

# The PASCAL Visual Object Classes Challenge 2012 (VOC2012)

## Part I – Classification Challenge

Mark Everingham, Luc Van Gool  
Chris Williams, John Winn  
Andrew Zisserman  
Yusuf Aytar, Ali Eslami



# Classification challenge

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- Predict whether at least one object of a given class is present in an image
- Competition 1: Train on the supplied data
  - Which methods perform best given specified training data?
- Competition 2: Train on any (non-test) data
  - How well do state-of-the-art methods perform on these problems?

# 20 classes – examples

Aeroplane



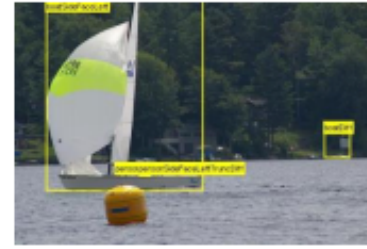
Bicycle



Bird



Boat



Bottle



Bus



Car



Cat



Chair



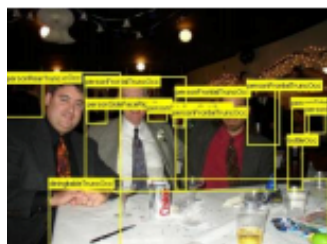
Cow



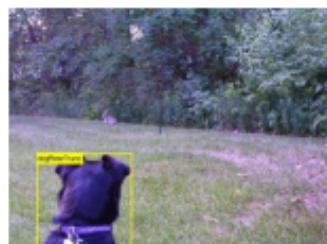


# 20 classes – examples

Dining Table



Dog



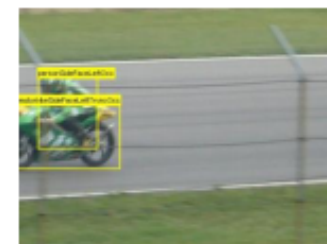
Horse



Motorbike



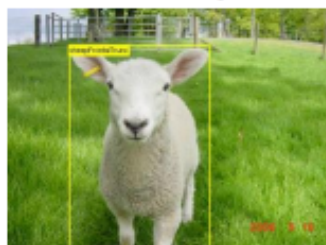
Person



Potted Plant



Sheep



Sofa



Train



TV/Monitor



# Annotation

- Complete annotation of objects from 20 categories

## Occluded

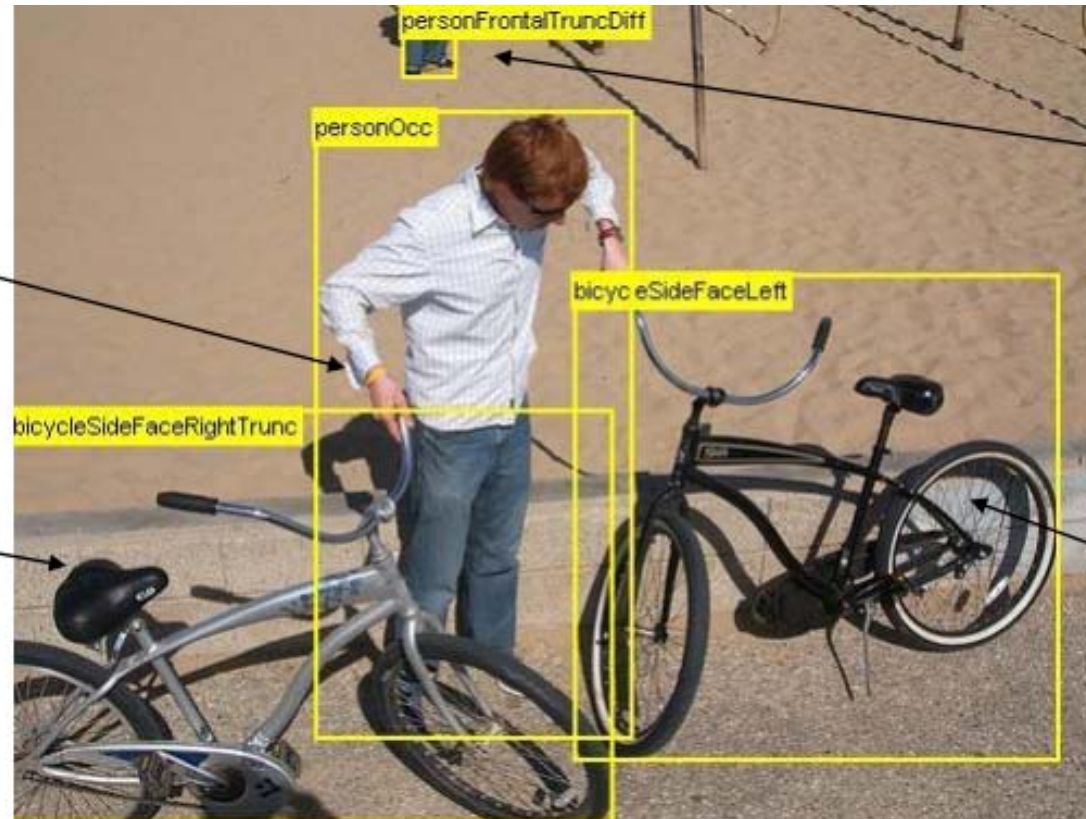
Object is significantly occluded within BB

## Difficult

Not scored in evaluation

## Truncated

Object extends beyond BB

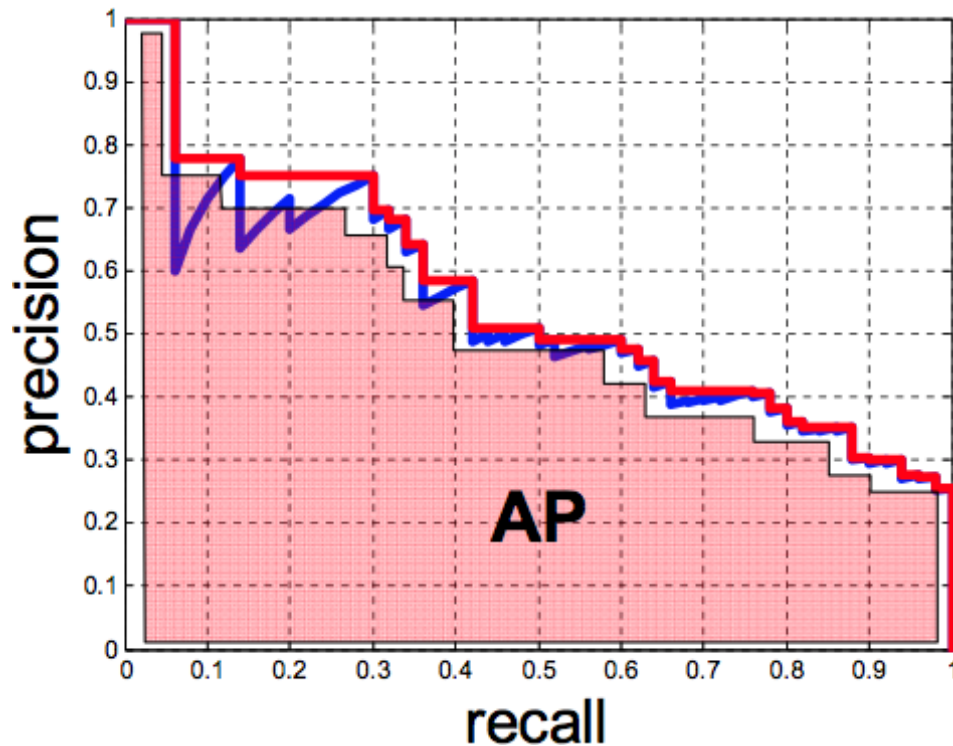


## Pose

Facing left



# Average precision: VOC2010-2012



- Interpolate curve to create version for which the precision is monotonically non-increasing
  - Measure area under interpolated curve
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- Sawtooth shape is ignored
  - Area is measured with maximum accuracy

# Dataset statistics

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- Same size as VOC2011

	Training	Testing
<b>Images</b>	11,540	10,994
<b>Objects</b>	27,450	27,078

- Minimum ~600 training objects per category
- ~2,000 cars, 1,500 dogs, 8,500 people
- Approximately equal distribution across training and test datasets

