SeqGrowGraph: Learning Lane Topology as a Chain of Graph Expansions

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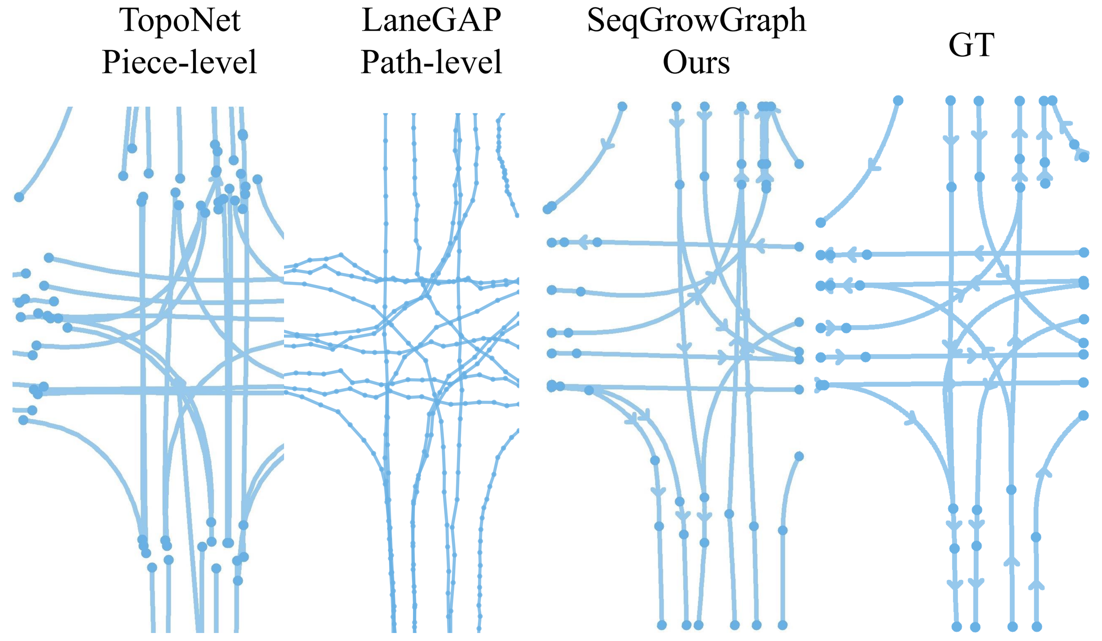
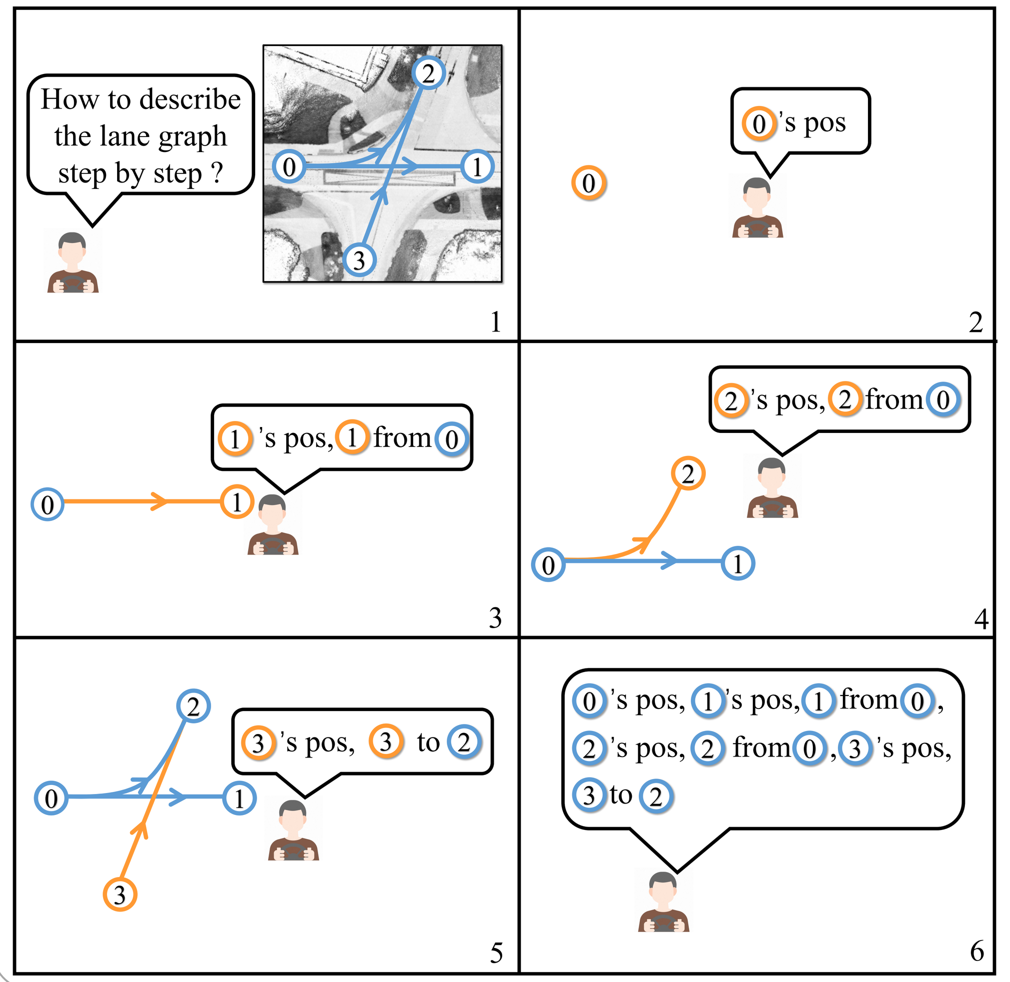
How to Model Lane Graphs

