Visual Person Understanding through Multi-Task and Multi-Dataset Learning

Kilian Pfeiffer, Alexander Hermans, István Sárándi, Mark Weber, and Bastian Leibe

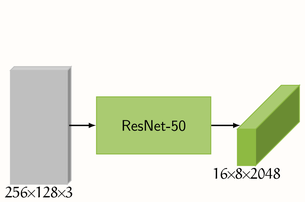
Visual Computing Institute, RWTH Aachen University

Summary

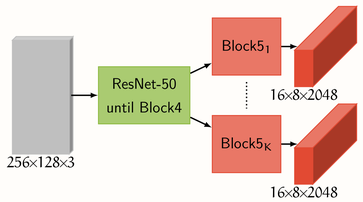
- Mobile vision applications need to perform many person-related tasks. We focus on:
  - Person re-identification (Market-1501)
  - Body part segmentation (LIP)
  - Human pose estimation (MPII, LIP)
  - Attribute classification: gender, clothing etc. (Market-1501)
- These tasks are interdependent and mobile platforms are resource-constrained:
  $\longrightarrow$ Joint multi-task learning is needed.
- There exists no single dataset that provides annotations for all tasks:
  $\longrightarrow$ Option 1: Generate pseudo-labels for a single dataset.
  $\longrightarrow$ Option 2: Combine multiple datasets during training.
- We investigate architectural design choices and their effects on joint training, compared to single-task baselines and the state-of-the-art.

Architecture

How much to share among tasks?

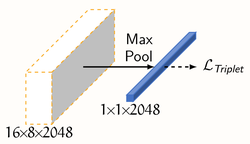


Single-branch backbone $\mathcal{M}^{SB}$

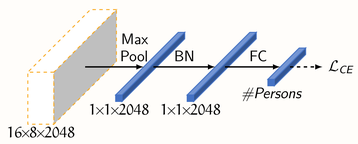


Multi-branch backbone $\mathcal{M}^{MB}$

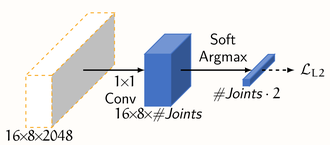
Individual Task Heads



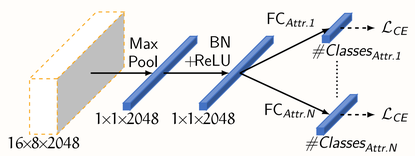
Triplet ReID embedding head



Person classification head

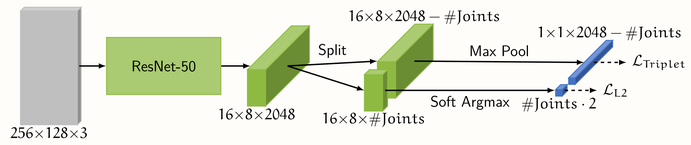


Pose estimation head



Attribute classification head

ReID task ↯ ↯ Pose task



Split ReID and pose head to avoid interference.

Automatic Annotations

Automatic annotations on the Market-1501 dataset for pose estimation (top) and part segmentation (bottom).

Qualitative Results

Given person detections, we can perform all tasks simultaneously with 50 detections/s.

Results

Automatic Annotations

	Tripl.	Clas.	Attr.	Pose	Seg.	Market Manual/Auto	Market ReID mAP	Market Attr. acc	MPII Pose PCKh	LIP Pose PCKh	LIP Segmentation mIoU	LIP Segmentation mIoU$_5$
$\mathcal{M}^{SB}$	✓			✓	✓		78.6	–	30.8	22.4	–	49.6
	✓	✓	✓	✓	✓		79.2	88.0	28.8	21.3	–	47.9
$\mathcal{M}^{MB}$	✓			✓	✓		77.7	–	40.4	28.4	–	47.9
	✓	✓	✓	✓	✓		78.2	87.9	39.7	28.1	–	46.7
Baseline							77.4	88.2	46.9	29.9	–	48.7

Multi-Dataset Learning

	Tripl.	Clas.	Attr.	Pose	Pose	Seg.	Training Market	Training MPII	Training LIP	Market ReID mAP	Market Attr. acc	MPII Pose PCKh	LIP Pose PCKh	LIP Segmentation mIoU	LIP Segmentation mIoU$_5$
$\mathcal{M}^{SB}$	✓			✓	✓	✓				78.0	–	86.8	74.3	49.9	71.8
	✓	✓	✓	✓	✓	✓				78.3	87.1	86.7	73.8	49.6	71.6
$\mathcal{M}^{MB}$	✓			✓	✓	✓				77.9	–	86.9	75.0	48.5	71.6
	✓	✓	✓	✓	✓	✓				—— out of GPU memory ——					
$\mathcal{M}^{SB/Split}$	✓	✓	✓	✓	✓	✓				79.1	86.7	86.5	74.4	49.6	71.6
Baselines										77.4	88.2	86.6	73.9	47.8	71.0
SOTA										86.9[5]	89.7[3]	88.5[4]	82.5[2]	54.4[1]	-

Findings and Conclusions

- GroupNorm > BatchNorm for multi-dataset training.
- Using more training data is beneficial.
- Synergy effects between tasks:
  - ReID & Part Segmentation
  - ReID & Attribute
  - Pose & Part Segmentation

Acknowledgements

This project was funded, in parts, by ERC Consolidator Grant project "DeeViSe" (ERC-CoG-2017-773161) and the BMBF projects "FRAME" (16SV7830) and "PARIS" (16ES0602). Istvan Sarandi's research is funded by a grant from the Bosch Research Foundation. Most experiments were performed on the RWTH Aachen University CLAIX 2018 GPU Cluster.

References

[1] Jin, X., Lan, C., Zeng, W., Zhang, Z., Chen, Z.: CaseNet: Content-Adaptive Scale Interaction Networks for Scene Parsing. arXiv:1904.08170 (2019)

[2] Liang, X., Gong, K., Shen, X., Lin, L.: Look into Person: Joint Body Parsing & Pose Estimation Network and a New Benchmark. PAMI **41**(4), 871–885 (2018)

[3] Liu, H., Wu, J., Jiang, J., Qi, M., Bo, R.: Sequence-based Person Attribute Recognition with Joint CTC-Attention Model. W:1811.08115 (2018)

[4] Yang, W., Li, S., Ouyang, W., Li, H., Wang, X.: Learning Feature Pyramids for Human Pose Estimation. In: ICCV (2017)

[5] Zheng, F., Deng, C., Sun, X., Jiang, X., Guo, X., Yu, Z., Huang, F., Ji, R.: Pyramidal Person Re-IDentification via Multi-Loss Dynamic Training (2019)