A modified Single-Shot multibox Detector for beyond Real-Time Object Detection

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Aims & Objectives

- ❑Object detection remains a fundamental problem in computer vision
- ❑Objective: **localize** (provide a bounding box) and **identify** (provide a label) for objects of interest inside and image.

- ❑Solution: **Convolutional Neural Networks (CNN)** lead to huge improvements
  - ➢Typical State-of-the-Art models are **computationally expensive**
  - ➢Restricted integration on systems with limited resources.
  - ➢**Lighter versions** have emerged: Tiny-YOLO, SqueezeDet, MobileNet-SSD
- ❑Current work is based on standard **Single Shot Detector (SSD)** architecture
  - ➢Relies on simple **conv3x3** filters

Related work

- ❑Object detection is divided into two major categories based on the potential use of a **Region Proposal Network (RPN)**:
  - ➢the single phase detectors and
    - •SSD, YOLO, YOLOv2, Retinanet etc
  - ➢the two-phase detectors
    - Fast R-CNN, Faster R-CNN and R-FCN
- ❑Another categorization regarding the **object detection models' purpose**:
  - ➢**state-of-the-art performances** with no resource restrictions
  - ➢best performance in **resource restricted environments**
  - ➢It is almost exclusively dominated by the **single-phase detectors** due to the efficiency they inherently possess

Proposed method

- ❑Original SSD modifies VGG network.
- ❑ VGG is a robust network but:
  - ➢Uses huge number of parameters, nonetheless
  - ➢Has limited use in resource-restricted applications.
- ❑SSD suffers in identifying small objects.
  - ➢The shallowest layer which is being used is **conv4_3** of VGG
  - ➢typical input size 300x300 ⟶ corresponds to a **38x38 feature map**
  - ➢too small to identify objects
- ❑SSD includes 10 blocks of CNNs in order to extract features.
  - ➢ first **6 blocks** belong to the VGG
  - ➢each next block has **double the filters** of the previous one
  - ➢The initial number of filters is 64 for the 1st block.
- ❑We added an extra shallower decision layer at **conv3_3**
  - ➢with **75x75 feature map**
  - ➢number of default boxes number 8732 ⟶ 31232
  - ➢Are shallower features discrimant enough?
- ❑Decreased both the initial number of filters as well as exponent for increase for the next blocks.
- ❑Formula for filter blocks:
  - ➢$k_n = b^{an}$
  - ➢Initial numbers of filters, **parameter b**, 48 and 32 were examined
  - ➢**parameter a** was fixed to 1.7 (from 2 to the original VGG)

❑**Number of filters** used in the various adaptations

	block name	Formula for #f lters		
		full SSD 64^2	SSD_lite_48 $48^{1.7}$	SSD_lite_32 $32^{1.7}$
VGG layers	conv1_x	64	48	32
	conv2_x	128	81	54
	conv3_x	256	138	92
	conv4_x	512	235	157
	conv5_x	512	235	157
	fc_x	1024	400	267
Additional layers	conv6_x	256/512	138/235	92/157
	conv7_x	128/256	81/138	54/92
	conv8_x	128/256	81/138	54/92
	conv9_x	128/256	81/138	54/92

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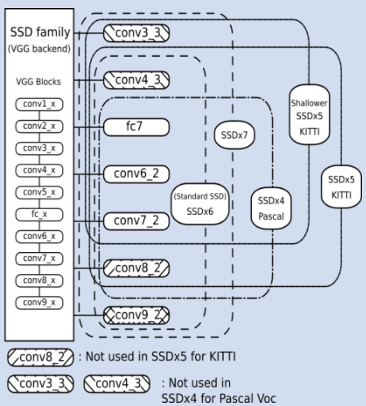
Proposed method - Adjusted loss classification weights

- ❑Compensate for unbalanced datasets
- ❑ **Modified version** of SSD classification **loss function**
  - ➢different weight coefficients for different classes
- ❑**KITTI** dataset:
  - ➢$loss = w_{ped} * loss_{ped} + w_{cycl} * loss_{cycl} + w_{car} * loss_{car}$
  - ➢$w_{ped} = 2.2$, $w_{cycl} = 2.0$, $w_{car} = 1.0$
- ❑ **Pascal Voc** dataset:
  - ➢$loss = w_1 * loss_1 + \ldots + w_{20} * loss_{20}$
  - ➢$w_i =$
- ❑Improves performance for classes of **lower overall performance**

