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TopDiG: Class-agnostic Topological Directional Graph Extraction from Remote Sensing Images

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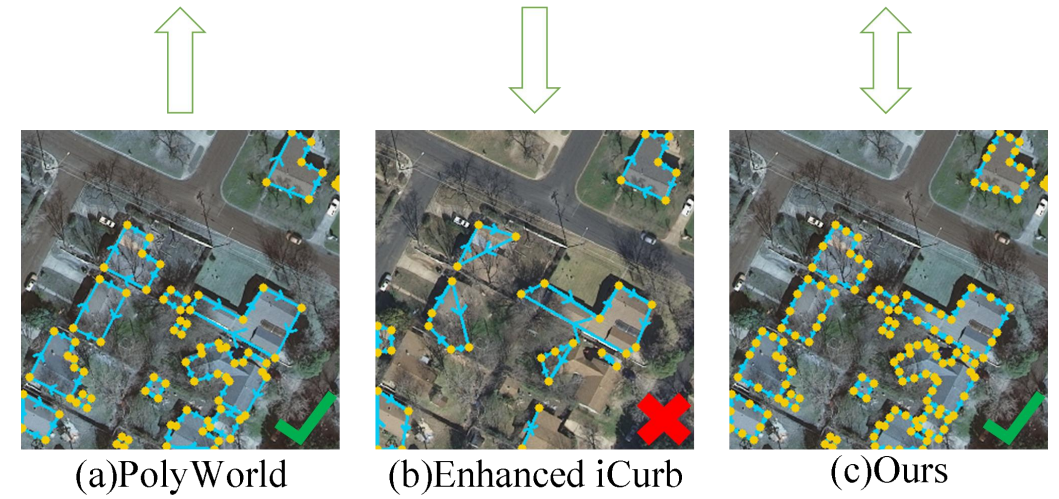


Challenges:

- Most existing vector extraction works **focus on a specific target** and are **fragile to category variety**;
- Especially Line- and polygon-shape objects are very **different in topological structure**.

Contributions:

- We propose an innovative **class-agnostic** model **TopDiG**, to directly extract topological directional graphs from remote sensing images **regardless of target types**.
- We design topology-concentrated **node detector** to extract nodes and corresponding features **for both line- and polygon-shape targets**.
- We conduct **dynamic graph supervision** strategy to **facilitate inference in practice**.



