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A Computation-Aware Shape Loss Function for Point Cloud Completion

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Introduction

- **Challenges with LiDAR-Generated Point Clouds**
- Occlusions and limited angles may not fully capture object surfaces.
- Impacts registration and object detection tasks.
- **Prior Approaches to 3D Shape Completion**
- Learning-based techniques confront complexity with irregular and unordered point clouds for **loss function.**
- Existing metrics like Chamfer Distance and Earth Mover's Distance have drawbacks.
  - Chamfer Distance (CD) is efficient but **not sensitive enough.**
  - Earth Mover's Distance (EMD) is accurate but **computationally intensive.**
- **Key Contribution: Adaptive Auction with Initial Price Algorithm (AAIP)**
- Introduces initial prices to accelerate convergence in auction algorithms.
- Proposes an efficient algorithm for the computation of initial prices.
- Presents an adaptive Earth Mover's Distance approximation scheme for shape loss functions.
- Experimental results show reduced errors and superior training outcomes.

Point Cloud Completion Problem

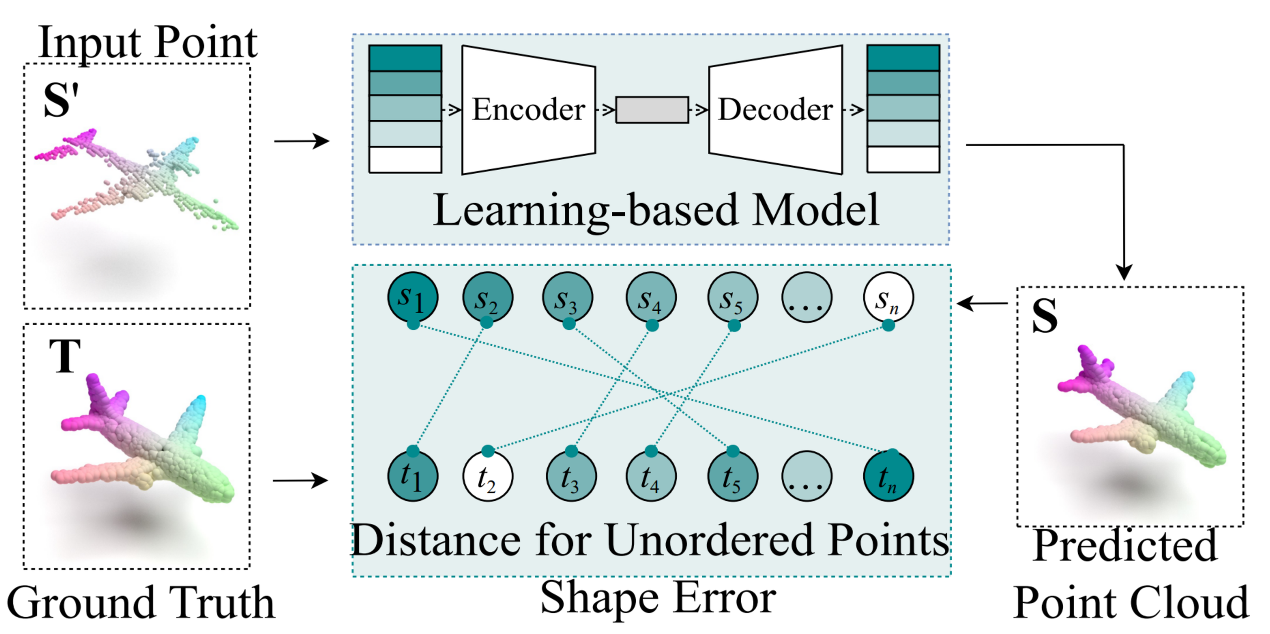

Figure 1:The illustration of point cloud completion problem.

- Define the point cloud completion problem as predicting **T** given **S'**.
- **S'** is not necessarily a subset of **T** and there is no explicit correspondence between points in **S'** and points in **T**, because they are independently sampled from the underlying object surfaces.

