Combinatorial Optimization for Panoptic Segmentation: A Fully Differentiable Approach

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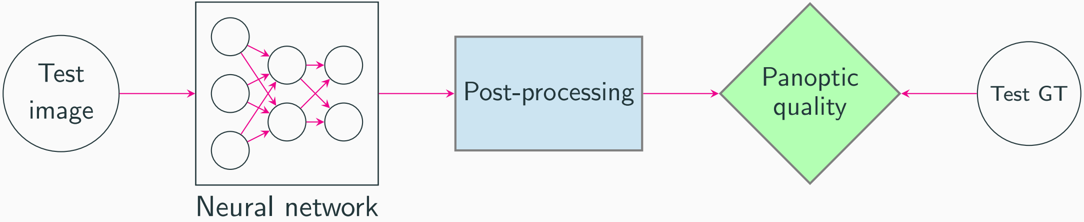
Panoptic segmentation = Semantic / Instance seg.

$\longrightarrow$

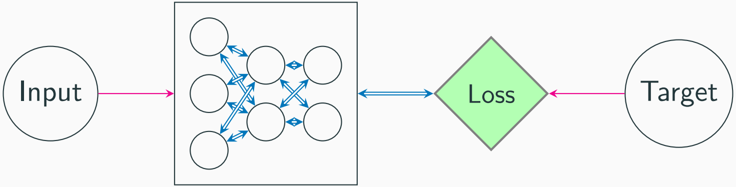
Kirillov 2019

Evaluation pipeline for panoptic segmentation



Conventional training pipeline

- Post-processing block not part of training
- Test-time evaluation metric not used in training



Motivation

Existing methods

1. Do not optimize for panoptic labels
2. Require many parameters (e.g. loss balancing weights, post-processing)
3. Complex architecture (e.g. additional Mask-RCNN for ROI)

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Our aims

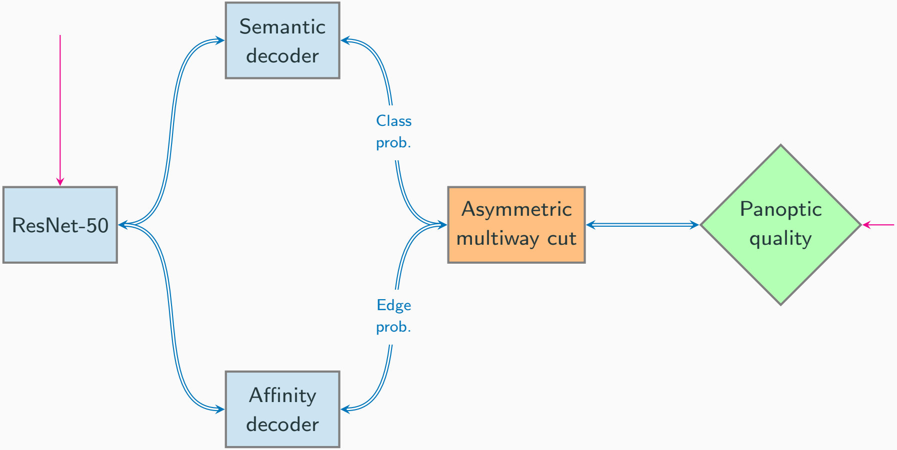
1. Fully differentiable pipeline
2. Optimize for the evaluation metric
3. Fewer hyperparameters
4. Use ‘standard’ neural network architecture (ResNet50)

Literature review

Methods	Simplicity	Params.		End-to-end	Optimize PQ	Performance
		Train	Eval			
MaxDeepLab[1]						
E cientPS[2]						
AxialDeepLab[3]						
PanopticDeepLab[4]						
UPSNet[5]						
SMW[6]						
SSAP[7]						
Our aim						?

