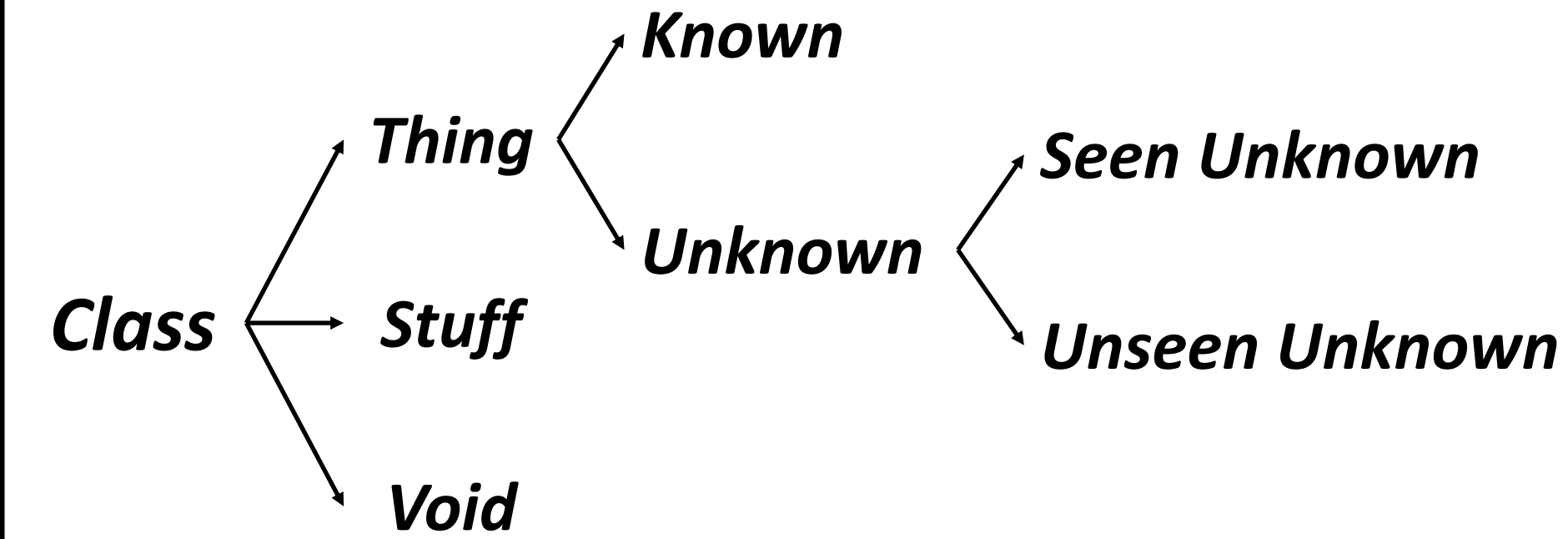




## Open-Set Panoptic Segmentation

### Labels

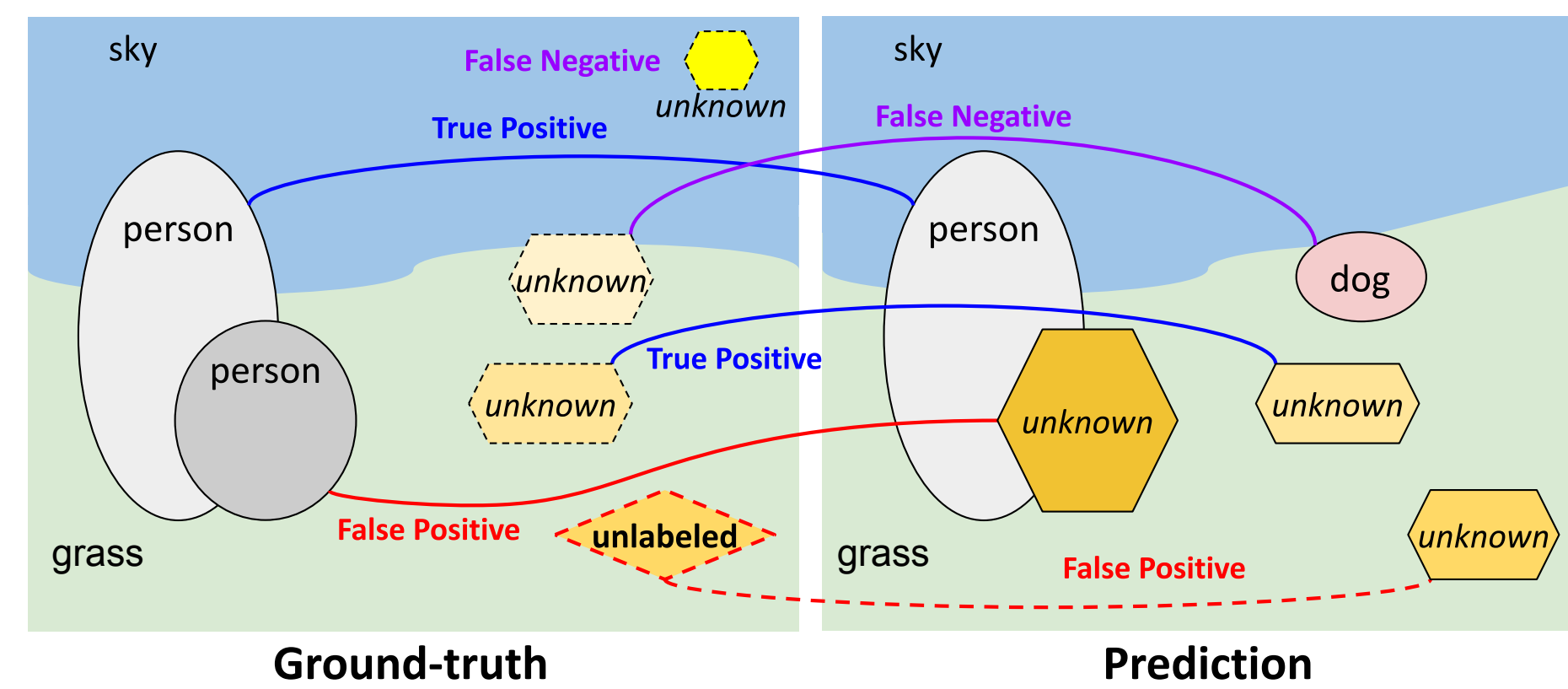


### Evaluation Metrics

$$PQ = \underbrace{\frac{\sum_{(p,g) \in TP} \text{IoU}(p,g)}{|TP|}}_{\text{segmentation quality (SQ)}} \cdot \underbrace{\frac{|TP|}{|TP| + \frac{1}{2}|FP| + \frac{1}{2}|FN|}}_{\text{recognition quality (RQ)}}$$

### Challenges

- Finding *unknown* instances is more difficult.
- Annotating  $\forall$  objects is almost impossible.
- Find unlabeled *unknown* instances  $\Rightarrow$  PQ $\downarrow$ , RQ $\downarrow$



