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CP³: Channel Pruning Plug-in for Point-based Networks

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1. Overview

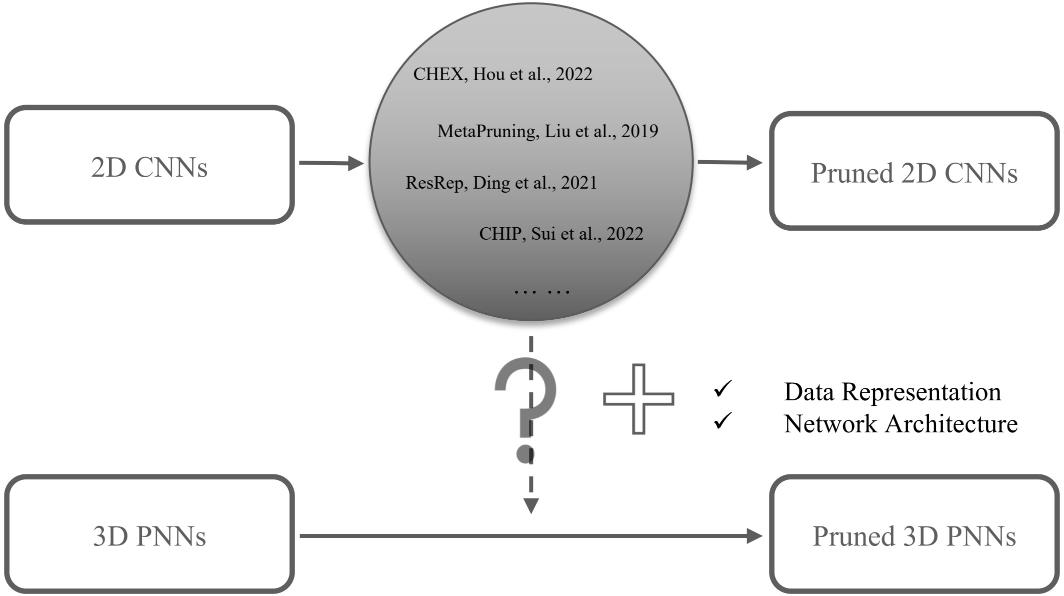


Table1. Classification on ScanObjectNN test set with PointNeXt-s

Method	OA	mAcc	Params. (M)	GFLOPs
Baseline	87.40	85.39	1.37	1.64
HRank	84.79	81.93	0.50	0.39
HRank +CP³	86.40	83.94	0.48	0.37
CHIP	81.37	78.99	0.34	0.19
CHIP+ CP³	82.12	79.41	0.33	0.18

Table2. Segmentation on S3DIS with PointNeXt-L

Method	OA	mAcc	Params. (M)	GFLOPs
Baseline	90.10	75.50	7.13	15.24
HRank	88.88	73.61	3.20	6.83
HRank +CP³	89.44	74.27	3.00	6.48
CHIP	88.58	71.58	1.50	3.27
CHIP+ CP³	89.20	71.66	1.38	3.04

2. Introduction

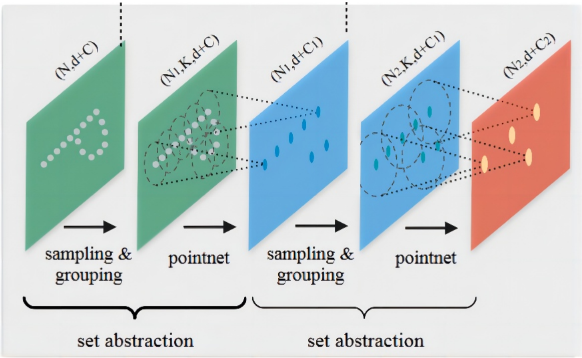
Question: *shall we directly implement the existing pruning methods to PNNs following the proposed channel importance metrics in 2D CNNs pruning?*

Motivation:

➢**Data Representation**: Point cloud offers a more extensive 3D feature representation compared to 2D images, but this comes with a higher sensitivity to the channel capacity of the network.

