PKU_ICST at TRECVID 2017: Instance Search Task

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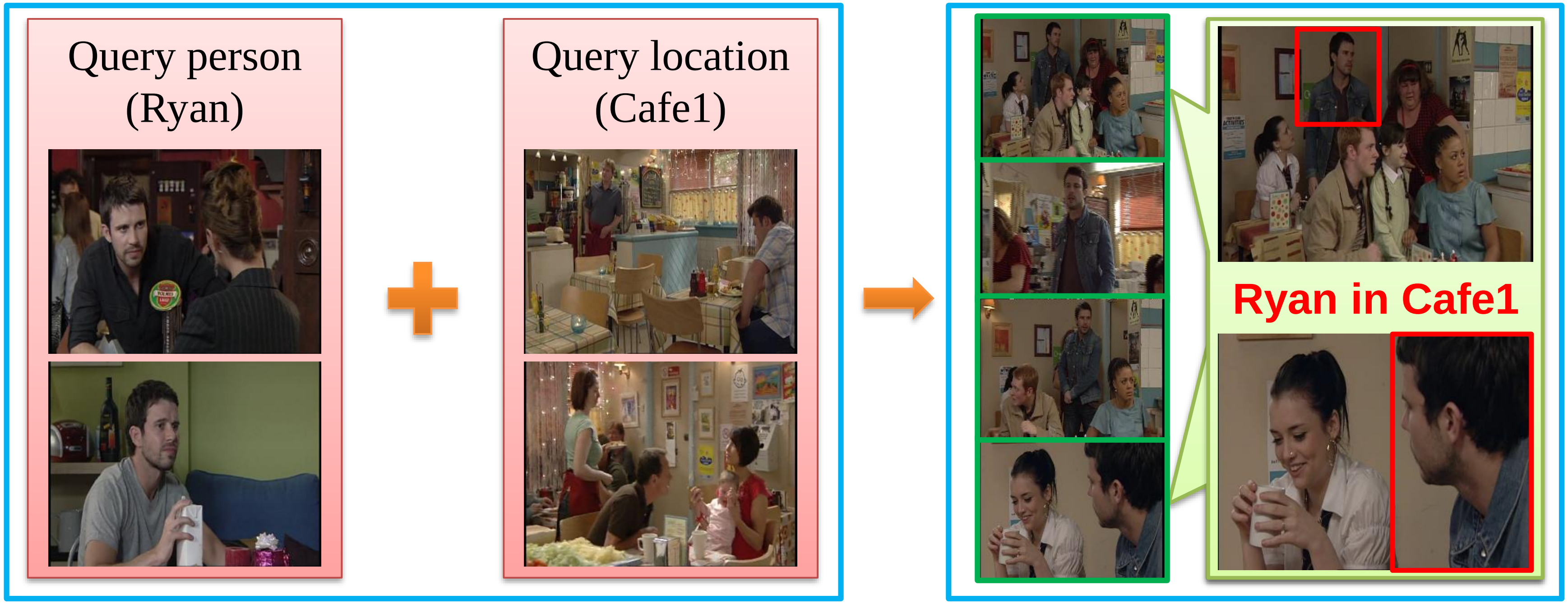
Outline

- Introduction
- Our approach
- Results and conclusions
- Our related works

Introduction

- **Instance search (INS) task**
  - Provided: separate person and location examples
  - Topic: combination of a person and a location
  - Target: retrieve specific persons in specific locations



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Our approach

- **Overview**

Location-specific search

Similarity computing stage

Result re-ranking stage

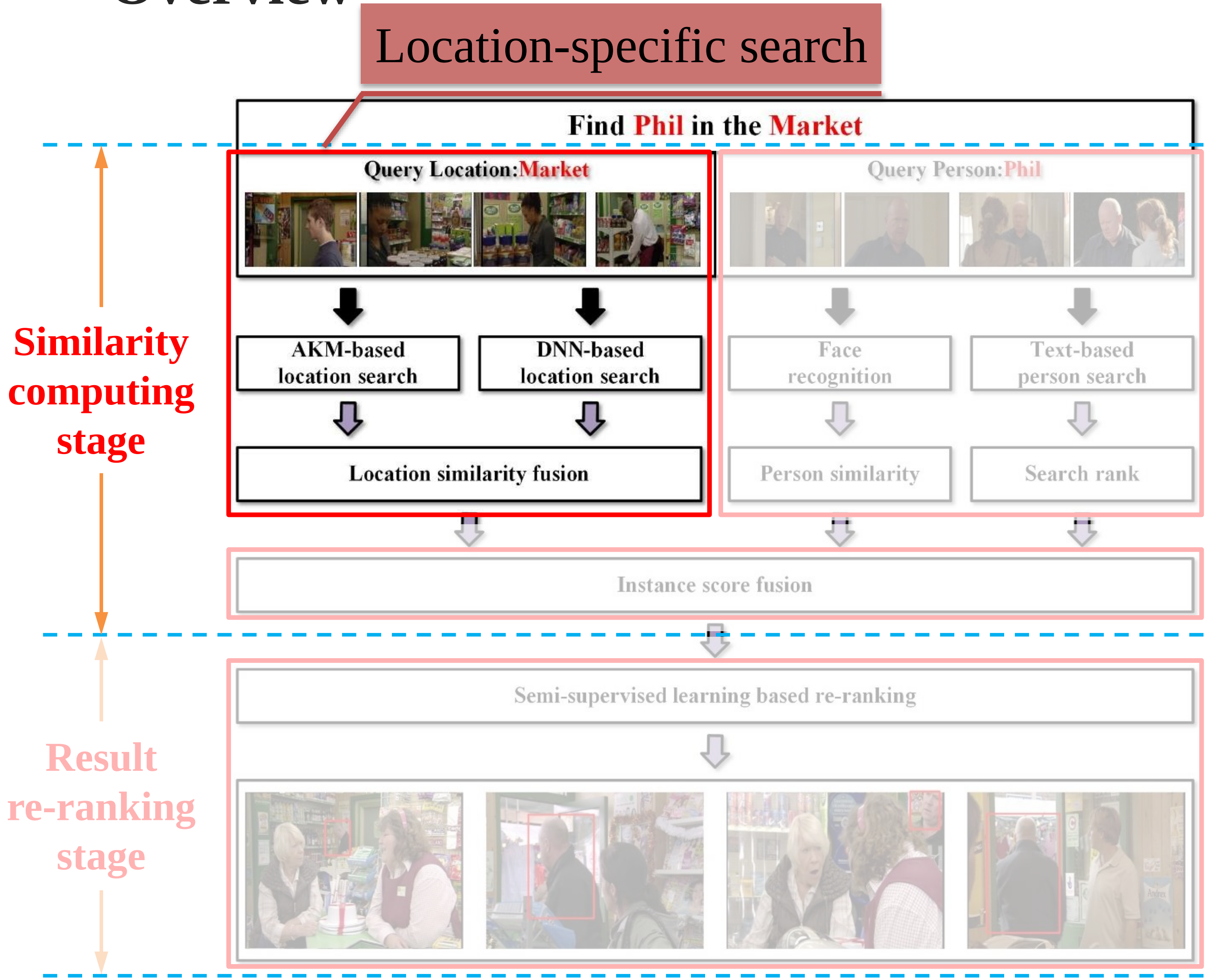
Person-specific search

Fusion

Semi-supervised re-ranking

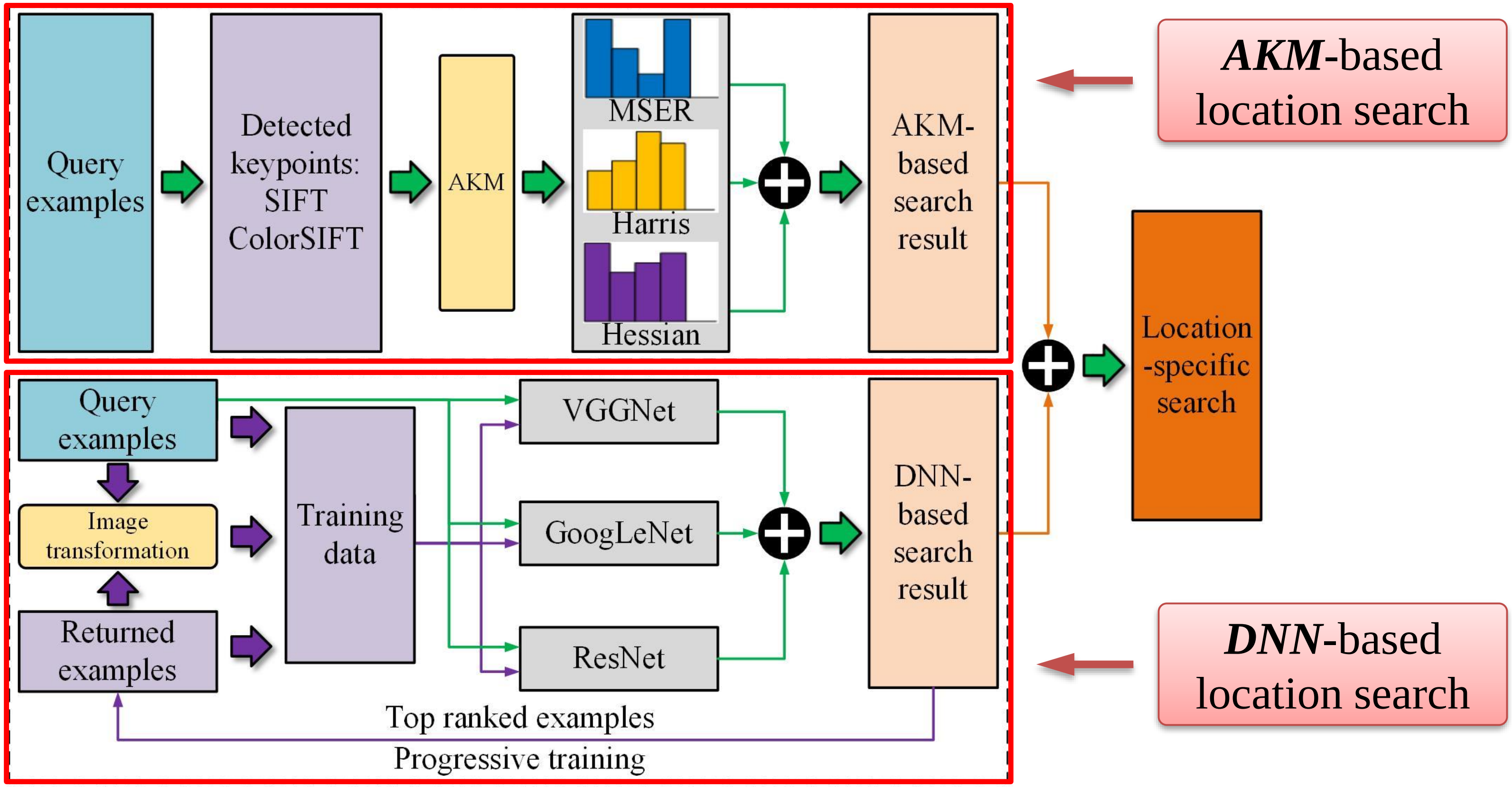
Our approach

- **Overview**



Our approach

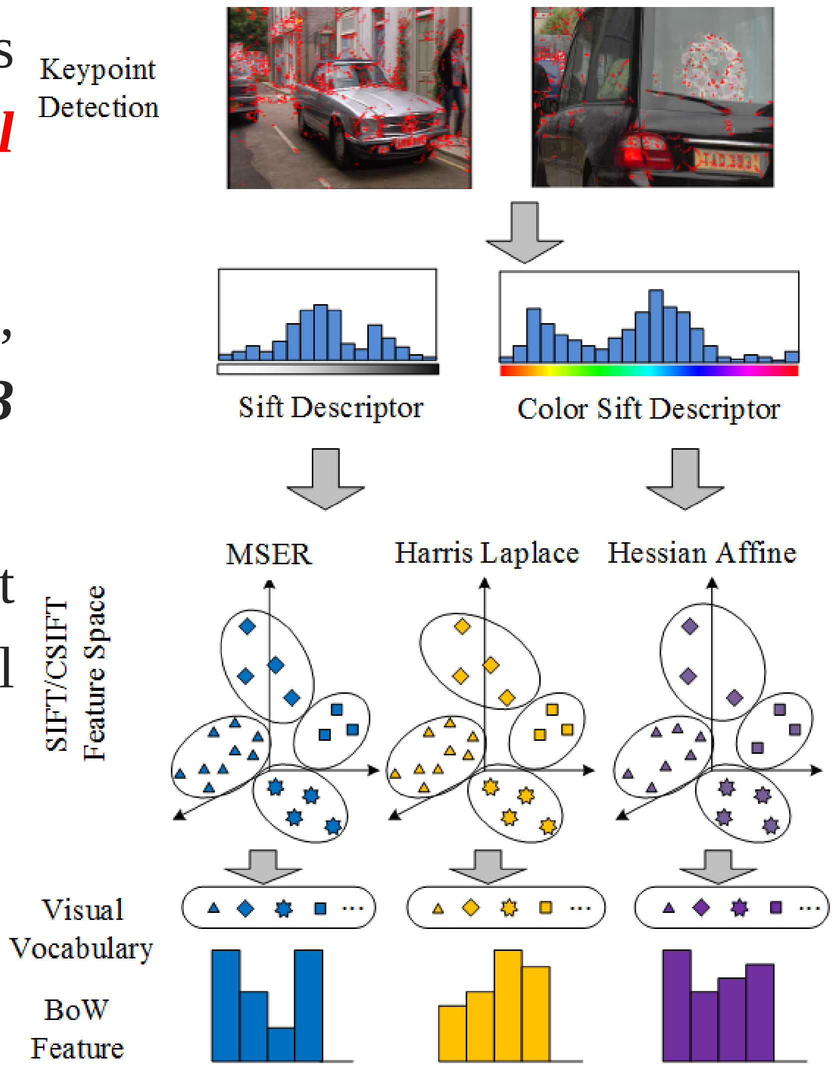
- **Location-specific search**
  - Integrates ***handcrafted*** and ***deep*** features
  - Similarity score: $sim_{location} = w_1 \cdot AKM + w_2 \cdot DNN$



Location-specific search

- **AKM-based location search**
  - Keypoint-based BoW features are applied to capture ***local details***
  - Total 6 kinds of BoW features, which are combinations of ***3 detectors*** and ***2 descriptors***
  - AKM algorithm is used to get ***one-million*** dimensional visual words
- Similarity score:

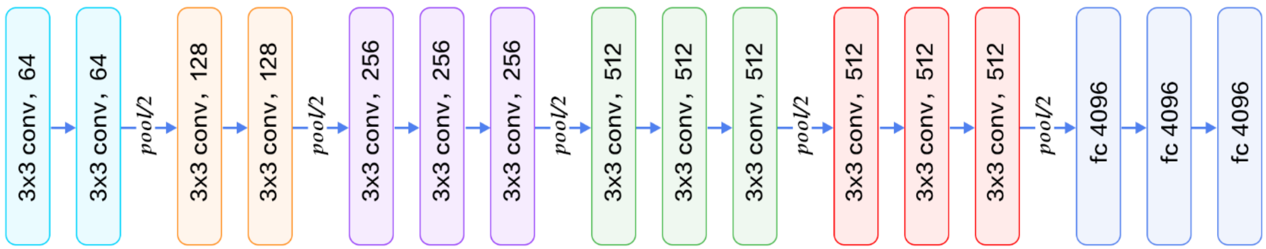
$$AKM = \frac{1}{N}\sum_{k} BOW^{(k)}$$



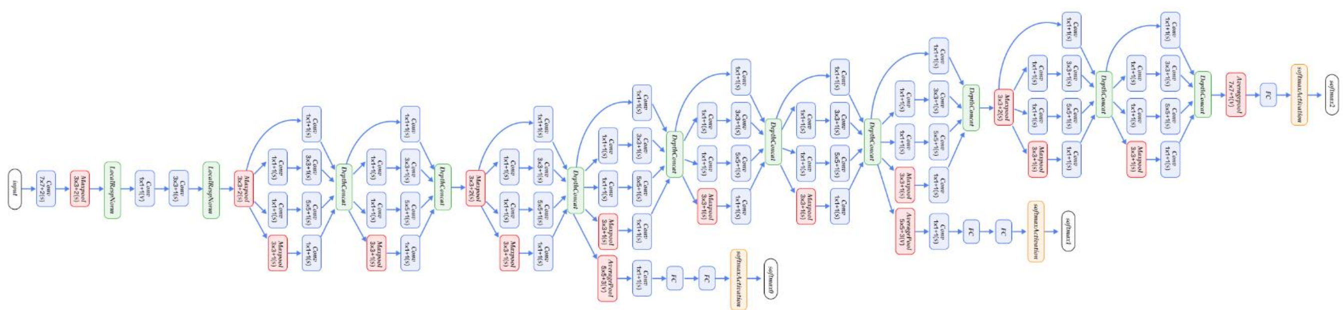
Location-specific search

- **DNN-based location search**
  - DNN features are used to capture ***semantic information***
  - Ensemble of 3 CNN models

