TransFGU: A Top-down Approach to Fine-Grained Unsupervised Semantic Segmentation

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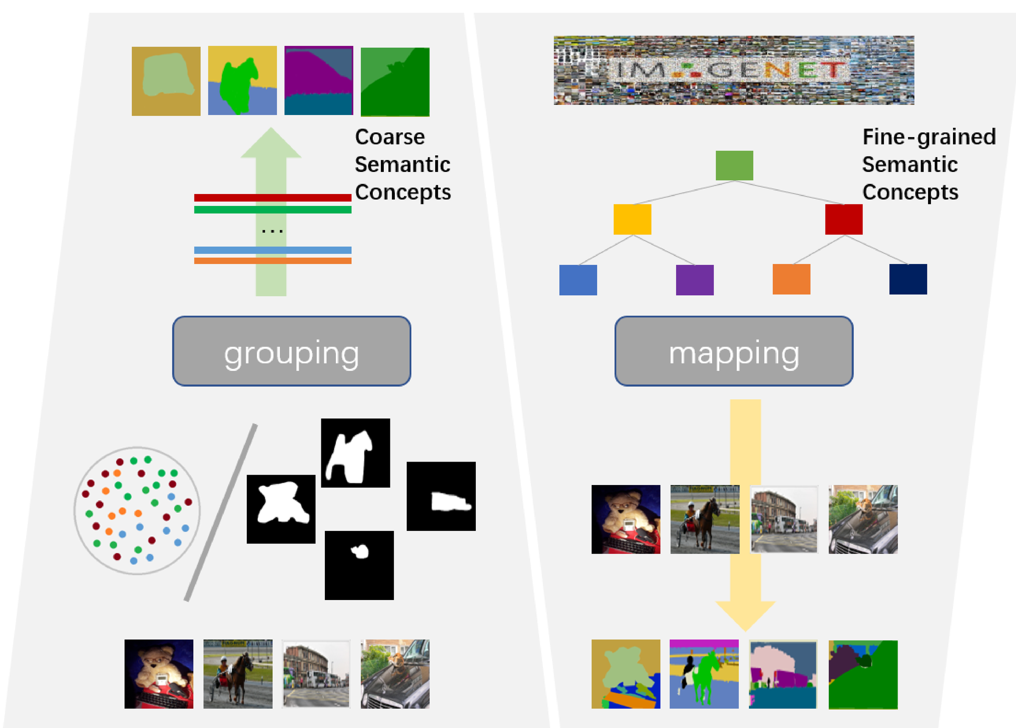
Bottom-up *vs.* Top-down.



Bottom-up manners:

- deduces semantic concepts from pixel features.
- under the guide of pre-defined rules or visual cues.
- the result usually coarse.

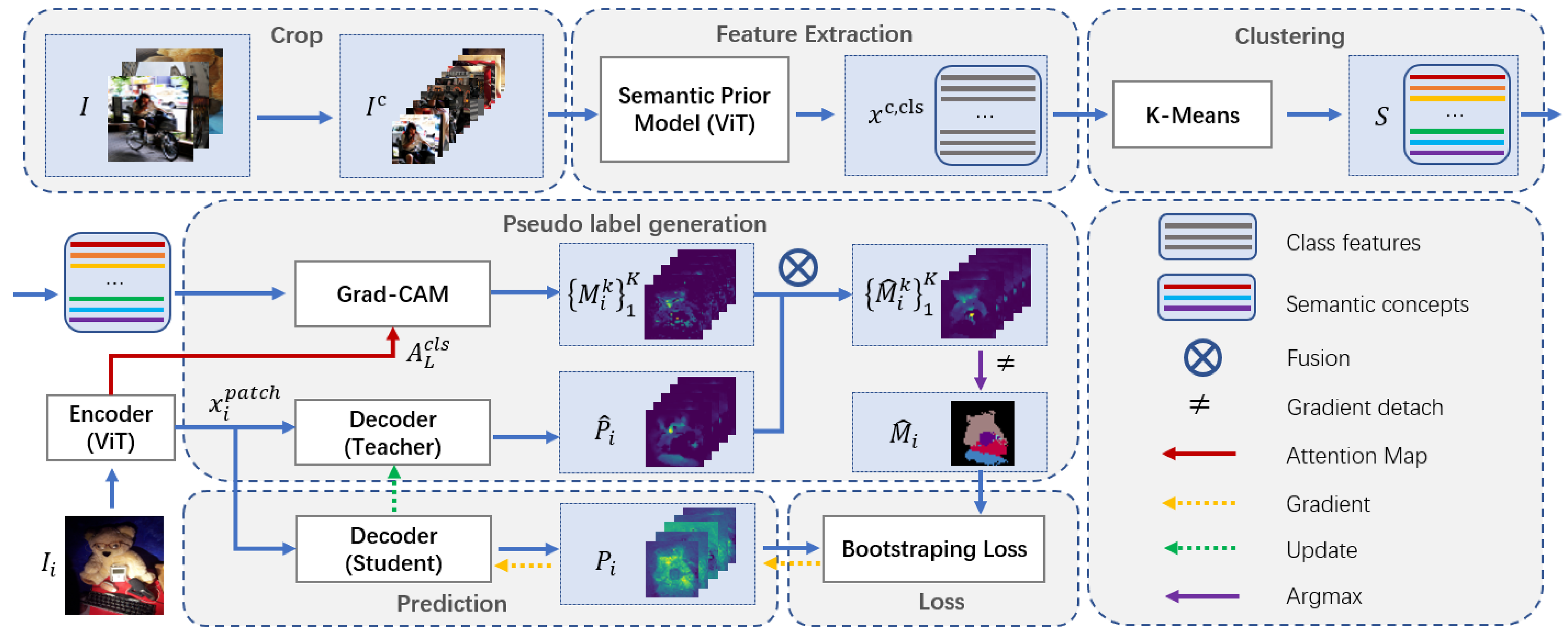
Top-down manner:

