DSP301-AIML-2025-26-M

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Outline

Introduction

2 Content

3 Conclusion

Schedule

Time and Venue

• **Time:** Thursday (2:30 PM – 5:30 PM)

• **Venue:** ED1 105 (Lab)

About Course

Areas Covered

- Language Translation (Text Processing)
- Voice Identification or Text to Voice (Audio-Speech Processing)
- Computer Vision (Segmentation and Classification)
- Reinforcement Learning
- Game Development
- Hardware Deployment

Course Objectives

- Provide hands-on experience in various AI/ML techniques
- Develop practical skills in implementing AI/ML solutions
- Enable students to work on real-world AI/ML projects

Grading Schema

Table 1: Grading Scheme

Score (%)	Grade
100% to 94%	A+
<94% to 85%	A
<85% to 75%	A-
<75% to 65%	В
<65% to 55%	B-
<55% to 45%	С
<45% to 35%	C-
<35% to 30%	D
<30% to 0%	F

About the Course - Content

Evaluation Phases

- Research
- 2 Implementation
- Open Deployment/Validation

Content

- Text Processing
- Speech Processing
- Computer Vision
- Game Playing
- AI/ML Development Boards/Kits/Drones

About the Course - Syllabus

Syllabus

- Design and implementation of AI/ML models for Text processing
- Design and implementation of AI/ML models for speech processing
- Design and implementation of AI/ML models for computer vision
- Design and implementation of AI/ML models for game playing
- Deploying ML models on hardware tools
- Developing applications with AI/ML development boards/kits/drones

Course Outline

Course Topics

- Natural Language Processing
 - Text & Speech Processing
 - Transformers for NLP Speech
- Computer Vision
 - Introduction to CV
 - Segmentation & Classification
- Advanced Topics
 - Reinforcement Learning: Game Design
 - Multimodality
 - LLMs (Hands-on, optional)

Lab Sessions

- Hardware Assembly
 - Lab 1: PC Assembly Booting
 - Lab 2: Drone Assembly Vision Setup
- Robotics Ground Vehicle
 - Lab 3: Path Tracking
 - Lab 4-5: Collision Avoidance
- Robotics Aerial Drone
 - Lab 6: Human Tracking
 - Lab 8: Advanced Maneuvers
- Integrated Systems
 - Lab 7: Real-time Recognition

Hardware Requirements

Core Compute Robotics

• Primary Compute Modules

- Nvidia Jetson Nano Dev Kit (4GB)
- Raspberry Pi 5 w/ Power Supply
- Arduino Uno Rev3
- ESP32 Development Board

• Robotics Kits Chassis

- DIY JetBot Kit (for Jetson Nano)
- Generic Robotic Car Chassis

• Specialized AI Sensors

- HUSKYLENS
- Arduino Nicla Vision

• J

Peripherals Components

• Sensors I/O

- Raspberry Pi Camera Module 3
- USB Desktop Microphone
- General Sensor Packet

• Power System

- 18650 Li-ion Batteries (3000mAh)
- 18650 Battery Holder Charger
- USB Power Bank

• Prototyping Tools

- Breadboard (840 points)
- Jumper Wire Sets (M-M,

Required Libraries

- Audacity Software
- Python speech features
- Keras
- Tesseract Python library

Experiments

- Language Translation with Deep Learning
- Speaker Identification
- Face Detection
- Game Development (e.g., Hadron game)
- Path following robotic car
- And few Real world projects

Project Example: Language Translation with Deep Learning

Project Purpose

Build an RNN sequence-to-sequence model in Keras to translate a language A to language B.

- Sequence-to-sequence learning (Seq2Seq) converts sequences from one domain to another.
- The encoder LSTM turns input sequences into state vectors.
- The decoder LSTM generates target sequences based on the encoder's state vectors.
- In inference mode, the process involves encoding, decoding, and sampling characters until the end-of-sequence.

Introduction

Transformer is a deep learning architecture introduced by Vaswani et al. (2017) in the paper "Attention is All You Need".

- Foundation for models like BERT, GPT, T5, RoBERTa.
- Revolutionized Natural Language Processing (NLP).

Core Idea

- Traditional models (RNNs, LSTMs) process text **sequentially**.
- Transformers process in parallel using self-attention.
- Better for capturing long-range dependencies.

Transformer Architecture

- **Input Embeddings**: Word vectors + positional encoding.
- Encoder-Decoder:
 - Encoder (6 layers): Understands input.
 - Decoder (6 layers): Generates output.
- BERT uses only encoder, GPT uses only decoder.

Self-Attention Mechanism

Attention
$$(Q, K, V) = \operatorname{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

- Allows attending to all words in the sentence.
- \bullet Q = Queries, K = Keys, V = Values.

Key Components

- Multi-Head Attention: Parallel attention layers.
- Feed-Forward Network: Applied at each position.
- Layer Normalization & Residual Connections:
 - Stabilizes training of deep networks.

Applications in NLP

Task Machine Translation Text Classification Question Answering

Text Generation

Summarization

NER

How Transformers Help

Encoder-decoder setup

BERT/RoBERTa encoders

Contextual embeddings

GPT/T5 generate text

Generate concise summaries

Word-level classification (BERT)

Popular Transformer Models

Model	\mathbf{Type}	$\mathbf{U}\mathbf{sage}$
BERT	Encoder	Classification, QA, NER
GPT $(1/2/3/4)$	Decoder	Text generation
T5	Enc-Dec	Summarization, translation
RoBERTa	Encoder	Better-trained BERT
XLNet	Encoder	Permuted LM, BERT $++$

Example: Hugging Face with BERT

from transformers import AutoTokenizer, AutoModelForSequenceClassifimport torch

```
tokenizer = AutoTokenizer.from_pretrained("bert-base-uncased")
model = AutoModelForSequenceClassification.from_pretrained("bert-base
inputs = tokenizer("Transformers are amazing!", return_tensors="pt")
outputs = model(**inputs)
logits = outputs.logits
```

Conclusion

- Transformers are powerful and efficient for NLP.
- Basis for modern models like BERT, GPT, T5.
- Great for tasks like classification, QA, generation.

Conclusion

This course offers a comprehensive and practical overview of implementing Artificial Intelligence and Machine Learning solutions, from text and speech processing to computer vision and hardware deployment.

Thank You!

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