(a)PolyWorld

(b)Enhanced iCurb

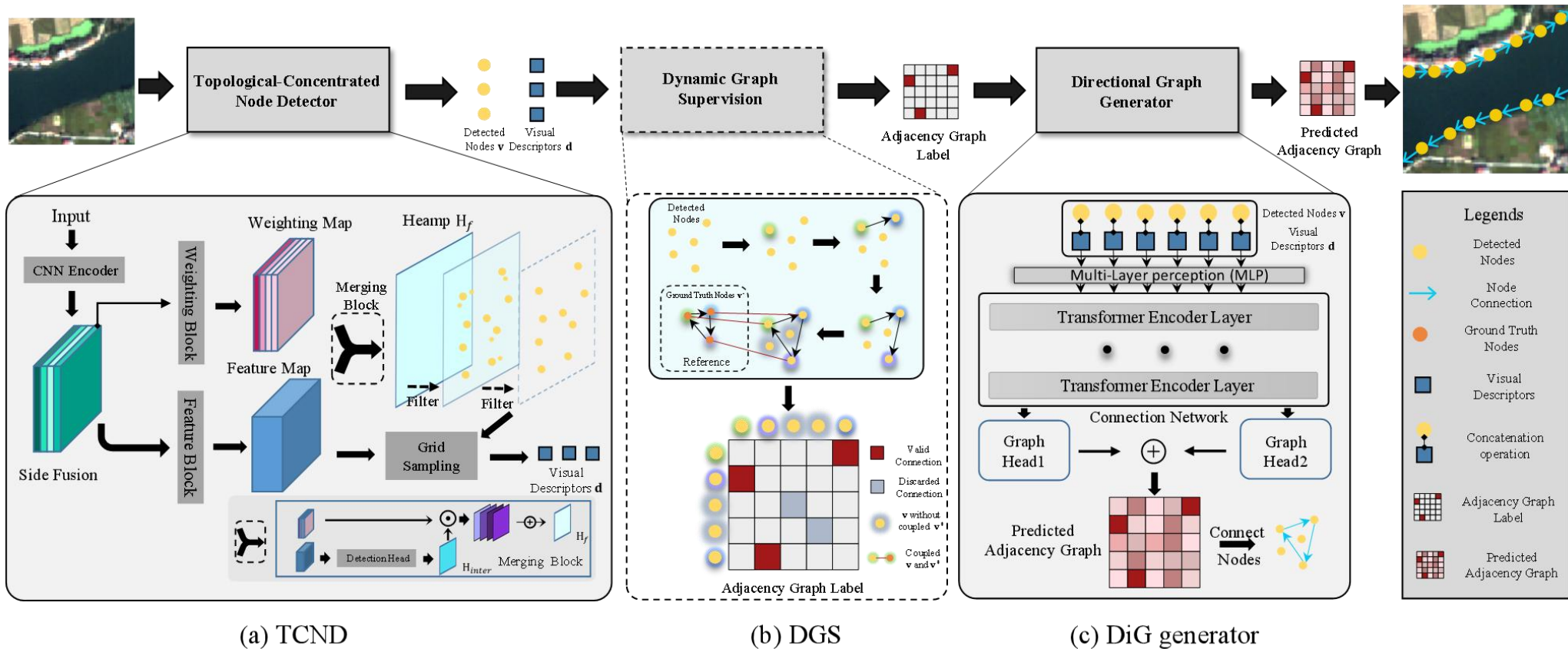
(c)Ours

TopDiG can extract vector topology of both line- and polygon-shape objects





TopDiG formulates diverse vector topological structures as **directional graphs** and works by **sequentially predicting target nodes and their connections**.



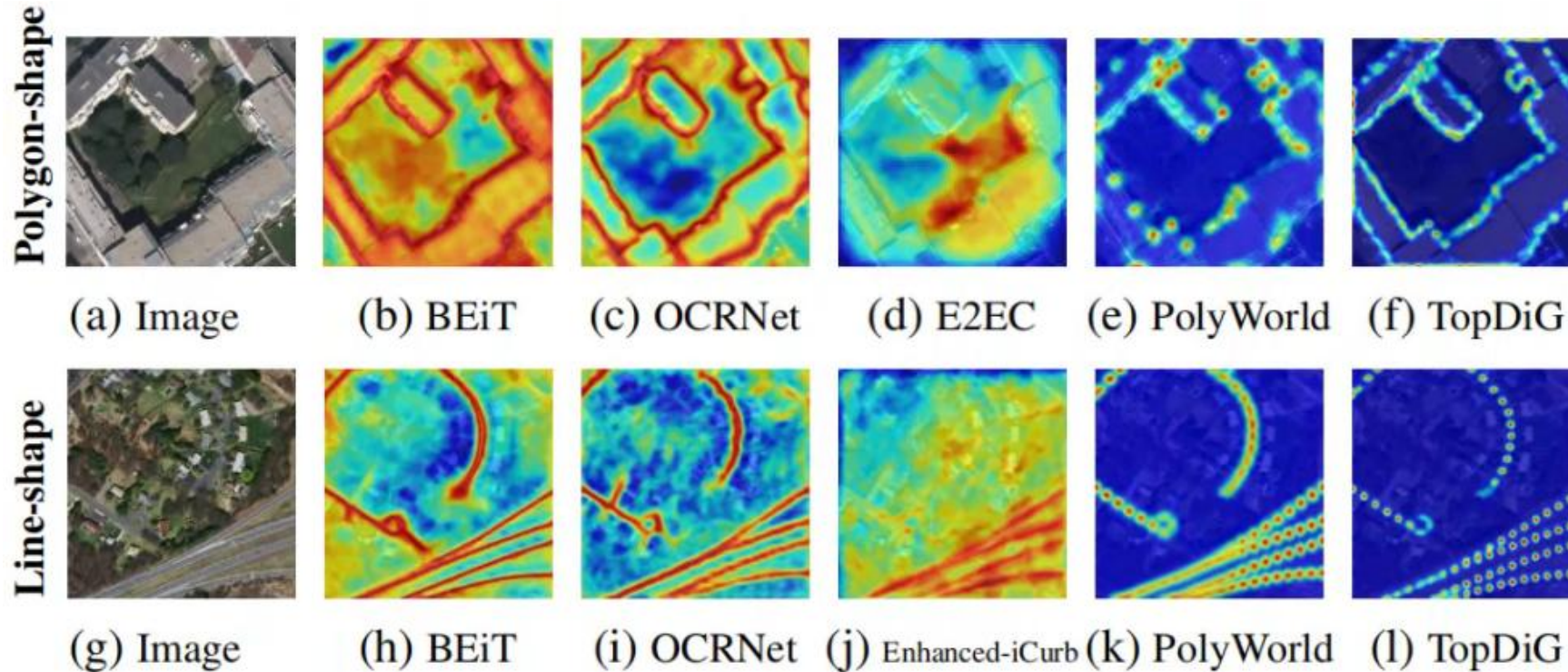
The pipeline of TopDiG





Topology-Concentrated Node detector(TCND):