[1]Wang 2020b, [2]Mohan 2021, [3]Wang 2020a, [4]Cheng 2020, [5]Xiong 2019, [6]Wolf 2020, [7]Gao 2019

Our pipeline



Panoptic labels

Multiway cut (MWC) - Calinescu 2008

Generalization of graph-cut on $G = (V, E)$ for $K > 2$

$$
\begin{aligned}
\min_{\substack{x: V \to \{1, \dots, K\}, \\ y: E \to \mathbb{B} \cap \{0,1\}}} \quad & \sum_{i \in V} c_V(i, x(i)) + \sum_{ij \in E} c_E(ij) y(ij) \\
\text{s.t.} \quad & y(ij) = 0, \ \text{if } x(i) = x(j) \\
& y(ij) = 1, \ \text{if } x(i) \neq x(j)
\end{aligned}
$$

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c_V, c_E : Semantic, edge costs

$x(i)$: Semantic label of i in V

$$y(ij) = \begin{cases} 0, & i, j \text{ belong to same instance} \\ 1, & i, j \text{ belong to different instance} \end{cases}$$

B : Enforce valid clustering

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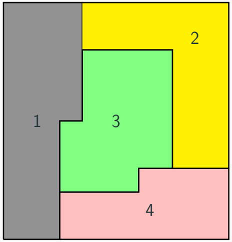
B : Enforce valid clustering

$K = 4$



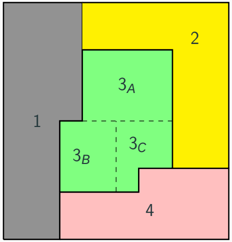
Asymmetric multiway cut (AMWC) - Kroeger 2014

AMWC on graph $G = (V, E)$

$$\min_{\substack{x:V \to \{1,\dots,K\},\\ y:E \to B \cap \{0,1\}}} \sum_{i \in V} c_V(i, x(i)) + \sum_{ij \in E} c_E(ij) y(ij)$$

$$\text{s.t.} \quad y(ij) = 0, \ \text{if } x(i) = x(j) \notin P$$
$$y(ij) = 1, \ \text{if } x(i) \neq x(j)$$

$K = 4, P = \{3\}$



c_V, c_E : Semantic, edge costs

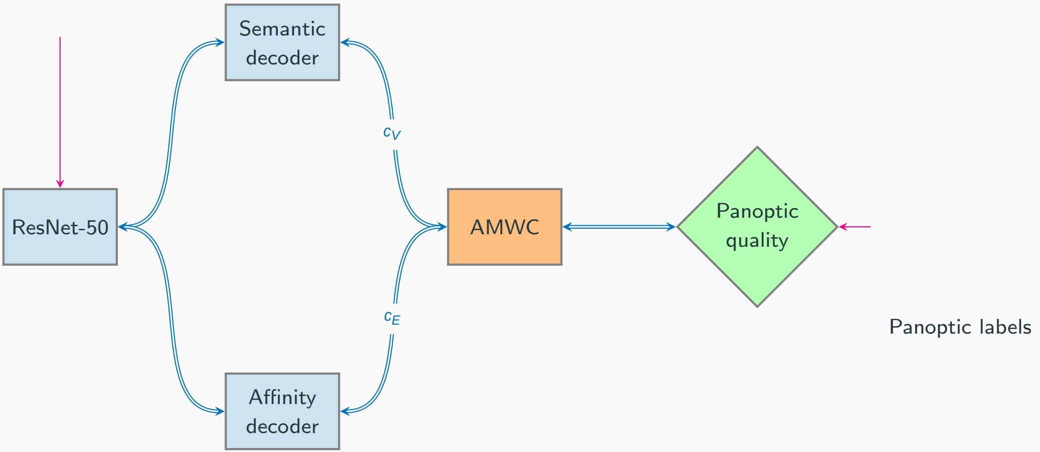
B : Enforce valid clustering

$P \subseteq [K]$: Partitionable classes

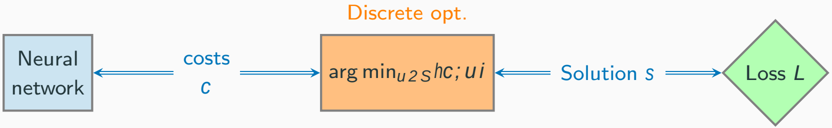
$x(i)$: Semantic label of i in V

$$y(ij) = \begin{cases} 0, & i, j \text{ belong to same instance} \\ 1, & i, j \text{ belong to different instance} \end{cases}$$

