Learning to Sample Ray Paths for Faster Point-to-Point Ray Tracing

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June 2024

COST INTERACT meeting, Helsinki

Ray Tracing for Radio Propagation

	Point-to-Point (P2P) Ray Tracing (RT)	Ray Launching (RL)
Complexity		
Accuracy		
Best for		

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*: Depends on the number of rays launched.

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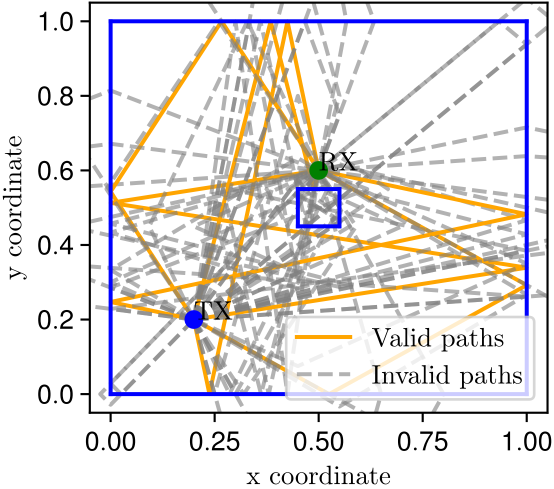
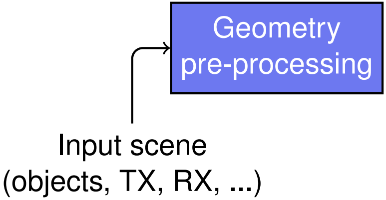
The curse of P2P RT



The typical P2P RT pipeline

Input scene
(objects, TX, RX, ...)

The typical P2P RT pipeline



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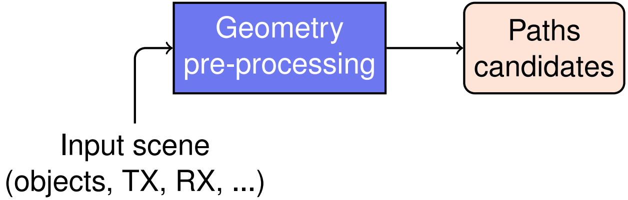

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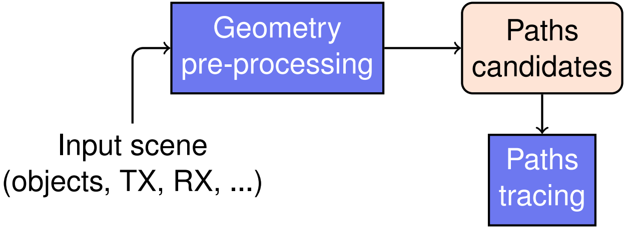

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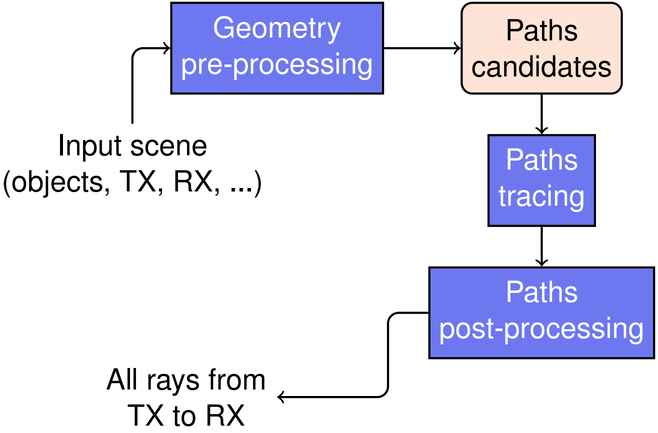

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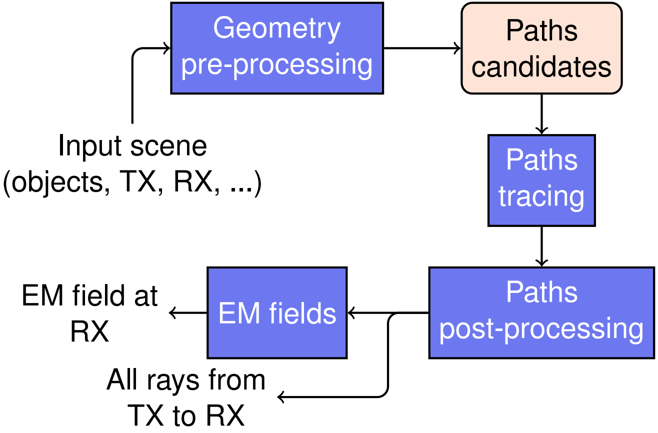

Circumventing the exponential complexity

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3. pre-compute some kind of visibility tree.