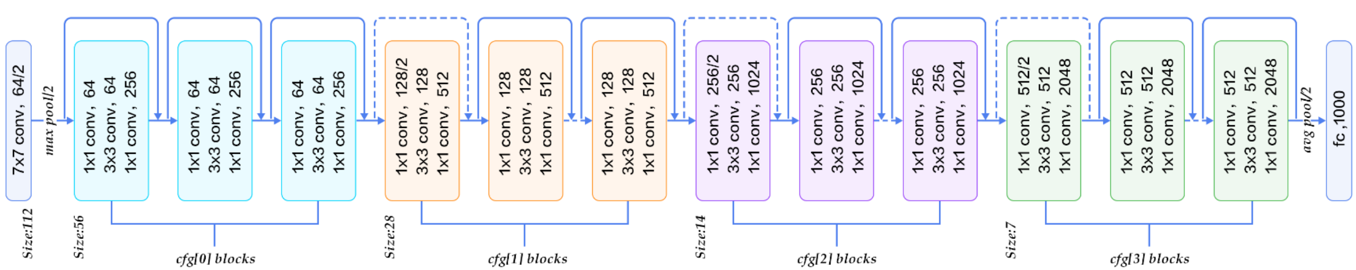
VGGNet



GoogLeNet

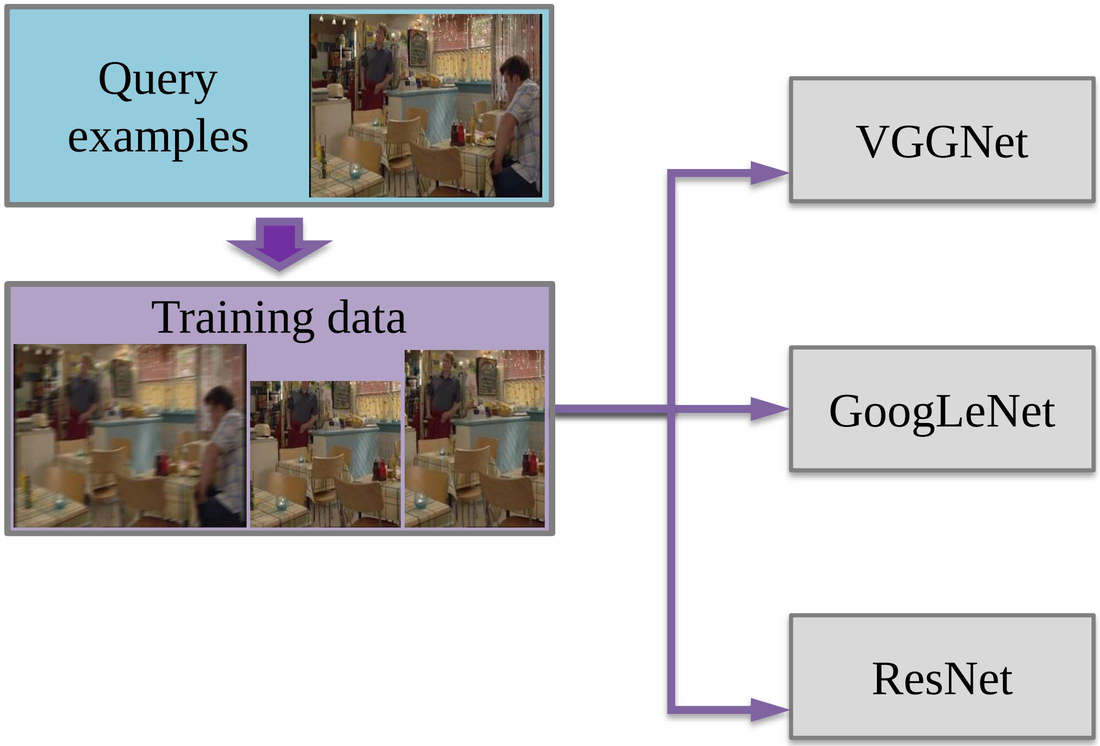


ResNet



Location-specific search

- **DNN-based location search**
  - All 3 CNNs are trained with ***progressive training*** strategy
- **Progressive training**



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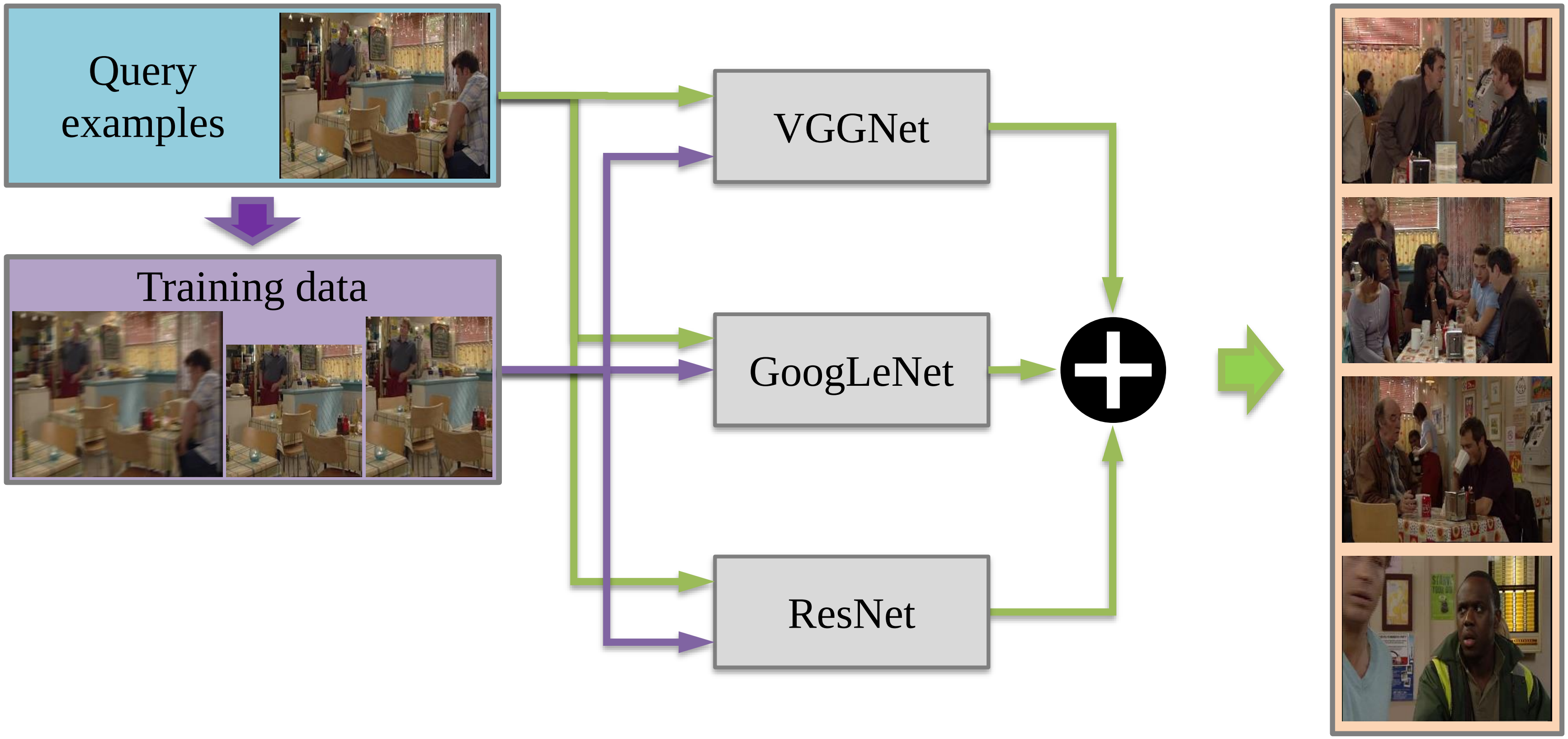

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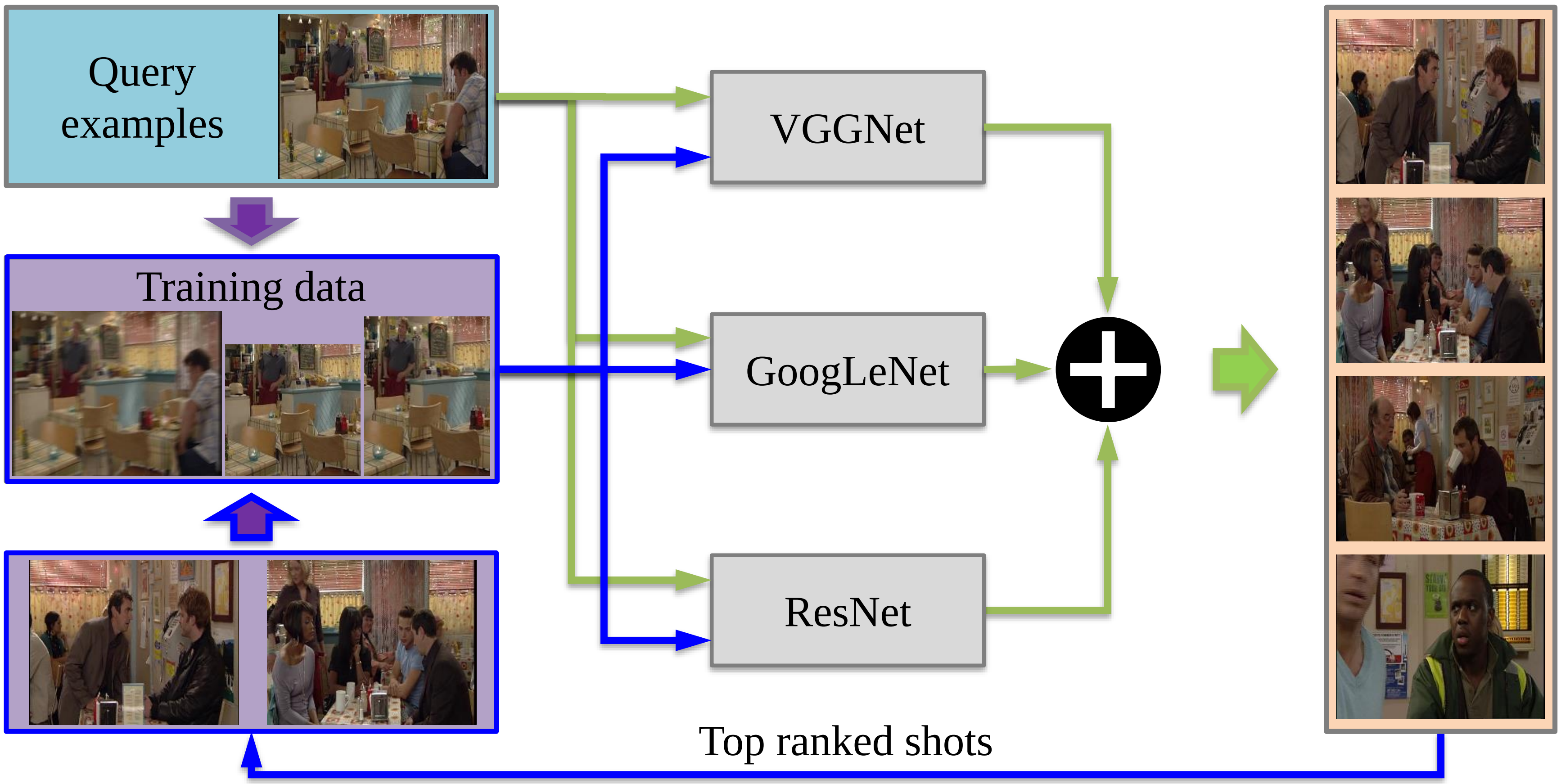

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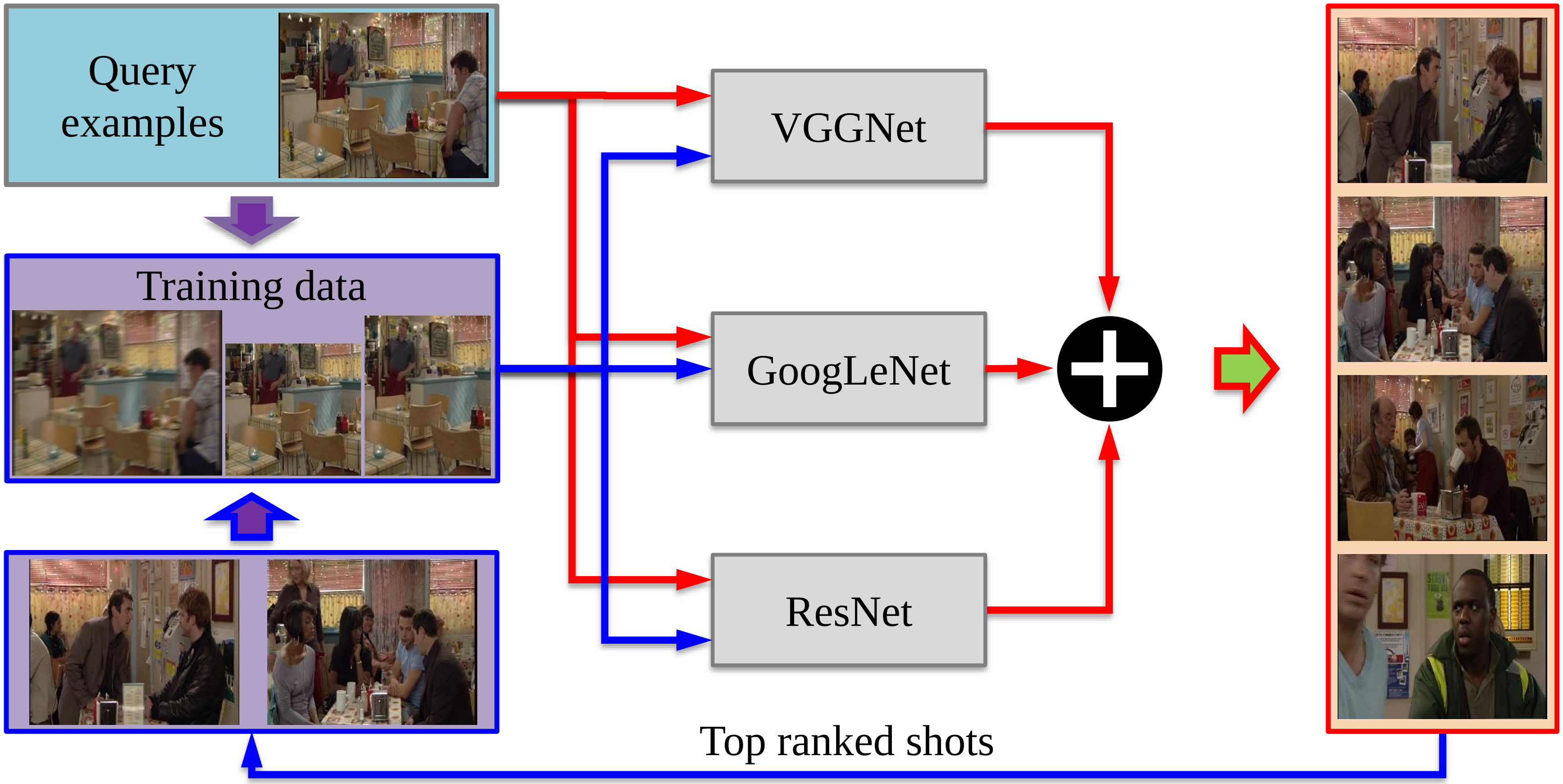

