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DL Assignment : 5

Q1. What is representation learning? Why do you need representation learnining? Explain how representation learning works? How do deep neural networks carry out representation learning?

→ What ?:-

Representation learning is the process of automatically discovering useful features or patterns from raw data, rather than relying on manually engineered features.

Need :-

- Reduces manual features engineering.
- Captures complex patterns that may not be easily identified by humans.
- Improves performance and generalization of machine learning models.
- Handles high-dimensional data (eg., images, text).

How works :-

Models like autoencoders, convolutional neural networks (CNNs), and work embeddings transform raw data into more abstract and useful forms through layers of transformations. These learned representation help with downstream tasks like classification or clustering.

How do deep neural networks carray out representation learning.

- Early layers capture basic features (e.g., edges in images).
- Deeper layers learn more complex, abstract features (e.g., objects or scenes).
- The model uses these representations to make predictions.

Q2. How can you use an autoencoder for representation learning?

→ ~~You~~ You can use an autoencoder for representation learning by training it to compress data into a lower-dimensional form (latent space) and then reconstruct the original data.

Steps to use autoencoders for representation learning:

1. Train the autoencoder :
 - Feed raw data (eg., images, text) into the autoencoder.
 - The encoder compresses the data into ~~#~~ a lower-dimensional latent representation, while the decoder reconstructs the original data.
 - The network is trained to minimize the difference between the input and the reconstructed output.

2. Extract Latent Representation :
 - After training, use the encoder to generate the latent representation for new input data. This compact, compressed form captures key features of the data.

3. Use Latent Representation for Tasks :
 - The learned representation can be used for downstream tasks like classification, clustering or ~~visut~~ visualization.

For example, you can feed the latent features into a classifier or use them for dimensionality reduction.

Q3. Explain few factors that may be used for getting good representation?

→ 1. Data Quality : Clean, diverse and representative data improves the learned features.

2. Model Depth : Deep models (eg., deep neural networks) can capture more complex patterns & hierarchical representations.

3. Regularization: Techniques like dropout, weight decay, or batch normalization help prevent overfitting and improve generalization.

4. Sufficient Training: Adequate training with enough epochs and data helps models learn meaningful representations.

5. Task-Specific Objectives: Tailoring the learning process to the task (e.g., using a relevant loss function) can guide the model to capture important features.

Q4. Write a short note on greedy layer-wise pre training? Describe the meaning of each word in greedy layer-wise pretraining? Write greedy layer-wise unsupervised pre training algorithm?

→ Greedy Layer-wise Pretraining is a technique used in training deep neural networks, especially for unsupervised learning. It involves training the model one layer at a time, starting from the input layer and moving towards the output layer. This method helps in initializing the weights the model effectively, leading to better performance and faster convergence during the subsequent fine-turning stage.

Meaning of Each Word:

- Greedy: Refers to the approach of making the best local choice (training one layer at a time) without considering the global consequences, aiming for improved performance incrementally.

- Layer-wise: Indicate that the training process is conducted one layer at a time, for focusing one each layer's representation before stacking the next one.

- Pretraining : The initial training phase where each layer is trained independently to learn useful representation before the full model is trained end-to-end.

Algorithm :

$f \leftarrow$ Identity function

$\tilde{x} = x$

for $k = 1, \ldots, m$ do

$\quad f^{(k)} = L(\tilde{x})$

$\quad f \leftarrow f^{(k)} \circ f$

$\quad \tilde{x} \leftarrow f^{(k)} \tilde{x}$

end for

if fine-tuning then

$f \leftarrow T(f, x, y)$

end if

Return f

Q5. List advantages and disadvantages of unsupervised pretraining ?

Advantages :-

① Effective Initialization : Provides better weight initialization for deeper networks, leading to improved convergence and performance

② Data Utilization : Makes use of unlabeled data, which is often more abundant and easier to obtain than labeled data.

③ Feature Learning : Learns meaningful representation and features from data, improving the model's ability to generalize.

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(4) Redued Overfitting: Can help reduce overfitting by introducing regularization through unsupervised learning.

(5) Improved Training Time: Often leads to faster Training times during the fine-tuning phase due to better initial weights.

Disadvantages :-

(1) Training Complexity: The process can be more complex and time-consuming, requiring separate training for each layer.

(2) Suboptimal Representations: The learned representations might not be optimal for the final task, especially if the pretraining data is not relevant.

(3) Lack of Supervision: Without labeled data, learning process may capture irrelevant features that do not contribute to task performance.

(4) Implementation Difficulty: Can be challenging to implement effectively, especially when deciding on architecture and unsupervised learning algorithms.

(5) Limited Improvement: In some cases, the performace gains from unsupervised pretraining may be marginal compared to directly training the network with labled data.

Q. What do you mean by Trasfer learning and domain adaption? Explain with an example.

→

Transfer Learning :-

- Transfer learning is a machine learning technique where a model trained on one task is reused or adapted for a different but related task. It leverage knowledge gained from the source task to improve performance on the target task, especially when labeled data is scarce.

Example : A model trained on a large dataset for image classification (like ImageNet) can be fine-tuned for a specific task, such as identifying species of birds. The pre-trained model retains learned features (like edges and shapes) that are relevant reducing the need for extensive training on the smaller bird dataset.

