











#### **ABSTRACT**

, {v.poncelopez, tb2935, sh1670, dima.damen, a.masullo, m.mirmehdi}@bristol.ac.uk

Deep person Re-ID approach that combines semantically selective, deep data augmentation with clustering-based network compression to generate high performance, light and fast inference networks. Augmented limited training data via sampling from DCGAN, whose discriminator is constrained by a semantic classifier to steer domain-specific adversarial synthesis and feed the ID-CondenseNet training. Variants on a number of datasets, outperforming SOTA for indoor long-term monitoring.

#### 1. Motivation

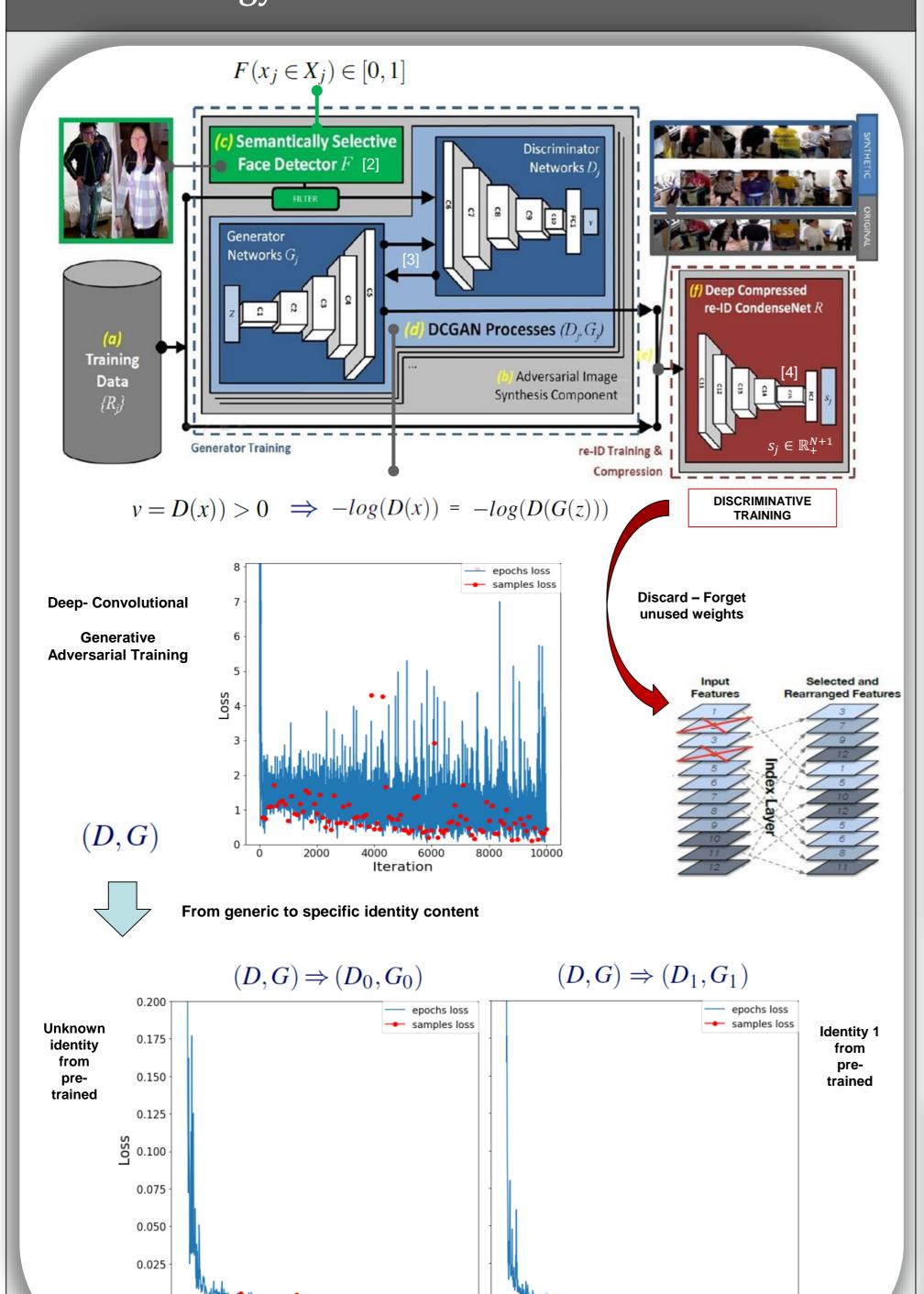
- Person Re-Identification has potential impact applications:
  - CCVT Surveillance.
  - e-health for indoor living environments.



