Person Re-ID: Recent Advances and Challenges

Session 3:

Benchmark and GANs in Person ReID

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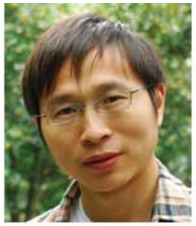

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Outline

- Our Benchmark Solution
- The Application of GANs in Person ReID
  - Overview of GANs
  - Our solution
- New Research Possibilities

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1. Benchmark Solution

- **Four person re-id datasets are progressively constructed**

- Market-1501 dataset for image-based re-identification
  - 1,501 identities, 500k distractor images – 【ICCV 2015】

- MARS dataset for video-based re-identification
  - 1,261 identities, over 20k tracklets - 【ECCV 2016】

- PRW dataset for end-to-end person re-identification
  - 932 identities, # boxes depend on the detector. - 【CVPR 2017】

- MSMT17 dataset for more realistic re-identification
  - 4,101 identities, 126,441 bounding boxes. - 【CVPR 2018】

1. Benchmark Solution

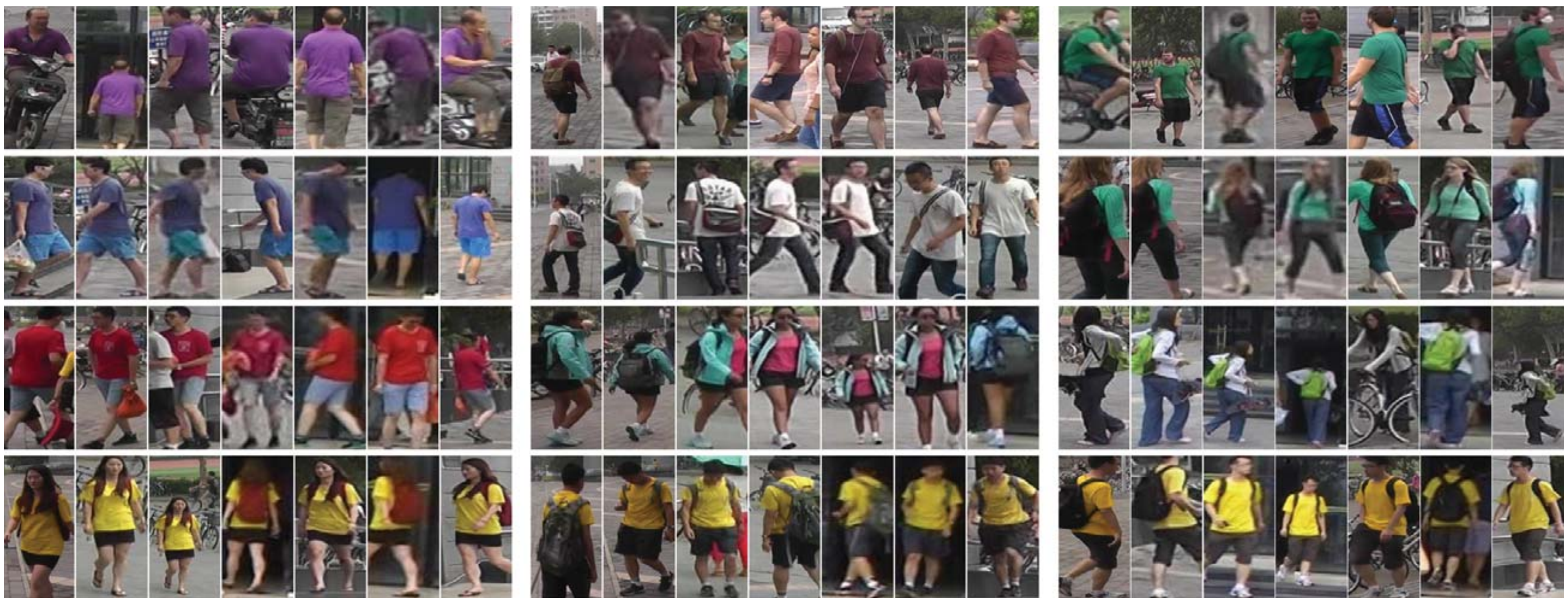
- The first three datasets are annotated from videos collected from Tsinghua University, China, in August 2014.

- We used 6 cameras
  - 5 HD (1920x1080) cameras, and 1 SD (720x576) camera
  - Moderate overlap exists among cameras

- The length of video is 10+ hours

1. Benchmark Solution – Market1501

- 1,501 identities; 32,668 bboxes by Deformable Part Model (DPM);
- 6 cameras; 3,368 queries ;



L. Zheng, L. Shen, L. Tian, S. Wang, J. Wang, and Q. Tian, "Scalable Person Re-identification: A Benchmark", ICCV 2015.

1. Benchmark Solution – Market1501

Comparison with existing image re-id datasets

Datasets	Market-1501	RAiD	CUHK03	VIPeR	i-LIDS	OPeRID	CUHK01	CUHK02	CAVIAR
# Identities	1,501	43	1,360	632	119	200	971	1,816	72
# Bboxes	32,668	6,920	13,164	1,264	476	7,413	1,942	7,264	610
# Cam. per ID	6	4	2	2	2	5	2	2	2
DPM or Hand	DPM	Hand	DPM	Hand	Hand	Hand	Hand	Hand	Hand
Evaluation	mAP+CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC

