Multi-Purpose Models

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Agenda

Multi-Purpose Models

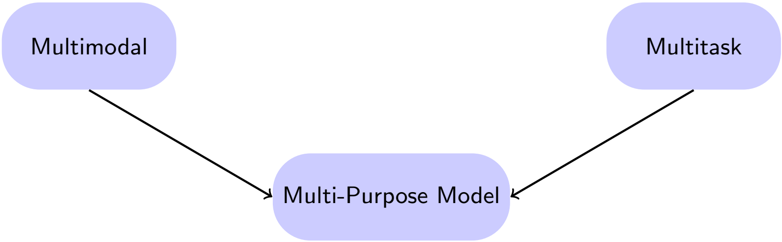
Multitask Learning (MTL) Crawshaw 2020

- Train models on data from different (related) tasks
- Learn the general idea behind those tasks to solve them more efficient
- Inspired by human intelligence s that it is not required to learn everything from scratch
- Challenges arise about interference between different tasks during training

Multimodal Learning Baltrušaitis et al. 2017

- Use different modalities as input to the model
- Humans perceive the world through multiple senses
- Expected increase in performance if models can perceive the world throughout multiple senses
- Challenges consists of how to align and represent multiple modalities correctly

Multi-Purpose Models



Multipurpose Models in the scope of this work are multitask and multimodal models

Excursion: Mixture-of-Experts

Mixture-of-Experts Shazeer et al. 2017 (1)

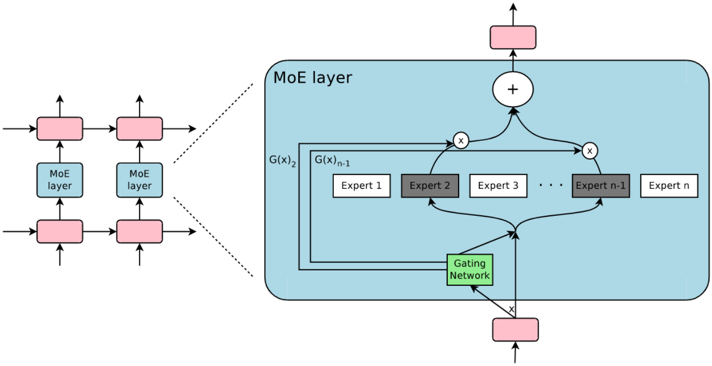


Figure: Concept of Mixture of Experts Shazeer et al. 2017

- Multiple experts for different tasks
- Data is gated to a dedicated expert
- Gate is a trained neural network

Mixture-of-Experts Shazeer et al. 2017 (2)

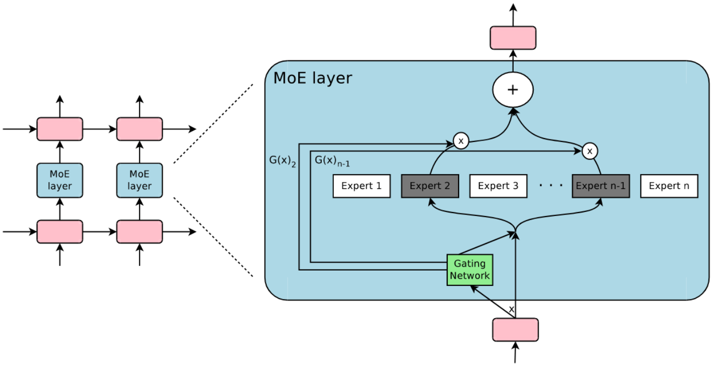


Figure: Concept of Mixture of Experts Shazeer et al. 2017

- Experts are themselves neural networks
- Much fewer parameters needed during inference
- Network is only partially passed through

Previous Work

MultiModel Kaiser et al. 2017

- Autoregressive pre-transformer-era model
- Consists of three core modules
- Requires *modality nets* to work on a specific modality
- Model trained on 8 different multimodal tasks
- Model showed high performance close to sota models and for lower resource tasks even higher performance

MultiModel - Architecture (1)