Source: SUN RGB-D dataset

➢**Network Architecture**: As a result of the required sampling process, a considerable number of points are randomly dropped, leading to the loss of a significant amount of unique information from the original data.

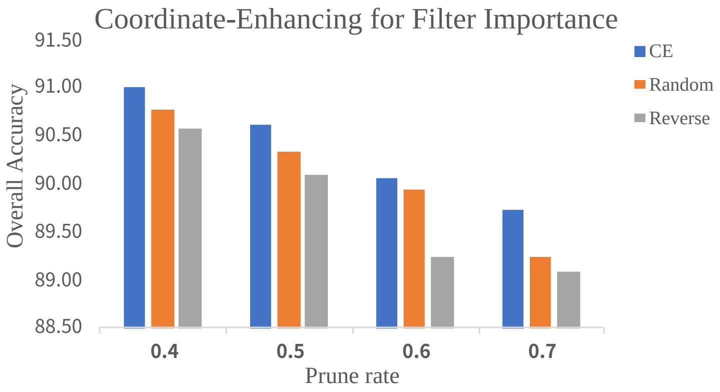


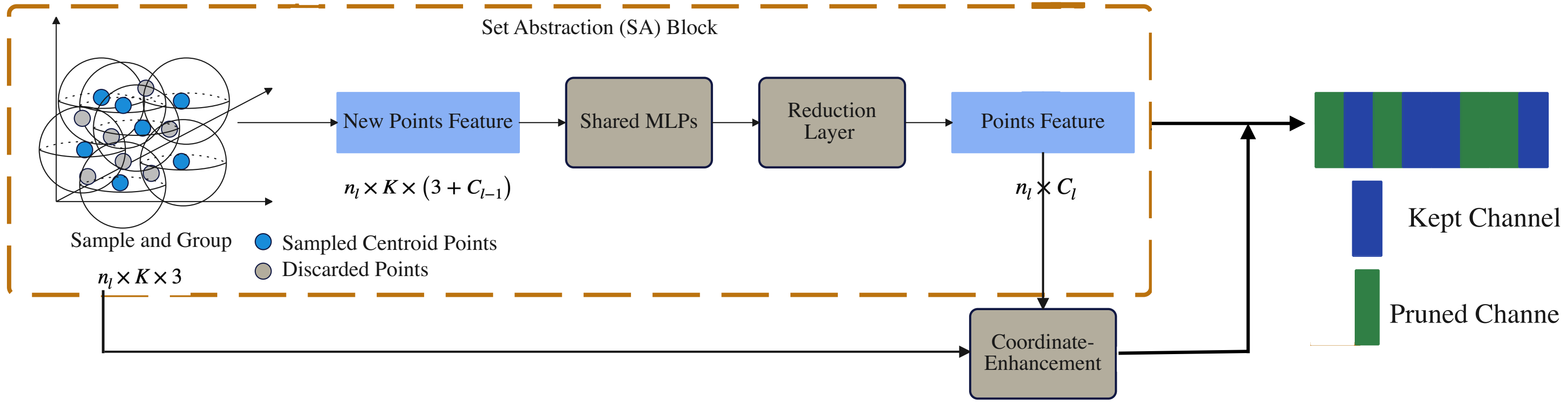
Source: PointNet++, Qi et al., 2017

3. Methodology ——Coordinate-Enhanced (CE)

We evaluate the correlation between the **current points feature** and the **input points coordinate**.