- CV & Practical Challenges:
  - Unobserved intervals, missing relevant images.
  - Varying appearance, clothes, low-resolution, non-frontal shot.
  - **Limited labelled** data.
  - Vast training data pools for deep learning,
  - Computational demand for network inference.

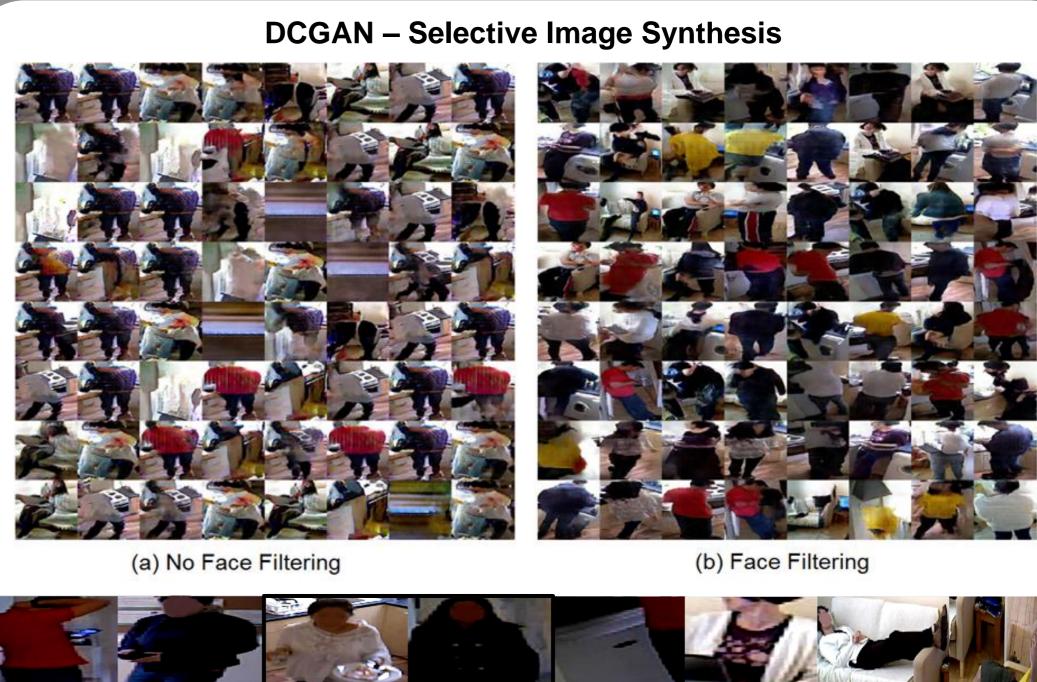


## 2. Methodology & Framework Overview



## 3. Experiments & Results

No Semantic Control





ALL prec@1 | p-ID prec@1 | ALL mAP | p-ID mAP

#### **INDOOR Re-ID RESULTS IN LIMA DATASET [5] - TEST ALL IDENTITIES**

1: Baseline (M2&ME) [14]		89.1		-		-		-		FR → Direct Semantic Control		
2: No Augmentation ( <i>R</i> )		91.98		93.49		90.90	9	96.28		The Direct Community Control		
3: Augmentation $24kG \rightarrow R$		92.43		94.27		91	9	96.95		G → Augmentation via DCGANs		
4: Augmentation $48kG \rightarrow R$		91.74		93.48		90.61	9	96.54		$+G_i$		
Semantic Control via F		ALL prec@1		p-ID prec@1		ALL mA	P p-II	p-ID mAP		∫ Individual-specific		
5: No Augmentation (FR)		82.02		92.14		72.90	9	95.48		gmenta	ation	
6: Augmentation $F322kG \rightarrow R$		92.58		94.57		91.14	9	97.02				
7: $(24kG_0+F24kG_i) \rightarrow R$		92.44		94.37		90.96	9	97.04			Turket a succession of	
Training resi									Training restriction down to only 39%			
	Semantic Contro	Semantic Control via F		@1 p-ID pr	ec@1	ALL mAP	p-ID mAP		L	_	withholds critical	
TEST ON	1. No Augmentation	. No Augmentation (R)		96.	58	93.38	97.73				identity-relevant	
FACE-FILTERED ONLY		2. Augmentation F24kG → R		96.	34	92.94	97.08			L	information	
	3. Augmentation F48	. Augmentation F48kG → R		97.	38	93.58	97.88					
IDO - 0.91 0.07 0.00 0.00 0.02 0.0	0 0.02 0.00 0.00	00 0.00 0.02 0.00	00 0.00 0.70 0.15 0.01 0.01 0		0.02 0.11 0.00	0.92 0.06 0	0.01 0.00 0.01 0.	00 0.00	0.90 0.07 0.00 0.00 0.01 0.01 0.00			
ID1 - 0.01 0.97 0.00 0.00 0.00 0.01 . 0.01 0.98 0.00 0				00 0.00 0.00 0.00			0.01 0.00 0.01		0.00 0.00 0.00 0.		0.01 0.97 0.00 0.00 0.00 0.00 0.01	
S		_		00 0.00 0.00 0.00		00 0.00 0.95 0.00	0.00 0.00 0.05		0.99 0.00 0.00 0.		0.00 0.00 0.99 0.00 0.00 0.00 0.00 -0.6	
0 103 001 006 000 093 000 000 000 001 001 002 000 0				00 0.98 0.00 0.00		02 0.03 0.05 0.07			0.00		0.01 0.06 0.00 0.92 0.00 0.00 0.00	
IDS . 0.02 0.01 0.00 0.02 0.00 0.9	_			00 0.02 0.01 0.94		03 0.01 0.00 0.04			0.00 0.02 0.00 0.		003 003 000 000 000 000	
ID6 - 0.02 0.01 0.01 0.03 0.07 0.0	4 0.82 _ 0.03 0.01 0.02 0.04	4 0.06 0.02 0.82	0.02 0.01 0	01 0.04 0.06 0.02	0.83	02 0.00 0.03 0.02	0.09 0.06 0.78	0.03 0.02 0	0.01 0.03 0.04 0.	01 0.87	003 001 001 005 004 001 005	