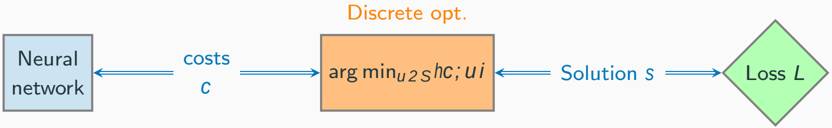
Recap: our pipeline



Gradient estimation through discrete optimization layers



Gradient estimation through discrete optimization layers



Build on the approach of Vlastelica 2019

$$\frac{\partial L}{\partial c} = \frac{1}{\ } \quad s(c + \quad \frac{\partial L}{\partial s}) \quad s(c)$$

Gradient estimation through discrete optimization layers

Build on the approach of Vlastelica 2019

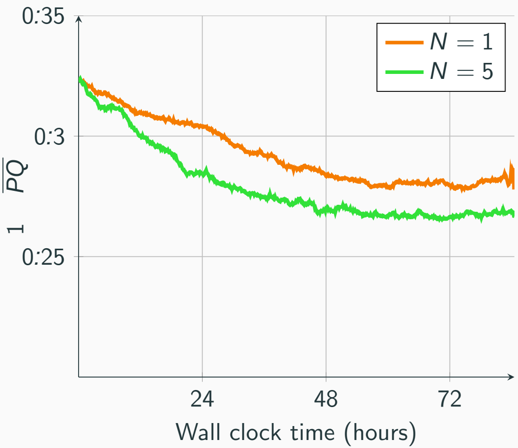
$$\frac{\partial L}{\partial c} = \frac{1}{\lambda}\left[s\left(c + \lambda \frac{\partial L}{\partial s}\right) - s(c)\right]$$

Our extension

$$\frac{\partial L_{avg}}{\partial c} = \frac{1}{N} \sum_{i}^{N} \frac{\partial L^{\lambda_i}}{\partial c}, \qquad \lambda_i \sim U(a, b)$$

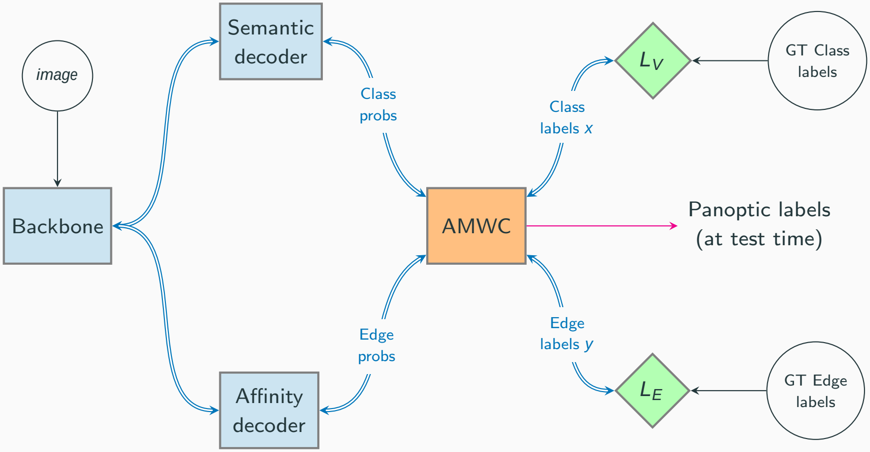
- Averages gradients over multiple scales
- 3 faster convergence

Contribution 1: Improved gradient estimation



Training loss comparison ($N = 5$: our extension with **improved convergence**)

Panoptic Segmentation: Naïve fully differentiable pipeline



Naïve pipeline: Gradient estimation through AMWC

Perturb semantic, edge costs by respective gradients

$$
\begin{aligned}
\min_{\substack{x:V \to \{1,\dots,K\},\\ y:E \to B \cap \{0,1\}}} \quad & \sum_i \left[c_V(i,x(i)) + \frac{\partial L_V}{\partial x}((i,x(i)) \right] + \sum_{ij} \left[c_E(ij) + \frac{\partial L_E}{\partial y}(ij) \right] y(ij) \\
\text{s.t.} \quad & y(ij) = 0, \ \text{if } x(i) = x(j) \notin P \\
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\end{aligned}
$$

Panoptic Segmentation: Naïve fully differentiable pipeline

Does not perform well:

- Edge misclassifications are **not** equally important
- At test-time we care about pixel labels not edge labels
- Need to optimize test-time metric of panoptic quality (PQ)