Our approach

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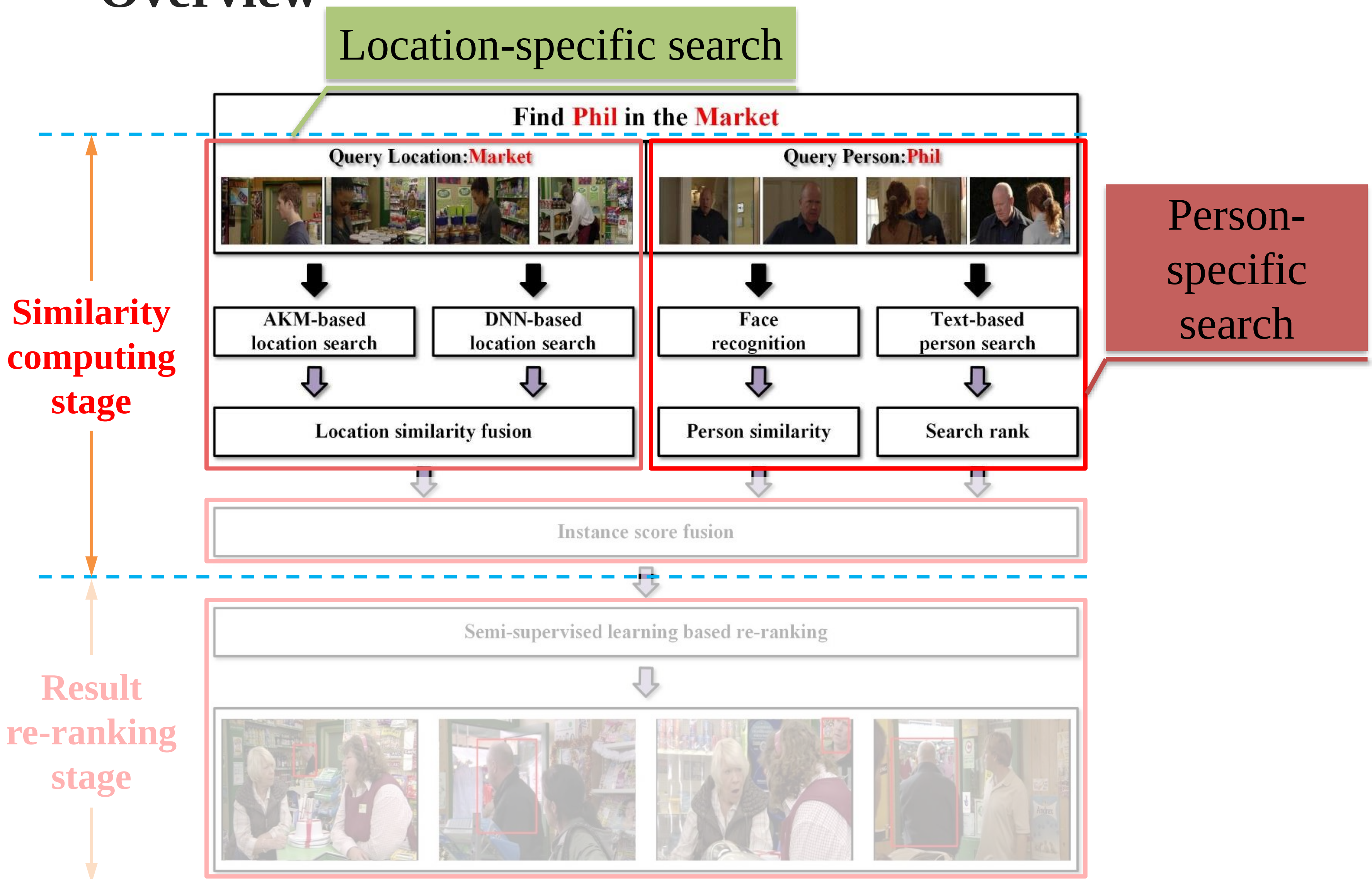
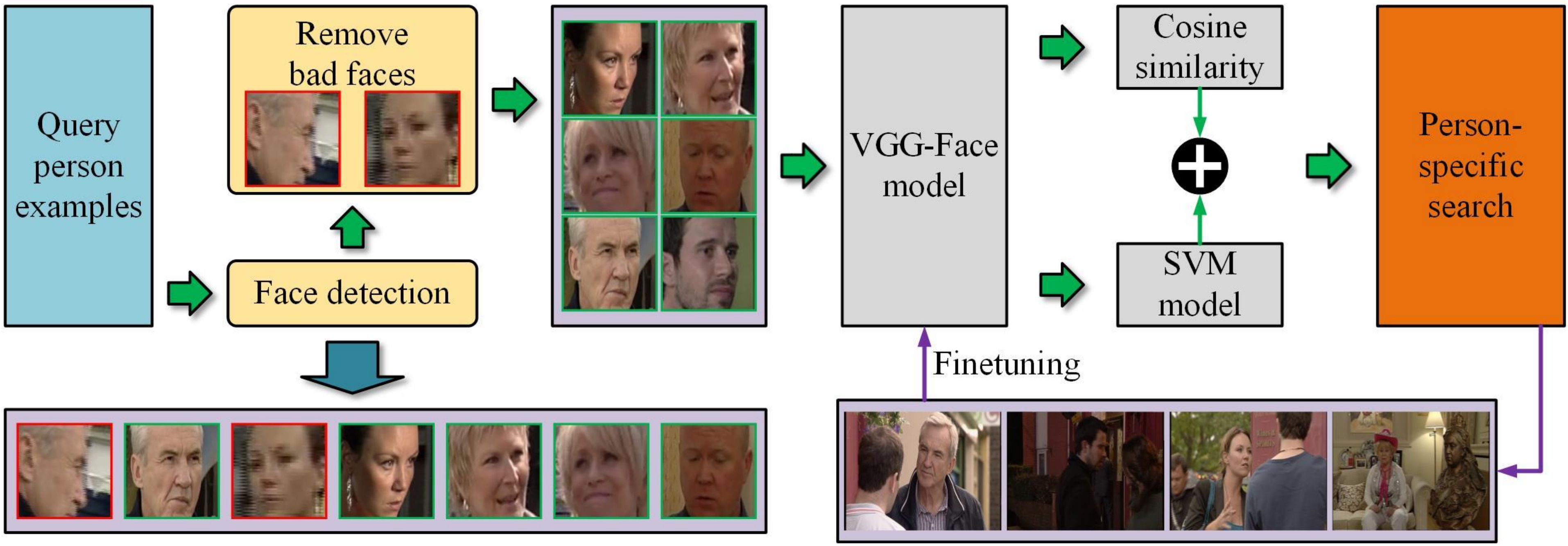


Our approach

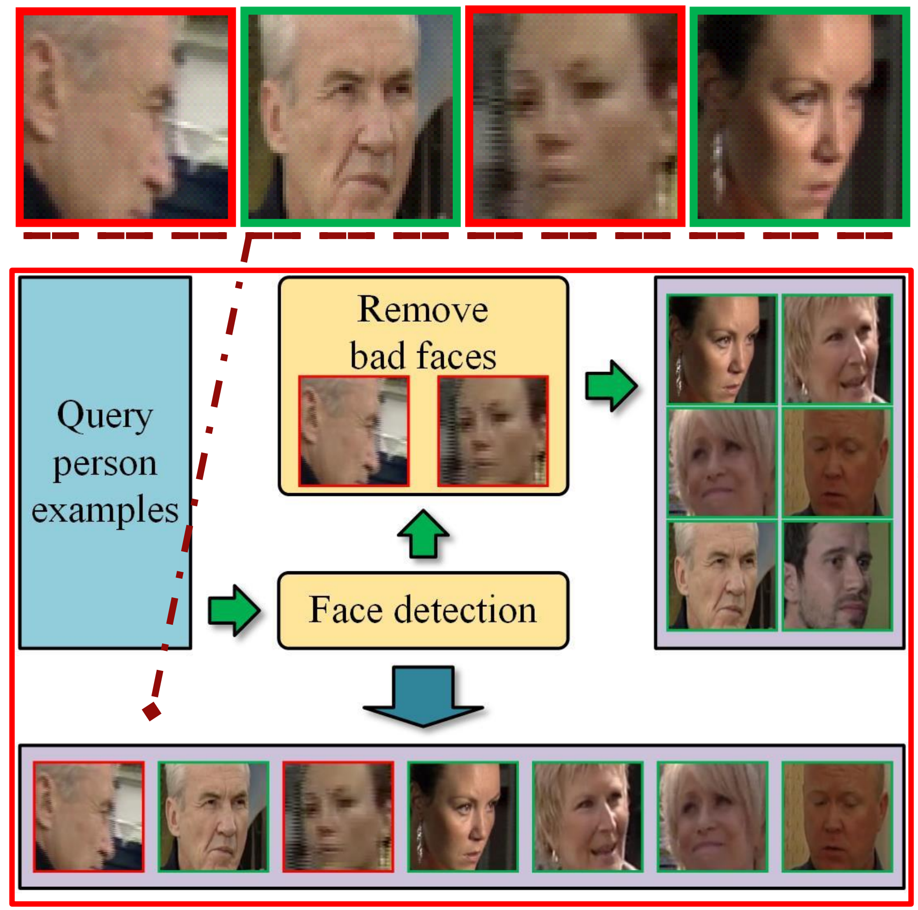
- **Person-specific search**
  - We apply ***face recognition*** technique based on deep model



  - We also conduct ***text-based person search,*** where persons' auxiliary information is minded from the provided video transcripts

Person-specific search

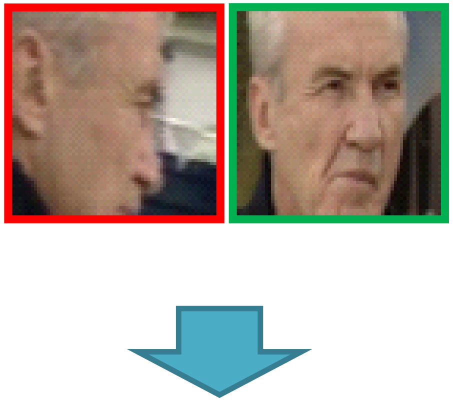
- **Face recognition based person search**
  - Face detection

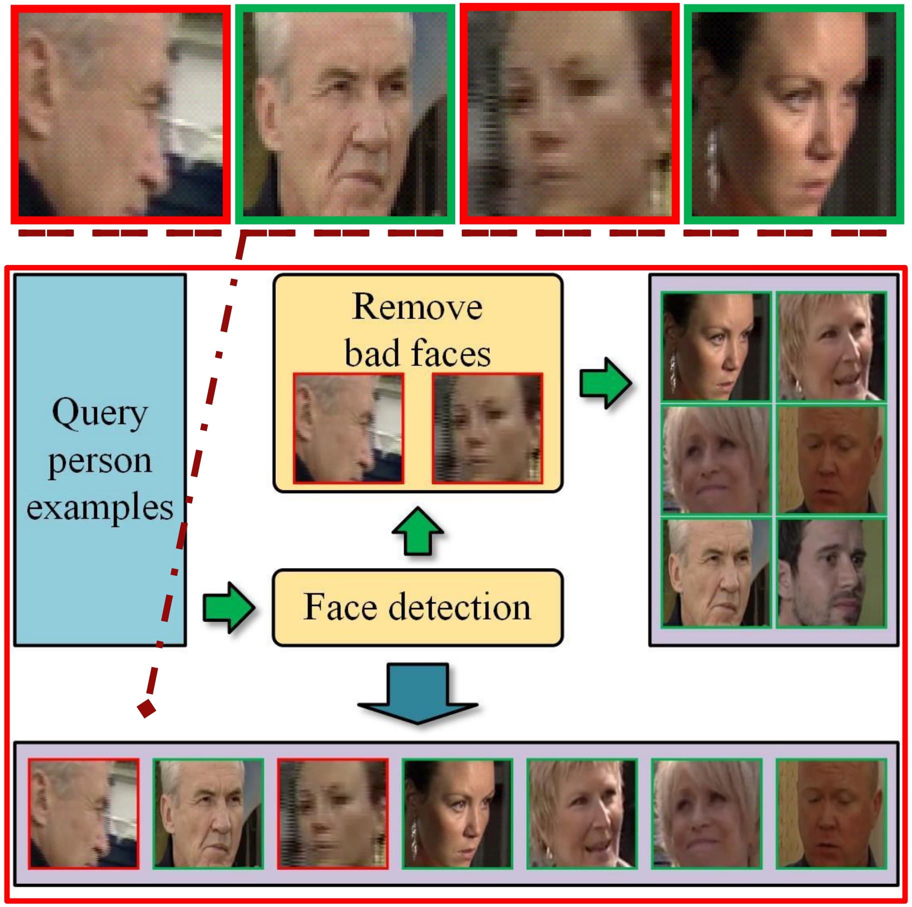


Person-specific search

- **Face recognition based person search**
  - Face detection
  - ***Remove "bad" faces*** automatically: hard to distingush

Before removal of bad faces:





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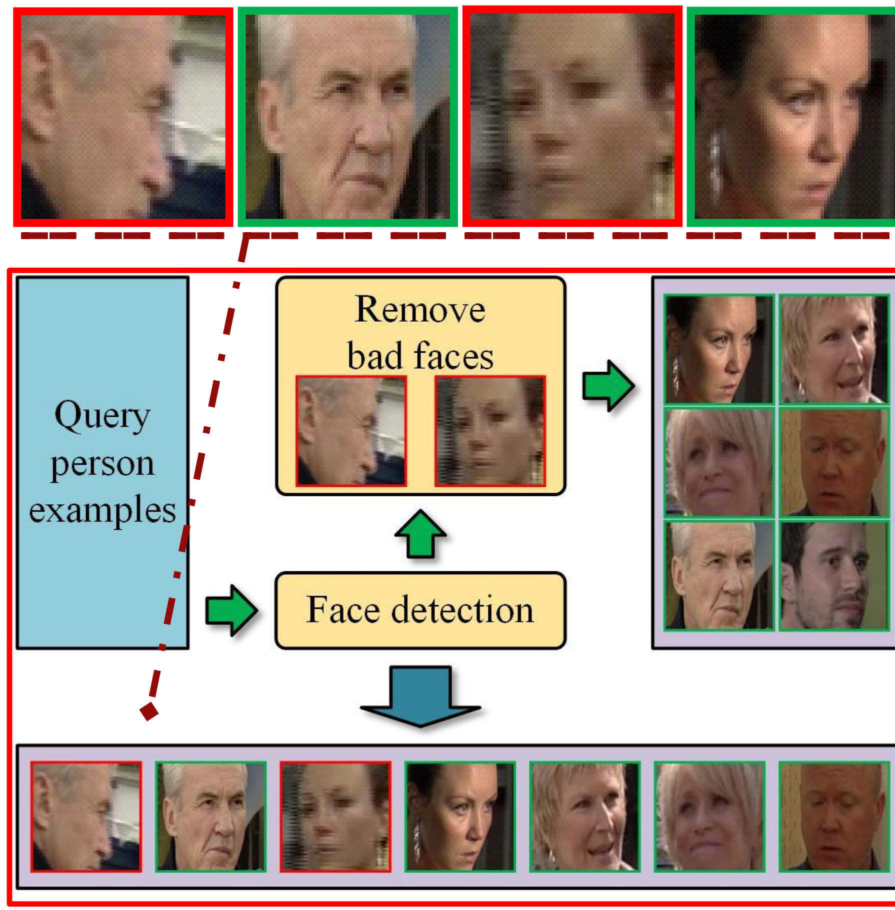
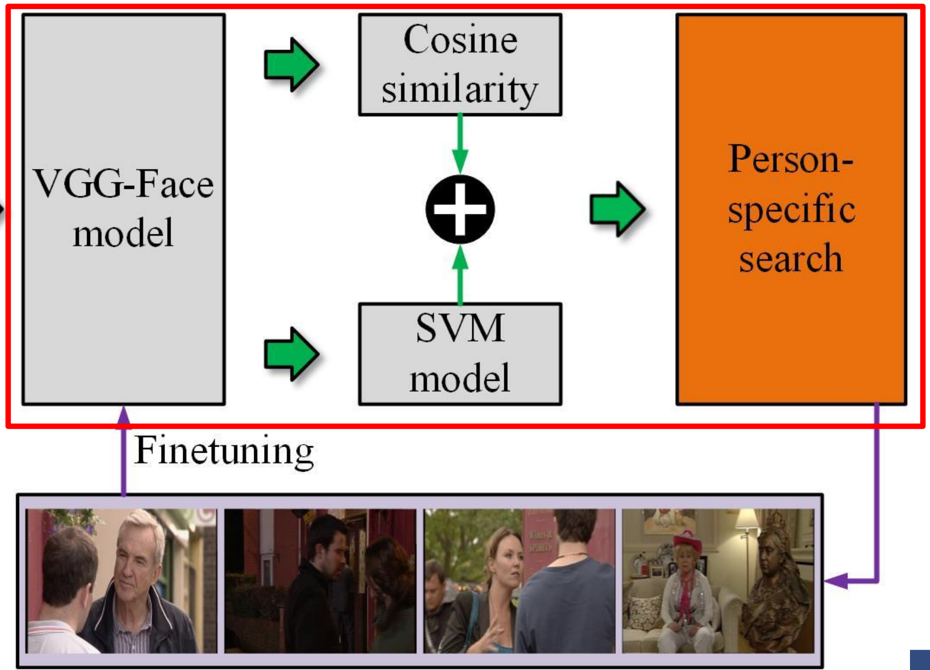


Person-specific search

- **Face recognition based person search**
  - We use VGG-Face model to extract face features
  - We integrate ***cosine similarity*** and ***SVM prediction*** scores to get the person similarity scores.