L. Zheng, L. Shen, L. Tian, S. Wang, J. Wang, and Q. Tian, "Scalable Person Re-identification: A Benchmark", ICCV 2015.

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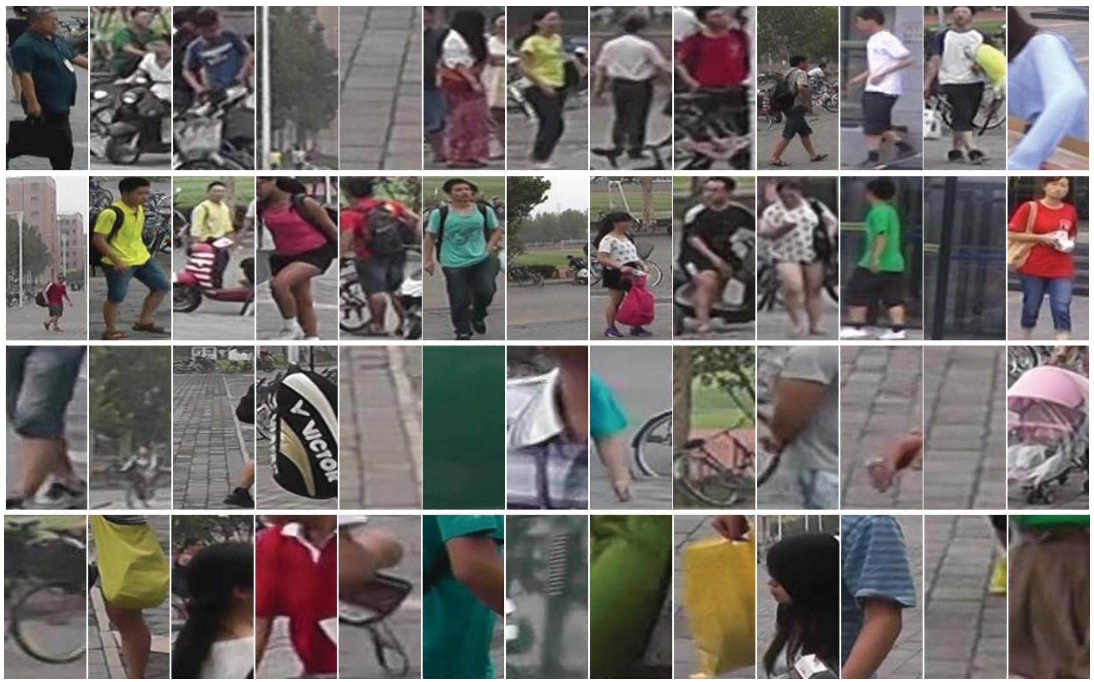
1. Benchmark Solution – Market1501

- **We further add** **500k distractor images**: **Market-1501 + 500k dataset**



Distractors include:

- ✓ Incorrect detection results on the background
- ✓ Non-overlapping pedestrians with Market-1501

1. Market1501-Summary

- Summary
  - Large-scale benchmark
  - DPM detected bounding boxes
  - Multiple queries, multiple ground truths

- Limitations
  - Does not use the rich information in videos → MARS dataset [ECCV 2016]
  - No evaluation of pedestrian detectors → PRW dataset [CVPR 2017]
  - Short-time, single scene, bad detector → MSMT17 dataset [CVPR 2018]

1. Benchmark Solution – MARS

- 1,261 identities; Over 20k tracklets by DPM detector & GMMCP tracker (CVPR'15); Over 1 million frames
- 6 cameras; 2,009 queries ;

1. Benchmark Solution – MARS

- Testing Procedure
  - Given a query tracklet, we aim to search for tracklets containing the same person from other cameras.
  - mAP & CMC curve are used for evaluation

1. Benchmark Solution – MARS

Comparison with existing video re-id datasets

Datasets	MARS	**iLIDS-VID**	**PRID**	**3DPES**	**ETH**
# identities	**1,261**	300	200	200	146
# tracklets	**20,715**	600	400	1,000	146
# BBoxes	**1,067,516**	43,800	40,000	200k	8,580
# distractors	**3,248**	0	0	0	0
# cam. Per ID	**6**	2	2	8	1
Produced by	**DPM+GMMCP**	Hand	Hand	Hand	Hand
Evaluation	**mAP+CMC**	CMC	CMC	CMC	CMC

L. Zheng, Z. Bie, Y. Sun, C. Su, S. Wang, J. Wang, and Q. Tian, "MARS: A Video for Large-Scale Person Re-identification", ECCV 2016.