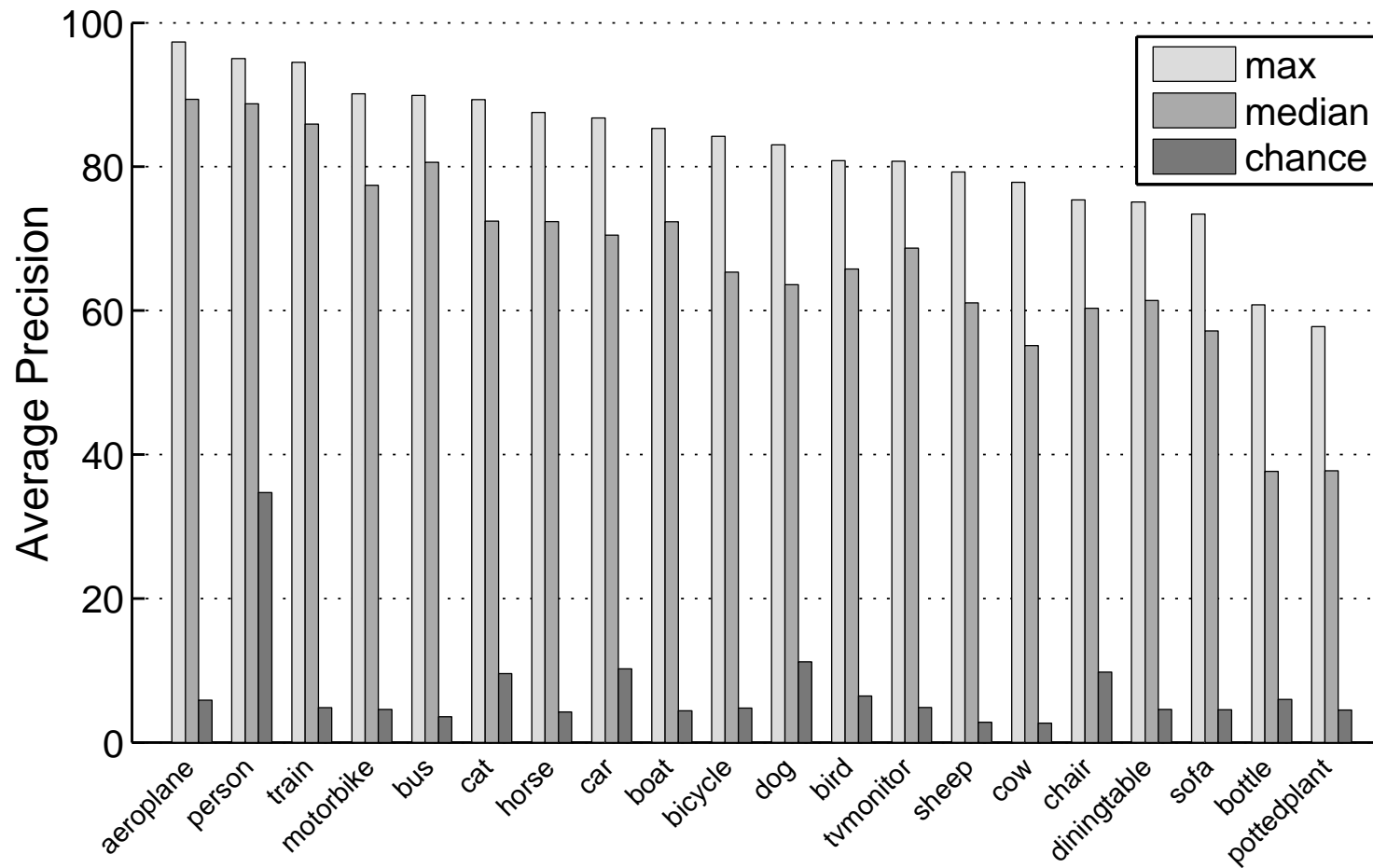
# Submitted methods

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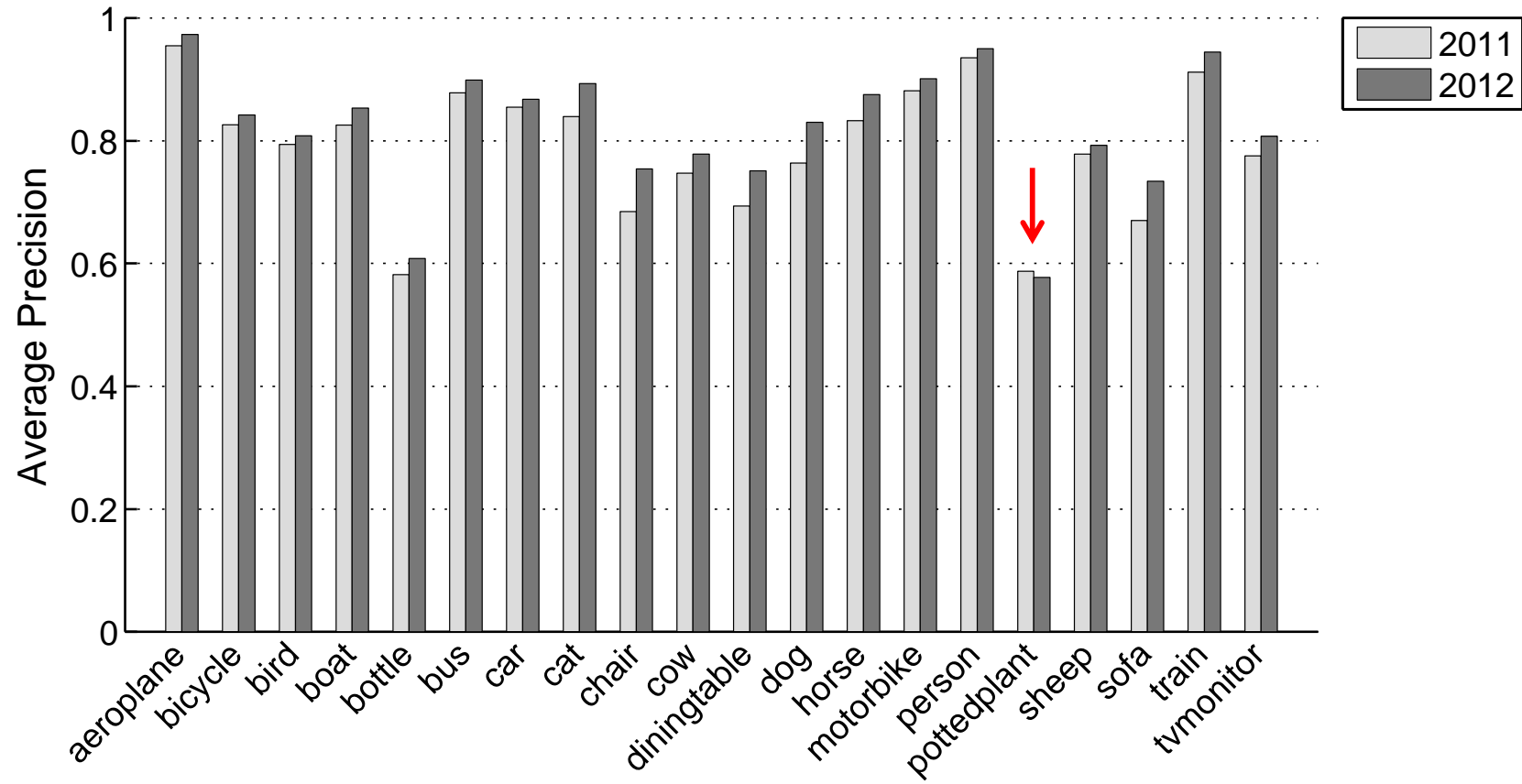
- 7 methods, 5 groups
  - VOC 2011: 19 methods, 11 groups
- Basic recipe:
  - Features: Dense SIFT, HOG, colour
  - Encodings: spatial pyramid, BOW, Fisher vector
  - Detectors: DPM
  - Classifier: SVM
- Additional ingredients:
  - Complex log-normal features
  - Sub-clusters for classes
  - Combinations of clusterings and projections



# Average precision by class



# Improvement over VOC2011



# AP by class and method

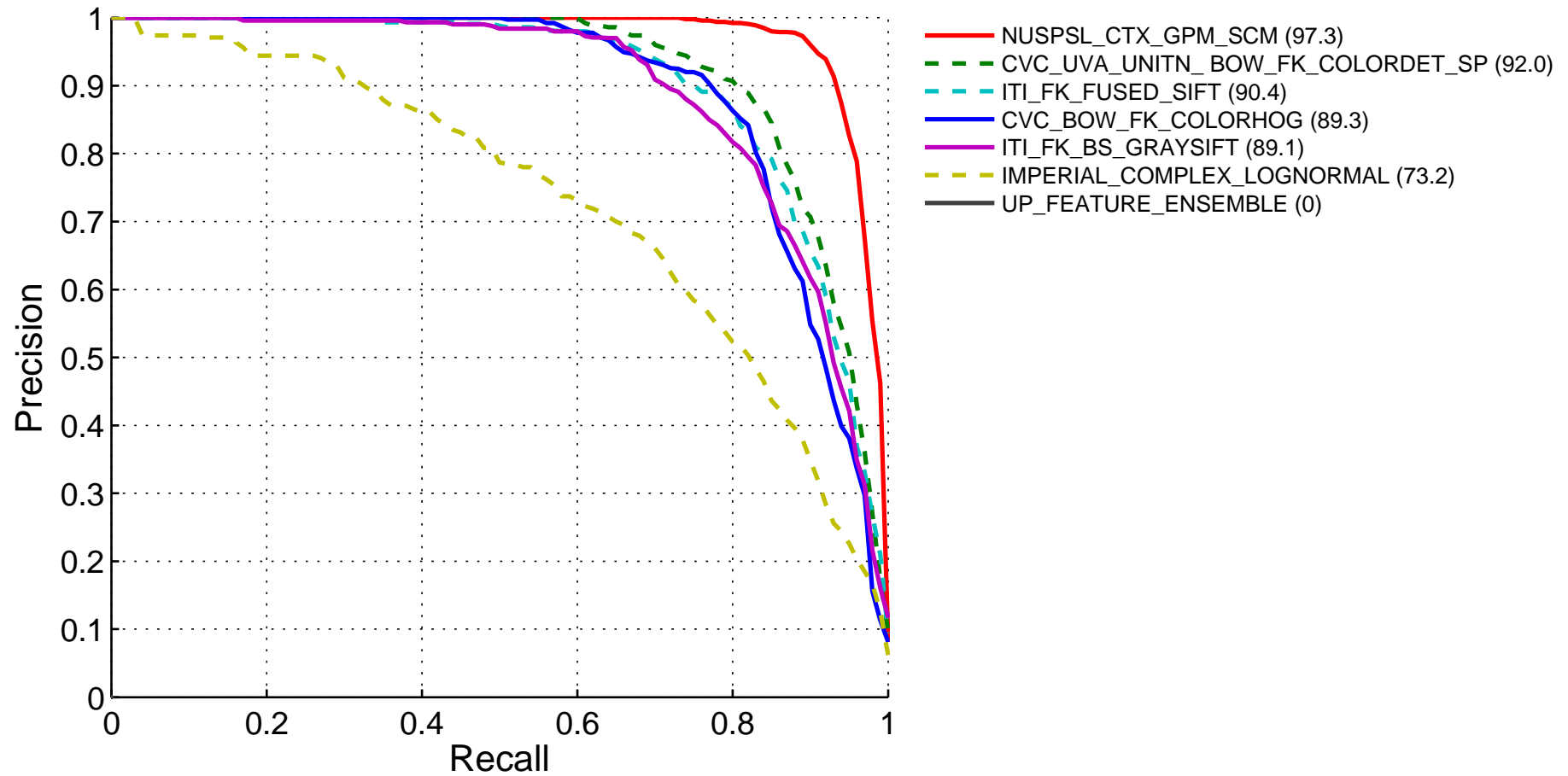
## Trained on VOC 2012 data

	aeroplane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	diningtable	dog	horse	motorbike	person	pottedplant	sheep	sofa	train	tvmonitor
CVC_BOW_FK_COLORHOG	89.3	70.9	69.8	73.9	51.3	84.8	79.6	72.9	63.8	59.4	64.1	64.7	75.5	79.2	91.4	42.7	63.2	61.9	86.7	73.8
CVC_UVA_UNITN_BOW_FK_COLORDET_SP	92.0	74.2	73.0	77.5	54.3	85.2	81.9	76.4	65.2	63.2	68.5	68.9	78.2	81.0	91.6	55.9	69.4	65.4	86.7	77.4
IMPERIAL_COMPLEX_LOGNORMAL	73.2	33.4	31.0	44.7	17.0	57.7	34.4	45.9	41.2	18.1	30.2	34.3	23.1	39.3	57.3	11.9	23.1	25.3	51.2	36.2
ITI_FK_BS_GRAYSIPT	89.1	62.3	60.0	68.1	33.4	79.8	66.9	70.3	57.4	51.0	55.0	59.3	68.6	74.5	83.1	25.6	57.2	53.8	83.4	64.9
ITI_FK_FUSED_SIFT	90.4	65.4	65.8	72.3	37.7	80.6	70.5	72.4	60.3	55.1	61.4	63.6	72.4	77.4	86.8	37.7	61.1	57.2	85.9	68.7
NUSPSL_CTX_GPM_SCM	97.3	84.2	80.8	85.3	60.8	89.9	86.8	89.3	75.4	77.8	75.1	83.0	87.5	90.1	95.0	57.8	79.2	73.4	94.5	80.7
UP_FEATURE_ENSEMBLE	-	-	-	-	-	-	-	-	-	-	-	-	-	-	88.7	-	-	-	-	-

## Trained on external data

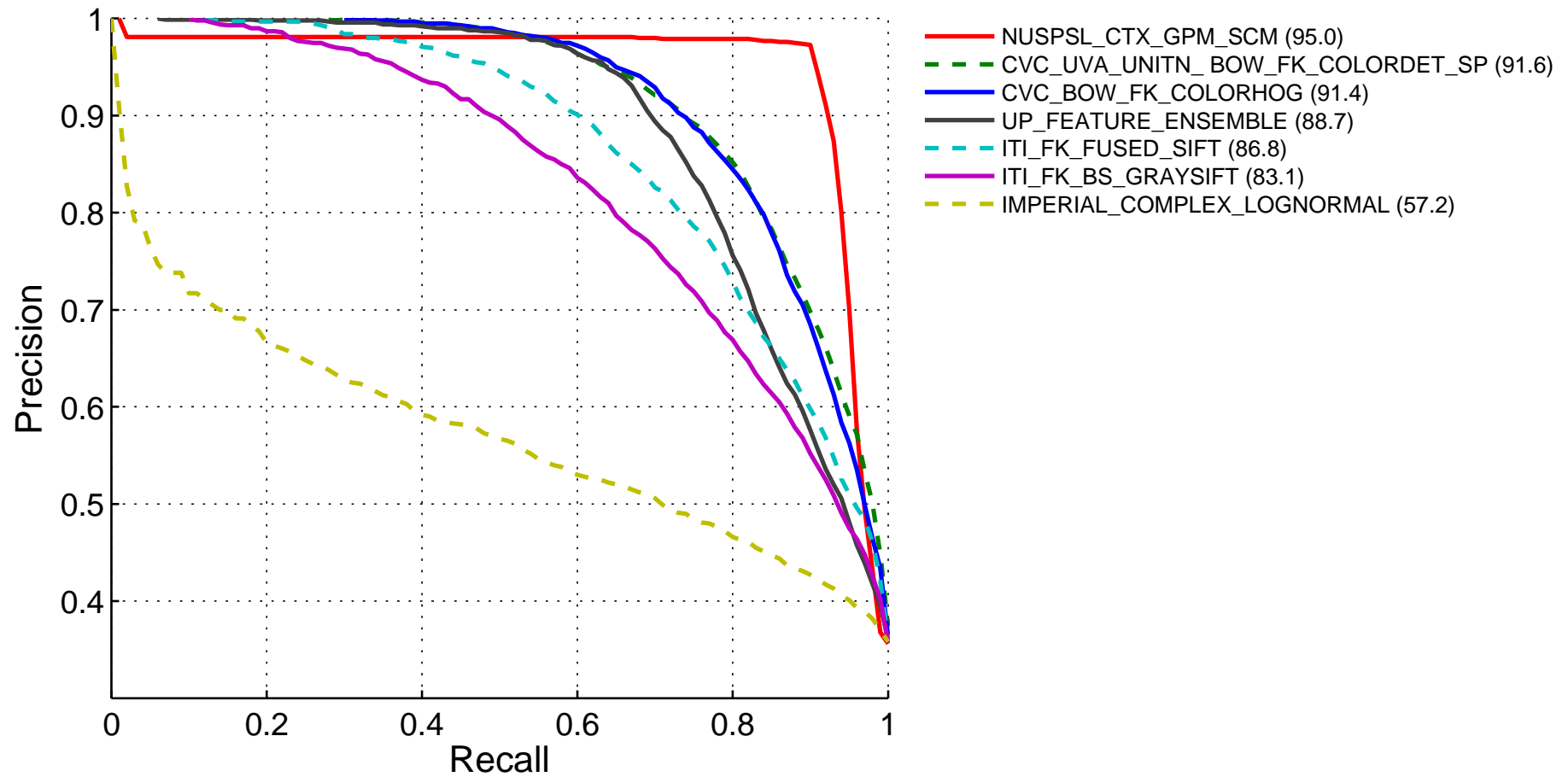
	aeroplane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	diningtable	dog	horse	motorbike	person	pottedplant	sheep	sofa	train	tvmonitor
ITI_FK_FLICKR_GRAYSIPT_ENTROPY	88.1	63.0	61.9	68.6	34.9	79.6	67.4	70.5	57.5	52.0	55.3	60.1	68.7	74.3	83.2	26.4	57.6	53.4	83.0	64.0