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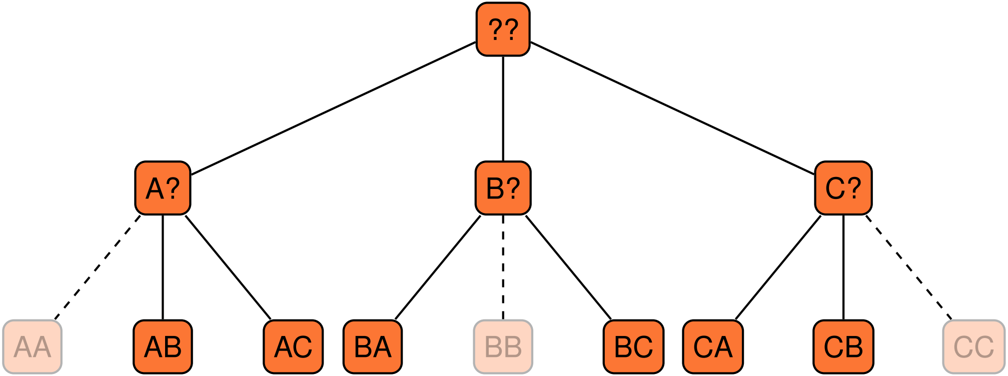
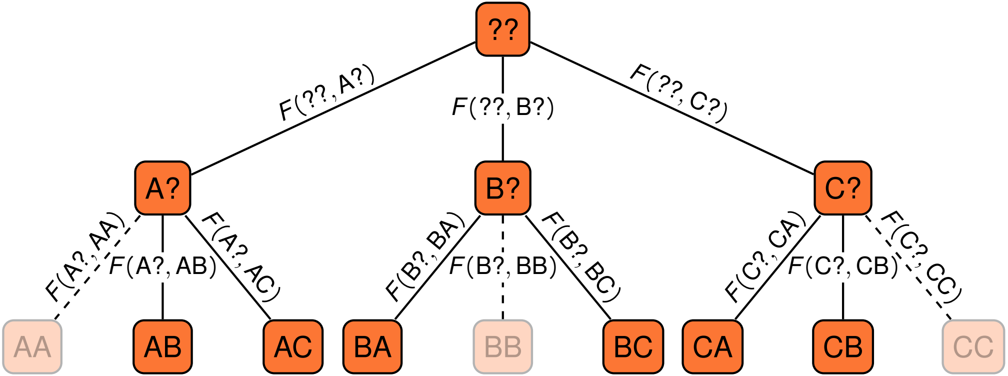
How path candidates are generated



A GFlowNet-like architecture



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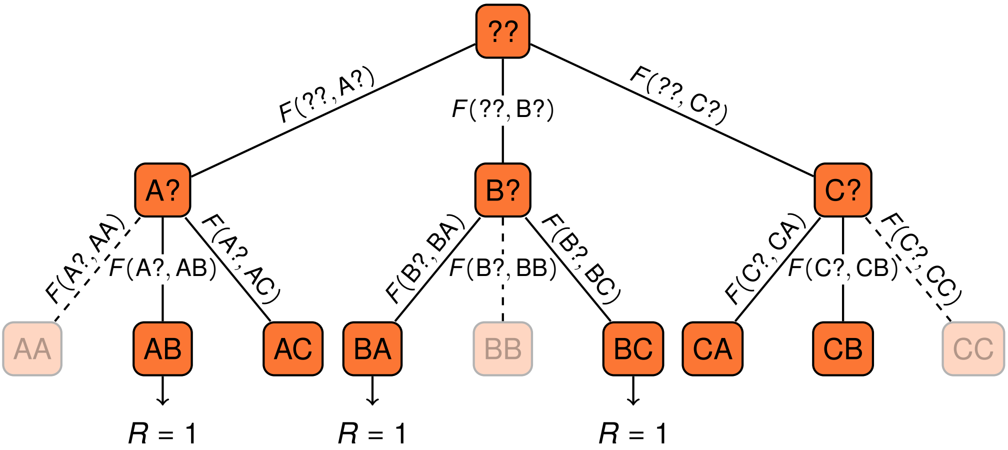