Edge labels: ground-truth, prediction, correct predictions

Contribution 2: Optimize panoptic quality surrogate

Approximate non-differentiable panoptic quality metric

$$PQ = \frac{\sum_{(p,g)\in TP} IoU(p,g)}{|TP| + 0.5(|FP| + |FN|)}$$

by

$$\overline{PQ} = \frac{\sum_{(p,g)\in\overline{TP}} h(IoU(p,g)) \quad (p)\, IoU(p,g)}{\sum_{(p,g)\in\overline{TP}} h(IoU(p,g)) \quad (p) + 0.5\{\sum_{p\in\overline{FP}} \quad (p) + |\overline{FN}|\}}$$

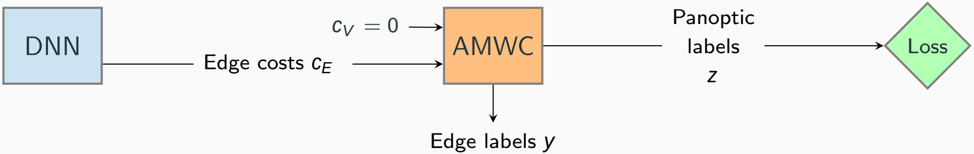
where

$h(\ )$: Soft-thresholding

$\ (p)$: Foreground probability (from mask area)

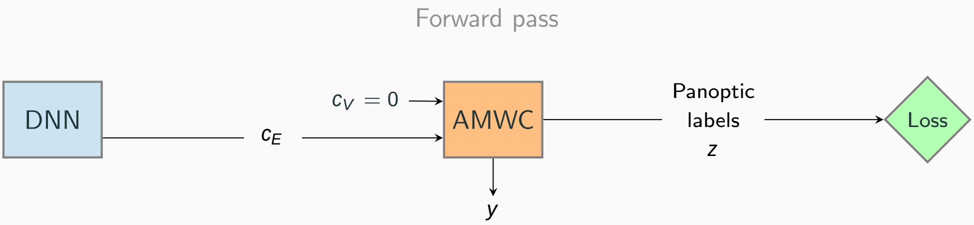
Contribution 3: Backprop with loss on panoptic labels ($K = 1$)

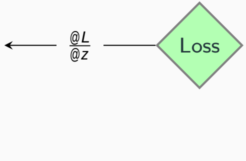
Forward pass



Ignored semantic costs c_V for brevity

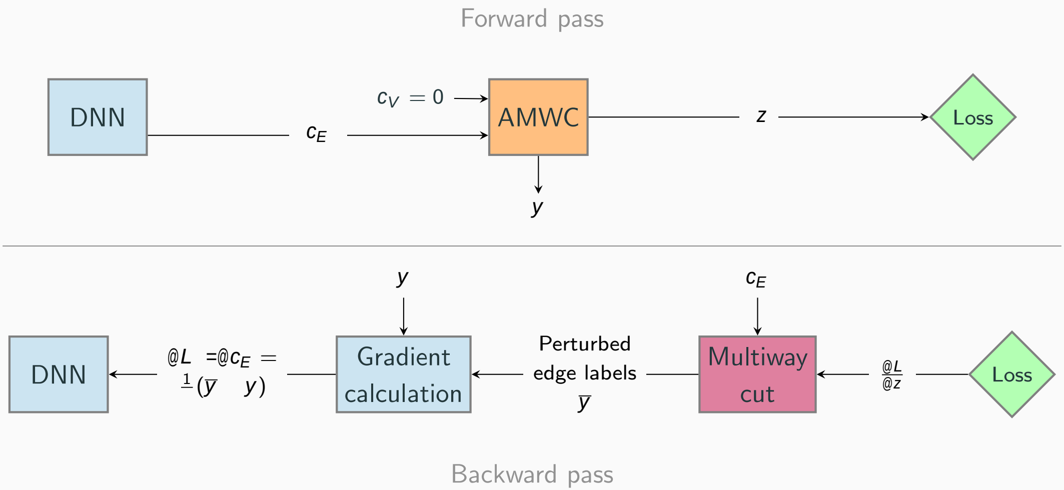
Contribution 3: Backprop with loss on panoptic labels ($K = 1$)