The Auction Algorithm

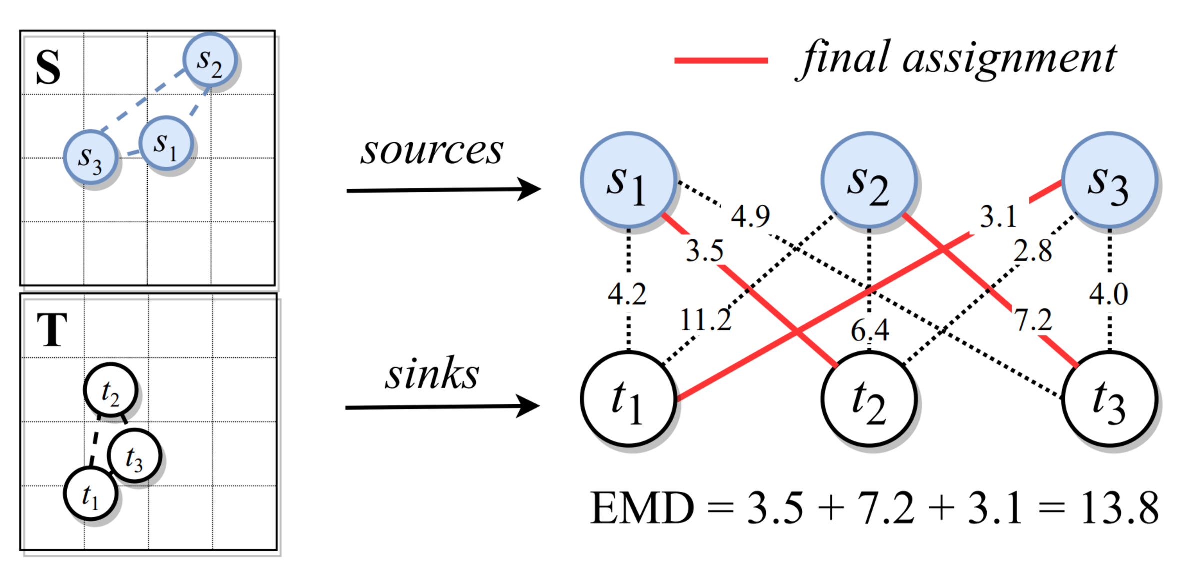

Figure 2: An example illustrates the efficacy of the method.

- **Expression of the Optimization Problem**
  - $\mathrm{EMD}(\mathbf{S},\mathbf{T}) = \min_{\Phi:\mathbf{S}\rightarrow\mathbf{T}} \frac{1}{|\mathbf{S}|}\sum_{x\in\mathbf{S}} \|x-\Phi(x)\|_2$.
- **The Challenges of Computing the Loss Function Using the Auction Algorithm[1]**
  - The number of iterations required for auction algorithm termination is difficult to estimate.
  - For certain point cloud, the number of iterations needed can be extremely high.

References

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Auction Algorithm with Initial Prices