# Precision/recall curves (aeroplane)

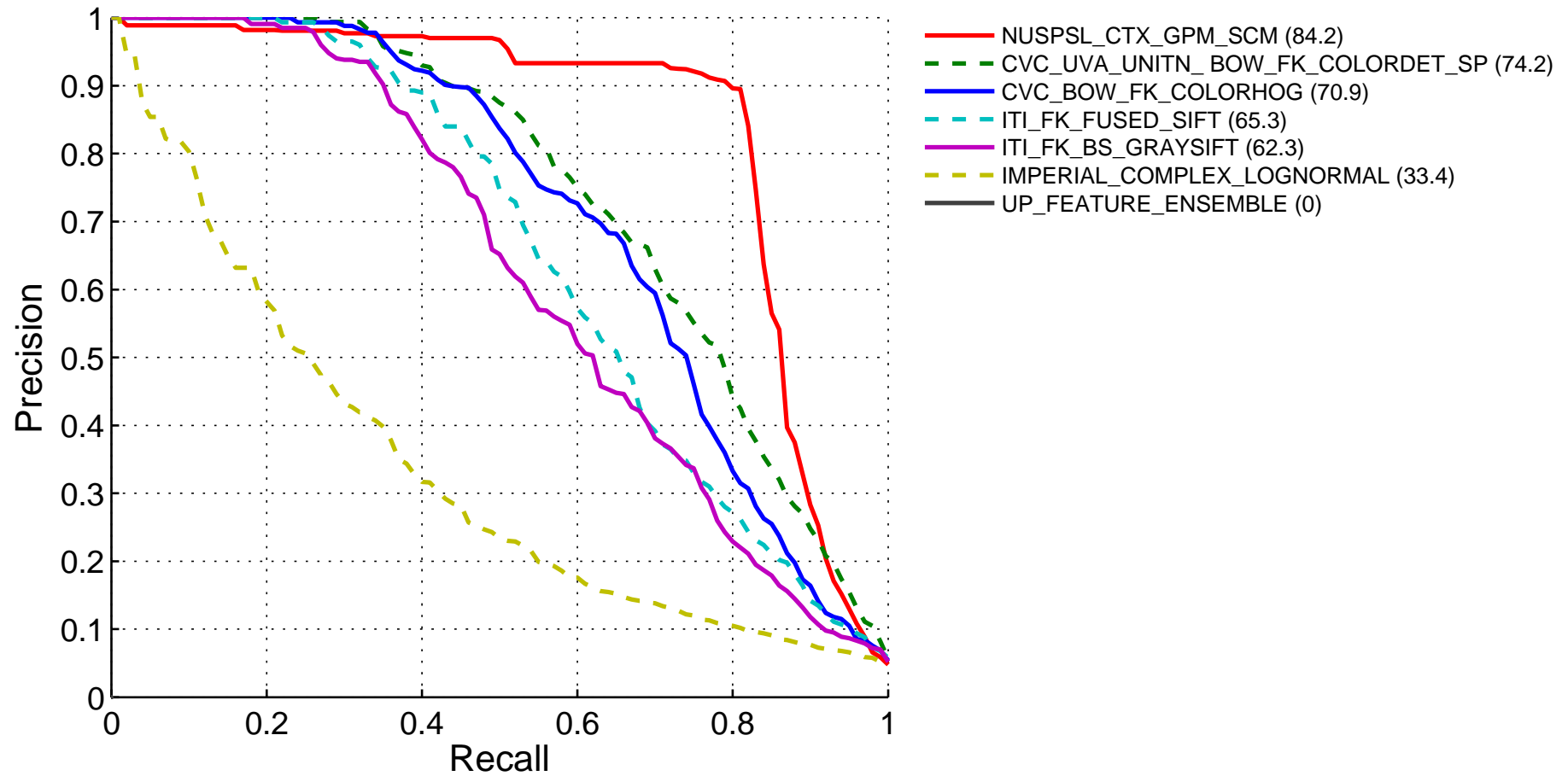




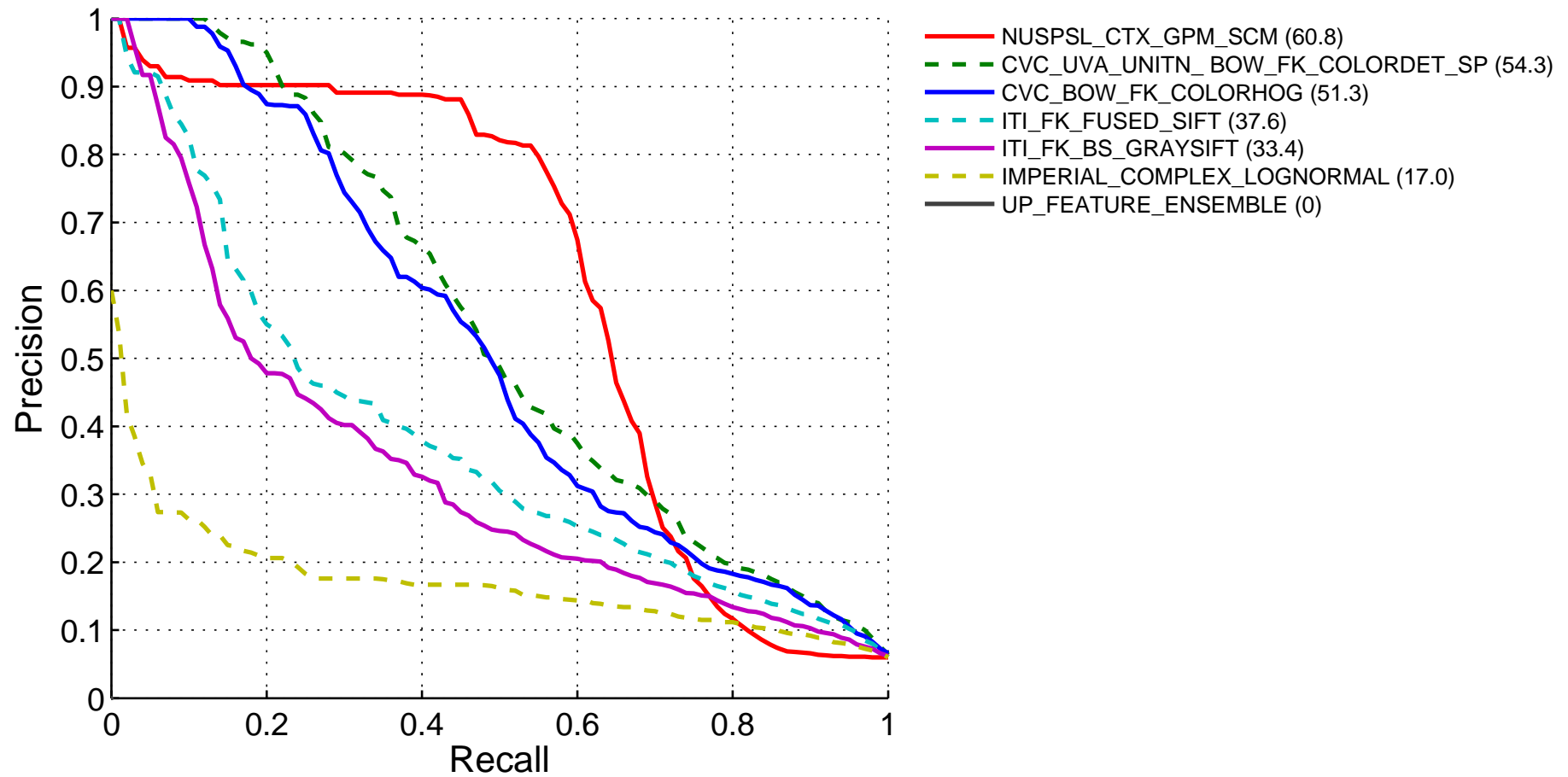
# Precision/recall curves (person)



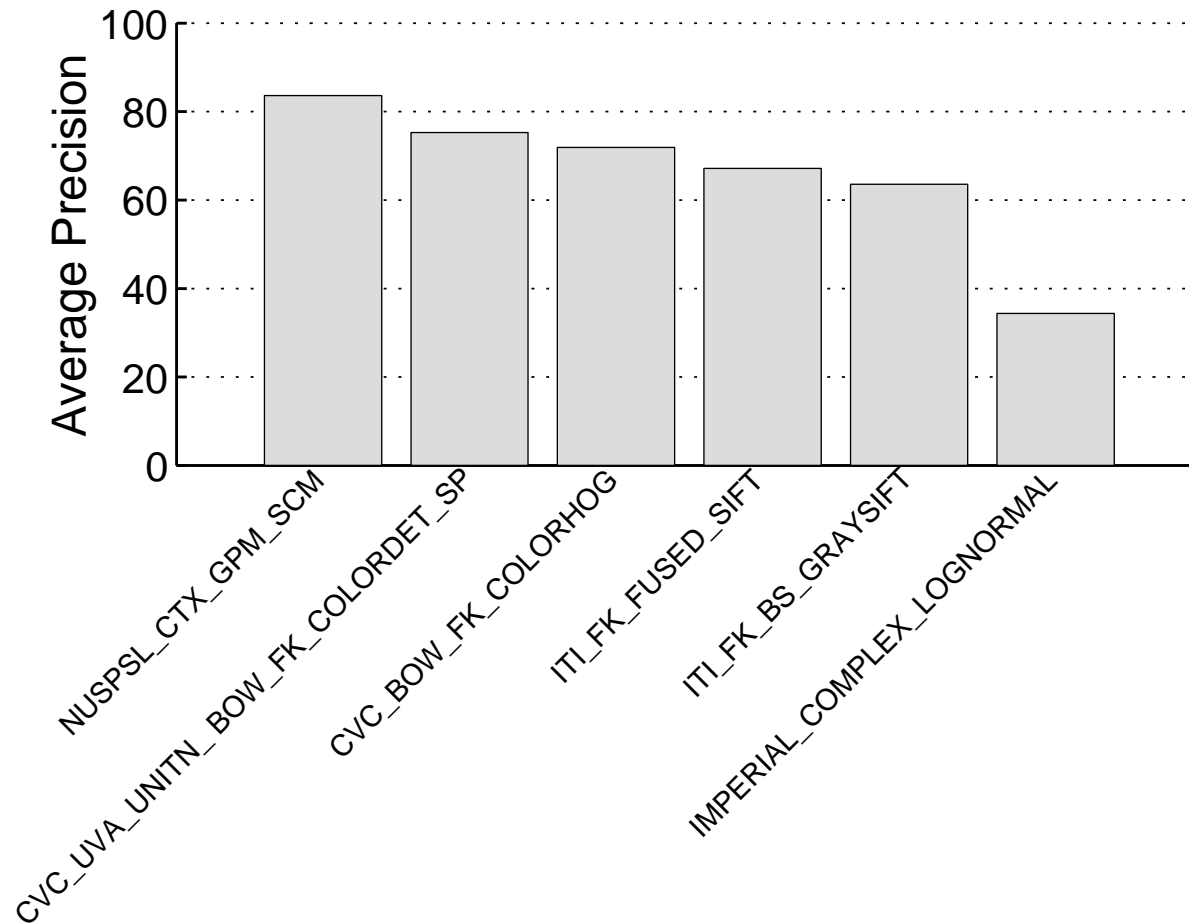
# Precision/recall curves (bicycle)



# Precision/recall curves (bottle)



# Median average precision by method





# Prizes



- Winner

- **NUSPSL\_CTX\_GPM\_SCM**

Dong Jian, Chen Qiang, Song Zheng,  
Pan Yan, Xia Wei, Yan Shuicheng,  
Hua Yang, Huang Zhongyang, Shen Shengmei  
*National University of Singapore*  
*Panasonic Singapore Laboratories*  
*Sun Yat-sen University*

- Honourable mention

- **CVC\_UVA\_UNITN\_  
BOW\_FK\_COLORDET\_SP**

Fahad Khan, Jan van Gemert, Camp Davesa, Jasper  
Uijlings , Albert Gordo, Sezer Karaoglu, Koen van de  
Sande, Pep Gonfaus, Rao Muhammad Anwer, Joost  
van de Weijer, Cees Snoek, Ramon Baldrich, Nicu  
Sebe, Theo Gevers