- In satellite and aerial images, **line shape objects can be seen as edges**
- TCND **minimizes semantic contexts** and **concentrates on low-level geometric features** to achieve category independency



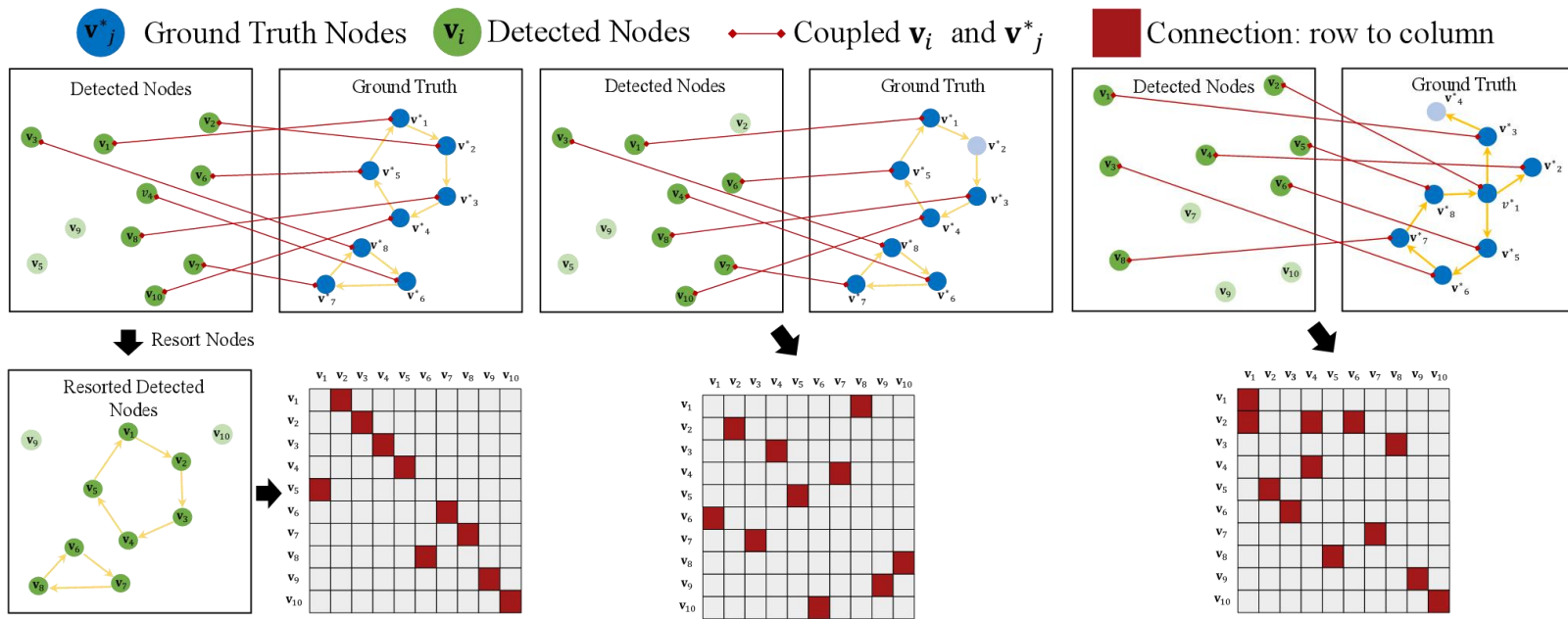
Visual comparison of attentive maps for a few methods





Dynamic Graph Supervision(DGS):

- Dynamically generates adjacency matrix labels according to **real-time unordered predict nodes** in each training



(a) Previous works

(b) DGS for polygons

(c) DGS for lines

Visual comparison of the adjacency matrix label generation by previous works and DGS





