



**Machine Learning and Artificial
Intelligence Technologies Workshop**
22-28 November 2021 | Sirius, Russia

Effective Multi-modal Multi-task models

Aleksandr Petiushko

November 24, 2021



AGENDA

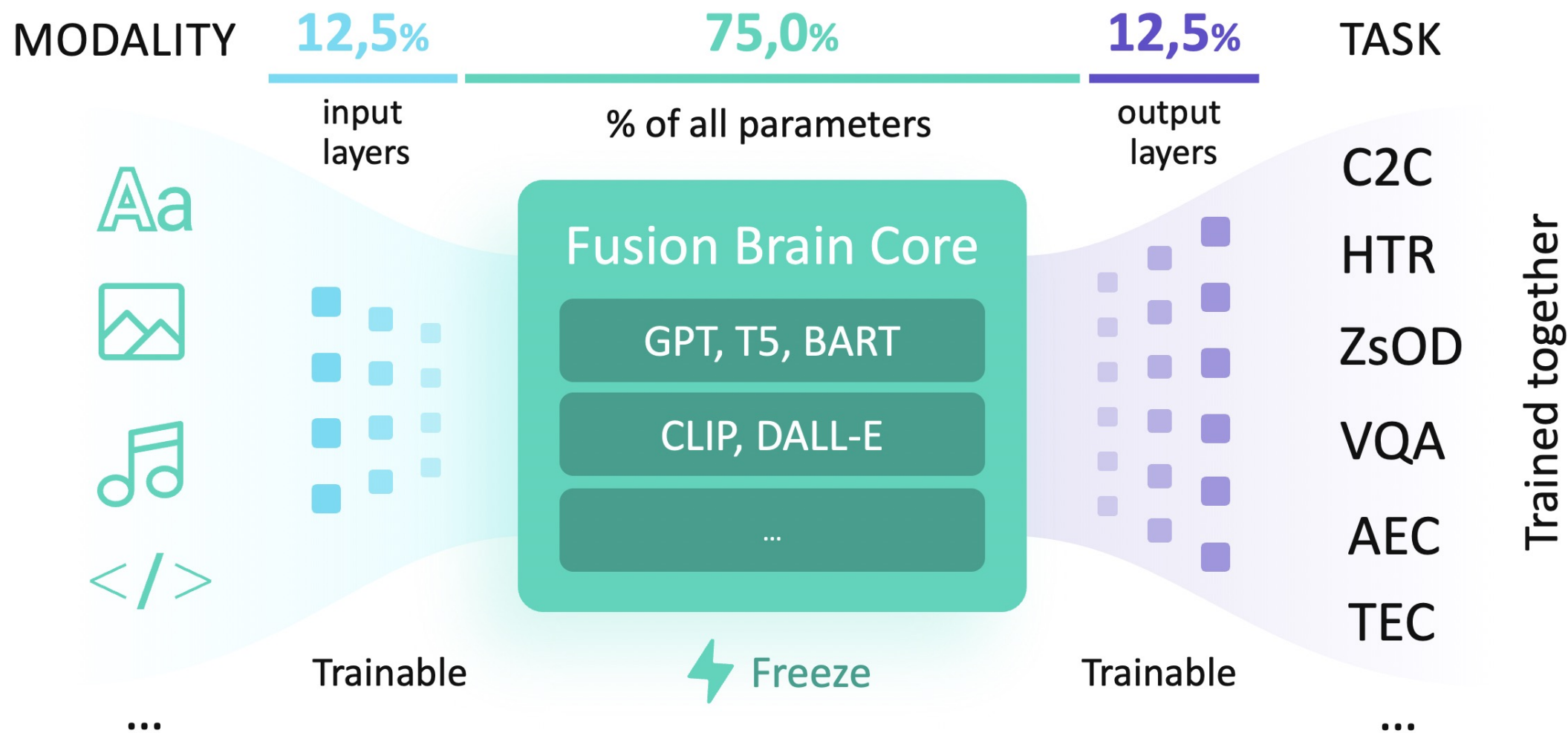
- 01 Motivation
- 02 Multi-modality
- 03 Multi-tasking
- 04 Fusion Brain approach
- 05 Retrieval-based models
- 06 Open Questions

01



Motivation

Motivation



Motivation: business part

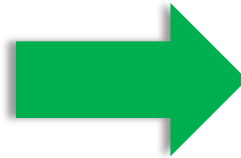
Problem

Retraining model from scratch is \$\$\$

Separate **training**

- Generation of good text description
- Zero-shot object detection
- Handwritten text recognition
- Code2Code
- Visual Q&A
- ...

Totally: ~ \$\$\$ M



Solution

Fine-tuning large pretrained model \$\$

Single **pre-training**

- GPT-3, DALL-E, CLIP

Separate **fine-tuning**

- Generation of good text description
- Zero-shot object detection
- Handwritten text recognition
- Code2Code
- Visual Q&A
- ...

Totally: ~ \$\$ M

Motivation: ecological part

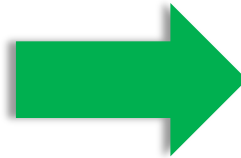
Problem

Retraining model from scratch: CO₂ ↑ ↑ ↑

Separate **training**

- Generation of good text description
- Zero-shot object detection
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- Visual Q&A
- ...

Totally: ~ **XXX kg CO₂e**



Solution

Fine-tuning large pretrained model: CO₂ ↑ ↑

Single **pre-training**

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Separate **fine-tuning**

- Generation of good text description
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- ...

Totally: ~ **XX kg CO₂e**

Motivation: trends

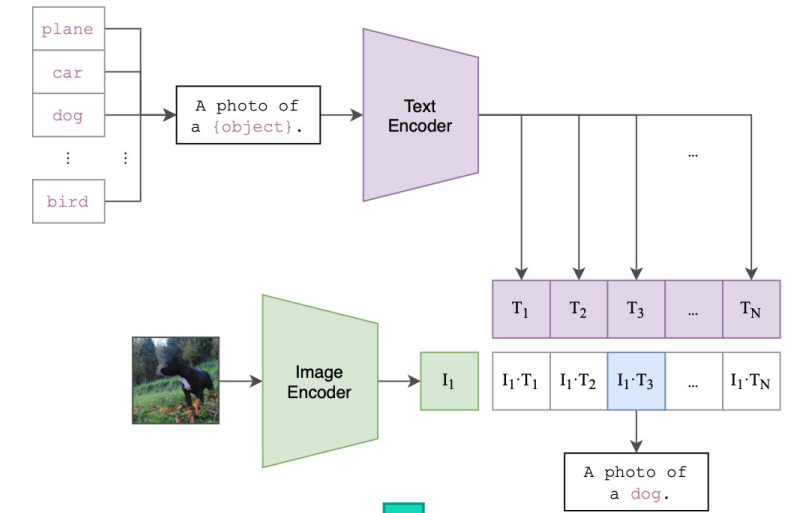
Current trends:

- Large pre-trained models (BERT, GPT-3)
- Multi-modality and multi-tasking (CLIP, DALL-E, UniT)

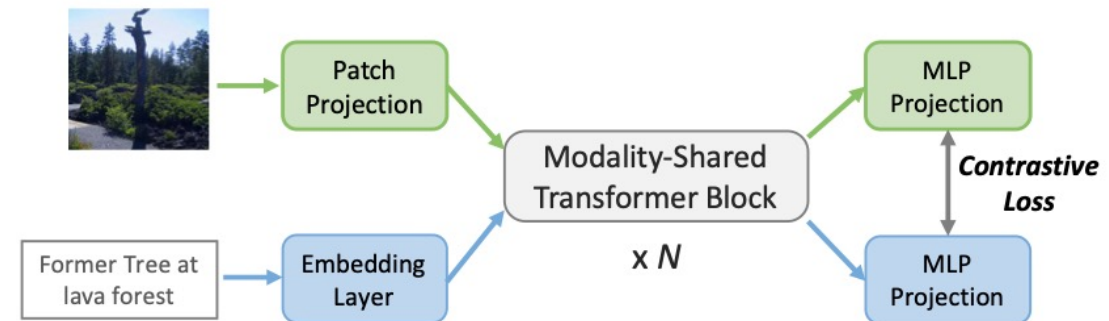
Target modalities: texts, images, sounds and other modalities like videos, programming languages, graphs and time series

Target tasks: NLP, CV and combined tasks like VQA

CLIP, 2021



MA-CLIP, 2022, ICLR



[1] Radford, Alec, et al. "Learning transferable visual models from natural language supervision." 2021 (OpenAI).

