Multimodal Pre-training for Recommendation

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HUAWEI

Multimodal models are reshaping the world
with understanding, creation, and interaction capabilities

Multimodal Understanding

Image captioning

Input Image

Human Describe this image as detailed as possible.

BLIP-2 A city street with many people walking and riding motorcycles.

MiniGPT-4 The image shows a busy city street with a clock tower in the background. The street is lined with shops and restaurants on both sides. There are several motorcycles parked on the side of the road, and people are walking down the street. The clock tower has a large clock face with Roman numerals and a small spire on top. The buildings on either side of the street have ornate facades and balconies. The street is paved with cobblestones and there are streetlights on either side of the road. The sky is clear and blue, and there are a few clouds in the distance.

Fig. from: Zhu et al., MiniGPT-4…, 2023

Visual question answering

GPT-4 visual input example, Extreme Ironing:

User What is unusual about this image?

Source: https://www.barnorama.com/wp-content/uploads/2016/12/03-Confusing-Pictures.jpg

GPT-4 The unusual thing about this image is that a man is ironing clothes on an ironing board attached to the roof of a moving taxi.

Fig. from: OpenAI et al., GPT-4 Technical Report, 2023

Cross-Modal Retrieval

Text-to-image retrieval

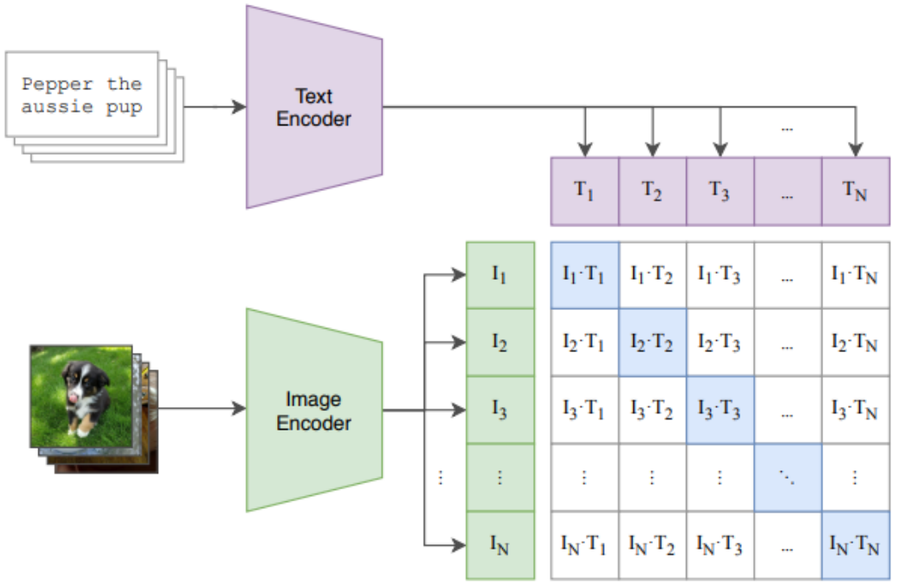


Fig. from: Radford et al., Learning Transferable Visual Models From Natural Language Supervision, 2021

Image-to-audio retrieval

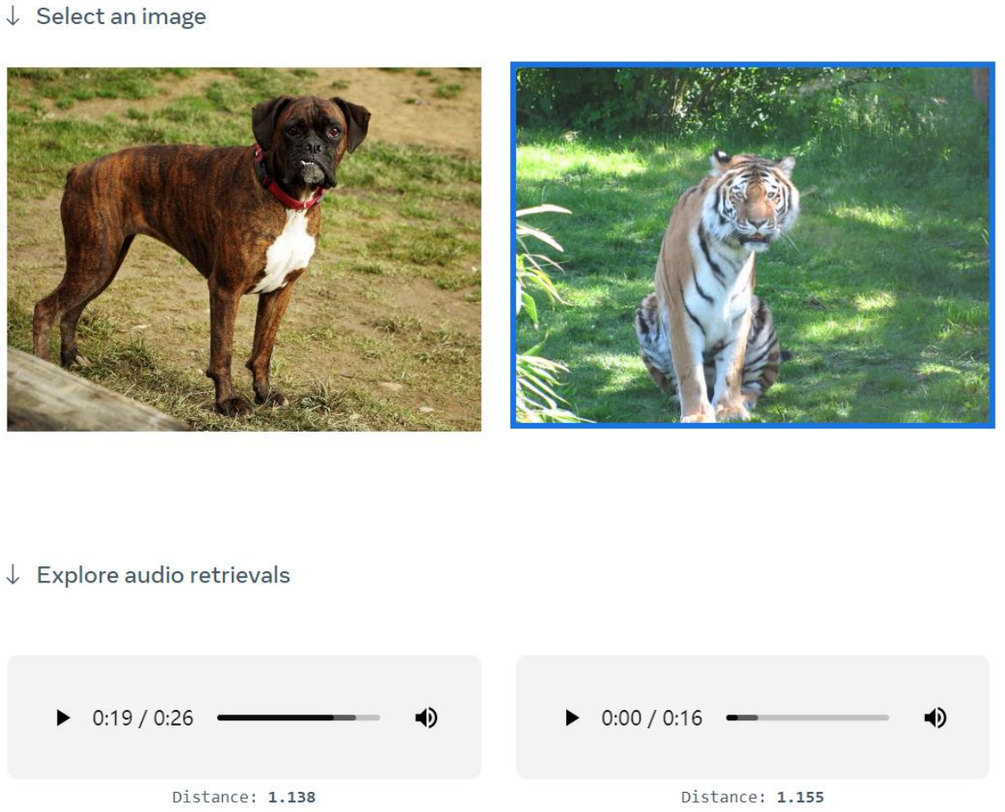


Fig. from: Girdhar et al., ImageBind: One Embedding Space To Bind Them All, 2023

Multimodal Generation

Text-to-image generation

Fig. from: Stable Diffusion 2. https://github.com/Stability-AI/stablediffusion

Text-to-video generation

Prompt: A stylish woman walks down a Tokyo street filled with warm glowing neon and animated city signage. She wears a black leather jacket, a long red dress,…

Fig. from: https://openai.com/index/video-generation-models-as-world-simulators/

More and More Applications…

What can multimodal models do for recommendation?

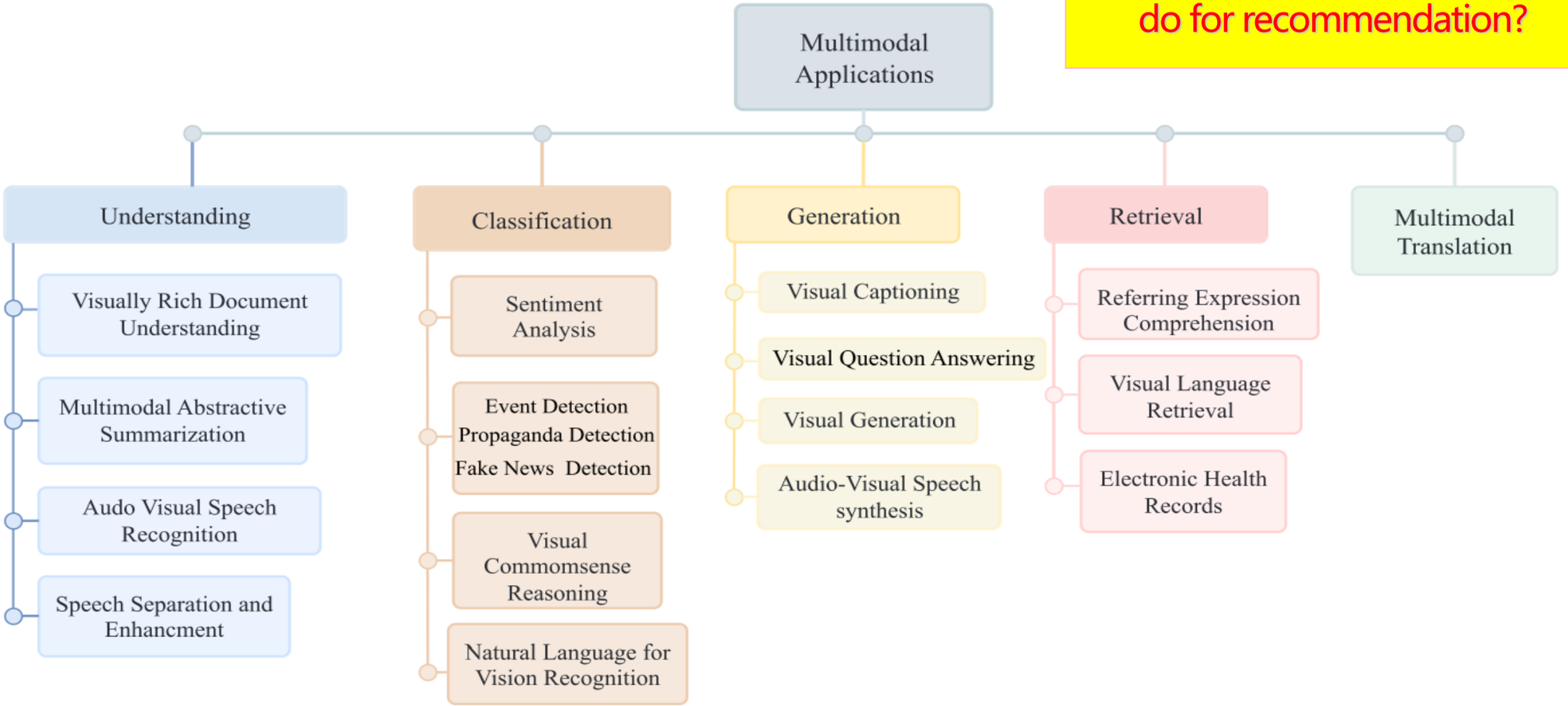


Fig. from: Manzoor et al., Multimodality Representation Learning: A Survey on Evolution, Pretraining and Its Applications, 2023

Outline

- **General-Domain Multimodal Pretraining**
  - Pretraining tasks
  - Pretraining modalities
  - Pretrained models
- **Multimodal Pretraining for Recommendation**
  - Domain data
  - In-domain pretraining tasks
  - Downstream recommendation tasks
- **Open Challenges and Opportunities**
  - Pretraining
  - Adaptation

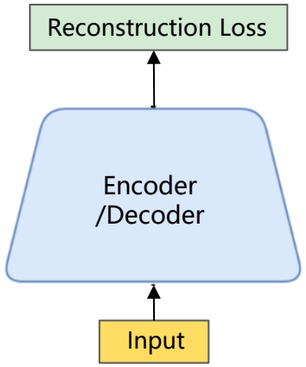
General-Domain Multimodal Pretraining

- **Pretraining tasks**
  - Reconstructive
  - Contrastive
  - Generative
- **Pretraining modalities**
  - Text
  - Image
  - Audio
  - More modalities
- **Pretrained models**
  - CLIP
  - BLIP-2
  - ImageBind
  - UnifiedIO-2

Self-supervised Pretraining

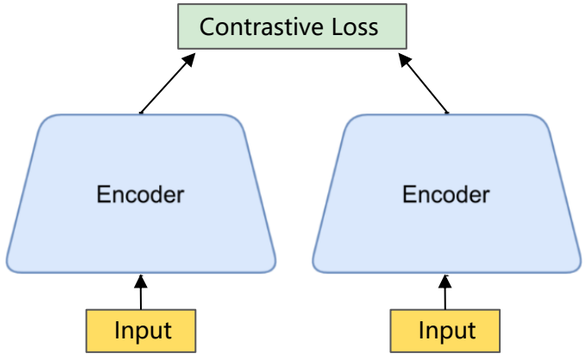
Typical pretraining paradigms: reconstructive, contrastive, and generative

BERT
StableDiffusion



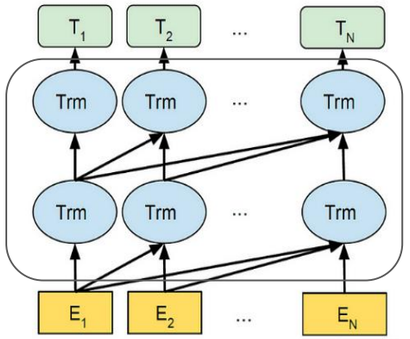
Reconstructive

CLIP
ImageBind



Contrastive

GPT
DALL-E



Generative

Pretrained Multimodal Models (2019~2022)

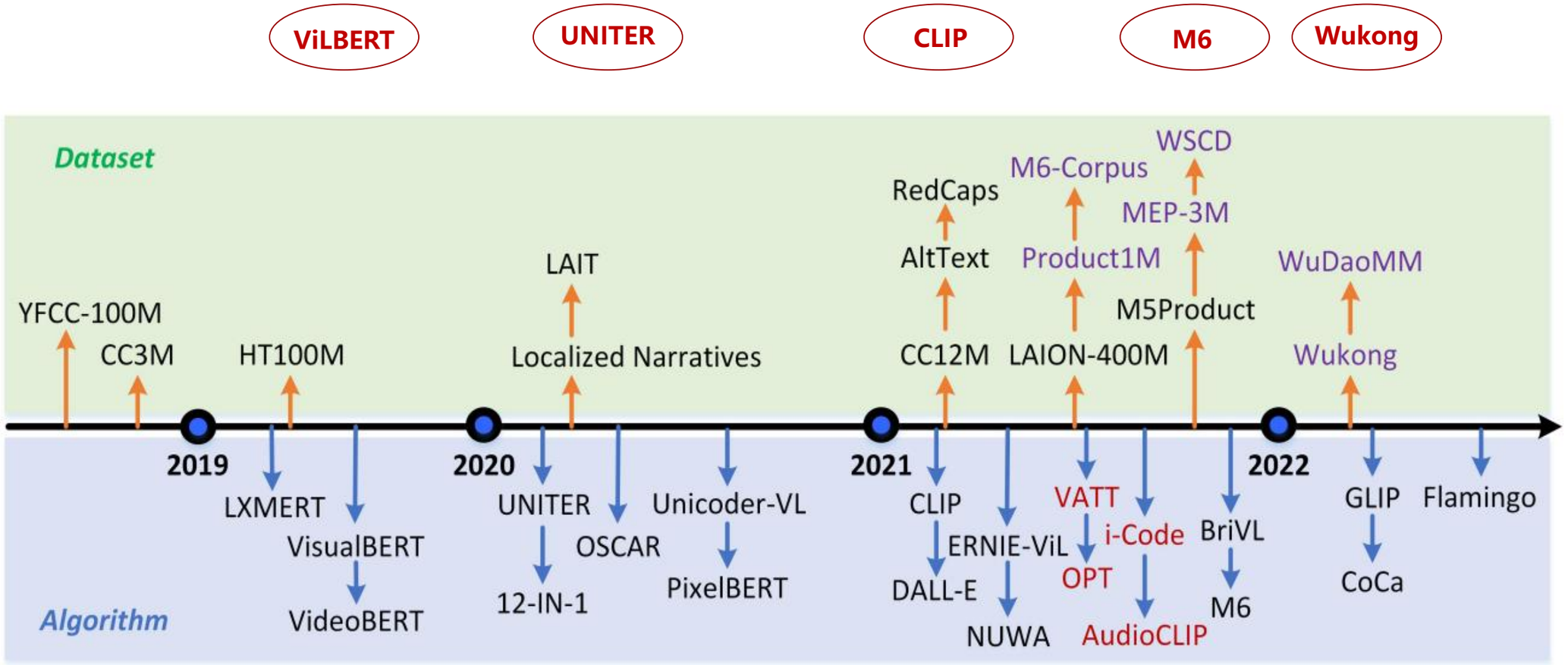
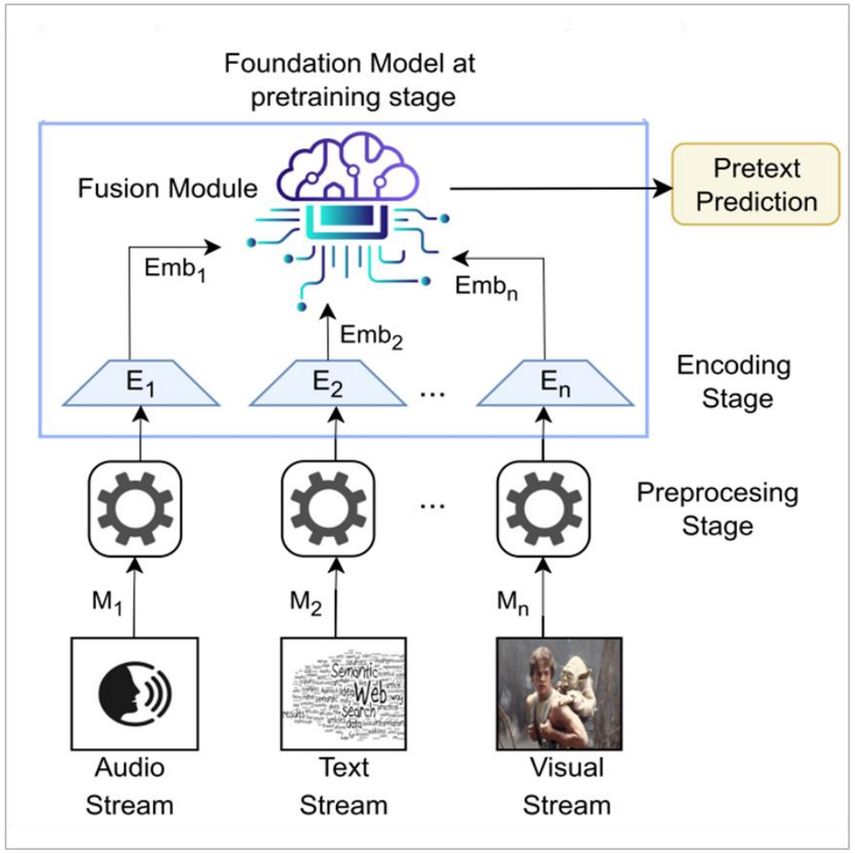
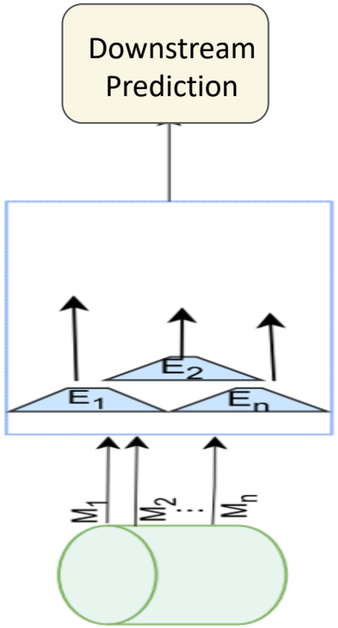