$$sim_{person} = w_1 \cdot COS + w_2 \cdot SVM$$

Person-specific search

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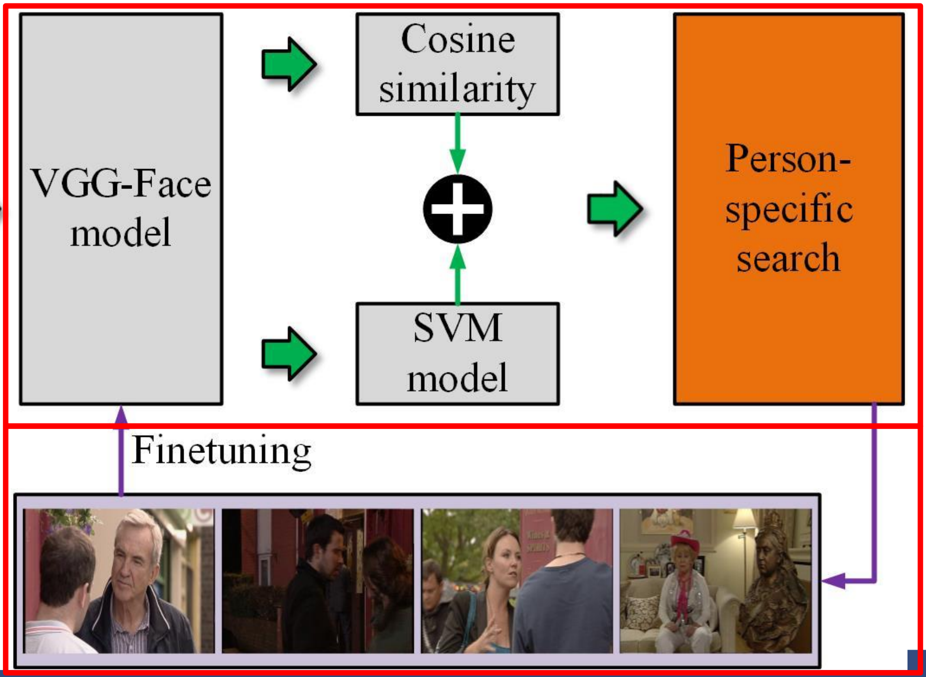
  - We use VGG-Face model to extract face features
  - We integrate ***cosine similarity*** and ***SVM prediction*** scores to get the person similarity scores.
  - We adopt similar progressive training strategy to finetune the VGG-Face model



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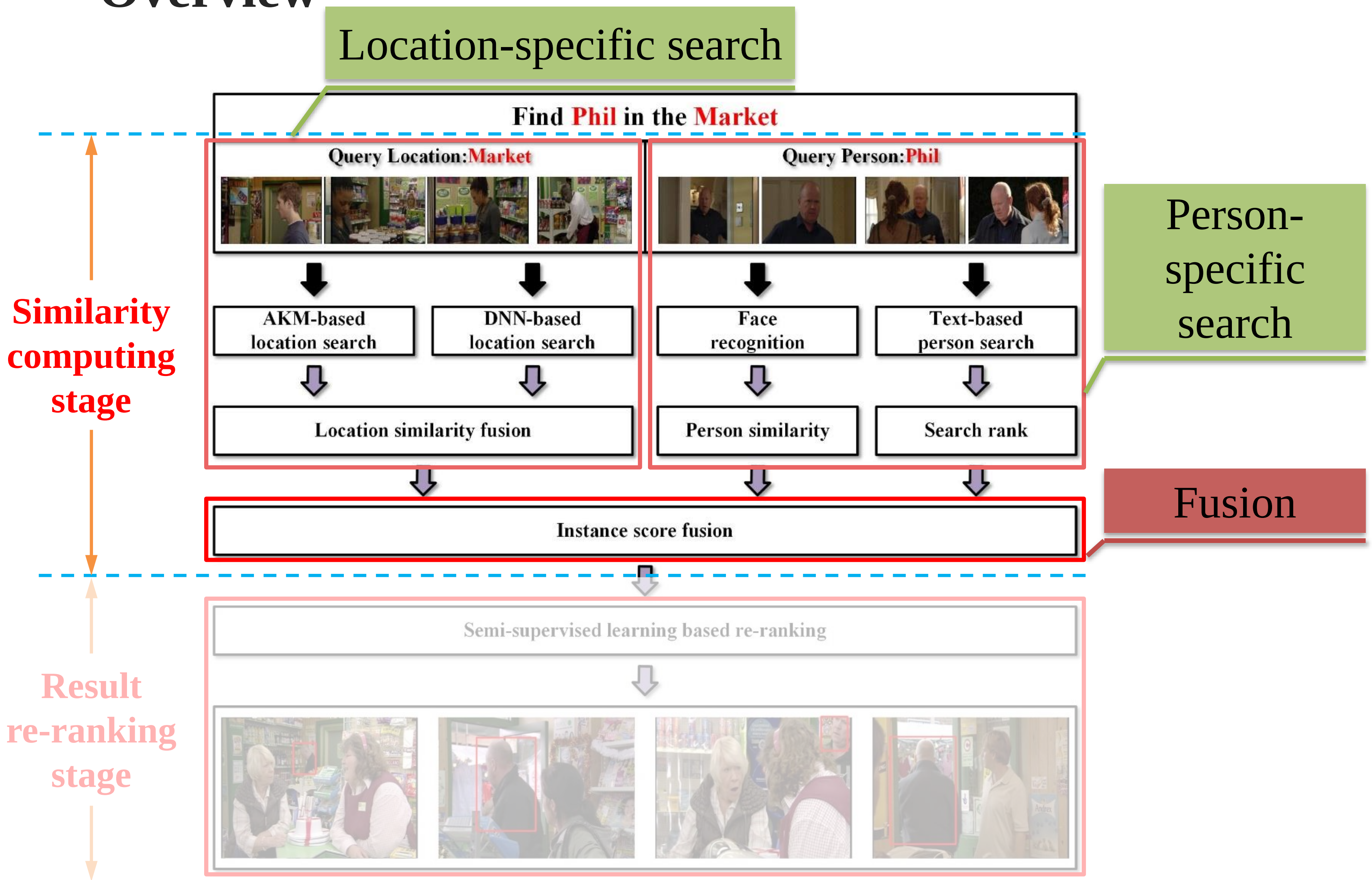
Progressive training

Our approach

- **Overview**

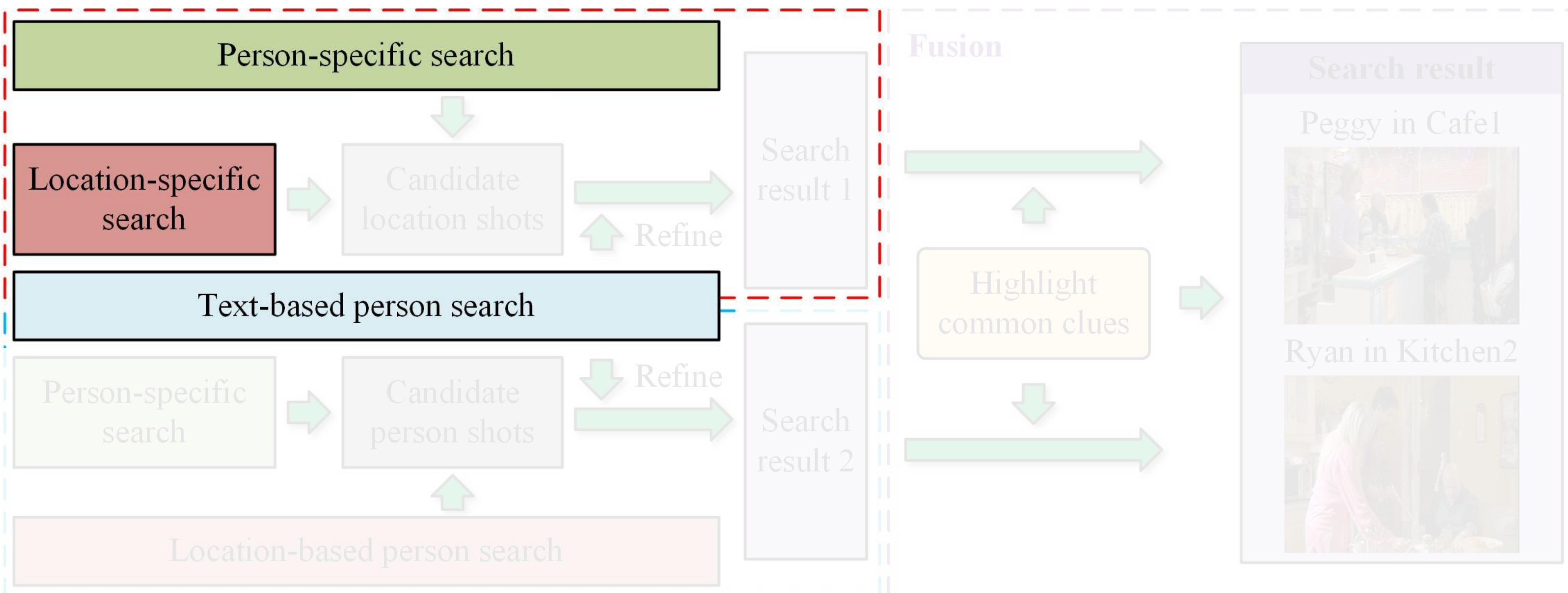


Our approach

- **Instance score fusion**
  - Direction 1, we ***search person in specific location***

$$s_1 = \mu \cdot sim_{person}$$

  - μ is a bonus parameter based on text-based person search



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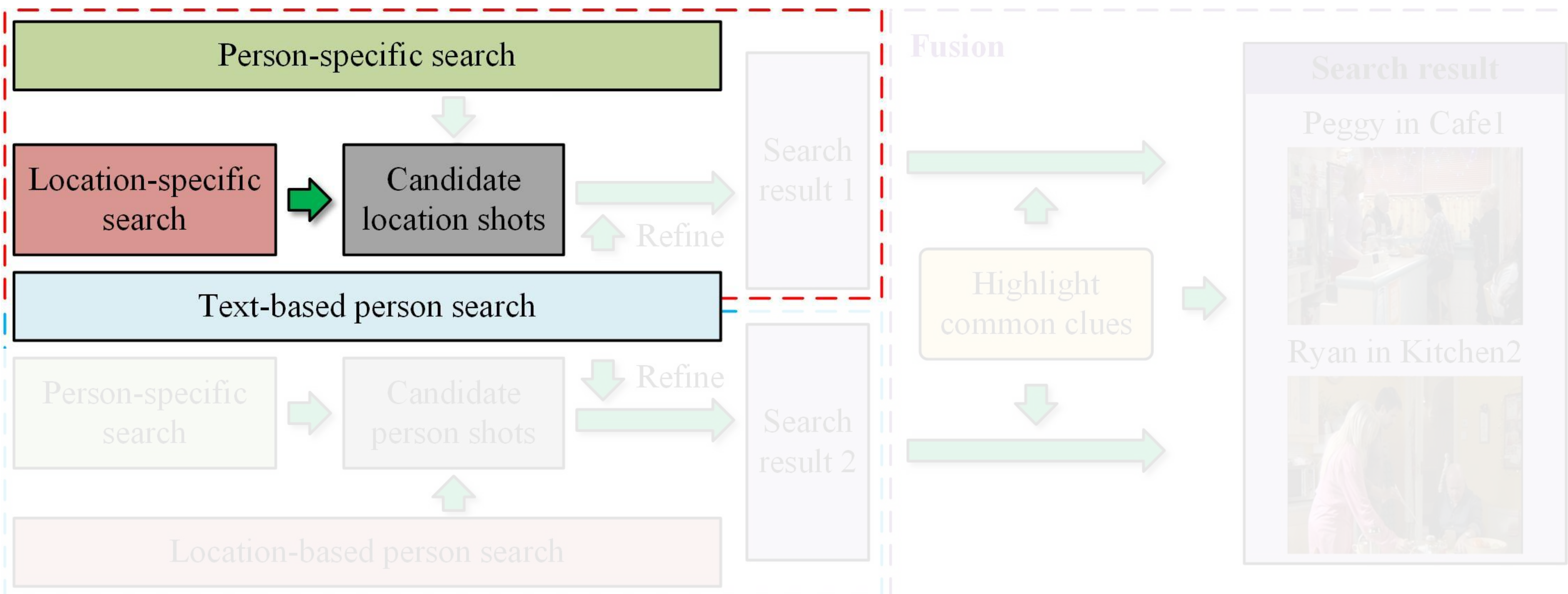

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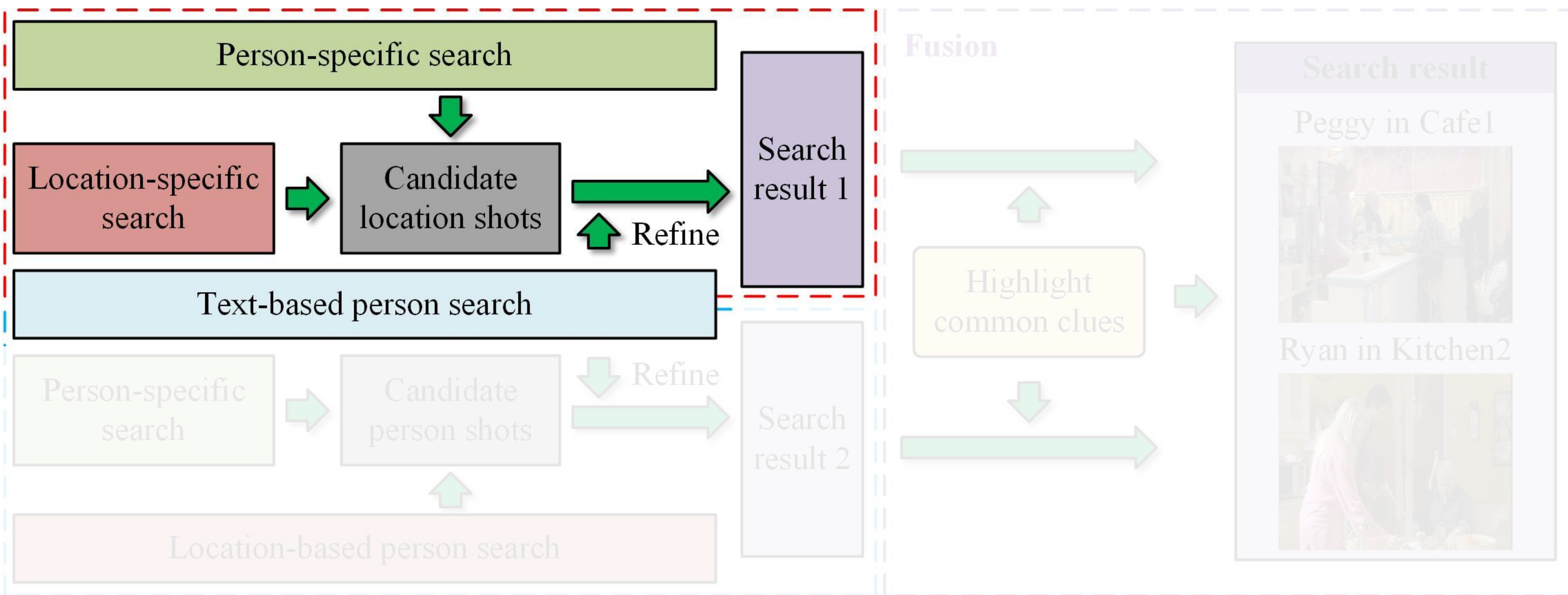
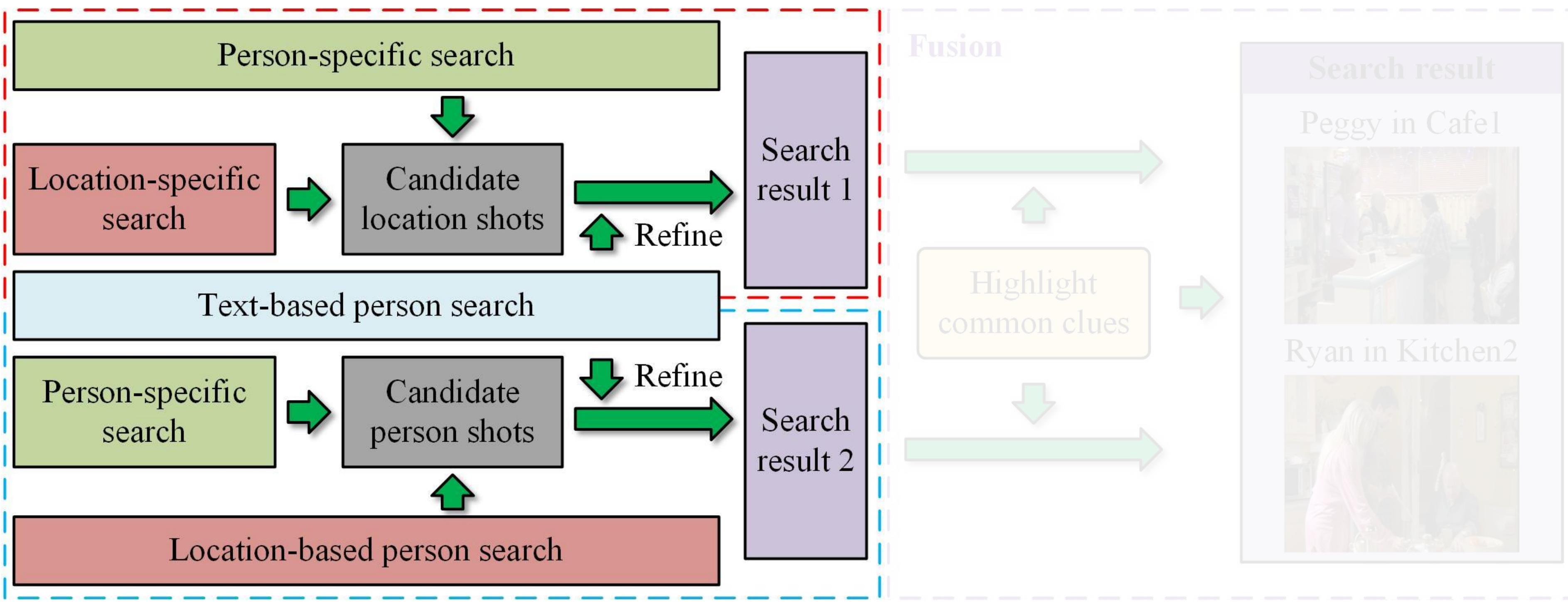