1. MARS - Summary

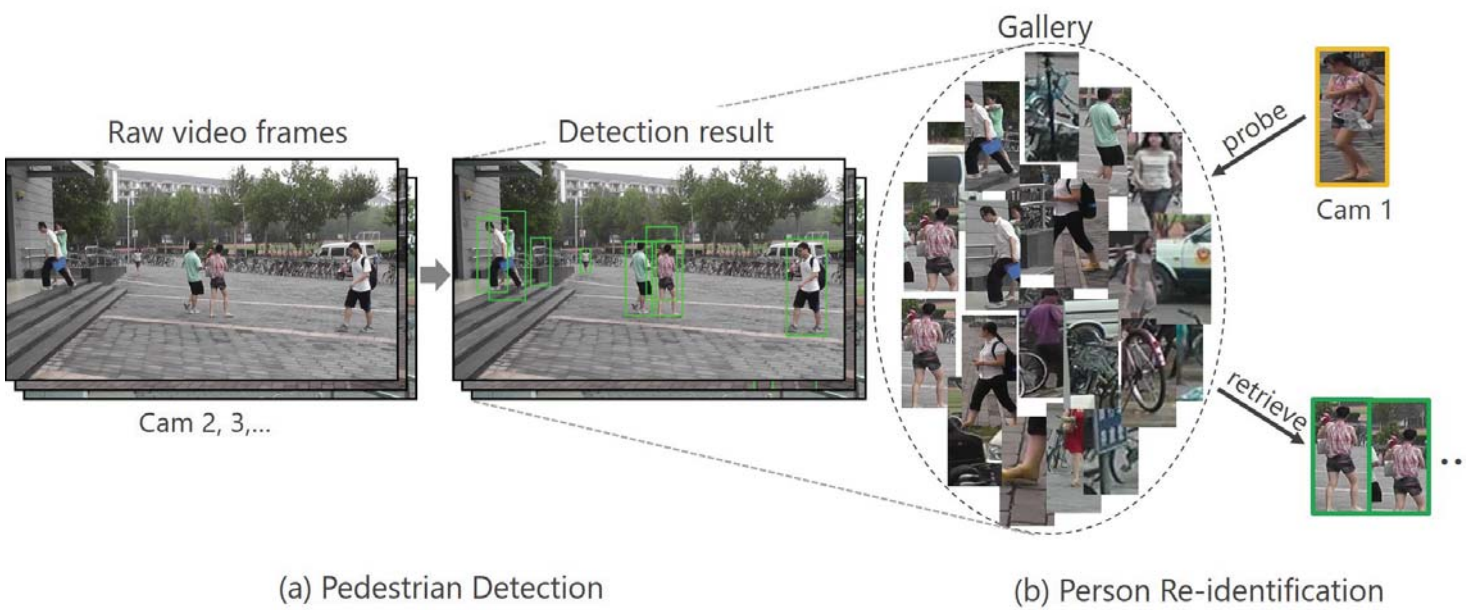
- Summary
  - Tracklets are used instead of single images
  - Tracklets contain more information
  - Large-scale

- Limitation
  - How does pedestrian detection error affect re-id accuracy?

→ PRW: [CVPR 2017]

1. Benchmark Solution – PRW

- PRW (Person Re-identification in the Wild)
  - We focus on both pedestrian detection and recognition



L. Zheng, H. Zhang, S. Sun, M. Chandraker, and Q. Tian, "Person Re-identification in the Wild", CVPR, 2017.

1. Benchmark Solution – PRW

Comparison with existing re-id datasets

Datasets	#frame	#ID	#anno. Box	#box/ID	#gallery box	#cam
PRW	11,816	932	34,304	36.8	100-500k	6
Market-1501	0	1,501	25,259	19.9	19,732	6
RAiD	0	43	6,920	160.9	6,920	4
VIPeR	0	632	1,264	2	1,264	2
i-LIDS	0	119	476	2	476	2
CUHK03	0	1,360	13,164	9.7	13,164	2

1. PRW - Summary

- Summary
  - Extensive benchmark of pedestrian detection and person re-identification
  - Tested on how detection aids re-identification

Existing Dataset vs. Real Ones

Datasets	*Duke*	*Market*	*CUHK03*	*CUHK01*	*VIPeR*	**Real World**
BBoxes	36,411	32,668	28,192	3,884	1,264	**1M +**
Identities	1,812	1,501	1,467	971	632	**10K +**
Cameras	8	6	2	10	2	**20 +**
Time Span	Short	Short	Short	Short	Short	**Long**
Scene	Outdoor	Outdoor	Indoor	Indoor	Outdoor	**Outdoor, Indoor**

- Existing public datasets differ from real data
  - Smaller scale
  - Fixed scenes
  - Shot term data, simple lighting condition