Fig. from: Wang et al., Large-scale Multi-Modal Pre-trained Models: A Comprehensive Survey, 2023

Learning Paradigm: Pretraining-Finetuning



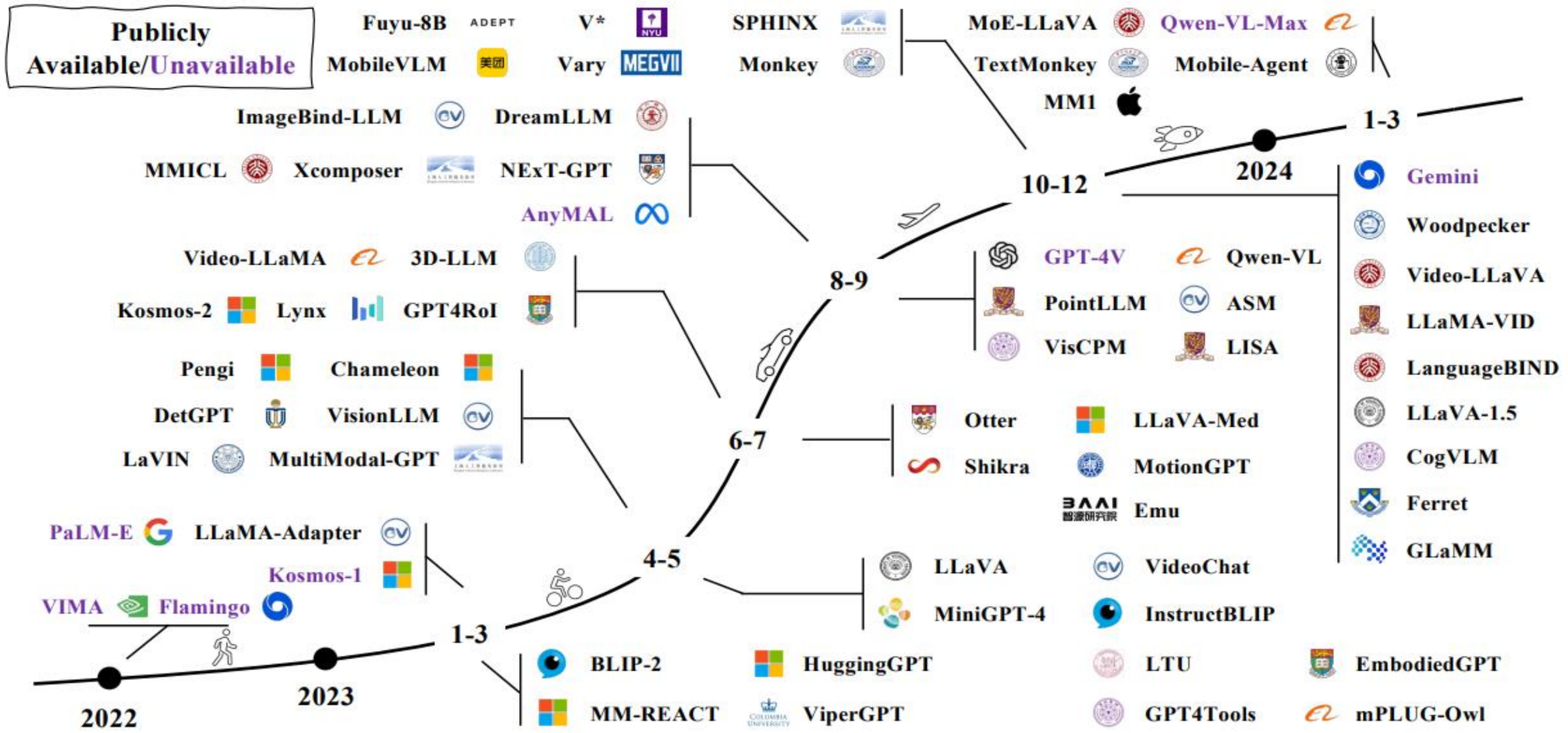
Pretraining



Finetuning

Fig. from: MANZOOR et al., Multimodality Representation Learning: A Survey on Evolution, Pretraining and Its Applications, 2023

Multimodal Large Language Models (2023~2024)



Yin et al., A Survey on Multimodal Large Language Models, 2023

Learning Paradigm: Prompting + In-Context Learning

- **In-context learning** involves the injection of few-shot samples into the prompts, allowing the model to learn from in-context examples and output similar logits.
- **Chain-of-thought prompting** centers on the user's approach to crafting interconnected prompts to guide the model through a conversation or task.

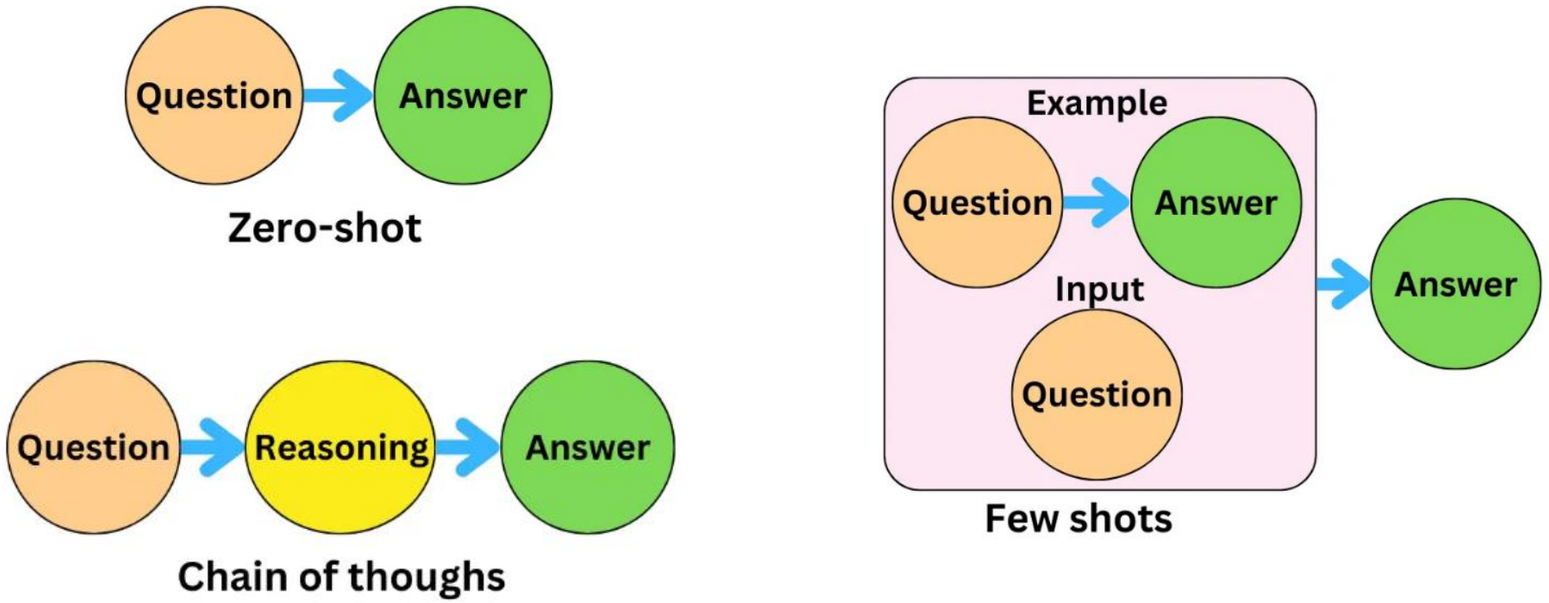
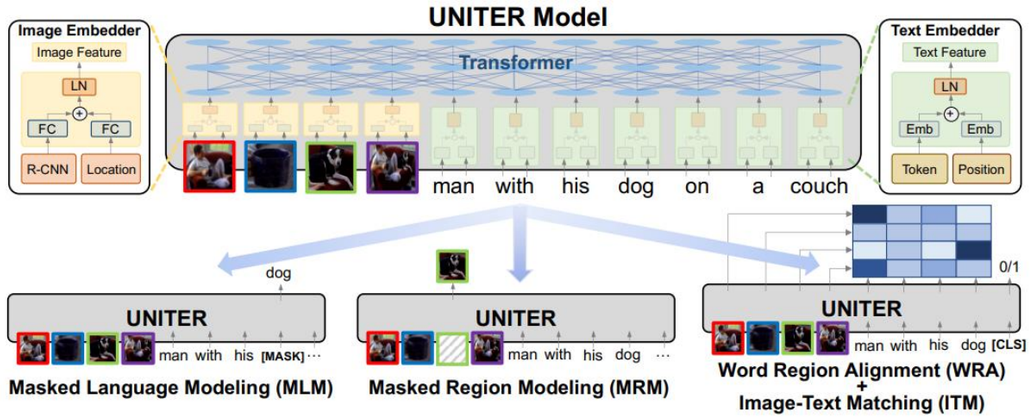
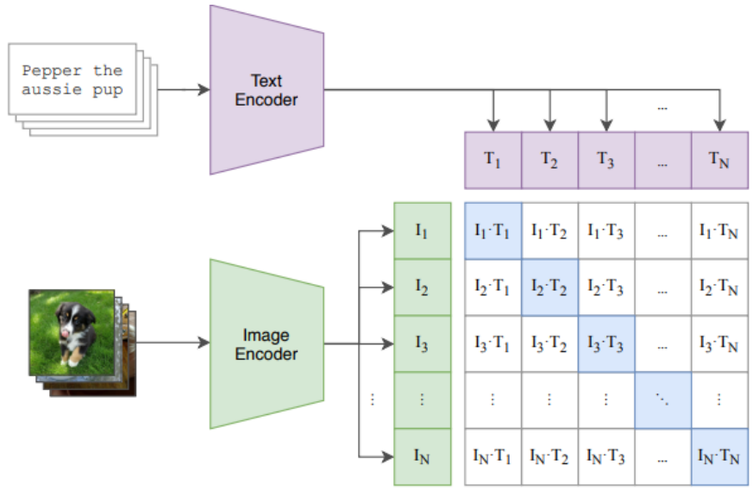


Fig. from https://newsletter.theaiedge.io/p/prompt-engineering-and-llmops-building

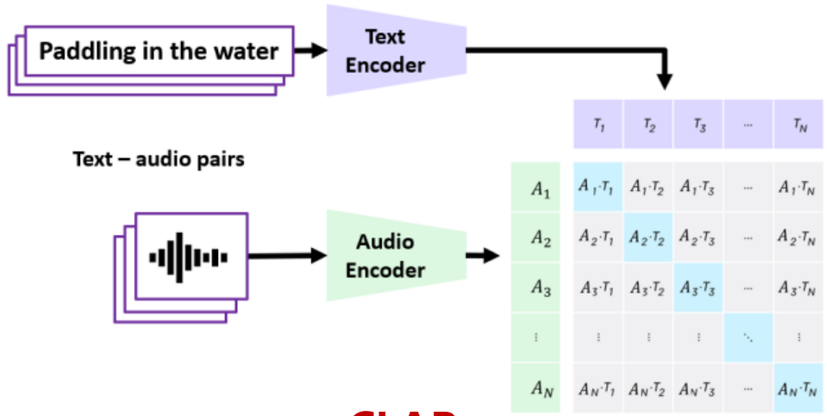
Multimodal Large Models (1)