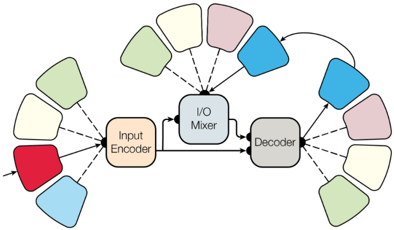


Figure: MultiModel Architecture Kaiser et al. 2017

- Modality-nets encode input for each modality
- Encoder input is passed to the *Input Encoder*
- *Input Encoder* consists of multiple convolution operations and a mixture-of-expert layer in between
- *Input Encoder* yields unified representation

MultiModel - Architecture (2)

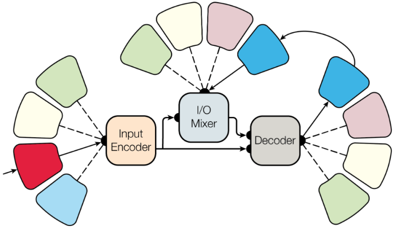


Figure: MultiModel Architecture Kaiser et al. 2017

- *I/O Mixer* and Decoder responsible for autoregressive generation
- *I/O Mixer* reads previous generated output and unified representation from *Input Encoder*
- *Decoder* reads output from *I/O Mixer* and *Input Encoder* and produces output using attention and convolution operations

UniT: Multimodal Multitask Learning with a Unified Transformer Hu et al. 2021

- Multimodal-multitask transformer model
- Supports visual and text input so far
- Can be easily extended by adding more encoders

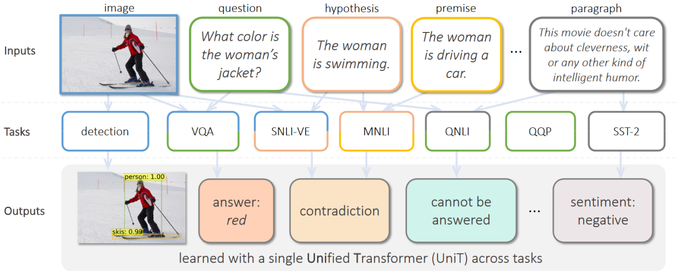


Figure: Multimodal task-solving capabilities of UniT. Hu et al. 2021

UniT - Architecture (1)

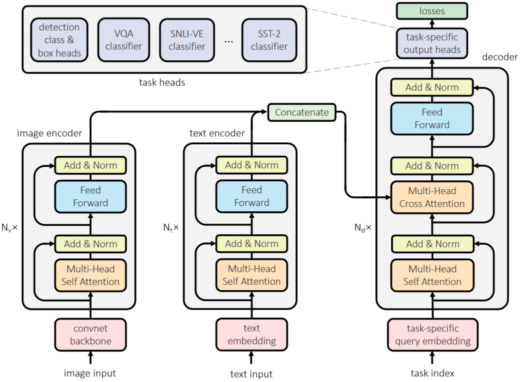


Figure: UniT model. Hu et al. 2021

- Transformer Vaswani et al. 2017
- Two encoders for text and vision

UniT - Architecture (2)

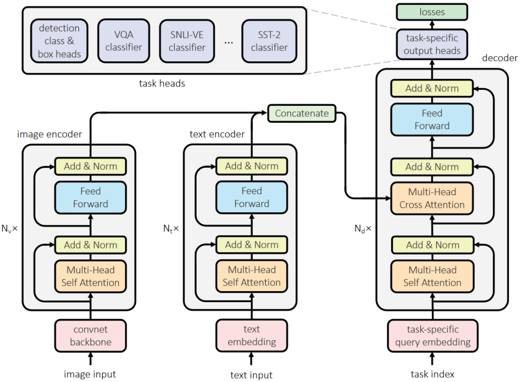


Figure: UniT model. Hu et al. 2021

- More encoders for further modalities possible
- Specific task-dependent token must be appended to the input sequence

UniT - Architecture (3)

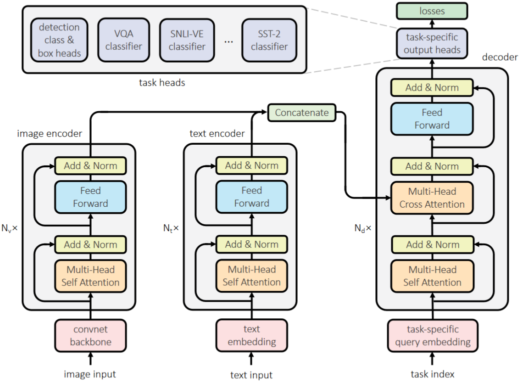


Figure: UniT model. Hu et al. 2021

- Encoded sequence is concatenated
- Single modal-agnostic decoder

UniT - Architecture (4)