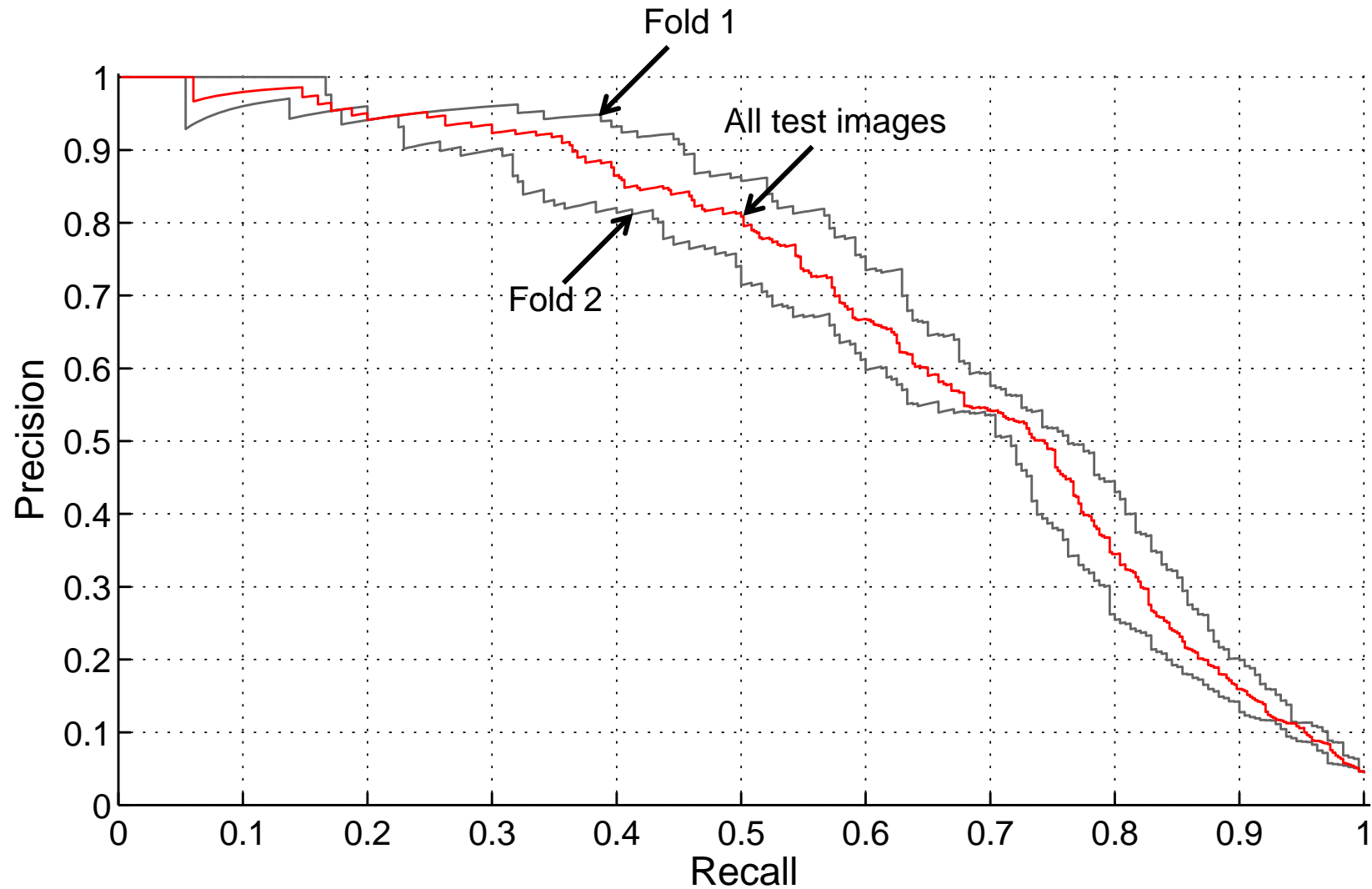
*Computer Vision Barcelona*  
*University of Amsterdam*  
*University of Trento*

# Super-classifiers

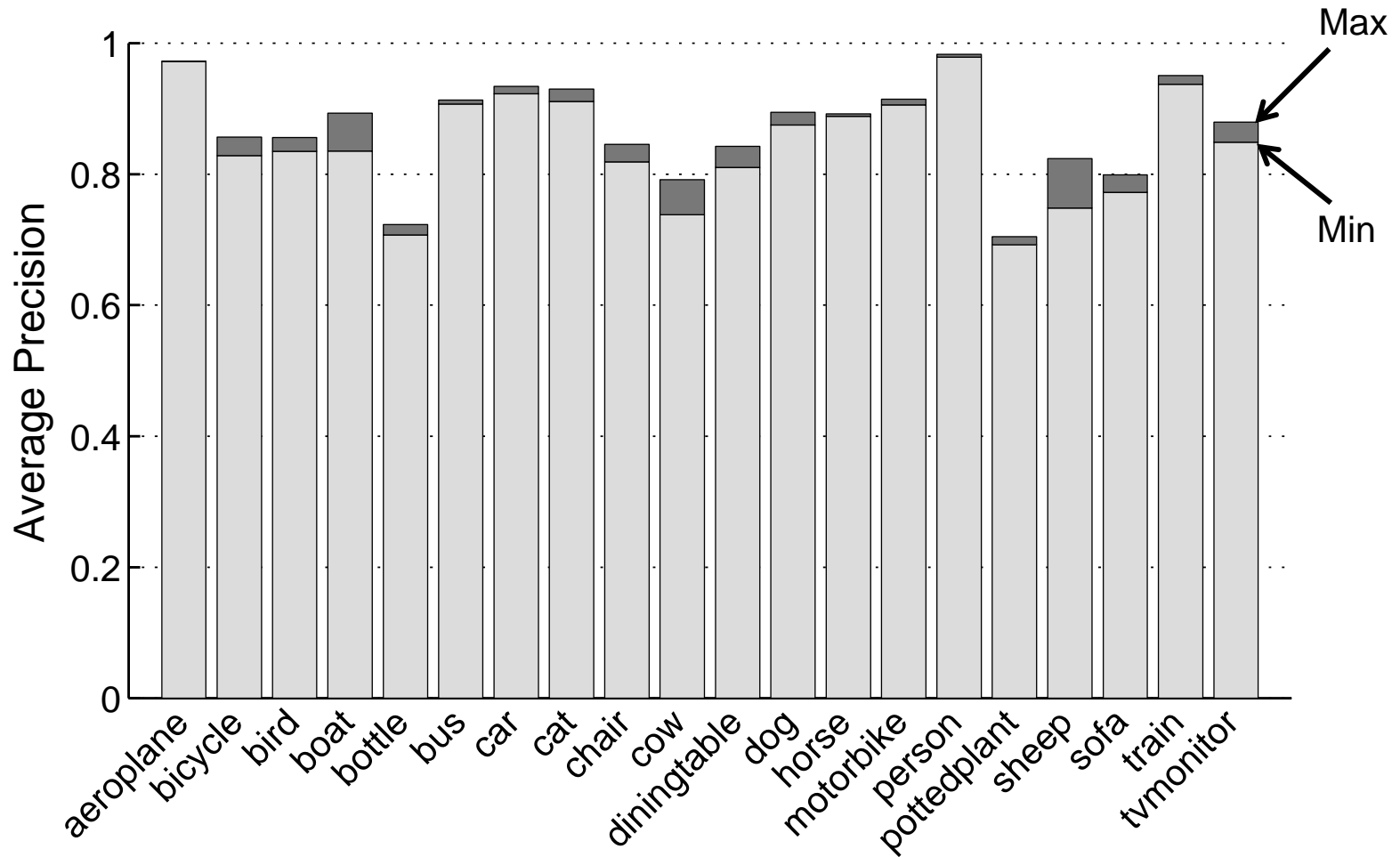
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- Split test data into two sets, **A** and **B**
- Use the score of each method as a feature for each image of set **A** (feature vector length is equal to number of methods)
- Learn a linear L2 binary SVM classifier (with  $C=1$ ) to predict classification of each image for each class (learn 20 classifiers)
- Compute PR curves and AP for each classifier
- Repeat by training on **B** and testing on **A**