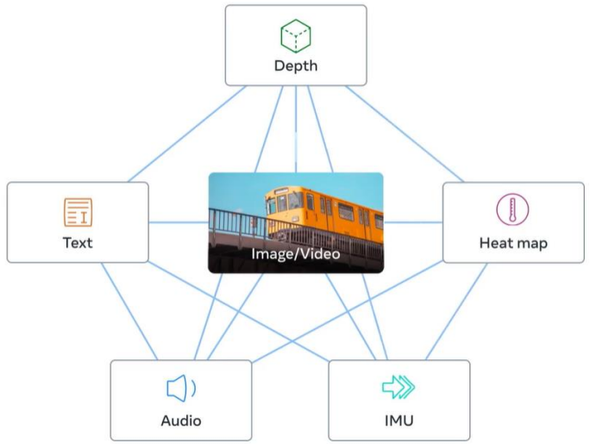
UNITER



CLIP



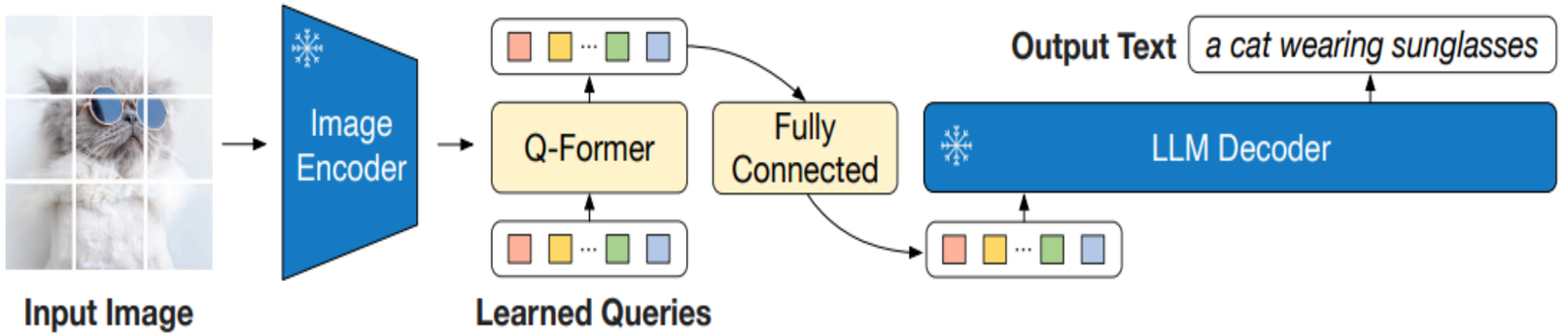
CLAP



ImageBind

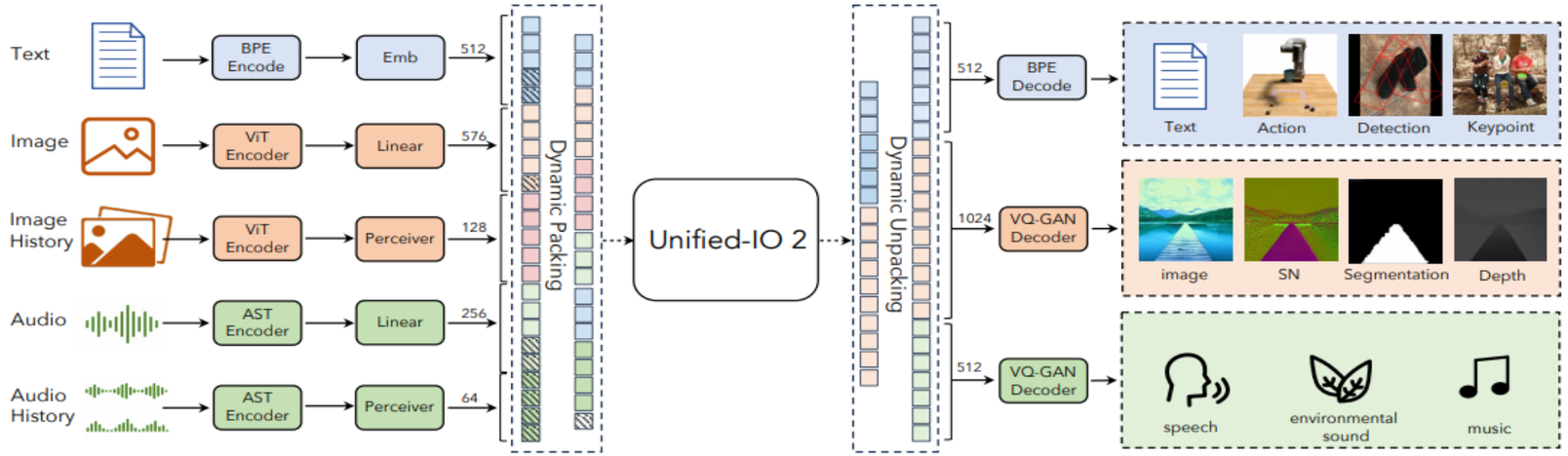
Chen et al., UNITER: UNiversal Image-TExt Representation Learning, 2019
Lu et al., Learning Transferable Visual Models From Natural Language Supervision, 2021
Elizalde et al., CLAP: Learning Audio Concepts From Natural Language Supervision, 2022
Girdhar et al., ImageBind: One Embedding Space To Bind Them All, 2023

Multimodal Large Models (2)



BLIP-2

- **Image-to-text**: Visual understanding and conversation



UnifiedIO-2

- **Any-to-any**: Taking multimodal inputs and generating multimodal outputs

Li et al., BLIP-2: Bootstrapping Language-Image Pre-training with Frozen Image Encoders and Large Language Models, 2023
Lu et al., Unified-IO 2: Scaling Autoregressive Multimodal Models with Vision, Language, Audio, and Action, 2023

Multimodal Pretraining for Recommendation

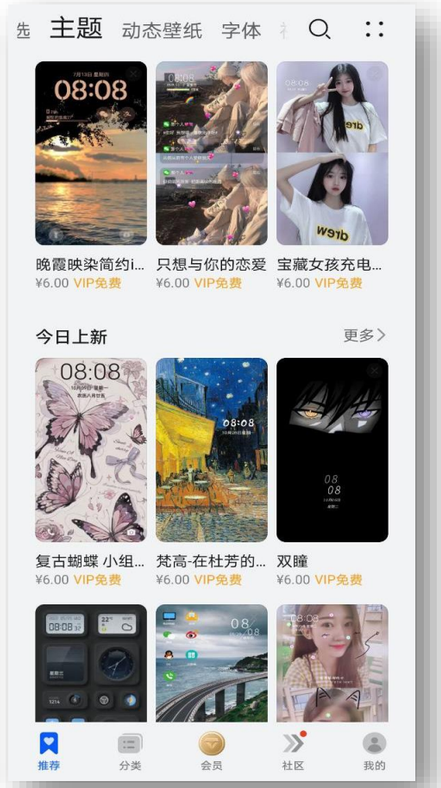
- **Domain data**
  - Item contents
  - User behavior sequences
  - User/item graphs
- **In-domain pretraining tasks**
  - Representation learning
  - Masked item prediction
  - Next item prediction
- **Downstream recommendation tasks**
  - Tagging
  - Matching: Sequential recommendation
  - Ranking: CTR prediction
  - Reranking: diversity awareness

Multimodal Recommendation Scenarios

News Feed

Micro-Video

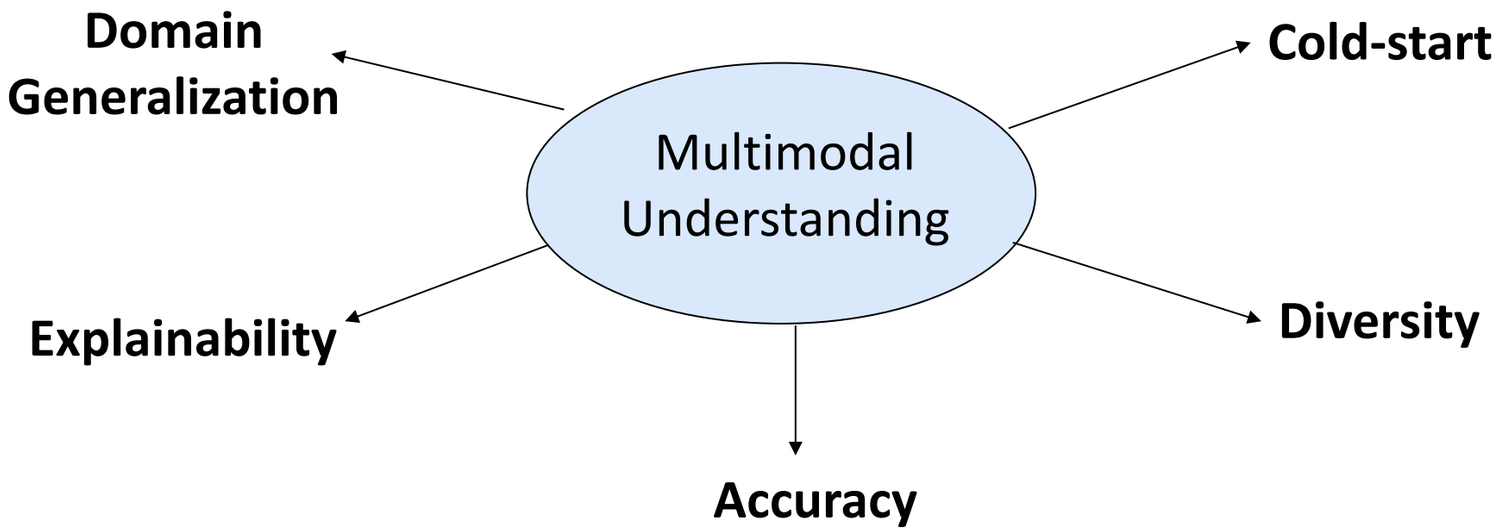
Music Streaming



Mobile Theme

And many more...

Why Multimodal Recommendation?



Why Multimodal Pretraining for Recommendation?

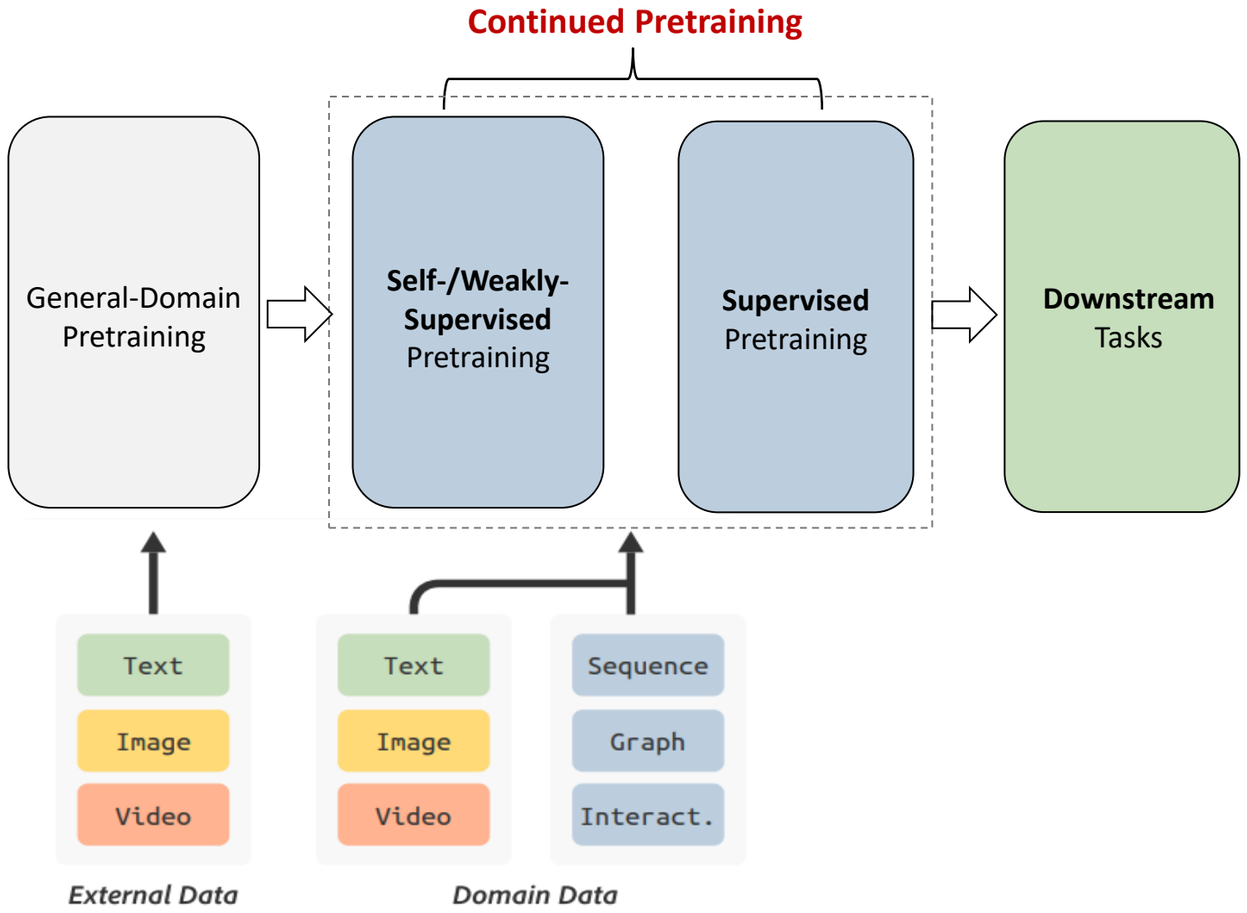
Multimodal pretraining for recommendation

How to learn a good representation for recommendation?

Traditional multimodal recommendation

How to learn a good recommender given pretrained representations?

Overall Framework



Domain Data:

- **Content data**: text、image、video、category、tags…
- **Behavior data**: user-item pairs, sequences、graphs…

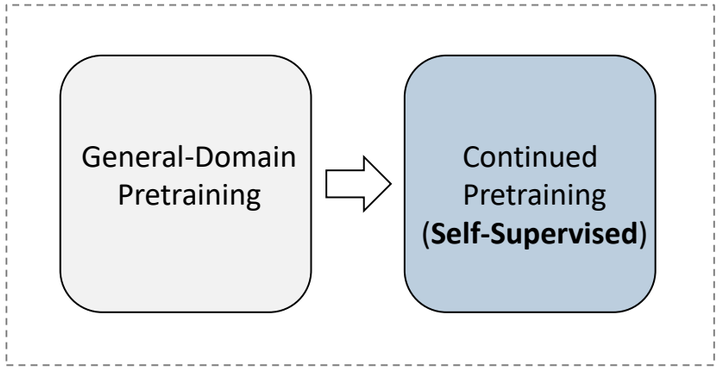
Continued Pretraining:

- A way to incorporate new domain knowledge into a pretrained model without having to retrain it from scratch

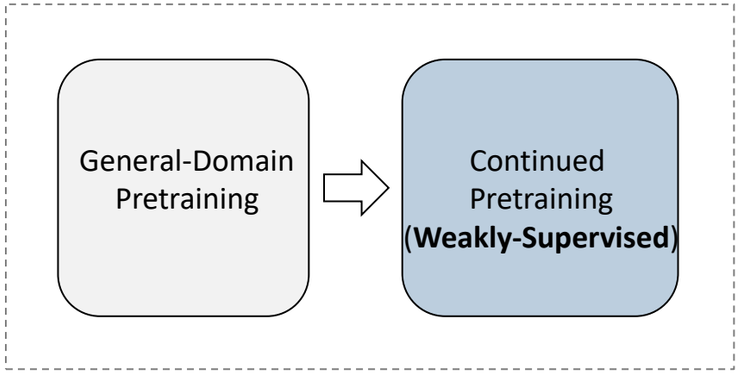
Downstream Tasks

- Representation transfer
- Supervised finetuning
- Adapter tuning

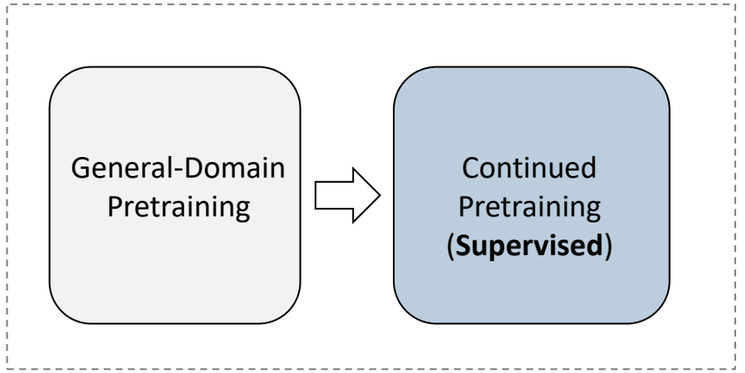
Categorization of Existing Work



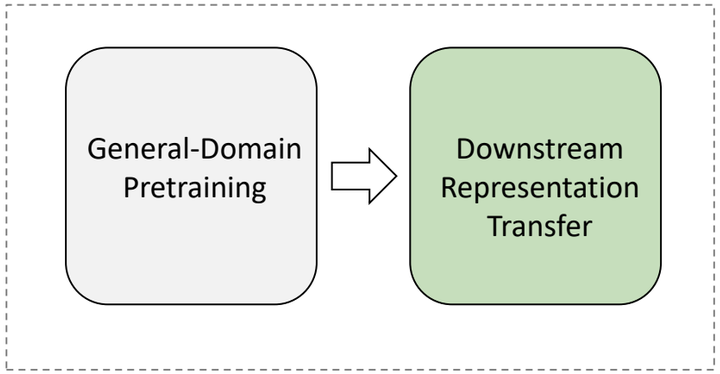
C1



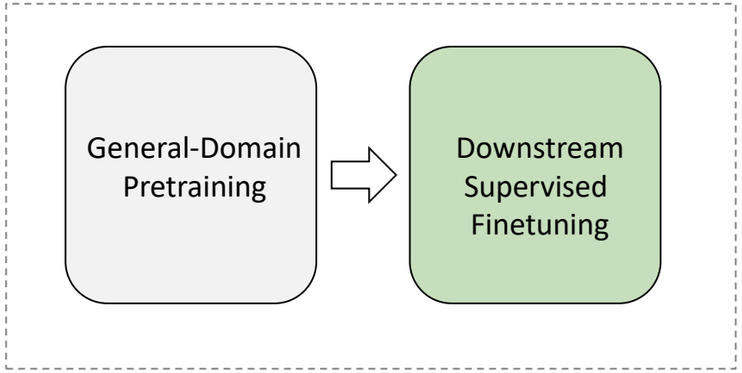
C2



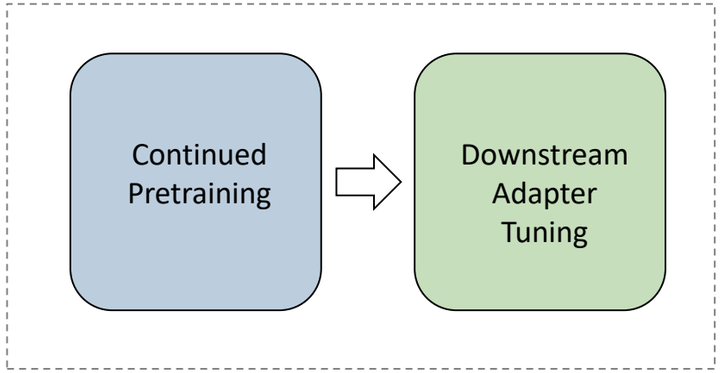
C3



C4



C5



C6

C1: Continued Pretraining w/ Self-Supervised Tasks

Reconstructive:

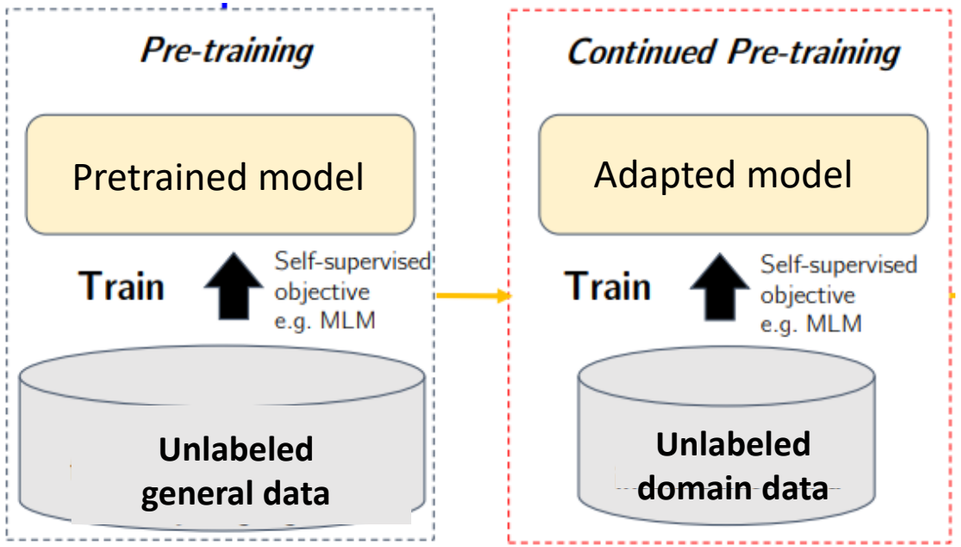
- Masked token prediction (PREC、RecoBERT)
- Masked attribute prediction (PREC、S3-Rec)
- Masked item prediction (PREC、S3-Rec)

Contrastive:

- Contrastive learning (MMSRec、VisualEncoder)
- Title-body alignment (RecoBERT)
- Cross-modal alignment

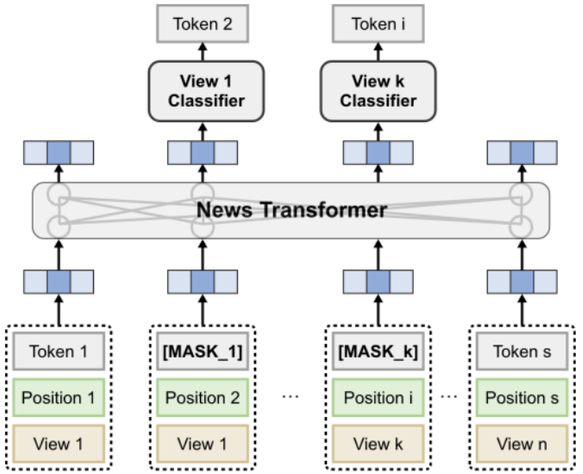
Generative:

- ……



Liu et al., Boosting Deep CTR Prediction with a Plug-and-Play Pre-trainer for News Recommendation, 2022
Malkiel et al., RecoBERT: A Catalog Language Model for Text-Based Recommendations, 2020
Zhou et al., S^3-Rec: Self-Supervised Learning for Sequential Recommendation with Mutual Information Maximization, 2020
Song et al., Self-Supervised Multi-Modal Sequential Recommendation, 2023
Chen et al., Visual Encoding and Debiasing for CTR Prediction, 2022

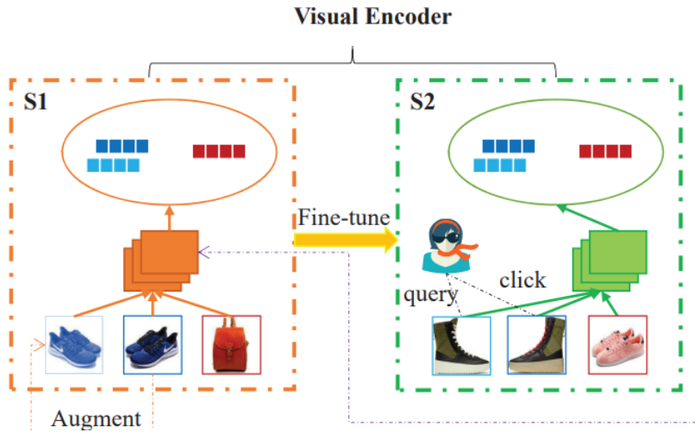
C1: Continued Pretraining w/ Self-Supervised Tasks



(a) Masked news token prediction.

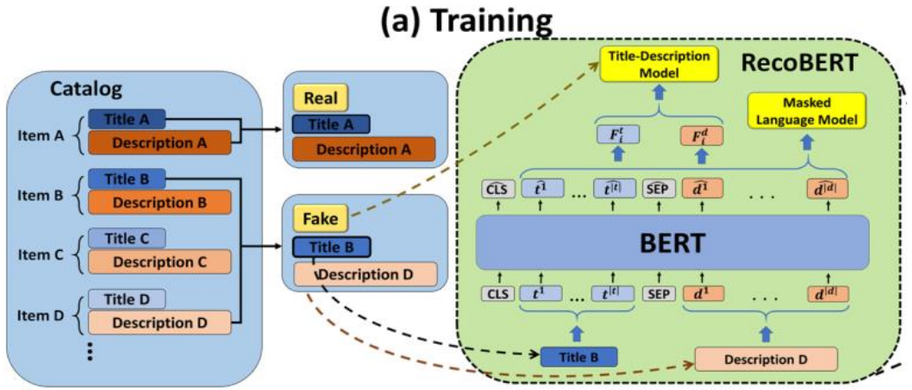
PREC [Huawei] *Liu et al., 2022*

Masked token/category prediction



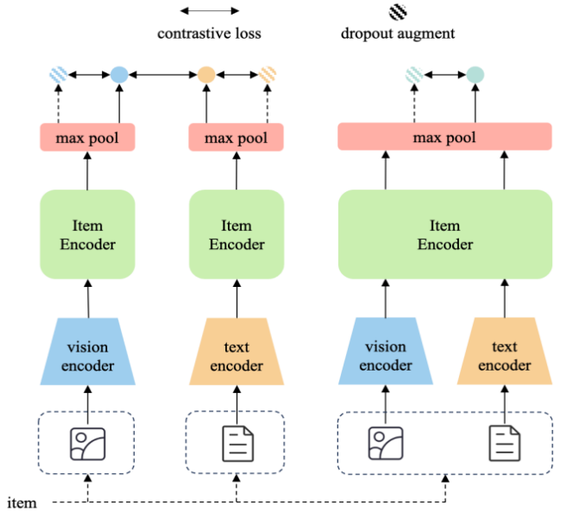
VisualEncoder *Chen et al., 2022*

Contrastive learning



RecoBERT Malkiel *et al., 2020*

Masked language model / alignment between title and description



MMSRec *Song et al., 2023*

Contrastive learning within modality & across modalities

C2: Continued Pretraining w/ Weakly-Supervised Tasks

Weakly-Supervised Signals:

- Category/tags/topics
- Correlated item pairs
- Knowledge graphs
- Query-document pairs
- ……

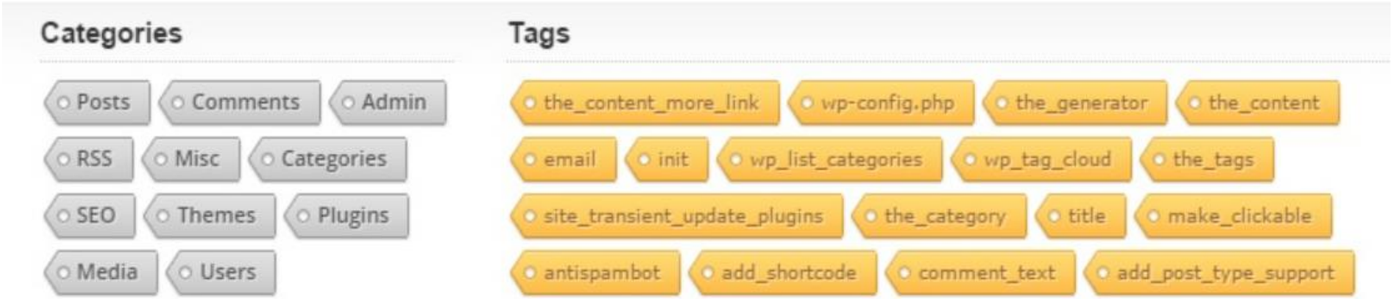


Fig. from: https://www.wpexplorer.com/plugins-add-categories-tags/

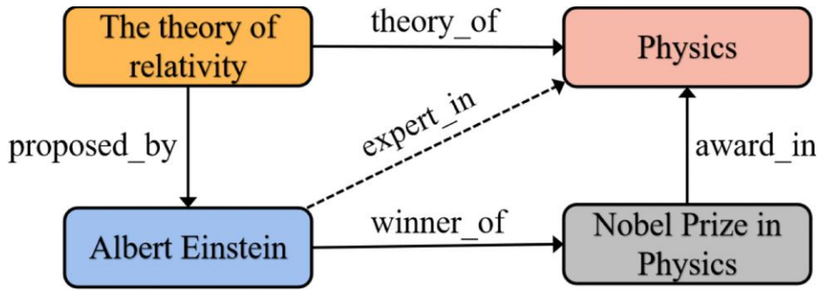
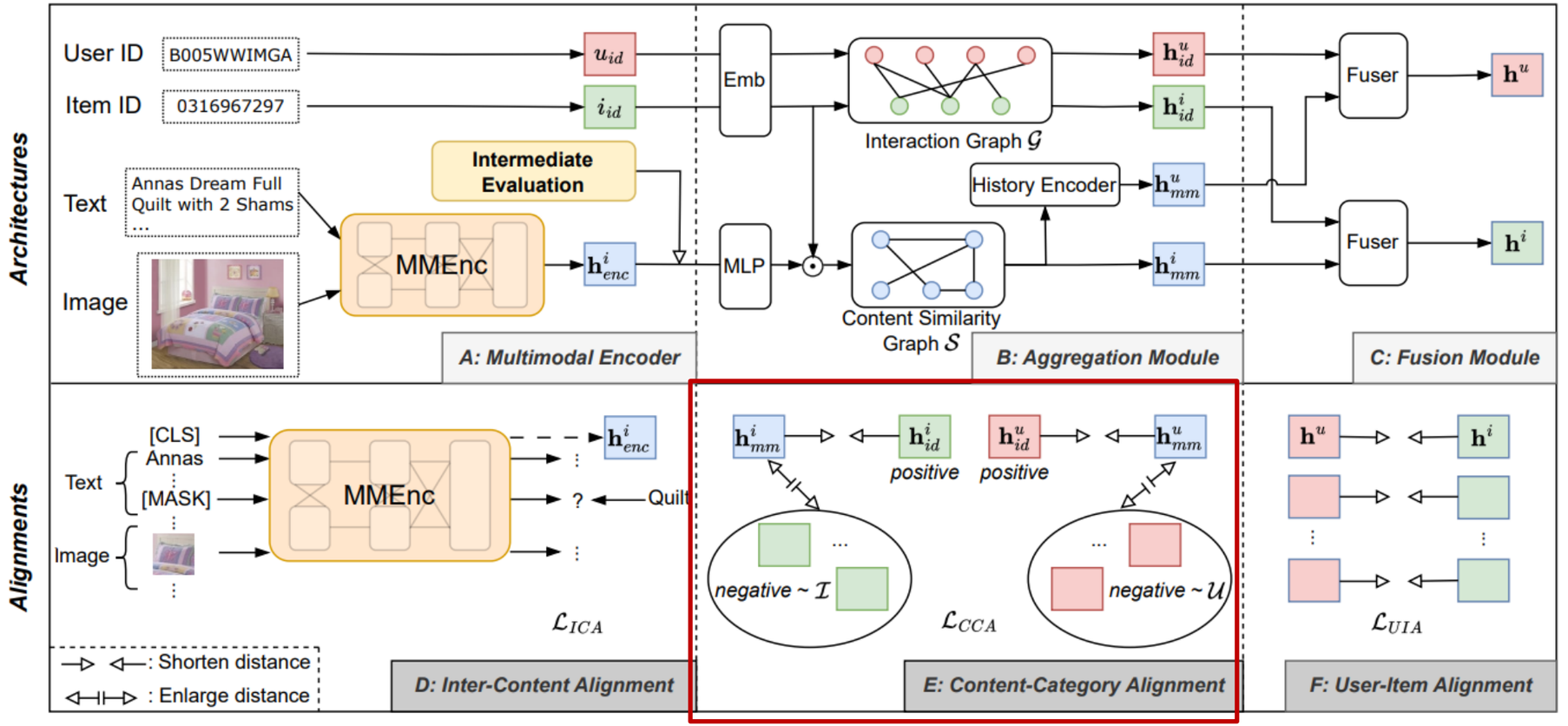


Fig. from: TDN: Triplet Distributor Network for Knowledge Graph Completion, 2023

C2: Continued Pretraining w/ Weakly-Supervised Tasks

AlignRec

- **Content-category alignment**: aligning the item representations of the same category

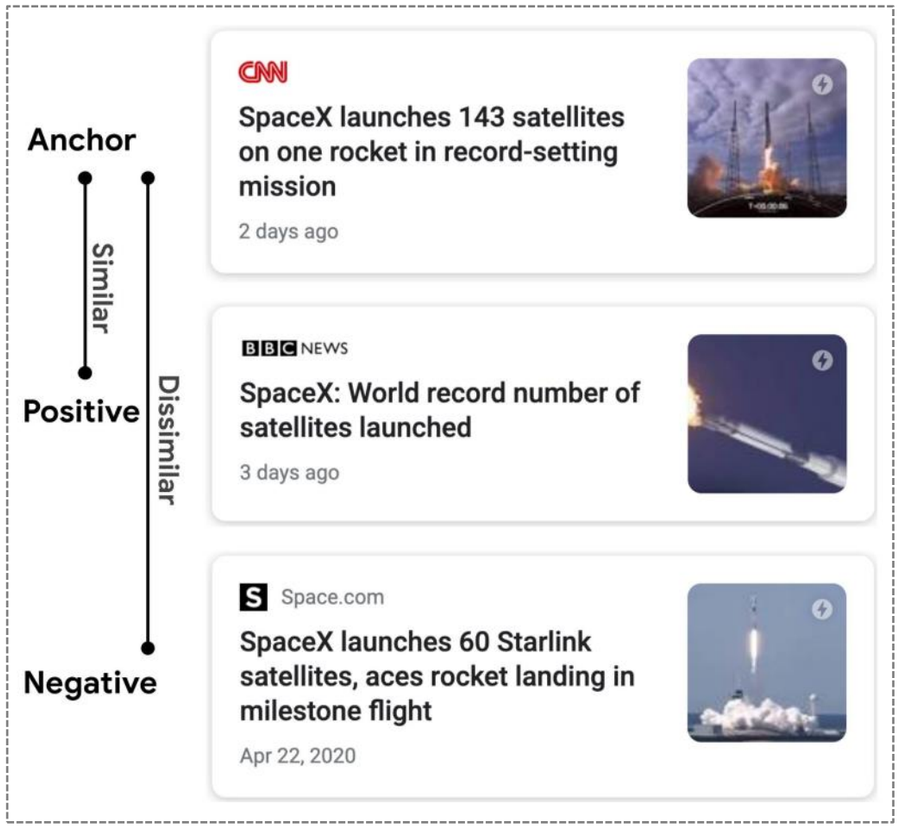


Liu et al., An Aligning and Training Framework for Multimodal Recommendations, 2024