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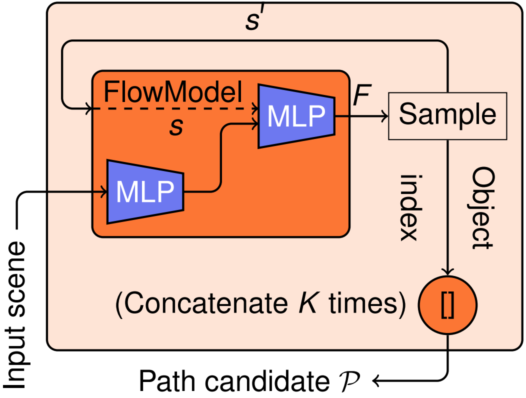

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1. does **not** learn a specific scene;
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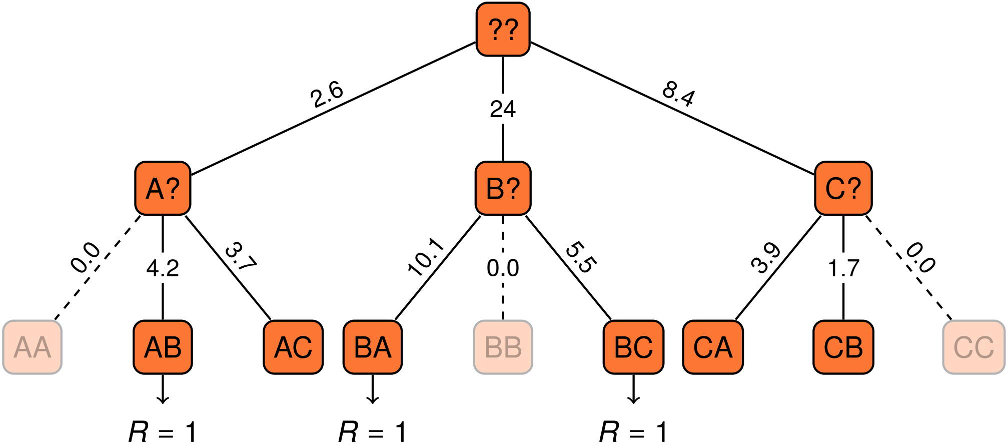
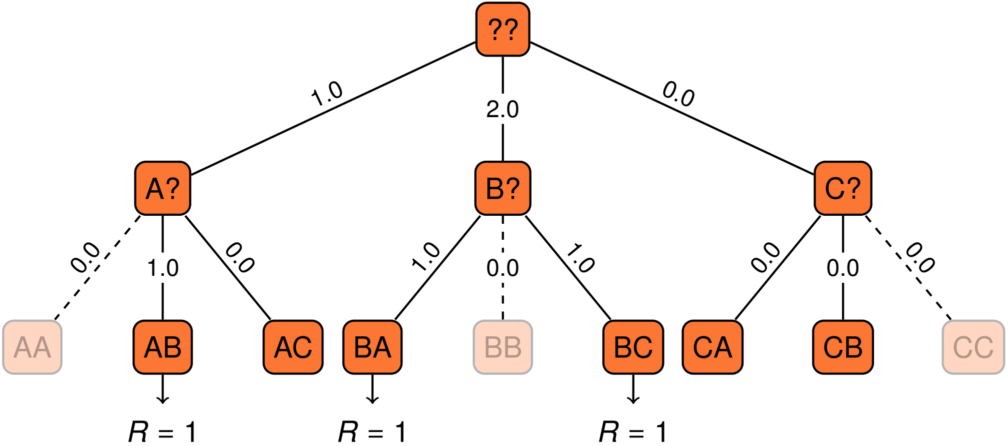
3. generates **one** path candidate at a time;
4. and **aims at accelerating RT**, not replacing it.