[2] You, Haoxuan, et al. "MA-CLIP: Towards Modality-Agnostic Contrastive Language-Image Pre-training." 2021 (Withdrawn submission to ICLR-2022)

Motivation: WHY it is reasonable

Efficient

multi-modality

multi-task

models

WHY we need multi-*

decoder setup	COCO det. mAP	VG det. mAP	VQAv2 accuracy
single-task training	40.6 / –	3.87	66.38 / –
shared (COCO init.)	40.8 / 41.1	4.53	67.30 / 67.47

WHY we need efficiency

Model	#Params
GPT-3	175 B
Retrieval-based models	1 B (3*BERT-Large)

Motivation: WHY it is still non-solved

Model	#params	GLUE	SuperGLUE
RoBERTa-Large ST	8,5B	88.2	76.5
RoBERTa-Large MTL	355M	86.0	78.6
CA-MTL (RoBERTa-Large)	397,6M	89.4	80.0

Encoder (BERT)-based
Multi-task: **better**

T5 (3B) STL	48B	88.5	86.4
HyperGrid (3B) MTL	3B	88.2	84.7
T5 (11B) STL	176B	89.7	88.9
HyperGrid (11B) MTL	11B	89.4	87.7

Decoder (T5)-based
Single-task: **better**

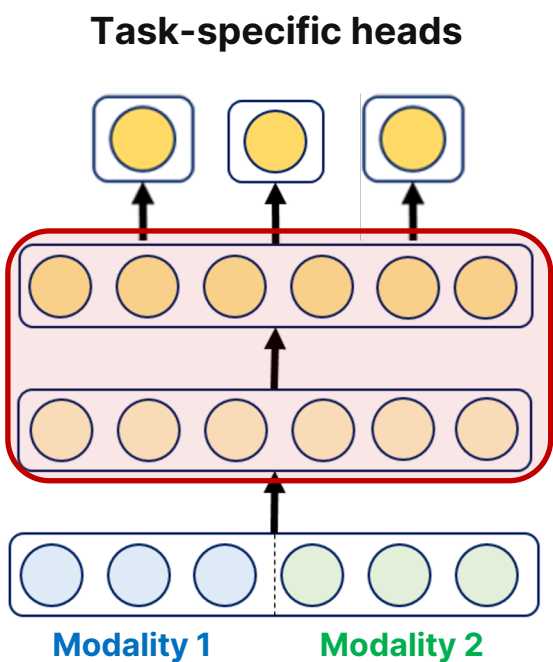
02



Multi-modality

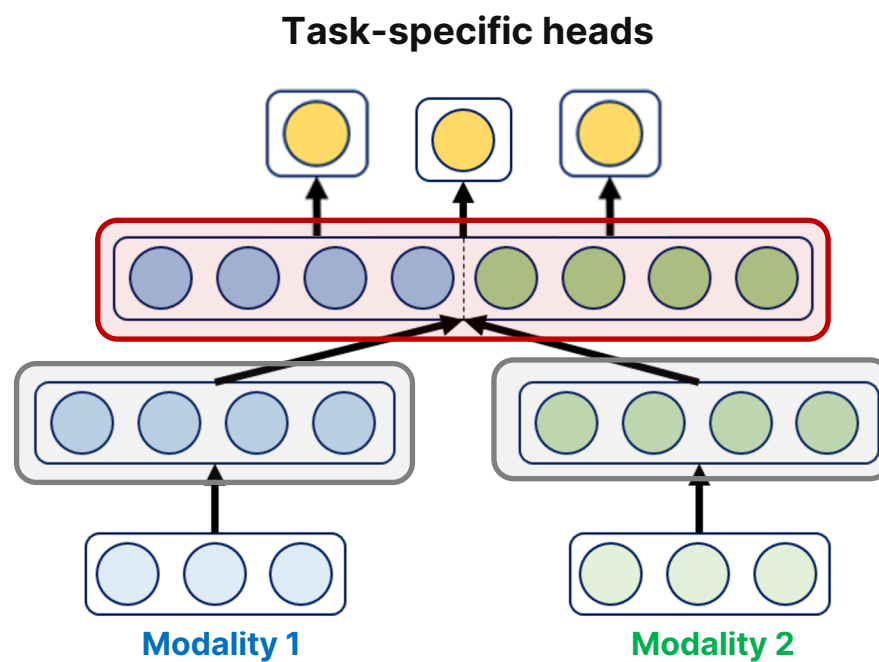
Multi-modality: concepts

A. Early fusion



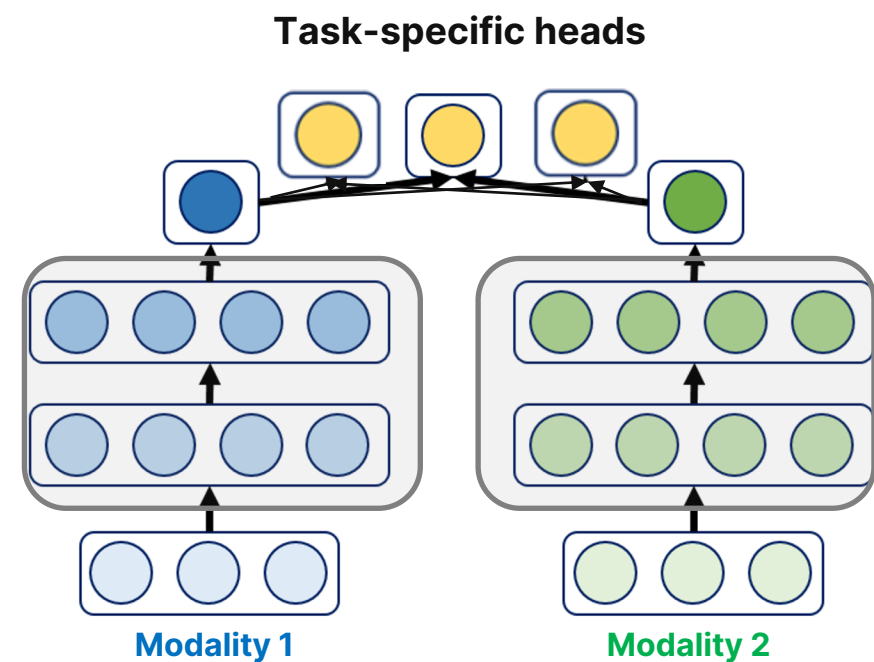
Combined input

C. Middle fusion



Separate input

B. Late fusion



Separate input



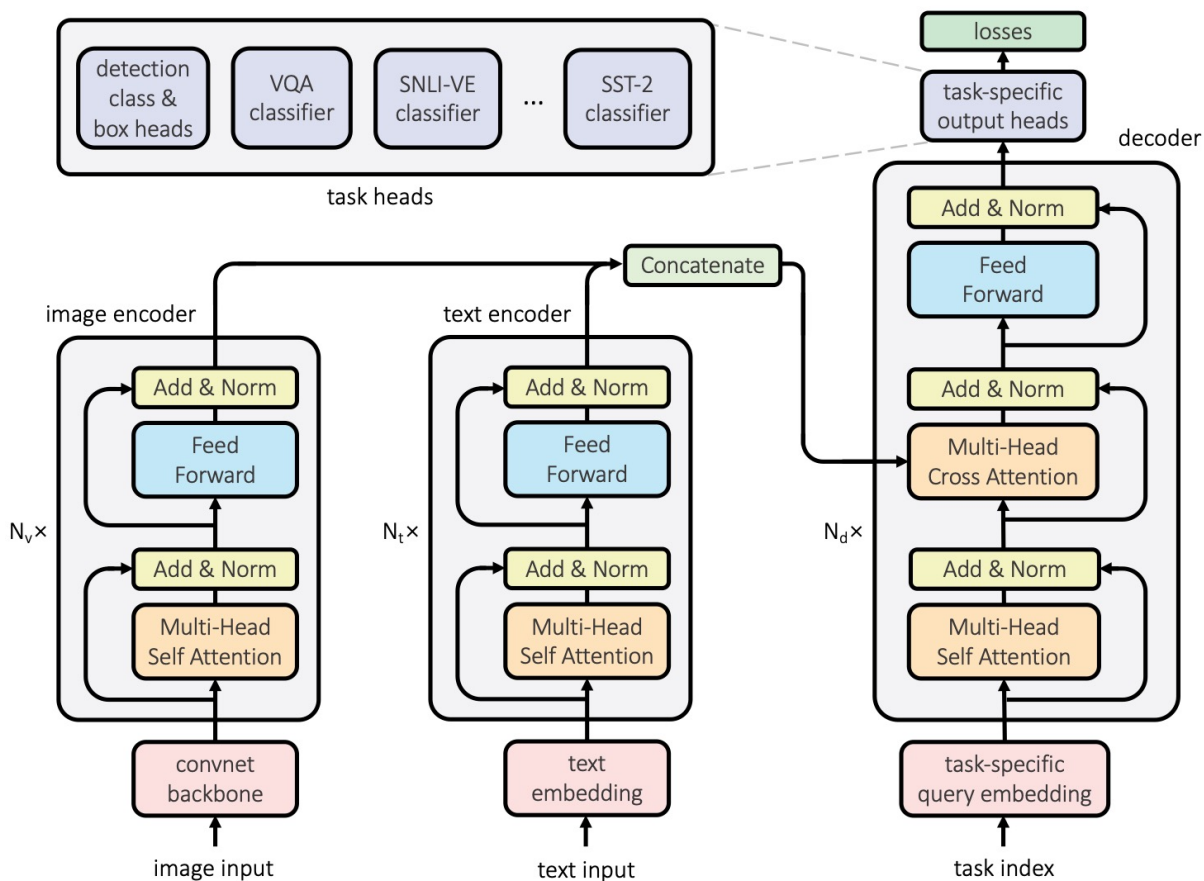
Fusion processing



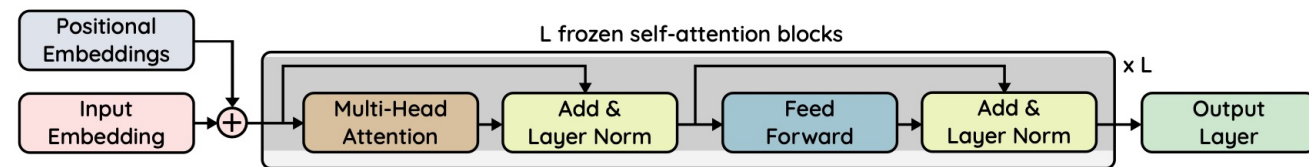
Modality-specific processing

Multi-modality: current trends

UniT¹: via cross-attention



FPT²: via frozen MHA/FFN, tunable LN

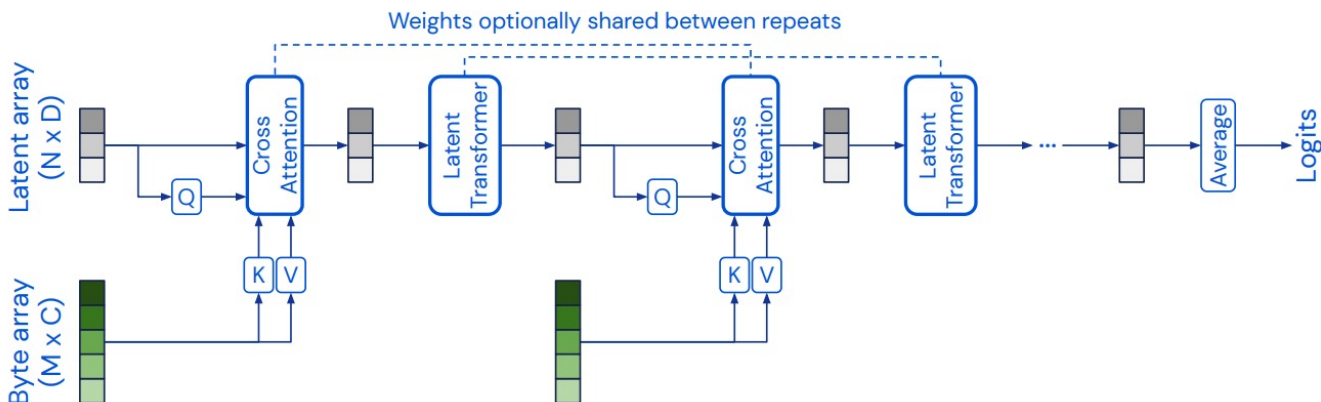


[1] Hu, Ronghang, and Amanpreet Singh. "UniT: Multimodal Multitask Learning with a Unified Transformer." 2021 (Facebook).

