

Fine-tuning for one-look regression vehicle counting in low-shot aerial datasets

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Outline

- Project overview
- Existing approaches
- Methods
- Experiments and results



Project Overview

- Regress the count of vehicles present in PUCPR+ and CARPK
- PUCPR+:
 - Training: 100 images
 - Test: 25 images
- CARPK:
 - Training: 989 images
 - Test: 459 images



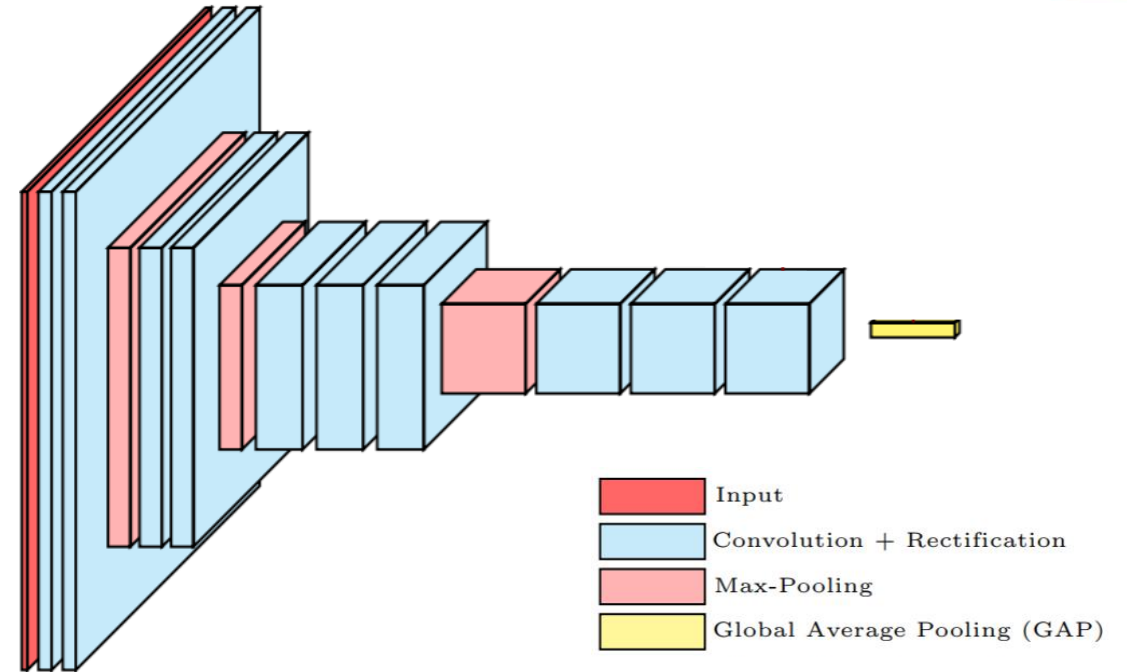
Existing Approaches

- Broadly classified into two categories:
 - Counting by detection
 - Counting by regression



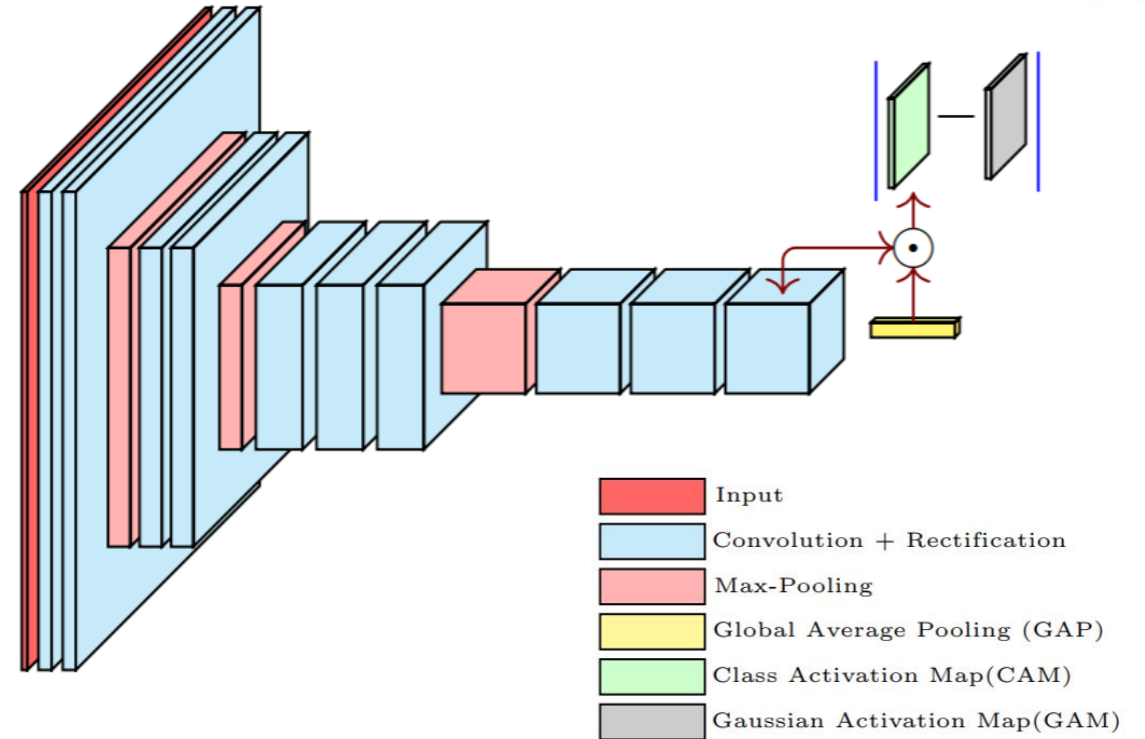
Existing Approaches

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- We focus on counting by regression:
 - Heatmap Regulation



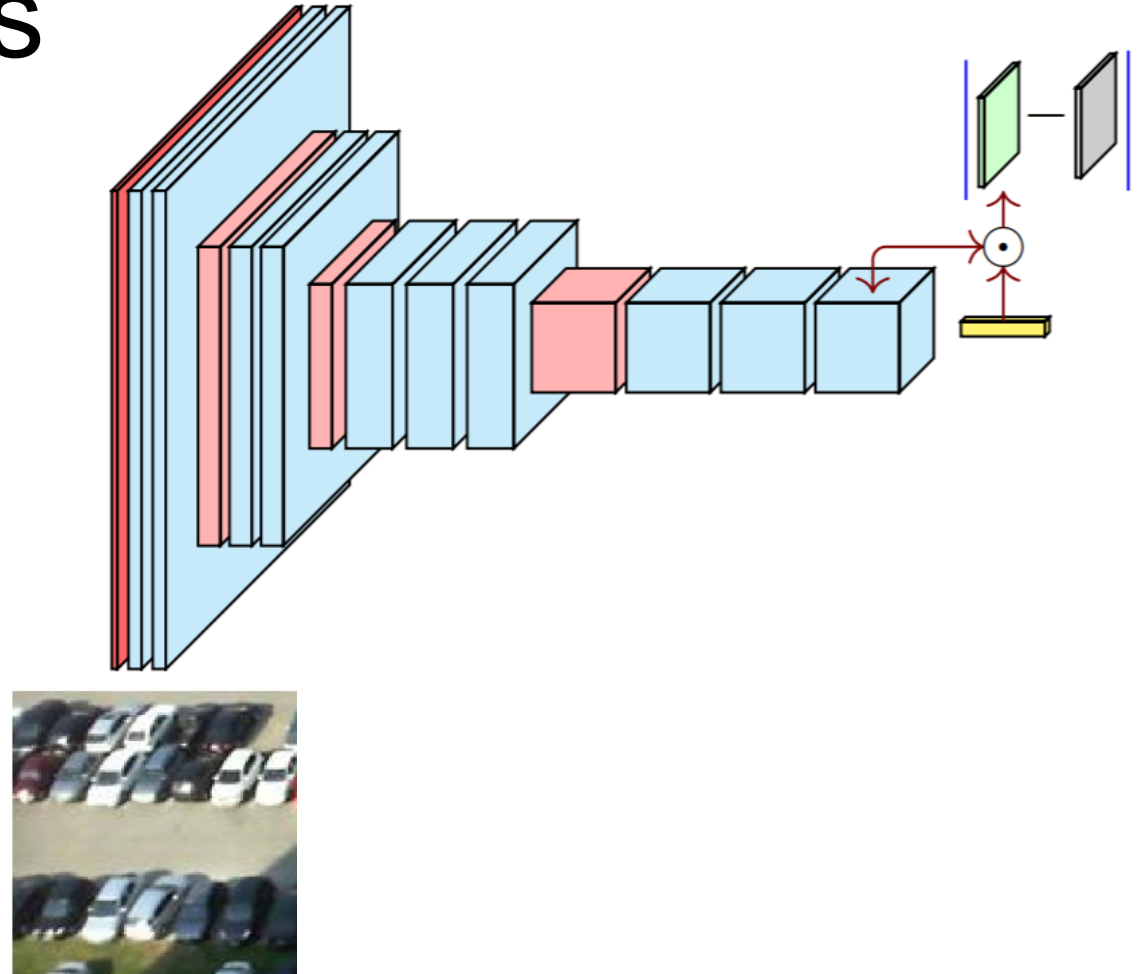
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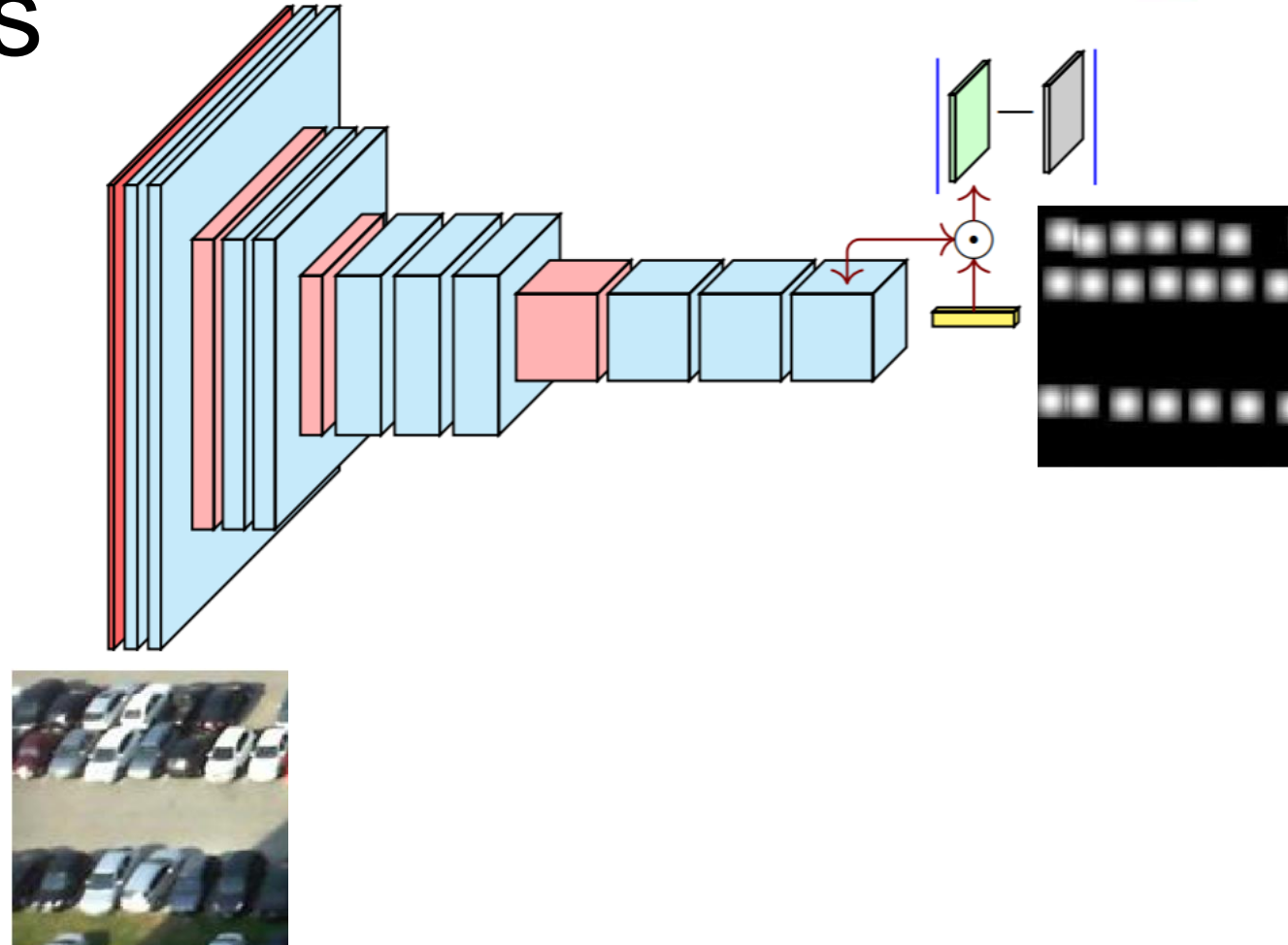
Existing Approaches