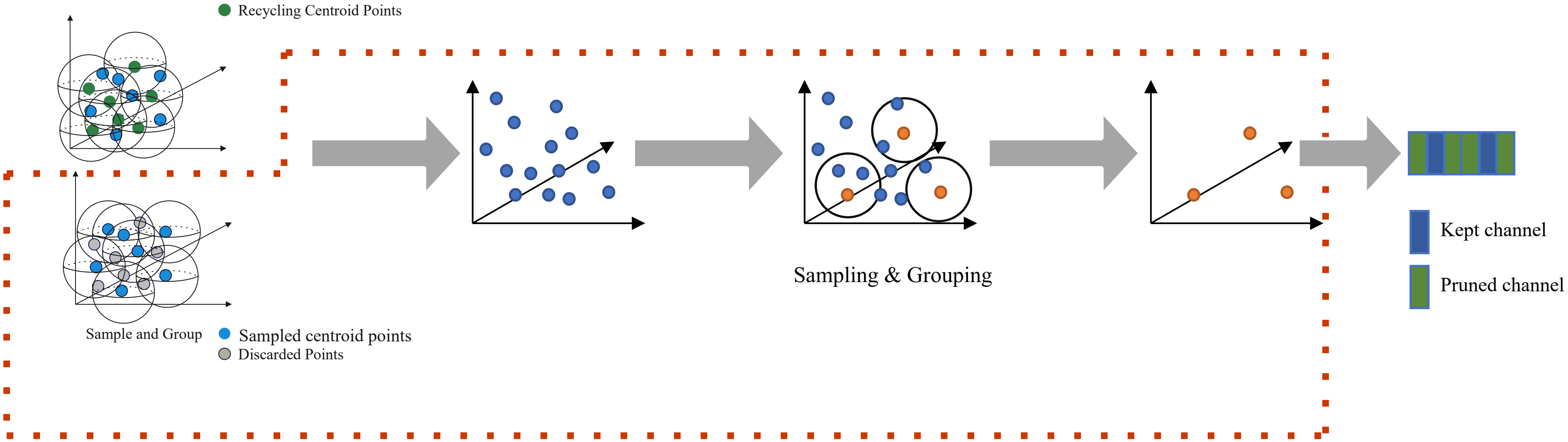
The figure on the right compares the performance of our method with respect to channel retention using **CE scores**, **random selection**, and **reverse order** retention.





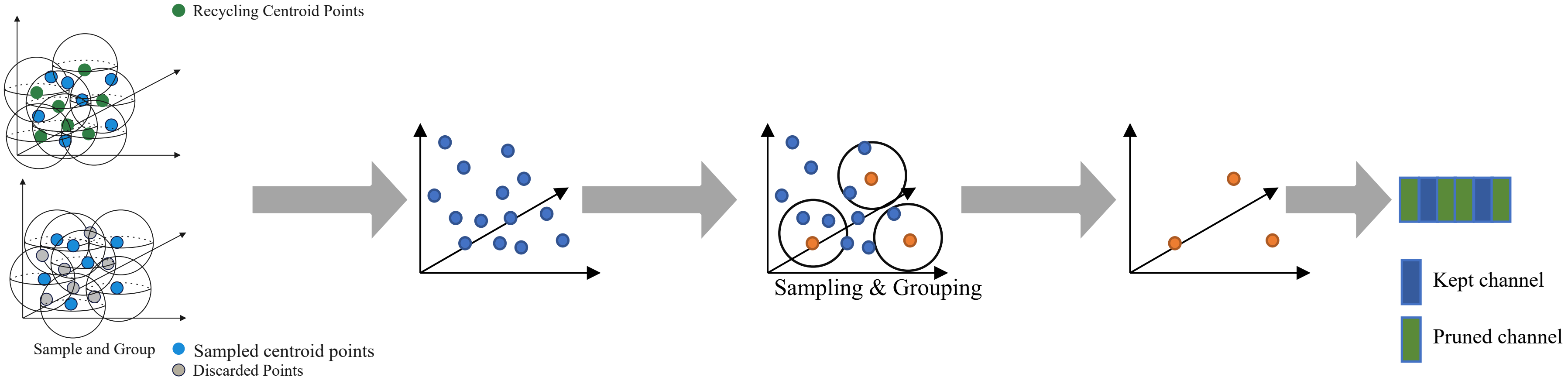
3. Methodology —— Knowledge-Recycling (KR)

Point-based neural network (PNNs) leverage neighborhoods at multiple scales to obtain both robust and detailed features. Due to the necessary *sampling steps*, the issue of **insufficient knowledge** becomes more severe.