Accurate lane graph modeling is vital for autonomous driving. But…

- Detection-based methods, including pixel-level, piece-level, and path-level, suffer from discontinuities, misalignments, and reliance on post-processing.
- Current graph-to-sequence conversions often disrupt original structures, struggling with loops, bidirectional lanes, and holistic topology representation.





How Humans Build Lane Graphs?

Instead of processing an entire graph at once, people naturally start from a single node and progressively add new elements, continuously expanding the graph by establishing connections with previously defined nodes .

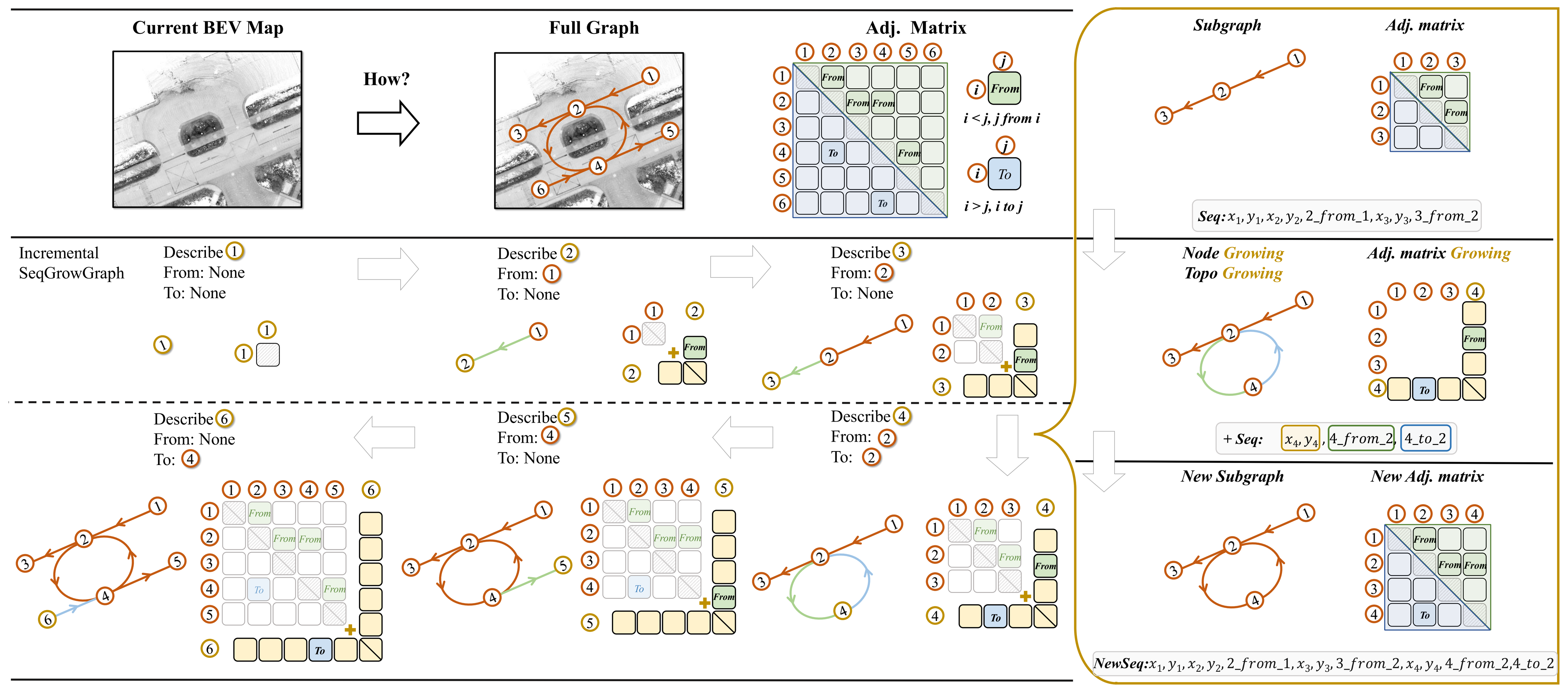
- Modeling lane graph construction as a chain of stepwise expansion process.
- Using sequence modeling to capture incremental adjacency matrix updates.