Ignored semantic costs c_V for brevity

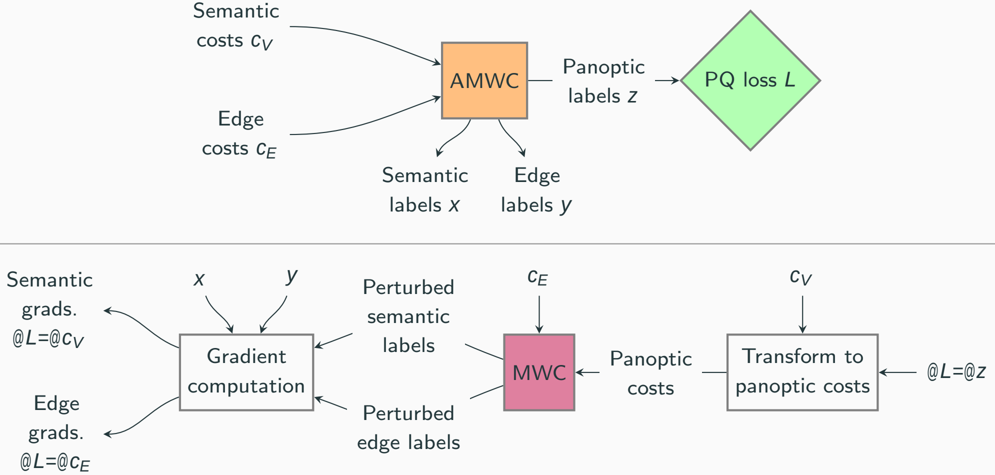
Contribution 3: Backprop with loss on panoptic labels ($K = 1$)



Ignored semantic costs c_V for brevity

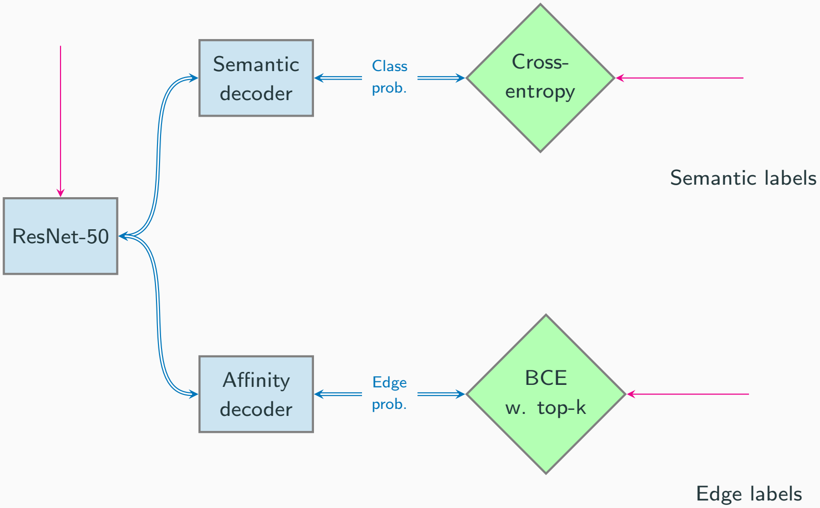
Contribution 3: Full backprop (K 1) with loss on panoptic labels

Forward pass



Backward pass with transformation to panoptic label space

Baseline: train by 'usual' losses



Results

- Outperform all comparable approaches
- Sometimes, even with a disadvantage (e.g. smaller backbone)

Methods	Architecture	Hyperparameters		E-to-E	Opt. PQ	Panoptic qual.	
		Train	Eval			Citysc.	COCO
MaxDeepLab						-	49.3
E cientPS						63.9	-
AxialDeepLab						63.9	41.8
UPSNet						59.3	42.5
SSAP						61.1	36.5
SMW						59.3	-
PanopticDeepLab						60.2	35.1
Our baseline						58.5	34.3
Our fully differentiable						**62.1**	**38.4**

Summary

- Simple and fully differentiable pipeline for panoptic segmentation
- Improved gradient estimation through discrete optimization problems
- Optimize panoptic quality differentiable surrogate
- Transformation to MWC in backward pass to compute gradients
- First large-scale study of backpropagation through heuristic optimization solvers
- *Shortcoming:* Inference time of around $2s$ per image
- Code available at: `github.com/aabbas90/COPS`

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