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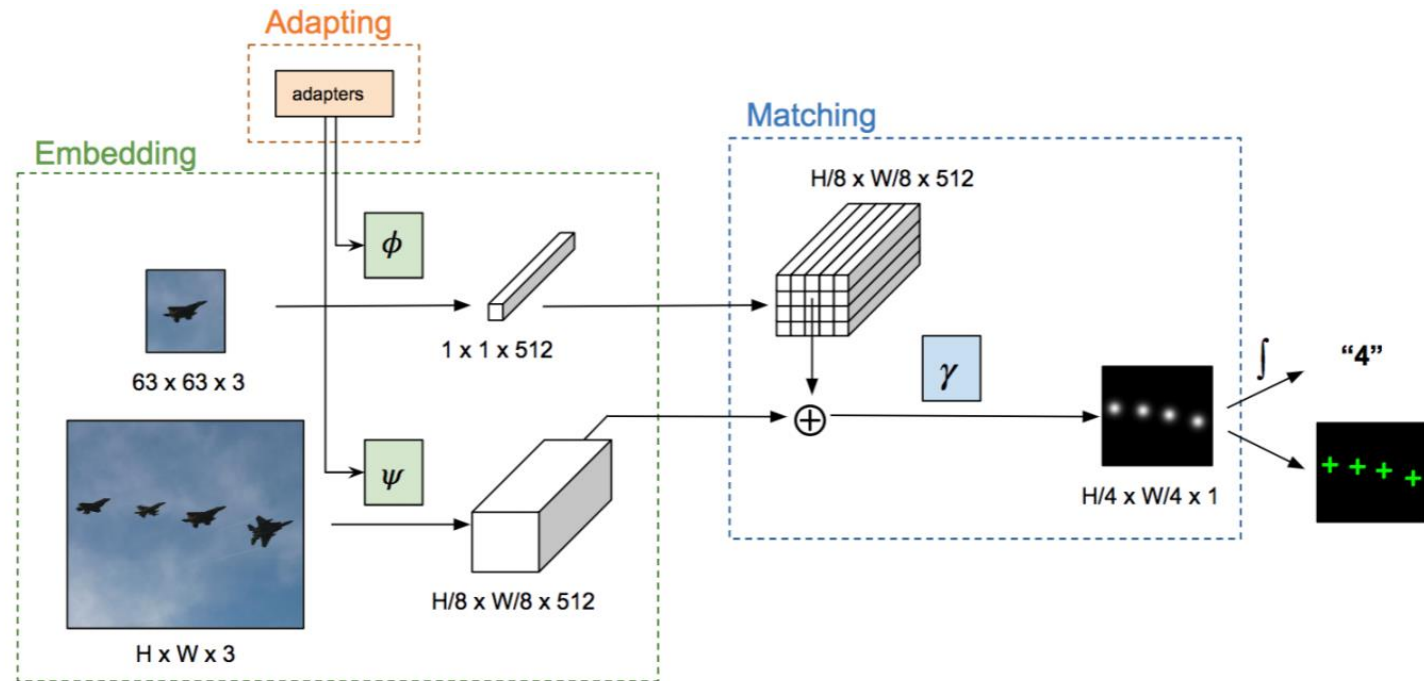
Existing Approaches

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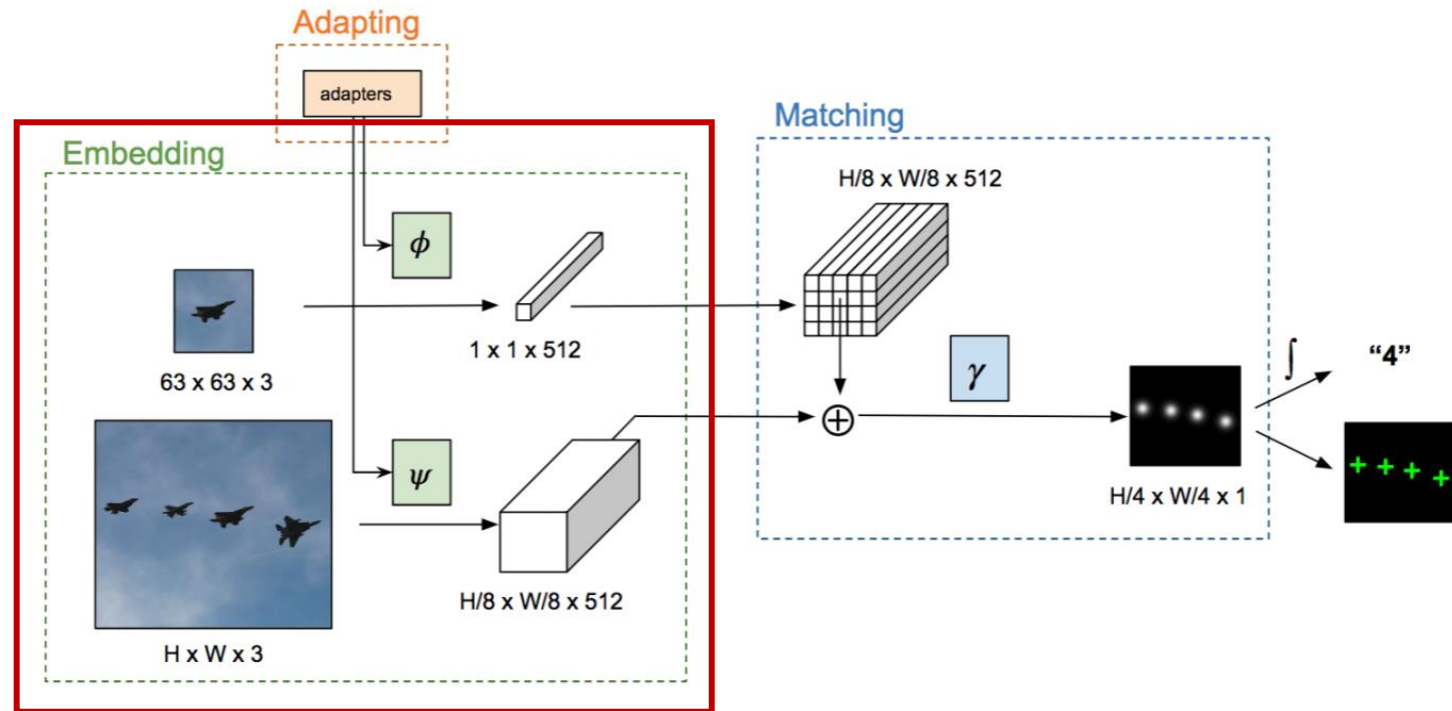
Existing Approaches