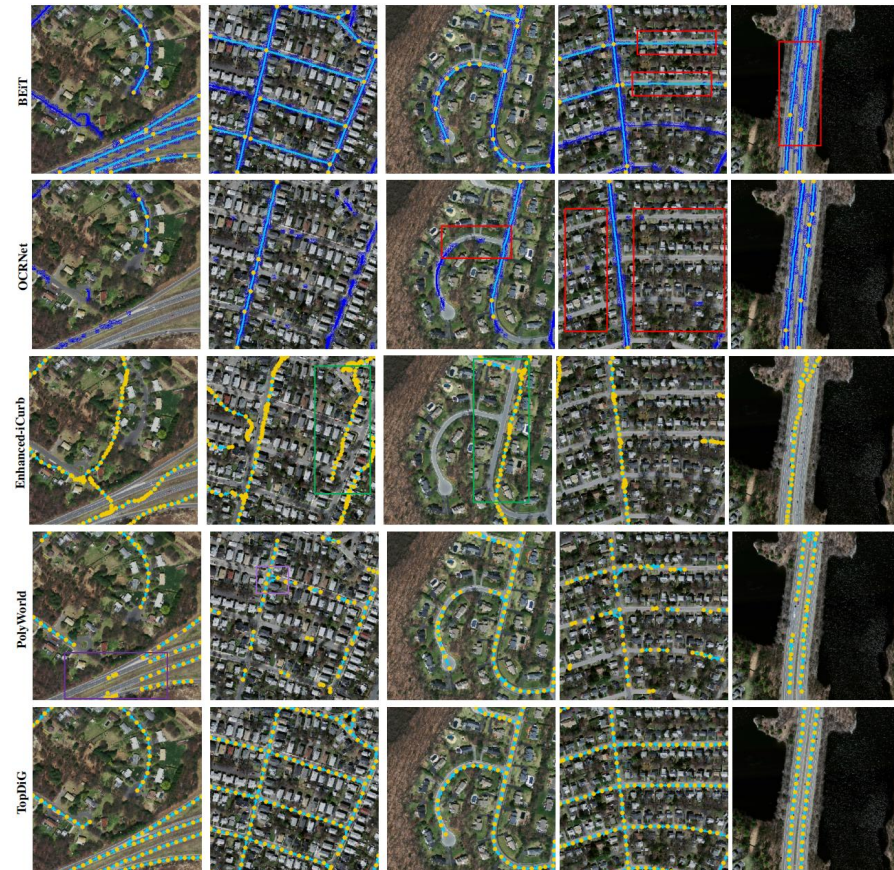
Visual comparison:

- TopDiG performs **better in topology quality and completeness**, especially in **concave/hierarchical polygon contours** and **parallel/crossing line object centerlines**

Comparison in Inria dataset



Comparison in Massachusetts dataset





Quantitative comparison:

- TopDiG obtains competitive scores in pixel-wise metrics
- TopDiG achieve state-of-the-art performance in topology-wise metrics

Dataset	Method	Pixel-wise Metrics			Topology-wise Metrics			
		PA ^{mask} ↑	F1 ^{mask} ↑	mIoU ^{mask} ↑	PA ^{topo} ↑	F1 ^{topo} ↑	mIoU ^{topo} ↑	APLS ↑
Inria [20]	DeepLabV3	94.94	91.93	85.45	93.20	76.77	66.48	40.48
	E2EC	88.46	70.85	63.64	92.69	65.83	58.61	39.46
	PolyWorld	90.82	83.54	73.41	92.92	73.60	63.47	40.03
	Ours	94.70	91.32	84.56	93.88	78.47	68.39	48.09
CrowdAI [20]	DeepLabV3	97.08	95.74	91.92	94.82	83.49	74.06	48.07
	E2EC	95.62	92.11	86.72	93.70	78.67	69.13	36.05
	PolyWorld	93.67	90.29	82.89	93.21	77.71	67.43	51.73
	Ours	96.45	94.77	90.23	94.51	82.20	72.51	59.61
GID [27]	DeepLabV3	99.05	97.34	94.92	99.23	79.27	70.55	80.14
	E2EC	98.85	76.03	69.68	99.16	73.90	66.32	76.17
	PolyWorld	98.07	90.05	85.66	99.17	73.65	66.04	75.84
	Ours	99.17	96.52	93.94	99.39	82.56	74.51	85.24
GF2 [37]	DeepLabV3	99.24	98.14	96.40	99.11	79.46	70.70	77.90
	E2EC	99.25	81.29	75.37	99.01	75.96	67.83	74.34
	PolyWorld	98.55	94.68	91.10	98.98	75.51	67.20	73.63
	Ours	99.40	98.20	96.56	99.28	83.57	75.28	81.31
Massachusetts [19]	DeepLabV3	-	-	-	95.75	77.94	68.30	51.40
	PolyWorld	-	-	-	94.28	76.56	66.59	47.74
	Ours	-	-	-	95.16	80.33	70.66	64.60

Quantitative comparison of TopDiG with segmentation-based, contour-based and graph generation methods