Our approach

- **Instance score fusion**
  - Direction 2, we ***search location containing specific person***

$$s_2 = \mu \cdot sim_{location}$$

  - μ is a bonus parameter based on text-based person search

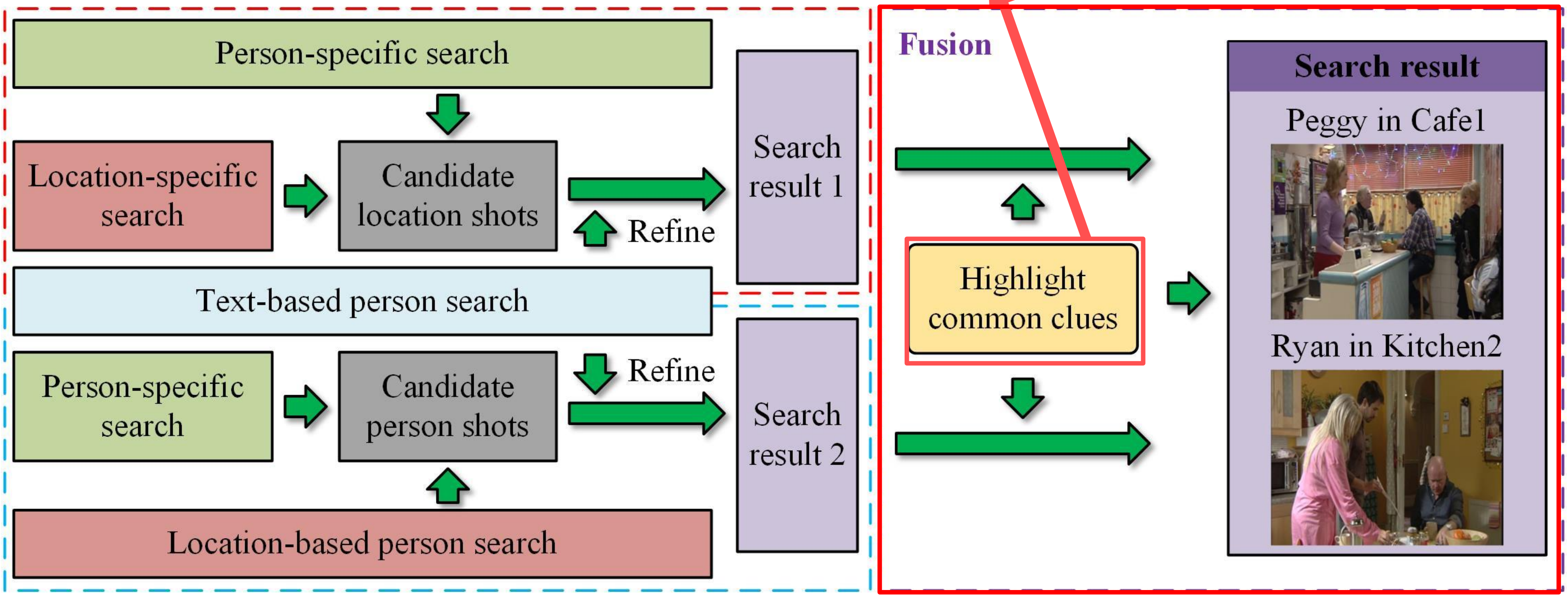


Our approach

- **Instance score fusion**
  - Combine scores of above two directions:

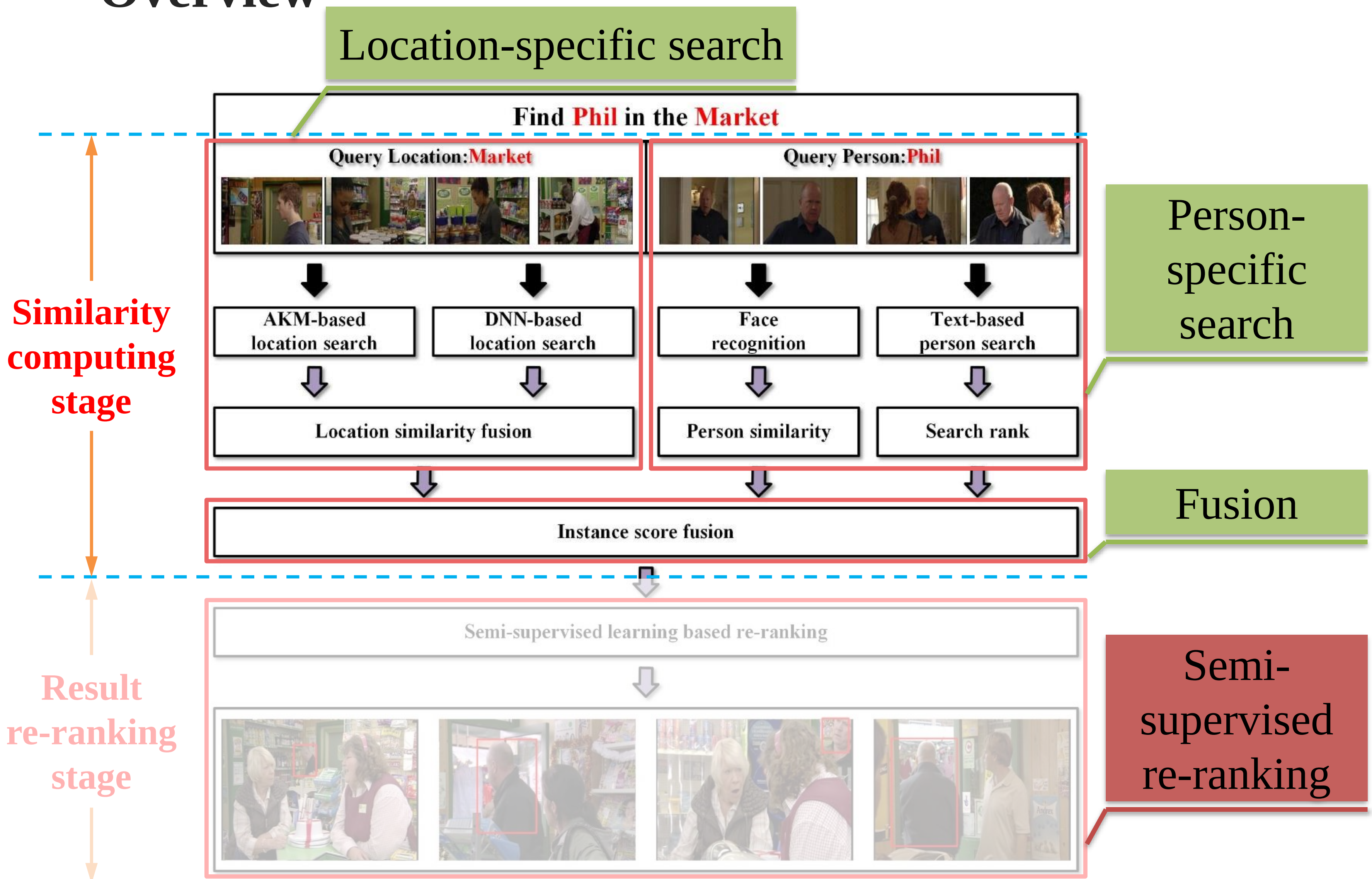
$$s_f = \omega \cdot (\alpha \cdot s_1 + \beta \cdot s_2)$$

  - $\boldsymbol{\omega}$ indicates whether the shot is ***simultaneously*** included in candidate location shots and candidate person shots



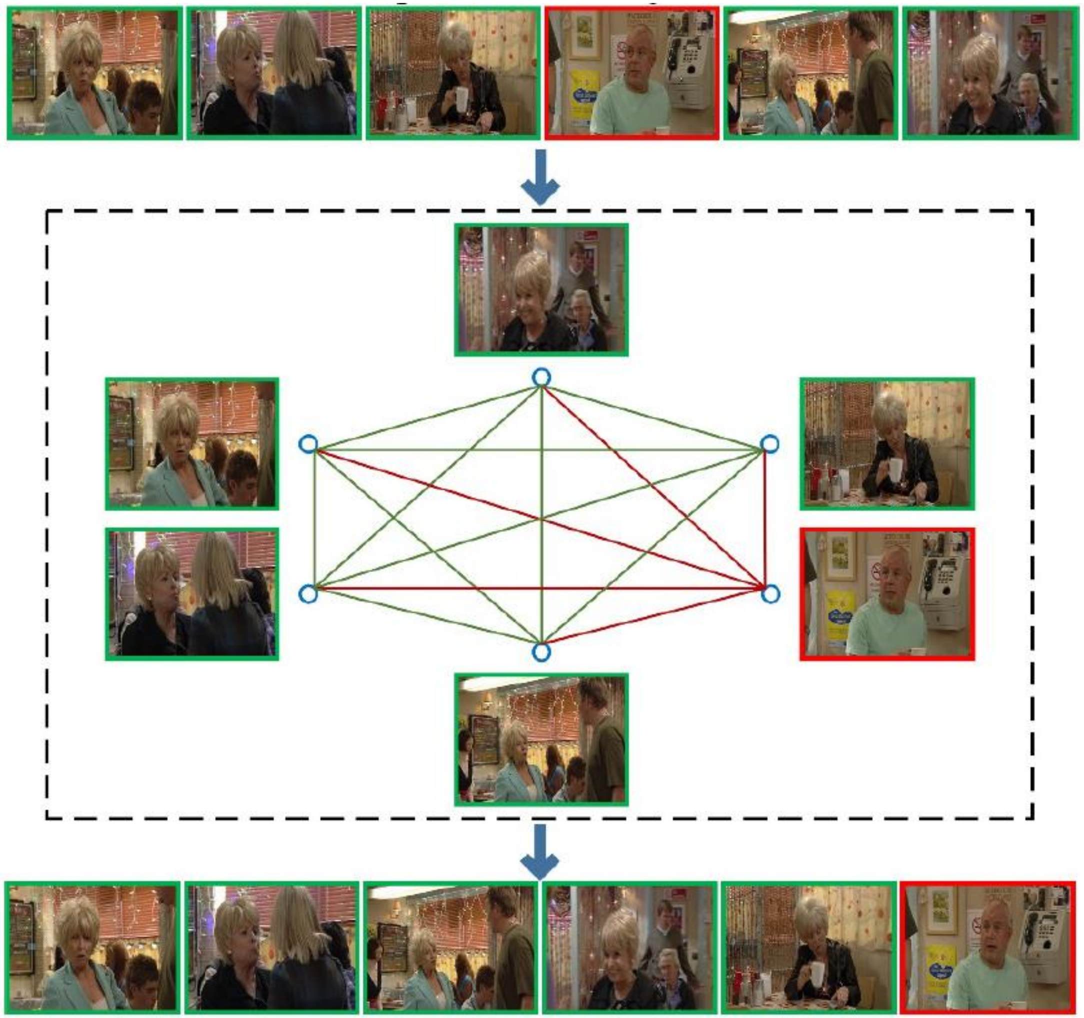
Our approach

- **Overview**



Our approach

- **Re-ranking**
  - Most of the top ranked shots are correct and look similar
  - Noisy shots with ***large dissimilarity*** can be filtered using similarity scores among top ranked shots
  - A ***semi-supervised re-ranking method*** is proposed to refine the result



Re-ranking

- **Semi-supervised re-ranking algorithm**
  - Obtain affinity matrix *W* of top-ranked shots *F*:
  - $$W_{ij} = \begin{cases} \frac{F_i^T \cdot F_j}{|F_i| \cdot |F_j|}, i \neq j \\ 0, \quad i = j \end{cases}, \qquad i,j = \{1,2,\cdots,n\}$$
  - Update *W* according to *k-NN* graph:

$$W_{ij} = \begin{cases} W_{ij}, F_i \in KNN(F_j) \\ 0, \quad otherwise \end{cases}, \qquad i,j = \{1,2,\cdots,n\}$$

  - Construct the matrix:

$$S = D^{-\frac{1}{2}} W D^{-\frac{1}{2}}$$

  - Re-rank search result:

$$G_{t+1} = \alpha S G_t + (1-\alpha) Y$$

where *Y* is the ranked list obtained by above ***fusion*** step

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Results and Conclusions

- **Results**
  - We submitted 7 runs, and ranked ***1st*** in ***both automatic and interactive search***
  - Interactive run is performed based on RUN2 with expanding positive examples as queries

Type	ID	MAP	Brief description
Automatic	RUN1_A	0.448	AKM+DNN+Face
	RUN1_E	0.471	AKM+DNN+Face
	RUN2_A	0.531	RUN1+Text
	RUN2_E	0.549	RUN1+Text
	RUN3_A	0.528	RUN2+Re-rank
	RUN3_E	**0.549**	RUN2+Re-rank
Interactive	RUN4	**0.677**	RUN2+Human feedback

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Results and Conclusions

- **Conclusions**
  - Video examples are helpful for accuracy improvement
  - Automatic removal of “bad faces” is important
  - Fusion of location and person similarity is a key factor of the instance search

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1. Video concept recognition (1/2)

- **Video concept recognition**
  - Learn semantics from video content and classify videos into pre-defined categories automatically.
  - For examples: human action recognition and multimedia event detection, etc.