- Broadly classified into two categories:
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- We focus on counting by regression:
 - Heatmap Regulation
 - Class Agnostic Counting



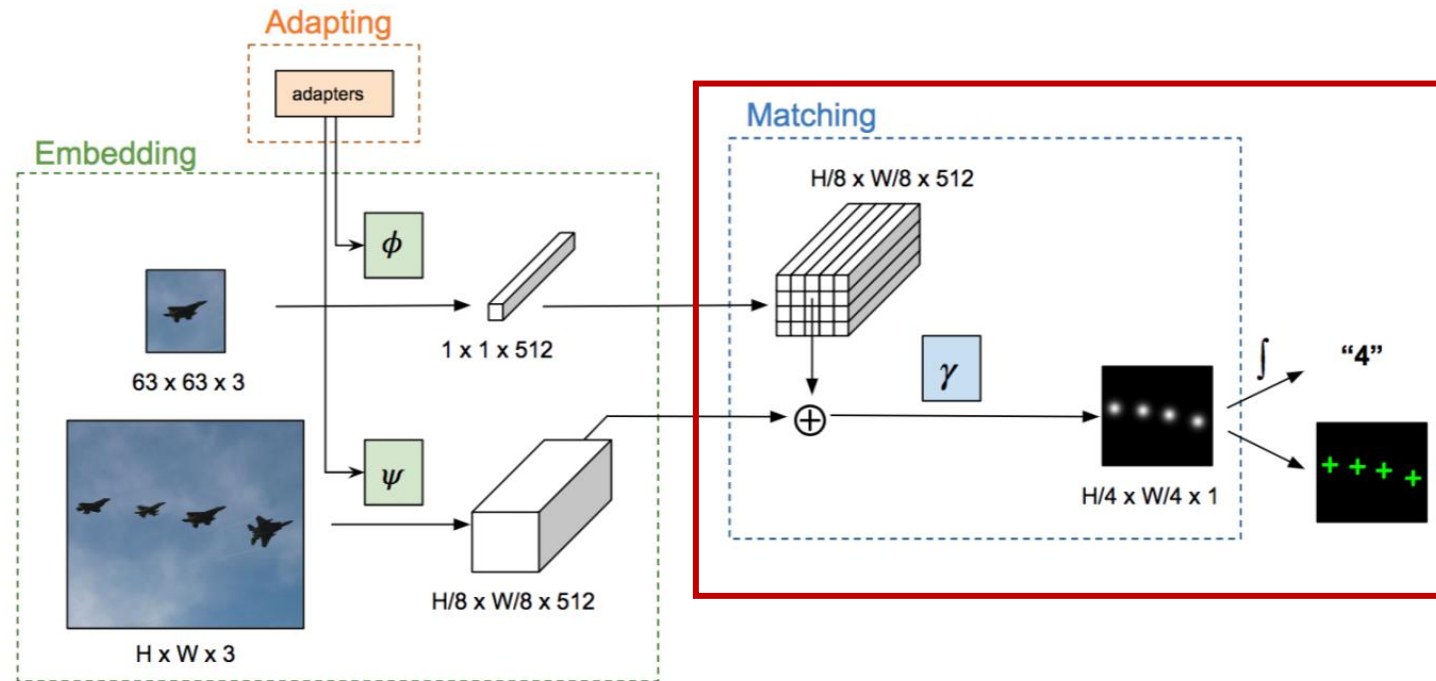
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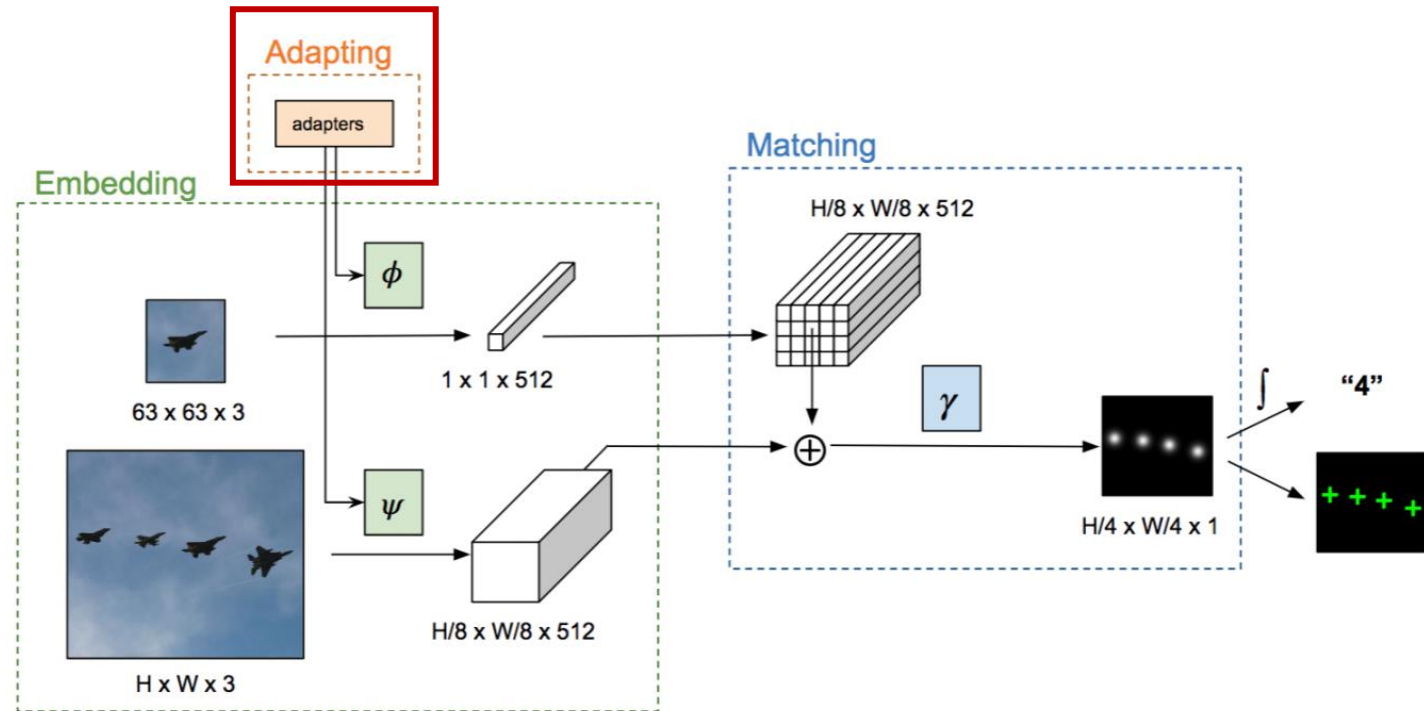
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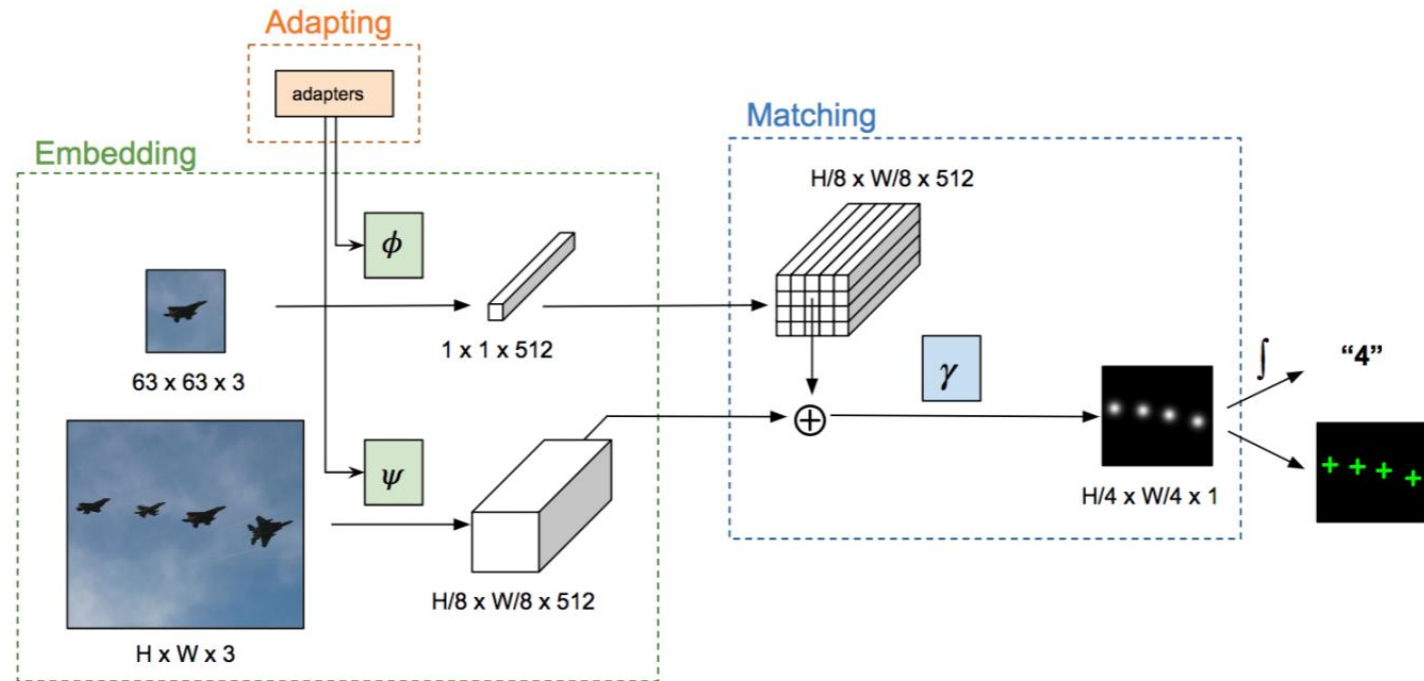
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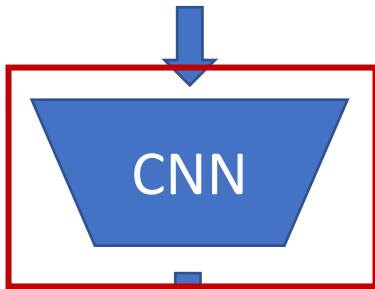