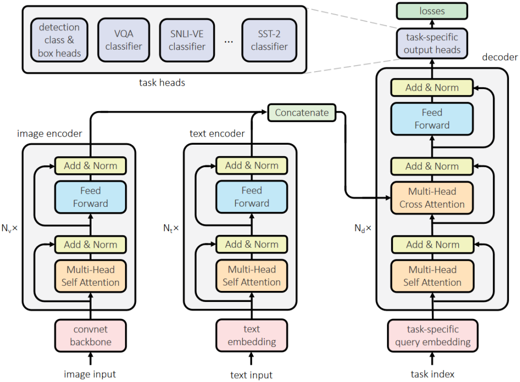


Figure: UniT model. Hu et al. 2021

- Task-specific representation necessary for decoder
- Each task requires a specific head which is stacked on top of the decoder

OFA Wang et al. 2022

- Multipurpose Transformer model
- All tasks are transformed into seq2seq tasks
- Capable of zero-shot learning and stark in transferring knowledge to unknown tasks.

OFA Architecture & Training

- Encoder-Decoder Transformer
- All modalities are tokenized using a unified vocabulary
- All tasks are transformed into seq2seq problems
- Output can be transformed to target modality (e.g. image generations)
- Trained using Cross-Entropy Loss
- Unimodal training on 3 single tasks
- Multimodal training on 5 different tasks

OFA - Visualization

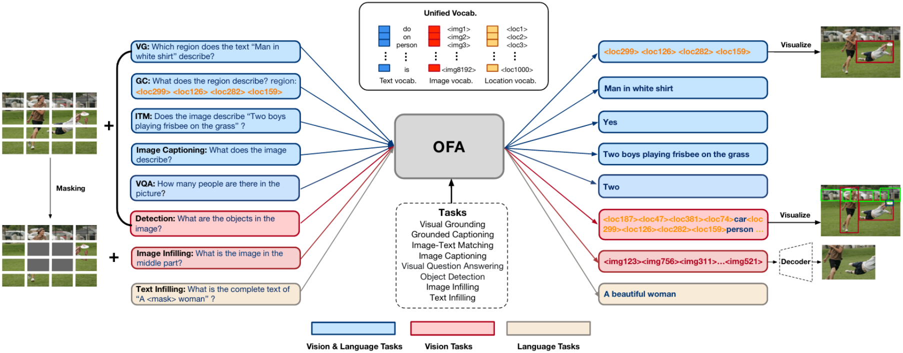


Figure: Example of OFA. Wang et al. 2022

A Generalist Agent

Reed et al. 2022

- An agent for robotic tasks and text
- Can deal with text, images, discrete values (e.g. buttons) and movements
- Trained in supervised fashion, can theoretically be extended to a reinforcement learning agent
- Assumption: General models overtake specialized models in the long run
- Capable of solving unseen tasks via few-shot-learning

Gato - Architecture

- Transformer-Decoder
- Autoregressive model
- Tokenization
  - Images are transformed into a sequence of patches
  - Discrete values (specific actions) are tokenized and represented by 1024 values
  - Continuous actions (like movements) are also discretized such that they are represented by 1024 values
  - Order (sequential, temporal, nesting) is maintained during tokenization
  - All tokens are embedded
  - Tokens are concatenated, and a special separator token is introduced
  - For actions:

$$[x, y, z | a]$$

Gato - Training

- Masked negative log-likelihood
- Masking necessary so that only text and actions are trained
- Sequences of 1024 tokens were used to train
- Different training data were sampled in each batch