C2: Continued Pretraining w/ Weakly-Supervised Tasks

NewsEmbed

- **Contrastive learning**: aligning the crawled news document triplets
- **Topic classification**: leveraging document-topic associations for multi-label classification



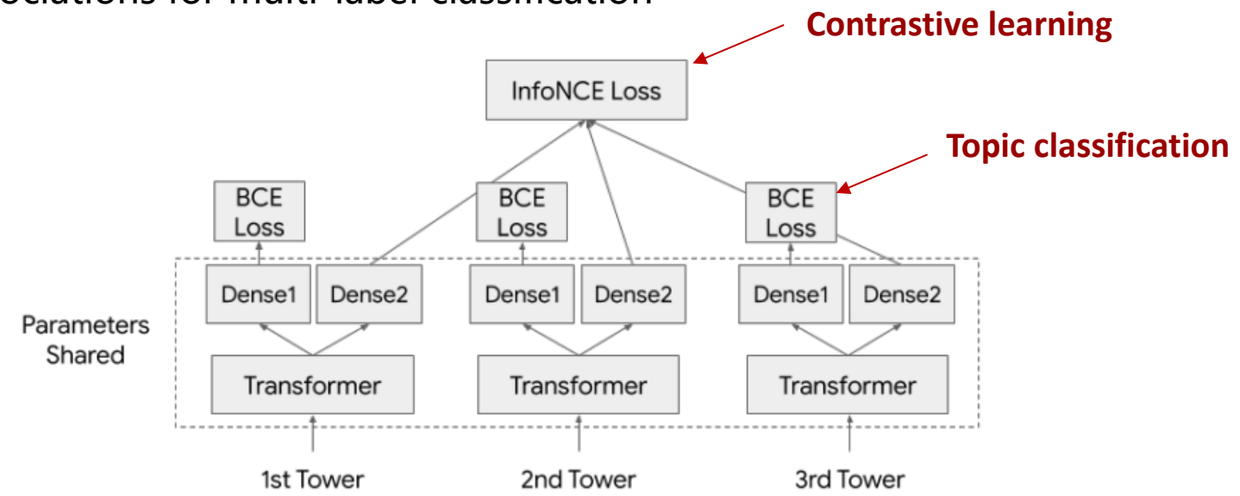


Figure 4: NewsEmbed model structure.

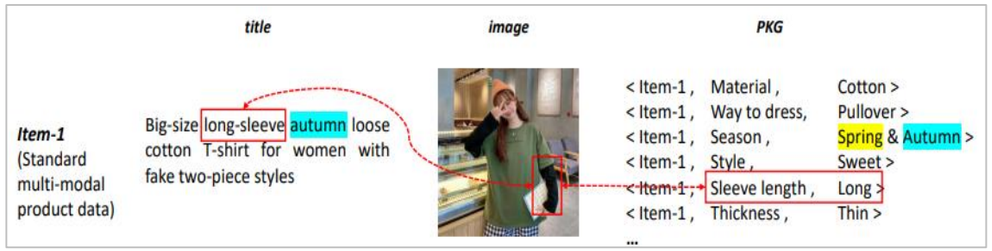
Model	BBC	20 Newsgroup	AG News	MIND	Avg.
SBERT	96.0	64.5	86.5	75.2	80.5
USE	97.3	66.4	85.8	75.0	81.1
mUSE	97.3	71.4	86.8	75.8	82.8
LaBSE	96.6	70.3	86.3	73.9	81.8
Laser	92.1	63.5	81.4	63.1	75.0
NewsEmbed	**97.5**	**73.9**	**89.1**	**77.0**	**84.2**

Liu et al., NewsEmbed: Modeling News through Pre-trained Document Representations, 2021

C2: Continued Pretraining w/ Weakly-Supervised Tasks

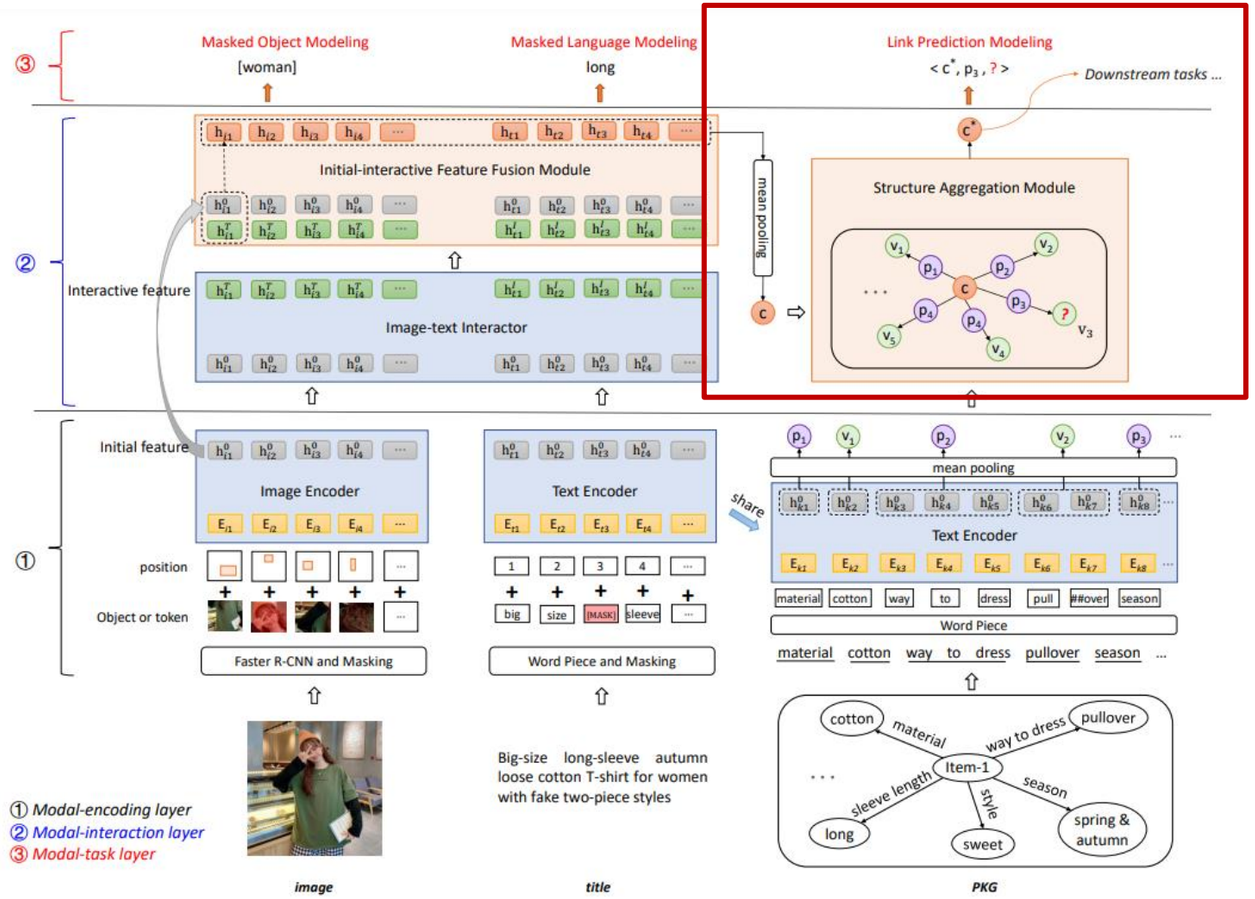
K3M

- **Link Prediction Modeling (LPM)**: learning modality encoders to perform link prediction in KGs



- Masked Object Modeling (MOM)
- Masked Language Modeling (MLM)
- Link Prediction Modeling (LPM)

Pretraining loss: $L_{pre} = l_{MLM} + l_{MOM} + l_{LPM}$.

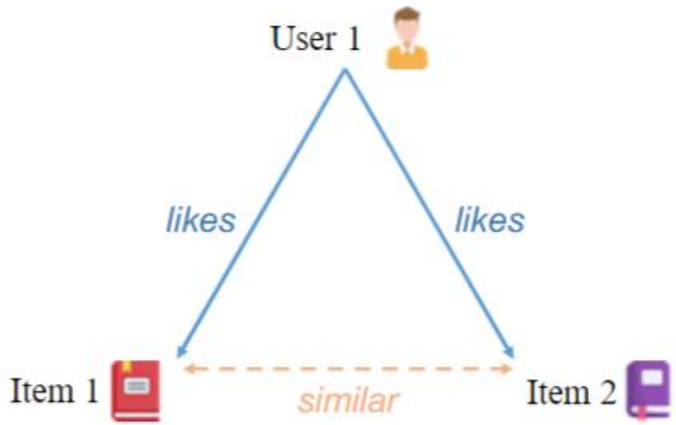


Zhu et al., Knowledge Perceived Multi-modal Pretraining in E-commerce, 2021

C3: Continued Pretraining w/ Supervised Tasks

Supervised Signals:

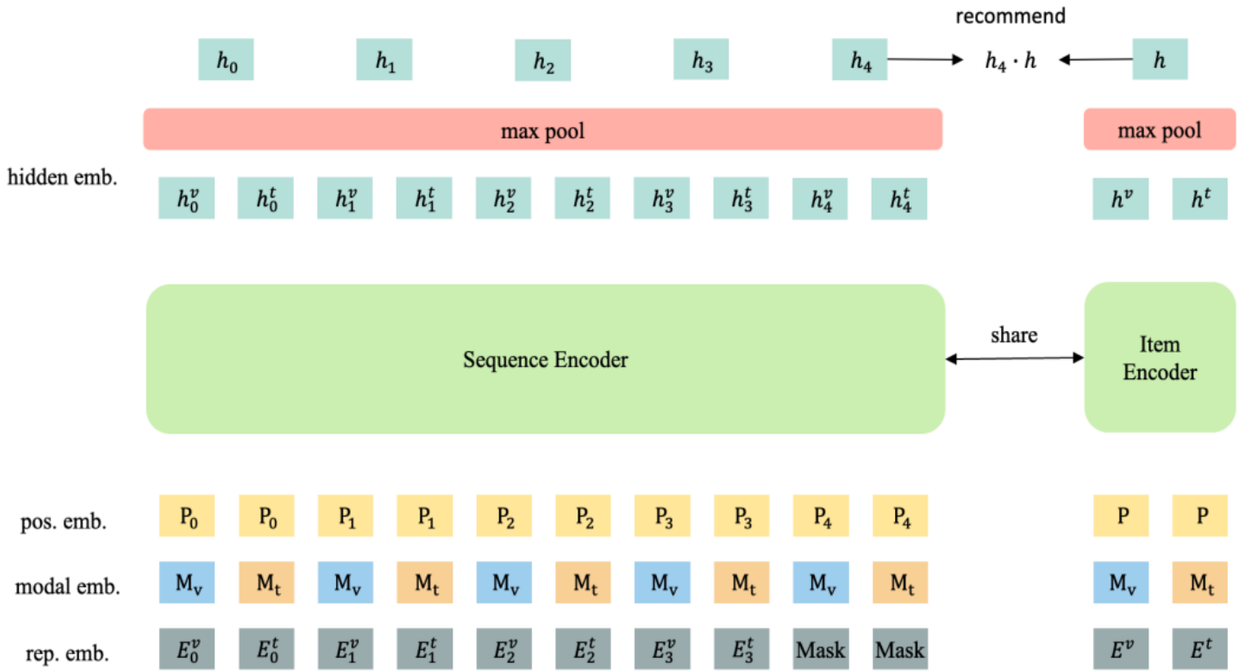
- User-to-item matching (MMSRec、MISSRec)
- Item-to-item matching (CB2CF、ItemSage)
- ID-to-modality alignment (CLCRec)
- User-to-item cross-encoder

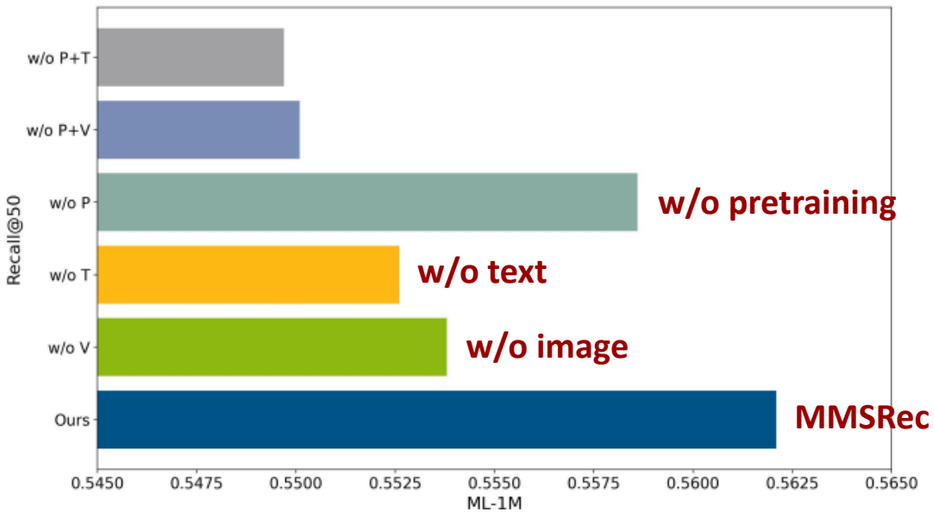


C3: Continued Pretraining w/ User-to-Item Matching

MMSRec

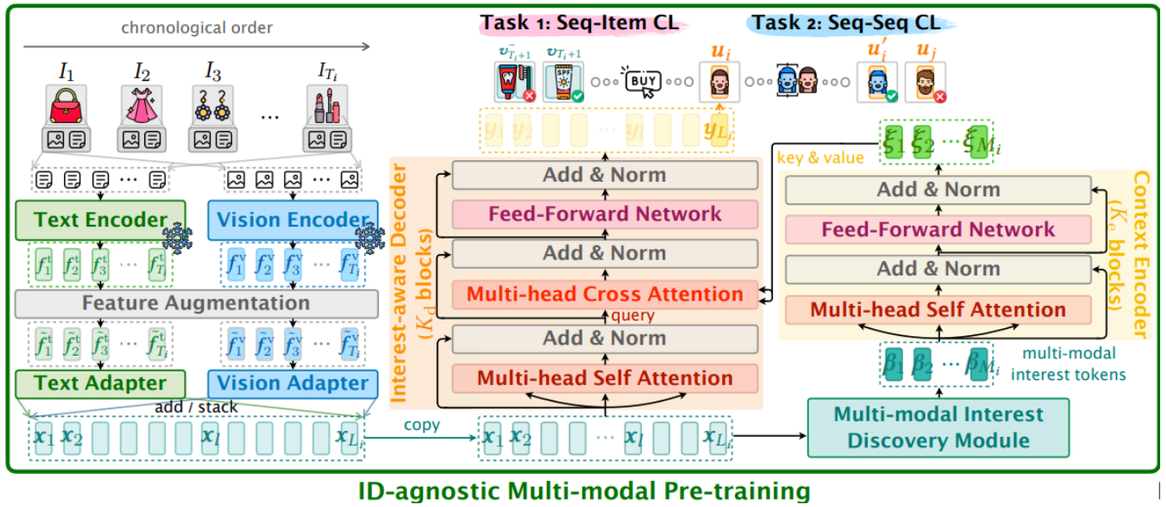
- **Masked Item Prediction**: mask the last position of the behavior sequence for next item prediction