Existing Approaches

- Broadly classified into two categories:
 - Counting by detection
 - Counting by regression
- We focus on counting by regression:
 - Heatmap Regulation
 - Class Agnostic Counting
- However, both approaches rely on using localization information



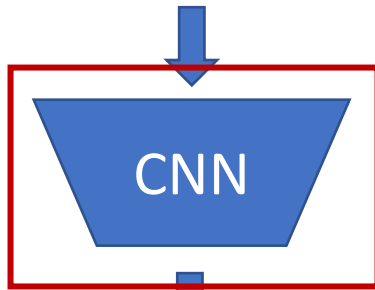
Methods



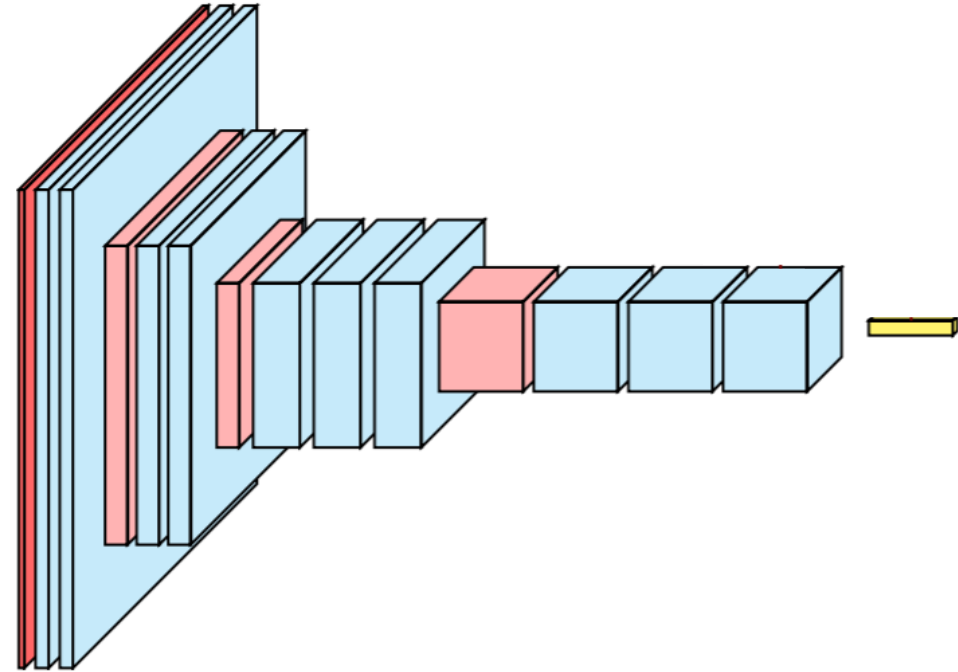
145



Methods



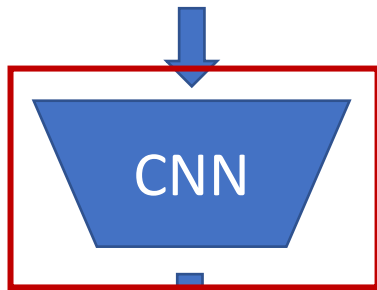
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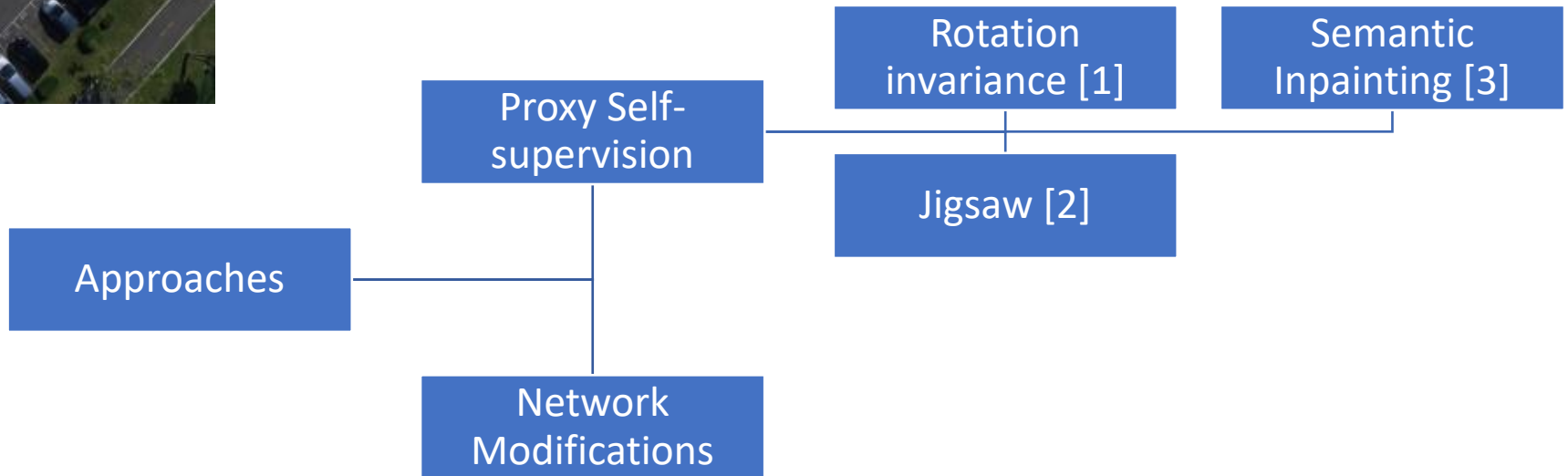
Aich, Shubhra, and Ian Stavness. "Improving object counting with heatmap regulation." European conference on computer vision. 2018..



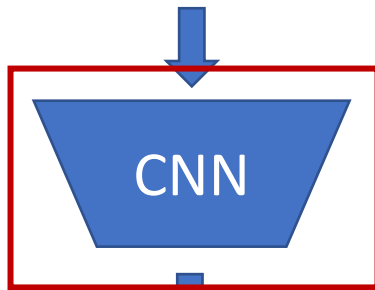
Methods



145

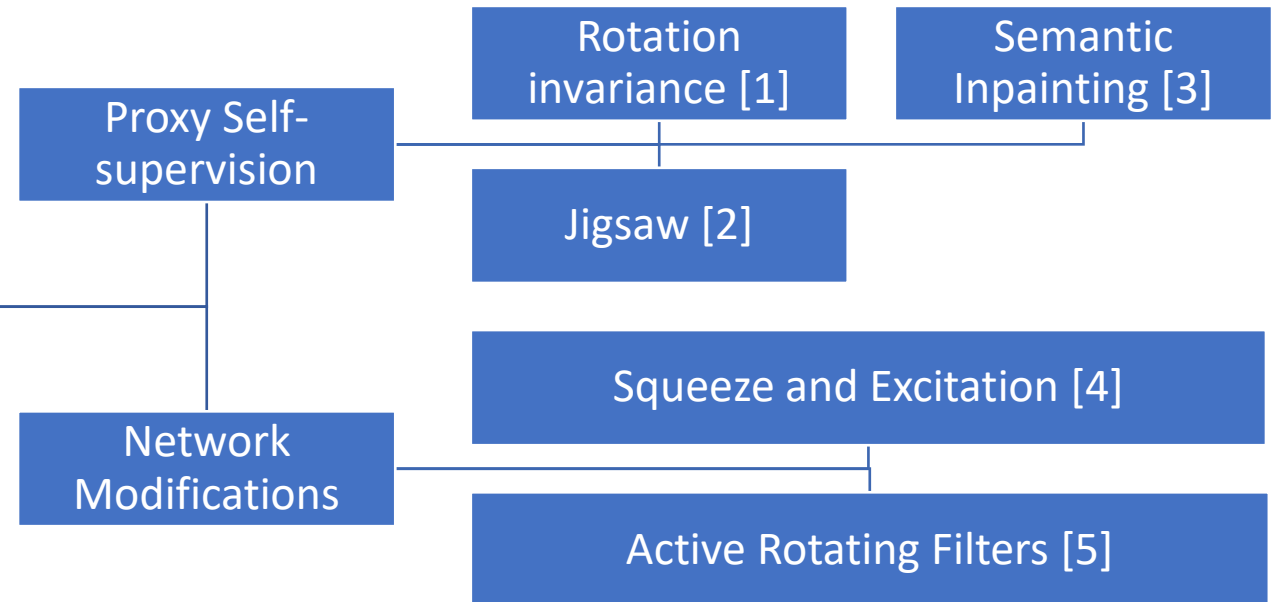


Methods



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Approaches



Methods

- Proxy self-supervision tasks



Methods

- Proxy self-supervision tasks
 - Rotation invariance



0|90|180|270?



Methods

- Proxy self-supervision tasks
 - Rotation invariance



0|90|180|270?