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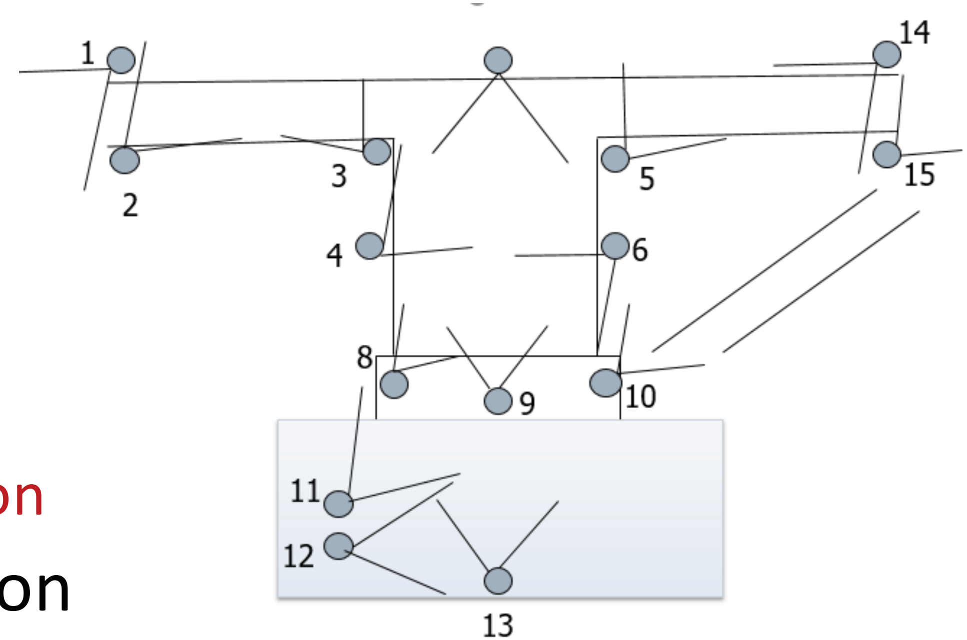
How to push forward the research?

- We need a more realistic dataset
  - **Larger Scales**: more pedestrians, cameras, bboxes
  - **More Complex Scenes**: both indoor and outdoor
  - **Longer Time Spans**: complex lighting changes

1. Benchmark Solution – MSMT17

- 15 cameras
  - 12 outdoor, 3 indoor
- Totally 180 hours video
  - 4 days in one month
  - 3 hours each day: morning, noon, afternoon
- Faster RCNN for detection
- Annotation takes two months
  - 126,411 bounding boxes
  - 4,101 identities, 1041 for training 3060 for testing



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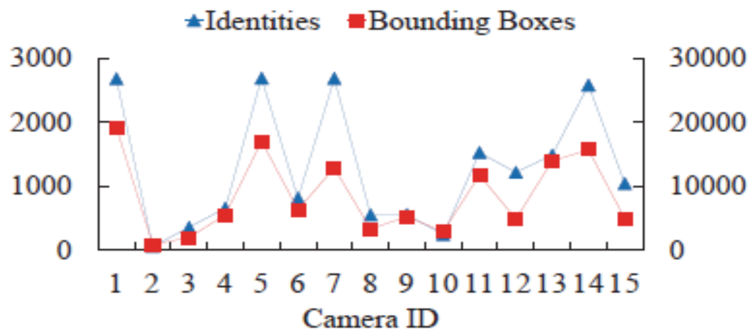
1. MSMT17 - Comparison

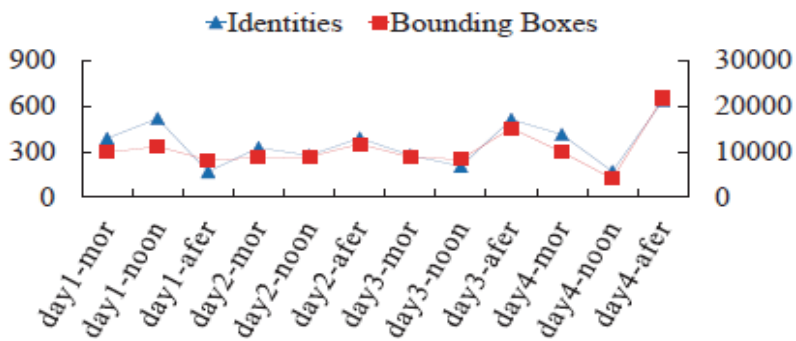
Datasets	MSMT17	Duke	Market	CUHK03	CUHK01	VIPeR	PRID
BBoxes	126,441	36,411	32,668	28,192	3,884	1,264	1,134
Identities	4,101	1,812	1,501	1,467	971	632	934
Cameras	15	8	6	2	10	2	2
Detector	Faster RCNN	Hand	DPM	DPM, Hand	Hand	Hand	Hand
Scene	Outdoor, Indoor	Outdoor	Outdoor	Indoor	Indoor	Outdoor	Outdoor
Time Span	1 month	short	short	short	short	short	short

- Largest size
- Complex scenes and backgrounds
- Multiple time slots
- State-of-the art auto detector