### Assumptions for preventing label conflict

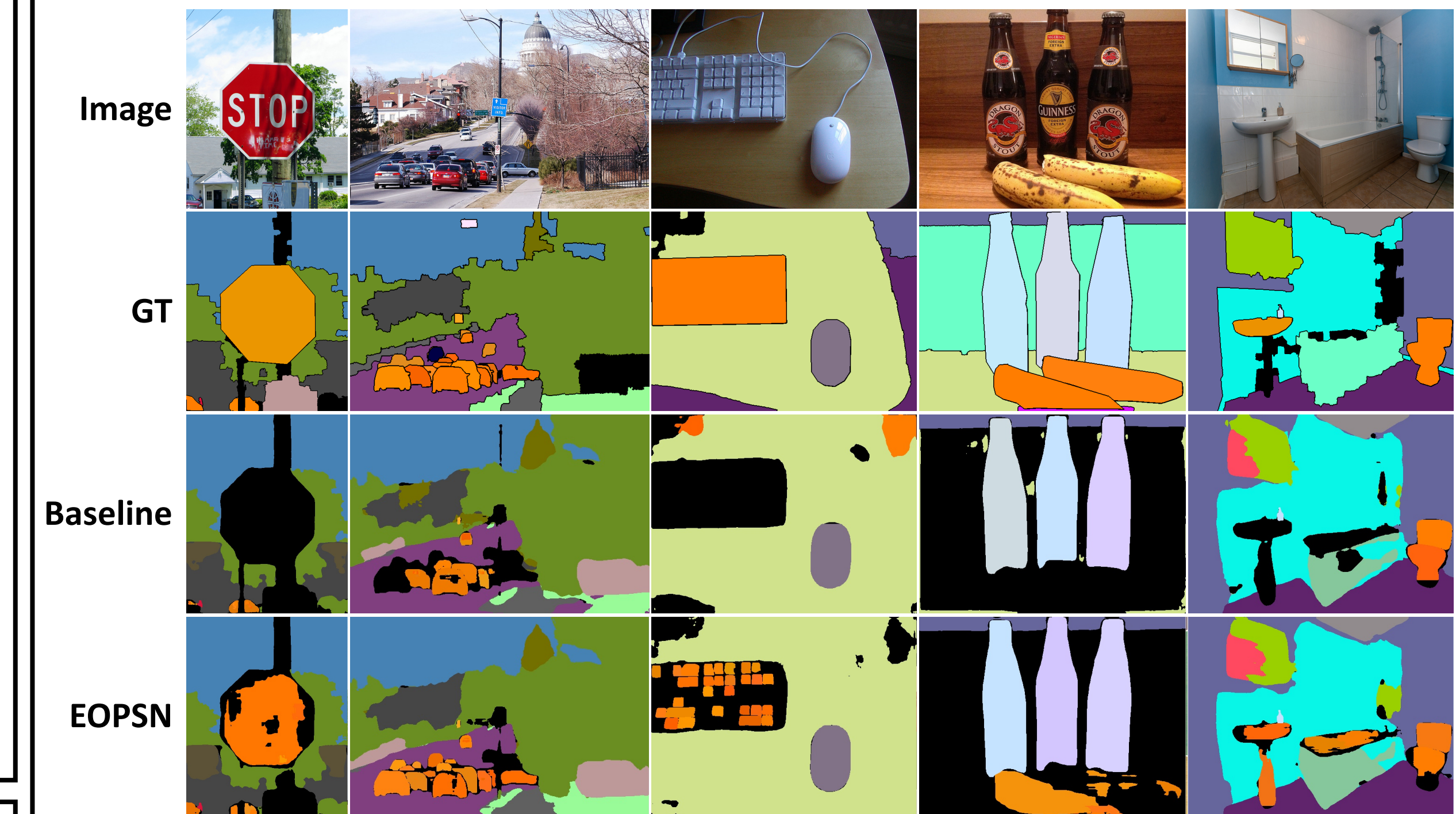
- $\forall$  *unknown* class  $\subset$  *thing* class.
- Parts of *known* objects  $\neq$  *unknown* class (e.g., tire in *car*).
- Unknown* classes in training images only appear on *void* regions.

### Dataset based on COCO [1]

- We construct different splits with different ratio,  $K$  of *unknown*  $n$  classes among *thing* classes.
  - 5%: *car, cow, pizza, toilet*
  - 10%: (5%) + *boat, tie, zebra, stop sign*
  - 20%: (10%) + *dining table, banana, bicycle, cake, sink, cat, keyboard, bear*
- We remove annotations for *unknown* classes during training.