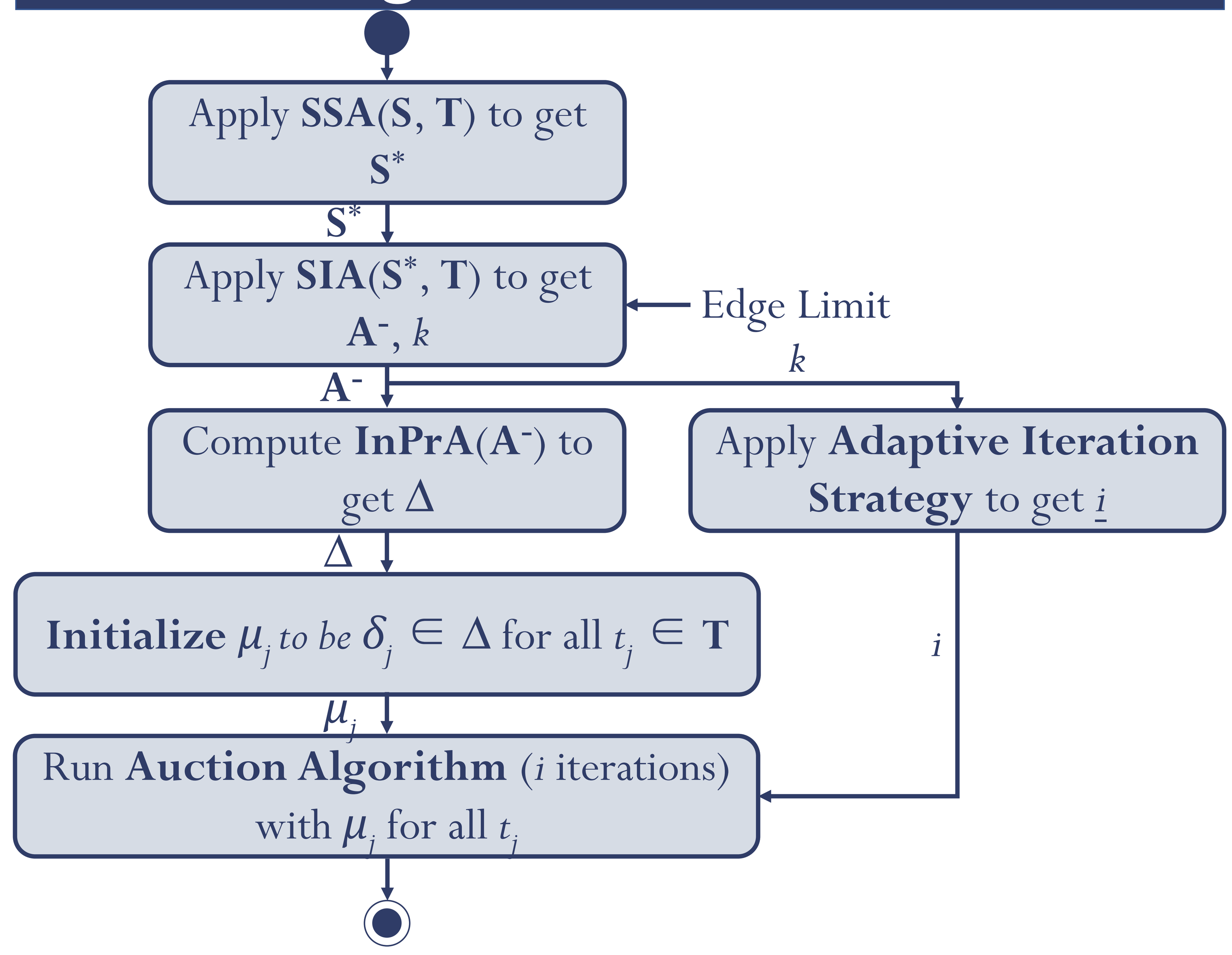

Figure 3: Adaptive Auction with Initial Price Algorithm Flowchart.

- Discern that given a local assignment A^- of $\mathbf{S}^- \subseteq \mathbf{S}$ and $\mathbf{T}^- \subseteq \mathbf{T}$, denoting the final selling price of the assigned $t_j \in \mathbf{T}^-$ in A^- as μ^-.
- **Definition 1** (Initial prices, Δ). *We say the set of initial prices* Δ *is* ***valid*** *if* $0 \le \delta_j \le \mu^-_j,\ \forall t_j \in \mathbf{T}^-$.
- **Correctness and Effectiveness** of **initial prices** have been proved. (cf. **Thm. 1** and **Lem.1**)
- **Configuration of Initial Prices**
- Objectives for setting initial prices:
  - Aim to configure initial prices to **meet criteria of Thm. 1**, ensuring $\delta_j \le \mu_j^-$ for each task t_j.
  - Seek to offer a controlled solution cost to **mitigate the overall computational expense**.
- **Lemma 2** (Configuration of initial prices). *Assuming that* (s_i, t_j) *is an assigned pair in a local assignment* A^-*. Furthermore, within this assignment,* $\forall s_p \in (\mathbf{S}^- - s_i)$*, the sink assigned to* s_p *is denoted as* $t_q \in \mathbf{T}^-$*. Considering the value* α_j *obtained by evaluating* $\max_{s_p \in \mathbf{S}^-} \{d_{pq} - d_{pj} + \varepsilon\}$*, we can set* $\delta_j = \max\{0, \alpha_j\}$*. This choice ensures that* δ_j *satisfies Theorem 1, specifically* $\delta_j \le \mu_j^-$.
- Utilized the core of the Successive Shortest Path algorithm (SSPA)[2] to calculate the proposed initial prices by Lem. 2.
- **Optimization Strategies**
- Simplified Graph Strategy[3].
  - Accelerated computational time cost for calculating initial prices.
- Source Sorted Algorithm (SSA).
  - Optimized the order of local assignment points to enhance the effectiveness of the initial price distribution.
- Adaptive iteration Strategy.
  - Adapted to deep learning processes to increase the algorithm's robustness to diverse feature point cloud data.