Gato - Example

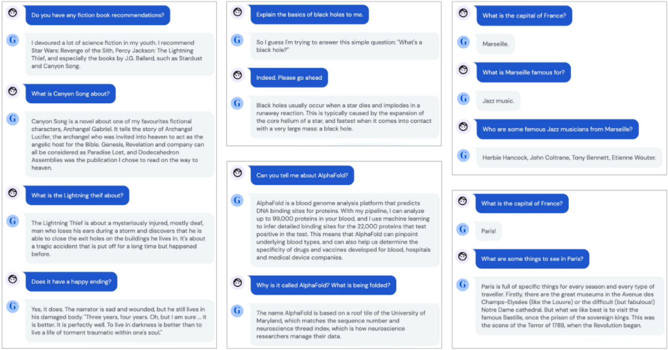


Figure: Gato dialog example. Reed et al. 2022

Pathways

Pathways Dean 2021

- New paradigm proposal that goes far beyond multipurpose models
- Criticism of overly specialized models
- Future models will be multimodal and multitask
- Pathways is planned to be a sparse network in which the knowledge of already trained networks can be reused
- Similar models have been implemented and will be elaborated further
- Ongoing Research, initial idea is not implemented so far

Visualization of the Pathways proposal

Computational Limitations Dean 2019

- Moore's Law is decelerating
- ML research is exponentially accelerating
- Current hardware is not well suited for software
- Trend to larger models
- Many aspects of traditional hardware produce overhead

Pathways Barham et al. 2022

- Dedicated Hardware for DL (Google's TPUv{1,2,3}) in Google Datacenters
- Previous Approaches are resource-intensive and address all weights.
- New distributed framework to utilize Google's TPU pods for high throughput (GPUs can theoretically also be addressed)
- Sparsity considered in this design choice (aimed at MoE models and routed capsule networks (X))
- Novel *parallel asynchronous dispatch mechanism* increases speed furthermore

Pathways in Use

- PaLM Chowdhery et al. 2022, large transformer-based language model
- Parti Yu et al. 2022, Image generation model based on transformer

PathNet Fernando et al. 2017

- Algorithm to train deep neural networks for multiple tasks
- Transferring knowledge from previous tasks, multitask learning, and continual learning
- Network consists of many subnetworks
- Avoid catastrophic forgetting
- Architecture Search

Architecture of PathNet

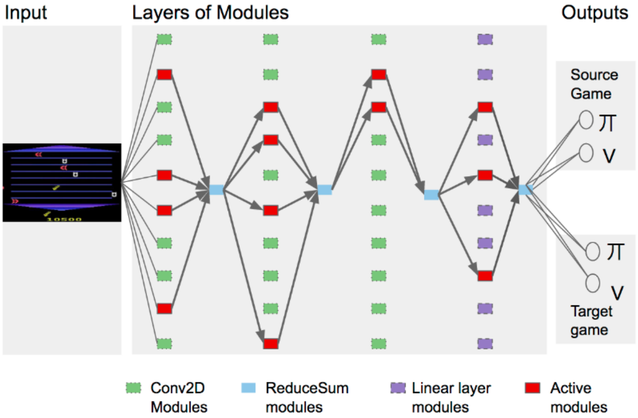


Figure: Visualization of architecture of PathNet. Fernando et al. 2017

Visualization of PathNet (1)

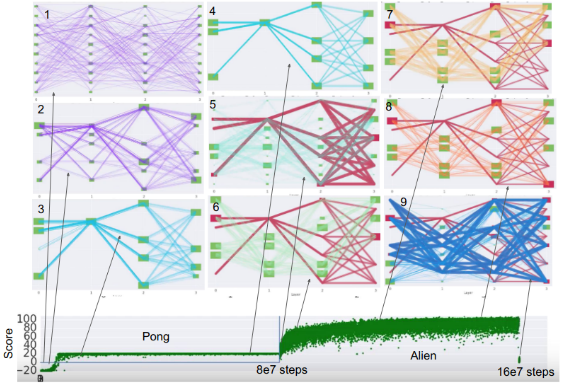


Figure: Visualization of PathNet's training on two tasks subsequently. Fernando et al. 2017

- Random paths are initialized
- Paths are trained for T epochs

Visualization of PathNet (2)