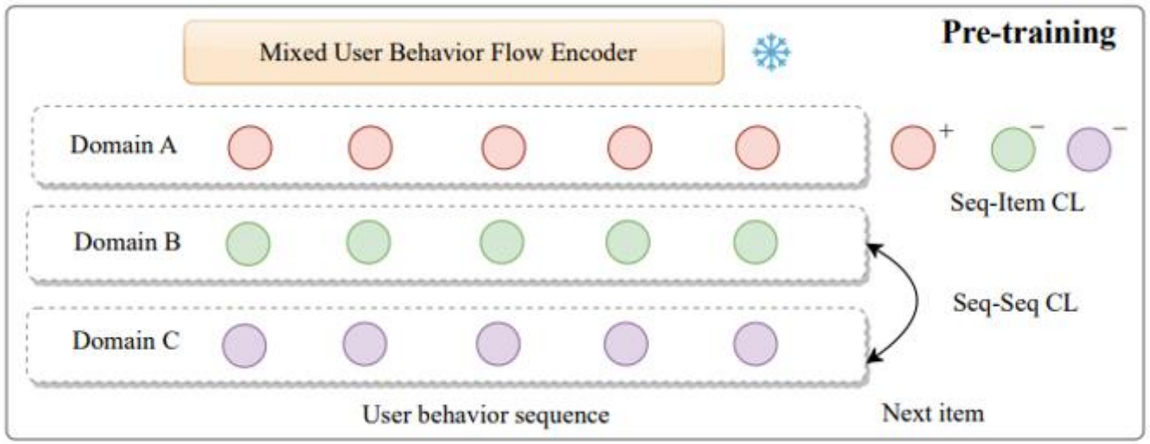
Song et al., Self-Supervised Multi-Modal Sequential Recommendation, 2023

C3: Continued Pretraining w/ User-to-Item Matching



MISSRec [Huawei]

- **Seq-item contrastive learning**: matching between user sequence and masked item
- **Multi-interest matching**: grouping interest prototypes and performing interest-aware sequence modeling



UniM2Rec

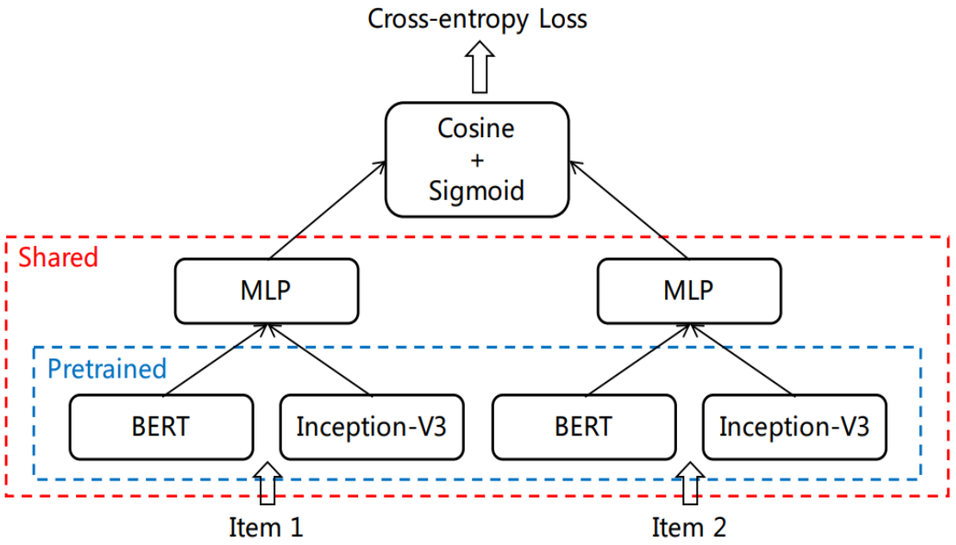
- **Seq-item contrastive learning**: matching between user sequence and masked item
- **Multi-domain matching**: matching across domains

Wang et al., MISSRec: Pre-training and Transferring Multi-modal Interest-aware Sequence Representation for Recommendation, 2023
Sun et al., Universal Multi-modal Multi-domain Pre-trained Recommendation, 2023

C3: Continued Pretraining w/ Item-to-Item Matching

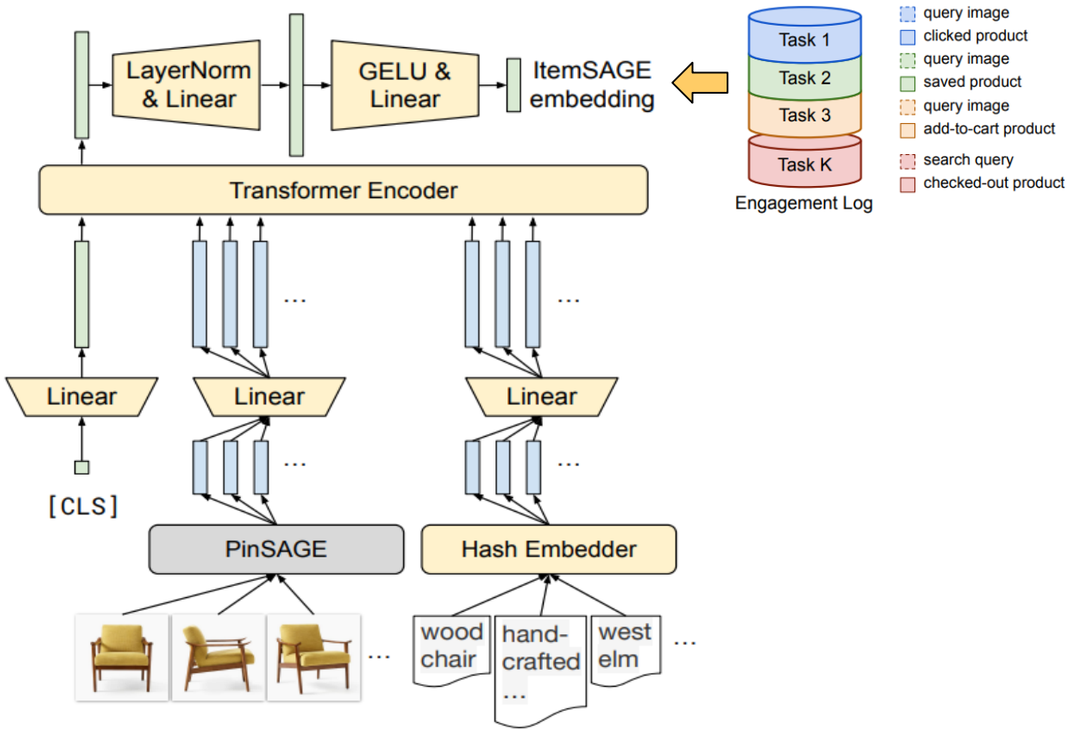
SSD

- **CB2CF**: leveraging item-to-item towers to pretrain multimodal item embeddings for recommendation diversity



ItemSage

- Applying all engagement logs with multi-tasks to train multimodal item embeddings

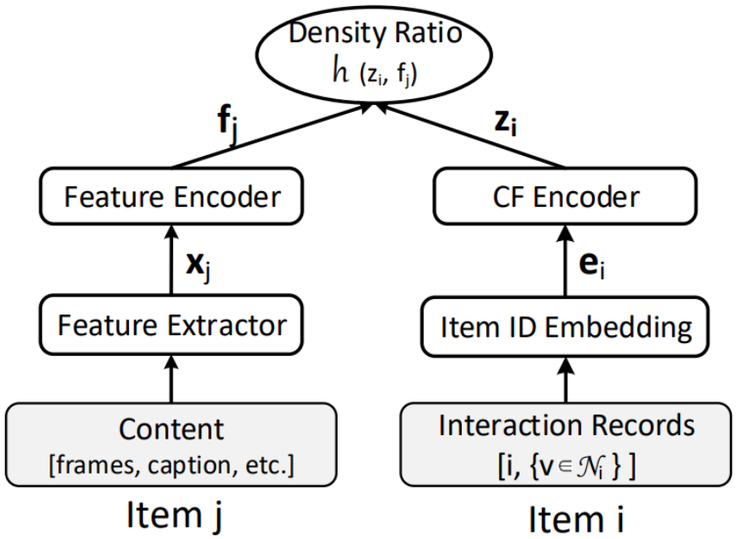


Huang et al., Sliding Spectrum Decomposition for Diversified Recommendation, 2021.
Baltescu et al., ItemSage: Learning Product Embeddings for Shopping Recommendations at Pinterest, 2022

C3: Continued Pretraining w/ ID-to-Modality Alignment

CLCRec

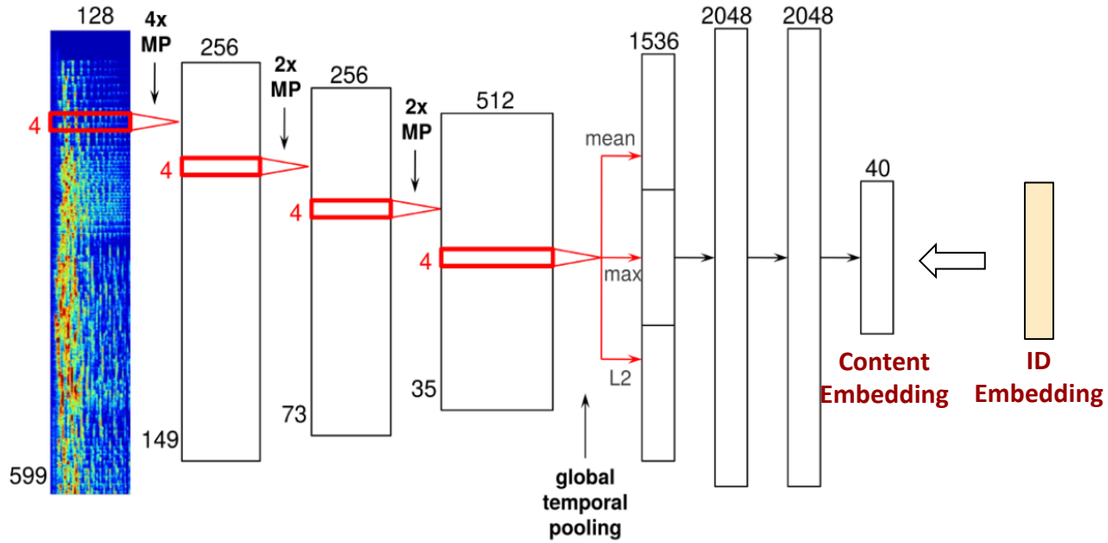
- Contrastive learning between CF encoder and content encoder



Wei et al., Contrastive Learning for Cold-Start Recommendation, 2021

DCMR

- Leveraging pretrained item ID embeddings as signals to train content encoders



Oord et al., Deep Content-based Music Recommendation, 2013
https://sander.ai/2014/08/05/spotify-cnns.html

Summarization

Continued Pretraining	Quality	Cost
Self-Supervised	Representation quality [★] **Representation robustness [★★★]**	Training cost [**$$**] Large unlabeled corpus
Weakly-Supervised	Representation quality [★★] Representation robustness [★★]	Training cost [**$**] Small labelled data
Supervised	**Representation quality [★★★]** Representation robustness [★]	**Training cost [$$$]** Huge engagement logs

Transfer to Downstream Tasks

Representation transfer:

- Multimodal features as side information
- User representation learning from multimodal sequences
- Multimodal sequence denoising and aggregation

Joint Finetuning:

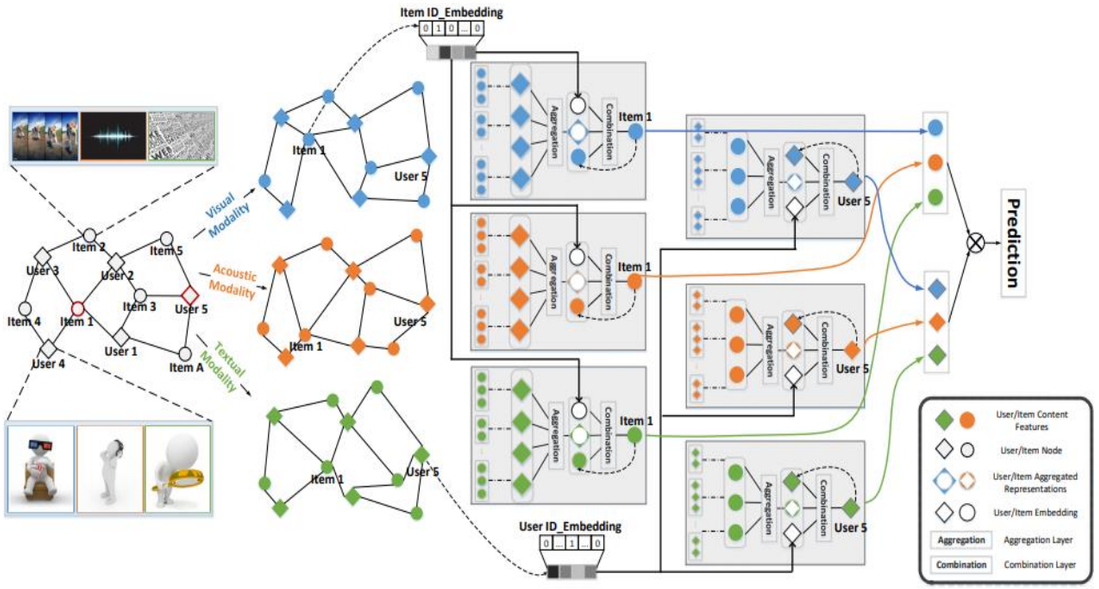
- Only finetuning item-side encoder
- Finetuning both item-side and user-side encoders
- Finetuning user-item cross encoder

Adapter Tuning:

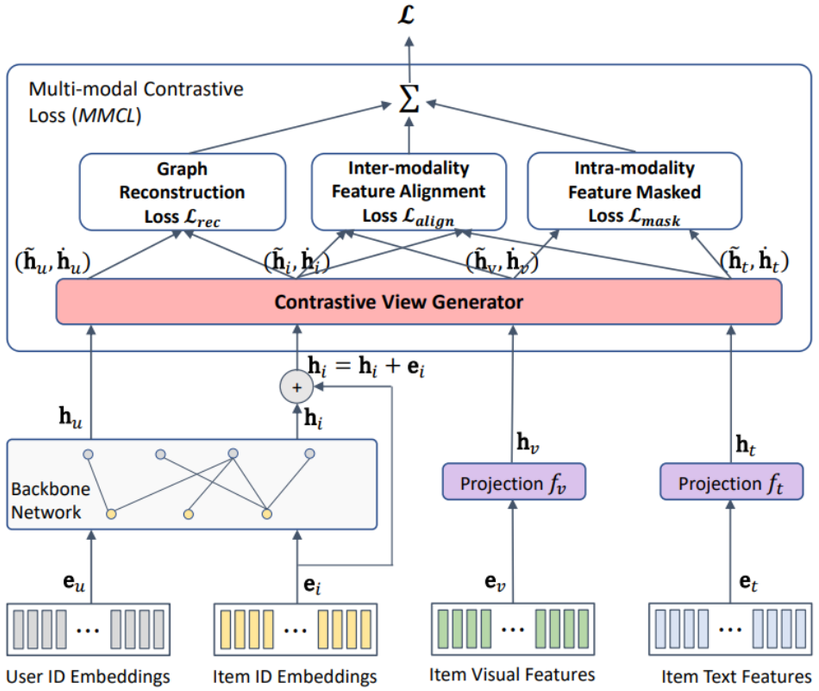
- Multimodal fusion adapter
- LLM adapter for multimodal recommendation

