REACT: Remainder Adaptive Compensation for Domain Adaptive Object Detection

REACT:基于剩余特征补偿的域自适应目标检测算法

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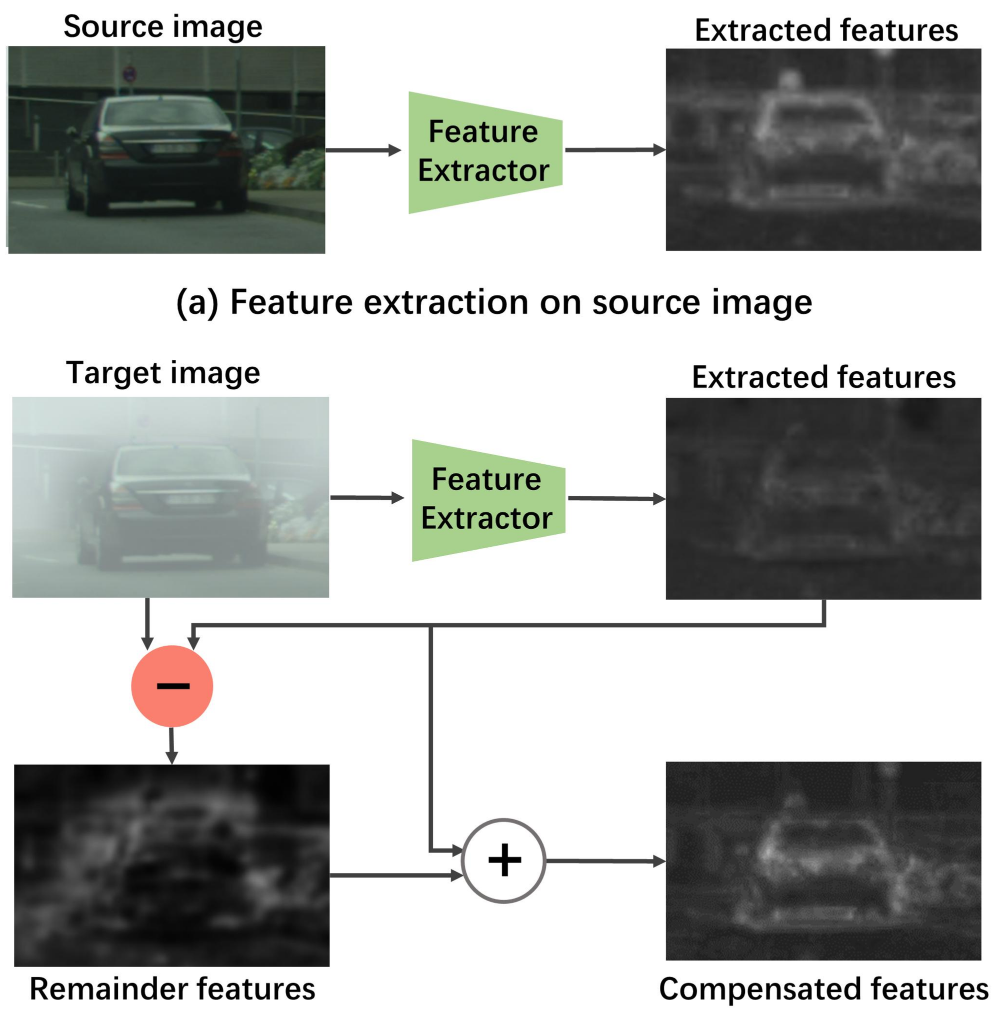
导言