Methods

- Proxy self-supervision tasks
 - Rotation invariance

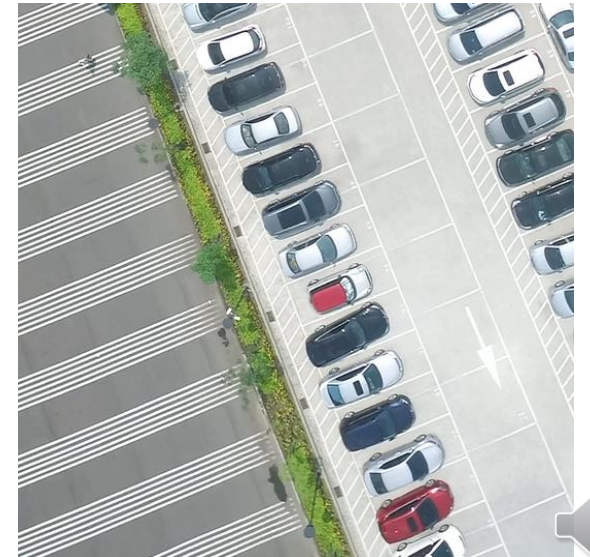
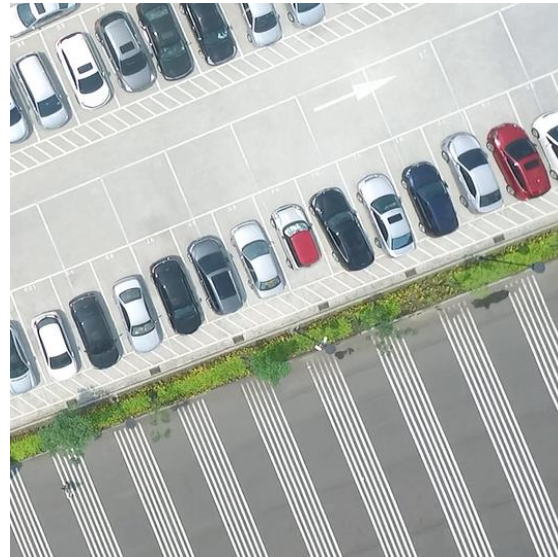
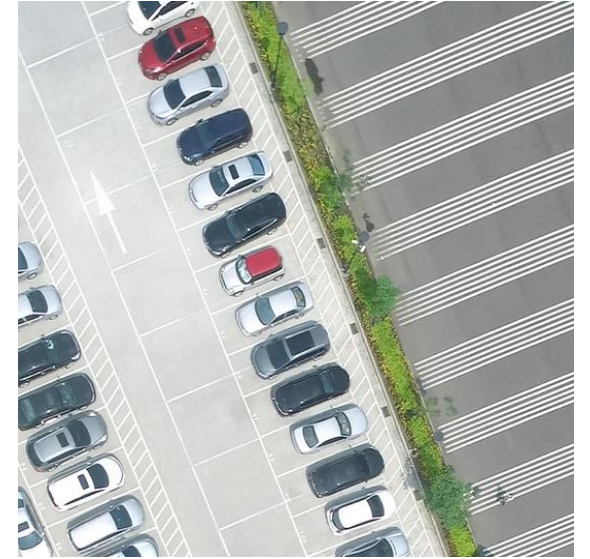
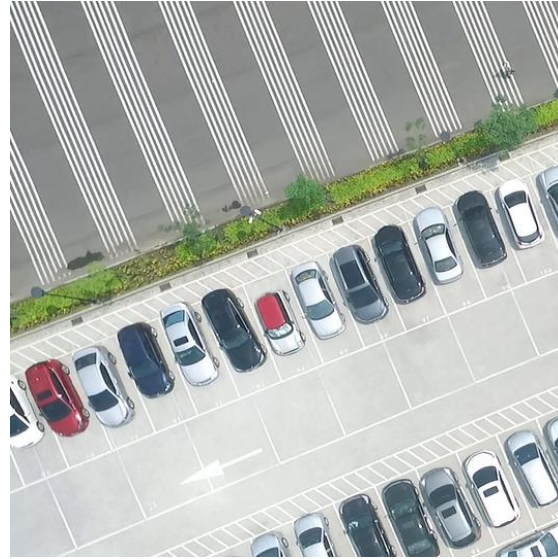


0|90|180|270?



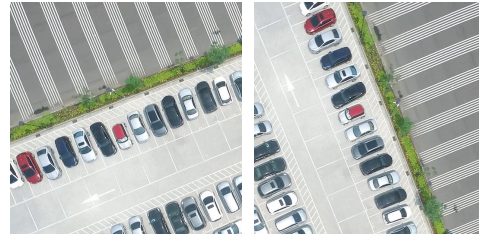
Methods

- Proxy self-supervision tasks
 - Rotation invariance



Methods

- Proxy self-supervision tasks
 - Rotation invariance

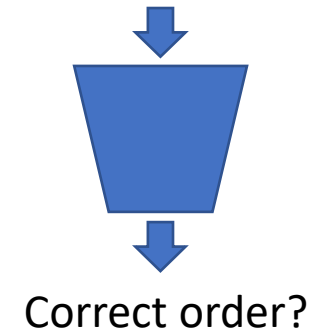
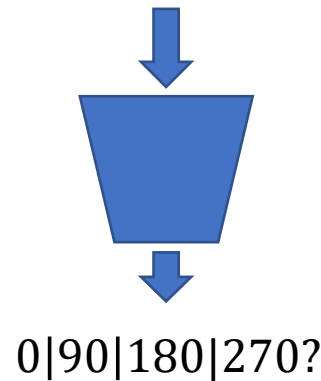
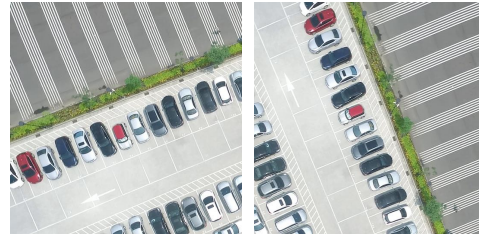


0|90|180|270?



Methods

- Proxy self-supervision tasks
 - Rotation invariance
- Jigsaw



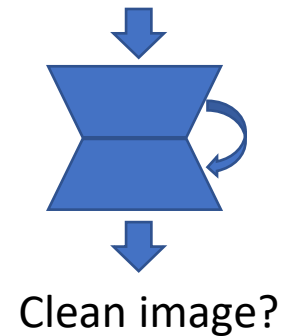
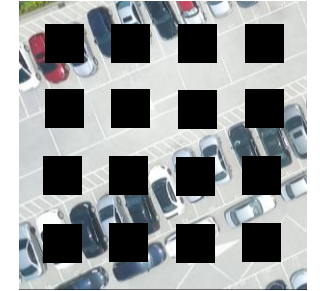
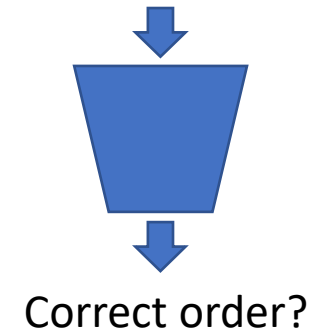
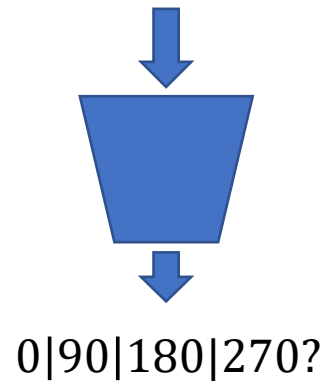
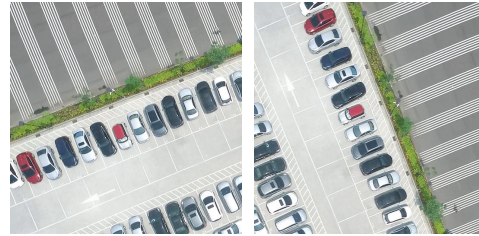
Methods