Experimental Results

Methods	chair	table	sofa	cabinet	lamp	car	airplane	watercraft	average
PCN (CD+CD)	62.46	66.88	52.85	61.07	102.88	50.86	38.17	52.22	60.93
PCN (emd_1+CD)	62.83	59.94	52.53	54.91	69.50	54.12	33.22	55.30	55.29
PCN (AAIP+CD)	52.73	49.77	48.21	49.66	**62.95**	38.15	27.22	44.13	46.60
PCN (CD+AAIP)	**43.23**	**43.54**	**34.58**	**35.56**	63.55	**31.13**	**25.79**	**35.96**	**39.17**
MSN (emd_2)	33.12	31.12	31.11	36.13	36.66	32.90	18.70	25.66	30.68
MSN (AAIP)	**28.99**	**28.25**	**28.48**	**34.18**	**31.53**	**31.45**	**16.58**	**22.58**	**27.71**

Table 1: The training results (EMD×10^3) of point cloud completion network on the ShapeNet dataset. We denote the compared methods as emd_1[4] and emd_2[5].

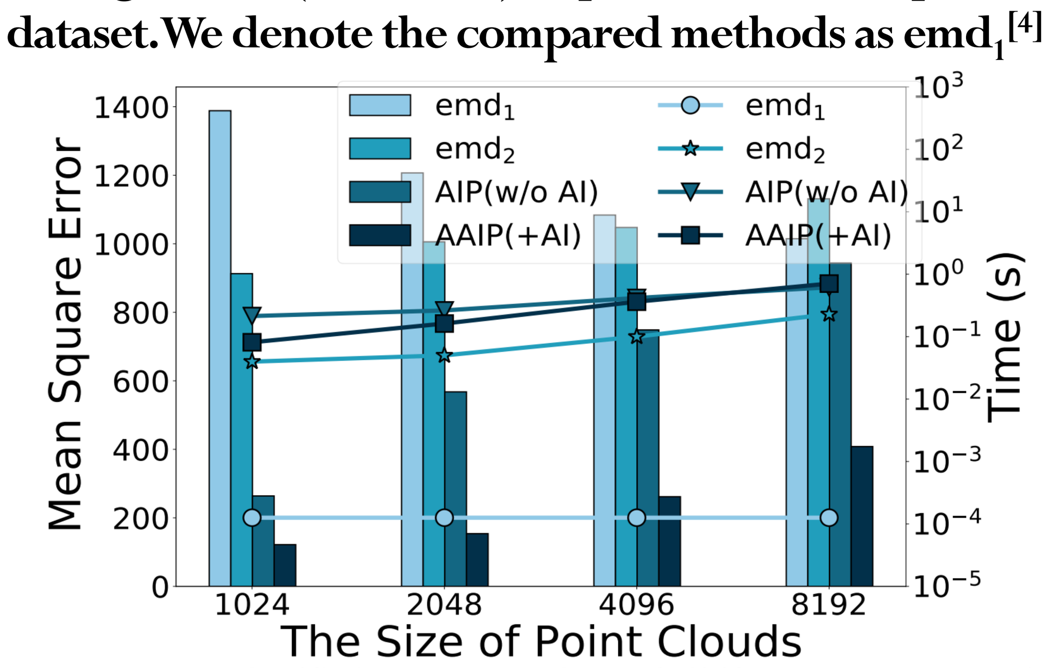

Figure 4:The accuracy and efficiency results of different EMD estimation methods