# Sensitivity to test split (boat)

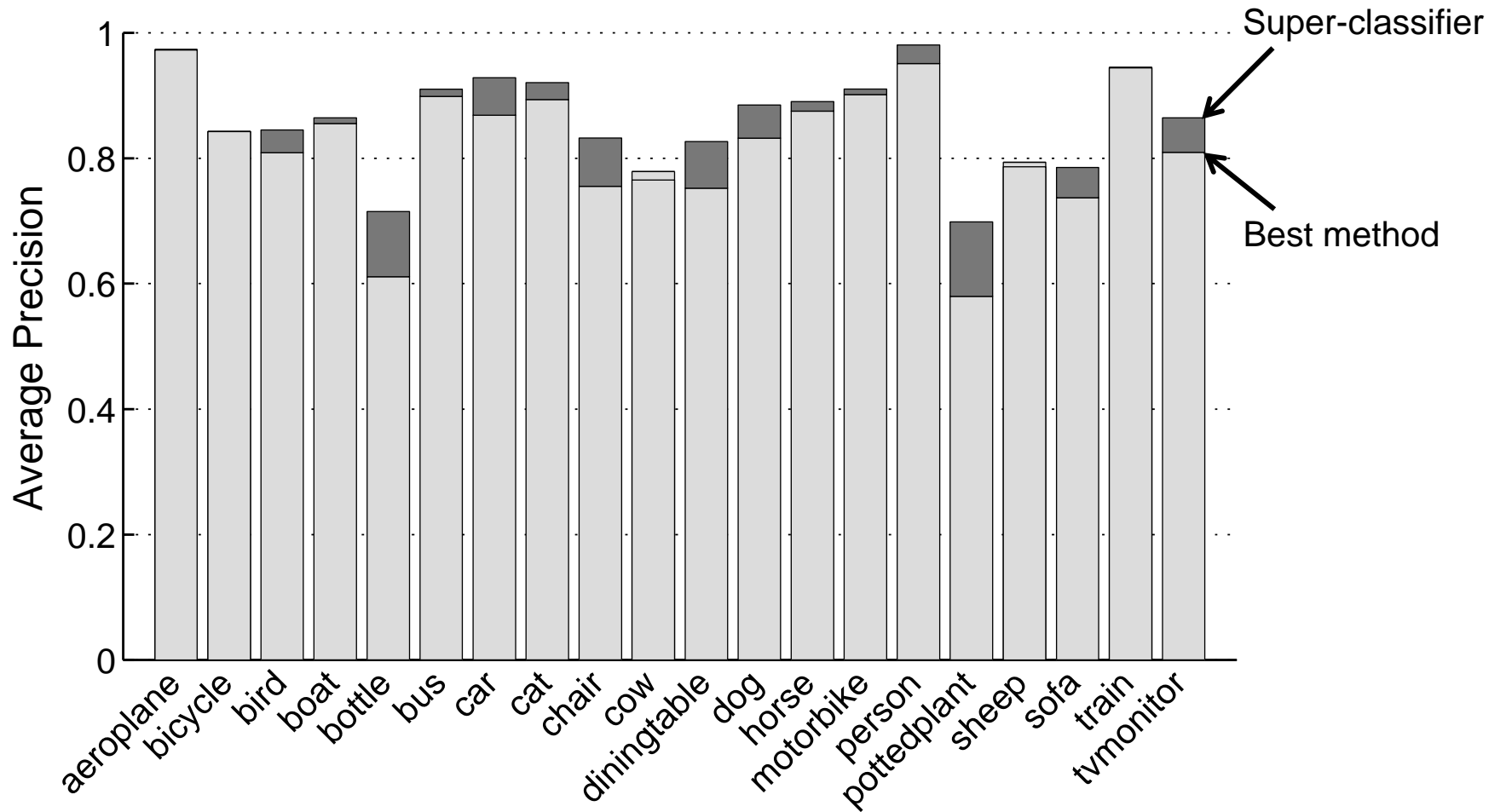


# Super-classifiers (sensitivity to test split)

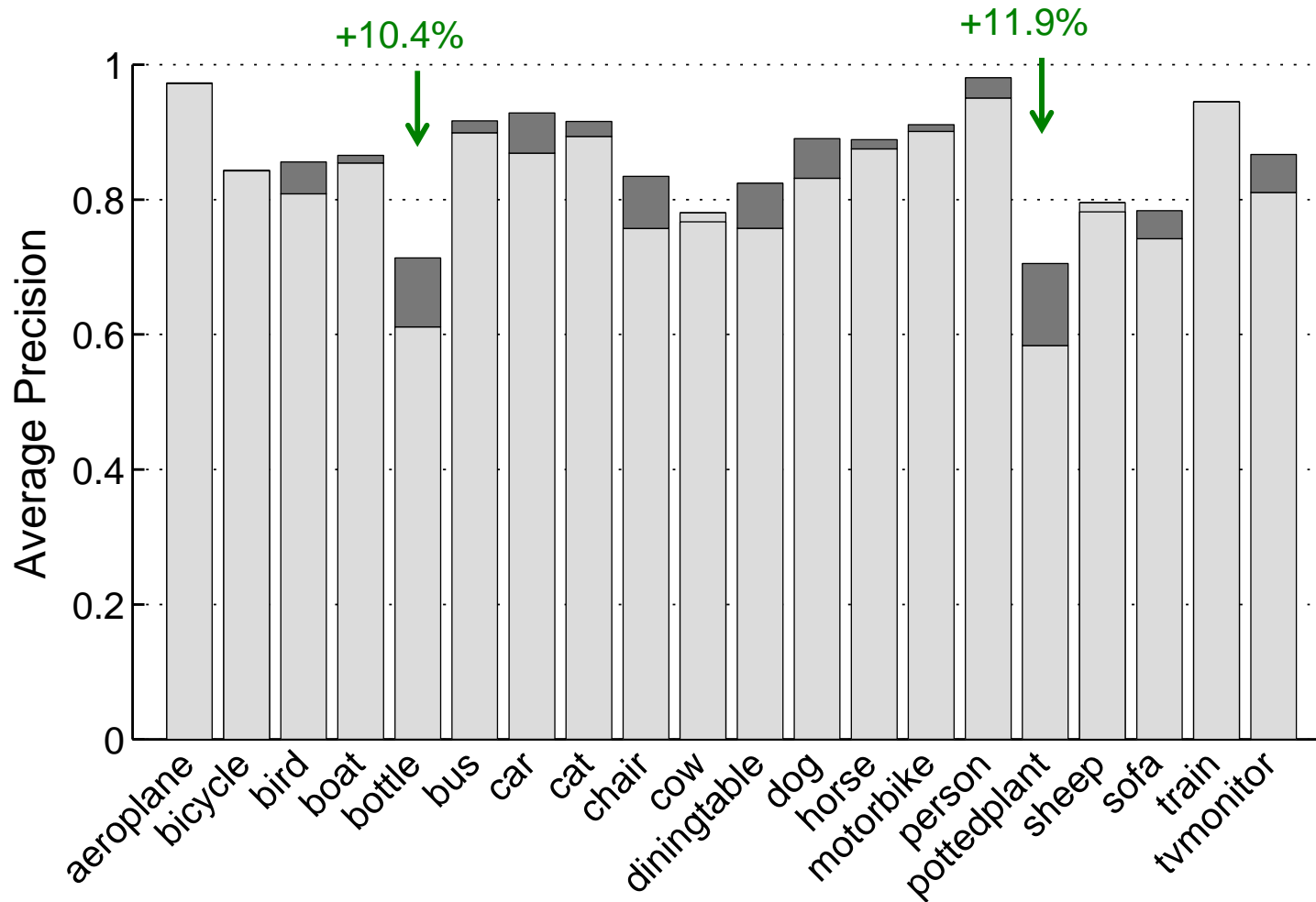




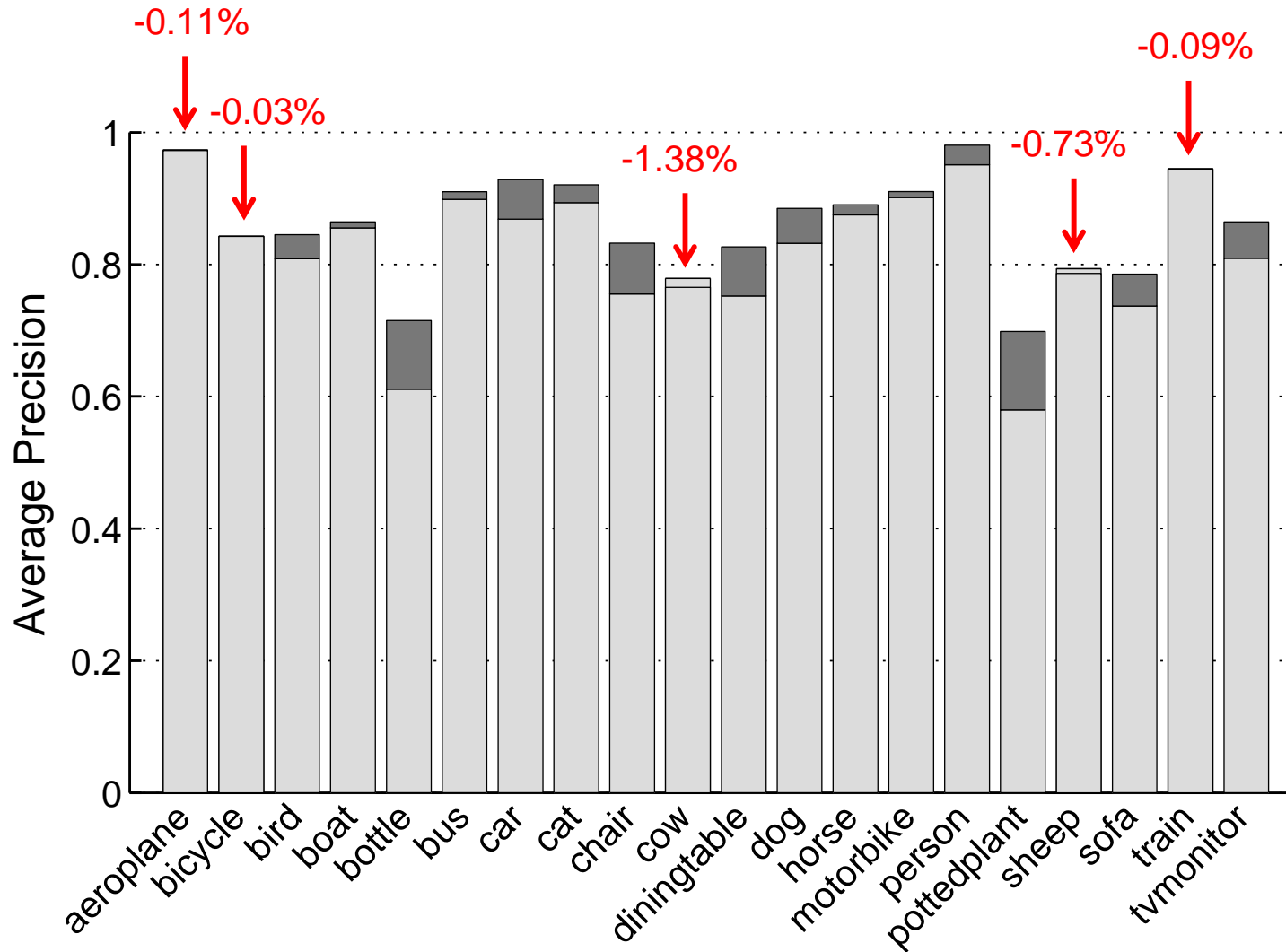
# Super-classifiers



# Super-classifiers

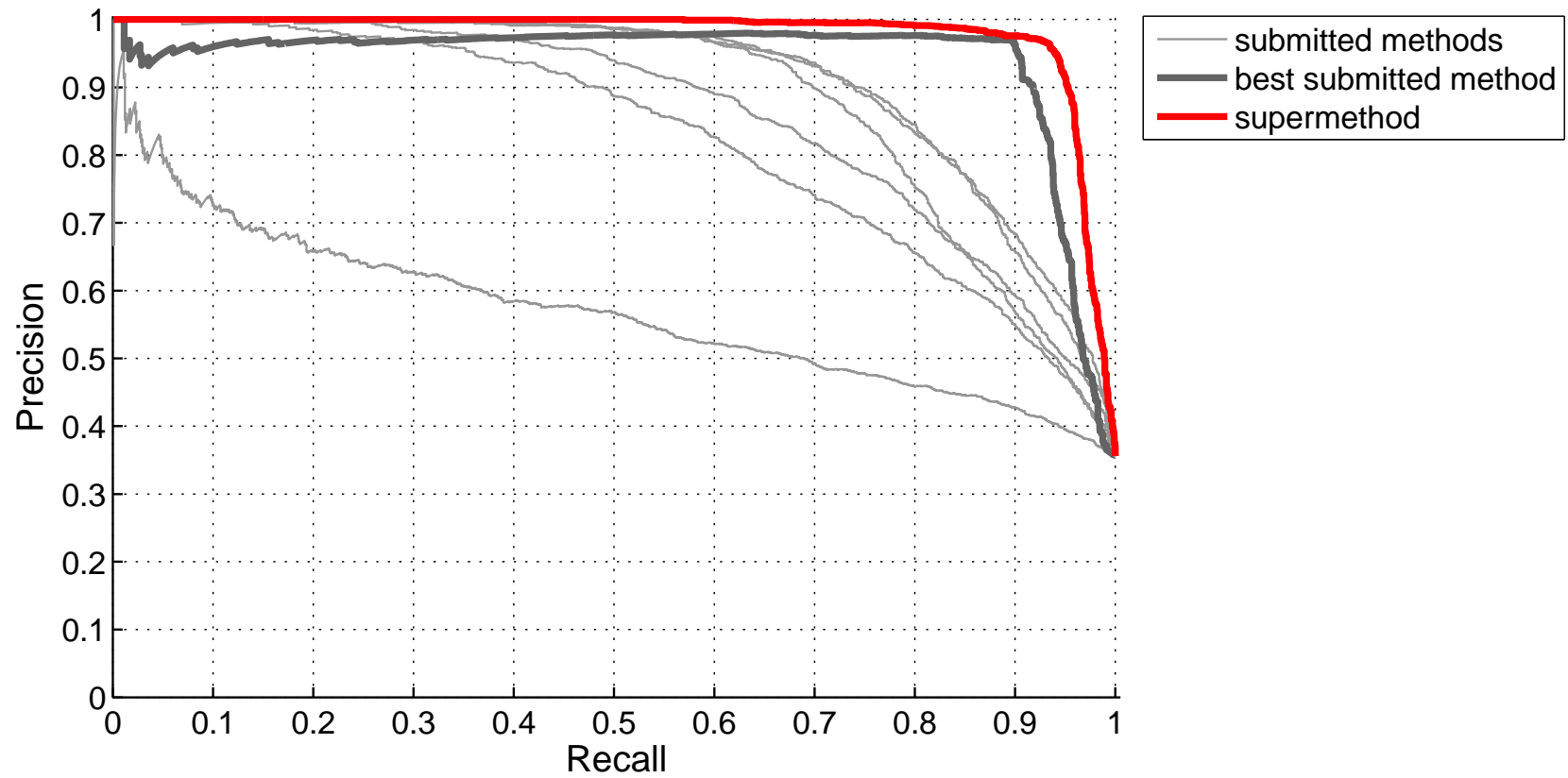


# Super-classifiers



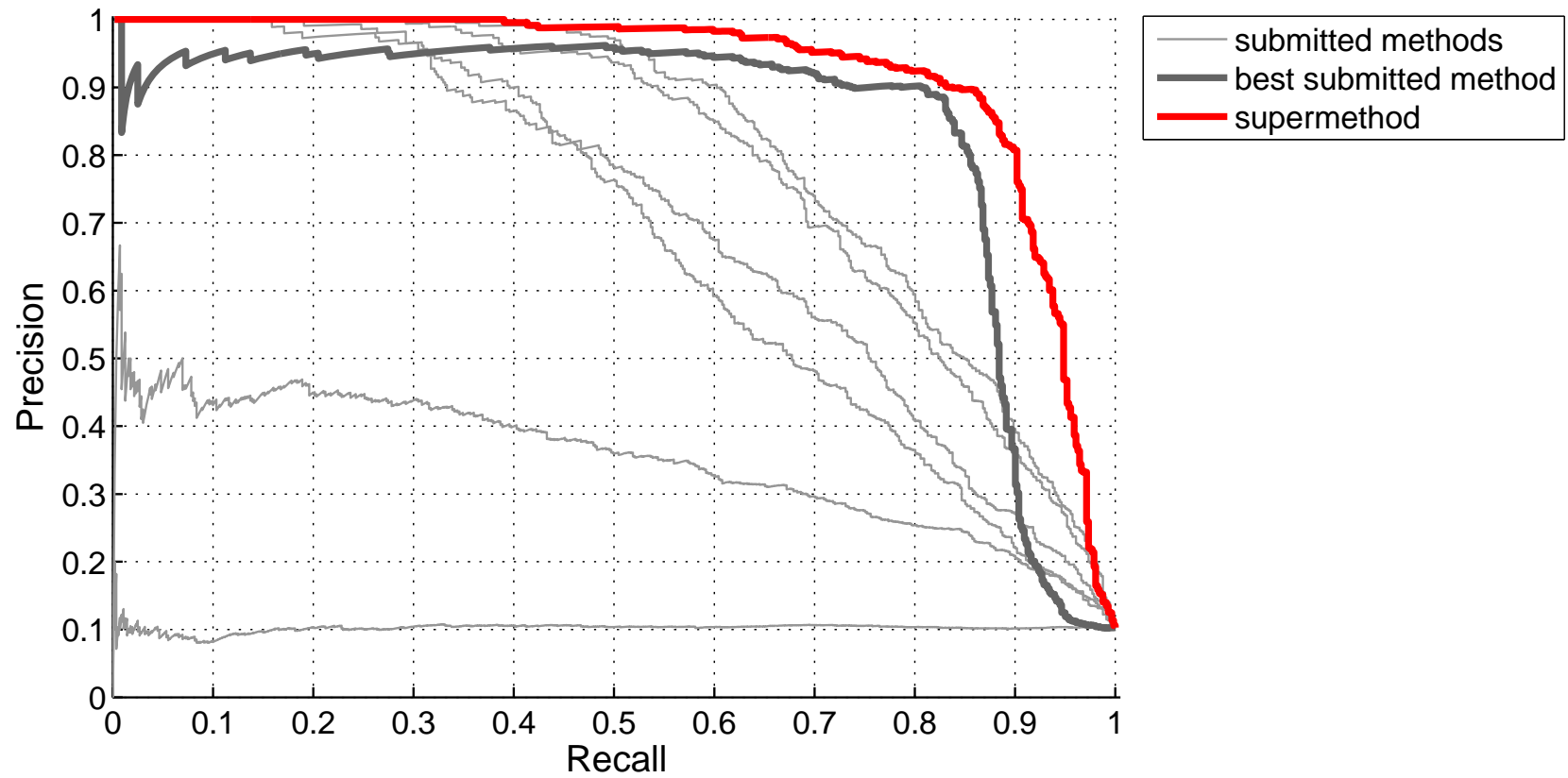
# Super-classifiers (person)