C4: Representation Transfer

- Multimodal features as side information



MMGCN: leveraging multimodal graph networks

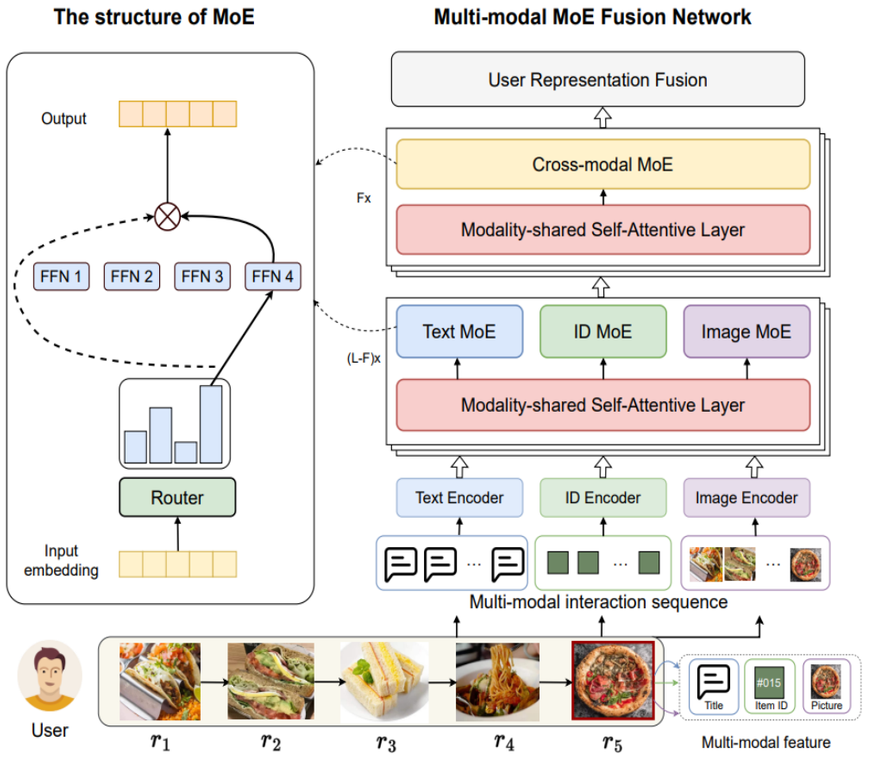


BM3: leveraging ID-modality alignment

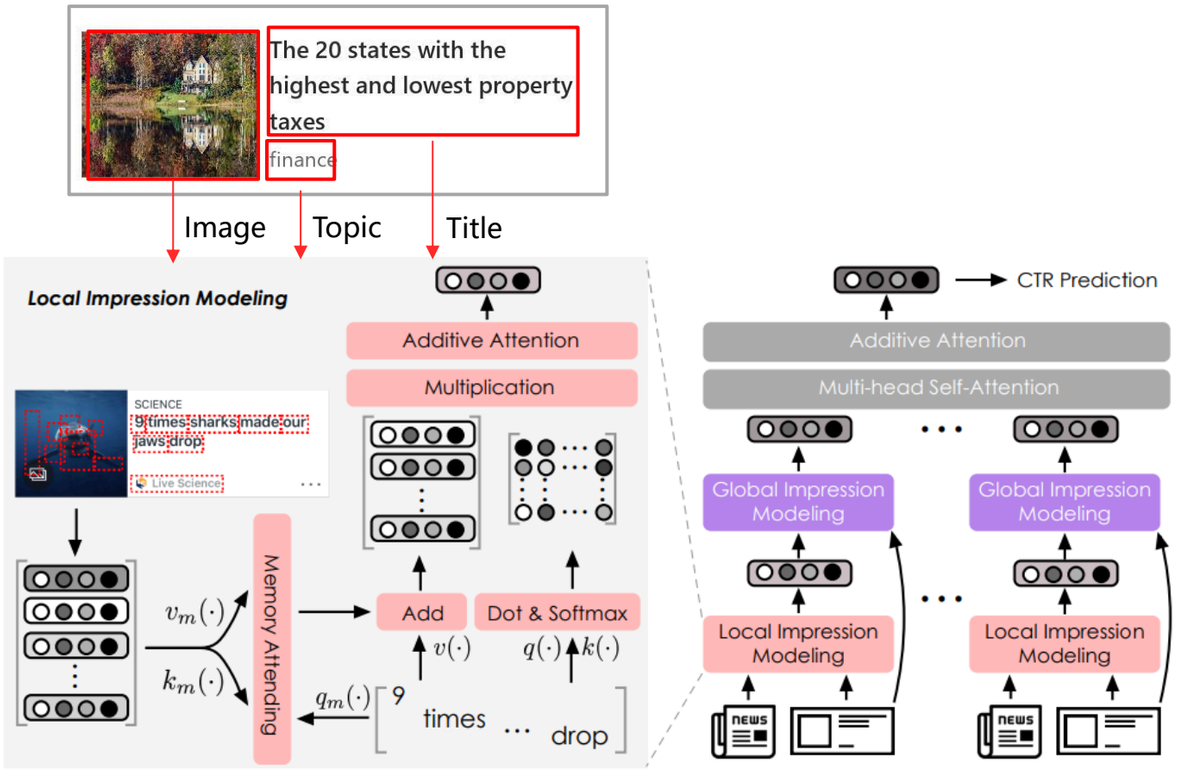
Wei et al., MMGCN: Multi-modal Graph Convolution Network for Personalized Recommendation of Micro-video, 2019
Zhou et al., Bootstrap Latent Representations for Multi-modal Recommendation, 2023

C4: Representation Transfer

- User representation learning from multimodal sequences



M3SRec: MOE-based multimodal fusion

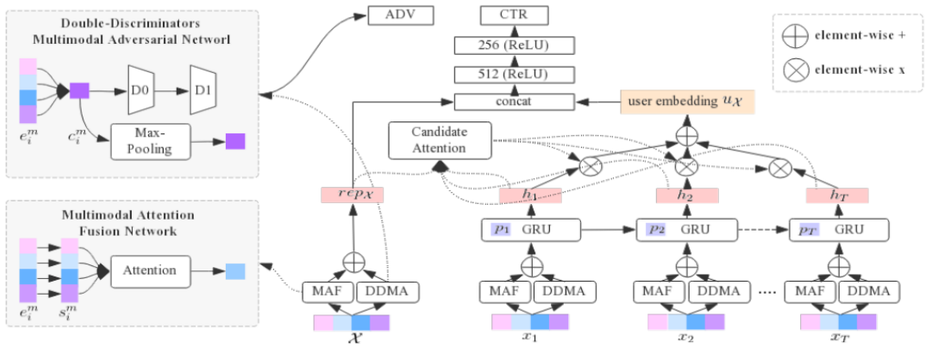


IMRec [Huawei]: local and global fusion

Bian et al., Multi-modal Mixture of Experts Represetation Learning for Sequential Recommendation, 2023
Xun et al., Why Do We Click: Visual Impression-aware News Recommendation, 2021

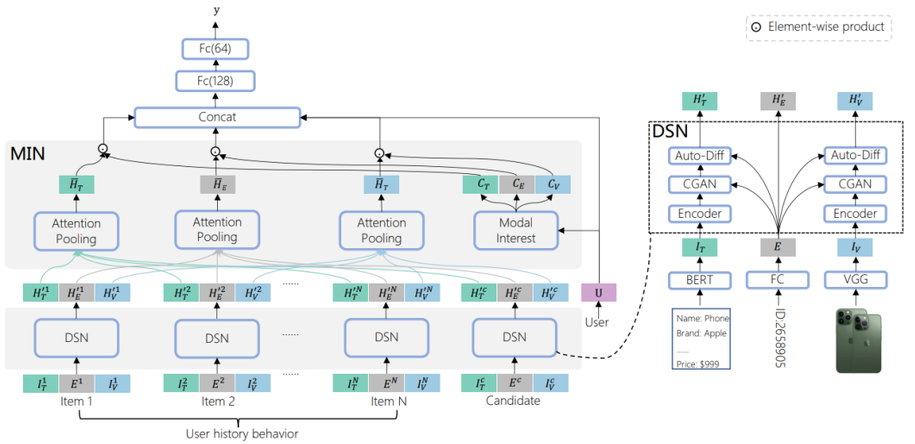
C4: Representation Transfer

- Multimodal sequence denoising and aggregation



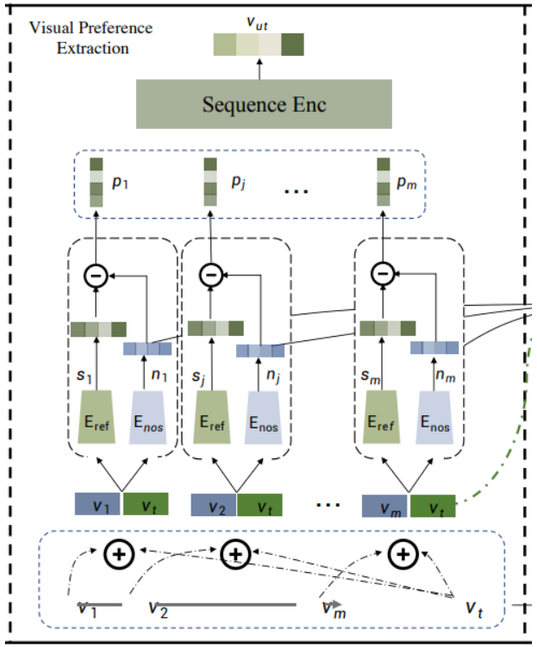
MARN:

- Multimodal attention network
- Multimodal adverseral network



GMMF:

- Difference set network
- Modal-interest network



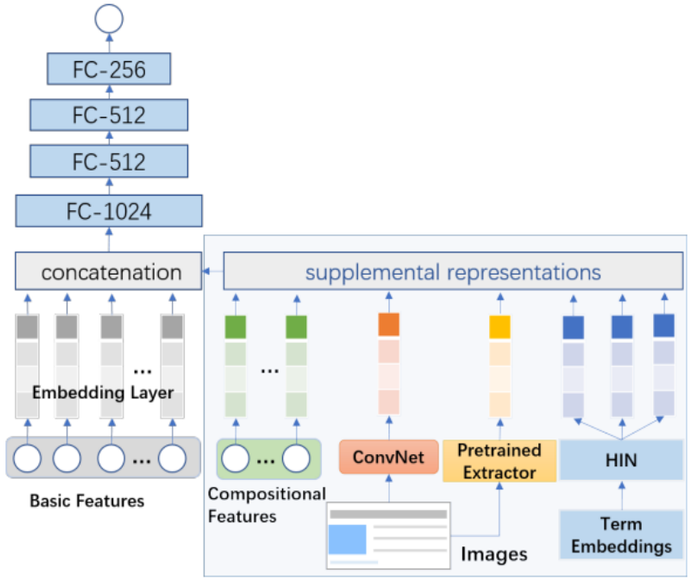
Tavern:

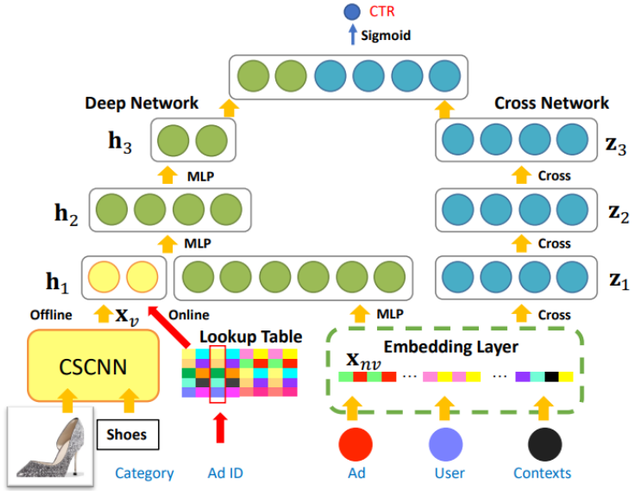
- Visual preference extraction
- Selective orthogonality disentanglement

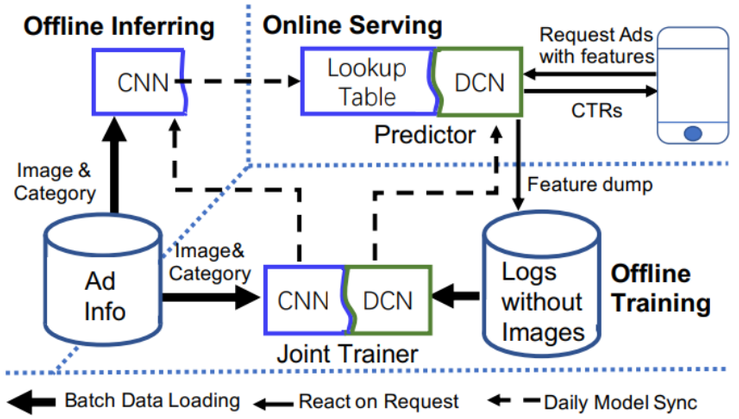
Li et al., Adversarial Multimodal Representation Learning for Click-Through Rate Prediction, 2020
Xiao et al., From Abstract to Details: A Generative Multimodal Fusion Framework for Recommendation, 2022
Wen et al., Unified Visual Preference Learning for User Intent Understanding, 2024

C5: Joint Finetuning

- Only finetuning item-side encoder







HIN-CTR:

- Using both pretrained and finetuned CNNs
- Leveraging text term embeddings

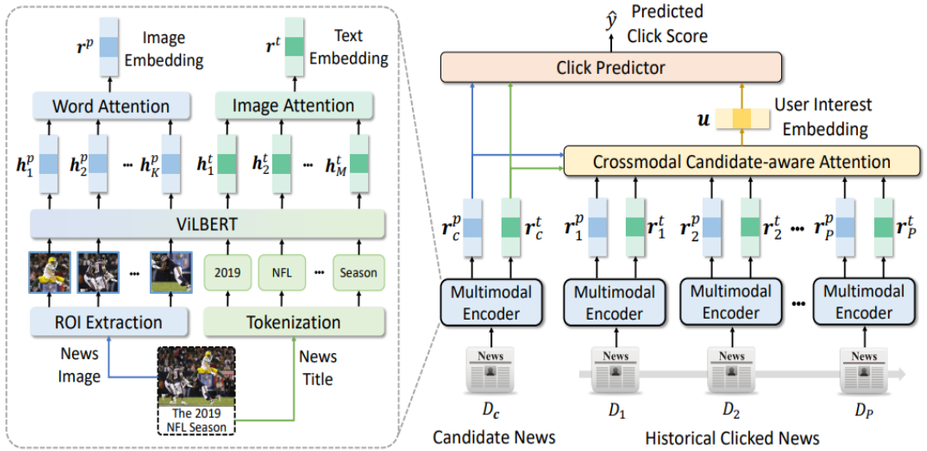
CSCNN:

- Leveraging category-aware CNN encoder
- Caching the embeddings after training for online serving

Yang et al., Learning Compositional, Visual and Relational Representations for CTR Prediction in Sponsored Search, 2019
Liu et al., Category-Specific CNN for Visual-aware CTR Prediction at JD.com, 2020