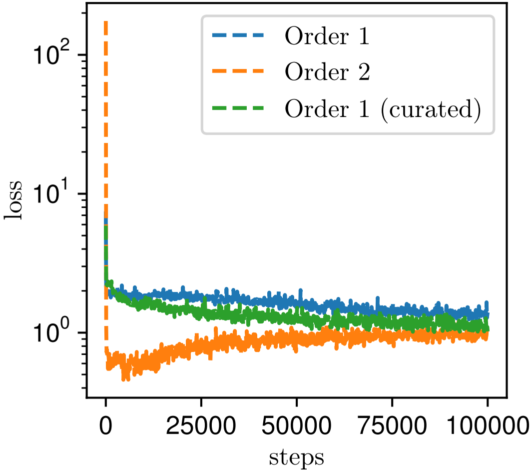
How we train our model - before



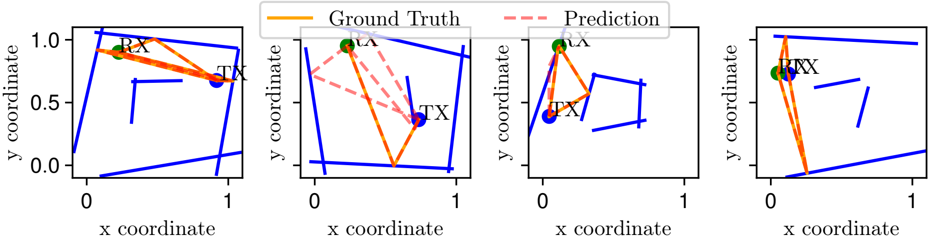
How we train our model - after



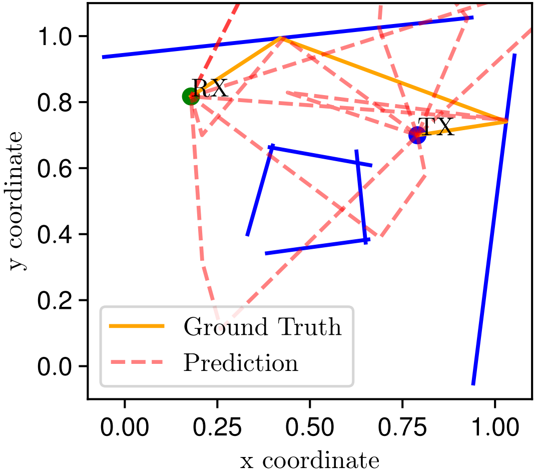
Learning reflection paths in 2D scenes



Predicting 1st order path candidates



Predicting 2nd order path candidates



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- the study of sparse reward functions, or smoothed ones using our recent work (EuCAP 2024);
- and the general shaping of the model (layers size, etc.).

Thanks

Any questions?

GFlowNet constraints

To achieve this, the model must be trained to respect the following fundamental properties:

1. Each edge in the search graph must be assigned a positive *flow*, $F(s, s') > 0$, where s is the parent state and s' is the child state;
2. Flow conservation between ingoing and outgoing edges must be ensured:

$$\forall s', F(s, s') = R(s') + \sum_{s''} F(s', s''), \tag{1}$$

   that is, the sum of output flows, $F(s', s'')$, must be equal to the input flow, $F(s, s')$, minus the reward;

GFlowNet constraints (continued)

3. The probability of choosing state s' given state s must be defined as

$$p(s'|s) = \frac{F(s,s')}{\sum_{s''} F(s,s'')}, \tag{2}$$

that is, the probability of traversing an edge in the search graph is equal to its flow value normalized over all outgoing edges.

Loss function

For training our model, we minimize the GFlowNets loss function, which rewrites (1) as a mean squared error:

$$L(s') = \left(F(s, s') - R(s') - \sum_{s''} F(s', s'') \right)^2 . \tag{3}$$