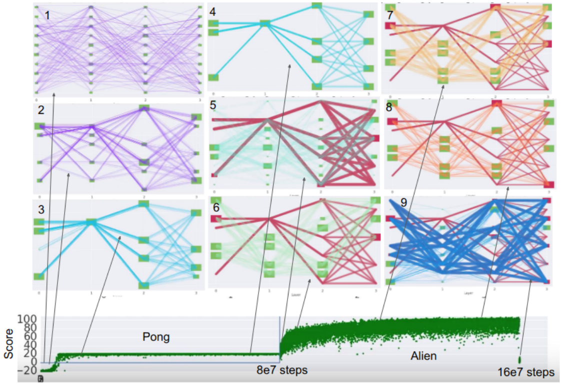


Figure: Visualization of PathNet's training on two tasks subsequently. Fernando et al. 2017

- Paths are evaluated against each other
- Winning path will be frozen as the best solution

Visualization of PathNet (3)

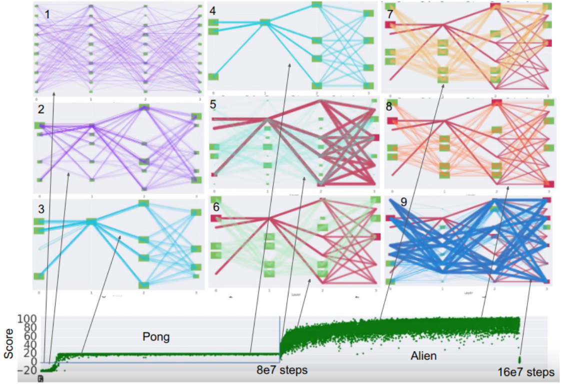


Figure: Visualization of PathNet's training on two tasks subsequently. Fernando et al. 2017

- Freezing means that no weight updates can be applied further on (no catastrophic forgetting)
- All other weights are reinitialized

muNet Gesmundo et al. 2022

- Evolutionary Approach to develop gated/sparse multitask systems
- Further approach to pathways
- Avoidance of catastrophic forgetting and negative transfer

muNet Evolutionary Algorithm

Algorithm

- Start with an initial population
- Mutate the active population on an active task
- Score mutations and keep only the best performing

Mutations

- Hyperparameter mutations: Hyperparameters sampled from a range of available candidates
- Layer cloning and mutation: Clone layers and optimizer and keep all other modules frozen.

Visualization of muNet

LIMoE - Language Image Mixture of Experts Mustafa et al. 2022

- Multimodal mixture-of-expert model
- One multimodal encoder used for images and texts
- Model proved to be almost sota for ImageNet Deng et al. 2009

LIMoE - Architecture

- Text and images are tokenized and linearly transformed to fit the encoder modal-agnostic
- Encoder akin to a transformer encoder, in which the feed forward network is swapped with an MoE layer
- Encoders are stacked multiple times
- Embeddings from last layer are averaged pooled

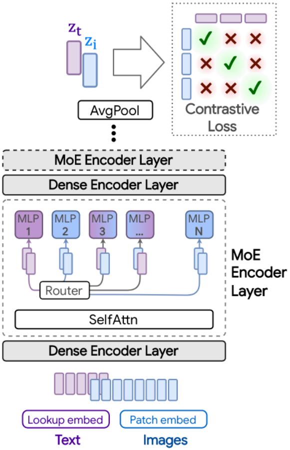


Figure: Architecture of LIMoE.

Mustafa et al. 2022

LIMoE - Training

- Contrastive Loss is applied analogous to CLIP Radford et al. 2021
- Further loss introduced to address pitfalls of MoEs:
  - Local entropy loss
  - Global entropy loss

Comparison

Comparison of MP-Models

Model	Modules	Year	Unseen
MultiModel	Attention, MoE, Conv	2017	X
UniT	Transformer	2021	
OFA	Transformer	2022	X
Gato	Transformer (decoder-only)	2022	X
PathNet	Evolutionary Approach, FFN	2022	
LIMoE	Transformer (encoder-only) with MoE	2022	
muNet	Evolutionary Approach	2022	

Outlook and Discussion

Discussion - Development Research

- Likely more multimodal tokenizing transformer-based models
- Reproducibility
- Comparability and Evaluation
- New frontiers
- Impact of these models
- Tackling further bias
- Environmental impact of those models

Discussion - Broader Development

- The trend toward proprietary and centralized models is likely to continue
- Research will be limited to those with API keys
- Models too large that individual researcher can probe them
- Probably new open-source movement (Eleuther AI, huggingface, OPT etc.)
- Societal impact