## Experiments

### Qualitative Results (orange denotes *unknown* classes).



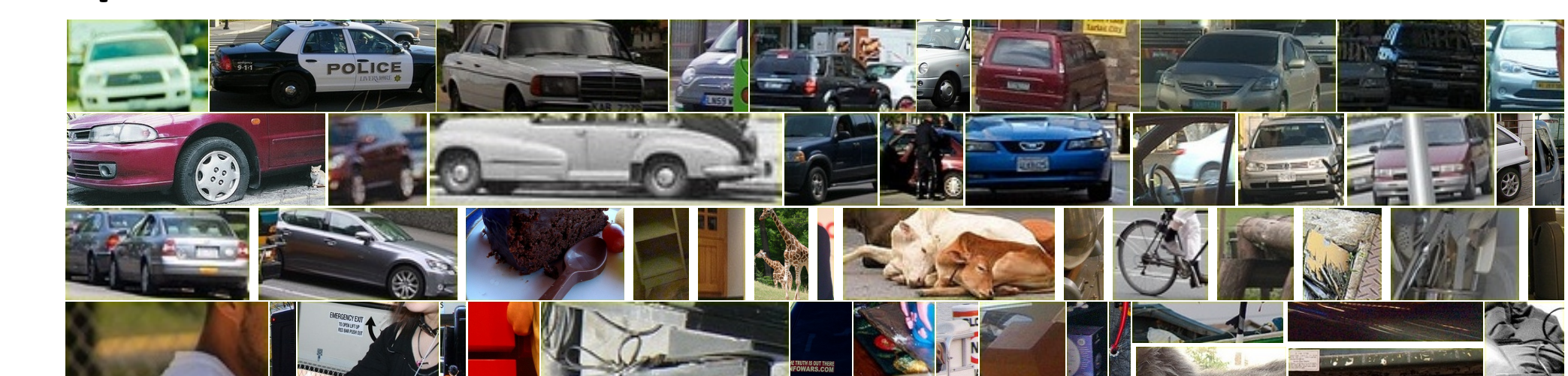
### Baselines on COCO validation set with $K=10\%$ .

Utilization of <i>void</i> regions	Known									Unknown		
	PQ	SQ	RQ	PQ <sup>Th</sup>	SQ <sup>Th</sup>	RQ <sup>Th</sup>	PQ <sup>St</sup>	SQ <sup>St</sup>	RQ <sup>St</sup>	PQ	SQ	RQ
Void-background	37.7	76.3	46.6	44.8	79.3	54.1	29.2	72.8	37.5	4.0	71.1	5.7
Void-ignorance	37.2	76.3	45.9	43.9	79.0	53.1	29.1	73.0	37.3	3.7	71.8	5.2
Void-suppression	37.5	75.9	46.1	45.1	80.6	54.5	28.2	70.2	36.1	7.2	75.3	9.6
Void-train	36.9	76.4	45.5	44.0	80.3	53.3	28.2	71.7	36.0	7.8	73.4	10.7

### Comparison of Baseline and EOPSN with various $K$ .

$K$ (%)	Model	Known									Unknown		
		PQ	SQ	RQ	PQ <sup>Th</sup>	SQ <sup>Th</sup>	RQ <sup>Th</sup>	PQ <sup>St</sup>	SQ <sup>St</sup>	RQ <sup>St</sup>	PQ	SQ	RQ
	Supervised	39.4	77.7	48.4	45.8	80.7	55.4	29.7	73.1	38.0	-	-	-
5	Baseline ( <i>Void-train</i> )	37.7	76.7	46.4	44.2	80.4	53.5	28.3	71.3	36.2	10.0	73.8	13.5
	EOPSN	38.0	76.9	46.8	44.8	80.5	54.2	28.3	71.9	36.2	23.1	74.7	30.9
10	Baseline ( <i>Void-train</i> )	36.9	75.4	45.5	43.2	79.0	52.4	28.3	70.4	36.2	8.5	73.2	11.6
	EOPSN	37.7	76.8	46.3	44.5	80.6	53.8	28.4	71.8	36.2	17.9	76.8	23.3
20	Baseline ( <i>Void-train</i> )	36.9	76.4	45.5	44.0	80.3	53.3	28.2	71.7	36.0	7.8	73.4	10.7
	EOPSN	37.4	76.2	46.2	45.0	80.3	54.5	28.2	71.2	36.2	11.3	73.8	15.3