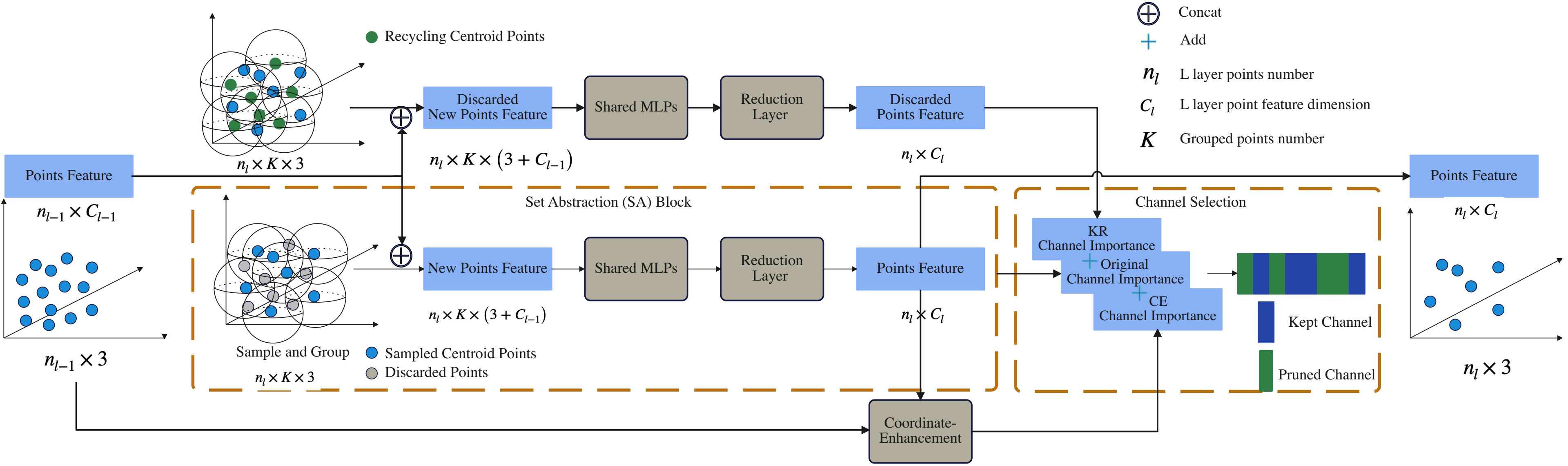
3. Methodology —— Knowledge-Recycling (KR)

Calculating channel importance is **data-driven** and sensitive to the input data, we make full use of the **discarded points** in the sampling process via a **Knowledge-Recycling** module.



3. Framework

Our method considers both the **data representation** of point clouds and the **network architecture**. It improves the original pruning method with the ***CE*** and ***KR*** modules, making it better suited for PNNs.



4. Experiments

Table3. Classification on ModelNet40 test set with PointNeXt-s (C=64)

Method	OA	mAcc	Params. (M)	GFLOPs
Baseline	93.44	91.05	4.52	6.49
HRank	92.23	89.81	2.12	2.69
HRank +CP³	93.52	90.33	2.01	2.58
CHIP	90.83	88.70	0.65	0.46
CHIP +CP³	92.87	90.25	0.63	0.44

Table4. Object detection on ScanNet test set with VoteNet

Method	mAP @0.25	mAP @0.5	Params. (K)	GFLOPs
Baseline	62.34	40.82	641.92	5.78
ResRep	62.45	40.95	251.23	2.45
ResRep +CP³	63.92	41.47	242.26	2.41

Table5. Ablation study of different components in CP³

Setting	CE	KR	Pruning Rate	OA	mAcc
Baseline			-	88.20	86.40
Hrank			0.75	84.79	81.93
		√	0.75	85.63	82.97
	√		0.75	85.11	82.13
HRank +CP³	√	√	0.75	86.63	83.63
Hrank			0.90	81.33	78.32
		√	0.90	83.66	81.32
	√		0.90	83.10	80.47
HRank +CP³	√	√	0.90	84.83	82.74

Thank you for watching!