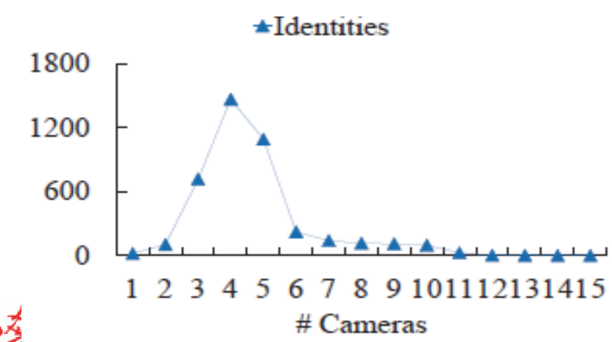
1. MSMT17 – More Statistics



Number of IDs and Bboxes on each camera



Number of IDs and Bboxes in each time slot



Number of IDs across different number of cameras

1. MSMT17 – Samples

1. MSMT17 – Performance

- Tested two of our recent works
  - PDC [ICCV'17], *R-1 88.7% on CUHK03*
  - GLAD [ACM MM'17], *R-1 89.9%, mAP 73.9% on Market*

Methods	R-1	R-5	R-10	R-20	mAP
GoogLeNet [1]	47.6	65.0	71.8	78.2	23.0
PDC [2]	58.0	73.6	79.4	84.5	29.7
GLAD [3]	61.4	76.8	81.6	85.9	34.0

[1] Szegedy, et al., "Going deeper with convolutions", In *CVPR*, 2015.
[2] Su, et al, "Pose- driven deep convolutional model for person re-identification", In *ICCV*, 2017.
[3] Wei, et al. Glad: Global-local-alignment descriptor for pedestrian retrieval. In *ACM MM*, 2017.

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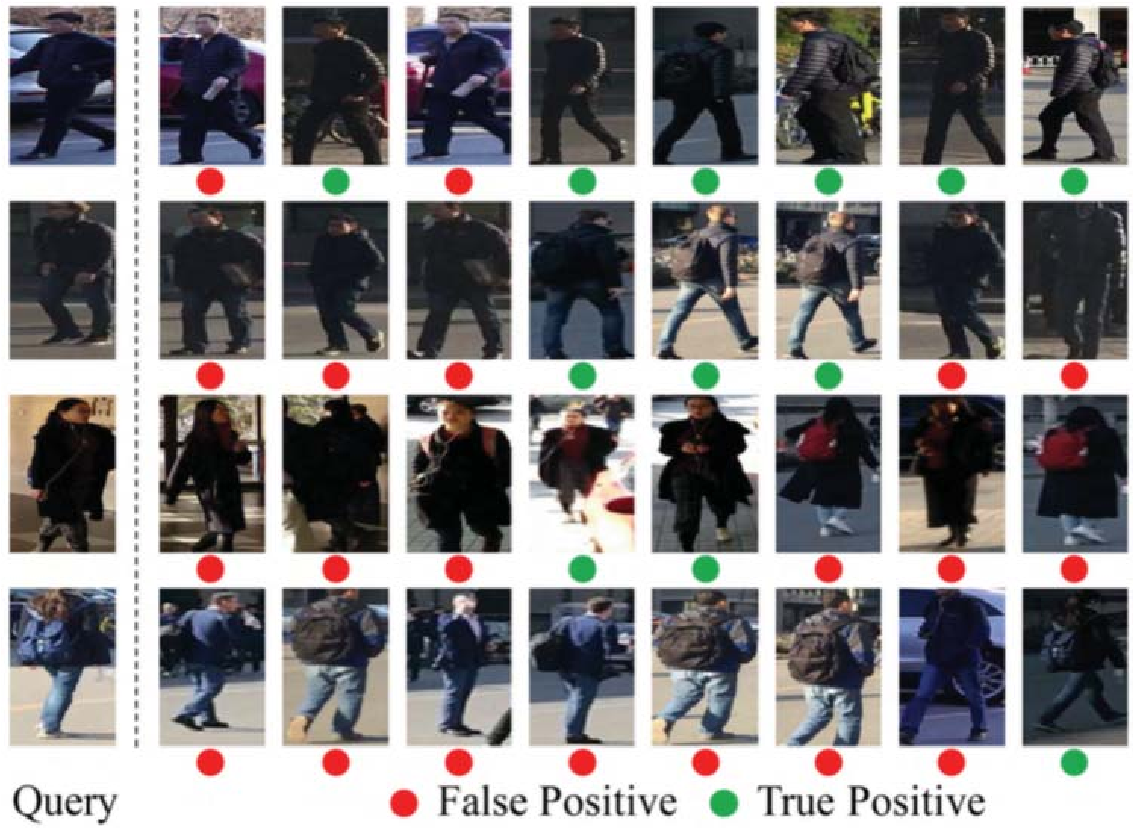
Performance on MSMT17



Sample retrieval results generated by the method of GLAD[1] on MSMT17.

[1] L. Wei, S. Zhang, H. Yao, W. Gao, and Q. Tian, "GLAD: Global-Local-Alignment Descriptor for Pedestrian Retrieval", In *ACM MM*, 2017.