PlayingGitar

HorseRiding

Birthday Celebration

Parade

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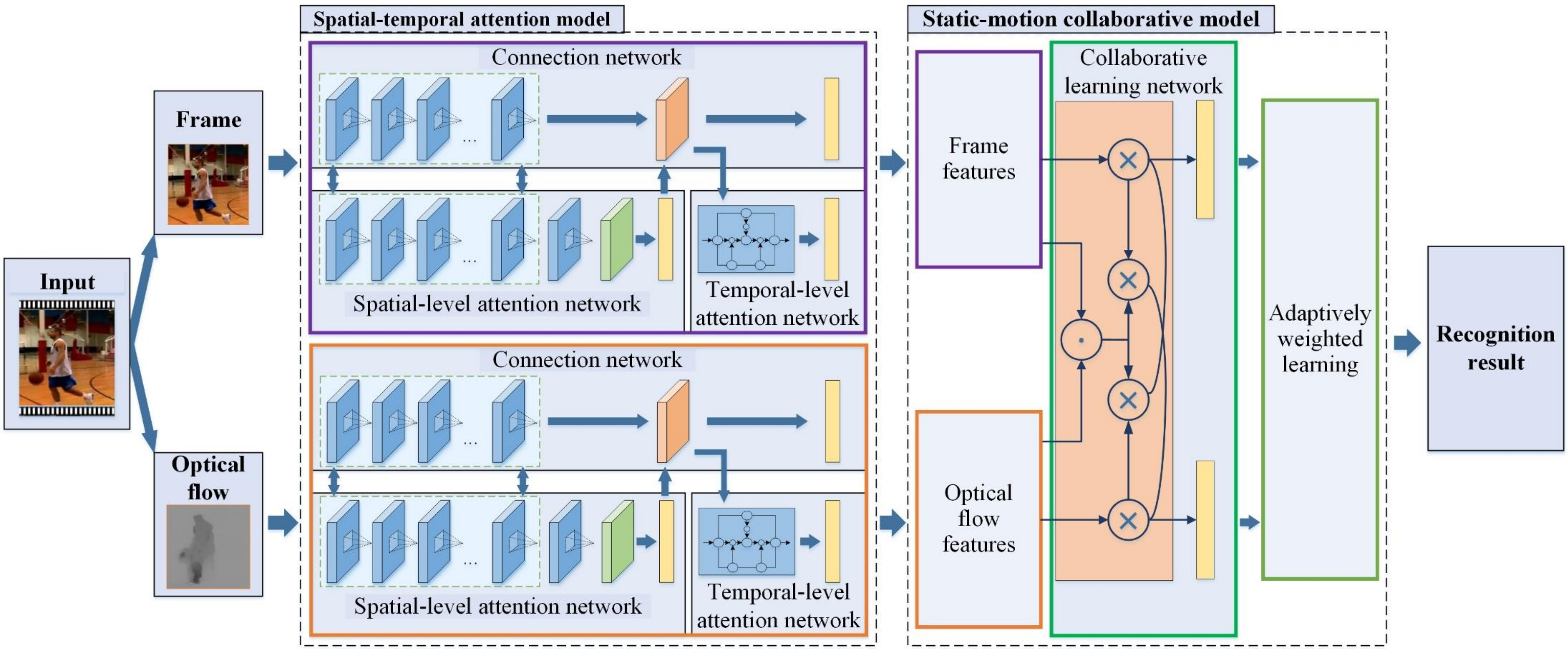
1. Video concept recognition (2/2)

- We propose **two-stream collaborative learning with spatial-temporal attention**
  - **spatial-temporal attention model**: jointly capture the video evolutions both in spatial and temporal domains
  - **static-motion collaborative model**: adopt collaborative guidance between static and motion information to promote feature learning



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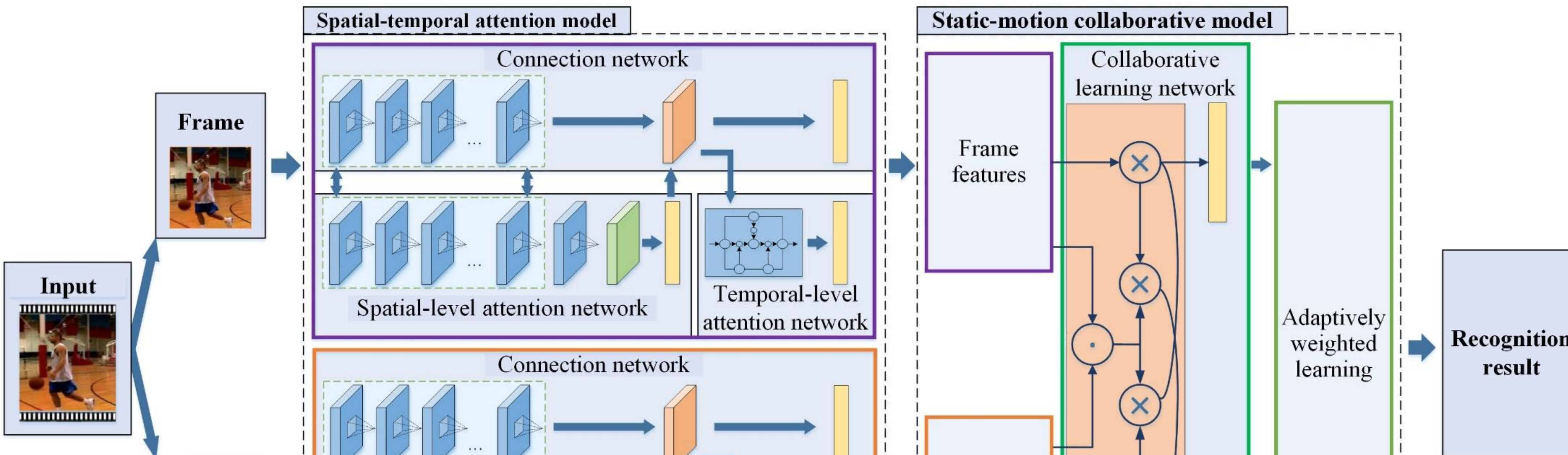
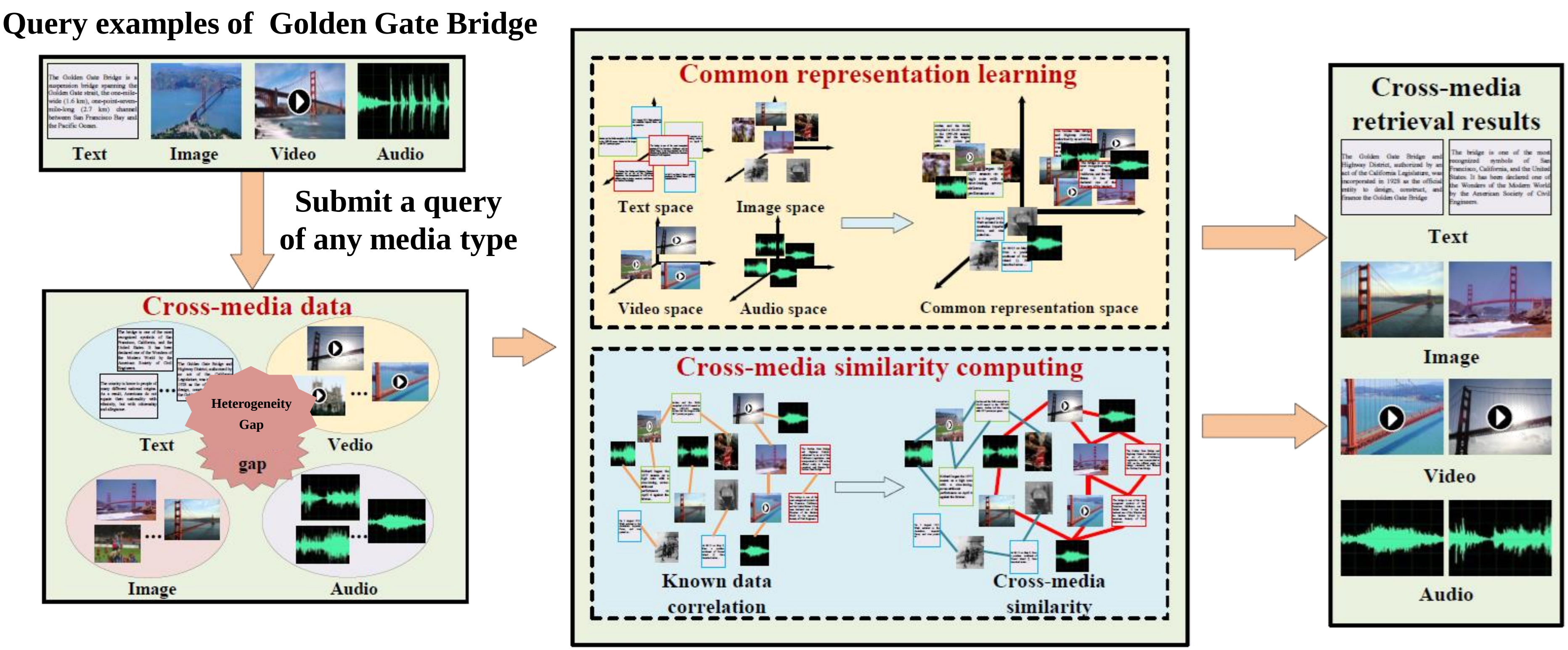


Yuxin Peng, Yunzhen Zhao, and Junchao Zhang, "Two-stream Collaborative Learning with Spatial-Temporal Attention for Video Classification", ***IEEE TCSVT 2017 (after minor revision) arXiv: 1704.01740***

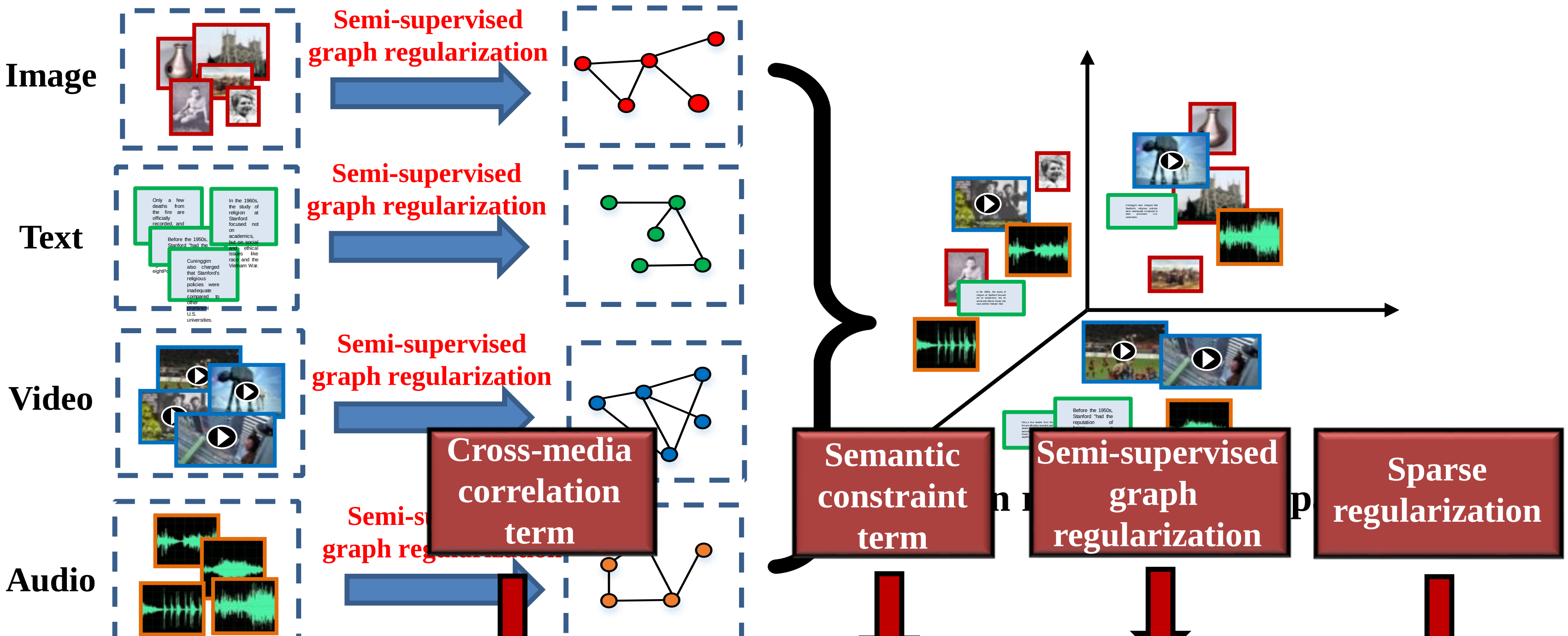
2. Cross-media Retrieval (1/5)

- **Cross-media retrieval:**
  - Perform retrieval among different media types, such as image, text, audio and video
- **Challenge:**
  - **Heterogeneity gap**: Different media types have inconsistent representations



2. Cross-media Retrieval (2/5)

- We propose **common representation learning based on sparse and semi-supervised regularization**, which models correlation and high-level semantics in a **unified framework**, and exploits complementary information among multiple media types to reduce noise



$$\underset{P^{(1)},\dots,P^{(s)}}{\operatorname{argmin}} \sum_{i=1}^{s}\sum_{j=i+1}^{s} \boxed{\left\| P^{(i)^T} X_{mij}^{(i)} - P^{(j)^T} X_{mij}^{(j)} \right\|_F^2} + \sum_{i=1}^{s}\left(\boxed{\left\| P^{(i)^T} X^{(i)} - Y^{(i)} \right\|_F^2} + \boxed{\lambda(\Omega(P^{(i)}))} + \boxed{\left\| P^{(i)} \right\|_{2,1}} \right)$$

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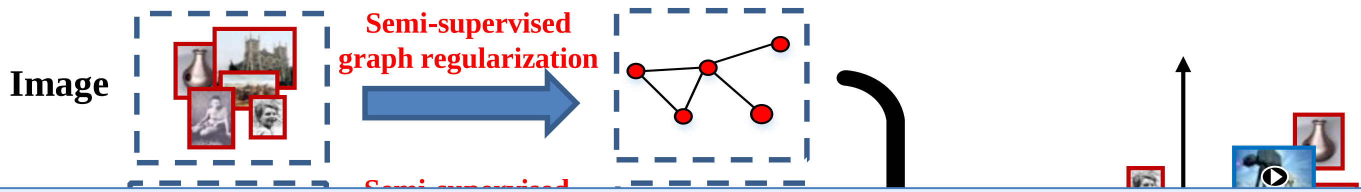
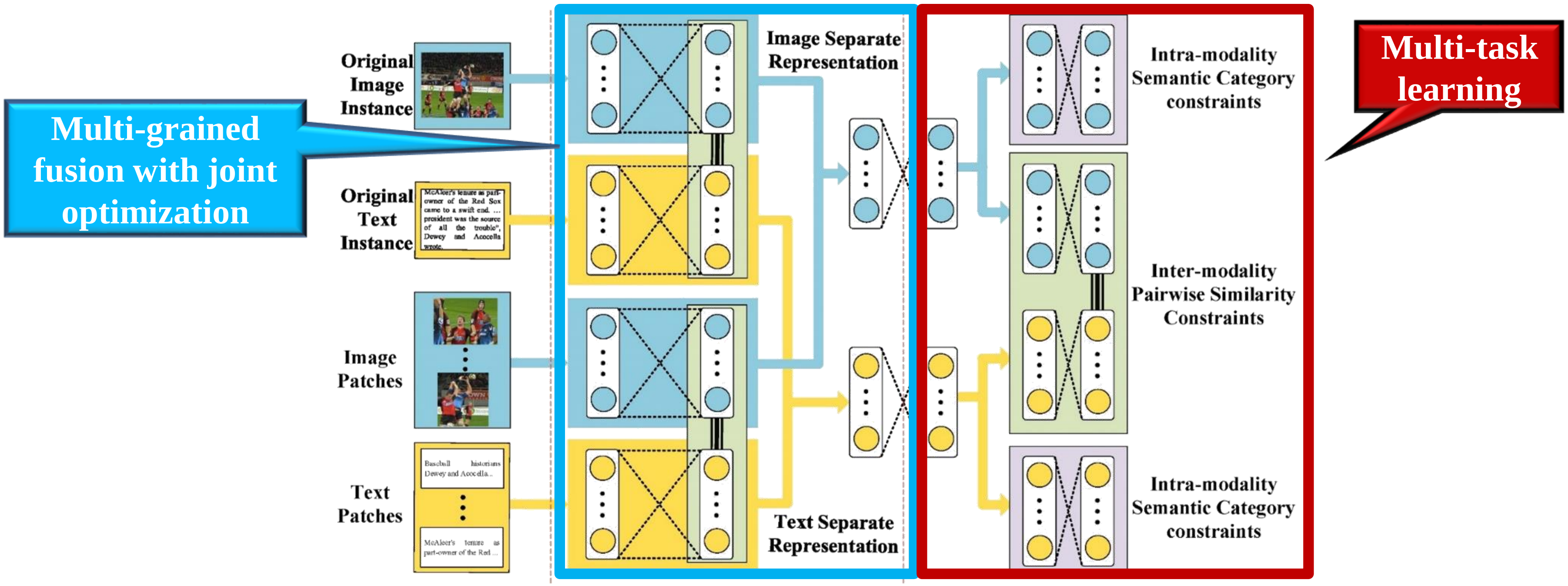


Comment from Reviewers of TCSVT: "the proposed method is **quite novel**.", and "**jointly represents several media** for cross-media retrieval, while the previous works usually deal with two different media"

- Yuxin Peng, Xiaohua Zhai, Yunzhen Zhao, and Xin Huang, "Semi-Supervised Cross-Media Feature Learning with Unified Patch Graph Regularization", ***IEEE TCSVT*** **2016**
- Xiaohua Zhai, Yuxin Peng, and Jianguo Xiao, "Learning Cross-Media Joint Representation with Sparse and Semisupervised Regularization", ***IEEE TCSVT 2014***

2. Cross-media Retrieval (3/5)

- We propose a **cross-modal correlation learning** approach with **multi-grained fusion** by hierarchical network. It exploits **multi-level association with joint optimization** and adopts **multi-task learning** to preserve intra-modality and inter-modality correlation