### Exemplars in a found unknown class



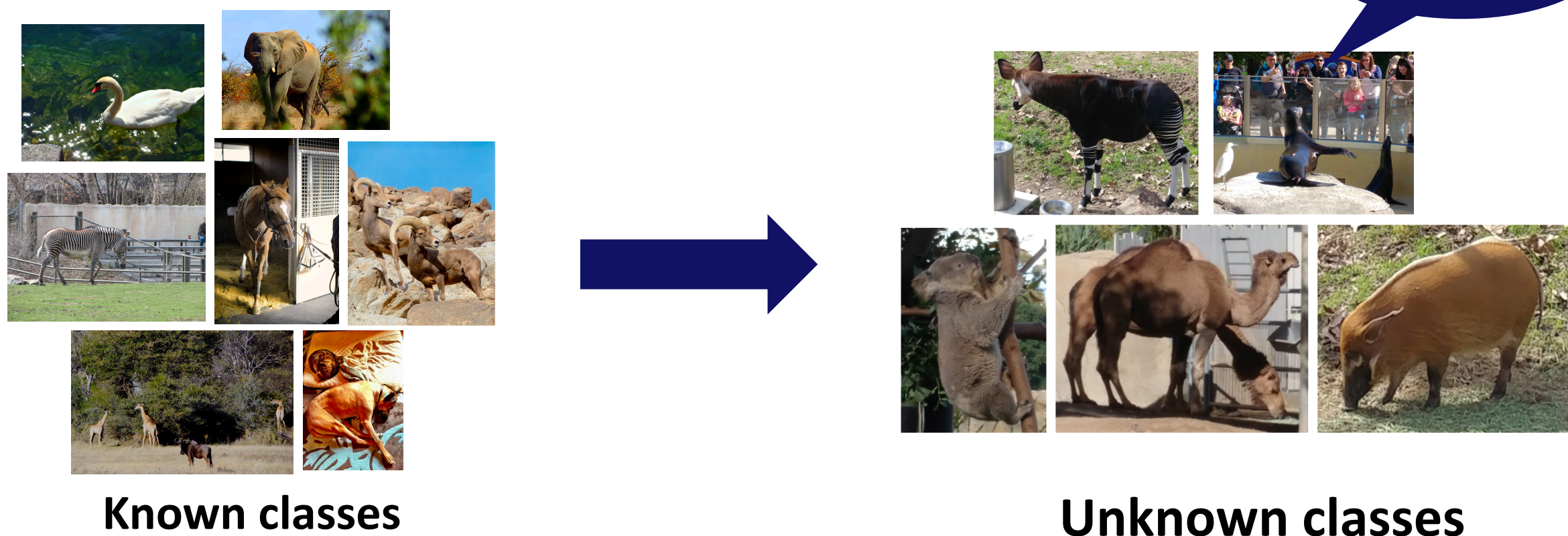
## Introduction

### Motivation

- Panoptic segmentation is widespread
- Real-world is an open-world** and annotating all instances and backgrounds are difficult
- In exemplar theory, people categorize a new object by comparing exemplars of each class.