1. MSMT17 - Summary

- Summary
  - Multi scenes, multi time
  - Largest, most challenging dataset
  - Faster RCNN detected boxes
  - A more realistic dataset you should try

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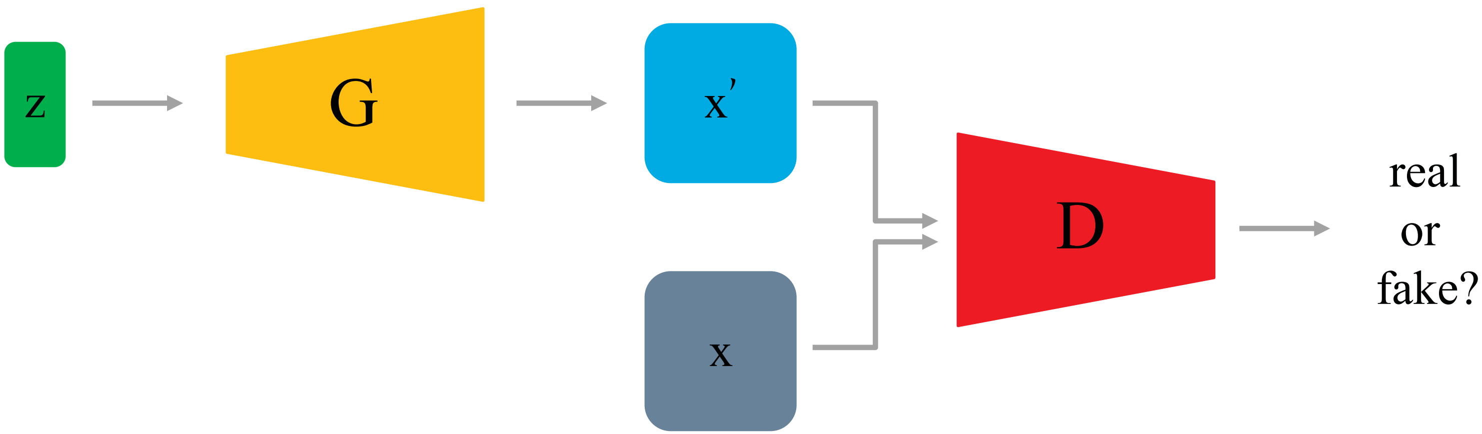
2.1 Overview of GANs

- **Generative Adversarial Nets** (Goodfellow *et al.* NIPS 2014)
  - Minimax two-player game

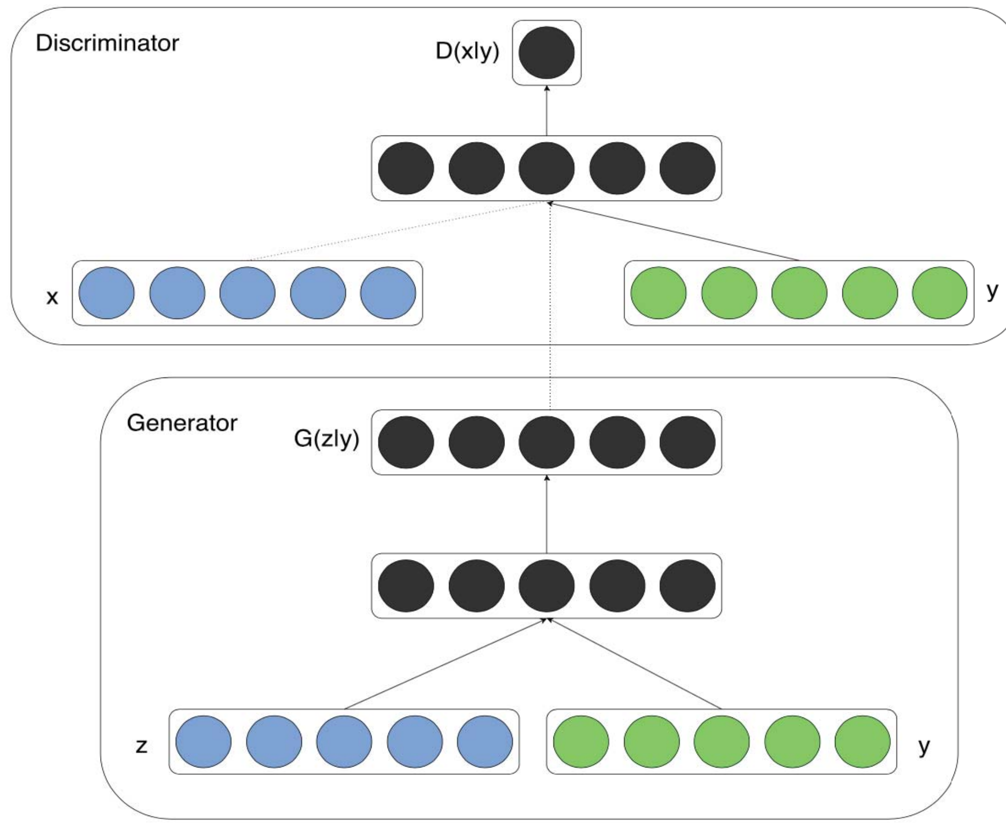


$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x})] + \mathbb{E}_{\boldsymbol{z}\sim p_{\boldsymbol{z}}(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z})))].$$

