net-depth-fea	tures	AP	AP_{50}	AP	75		AP	AP_{50}	AP_{75}		align?	bilinear?	agg.	AP	AP_{50}	AP_{75}	
ResNet-50-	C4	30.3	51.2	31.	5	softmax	24.8	44.1	25.1	RoIPool [12]			max	26.9	48.8	26.4	
ResNet-101	-C4	32.7	54.2	34.	3	sigmoid	30.3	51.2	31.5	<i>RoIWarp</i> [10]		√	max	27.2	49.2	27.1	
ResNet-50-I	FPN	33.6	55.2	35.	3		+5.5	+7.1	+6.4	Korwarp [10]		✓	ave	27.1	48.9	27.1	
ResNet-101-	FPN	35.4	57.3	37.	5					DolAlion	√	√	max	30.2	51.0	31.8	
ResNeXt-101	-FPN	36.7	59.5	38.	9					RoIAlign	✓	✓	ave	30.3	51.2	31.5	
(a) Backbone Architecture: Better back-						(b) Multinomial vs. Independent Masks (c) RoIAlign (ResNet-50-C4): Mask results with var									ious RoI		
bones bring expected gains: deeper networks					rks ((ResNet-50-C4): Decoupling via per- layers. Our RoIAlign layer in						nprove	s AP b	y ~3 pc	oints and		
do better, FPN outperforms C4 features, and						class binary masks (sigmoid) gives large AP ₇₅ by ~5 points. Us						Using pro	per al	ignmen	t is the	only fac-	
ResNeXt improves on ResNet.						gains over multinomial masks (softmax).				tor that contributes to the large gap between RoI layers.							
	AP	AP_5	$_0$ AP	75	AP^{bb}	$\mathrm{AP^{bb}_{50}}$	$\mathrm{AP^{bb}_{75}}$			mask bran	ch		A	P A	P_{50}	AP_{75}	
RoIPool	23.6	46.5	5 21	.6	28.2	52.7	26.9	MI	.P	fc: $1024 \rightarrow 1024 \rightarrow 80.28^2$		8^2	31	.5 .5	53.7	32.8	
RoIAlign	30.9	51.8	3 32	.1	34.0	55.3	36.4	ML	P fc	: 1024→1024→10)24→8	0.28^{2}	31	.5 .5	54.0	32.6	
	+7.3	+ 5.	3 +10	9.5	+5.8	+2.6	+9.5	FC	N conv:	$256 \rightarrow 256 \rightarrow 256 -$	→256→	256→80	33	.6 :	55.2	35.3	
(d) RoIAlign	(d) RoIAlign (ResNet-50- C5 , <i>stride 32</i>): Mask-level and box-level (e) Mask Branch (ResNet-50-FPN): Fully convolutional networks (FCN) vs.															CN) vs.	
AP using <i>large-stride</i> features. Misalignments are more severe than								n multi	multi-layer perceptrons (MLP, fully-connected) for mask prediction. FCNs im-								
with stride-16 features (Table 2c), resulting in big accuracy gaps.									prove results as they take advantage of explicitly encoding spatial layout.								
	Table	2. Abl	ations.	We	train o	n trainv	 7al35:	k, test on r	niniva	1, and report mas	sk AP	unless ot	herw	ise note	ed.		