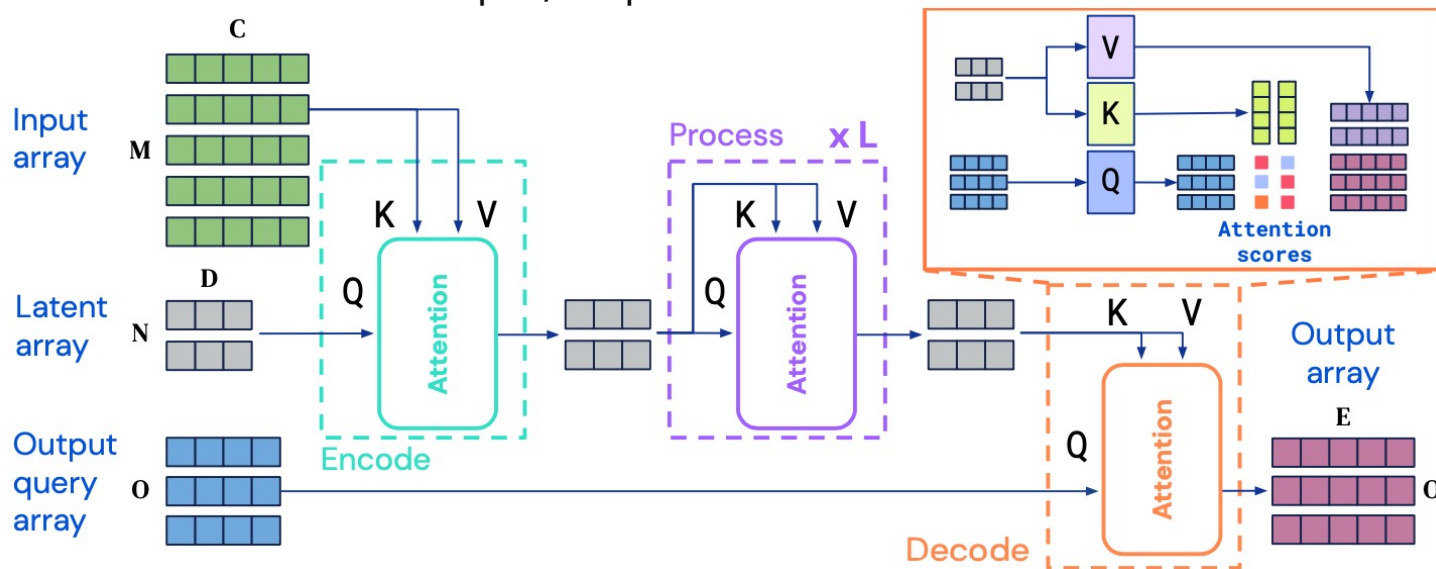
[2] Lu, Kevin, et al. "Pretrained transformers as universal computation engines." 2021 (Google)

Multi-modality: current trends

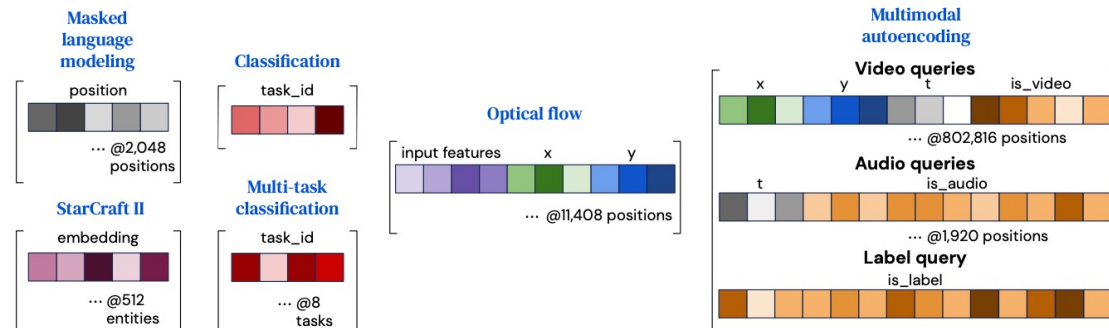
Perceiver¹: iterative CA



Perceiver IO²: CA on input/output



Perceiver IO: output queries



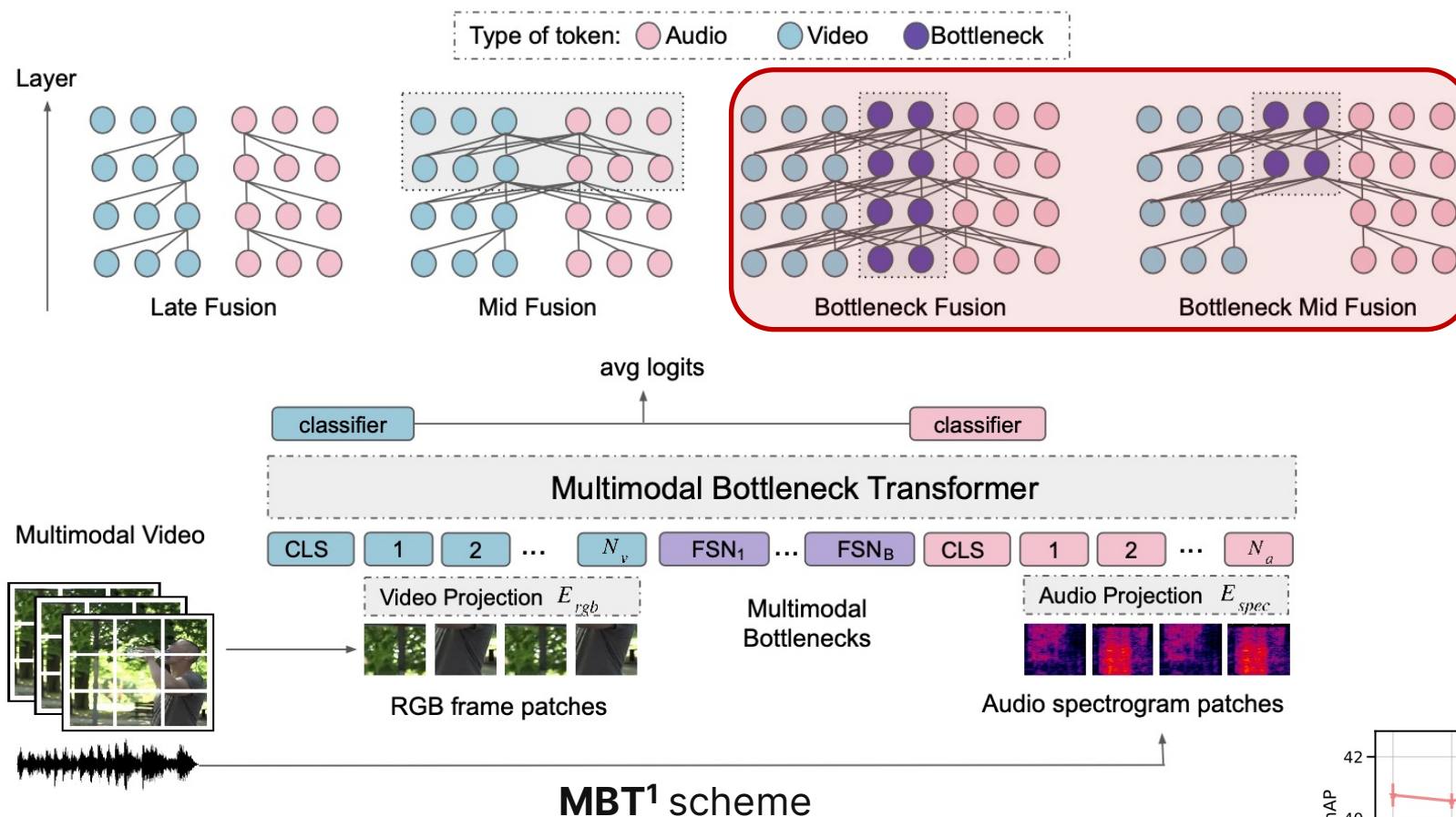
Main idea:

- **Iterative fusion** through **cross-attention** (query – latents, KV – input) allowing **linear** scaling on **input** size (not quadratic)
- Latent transformer is **GPT-2** like
- Weights of CA/SA are **shared**
- **Perceiver IO²** added ability to work with **multi-task and different output sizes** via CA where query is output structure, KV – latents (**complexity** – still the **linear** depending on the **output** size)

[1] Jaegle, Andrew, et al. "Perceiver: General perception with iterative attention." 2021 (*DeepMind*)

[2] Jaegle, Andrew, et al. "Perceiver io: A general architecture for structured inputs & outputs." 2021 (*DeepMind*)