Proposed method - Selecting the proper decision layers

- ❑SSD deployed 6 decision layers
  - ➢They are used to **extract discriminant features.**
  - ➢Each one with different feature map size.
  - ➢The **deepest layer** is useful for bigger objects only.
    - ➢They do not appear in KITTI
    - ➢Are non frequent in Pascal
- ❑Formation of **SSDx7**
  - ➢**1 additional shallower decision layer**
  - ➢Better performance in KITTI
  - ➢Decreased performance In Pascal Voc
- ❑Formation of **shallower SSDx6**
  - ❑**1 additional shallower decision layer** used.
  - ❑**1 deeper layer** being **removed**
- ❑Formation of **shallower SSDx5**
  - ➢**1 additional shallower decision layer**
  - ➢2 **deeper layers** were removed
  - ➢Only well performing in KITTI
- ❑Formation of **SSDx5**
  - ➢1 **deeper layer** was removed
  - ➢Only well performing in Pascal Voc
- ❑Formation of **SSDx4**
  - ➢1 **deeper layer** was removed
  - ➢1 **shallower layer** was also removed
  - ➢Only performing well in Pascal Voc



Experimental results - Balancing the dataset

- ❑**Experiments** were conducted in Pascal Voc and KITTI datasets
- ❑Both datasets are imbalanced.
- ❑ Repeat images containing objects from misperforming classes
- ❑Useful for KITTI not for Pascal

- ❑Balancing dataset **did not work** for **Pascal Voc** only for KITTI
  - ➢The repetition of images also **incorporate objects** of the **majority class**
  - ➢**Pascal Voc** is a **more complex** dataset with **20 classes** compared to **KITTI**, which involves only **3 classes**.
- ❑Might **improve** the performance of **some classes** but **decrease** the performance for the remaining classes.

Experimental results - Pascal Voc 2007

- ❑**Full model**:
  - ➢Incorporating an additional shallower layer **did not increase** the performance**.**
  - ➢**Weighted** version of **SSDx6, SSDx5** and **SSDx6** all tie at 77.6%
  - ➢Performance of **3 worst classes** did **improve on Weighted version.**
- ❑**Medium model**:
  - ➢**Removing** shallower layer **did not improve the overall performance** (almost 5% compared to baseline).
  - ➢Inclusion of **Last layer did not affect the results.**
  - ➢**Weighted** version of **SSDx4** model demonstrated best performance at 71.0% mAP.
- ❑**Lighter model**:
  - ➢**Removing** shallower layer **improved performance** (4% compared to baseline)**.**
  - ➢**Last layer do not affect results.**
  - ➢**Weighted** version **SSDx4** model demonstrated best performance at 64.1% mAP

Model name	Decision Layers (train/eval)			mAP
	num	initial	last	
Full SSDx6	6/6	conv4_3	conv9_2	**77.6%**
Full SSDx6 vs5	6/5	fc7	conv9_2	71.2%
Full SSDx6 vs5	6/5	conv4_3	conv8_2	**77.6%**
Full SSDx7	7/7	conv3_3	conv9_2	77.5%
w. Full SSDx6	6/6	conv4_3	conv9_2	**77.6%**
SSD lite 48x6	6/6	conv4_3	conv9_2	61.7%
SSD lite 48x6 vs5	6/5	fc7	conv9_2	66.6%
SSD lite 48x6 vs5	6/5	conv4_3	conv8_2	61.6%
SSD lite 48x4	4/4	fc7	conv9_2	70.6%
w. SSD lite 48x4	4/4	fc7	conv9_2	**71.0%**
SSD lite 32x6	6/6	conv4_3	conv9_2	55.9%
SSD lite 32x6 vs5	6/5	conv4_3	conv8_2	55.9%
SSD lite 32x6 vs5	6/5	fc7	conv9_2	59.9%
SSD lite 32x4	4/4	fc7	conv8_2	63.1%
w. SSD lite 32x4	4/4	fc7	conv8_2	**64.1%**

❑Various **light-weight models' performance** on **Pascal Voc 2007 test set**:

Model name	Num Decision Layers	mAP
Tiny-DSOD	6	72.1%
w. SSD lite 48x4	4	71.0%
Pelee	4	70.9%
MobileNet-SSD	4	68.1%
w. SSD lite 32x4	4	64.1%

Experimental results - KITTI

- ❑**Full model**:
  - ➢**A balanced dataset** was used.
  - ➢Additional **shallower layer improved the performance** significantly.
  - ➢**Shallower SSDx5** was used.
  - ➢**Weighted** version of **shallower SSDx5** demonstrated best performance with mAP 86.1%.
- ❑**Medium model**:
  - ➢**Balancing the dataset** improved to a point (best choice additional 1.5x of the original samples).
  - ➢Additional **shallower layer improved performance** significantly (50%+).
  - ➢**Weighted** version of **shallower SSDx5** demonstrated best performance at 84.1% mAP.
- ❑**Lighter model**:
  - ➢Using **a balanced dataset**.
  - ➢**Weighted** version of **shallower SSDx5** demonstrated best performance at 81.1% mAP.

Model name	Decision Layers (train/eval)			mAP
	num	initial	last	
Full SSDx5 b[1.5,1.5]	5/5	conv3_3	conv7_2	85.4%
w. Full SSDx5 b[1.5,1.5]	5/5	conv4_3	conv7_2	**86.1%**
SSD lite 48x6	6/6	conv4_3	conv9_2	23.2%
SSD lite 48x7	7/7	conv3_3	conv9_2	75.0%
SSD lite 48x7 b[1,1]	7/7	conv3_3	conv9_2	81.1%
SSD lite 48x7 b[1.5,1.5]	7/7	conv3_3	conv9_2	81.6%
SSD lite 48x7 b[1.5,1.5]	7/6	conv3_3	conv8_2	81.6%
SSD lite 48x7 b[1.5,1.5]	7/5	conv3_3	conv7_2	81.6%
SSD lite 48x7 b[2,2]	7/7	conv3_3	conv9_2	80.8%
SSD lite 48x5 b[1.5,1.5]	5/5	conv3_3	conv7_2	82.0%
w. SSD lite 48x5 b[1.5,1.5]	5/5	conv3_3	conv7_2	**84.0%**
SSD lite 32x7 b[1.5,1.5]	7/7	conv3_3	conv9_2	77.4%
SSD lite 32x5 b[1.5,1.5]	5/5	conv3_3	conv7_2	79.2%
w. SSD lite 32x5 b[1.5,1.5]	5/5	conv3_3	conv7_2	**81.1%**

❑Performance of various light-weight models in KITTI

Model name	Num Decision Layers	mAP
w. SSD lite 48x5 b[1.5, 1.5]	5	84.0%
w. SSD lite 32x5 b[1.5, 1.5]	5	81.1%
SqueezeDet+	1	80.4%
Tiny-DSOD	6	77.0%

Experimental results – Computational performance

❑ **Efficiency** comparison with other **lightweight models**:
Reported times are **indicative** due to hardware differences

Model name	Resolution	batch size	fps	GPU
Full SSDx6	300x300	1	44	GTX 1070 Ti 8GB
SSD lite 48x4	300x300	1	59	GTX 1070 Ti 8GB
SSD lite 32x4	300x300	1	90	GTX 1070 Ti 8GB
Pelee	304x304	1	77	TX2 (32FP)*
Tiny-DSOD	300x300	1	105	TitanX
MobileNet-SSD	300x300	1	59.3	TitanX
Full SSDx5	620x300	1	29	GTX 1070 Ti 8GB
SSD lite 48x5	620x300	1	51	GTX 1070 Ti 8GB
SSD lite 32x5	620x300	1	61	GTX 1070 Ti 8GB
SqueezeDet+	1242x375	1	32.1	TitanX
Tiny-DSOD	1200x300	1	64.9	TitanX
* excluding post processing time				

5. CONCLUSION

- ❑**Light-weight** versions of the SSD architecture were examined.
- ❑**Two** widely used **datasets** were utilized: Pascal Voc & KITTI.
- ❑SSD remains **competitive** even when **many** of the original **filters were removed.**
- ❑**Decision layer selection** affected **significantly** the **performance** especially on lighter versions.
- ❑Effectiveness drop counter-measures proved useful:
  - ❑**Class weights manipulation** played an important role.
  - ❑**A balanced dataset** also improved performance (only in KITTI).