AP +3.0



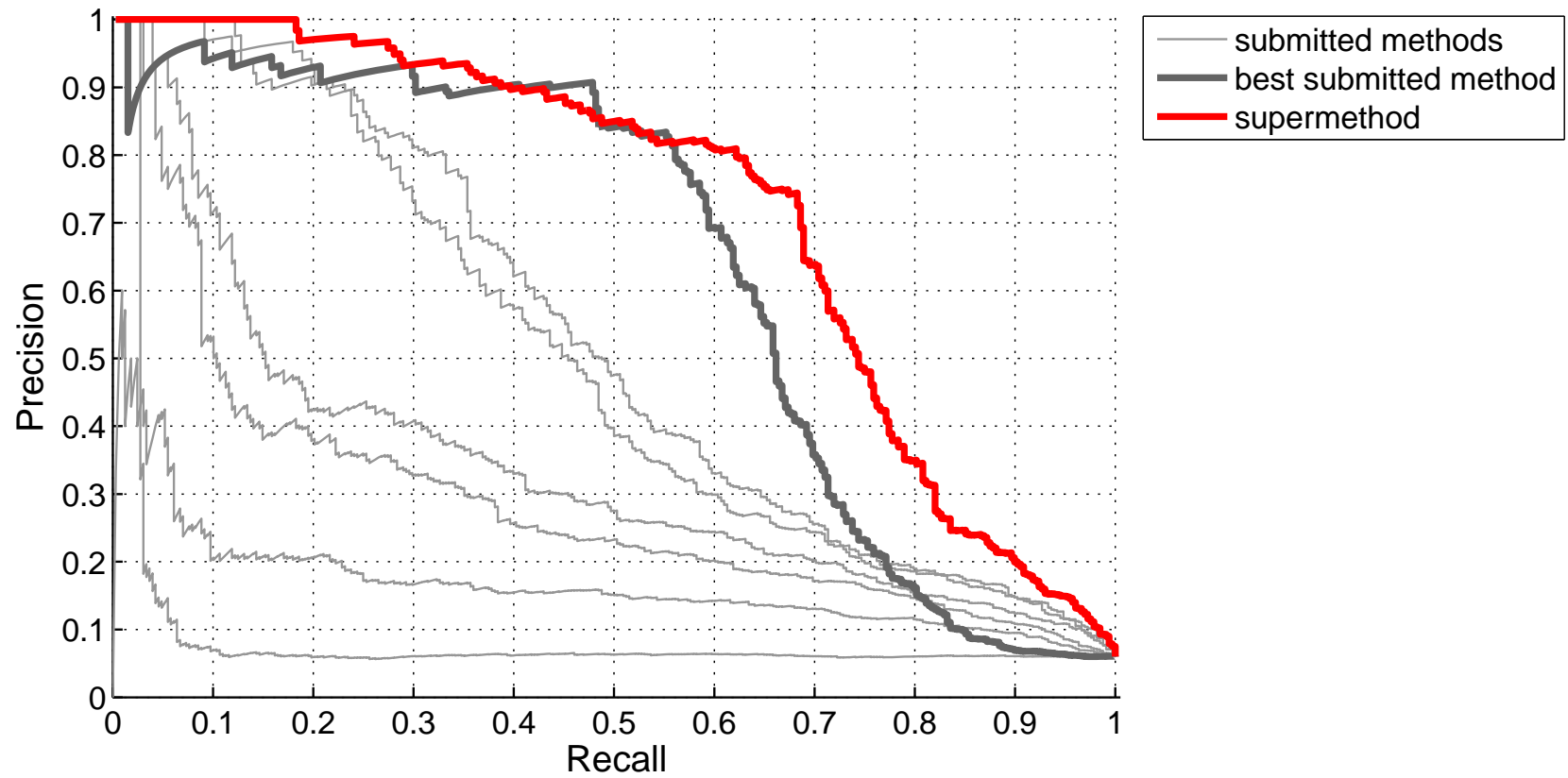
# Super-classifiers (car)

AP +6.0



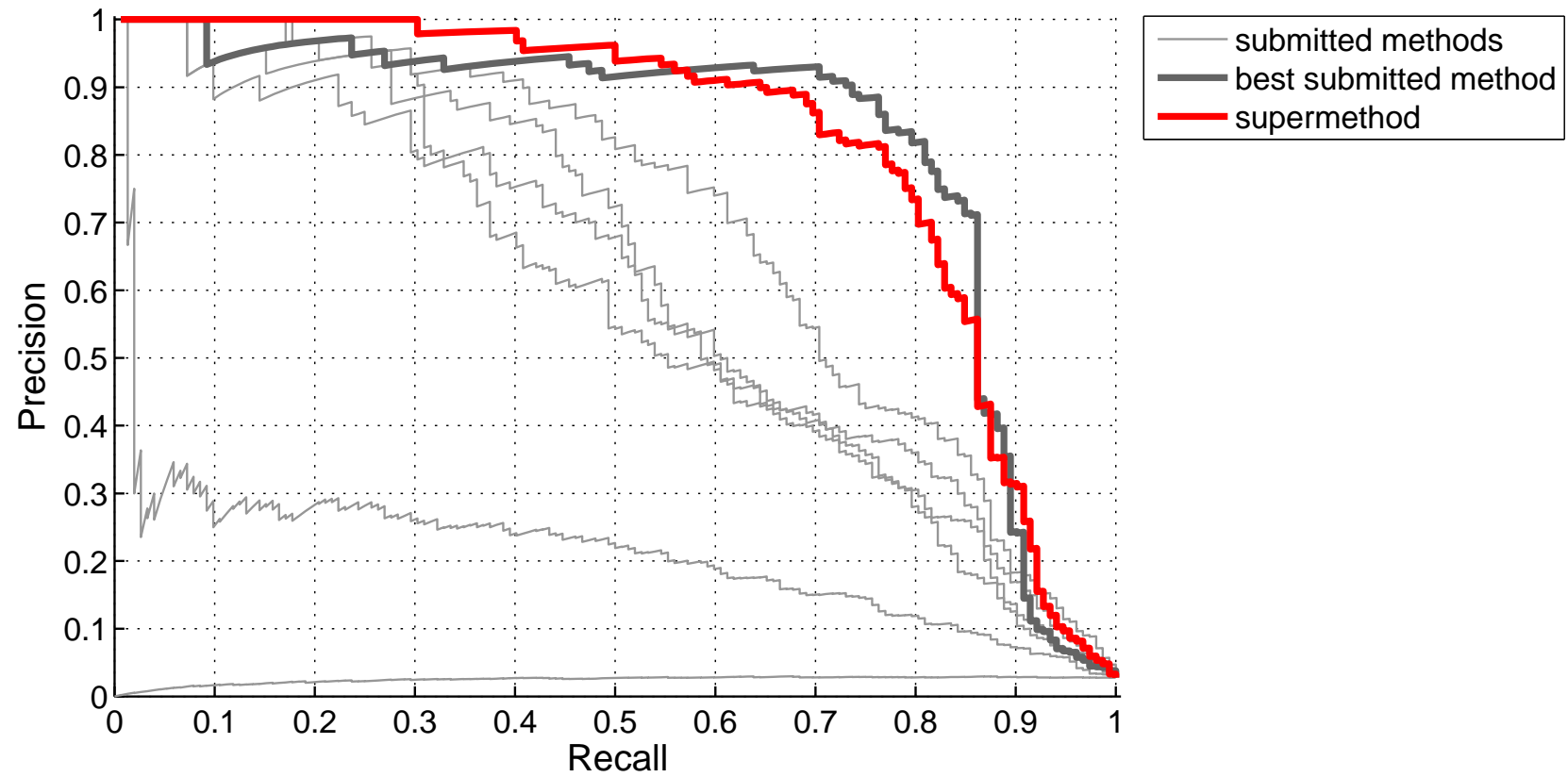
# Super-classifiers (bottle)

AP +10.4



# Super-classifiers (sheep)

**AP -0.73**



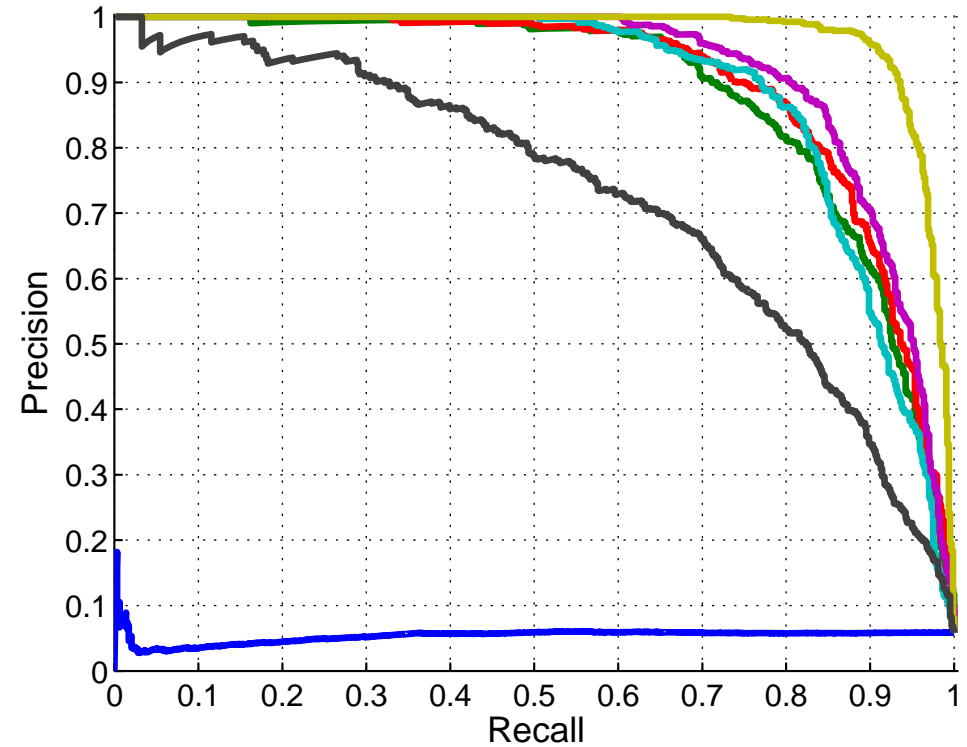
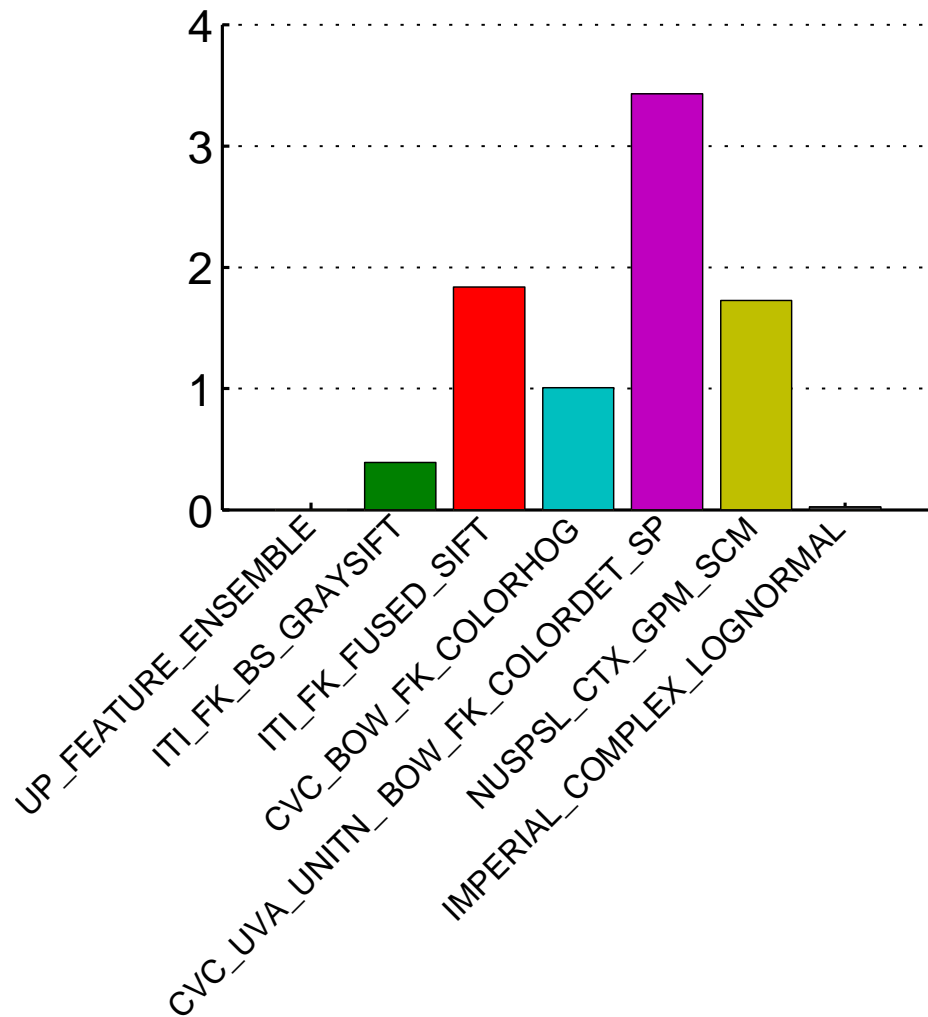