Multi-modality: through information bottleneck



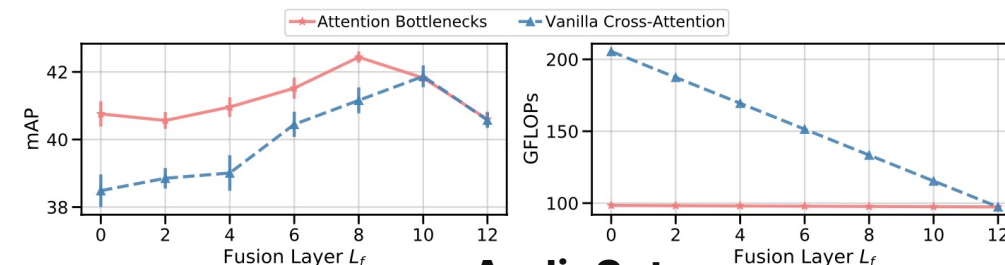
Main idea:

- **Middle-fusion through a small bottleneck** ($B = 4$ is used)
- **Fusion is needed closely to the top**

VGGSound²



Model	Modalities	Top-1 Acc	Top-5 Acc
Chen et al [†] [11]	A	48.8	76.5
AudioSlowFast [†] [34]	A	50.1	77.9
MBT	A	52.3	78.1
MBT	V	51.2	72.6
MBT	A,V	64.1	85.6



AudioSet

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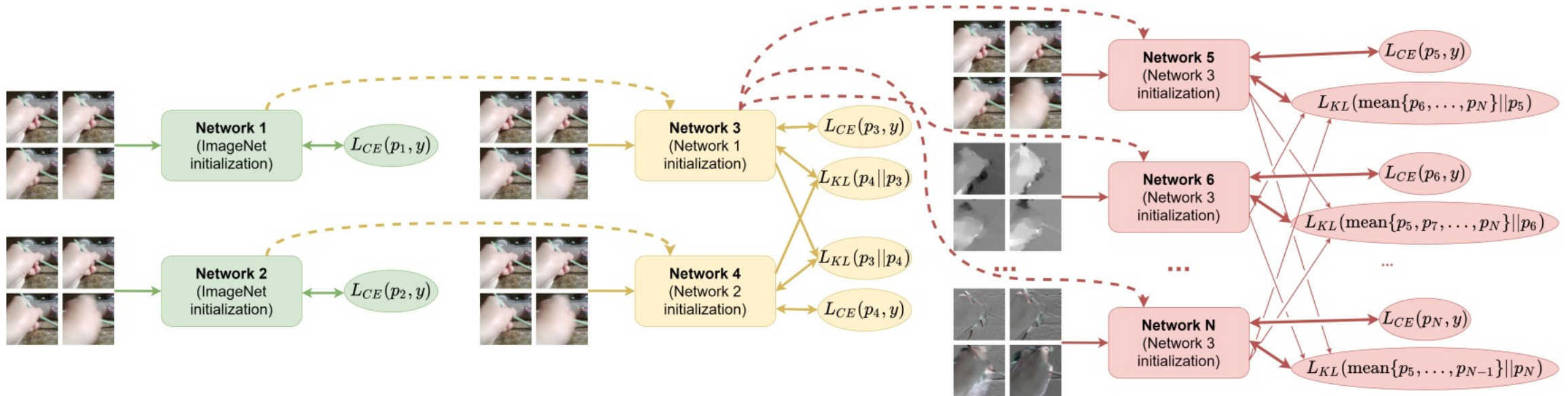
[1] Nagrani, Arsha, et al. "Attention Bottlenecks for Multimodal Fusion." 2021 (Google)

[2] <https://www.robots.ox.ac.uk/~vgg/data/vggsound/>

Multi-modality: through mutual learning

Main idea:

- **Pseudo multi-modality** through incorporation of knowledge by **mutual learning** technique
- **RGB** and **OpticalFlow** modalities for video action recognition were used