- 域自适应目标检测（Domain Adaptive Object Detection, DAOD）

  将在有标注的源域上训练的检测器泛化到无标注的目标域上，缓解跨域性能下降问题



(a) Feature extraction on source image

(b) Feature extraction and compensation on target image

- 现有DAOD方法

  ✓思路:使用特征对齐约束和源域标签来捕捉域不变特征和任务相关信息

  × 局限:由于域差异的存在，特征对齐时部分目标域的任务相关信息丢失

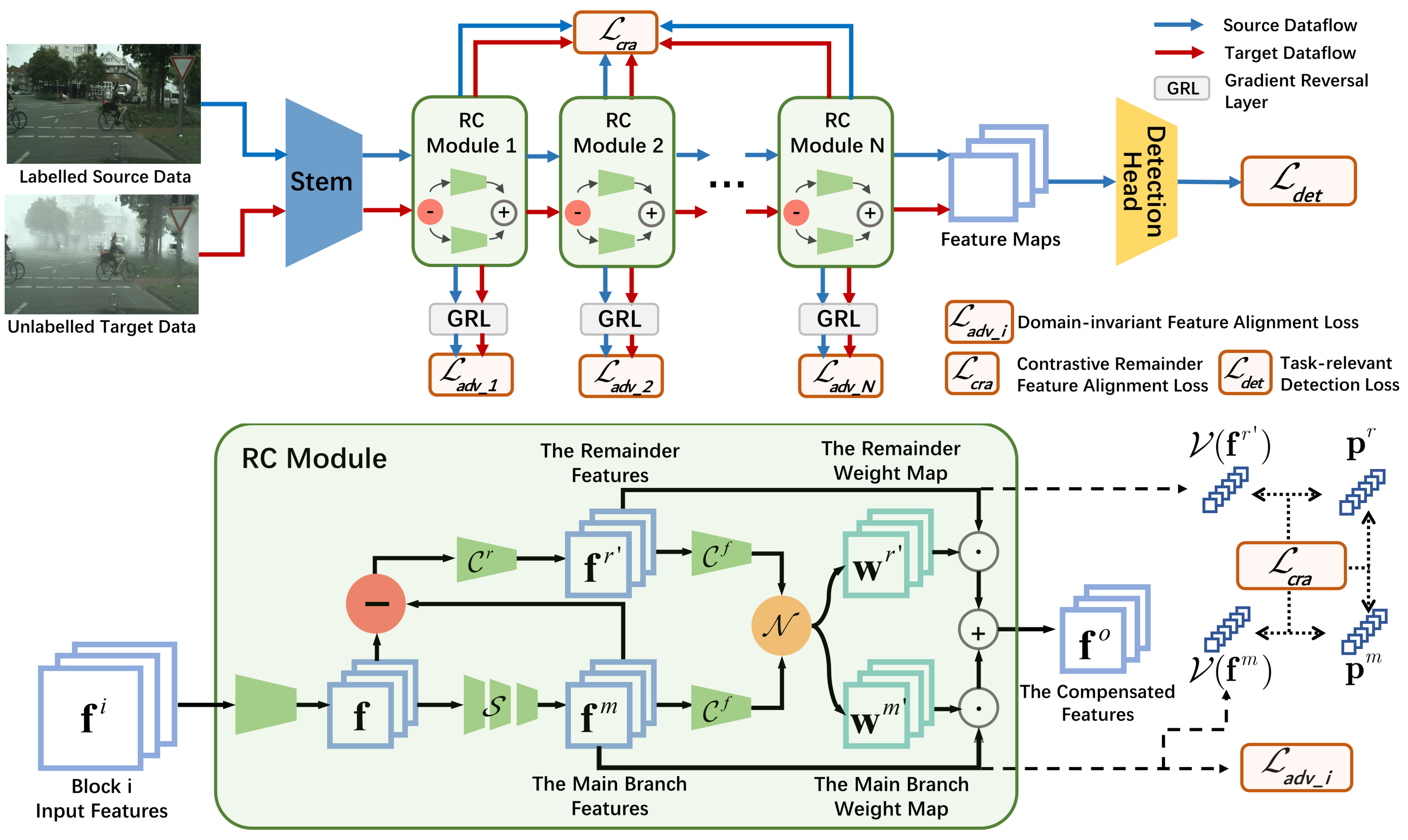
- 基于剩余特征补偿的域自适应目标检测算法 REACT

  ✓关键发现: 剩余特征包含了被丢弃的任务相关信息，可以用于补偿不充分的目标域特征