- Proxy self-supervision tasks

- Rotation invariance

- Jigsaw

- Semantic Inpainting



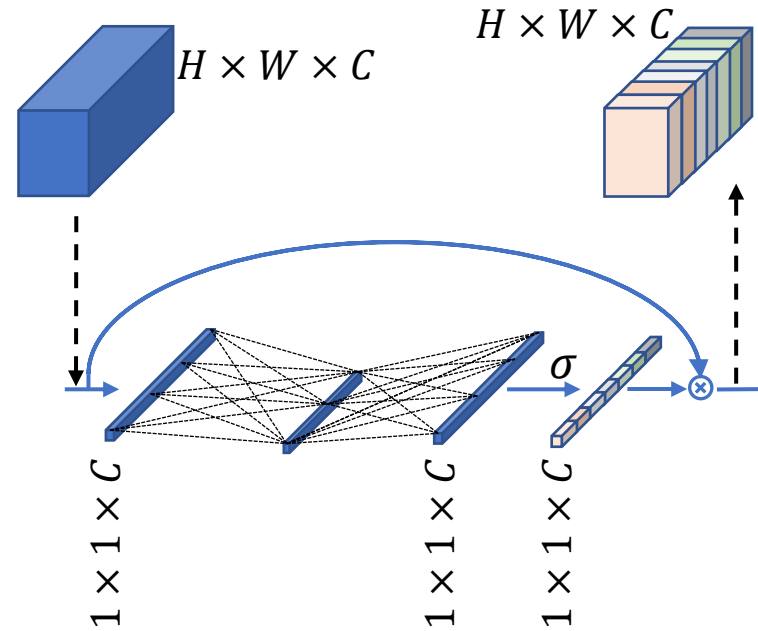
Methods

- Network modifications



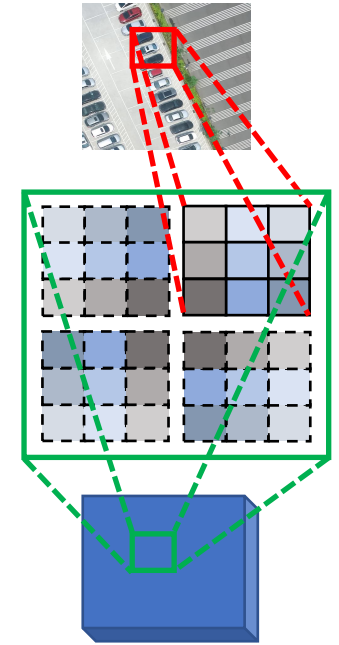
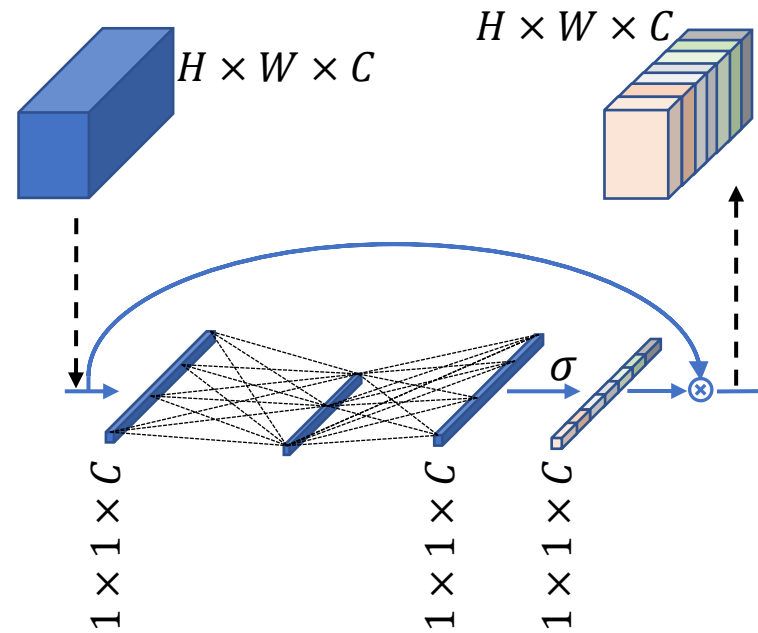
Methods

- Network modifications
 - Squeeze and excitation block network



Methods

- Network modifications
 - Squeeze and excitation block networks
- Active Rotating Filter



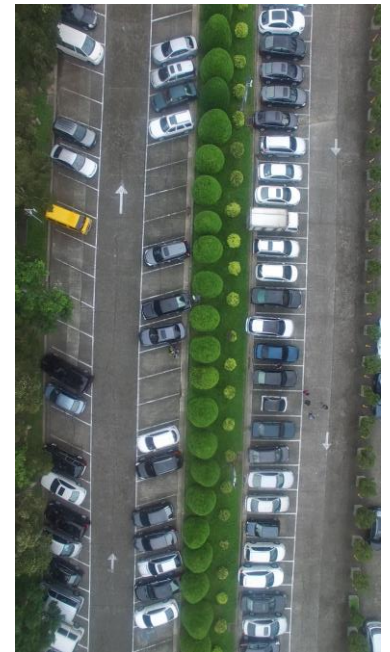
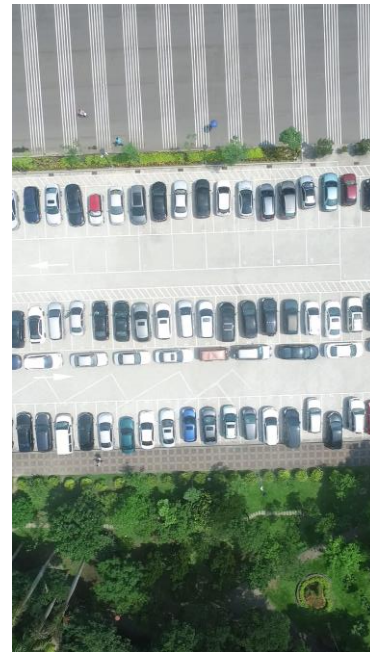
Results

Task/Blocks	PUCPR+				CARPK			
	MAE	RMSE	Over-est (%)	Under-est (%)	MAE	RMSE	Over-est (%)	Under-est (%)
VGG-16								
Pretrained	5.84	8.51	2.58	1.15	6.88	9.40	0.85	5.80
Rotation	3.72	6.32	1.00	1.38	7.81	10.02	2.10	5.45
Jigsaw	4.56	6.07	2.35	0.56	9.05	11.64	3.35	5.40
Inpainting	4.16	6.33	1.96	0.69	6.31	8.25	2.70	3.40
SE Block	5.76	9.50	1.45	2.22	5.93	7.90	1.79	3.94
ARF	4.12	5.84	1.89	0.74	12.38	15.83	0.77	11.99



Results

- Transposed Augmentations for CARPK dataset
- Similar to Random Rotation
- Pretrained VGG:
 - Without: 11.5 ± 1.4
 - With: 6.2 ± 0.6