MML¹ scheme

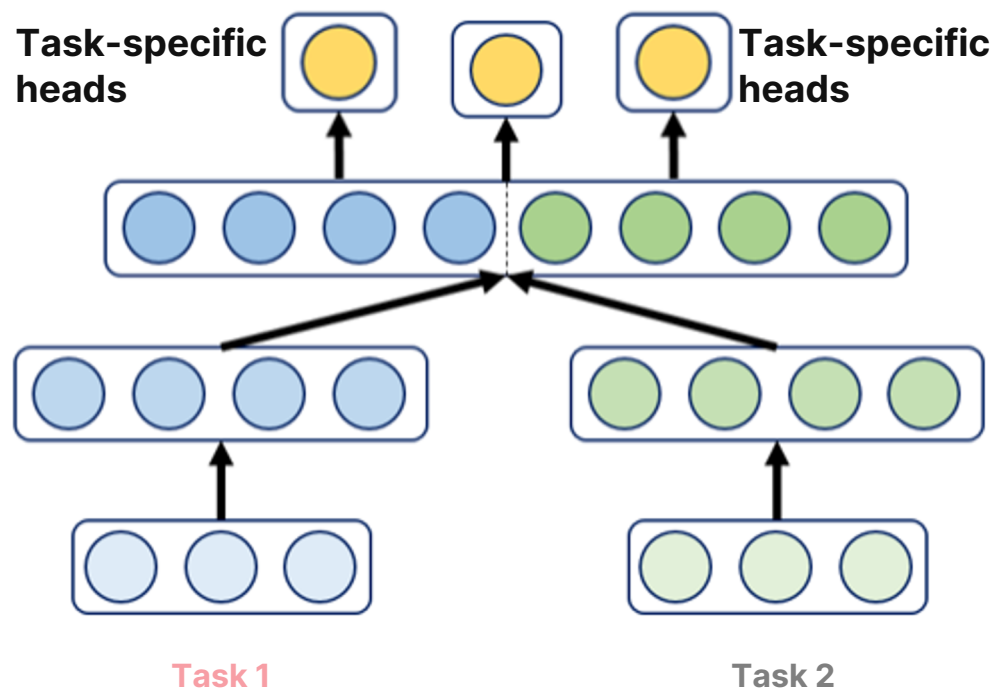
03



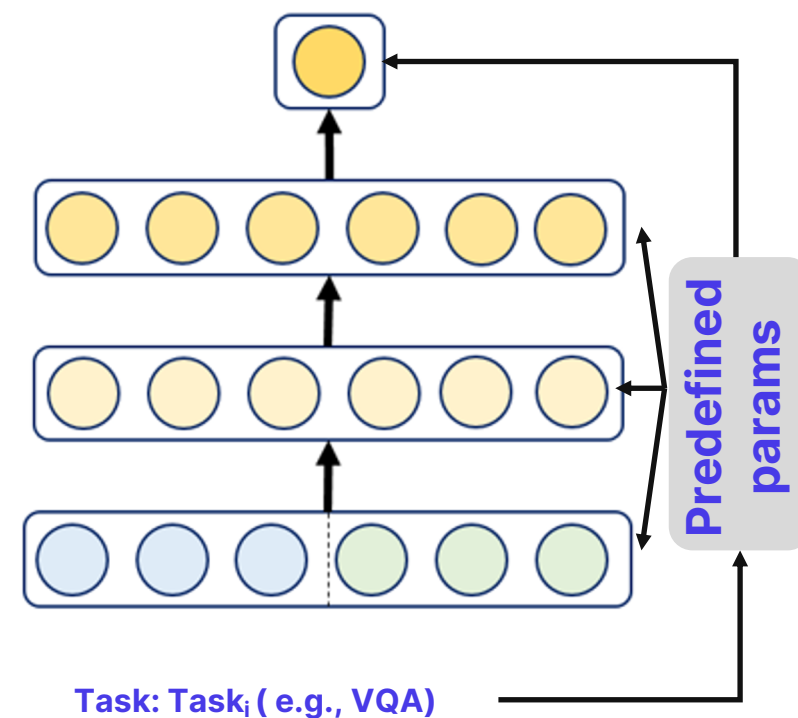
Multi-tasking

Multi-tasking: concepts

A. Known Head+FineTuning

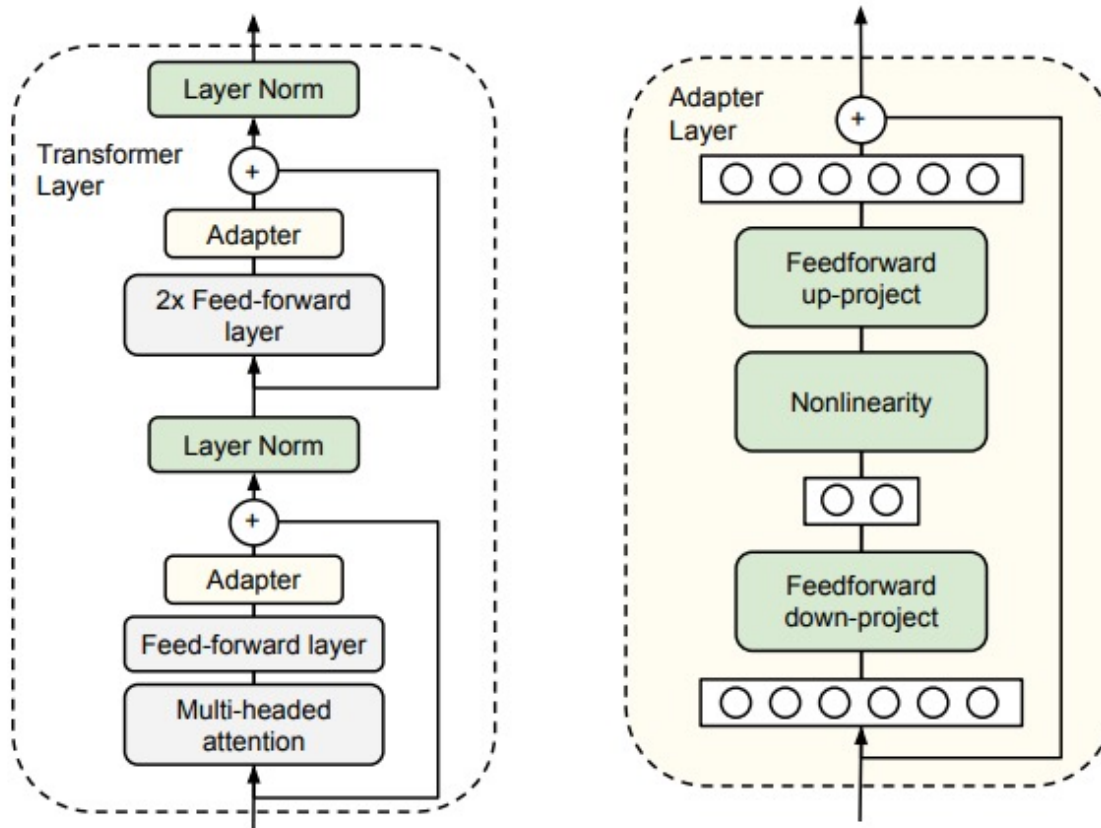


B. Learned Task Embedding



Multi-tasking: current trends

Adapters¹: via task-specific learnable modules

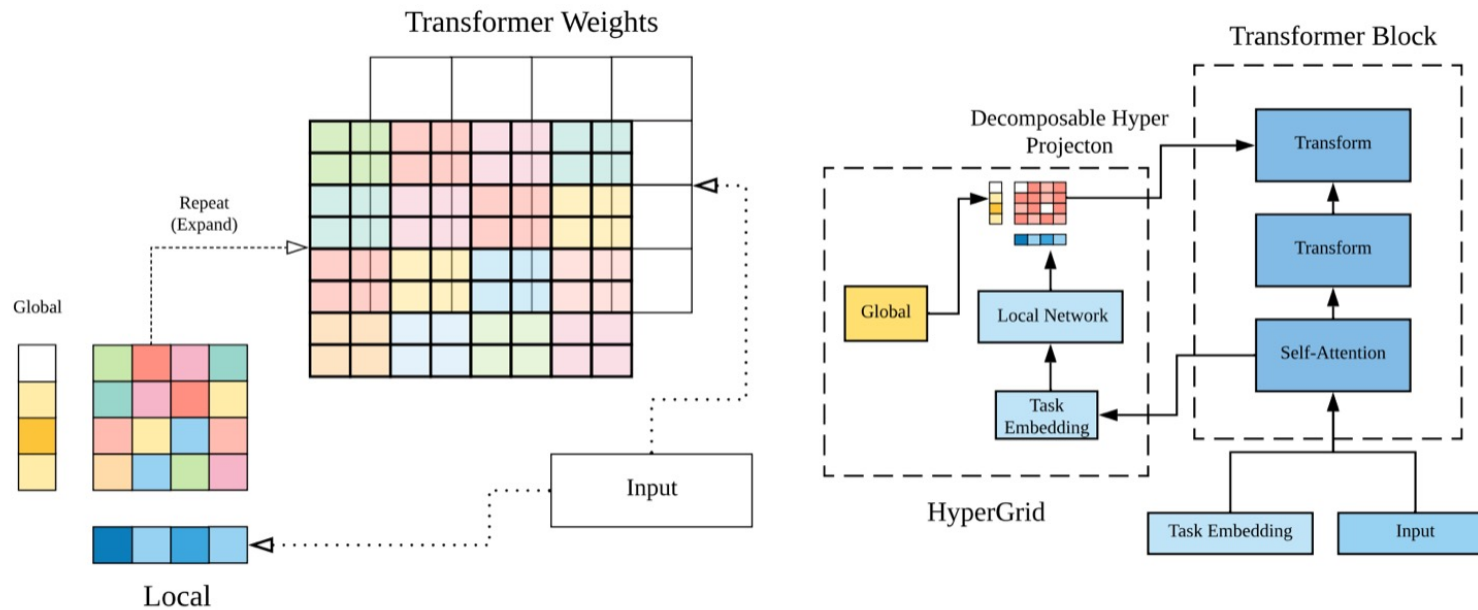


Main idea:

- **Freeze** the **Transformer** weights
- Add a small **learnable** task-specific module - **adapter**
- Performance close to single-task training, but **only +3.5% weights** for multi-task

Multi-tasking: current trends

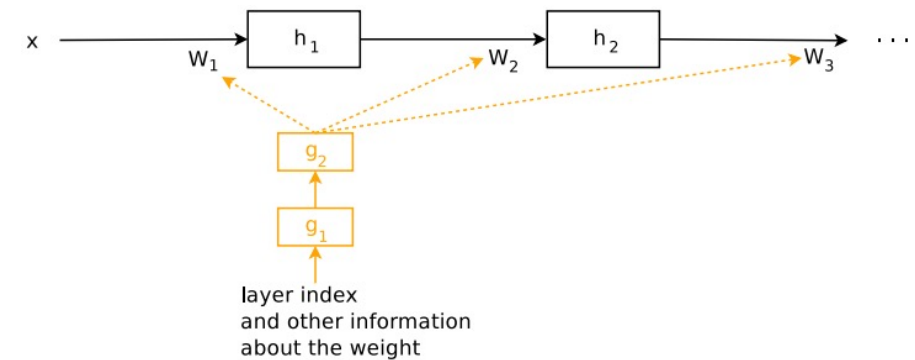
HyperGrid¹: via dynamical weight matrix adjustment by learned task embedding



Main idea:

- **Learned task embedding** used to construct transformer matrix
- Back-bone transformer is T5
- Idea borrowed from **HyperNets²** conception

HyperNet concept

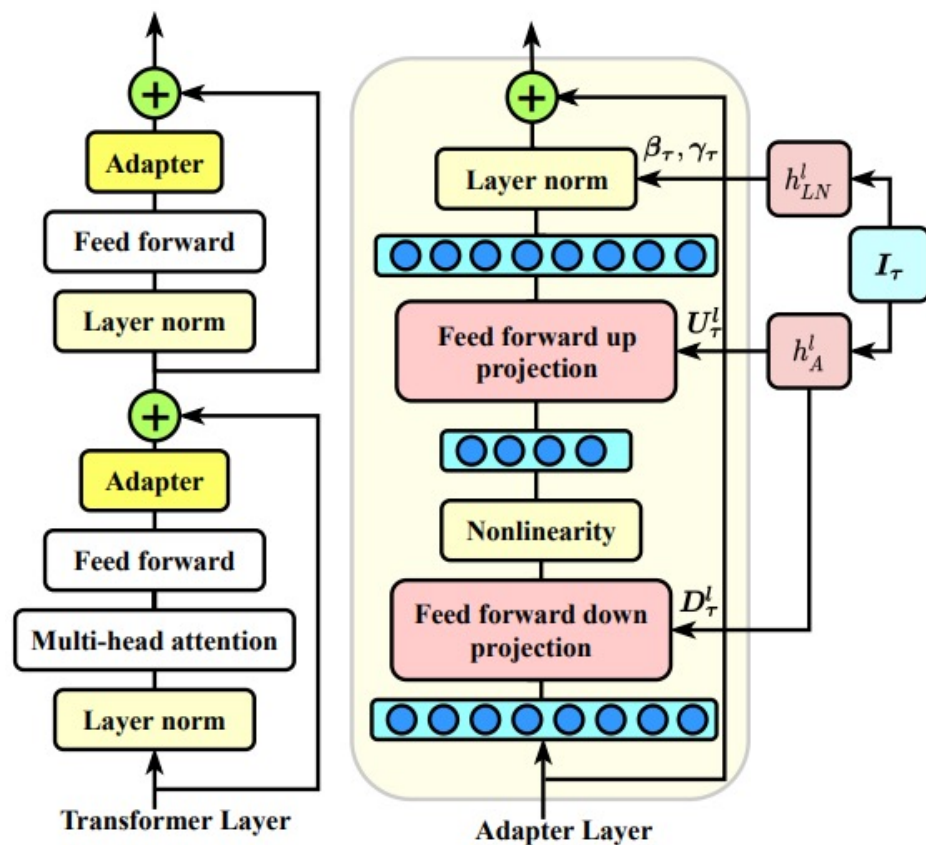


[1] Tay, Yi, et al. "HyperGrid Transformers: Towards A Single Model for Multiple Tasks." 2020 (Google)

[2] Ha, David, Andrew Dai, and Quoc V. Le. "Hypernetworks." 2016 (Google)

