NLP/ASR

Unit 3: Transfer Learning for NLP/ASR

3.1.1

Introduction to Transfer Learning

Transfer learning as Applied to NLP & ASR

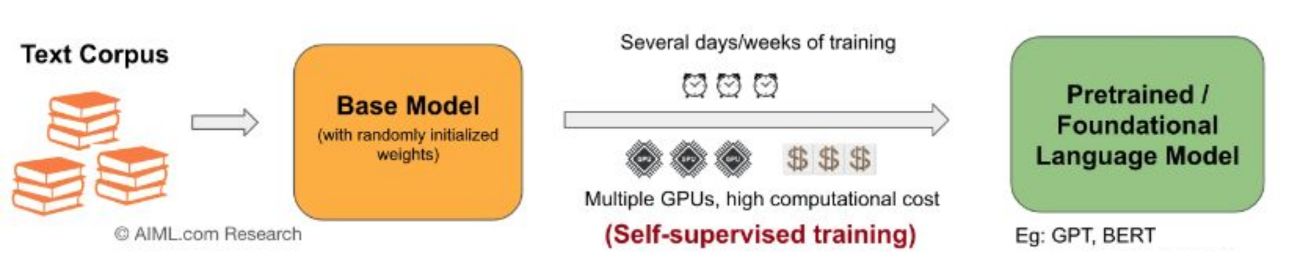
Transfer Learning in NLP

- Transfer learning is a machine learning paradigm where knowledge learned during the training of one model (source task) is applied to improve performance on a different but related task (target task)

- In NLP, transfer learning usually involves leveraging pre-trained language models that have been exposed to massive text datasets as our starting point

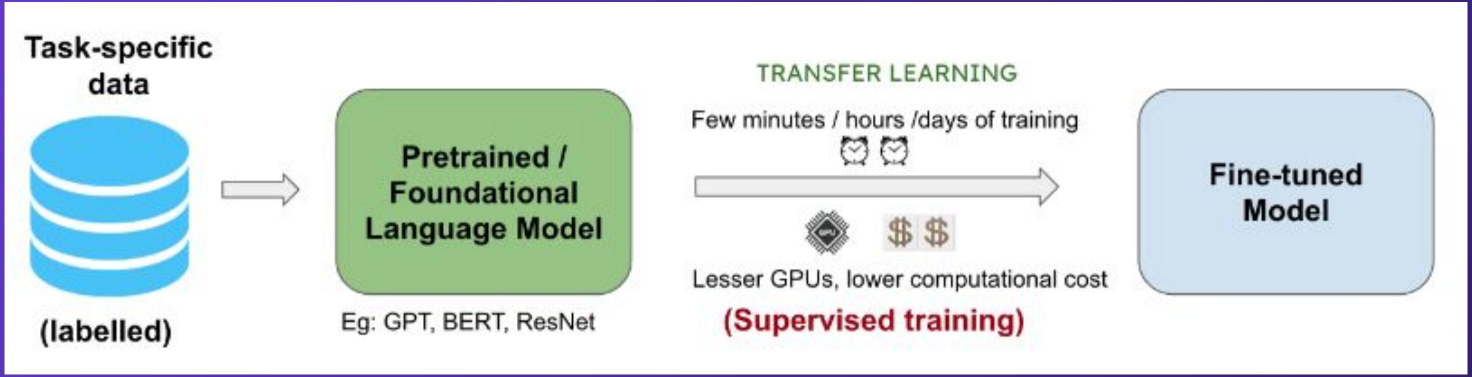
Pre-Trained Models

- Pre-trained Language Models are the powerhouse of Transfer Learning in NLP
- Trained on a massive corpus of text data
- Learns to understand the structure of language, relationships between words and other linguistic features



Transfer Learning (recap)

- Further training a pre-trained model on a smaller task-specific dataset
- Goal is to adapt the model's learned representations to perform well on a specific task without training from scratch



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Approaches to Transfer Learning

- Transfer Learning using Feature Extraction
  - The pre-trained model acts as a feature extractor, with its outputs fed into a new classifier built for the target task

- Full Fine-tuning
  - Most or all of the pre-trained model's parameters are updated during training on the task-specific data

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Advantages of Transfer Learning

- Models to achieve higher performance on specific tasks, even when labeled data is limited
- Reduced training time
- Generalization of knowledge from one task to another
- Adapts to different domains or languages by fine-tuning the pre-trained model on domain-specific or language-specific data