2.1 Overview of GANs

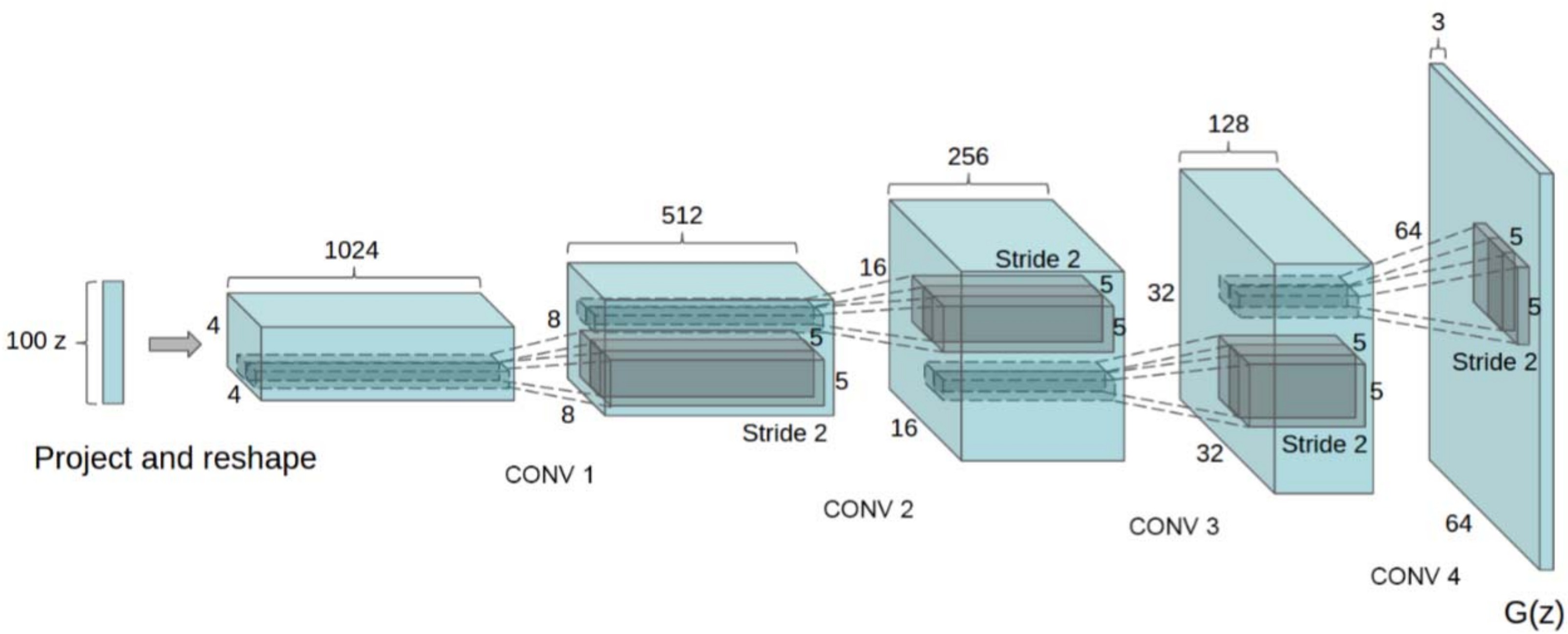
- **Conditional GANs** (Mirza *et al.* Arxiv 2014)
  - Feeding the conditional information to direct the data generation process

$$\min_G \max_D V(D,G) = \mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}(\boldsymbol{x})}[\log D(\boldsymbol{x}|\boldsymbol{y})] + \mathbb{E}_{\boldsymbol{z}\sim p_z(\boldsymbol{z})}[\log(1 - D(G(\boldsymbol{z}|\boldsymbol{y})))]$$



2.1 Overview of GANs

- **DCGANs** (Radford *et al.* ICLR 2016)
  - Propose certain constrains on the architecture topology of Convolutional GANs that make them stable to train
  - The first GAN model to learn to generate high resolution images in a single shot