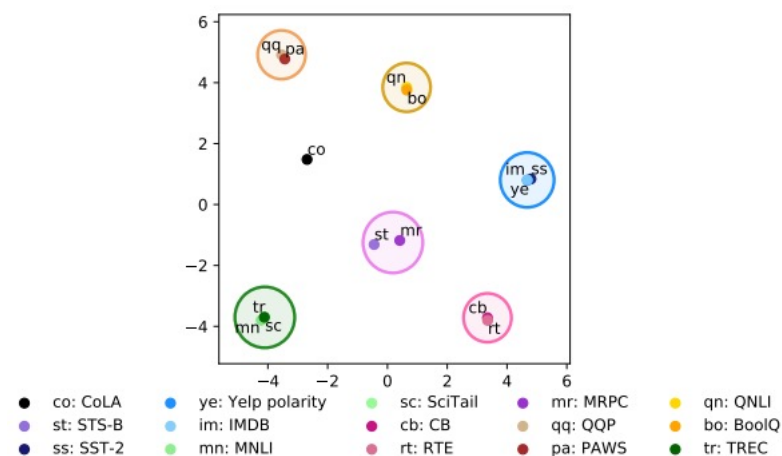
Multi-tasking: current trends

HyperFormer¹: Adapters + HyperNets

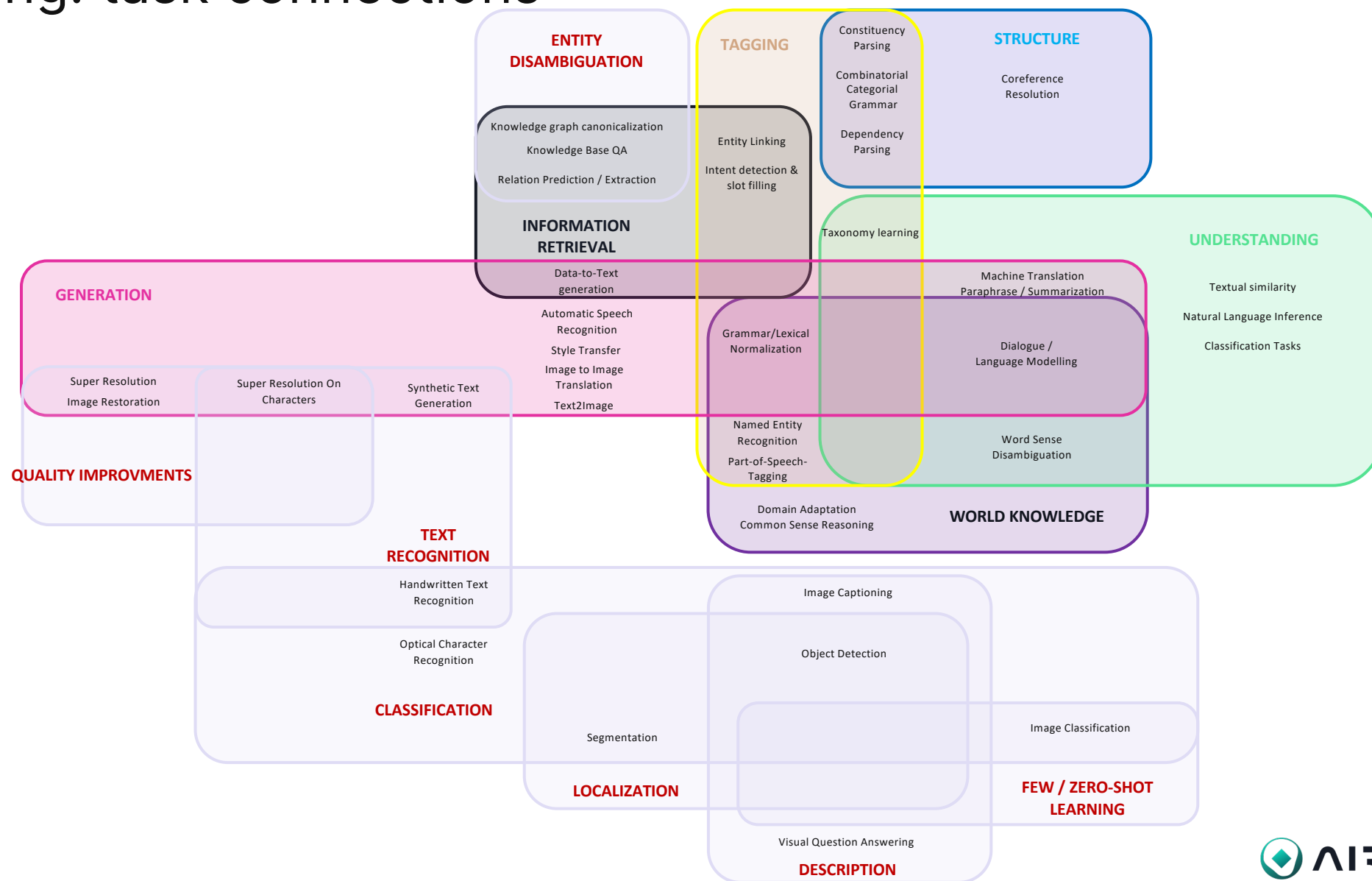


Main idea:

- Making the **Adapters** parameters *through HyperNets*
- New SotA with even **less** params than Adapters
- NLP task embeddings clusterization