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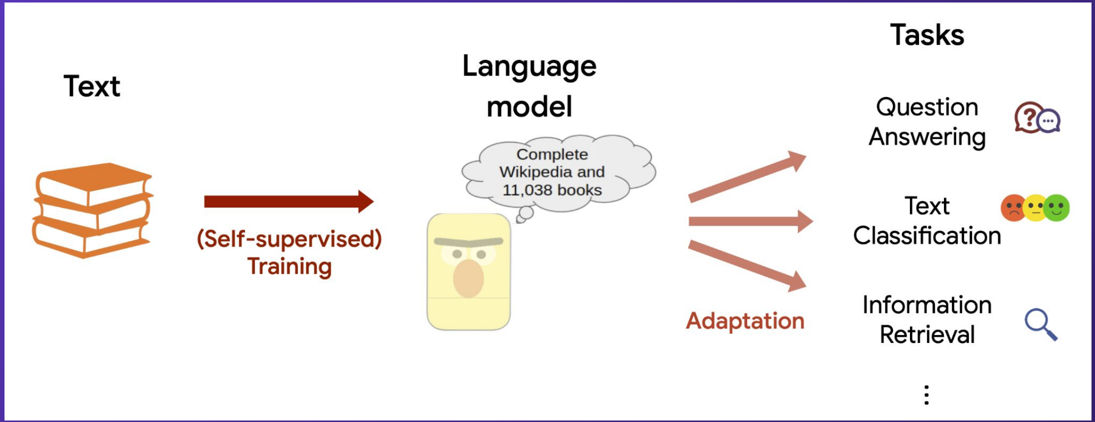
Applications in NLP

- Question Answering
- Text Classification
- Information Retrieval
- Machine Translation
- Sentiment Analysis
- Text Summarization
- Language Generation



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Transfer Learning in ASR

- Pre-trained ASR models are trained on massive datasets of transcribed speech

- They learn to recognize acoustic patterns and map them to corresponding text

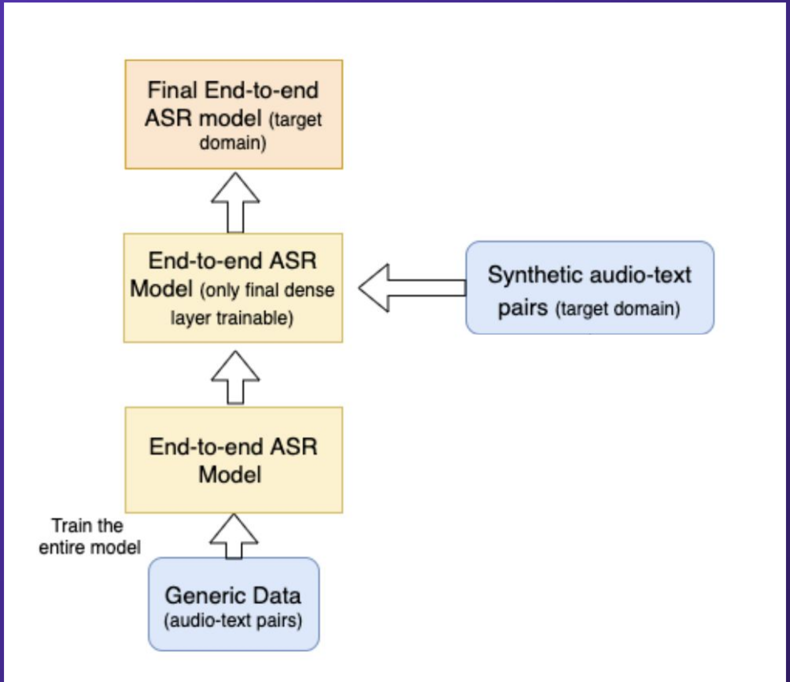
- Popular examples:
  - Wav2Vec
  - Whisper
  - DeepSpeech
  - NeMO

Fine-tuning for Domain Adaptation

- Pre-trained ASR models excel on large, generic datasets
- However, custom domain datasets often deviate in:
  - Background noise
  - Speaker accents
  - Specific vocabulary
  - Speech velocity
- Recognizing and preparing for these variations is key to effective model adaptation

Fine-tuning for Domain Adaptation

- The pre-trained model is first trained on general out-of-domain data
- Domain specific data is then used to fine-tune the final dense layers of ASR models
- Finetuning on domain specific data can achieve achieve considerable improvement over the generic model
- Selection of an appropriate pretrained model is a critical step in the adaptation process



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Applications of ASR Transfer Learning

- The SUPERB benchmark assesses models on a suite of downstream speech tasks such as:
  - Speaker identification
  - Keyword spotting
  - Intent classification
  - Emotion recognition

- To expand the scope of ASR models beyond speech recognition, transfer learning can be applied to various such downstream speech processing tasks