  ✓剩余补偿模块：我们设计了剩余补偿模块，引入额外的剩余分支，通过残差注意力设计来恢复剩余特征以及自适应地补偿主分支特征

  ✓对比剩余特征对齐：我们提出了对比剩余特征对齐损失，引导剩余分支与主分支正交化，从而保证剩余特征包含主分支中丢失的特征

方法



- REACT算法网络结构

  剩余特征补偿模块(Remainder Compensation Module，RC)以层叠结构堆叠构成特征提取网络

- 剩余特征补偿模块RC

  主分支：使用对抗损失约束，提取域不变特征和源域的任务相关信息

  剩余分支：首先，计算不同深度的特征残差来恢复剩余特征。随后，通过注意力机制，向主分支特征中自适应补偿目标域任务相关信息

- 对比剩余特征对齐

  特征原型：建立主分支特征原型和剩余分支特征原型

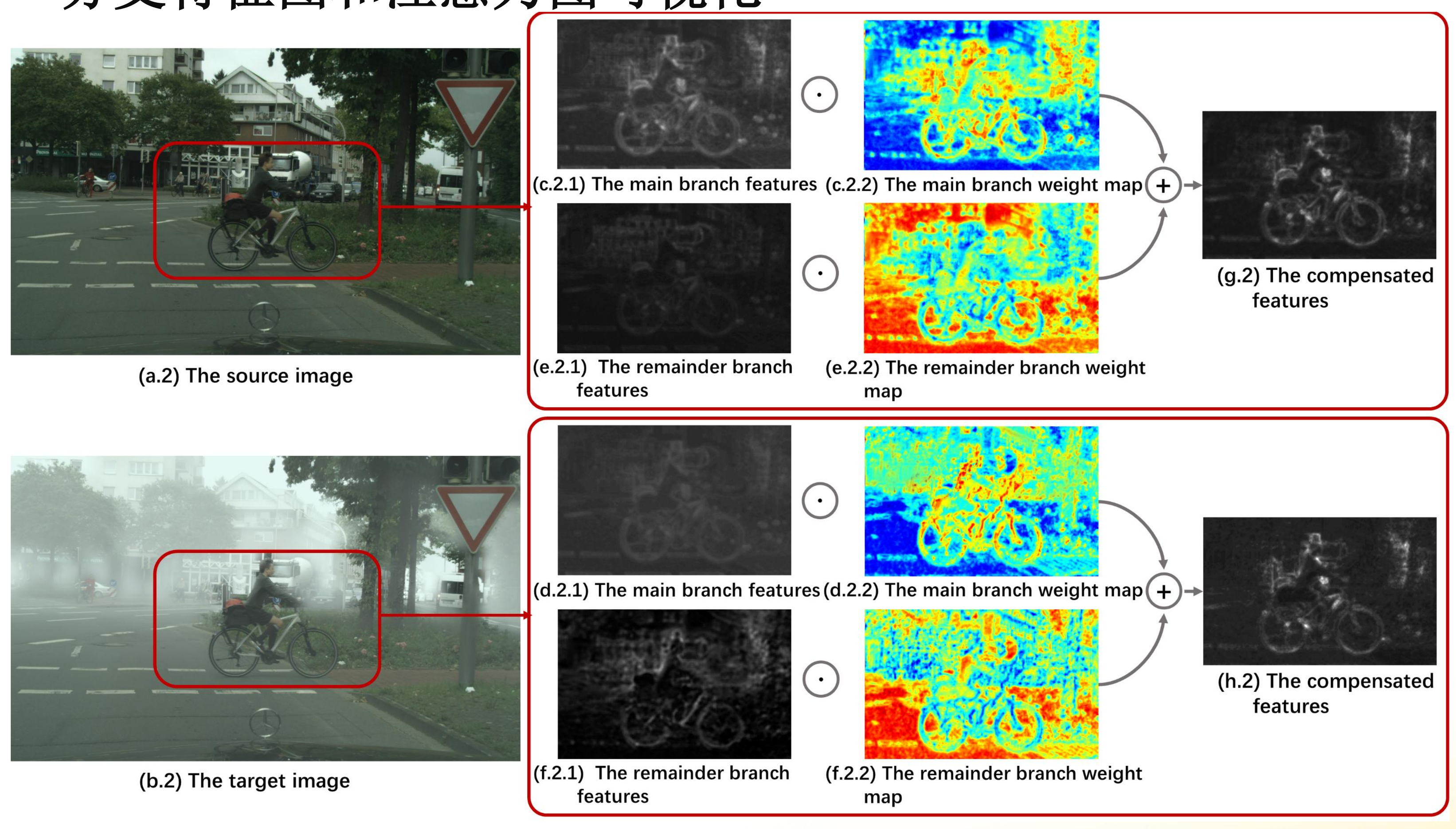
  特征对齐：通过对比学习策略，拉近各分支特征到各自原型的距离，以及扩大两个分支原型间的距离