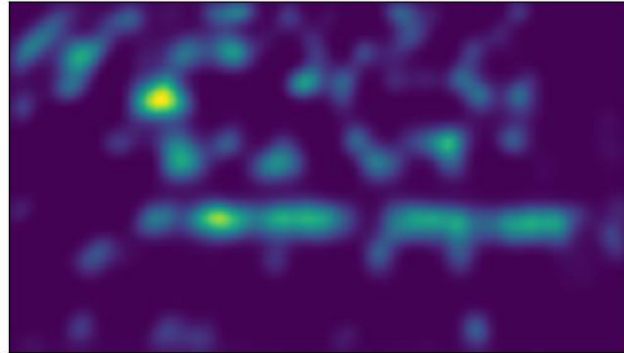


Results PUCPR+

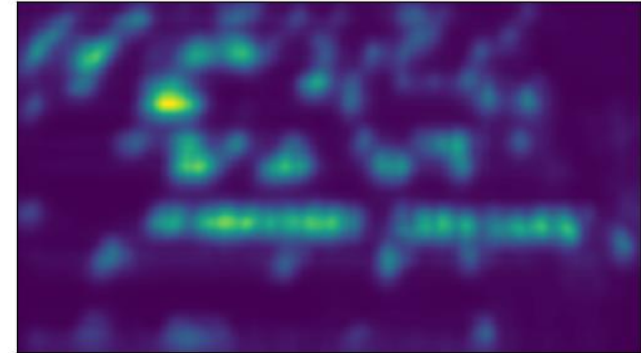
Count: 117



Count: 131.0



Count: 122.0



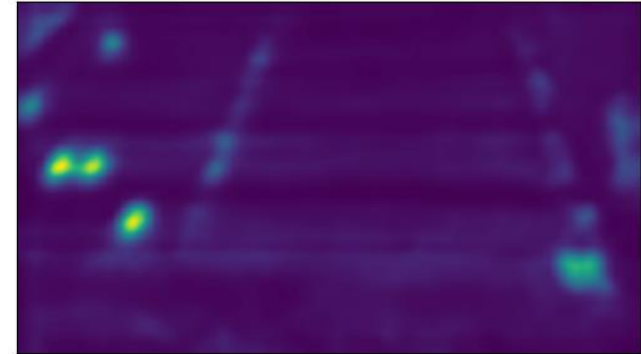
Count: 8



Count: 7.0



Count: 7.0



Images

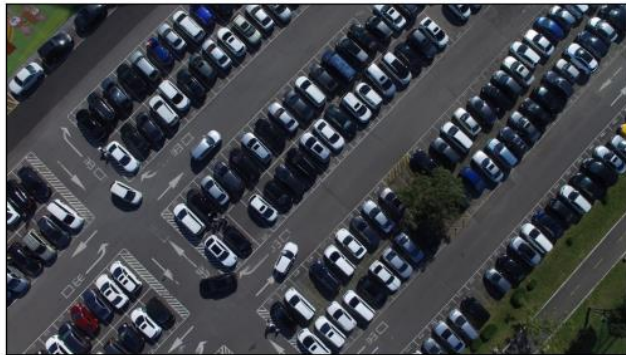
Pretrained

Rotation

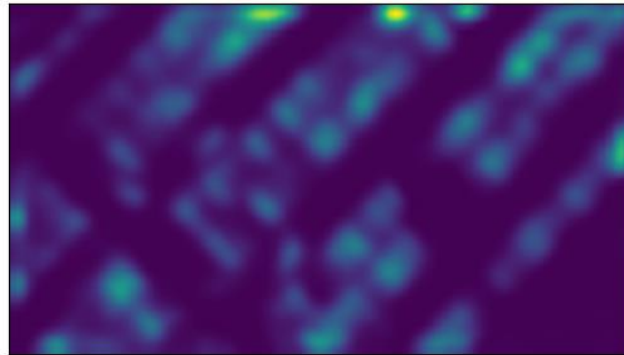


Results CARPK

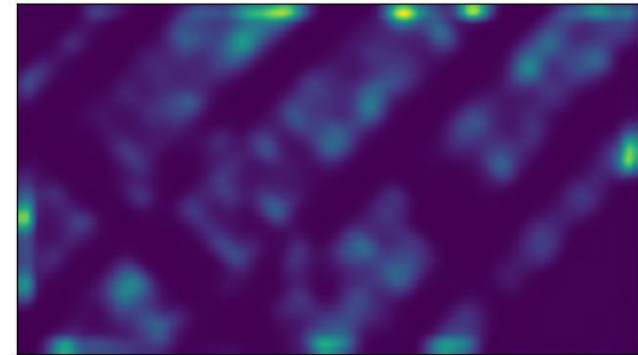
Count: 145



Count: 139.0



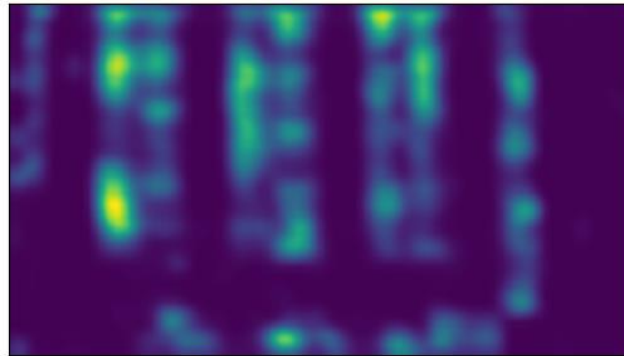
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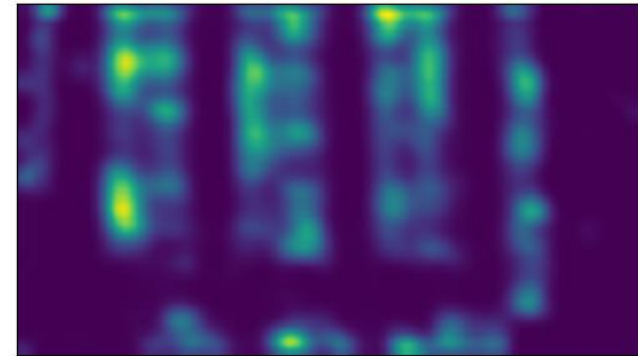
Count: 121



Count: 117.0



Count: 121.0



Images

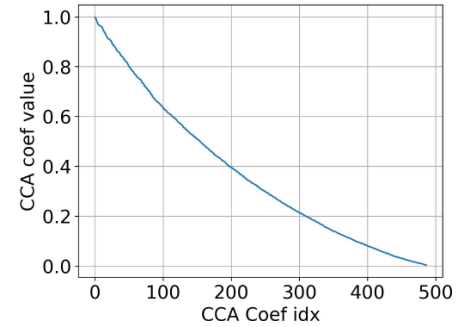
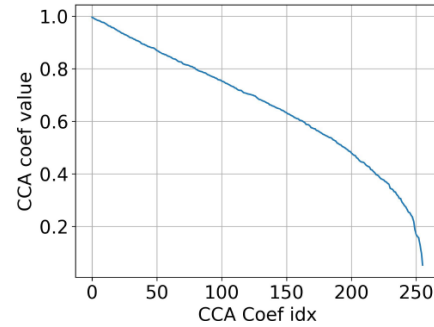
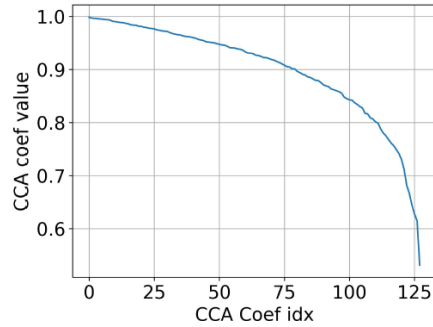
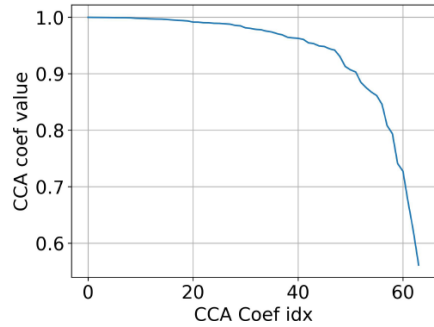
Pretrained

SE blocks

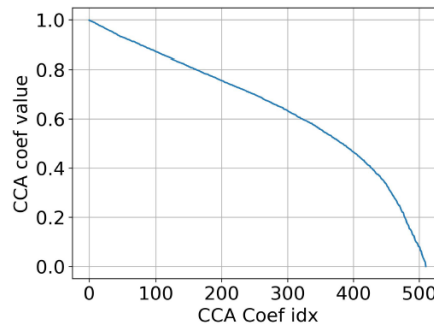
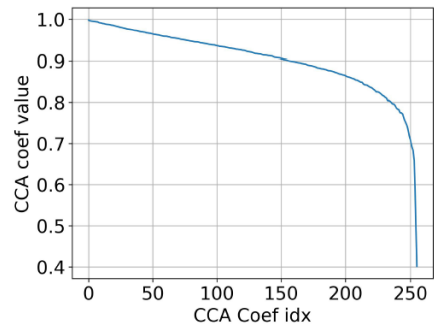
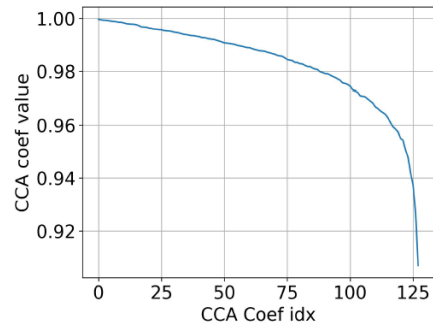
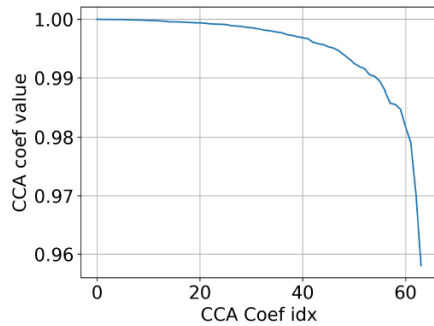


Results

- **SVCCA^[6] – PUCPR+**



- **SVCCA – CARPK**



MaxPool1

MaxPool2

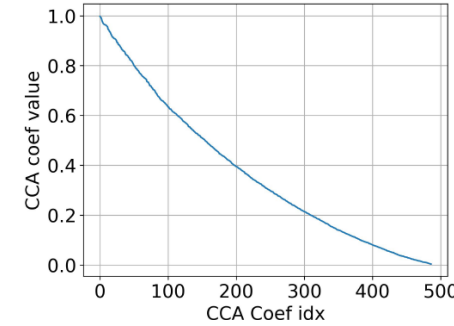
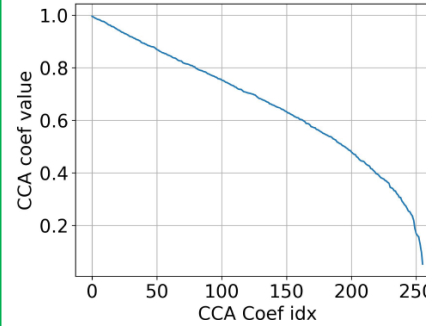
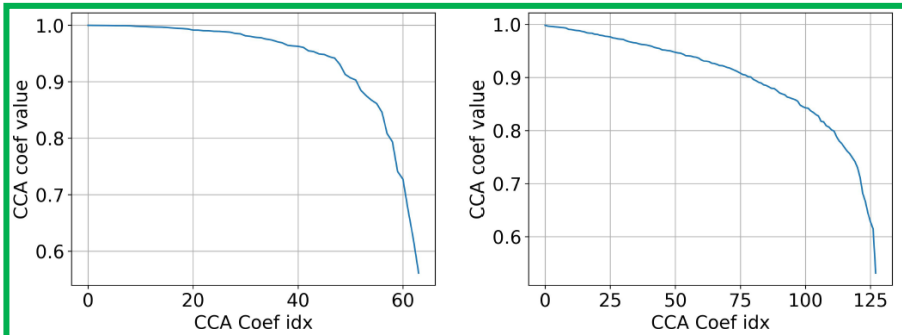
MaxPool3

PreGAP

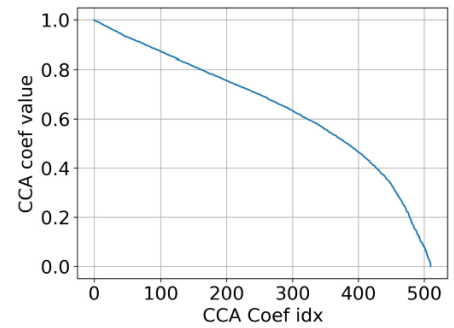
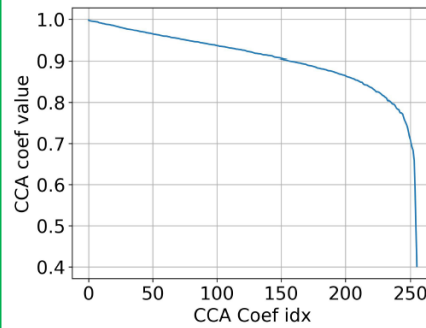
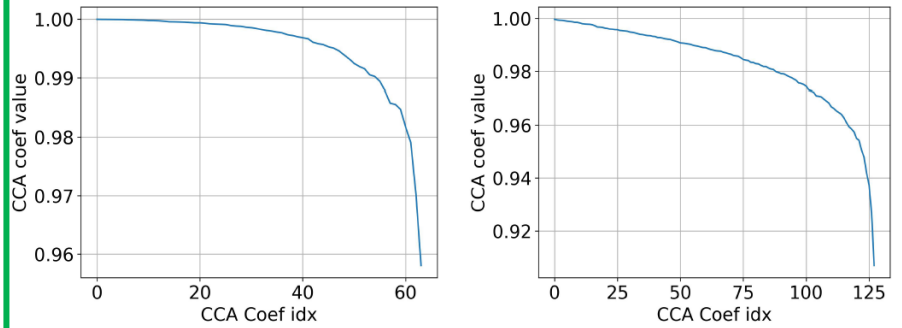


Results

- SVCCA – PUCPR+



- SVCCA – CARPK



High
Corr.