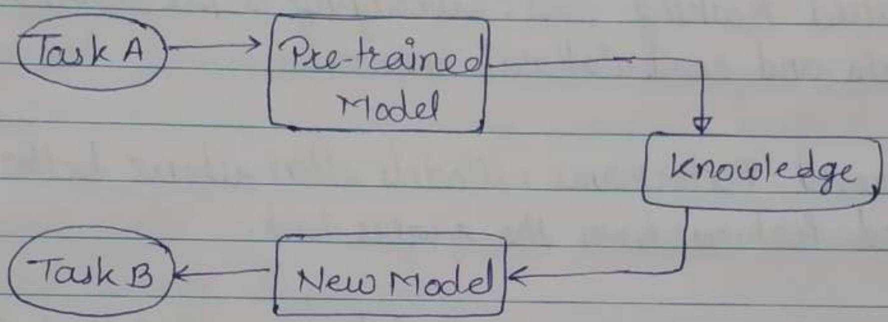
Domain Adaptation :-

- Domain Adaptation is a subset of transfer learning that focuses on adapting a model trained on one domain (source domain) to work effectively in a different but related domain (target domain) where data may come from different distributions.

Example: A sentiment analysis model trained on movie reviews (source domain) may need to be adapted for analyzing product reviews (target domain). Although both ~~a~~ tasks involve sentiment analysis, the language and context may differ. Domain adaptation techniques would help the model adjust to these differences, improving its accuracy on the product review dataset.

Q7. With a diagram explain the concept of transfer learning in machine learning? Describe various types and related advantages of transfer learning? What are three main questions that you answer during transfer learning? What are the different approaches taken with each answer?

→ Transfer learning involves taking a pre-trained model from one task or domain and adapting it to a new, but related task or domain..



Types of Transfer Learning

① Inductive Transfer Learning: The source and target tasks are different, but the model is adapted to improve performace on the target task.

• Example: Adapting a model trained on general image recognition to classify specific medical images.

② Transductive Transfer Learning: The source and target tasks are the same, but the domains differ (i.e, the data distributions vary).

• Example: Using a model trained on high-resolution images to perform on low resolution images.

③ Unsupervised Transfer Learning: The source domain is unsupervised, and the target domain may be supervised.

• Example: Using unsupervised clustering in one domain to help classification in another.

Advantages of Transfer Learning

• Reduced Training Time: Leveraging a pre-trained model requires less data and computational resources.

• Improved Performance: Models often achieve better accuracy due to learned features from the source task.

• Addressing Data Scarcity: Useful when labelled data for the target task is limited.

Questions During Transfer Learning :-

① What is the similarity between the source & target tasks?

• Approach : Analyse the features space and identify shared characteristics.

• Example : Use domain knowledge or empirical validation to assess similarities.

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② How much of the pre-trained model should be reused?

• Approach: Decide whether to fine-tune the entire model or just some layers based on the similarity.

• Example: Fine-tune only the last few layers if the source and target tasks are closely related.

③ What is the best way to adapt the model to the target task?

• Approach: Experiment with different strategies such as feature extraction, fine-tuning or using ensemble methods.

• Example: Use a learning rate schedule to carefully adjust the model during fine-tuning.

Q8. Write a short note on multi task learning?

→ Multi-Task Learning (MTL) is a machine learning approach where a model is trained to perform multiple tasks simultaneously, sharing knowledge across them. Instead of training separate models for each task, MTL leverages commonalities and differences among tasks to improve overall performance.

Features :-

• Shared Representation : MTL encourages the model to learn shared features that can be beneficial across different tasks, leading to improved generalization.

• Efficiency : By training on multiple tasks at once, MTL can reduces the overall training time and computational resources compared to training individual models.

- Regularization : learning multiple tasks simultaneously acts as as a form of regularization, helping to prevent overfitting on any single task.

Applications :-

- NLP :- A model could be trained to performed sentiment ~~ant~~ analysis, named entity recognition, and text classification simultaneously.

- Computer Vision : A model could learn to detect objects, segment images, and classify scenes in one united framework.

Q9. Explain the types of deep transfer learning ?

→ ① Inductive Transfer Learning :

- defⁿ : The source and target tasks are different, but labelled data is available for the target task.

- Example : Using a model trained on ImageNet (object classification) & fine-tuning it ~~o~~ for medical image analysis (diagnosis).

- Approach : Fine-tune the pre-trained model on the new task.

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② Transductive Transfer Learning:
• defn :- The source and target tasks are the same, but the data domains (distributions) differ.

• Example: Using a model trained on English text data for sentiment analysis and adapting it to a French text dataset.

• Approach: Domain adaptation techniques are used to adjust for distribution differences.

③ Unsupervised Transfer Learning:
• defn: The source and target tasks are different, and there is no labelled data in the target task.

• Example: Using a pre-trained model for clustering or dimensionality reduction in a new domain without any labels.

• Approach: The model learns meanigful representation from the source task, which are applied in the target task.

Q10. Write a short note on one-shot learning and zero-shot learning?
→

One-Shot learning :-
- One-short learning is a machine learning approach where a model is trained to recognize new classes or tasks using only one or very few examples.
- It is commonly used in situations where collecting large amounts of labeled data is difficult or expensive.
• Example: Facial recognition systems that learn to recognize a person's face from a single image.

• key Approach: Techniques like Siamese Networks or meta-learning are often used to compare new instances with known examples.

Zero-Shot Learning :-

- Zero-Short Learning (ZSL) enables a model to recognize new classes or tasks without any direct examples of those classes during training.

- Instead, it relies on additional information such as semantic attributes or descriptions to generalize to unseen categories.

• Example: A model trained to recognize animals can identify a zebra based on its description (black-and-white strips) without having seen any images of a zebra.

• key Approach: ZSL uses attribute-based or text-based embeddings to link known and unseen categories.