实验

- 跨天气场景数据集上的检测结果（mAP）

Methods	Arch.	Person	Rider	Car	Truck	Bus	Train	Motor	Bicycle	mAP
DA-Faster† [4]	FR	29.2	40.4	43.4	19.7	38.3	28.5	23.7	32.7	32.0
VDD† [5]	FR	33.4	44.0	51.7	33.9	52.0	34.7	34.2	36.8	40.0
DIDN [36]	FR	38.3	44.4	51.8	28.7	53.3	34.7	32.4	40.4	40.5
DSS† [7]	FR	42.9	51.2	53.6	33.6	49.2	18.9	36.2	41.8	40.9
MeGA [37]	FR	37.7	49.0	52.4	25.4	49.2	46.9	34.5	39.0	41.8
TIA [8]	FR+CycleGAN	52.1	38.1	49.7	37.7	34.8	46.3	48.6	31.1	42.3
D-adapt† [38]	FR	40.8	47.1	57.5	33.5	46.9	41.4	33.6	43.0	43.0
SDA [39]	FR	38.8	45.9	57.2	29.9	50.2	51.9	31.9	40.9	43.3
DICN† [40]	FR	47.3	57.4	64.0	22.7	45.6	29.6	38.6	47.4	44.1
MGADA [41]	FR	43.9	49.6	60.6	29.6	50.7	39.0	38.3	42.8	44.3
NLTE† [42]	FR+Graph	43.1	50.7	58.7	33.6	56.7	42.7	33.7	43.3	45.4
SCAN [43]	FCOS+Graph	41.7	43.9	57.3	28.7	48.6	48.7	31.0	37.3	42.1
SIGMA [9]	FCOS+Graph	44.0	43.9	60.3	31.6	50.4	51.5	31.7	40.6	44.2
SIGMA++ [44]	FCOS+Graph	46.4	45.1	61.0	32.1	52.2	44.6	34.8	39.9	44.5
CIGAR [45]	FCOS+Graph	46.1	47.3	62.1	27.8	56.6	44.3	33.7	41.3	44.9
REACT+DSS	FR	54.8	58.4	66.2	24.3	52.7	39.7	39.3	50.6	48.3
REACT+DSS†	FR	55.7	**60.4**	67.5	20.7	53.3	40.3	38.2	53.9	48.8
ATMT† [46]	FR+Teacher	44.7	37.6	51.1	34.0	34.0	46.7	35.1	27.1	38.8
UMT [47]	FR+Teacher	33.0	46.7	48.6	34.1	56.5	46.8	30.4	37.4	41.7
PT† [48]	FR+Teacher	43.2	52.4	63.4	33.4	56.6	37.8	41.3	48.7	47.1
MIC† [49]	FR+Teacher	50.9	55.3	67.0	33.9	52.4	33.7	40.6	47.5	47.6
TDD [33]	FR+Teacher	50.7	53.7	**68.2**	35.1	53.0	45.1	38.9	49.1	49.2
AT† [31]	FR+Teacher	**56.3**	51.9	64.2	38.5	45.5	**55.1**	**54.3**	35.0	50.9
CMT† [50]	FR+Teacher	47.0	55.7	64.5	**39.4**	**63.2**	51.9	40.3	53.1	51.9
HT [51]	FCOS+Teacher	52.1	55.8	67.5	32.7	55.9	49.1	40.1	50.3	50.4
REACT+AT	FR+Teacher	52.1	57.1	66.3	35.0	56.7	52.8	42.9	53.8	52.1
REACT+AT†	FR+Teacher	51.4	57.9	67.4	37.7	58.4	52.8	44.6	**54.6**	**53.1**