Contributions

- **SeqGrowGraph** reformulates lane graph generation as a sequential expansion process using adjacency updates and geometric modeling.
- An **autoregressive transformer** progressively constructs lane graphs, overcoming DAG method limitations.
- Experiments on **nuScenes** and **Argoverse 2** show state-of-the-art topology accuracy and network completeness.

SeqGrowGraph

The adjacency matrix expands from (n-1)×(n-1) → n×n to encode connectivity, with the upper triangle representing incoming edges ('from') and the lower triangle representing outgoing edges ('to').

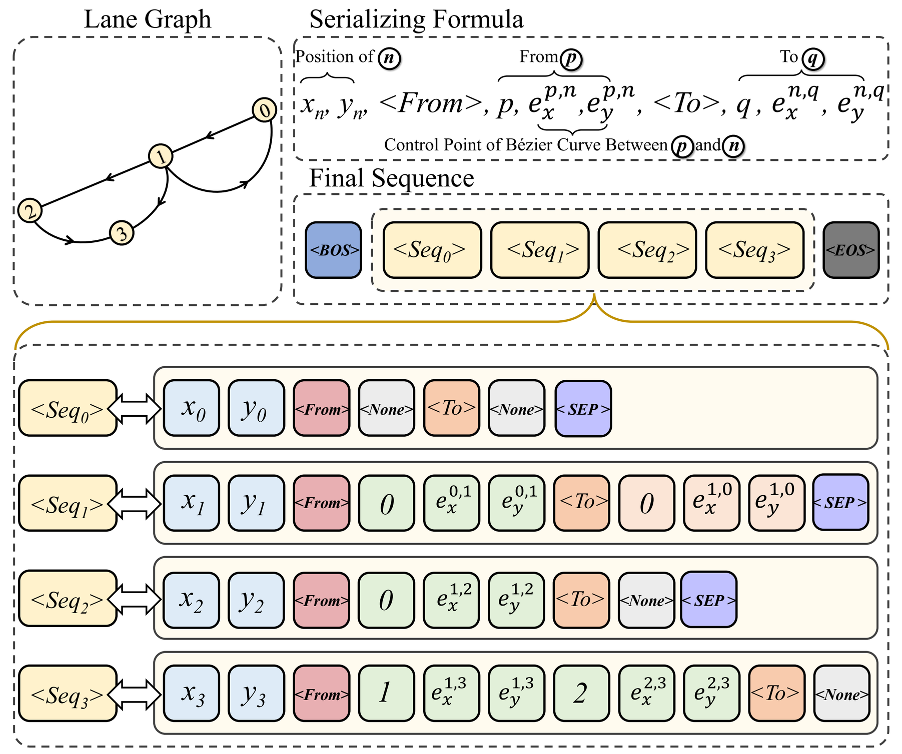


Mathematical Expression

- $V = \{v_1, v_2, v_3, \dots\}$ correspond to topological nodes where $\boldsymbol{v_n} = (\boldsymbol{x_n}, \boldsymbol{y_n})$ specifies its geographic position.
- **Adjacency matrix**: $A(i,j) = \begin{cases} 1, \textit{if there is an edge between } v_i \textit{ and } v_j \\ 0, \textit{otherwise} \end{cases}$
- **Matrix of centerline shapes**： $M(i,j) = \begin{cases} (\sigma_x^{i,j}, \sigma_y^{i,j}), \textit{if } A(i,j) = 1 \\ \emptyset, \textit{otherwise} \end{cases}$
- $F_n = \sum_{k=0}^{n-1} M(k,n)$ represents the centerlines among the previous (n-1) nodes **from** which node n can be reached.
- $T_n = \sum_{k=0}^{n-1} M(n,k)$ represents the centerlines among the previous (n-1) nodes **to** which node n can proceed.
- Sn denote the sequence representing the subgraph formed by the first n nodes.Our approach grows as follows:

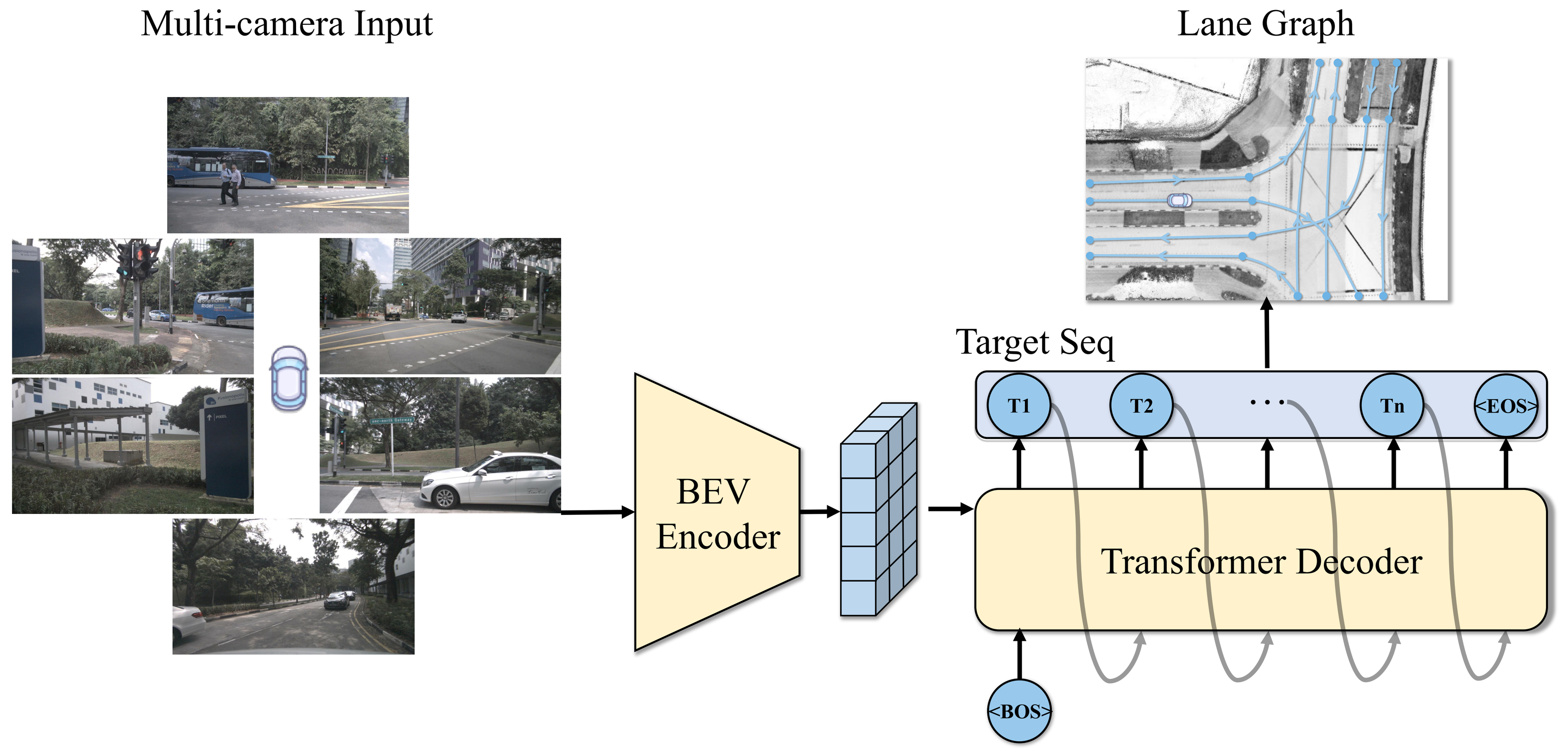
$$S_n = S_{n-1} + (v_n + F_n + T_n)$$

Model Formulation



Each node's sequence includes its shape, connected node indices, and the Bézier control points of the connecting centerlines.

The autoregressive transformer generates the target sequence token by token.



Experiment & Visualization

nuScenes

	Methods	Landmark L-P	Landmark L-R	Landmark L-F	Reachability R-P	Reachability R-R	Reachability R-F
Default	TopoNet [10]	52.5	47.1	49.6	46.9	10.8	17.5
	LaneGAP [15]	49.9	57.0	53.2	74.1	34.9	47.5
	RNTR [17]	57.1	42.7	48.9	63.7	45.2	52.8
	LaneGraph2Seq* [21]	46.9	43.7	45.2	63.7	36.3	46.2
	SeqGrowGraph	**63.6**	**50.8**	**56.4**	**75.5**	**61.4**	**67.8**
PON	RNTR* [17]	39.9	31.0	34.9	63.3	24.9	35.7
	LaneGraph2Seq* [21]	21.9	**39.9**	28.2	46.3	11.0	17.8
	SeqGrowGraph	**43.5**	33.3	**37.7**	**63.6**	**36.9**	**46.7**

Argoverse 2

Methods	Landmark L-P	Landmark L-R	Landmark L-F	Reachability R-P	Reachability R-R	Reachability R-F
RNTR* [17]	50.7	29.4	37.2	68.1	29.6	41.3
LaneGraph2Seq* [21]	60.6	48.7	53.9	75.5	37.8	50.4
SeqGrowGraph	**64.1**	**50.4**	**56.4**	**77.7**	**43.4**	**55.7**