# Super-classifiers (weights)

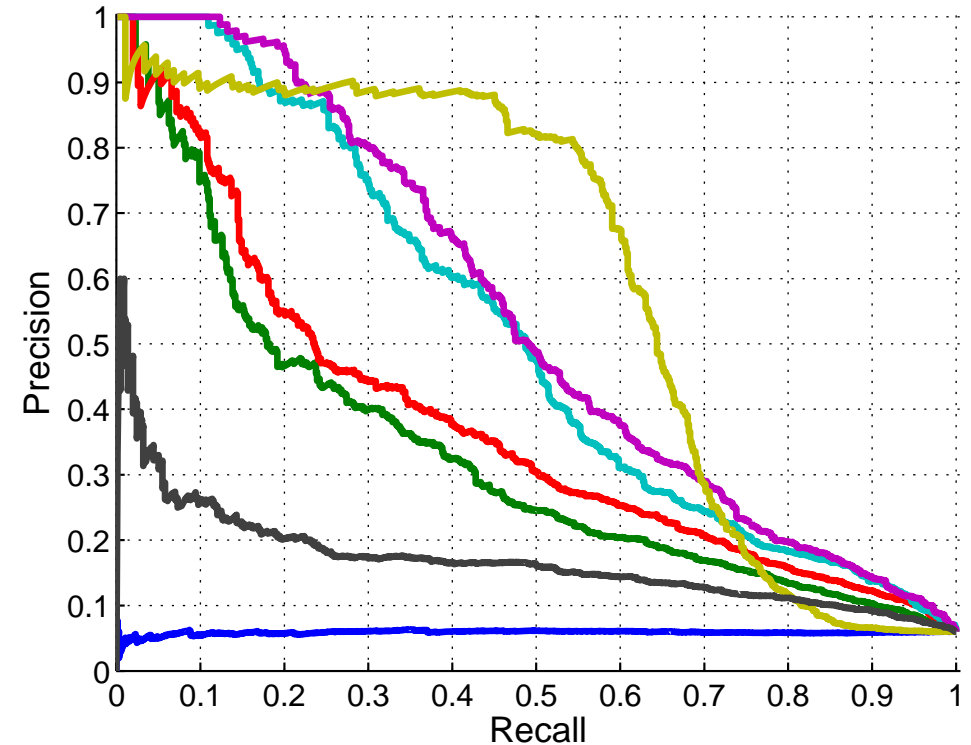
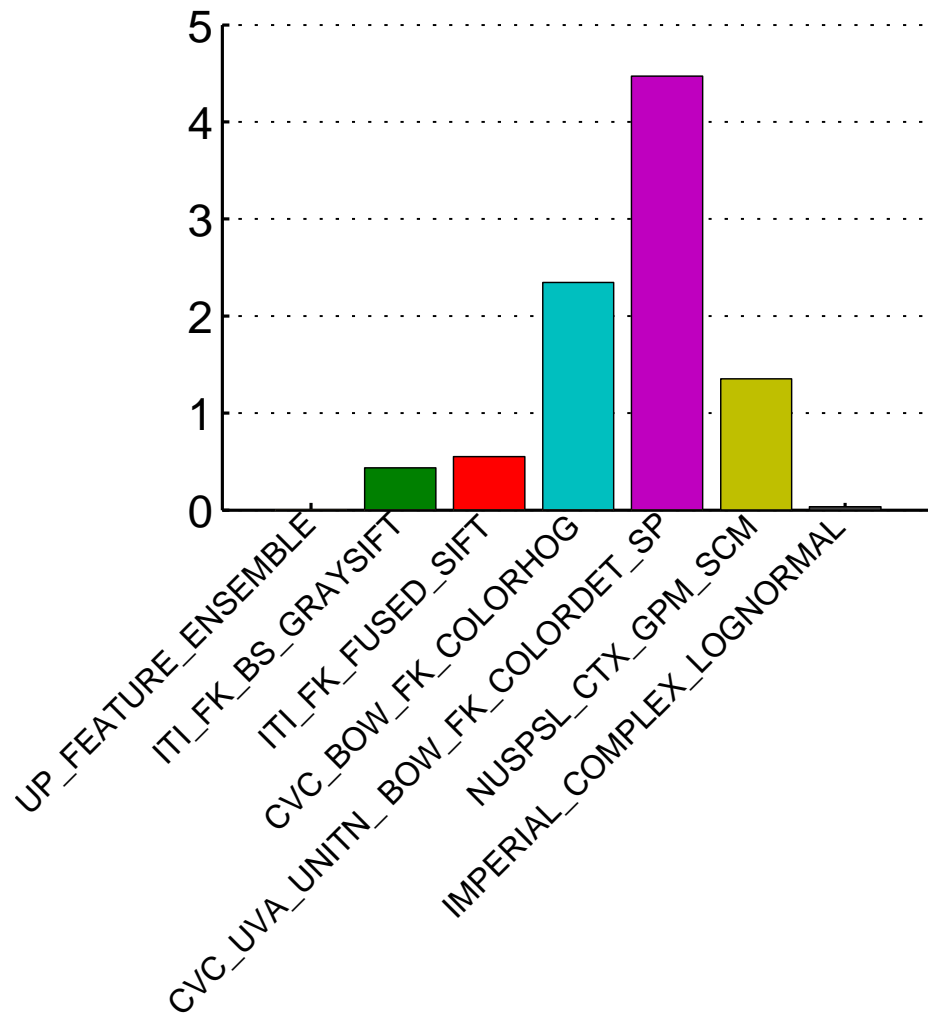
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- Train super-classifier on *all* of test data.
- Inspect weight magnitudes for different features.

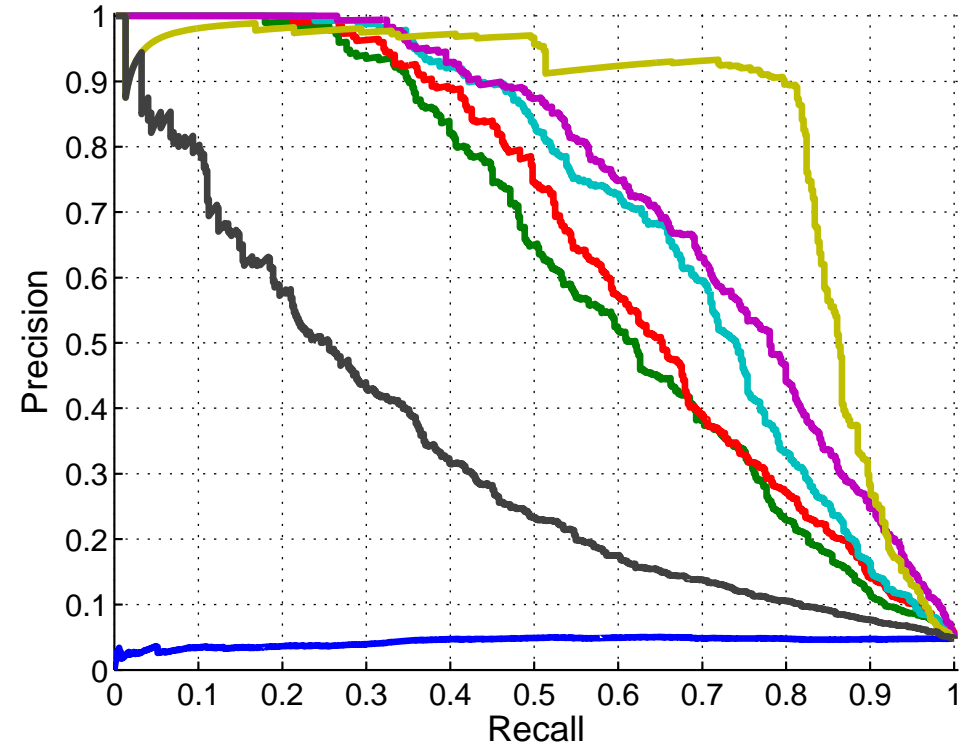
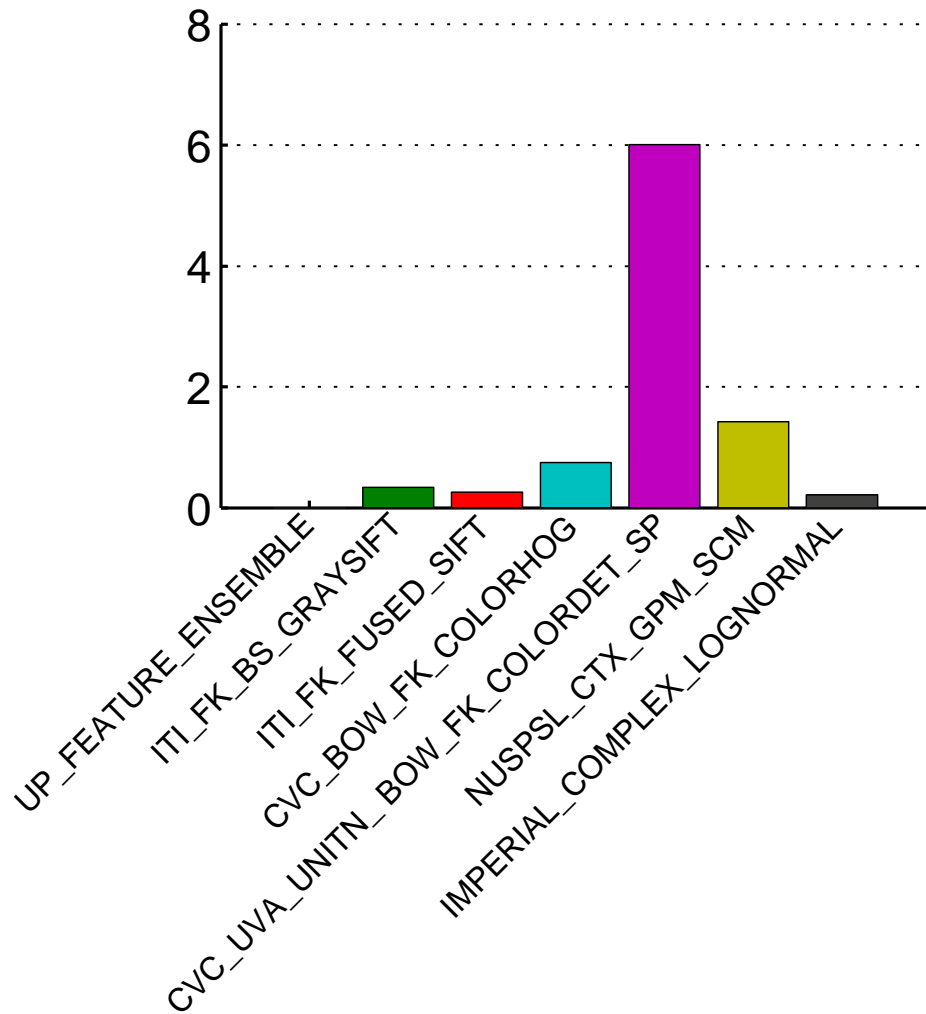
# Super-classifiers (weights - aeroplane)