MaxPool1

MaxPool2

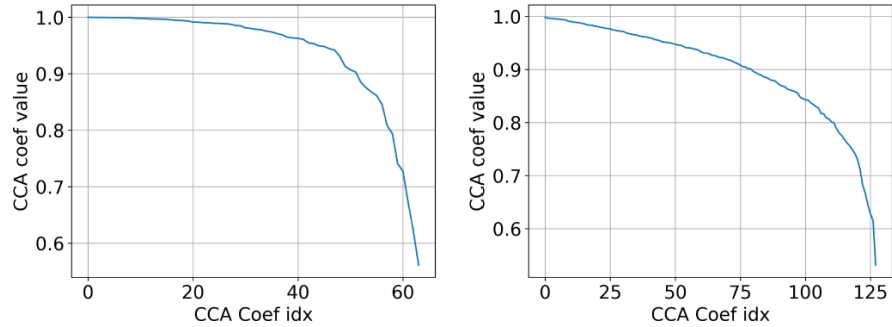
MaxPool3

PreGAP

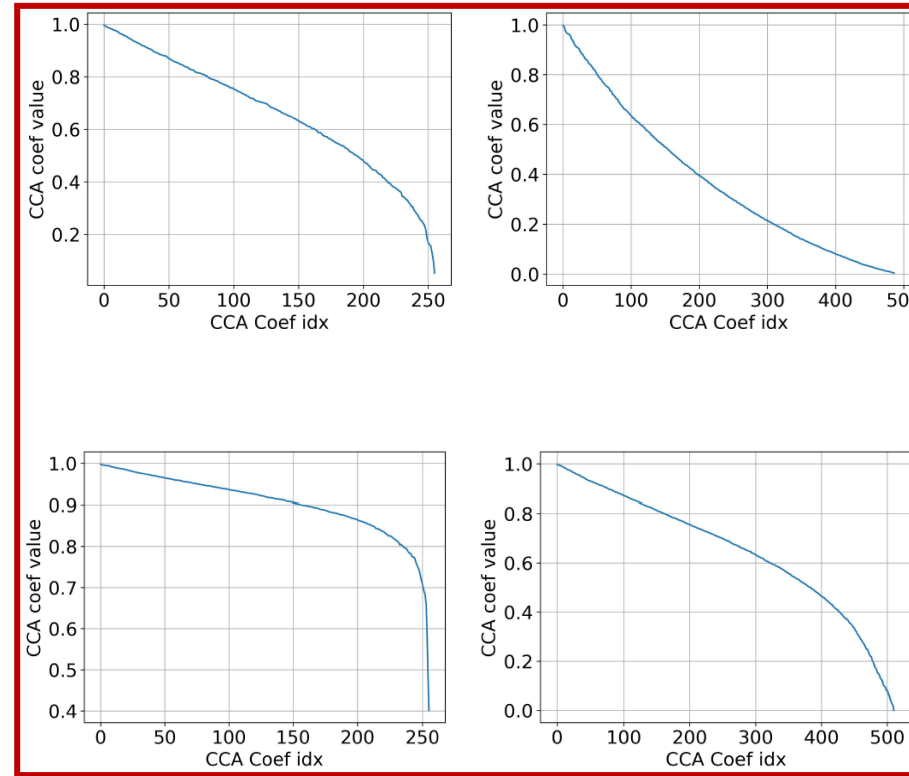
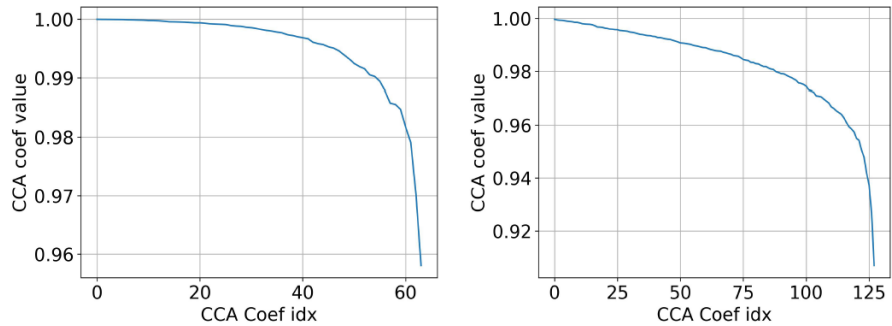


Results

- SVCCA – PUCPR+



- SVCCA – CARPK



MaxPool1

MaxPool2

MaxPool3

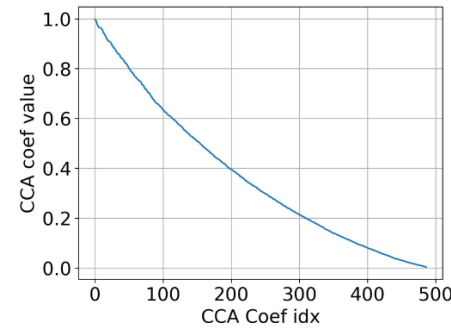
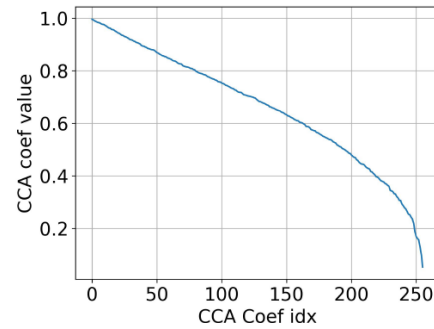
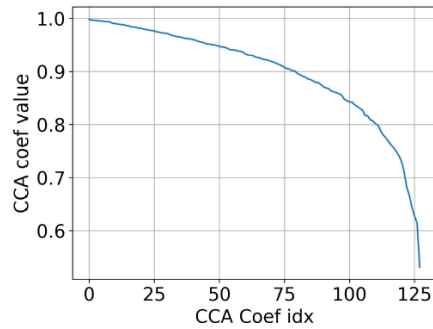
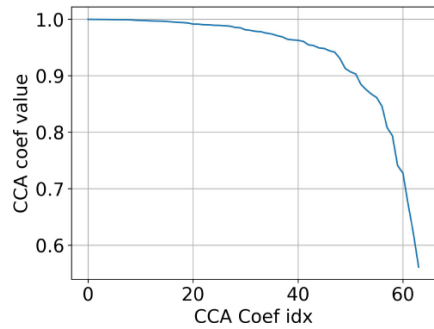
PreGAP

Low
Corr.

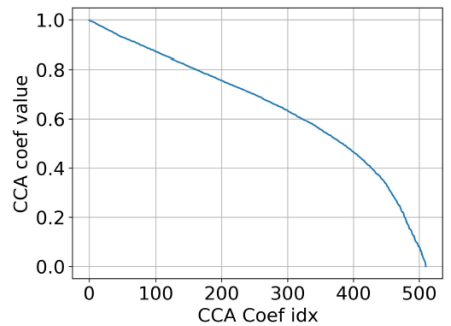
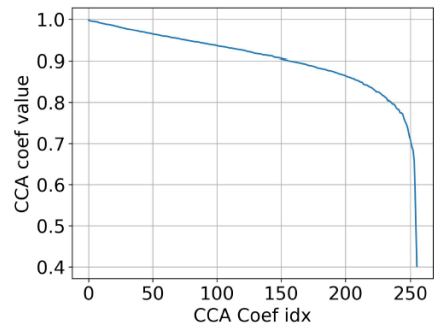
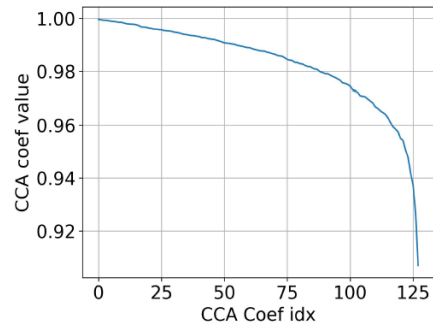
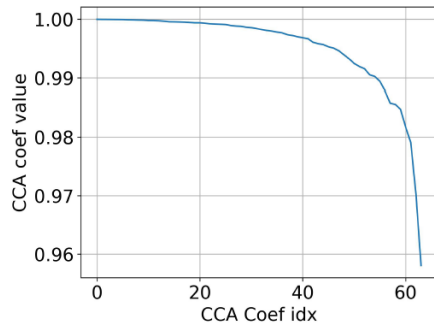


Results

- SVCCA – PUCPR+



- SVCCA – CARPK



MaxPool1

MaxPool2

MaxPool3

PreGAP

Indicates similar early level features and relatively different mid-deep features



References

- [1] Gidaris, Spyros, Praveer Singh, and Nikos Komodakis. "Unsupervised Representation Learning by Predicting Image Rotations." *ICLR 2018*. 2018.
- [2] Noroozi, Mehdi, and Paolo Favaro. "Unsupervised learning of visual representations by solving jigsaw puzzles." *European Conference on Computer Vision*. Springer, Cham, 2016.
- [3] Singh, Suriya, et al. "Self-Supervised Feature Learning for Semantic Segmentation of Overhead Imagery." *BMVC*. Vol. 1. No. 2. 2018.
- [4] Hu, Jie, Li Shen, and Gang Sun. "Squeeze-and-excitation networks." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.
- [5] Zhou, Yanzhao, et al. "Oriented response networks." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2017.
- [6] Raghu, Maithra, et al. "Svcca: Singular vector canonical correlation analysis for deep learning dynamics and interpretability." *Advances in neural information processing systems* 30 (2017): 6076-6085.

RIT



Thank you

Questions?