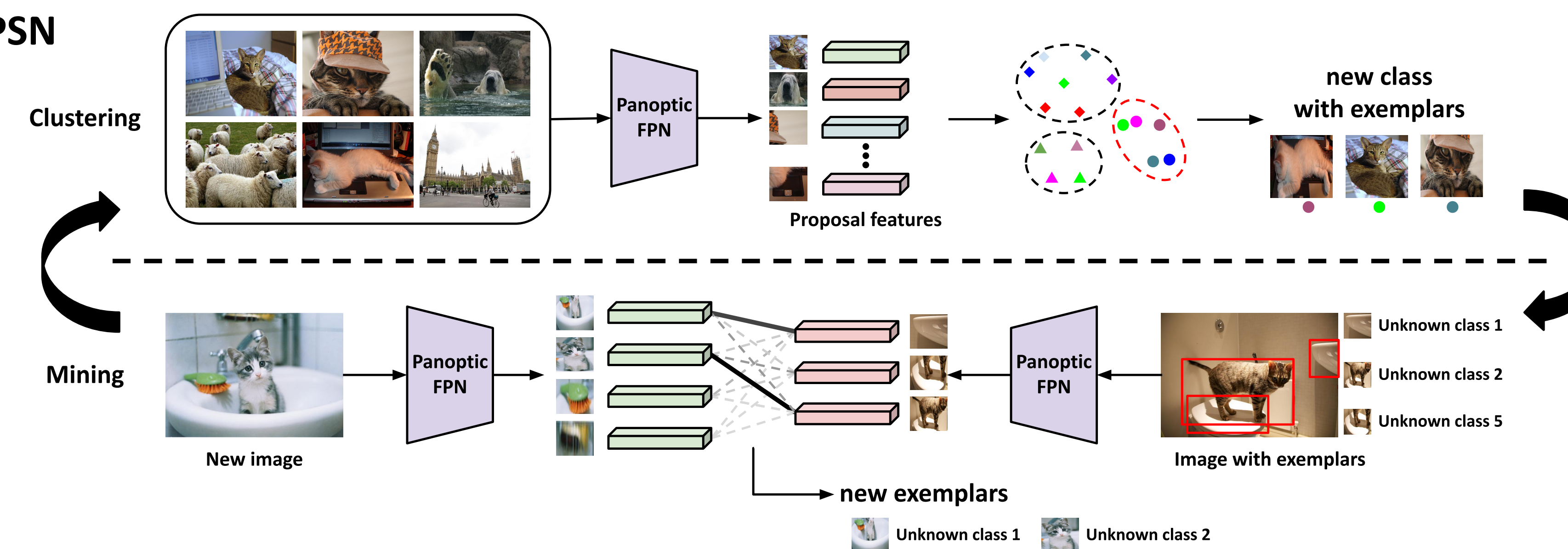
### Our contributions

- We define **open-set panoptic segmentation (OPS)** task and make it feasible using reasonable assumptions through in-depth analysis of its inherent challenges.
- We **construct a brand-new OPS benchmark** by reformatting COCO [1] and present performance of several baselines based on Panoptic FPN [2].
- We propose a novel framework for OPS, **EOPSN** based on the exemplar theory and present its effectiveness.



## Method

### EOPSN



### Clustering – find unknown class and exemplars

- Store candidate proposals with object features.
- K-means over-clustering and remove noisy clusters.
- Remining clusters  $\rightarrow$  *unknown* classes
- Elements in the clusters  $\rightarrow$  exemplars

### Mining – discover more exemplars

- Extract features of proposals and exemplars
- Compare features of proposals with exemplars.
- $\text{sim}(\text{proposal}, \text{exemplar}) > \text{threshold}$   
 $\Rightarrow$  the proposal is a new exemplar

### Baseline – Panoptic FPN [2]

- Class-agnostic** regressor and mask generator.
- Segment *known* first and then *unknowns* using objectness score from RPN.
- 4 different baselines with utilization of boxes on *void* regions

- Train as background (*void-background*)
- Ignore during training (*void-ignorance*)
- Avoid labeling as known (*void-suppression*)
- Train as a new class (*void-train*)

$$\mathcal{L}_{\text{void}} = \sum_{c \in C^{\text{Th}}} -\log(1 - p_c)$$

## Discussion

- Only tackle *seen unknown* but # of images $\uparrow \Rightarrow$  # of *seen unknown* $\uparrow$ .
- New evaluation metrics are needed.

## Reference

- [1] Lin, Tsung-Yi, et al. "Microsoft coco: Common objects in context." In ECCV, 2014.
- [2] Kirillov, Alexander, et al. "Panoptic feature pyramid networks." In CVPR, 2019.