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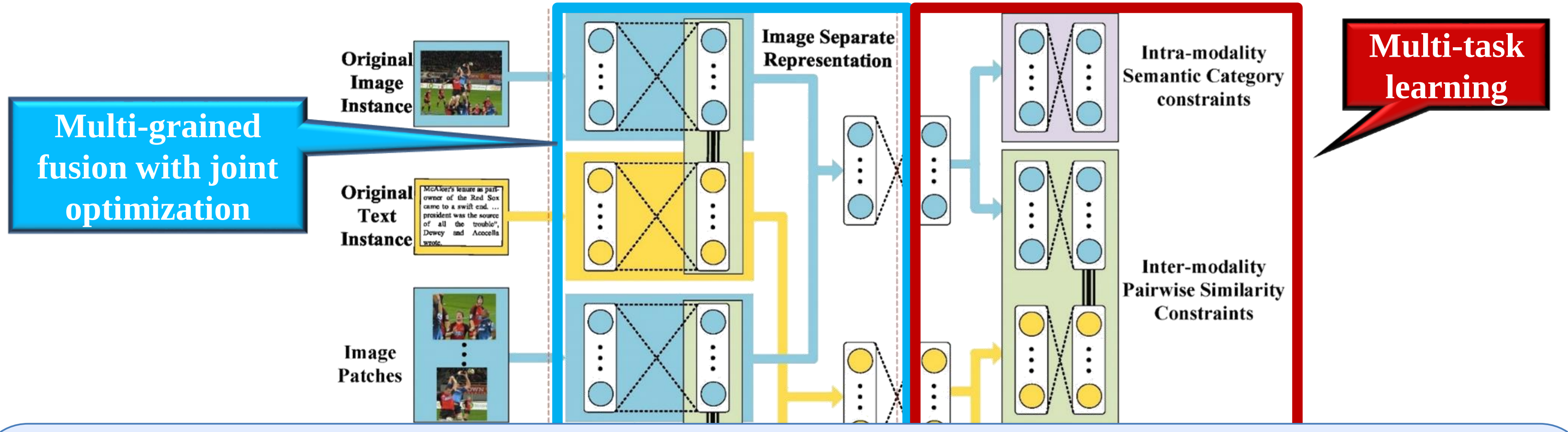
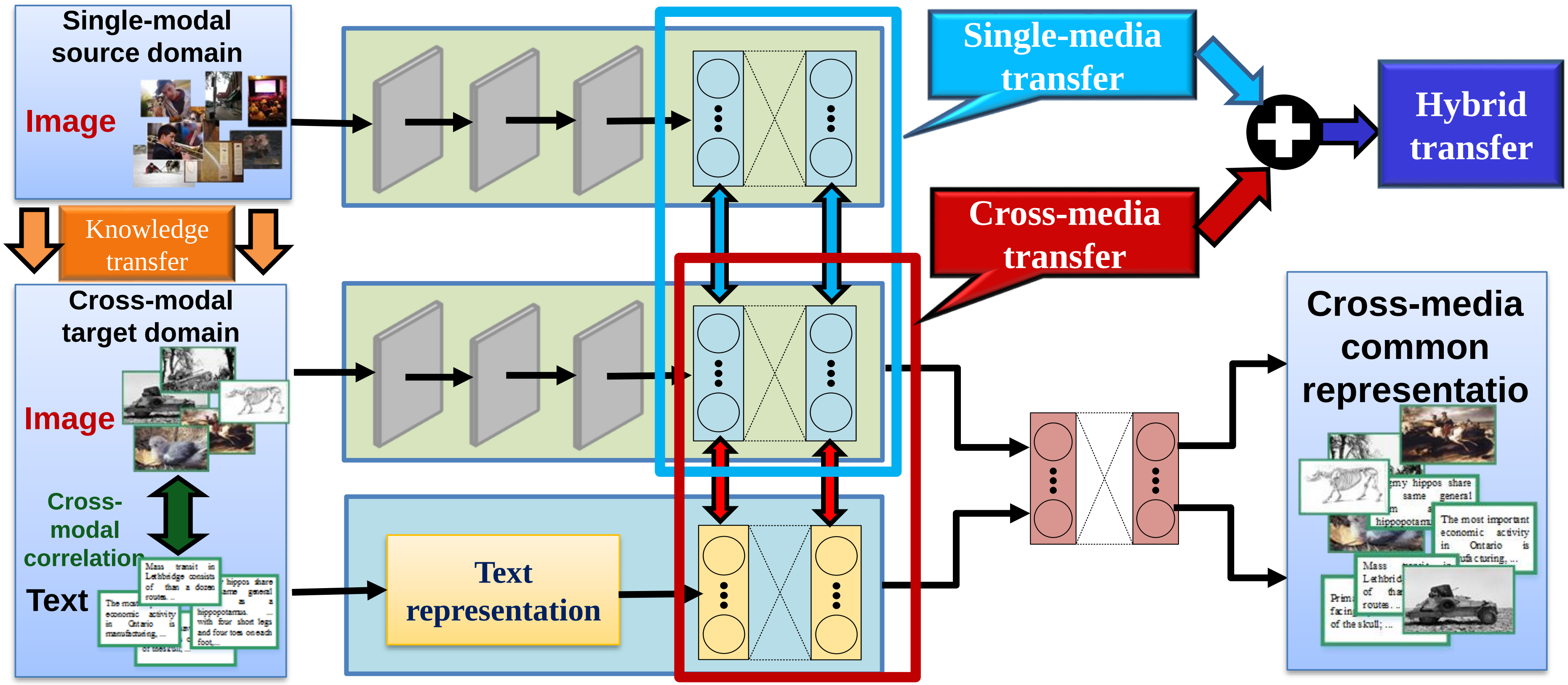


- Yuxin Peng, Xin Huang, and Jinwei Qi. "Cross-media Shared Representation by Hierarchical Learning with Multiple Deep Networks". ***IJCAI 2016.***
- Yuxin Peng, Jinwei Qi, Xin Huang, and Yuxin Yuan, "CCL: Cross-modal Correlation Learning with Multi-grained Fusion by Hierarchical Network", ***IEEE TMM* 2017**

2. Cross-media Retrieval (4/5)

- For addressing the problem of **insufficient training data** in DNN-based cross-media retrieval method, we propose **cross-media hybrid transfer network**, which exploits the semantic information of existing large-scale **single-media datasets** to promote the network training of cross-media common representation learning



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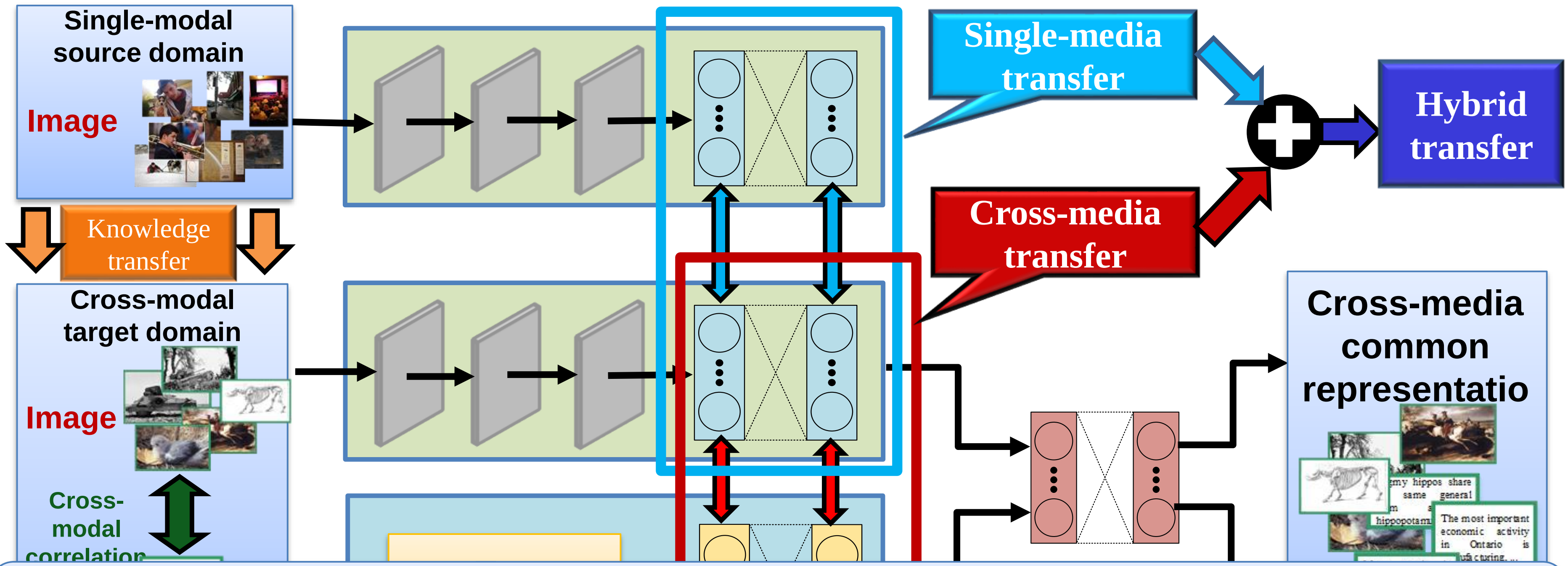
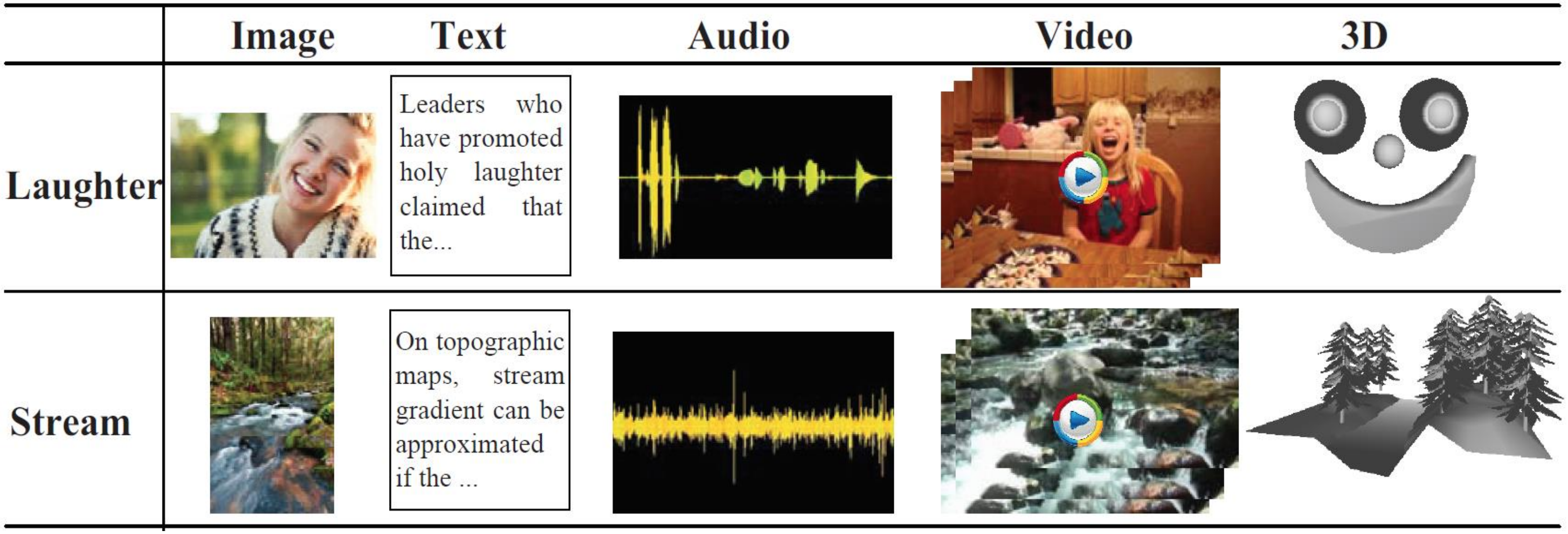


Xin Huang, Yuxin Peng, and Mingkuan Yuan, "Cross-modal Common Representation Learning by Hybrid Transfer Network", ***IJCAI 2017.***

2. Cross-media Retrieval (5/5)

- We have released **PKU-XMedia**、**PKU-XMediaNet** dataset with 5 media types. Datasets and source codes of our related works:

http://www.icst.pku.edu.cn/mipl/xmedia



- Interested in cross-media retrieval? Hope our recent overview is helpful for you

> Yuxin Peng, Xin Huang, and Yunzhen Zhao, "**An Overview of Cross-media Retrieval: Concepts, Methodologies, Benchmarks and Challenges**", IEEE TCSVT, 2017. arXiv: 1704.02223.

3. Fine-grained Image Classification (1/4)

- **Fine-grained Image Classification:**
  - Recognize hundreds of subcategories belonging to the same basic-level category
- **Challenges:**

Large variances in the same subcategory

Black Footed Albatross

Smart fortwo Convertible

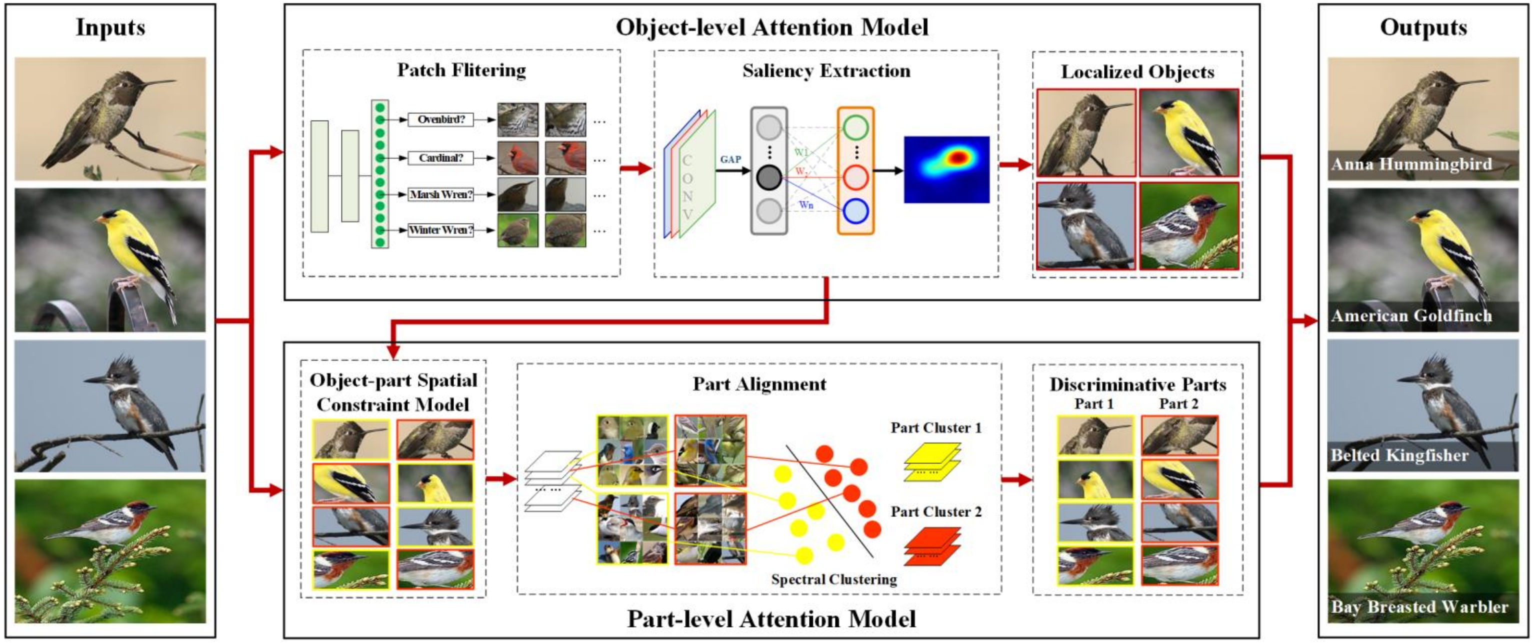
Small variances among different subcategories

Marsh Wren **Rock Wren** **Winter Wren**

BMW 1 **Hyundai Elantra** **Toyota Sequoia**

3. Fine-grained Image Classification (2/4)

- To address the problem of fine-grained image classification, **object-part attention model** is proposed, which is the **first work** to classify fine-grained images **without using object or parts annotations** in both training and testing phase, but still achieves promising results.