- induces semantic concepts from ImageNet (SSL).
- maps high-level semantic concepts into pixel-level feature space.
- robust to complicated scenarios and object appearance variations.

Contributions

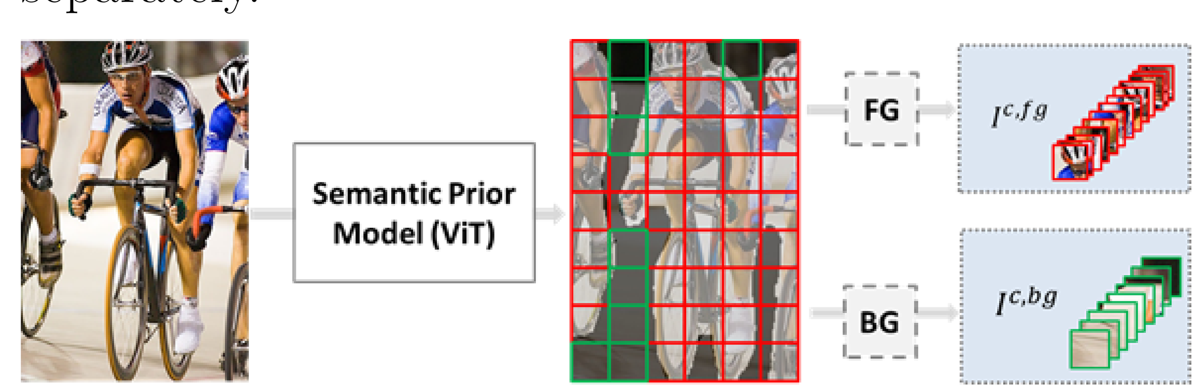
- We propose the first top-down framework for unsupervised semantic segmentation.
- We bridge the gap between high-level semantic features obtained by SSL and low-level pixel-wise features to produce high-quality fine-grained segmentation results.
- This is the first work to apply unsupervised algorithms on real complex datasets with a large number of classes.

Pipeline



Semantic concepts discovery.

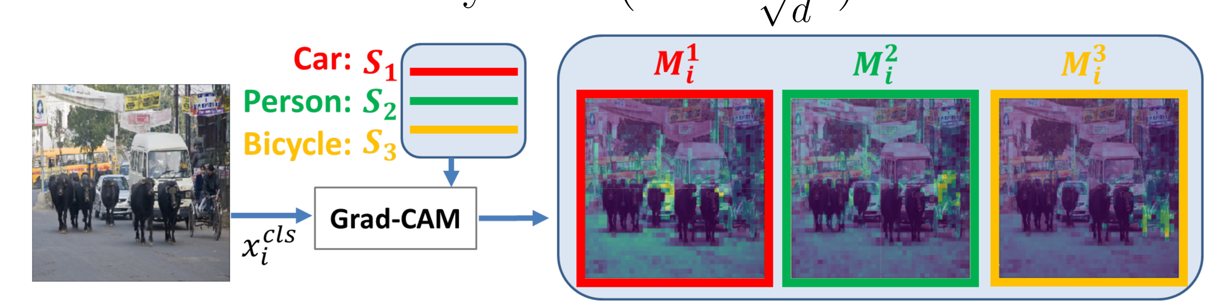
- crop each $I_i \in I$ with different sizes of sliding windows to form I^c.
- use attention map A_L^{cls} in class-token feature x_i^{cls} as foreground prior when foreground (things) and background (stuff) are required to segmented separately.



- obtains K target semantic concepts S based on the class-token feature of $x^{c,cls}$ by K-Means, K set as the number of classes w.r.t desired granularity levels.

Training.

- generate gradient on A_L^{cls} w.r.t S_k by maximizing the cosine similarity: $\min(1 - \frac{x_i^{cls} S_k^T}{\sqrt{d}})$.