- 分支特征图和注意力图可视化



- 跨风格场景数据集上的检测结果（mAP）

Methods	Aero	Bike	Bird	Boat	Bottle	Bus	Car	Cat	Chair	Cow	Table	Dog	Horse	Motor	Person	Plant	Sheep	Sofa	Train	Tv	mAP
NLTE [42]	39.1	50.3	33.6	34.7	35.0	40.5	44.2	5.9	36.8	45.8	23.1	17.3	31.8	39.5	60.7	45.4	17.9	28.4	49.0	51.3	36.5
UaDAN [53]	35.0	**73.7**	41.0	24.4	21.3	69.8	53.5	2.3	34.2	61.2	31.0	**29.5**	47.9	63.6	62.2	61.3	13.9	7.6	48.6	23.9	40.2
DBGL [55]	28.5	52.3	34.3	32.8	38.6	66.4	38.2	25.3	39.9	47.4	23.9	17.9	38.9	78.3	61.2	51.7	26.2	28.9	56.8	44.5	41.6
FGRR [56]	30.8	52.1	35.1	32.4	42.2	62.8	42.6	21.4	42.8	58.6	33.5	20.8	37.2	81.4	66.2	50.3	21.5	29.3	58.2	47.0	43.3
UMT [47]	39.6	59.1	32.4	35.0	45.1	61.9	48.4	7.5	46.0	**67.6**	21.4	**29.5**	48.2	75.9	70.5	**56.7**	25.9	28.9	39.4	43.6	44.1
SIGMA [9]	40.1	55.4	37.4	31.1	54.9	54.3	46.6	23.0	44.7	65.6	23.0	22.0	42.8	55.6	67.2	55.2	32.9	**40.8**	45.0	58.6	44.5
ATMT [46]	37.5	63.4	37.9	29.8	45.1	62.7	41.2	19.5	43.7	57.4	22.9	25.3	39.6	87.1	70.9	50.6	29.1	32.2	58.4	50.5	45.2
CIGAR [45]	35.2	55.0	39.2	30.7	60.1	58.1	46.9	31.8	47.0	61.0	21.8	26.7	44.6	52.4	68.5	54.4	31.3	38.8	56.5	63.5	46.2
TIA [8]	42.2	66.0	36.9	37.3	43.7	71.8	49.7	18.2	44.9	58.9	18.2	29.1	40.7	87.8	67.4	49.7	27.4	27.8	57.1	50.6	46.3
SIGMA++ [44]	36.3	54.6	40.1	31.6	58.0	60.4	46.2	**33.6**	44.4	66.2	25.7	25.3	44.4	58.8	64.8	55.4	**36.2**	38.6	54.1	59.3	46.7
CMT [50]	39.8	56.3	38.7	39.7	**60.4**	35.0	56.0	7.1	**60.1**	60.4	**35.8**	28.1	**67.8**	84.5	**80.1**	55.5	20.3	32.8	42.3	38.2	47.0
D-adapt [38]	**56.4**	63.2	**42.3**	40.9	45.3	**77.0**	48.7	25.4	44.3	58.4	31.4	24.5	47.1	75.3	69.3	43.5	27.9	34.1	**60.7**	**64.0**	49.0
REACT+AT	40.1	71.2	38.5	**44.0**	52.8	61.5	**58.7**	22.6	53.9	56.4	33.2	27.0	43.7	**89.9**	79.7	53.6	25.3	37.9	58.9	43.6	**49.6**

- 消融实验：分支设计

Training	Testing	RC Module	Cra Loss	mAP
C	F			40.3
C	F	✓		43.4
C + F	F			41.4
C + F	F	✓		47.8
C + F	F	✓	✓	48.8
C + F	C			55.5
C + F	C	✓		57.0

Compensation Features	-	$\mathbf{f}$	$\mathbf{f}^m$	$\mathbf{f}+\mathbf{f}^m$	$\mathbf{f}-\mathbf{f}^m$ $MaxPool$	$\mathbf{f}-\mathbf{f}^m$ $AvgPool$	$\mathbf{f}-\mathbf{f}^m$ *
mAP	41.4	43.3	41.6	42.9	44.6	45.6	**47.8**

- 泛化实验：三组不同架构

Method	Backbone	C→F	K→C	C→B	S→C	Backbone	P→C
DA-Faster*	ResNet-50	37.9	42.1	25.8	42.3	ResNet-101	36.1
REACT+DA-Faster	ResNet-50	42.1	45.8	28.2	48.4	ResNet-101	38.3
Gains	-	4.2	3.7	2.4	6.1	-	2.2
DSS*	ResNet-50	41.4	43.6	27.1	46.3	ResNet-101	39.9
REACT+DSS	ResNet-50	48.8	51.2	30.9	53.8	ResNet-101	44.3
Gains	-	7.4	7.6	3.8	7.5	-	4.4
AT*	VGG-16	50.2	54.2	32.1	53.8	ResNet-101	45.8
REACT+AT	VGG-16	53.1	59.5	35.8	58.6	ResNet-101	49.6
Gains	-	2.9	5.3	3.7	4.8	-	3.8