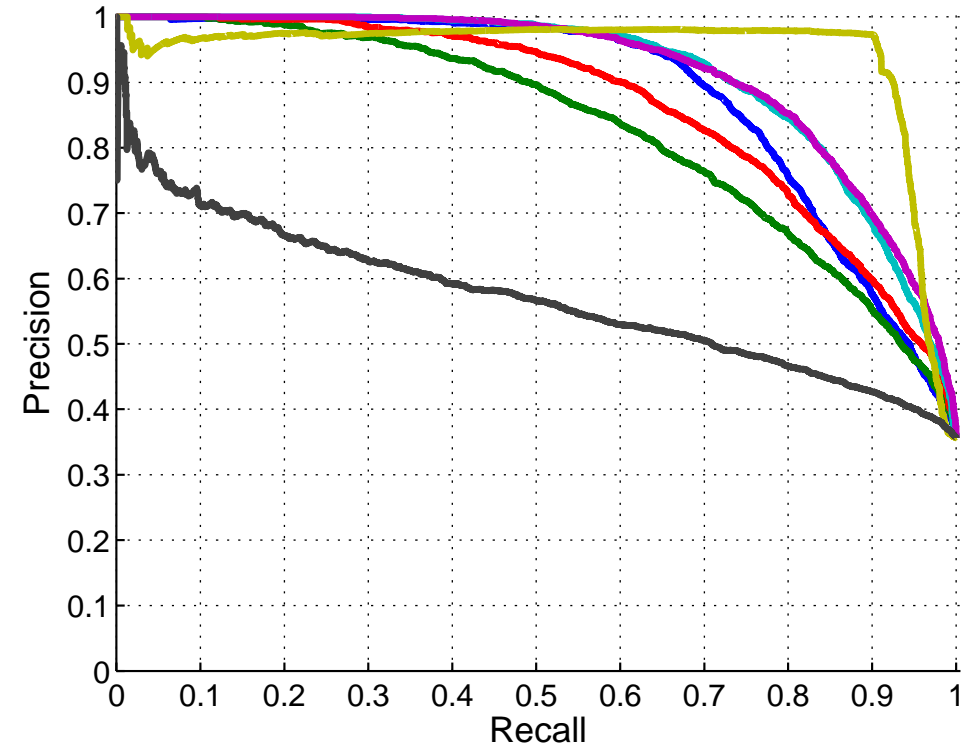
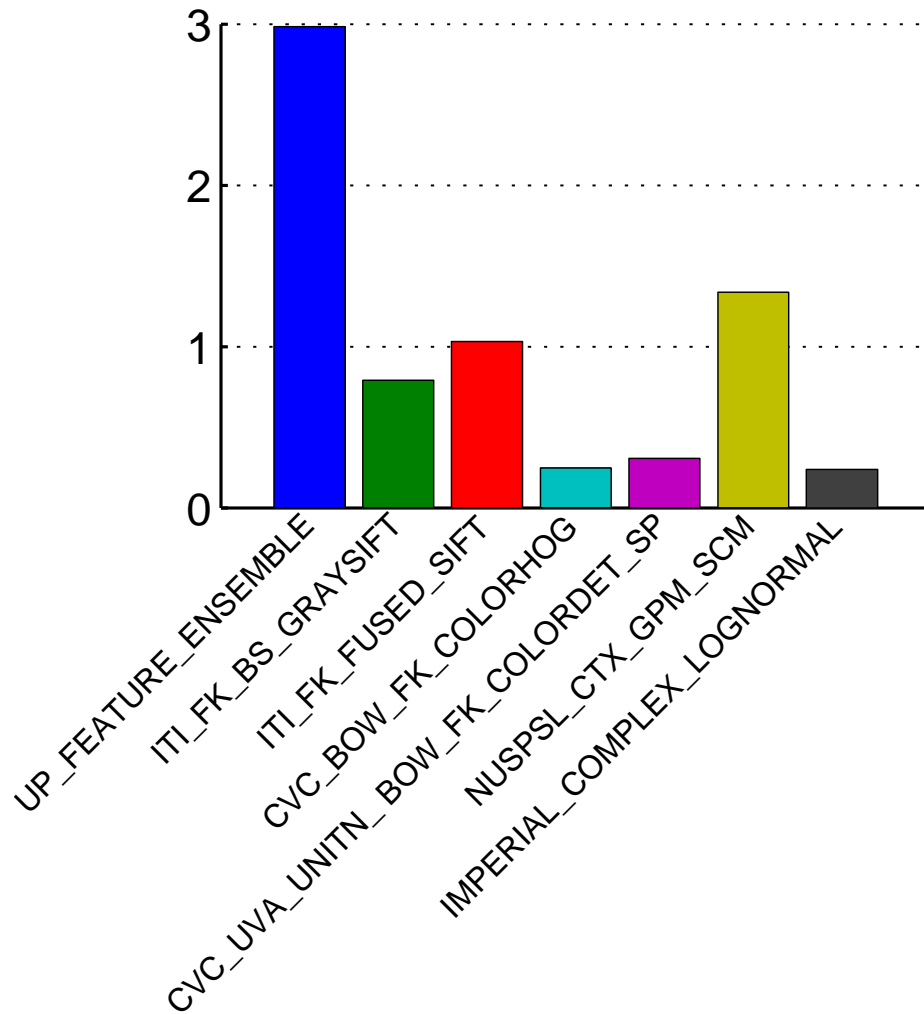
# Super-classifiers (weights - bottle)



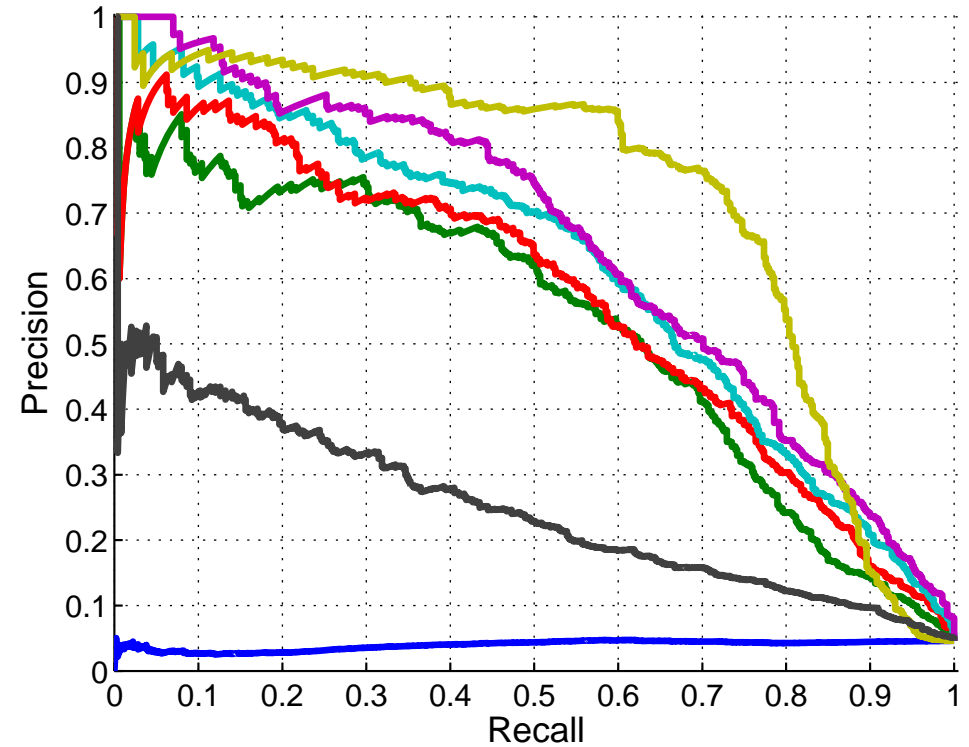
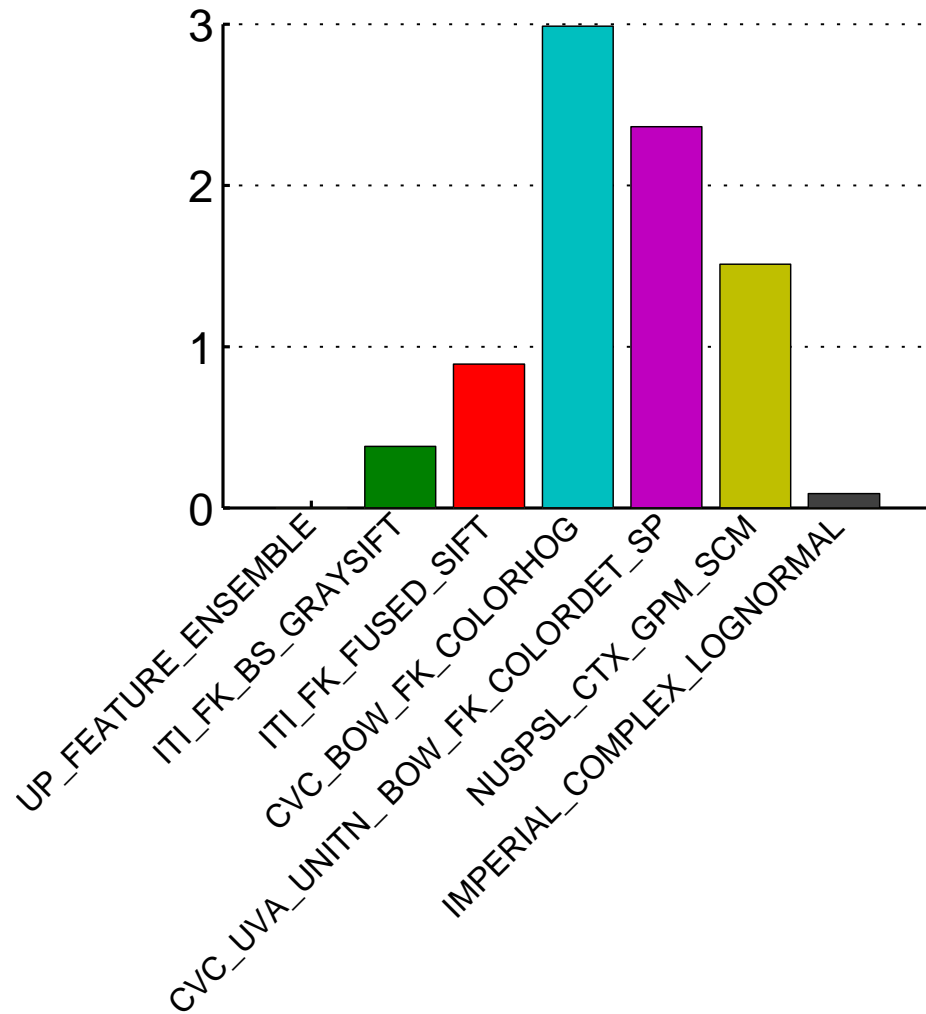
# Super-classifiers (weights - bicycle)



# Super-classifiers (weights - person)



# Super-classifiers (weights - sofa)



# Collaboration recommendations

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- Consider all combinations of pairs of submissions
- Train a super-classifier using only predictions of each pair as features
- Choose
  - The pair of submissions that leads to maximum possible (pairwise) AP
  - The pair of submissions that leads to maximum possible (pairwise) relative *increase* in AP



# Collaboration recommendations

Class	Top AP	Collaborator 1		Collaborator 2		C <sup>1</sup> +C <sup>2</sup> AP	All combined AP
		Name	AP	Name	AP		
aeroplane	97.34	UP_FEATURE_ENSEMBLE	6.00	NUSPSL_CTX_GPM_SCM	97.34	97.34	97.23
bicycle	84.28	ITI_FK_FUSED_SIFT	65.35	NUSPSL_CTX_GPM_SCM	84.28	85.30	84.25
bird	80.89	CVC_BOW_FK_COLORHOG	69.78	NUSPSL_CTX_GPM_SCM	80.89	85.09	84.54
boat	85.52	CVC_UVA_UNITN_BO...	77.53	NUSPSL_CTX_GPM_SCM	85.52	86.38	86.44
bottle	61.12	CVC_UVA_UNITN_BO...	54.37	NUSPSL_CTX_GPM_SCM	61.12	69.94	71.51
bus	89.86	CVC_BOW_FK_COLORHOG	84.79	NUSPSL_CTX_GPM_SCM	89.86	91.12	91.00
car	86.87	CVC_UVA_UNITN_BO...	81.90	NUSPSL_CTX_GPM_SCM	86.87	93.07	92.84
cat	89.37	CVC_UVA_UNITN_BO...	76.54	NUSPSL_CTX_GPM_SCM	89.37	92.19	92.06
chair	75.56	CVC_UVA_UNITN_BO...	65.21	NUSPSL_CTX_GPM_SCM	75.56	83.49	83.22
cow	77.88	UP_FEATURE_ENSEMBLE	3.93	NUSPSL_CTX_GPM_SCM	77.88	77.96	76.50
diningtable	75.24	CVC_UVA_UNITN_BO...	68.59	NUSPSL_CTX_GPM_SCM	75.24	82.26	82.64
dog	83.19	CVC_UVA_UNITN_BO...	68.94	NUSPSL_CTX_GPM_SCM	83.19	89.25	88.48
horse	87.53	ITI_FK_FUSED_SIFT	72.39	NUSPSL_CTX_GPM_SCM	87.53	88.84	89.02
motorbike	90.14	CVC_BOW_FK_COLORHOG	79.21	NUSPSL_CTX_GPM_SCM	90.14	90.78	91.03
person	95.11	CVC_UVA_UNITN_BO...	91.62	NUSPSL_CTX_GPM_SCM	95.11	97.87	98.08
pottedplant	57.99	CVC_UVA_UNITN_BO...	56.24	NUSPSL_CTX_GPM_SCM	57.99	70.11	69.86
sheep	79.34	NUSPSL_CTX_GPM_SCM	79.34	IMPERIAL_COMPLEX_...	23.86	79.48	78.61
sofa	73.69	ITI_FK_FUSED_SIFT	57.42	NUSPSL_CTX_GPM_SCM	73.69	78.56	78.55
train	94.49	UP_FEATURE_ENSEMBLE	5.10	NUSPSL_CTX_GPM_SCM	94.49	94.49	94.41
tvmonitor	80.95	CVC_UVA_UNITN_BO...	77.37	NUSPSL_CTX_GPM_SCM	80.95	85.75	86.41

Collaborations to maximise combined AP: AP<sup>1+2</sup>