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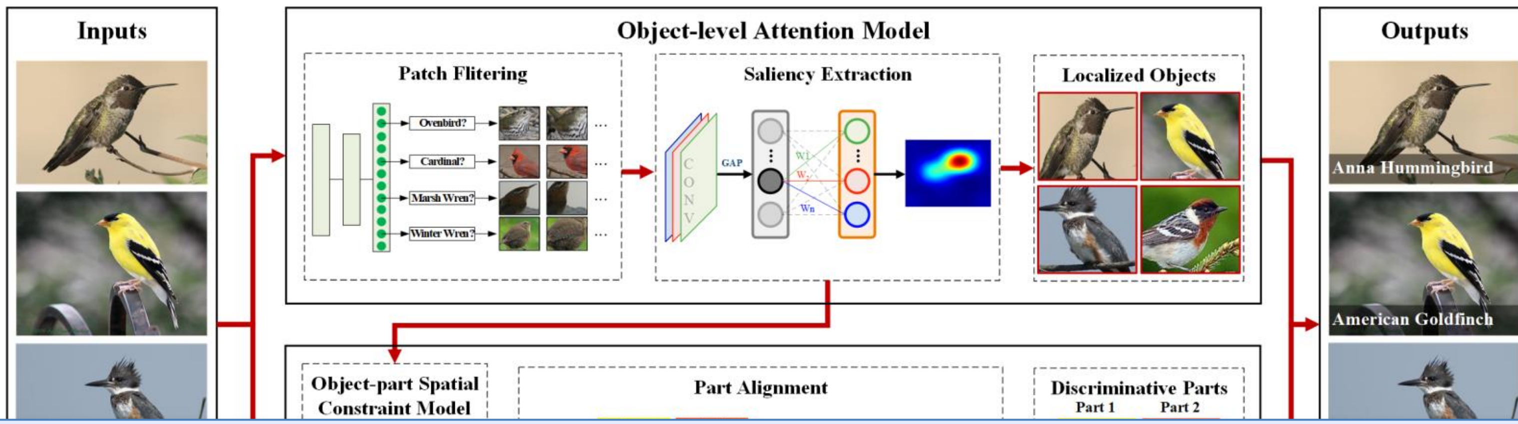
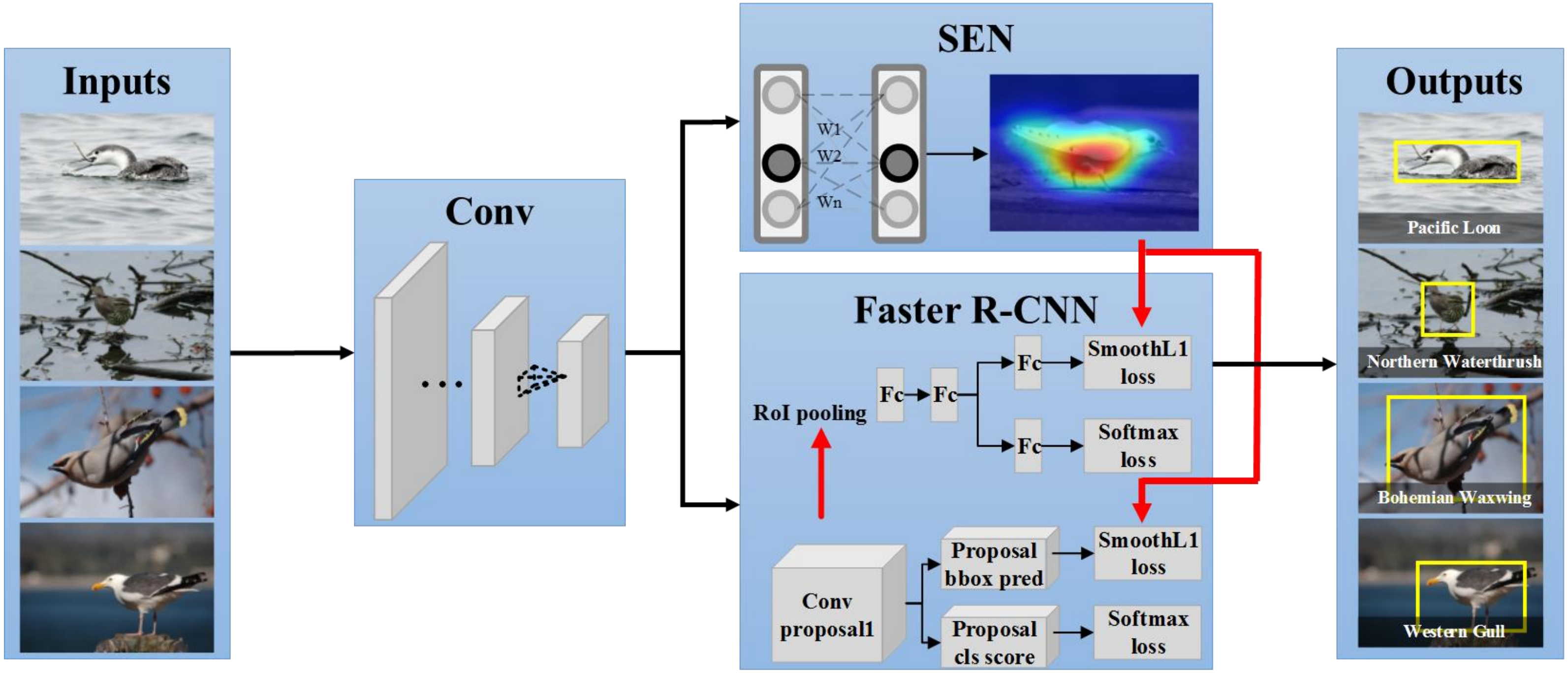


- Yuxin Peng, Xiangteng He, and Junjie Zhao, "Object-Part Attention Model for Fine-grained Image Classification", ***IEEE TIP 2017***
- Tianjun Xiao, Yichong Xu, Kuiyuan Yang, Jiaxing Zhang, Yuxin Peng, and Zheng Zhang, "The Application of Two-level Attention Models in Deep Convolutional Neural Network for Fine-grained Image Classification", ***CVPR 2015***

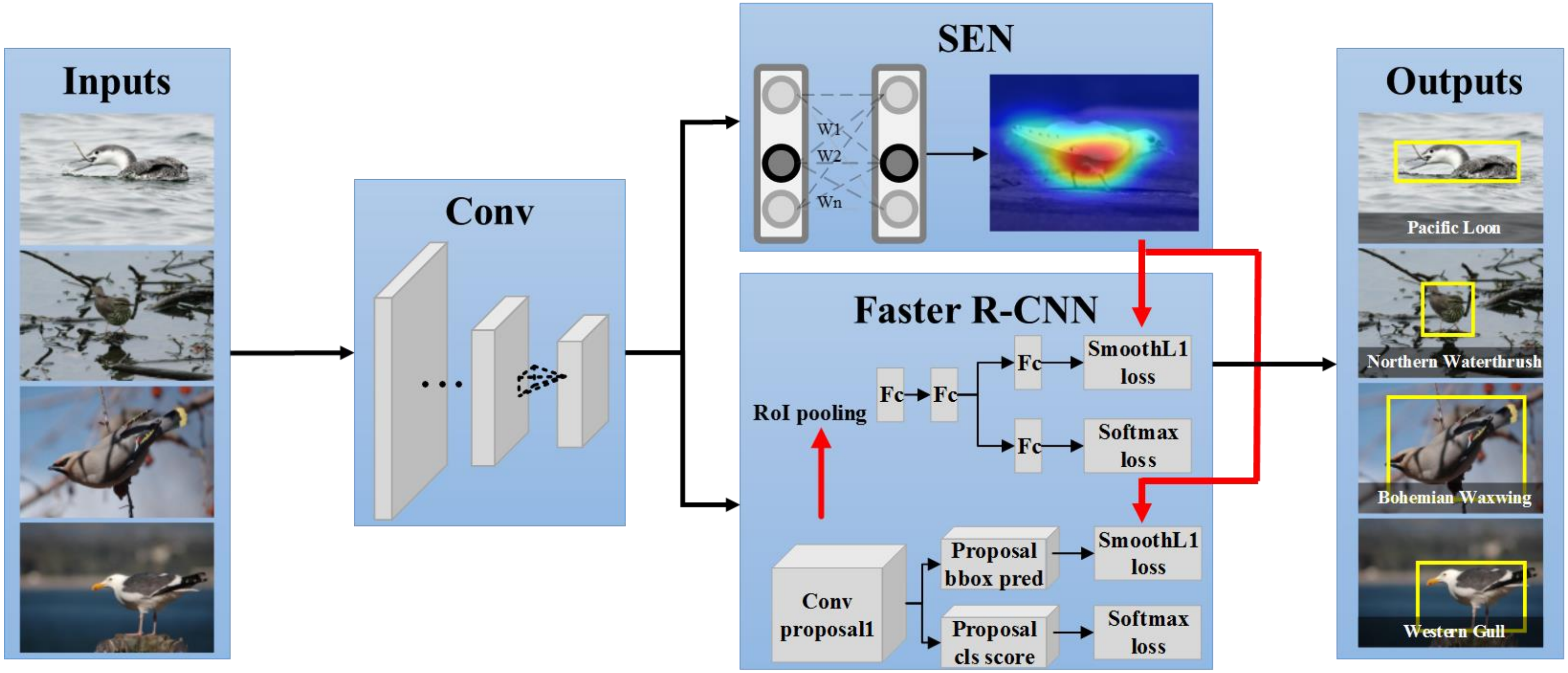
3. Fine-grained Image Classification (3/4)

- To accelerate classification speed, **saliency-guided fine-grained discriminative localization** is proposed, which jointly facilitates fine-grained image classification and discriminative localization



3. Fine-grained Image Classification (3/4)

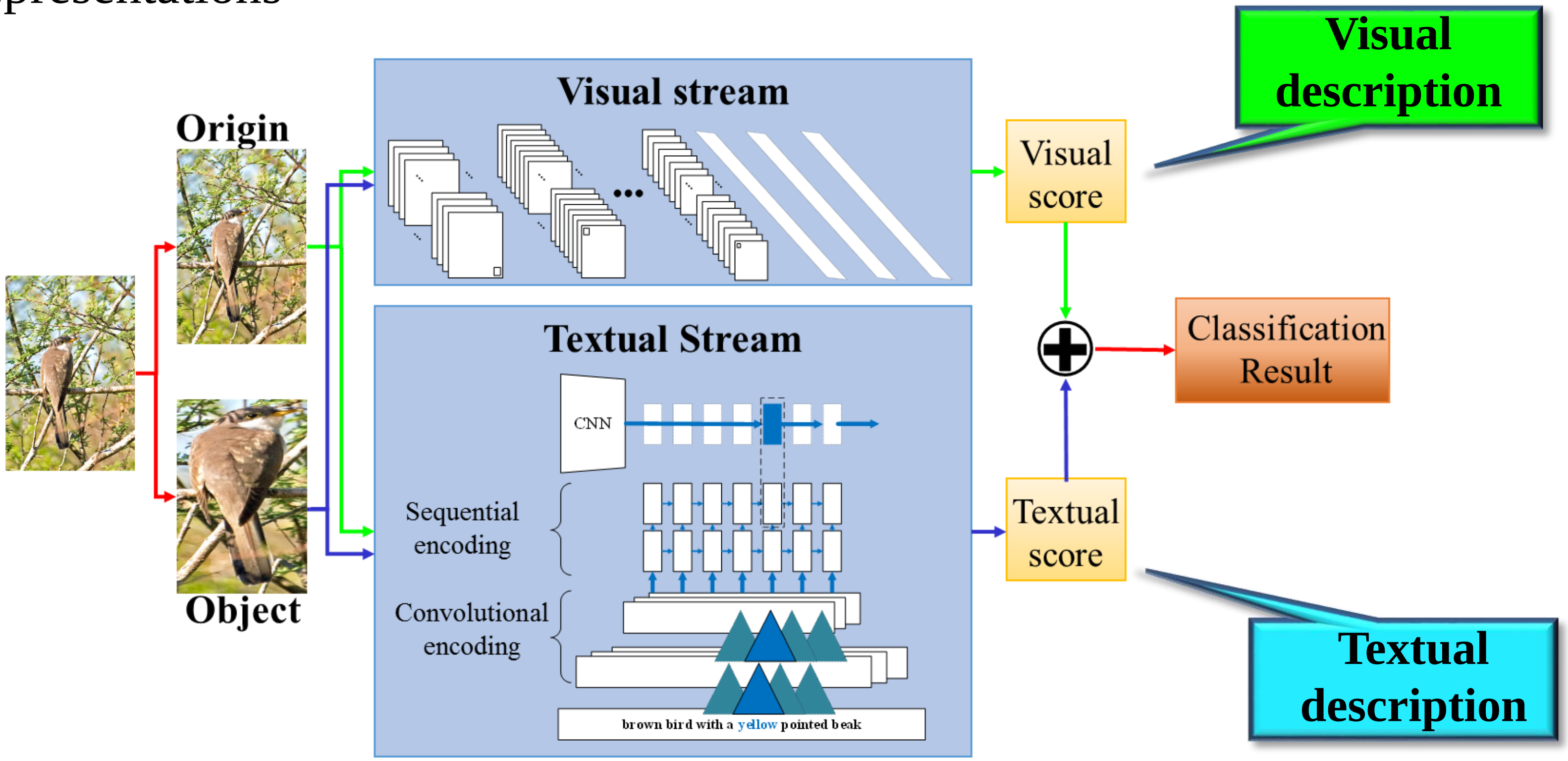
- To accelerate classification speed, **saliency-guided fine-grained discriminative localization** is proposed, which jointly facilitates fine-grained image classification and discriminative localization



Xiangteng He, Yuxin Peng and Junjie Zhao, "Fine-grained Discriminative Localization via Saliency-guided Faster R-CNN", ***ACM MM 2017.***

3. Fine-grained Image Classification (4/4)

- Considering the complementarity of text, **a two-stream model is proposed to combine vision and language** for learning multi-granularity, multi-view and multi-level representations



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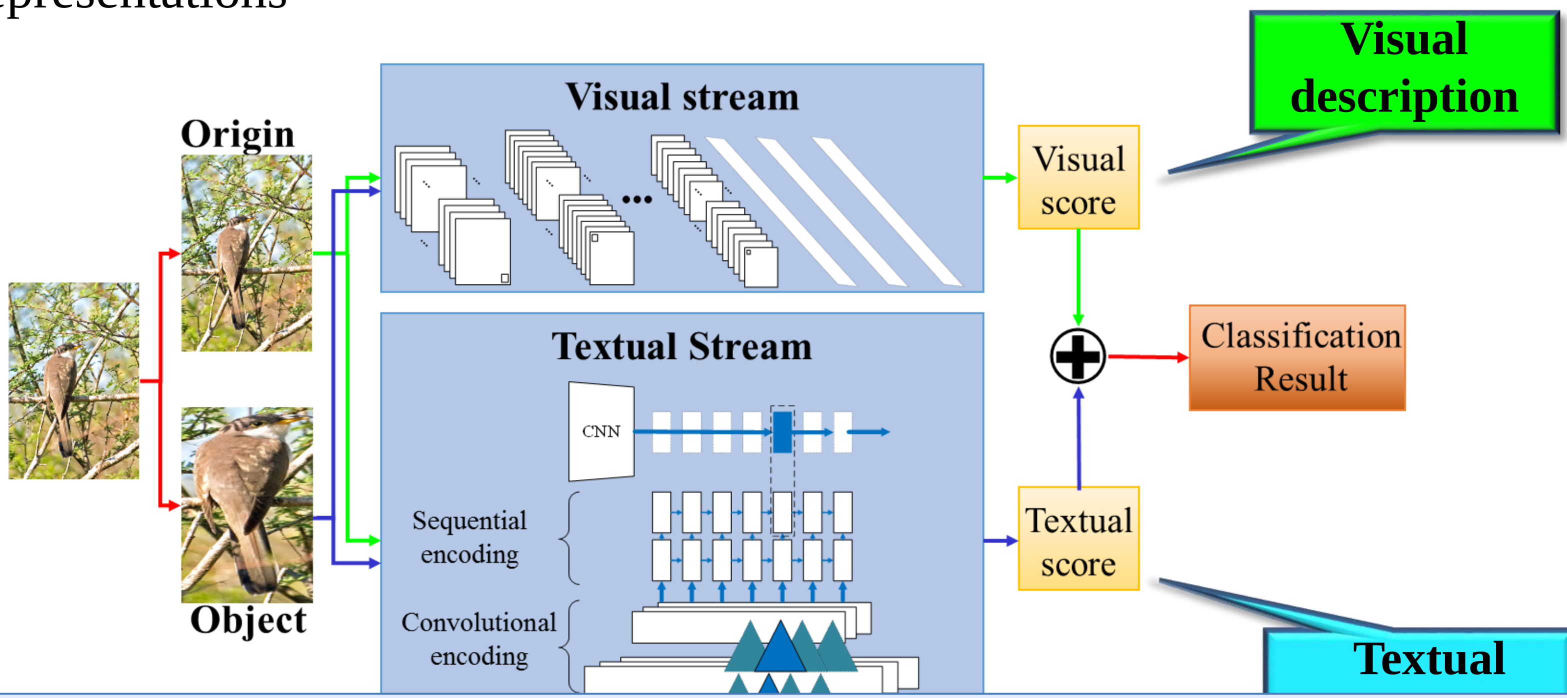
3. Fine-grained Image Classification (4/4)

- Considering the complementarity of text, **a two-stream model is proposed to combine vision and language** for learning multi-granularity, multi-view and multi-level representations



Xiangteng He and Yuxin Peng, “Fine-grained Image Classification via Combining Vision and Language”, ***CVPR 2017***.

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