Predicted labels												
	Method / No	Samantia	Control	prec@1	prec@	5 mAP	CMC@1	80 1	mAP S-Q	0.85		
OUTDOOR Re-ID	1: Baseline Bo			prec@1	prec@	3 IIIAF	25.13		12.17	0.8		
RESULTS IN		2: Baseline LOMO + XQDA [31]			-	-	30.75		17.04	0.75		
DukeMTMC	3: No Augmen	ntation (R)		87.70	95.54	87.79	29.04	1	15.99	0.65 0.6		
WITH Market1501		tion $24kG \rightarrow R$		88.08	95.73		36.45		21.11	0.55		
CROSS-		$4k(Market1501)G \rightarrow R$		88.84	95.82	88.64	35.95		20.6	0.45	1	
SUPPORT	SUPPORT 6: ResNet50-			-	-	-	67.68	3	47.13	0.35	10 20 30 40 50 Top 50 classes	

### 4. Conclusion & Future Hints

Deep compact Re-ID approach with semantically controlled data augmentation and compression for fast inference networks.

8x more parameters and operations required: 600 million more operations to perform inference on a single image [4].

- Face-constrained DCGAN sampling outperform SOTA on LIMA for long-term monitoring, and achieves competitive Re-ID performance.
- Explore generic semantic controllers for the discriminator networks.
- Learn generators from other person-like representations.

# References

0.000

- [1] V. Ponce-López, T. Burdghart, S. Hannuna, D. Damen, A. Masullo, M. Mirmehdi. Semantically Selective Augmentation for Deep Contact Person Re-Identification. arXiv:1806.04074 pre-print, 2018.
- [2] T. Simon, H. Joo, I. Matthews, Y. Sheikh. Hand Keypoint Detection in Single Images using Multiview Bootstrapping. Computer Vision and Pattern Recognition Conference (CVPR), 2017.
- [3] A. Radford, L. Metz, S. Chintala. Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks. International Conference on Learning Representations (ICLR), 2015. [4] G. Huang, S. Liu, L.-v.-d. Maaten, K,-Q. Weinberger. CondenseNet: An Efficient DenseNet using Learned Group Convolutions. arXiv preprint arXiv:1711.09224, 2017.
- [5] R. Layne, S. Hannuna, M. Camplani, J. Hall, T.-M. Hospedales, T. Xiang, M. Mirmehdi, D. Damen. A dataset for persistent multi-target multi-camera tracking in RGB-D. In CVPR Workshops, pages 1462–1470, 2017.
- [31] L. Zheng, L. Shen, L. Tian, S. Wang, J. Wang, Q. Tian. Scalable person re-identification: A benchmark. International Conference on Computer Vision (ICCV), pages 1116–1124, Dec 2015. [33] Z. Zheng, L. Zheng, Y. Yang. Unlabeled samples generated by GAN improve the person re-identification baseline in vitro. International Conference on Computer Vision (ICCV), pages 3754–3762, 2017.



R → Deep CondenseNet