- aggregate the output of Grad-CAM $\{M_i^k\}_1^K$ and teacher network $\hat{P}_i$ to refine pseudo label $\{\hat{M}_i^k\}_1^K$.
- $M_i^{bg} = \mathrm{RELU}(T^{bg} - \max_{k\in[0,K]} M_i^k)$ is background probability if only the foreground needs to be segmented:
- bootstrapping loss $\mathcal{L} = \mathcal{L}_{peer} + \omega_1 \cdot \mathcal{L}_{div} + \omega_2 \cdot \mathcal{L}_{unc}$.
- peer loss: $\mathcal{L}_{peer} = \mathrm{CE}(P, \hat{M}) - \alpha \cdot \mathrm{CE}(P, \hat{M}')$
- diversity loss: $\mathcal{L}_{div} = 1 + \frac{1}{K^2} \sum \frac{C \cdot C^T}{\sqrt{d}}$.
- uncertainty loss: $\mathcal{L}_{unc} = 1 - \frac{1}{hw} \sum_{(h',w')} (p' - p'')$.

Quantitative Results

Table 1:Results on four benchmarks. * indicates the results are evaluated on the "curated" samples. † denotes PiCIE trained without auxiliary clustering.

Dataset	Method	mIoU	Acc.
COCO-Stuff-27*	IIC	6.71	21.79
	PiCIE†	13.84	48.09
	PiCIE	14.36	49.99
	TransFGU	**17.47**	**52.66**
COCO-Stuff-27	IIC	2.36	21.02
	PiCIE	11.88	37.20
	TransFGU	**16.19**	**44.52**
COCO-Stuff-171	IIC	0.64	8.67
	PiCIE	4.56	24.66
	TransFGU	**11.93**	**34.32**
COCO-80	MaskContrast	3.73	8.81
	TransFGU	**12.69**	**64.31**
Cityscapes	IIC	6.35	47.88
	PiCIE	12.31	65.50
	TransFGU	**16.83**	**77.92**
Pascal-VOC	MaskContrast	35.00	79.84
	TransFGU	**37.15**	**83.59**
LIP-5	TransFGU	25.16	65.76
LIP-16	TransFGU	15.49	60.08
LIP-19	TransFGU	12.24	42.52

Quantitative Results

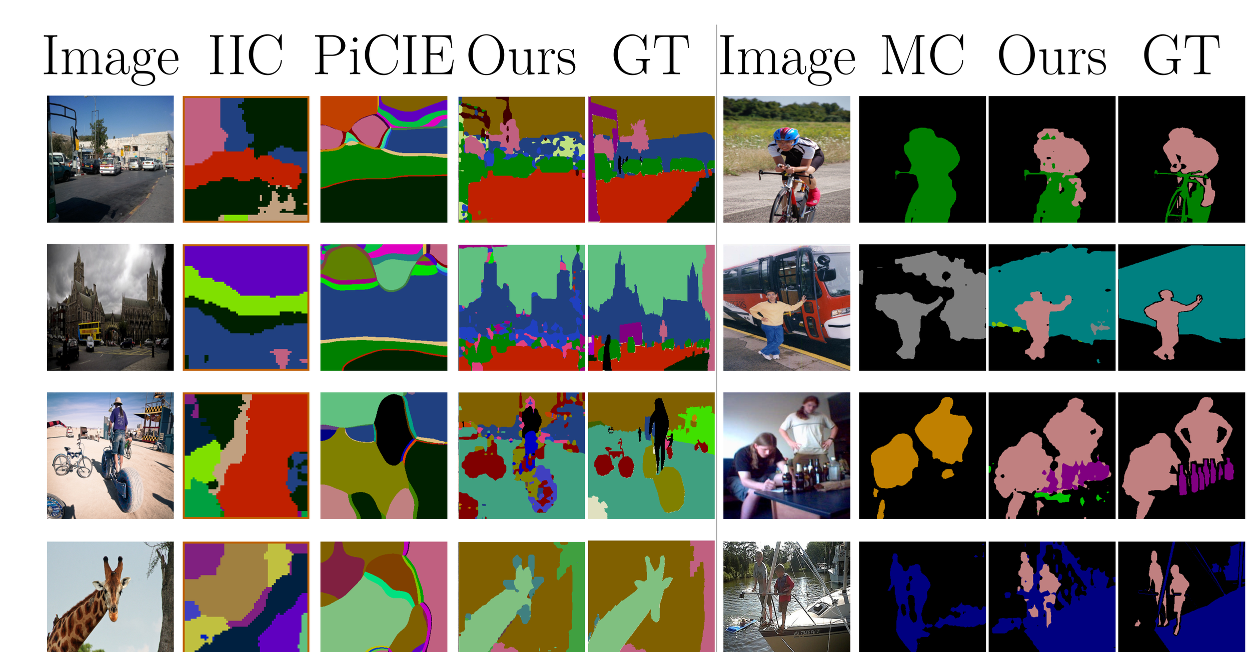


Figure 1:Qualitative comparison on COCO-Stuff-171 (left) and Pascal-VOC (right).