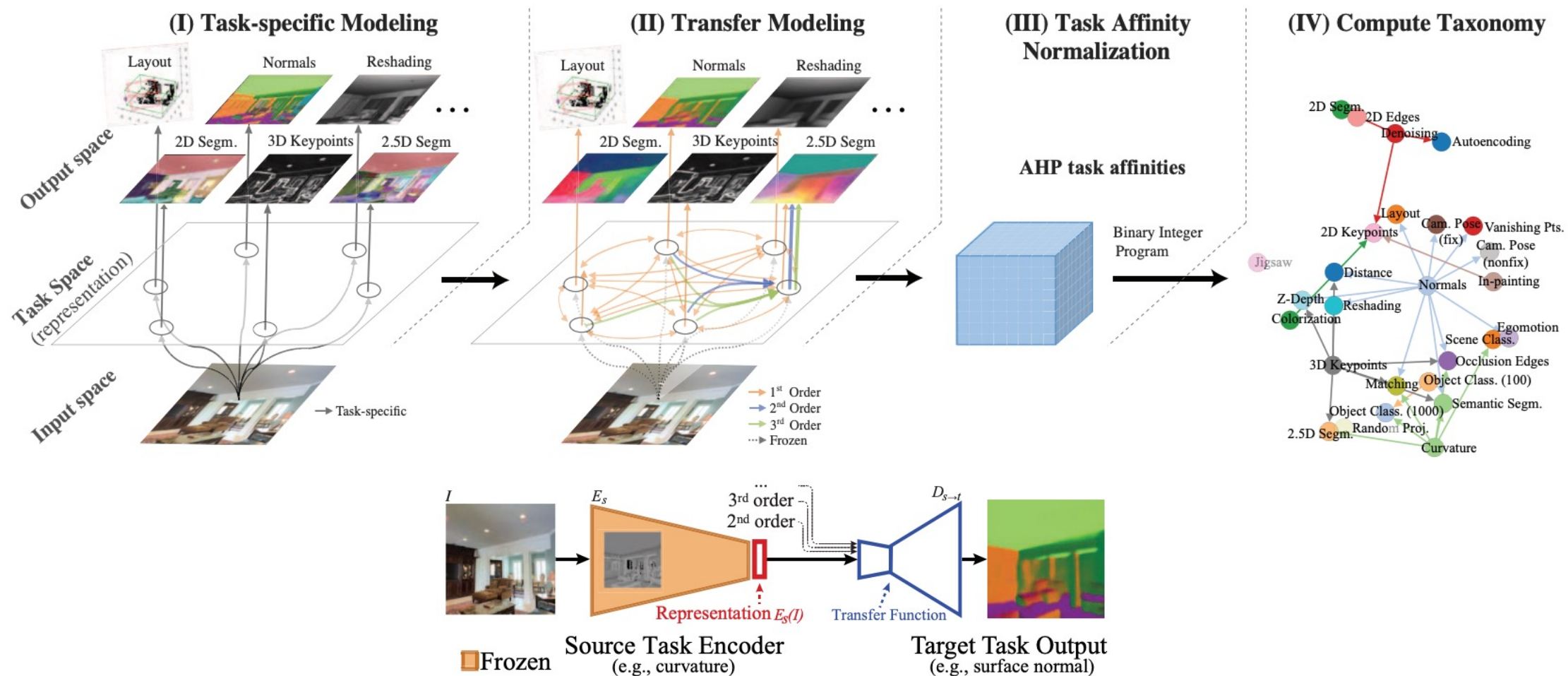


Multi-tasking: task connections



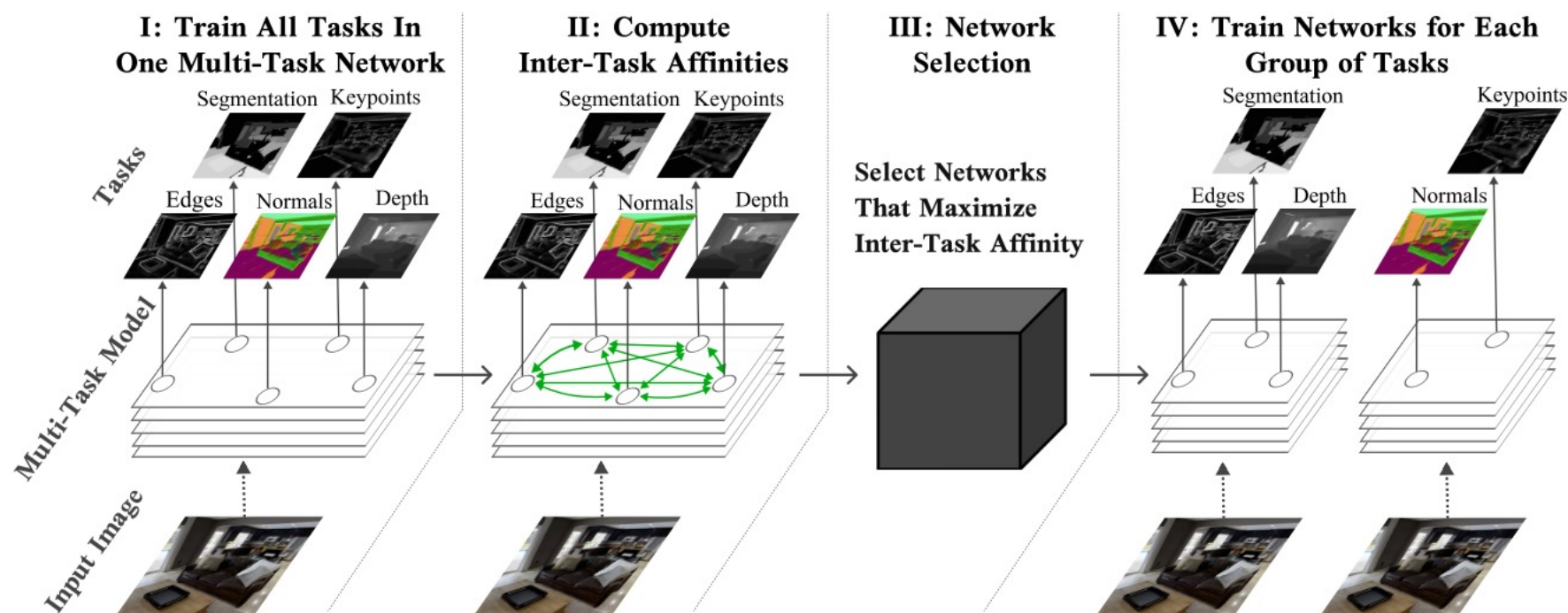
Multi-tasking: taskonomy

Taskonomy¹: Task grouping via pairwise transfer performance



Multi-tasking: how to group tasks

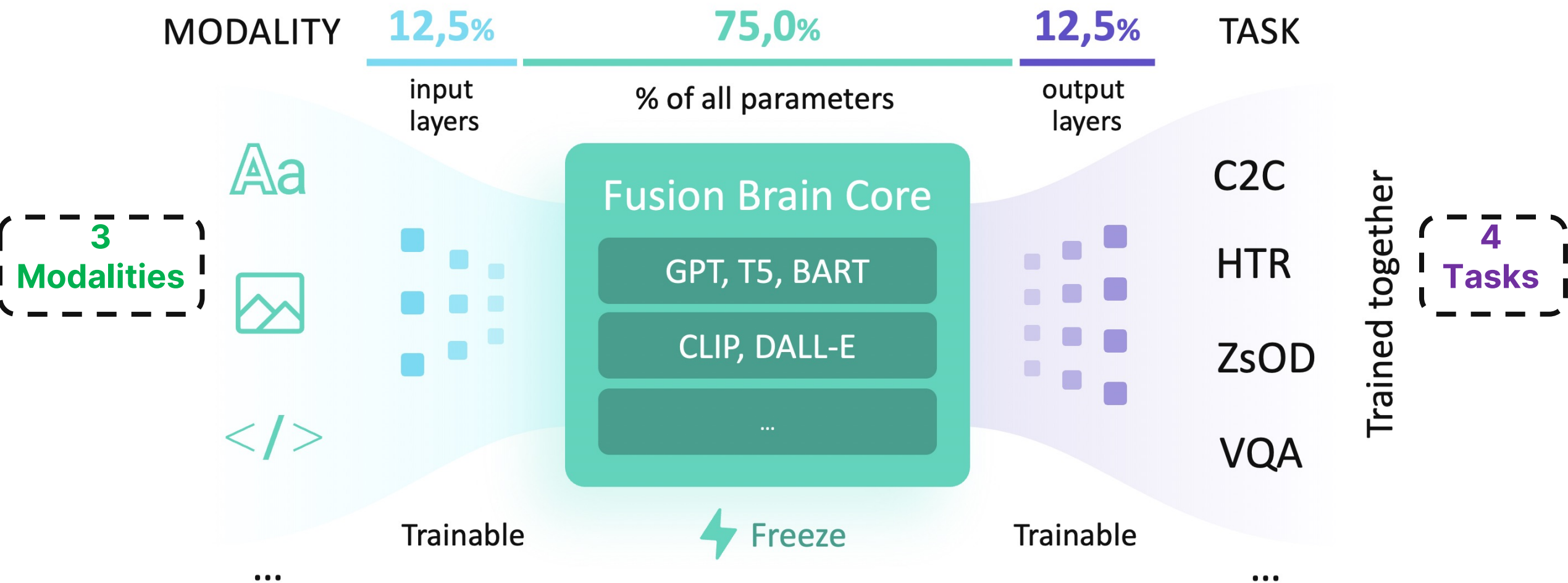
TAG¹: Task grouping via similar gradient update



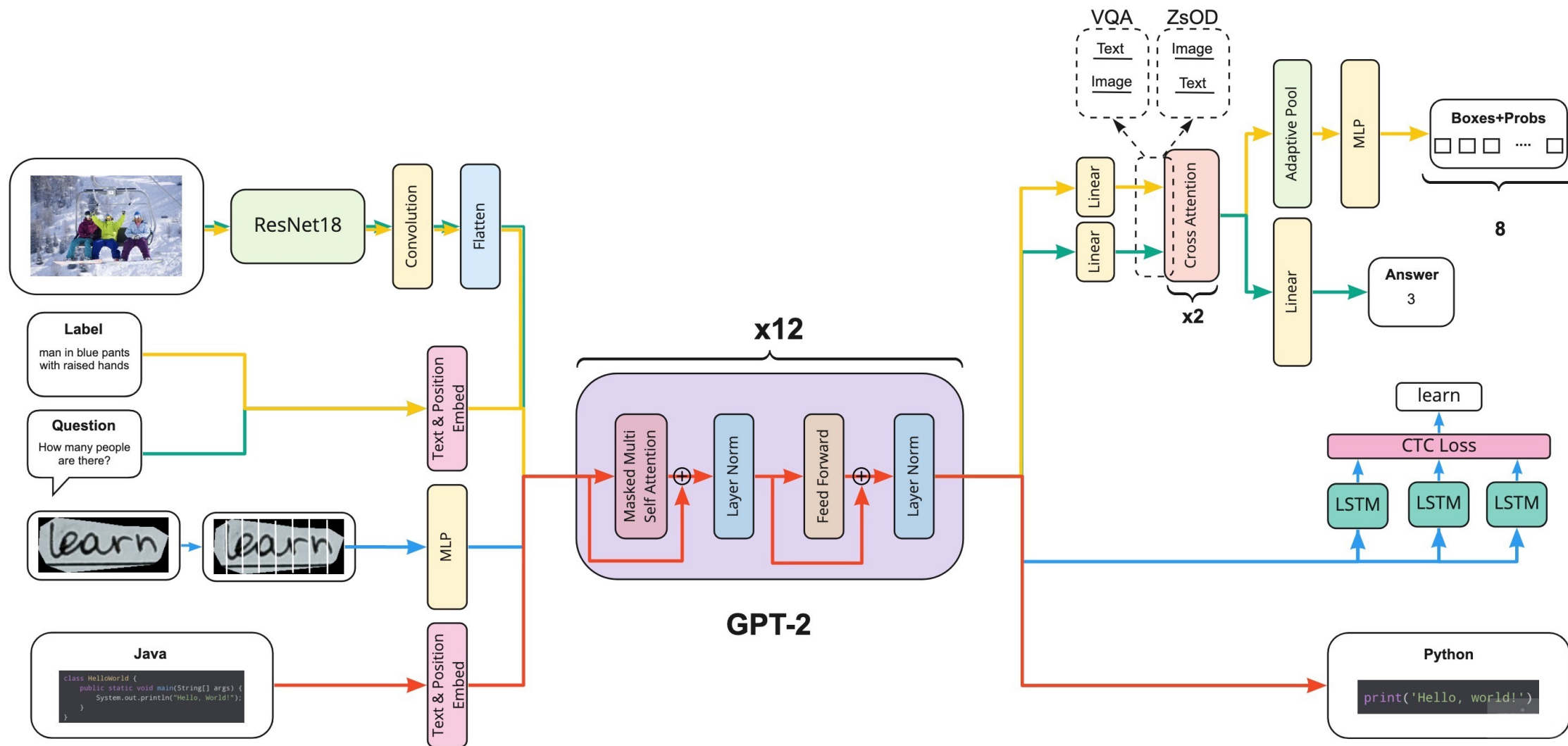
04

Fusion Brain approach

Fusion Brain concept¹: overview



Fusion Brain approach¹: FPT, GPT-2, cross-attention



Fusion Brain approach¹: results

Performance

training setup	C2C CodeBLEU	HTR Acc	ZsOD F1	VQA Acc	Overall
Single-task	0.34	0.63	0.17	0.25	1.39
Fusion	0.39	0.61	0.21	0.30	1.51

Efficiency

training setup	Training time (hours)	Training params	CO2 (kg)
Single-task	215.0	3,283,978,882	39.34
Fusion	150.5	988,272,474	27.45

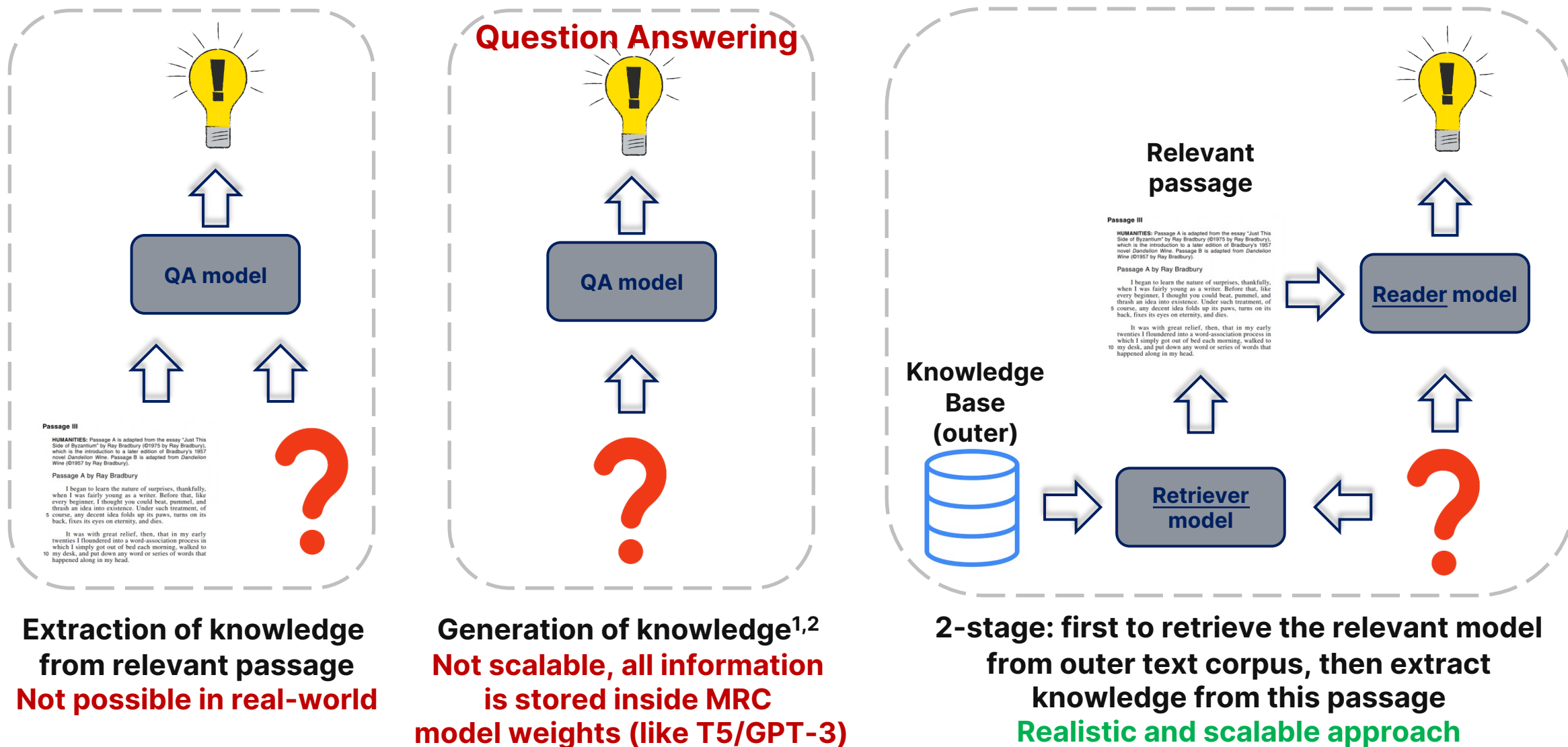
For comparison:

