
ARTIFICIAL NEURAL
NETWORKS

NETWORKS
ADVANCED
CONCEPTS IN
ARTIFICIAL NEURAL
NETWORKS

STEP 1: DATA PREPARATION

Preprocess the data.

STEP 2: MODEL DEFINITION

Define the neural network architecture.

STEP 3: TRAINING

Train the model using the training data.

STEP 4: EVALUATION

Evaluate the model using the testing data.



# BUILDING A SINGLE NEURON NEURAL NETWORK FROM SCRATCH IN PYTHON

```
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Learning
```

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Time Series Forecasting

Reinforcement Learning

Neural Networks

FUNDAMENTALS OF ARTIFICIAL NEURAL NETWORKS ADVANCED CONCEPTS IN ARTIFICIAL NEURAL NETWORKS

ARTIFICIAL NEURAL
NETWORKS
UNDERSTANDING
ACTIVATION
FUNCTIONS IN
NEURAL NETWORKS

```
def __init__(self, inputs, bias):
        self.weights = [random.random() for _ in range(inputs)]
       self.bias = bias
   def forward(self, inputs):
        output = sum([x * y for x, y in zip(inputs, self.weights)]) + self.bias
       return self.sigmoid(output)
   def sigmoid(self, x):
        return 1 / (1 + math.exp(-x))
neuron = Neuron(2, 1)
inputs = [0, 0]
output = neuron.forward(inputs)
print(output)
```



## Models of Artificial Neural Network

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Neural Networks

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Models of Artificial Neur Network

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TRAINING IN
PATHON

FEEDFORWARD NEURAL NETWORKS Information flows only in one direction.

RECURRENT NEURAL NETWORKS (RNNs) Information can flow in a loop.



# PRACTICAL IMPLEMENTATION OF NEURAL NETWORK TRAINING IN PYTHON

```
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Learning
```

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Time Series Forecasting

REINFORCEMENT LEARNING

NEURAL NETWORKS

PROJECTS

Models of
Artificial Neural
Network

PRACTICAL
IMPLEMENTATION OF
NEURAL NETWORK
TRAINING IN
PYTHON

```
# Define the neural network
   def __init__(self, inputs, hidden, outputs):
        self.weights1 = np.random.rand(inputs, hidden)
        self.weights2 = np.random.rand(hidden, outputs)
   def forward(self, inputs):
       hidden_layer = np.maximum(np.dot(inputs, self.weights1), 0)
        output_layer = np.dot(hidden_layer, self.weights2)
       return output_layer
# Train the neural network
nn = NeuralNetwork(2, 2, 1)
inputs = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
outputs = np.array([[0], [1], [1], [0]])
   output = nn.forward(inputs)
   error = outputs - output
    # Update weights
```



# IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORK FOR AND LOGIC GATE

```
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Machine
Learning
```

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Time Series Forecasting

REINFORCEMENT LEARNING

Neural Networks

PROJECTS

MODELS OF
ARTIFICIAL NEURAL
NETWORK

PRACTICAL
IMPLEMENTATION OF
NEURAL NETWORK
TRAINING IN

```
# Define the neural network
   def __init__(self, inputs, hidden, outputs):
        self.weights1 = np.random.rand(inputs, hidden)
        self.weights2 = np.random.rand(hidden, outputs)
   def forward(self, inputs):
        hidden_layer = np.maximum(np.dot(inputs, self.weights1), 0)
        output_layer = np.dot(hidden_layer, self.weights2)
       return output_layer
# Train the neural network
nn = NeuralNetwork(2, 2, 1)
inputs = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
outputs = np.array([[0], [0], [0], [1]])
   output = nn.forward(inputs)
   error = outputs - output
    # Update weights
```



# IMPLEMENTATION OF ARTIFICIAL NEURAL NETWORK FOR OR LOGIC GATE

```
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Advanced
Machine
Learning
```

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Time Series: Stochastic Models

Time Series Forecasting

REINFORCEMENT LEARNING

NEURAL NETWORKS

PROJECTS

MODELS OF
ARTIFICIAL NEURAL
NETWORK

PRACTICAL
IMPLEMENTATION OF
NEURAL NETWORK
TRAINING IN

```
# Define the neural network
   def __init__(self, inputs, hidden, outputs):
        self.weights1 = np.random.rand(inputs, hidden)
        self.weights2 = np.random.rand(hidden, outputs)
   def forward(self, inputs):
        hidden_layer = np.maximum(np.dot(inputs, self.weights1), 0)
        output_layer = np.dot(hidden_layer, self.weights2)
       return output_layer
# Train the neural network
nn = NeuralNetwork(2, 2, 1)
inputs = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
outputs = np.array([[0], [1], [1], [1]])
   output = nn.forward(inputs)
   error = outputs - output
    # Update weights
```



## Time Series Project - Future Prediction

```
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 MACHINE
             from sklearn.model_selection import train_test_split
 LEARNING
             from sklearn.metrics import mean_squared_error
             from keras.models import Sequential
             from keras.layers import LSTM, Dense
             # Load data
             data = pd.read_csv('data.csv')
             # Prepare data
             X = data.drop(['target'], axis=1)
REINFORCEMENT
             v = data['target']
             X train, X test, v train, v test = train test split(X, v, test size=0.2, random state=42)
             # Create LSTM model
             model = Sequential()
             model.add(LSTM(50, input_shape=(X.shape[1], 1)))
             model add(Dense(1))
             model.compile(loss='mean_squared_error', optimizer='adam') #continued in the next slide
```



### TIME SERIES PROJECT - FUTURE PREDICTION

```
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Time Series Forecasting

REINFORCEMENT LEARNING

Neural Networks

### PROJECTS Models of

Models of Artificial Neur Network

NEURAL NETW TRAINING IN PYTHON

```
# Train model
model.fit(X train, v_train, epochs=100, batch size=32, verbose=2)
```

# Fualuate model

```
y_pred = model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
```

```
print(f'MSE: {mse}')
```



## References

- BSDS-204 · MACHINE LEARNING
- Reinforcement
- References

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## THANK YOU

BSDS-204 : Advanced Machine Learning

> Gauri Sharan

Time Series: Stochastic Models

Time Series Forecasting

REINFORCEMENT LEARNING

Neural Network:

Projects

References

THANK YOU

Hope you liked this presentation.

#### Gauri Sharan

Student, School of Data Science AAFT Noida (Shobhit University) BSc Data Science 2022-25 Semester 4, 2024

■ LinkedIn: linkedin.com/in/gauri-sharan

■ GitHub: github.com/gaurisharan

■ Mail: gaurisharan123@gmail.com