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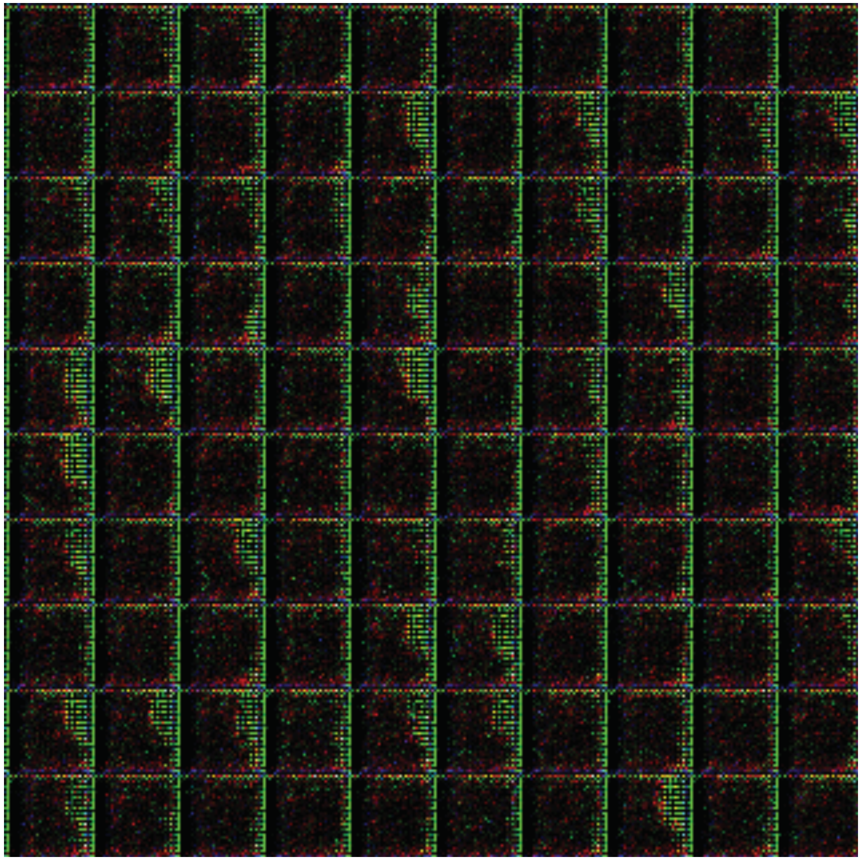
Architecture guidelines for stable Deep Convolutional GANs

- Replace any pooling layers with strided convolutions (discriminator) and fractional-strided convolutions (generator).
- Use batchnorm in both the generator and the discriminator.
- Remove fully connected hidden layers for deeper architectures.
- Use ReLU activation in generator for all layers except for the output, which uses Tanh.
- Use LeakyReLU activation in the discriminator for all layers.

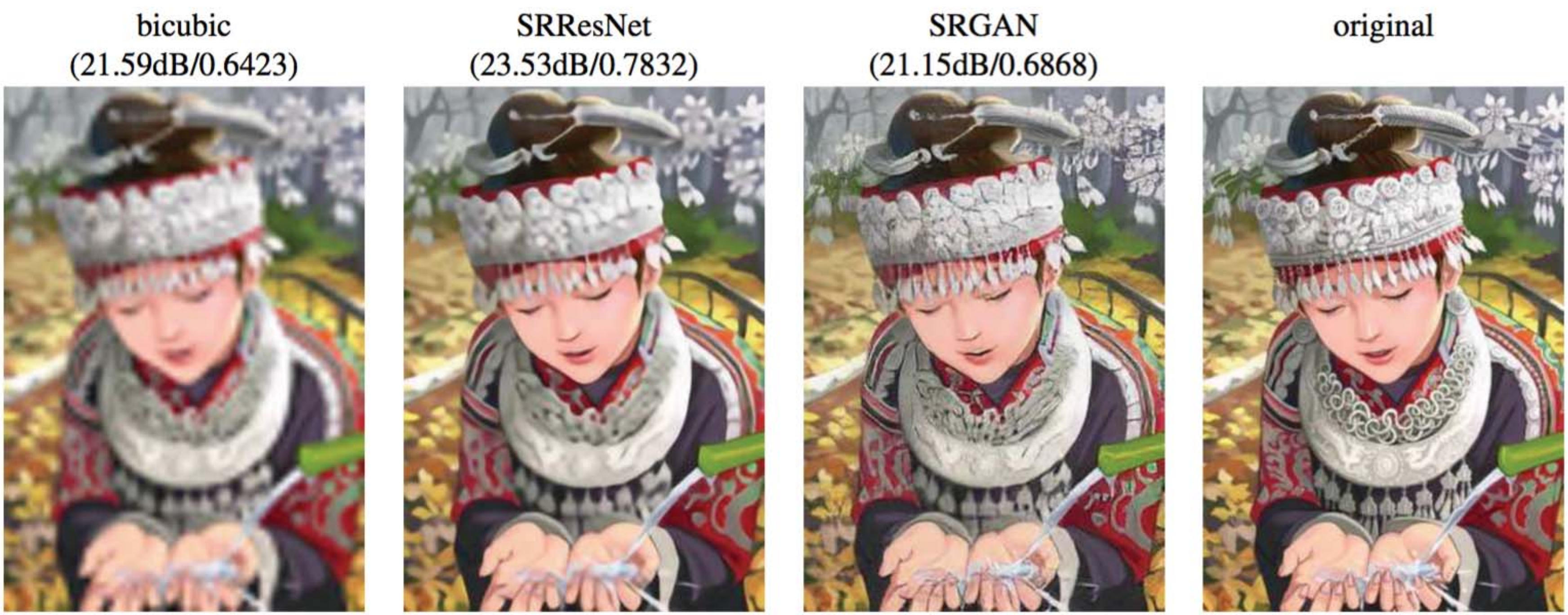
2.1 Overview of GANs

- **DCGANs** (Radford *et al.* ICLR 2016)



2.1 Overview of GANs

- **The Application of GANs in Computer Vision**
  - Image Super-Resolution[1]



[1] C. Ledig et al, “Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial”, in *CVPR*, 2017