	CO ₂ emissions
Human Life	5 ton
Car with fuel	57 ton

05

Retrieval-based models

Direction to add efficiency and explainability



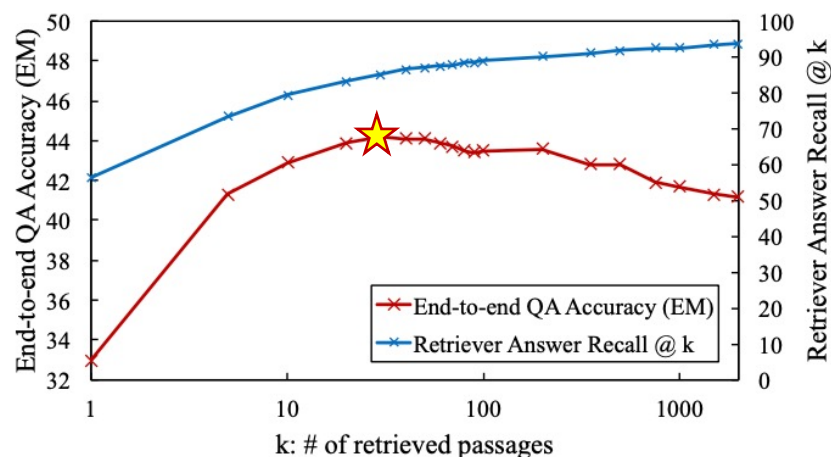
[1] Roberts, Adam, Colin Raffel, and Noam Shazeer. "How Much Knowledge Can You Pack Into the Parameters of a Language Model?" 2020 (Google)

[2] Brown, Tom B., et al. "Language models are few-shot learners." 2020 (OpenAI)

Retrieval-based (RB) modeling

WHY to decompose: Retriever \neq Reader¹

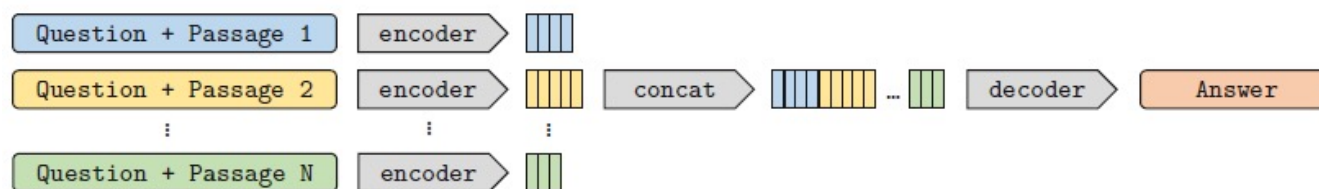
(a) End-to-end QA accuracy (Exact Match, y-axis on the left) of DPR reader and the retrieval recall rate (y-axis on the right) of DPR retriever.



Main idea:

- Retriever **is not approx.** of Reader: having more data helps a little for the Reader, and drops quickly
- **Retriever** is a sort of **representational bottleneck**

How to extract information from multiple sources²



Main idea:

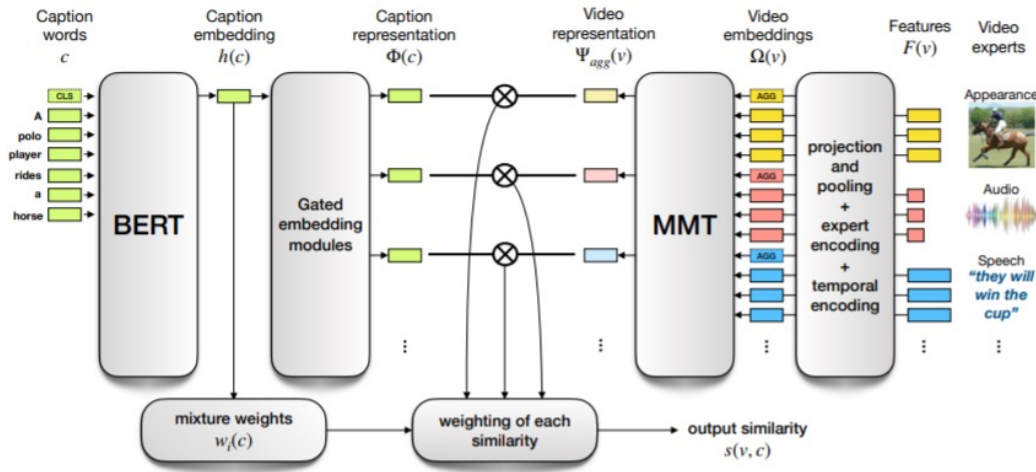
- **Retriever:** BERT-doc + BERT-query
- **Reader: seq2seq T5**, having **query + retrieved doc** as an **input**
 - added special tokens - `question:`, `title:` and `context:` before the question, title and text of each passage
- **Fusion-in-Decoder:** output based on **k > 1** passages

[1] Yang, Sohee, and Minjoon Seo. "Is Retriever Merely an Approximator of Reader?" 2020 (NAVER Corp)

[2] Izacard, Gautier, and Edouard Grave. "Leveraging passage retrieval with generative models for open domain question answering." 2020 (Facebook)

Multi-modality and multi-task in RB

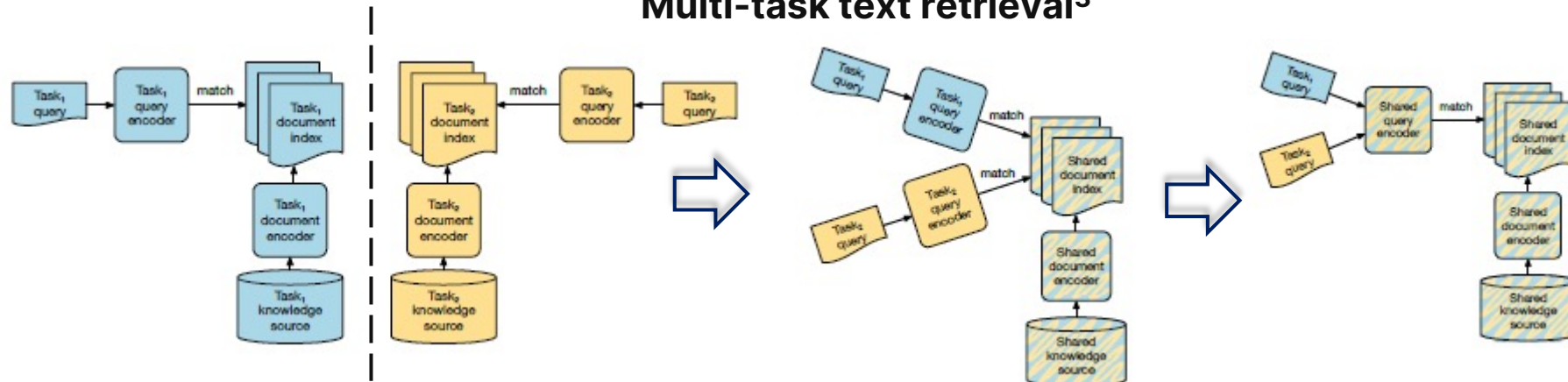
Multi-modality video retrieval^{1,2}



Main idea:

- **Video** – as a **doc** in NLP RB, text query by BERT
- Multi-modality: **middle fusion** of non-query modalities + **late fusion** with text query
- For different NLP tasks the **single retriever is beneficial**
- But the **training** of retriever should be done on **all datasets combined**
- **Retriever**: BERT-based; **Reader**/downstream: BART-based

Multi-task text retrieval³



[1] Gabeur, Valentin, et al. "Multi-modal transformer for video retrieval." 2020 (Google)

[2] Dzabaraev, Maksim, et al. "Mdmmt: Multidomain multimodal transformer for video retrieval." 2021 (Huawei)

[3] Maillard, Jean, et al. "Multi-task retrieval for knowledge-intensive tasks." 2021 (Facebook)

06

Open Questions

Open Questions

1. Effectiveness

Current trend: usage of *LARGE* pre-trained models

Q: How to *decrease* the *resource utilization* (while training as well as on inference)?

2. Universality

Q₁: How to add the new modality *agnostically* (with minimal architectural changes)?

Q₂: How to add the new task *agnostically* (without full retraining)?

Q₃: What tasks could and what tasks should not be combined?



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