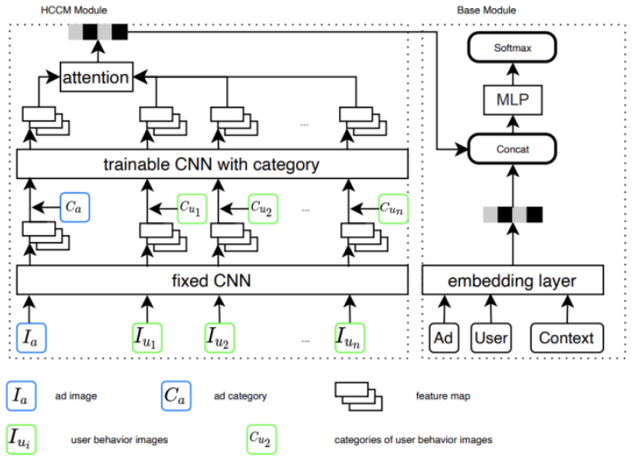
C5: Joint Finetuning

- Finetuning both item-side and user-side encoders



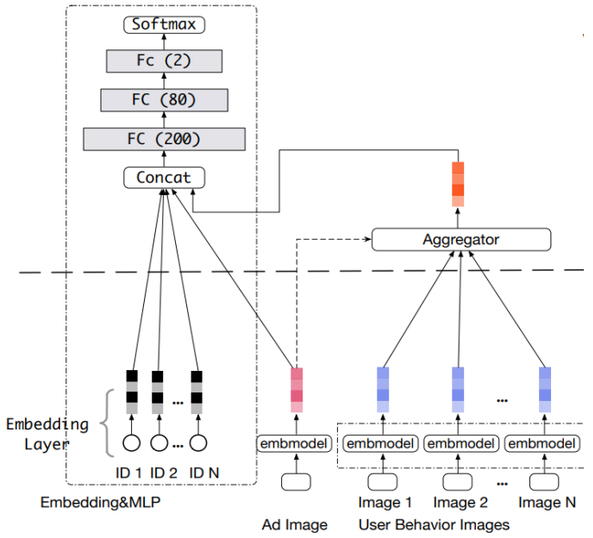
MM-Rec:

- Finetuning the last three layers of ViLBERT
- Caching the image and text embeddings



HCCM:

- Leveraging category-aware CNN encoder
- Caching the embeddings after training



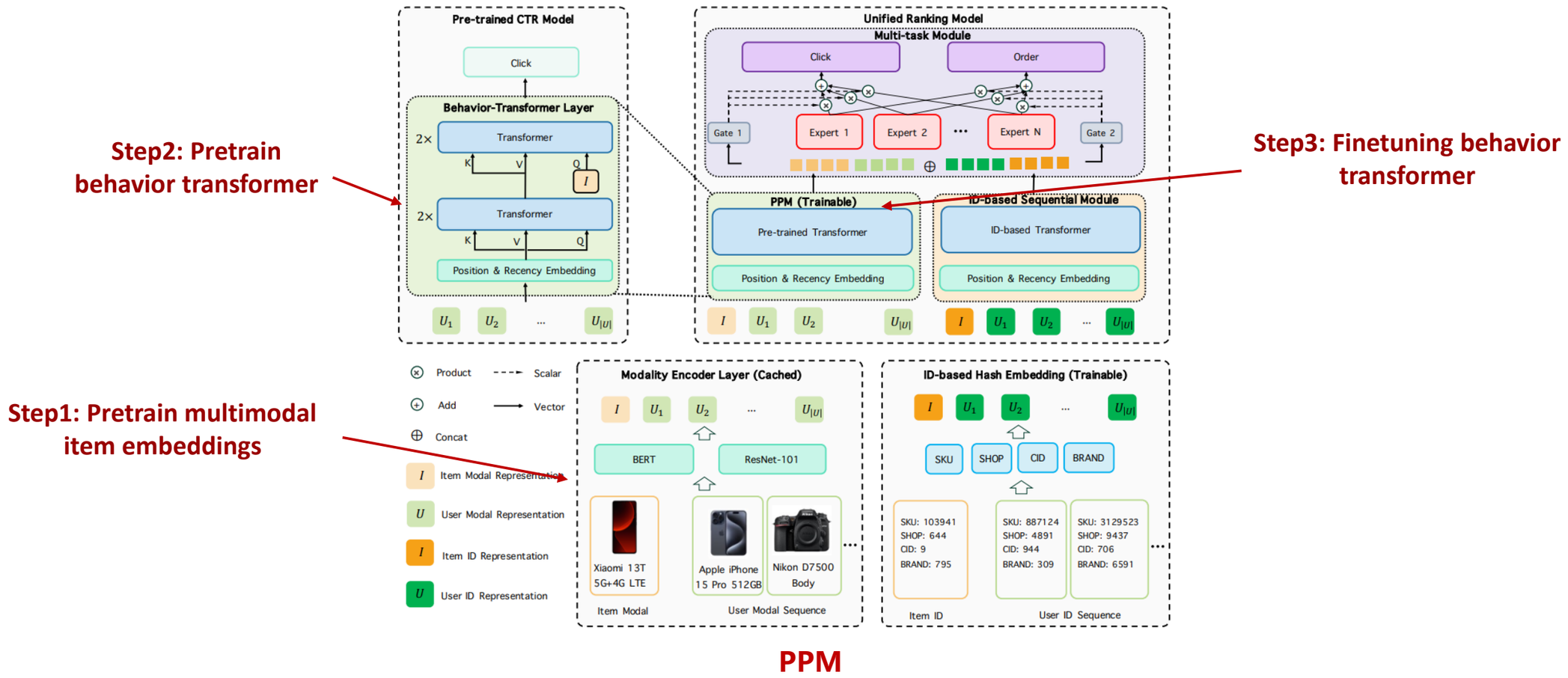
DCIM:

- Finetuning pretrained CNNs
- Caching the embeddings after training

Wu et al., MM-Rec: Multimodal News Recommendation, 2022
Chen et al., Hybrid CNN Based Attention with Category Prior for User Image Behavior Modeling, 2022
Ge et al., Image Matters: Visually modeling user behaviors using Advanced Model Server, 2018

C5: Joint Finetuning

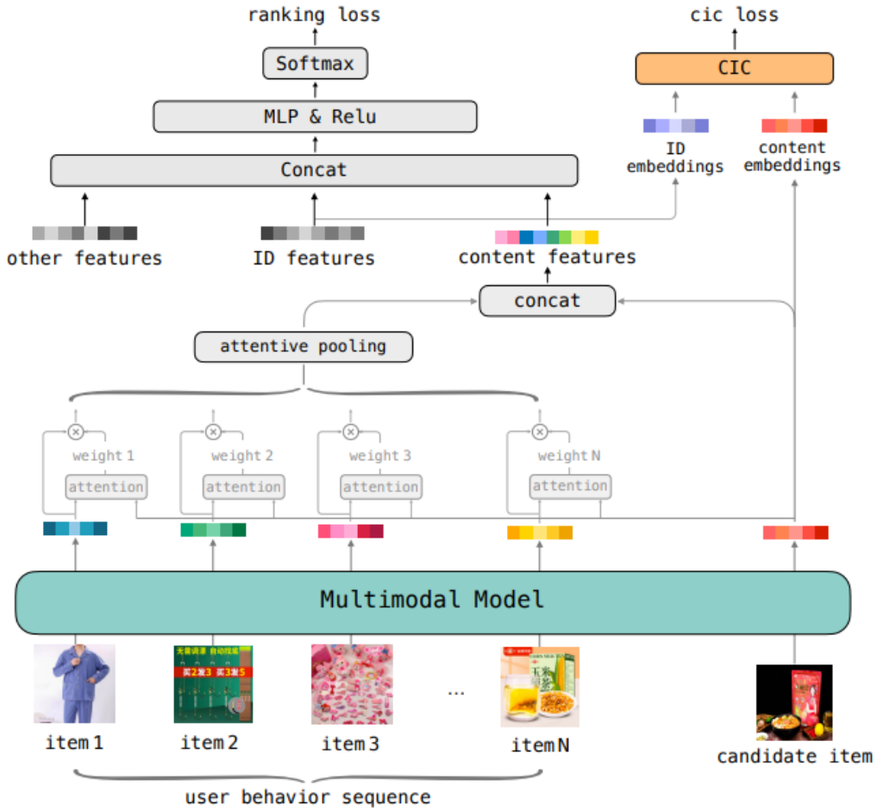
- Finetuning user-item cross encoder

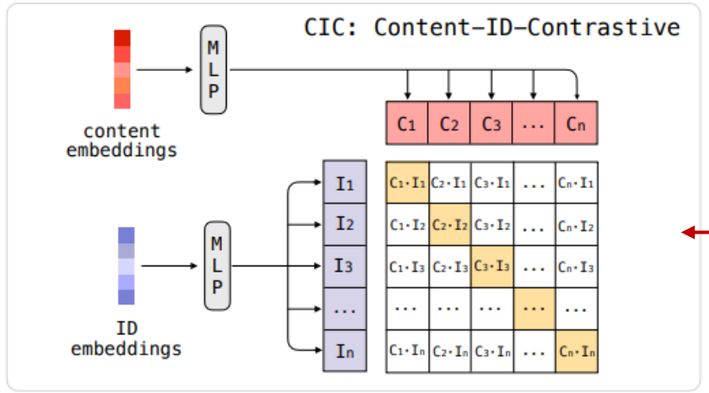


Gao et al, PPM : A Pre-trained Plug-in Model for Click-through Rate Prediction, 2024

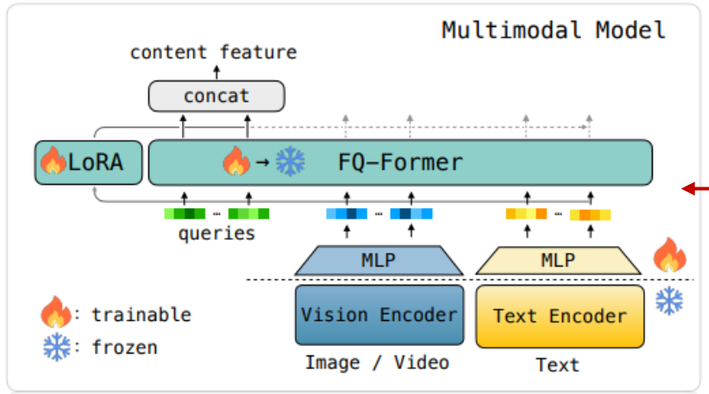
C6: Adapter Tuning

- Multimodal fusion adapter





Content-ID contrastive learning



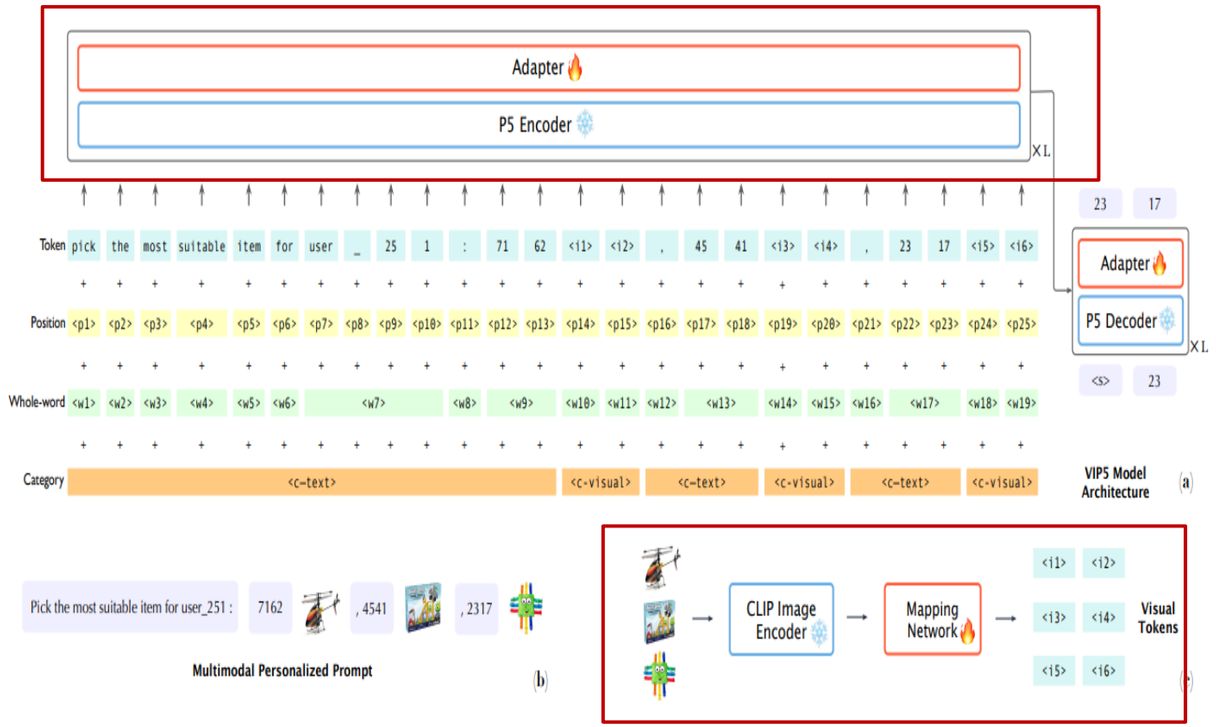
Multimodal fusion adapter

EM3

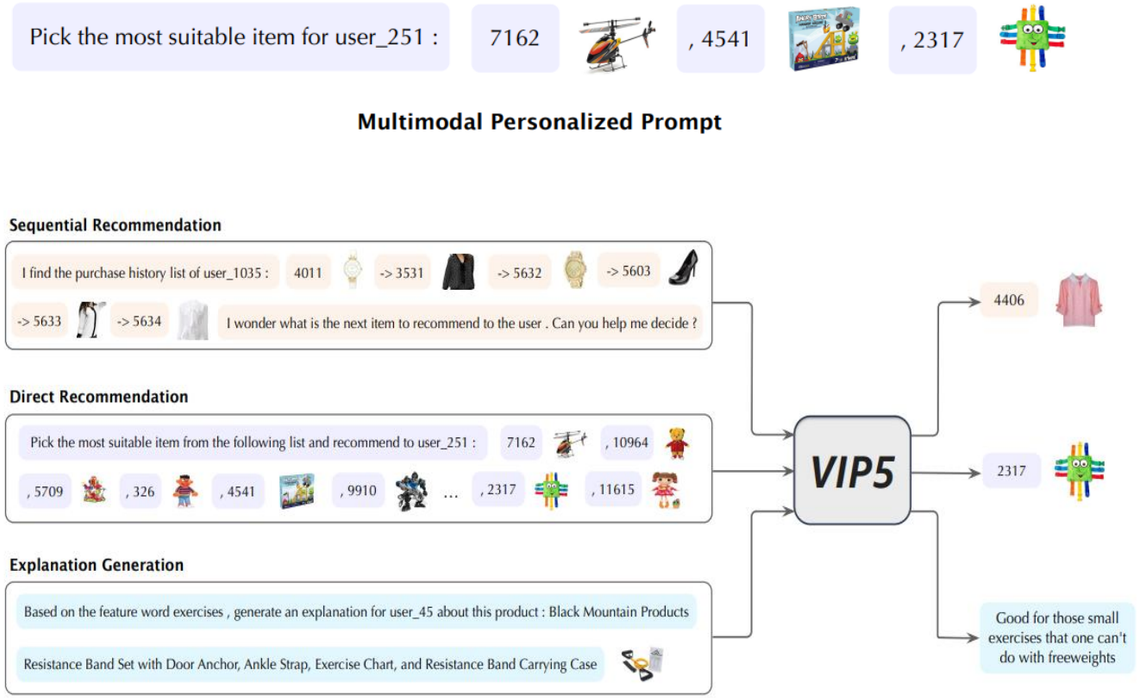
Deng et al., End-to-end Training of Multimodal Model and Ranking Model, 2024

C6: Adapter Tuning

- LLM adapter for multimodal recommendation



VIP5: P5 + Adapter



Geng et al., VIP5: Towards Multimodal Foundation Models for Recommendation, 2024

Summarization

Downstream Adaptation	Quality	Cost
Representation Transfer	**Alignment quality [★]**	**Training cost [$]**
Joint Finetuning	**Alignment quality [★★★]**	**Training cost [$$$]**
Adapter Tuning	Alignment quality [★★]	Training cost [**$$**]

Potential Future Directions

- **Vertical-domain foundational model**
  - Multimodal inputs
  - Multi-domain data
  - One model for multi-tasks
  - Unified modeling
- **Interplay with MLLMs**
  - Adapting LLMs/MLLMs to recommendation
  - From representation to generative modeling
  - Model scaling law
  - Model efficiency
- **Benchmarks and evaluation**
  - BARS/…
  - Amazon/MIND/PixelRec/MicroLens

Thank You!