Dynamic sampling pointnet notes

xyz

Feb 2018

Contents

1 Deep 3D Learning Notes

1.1 potential solutions for over fitting

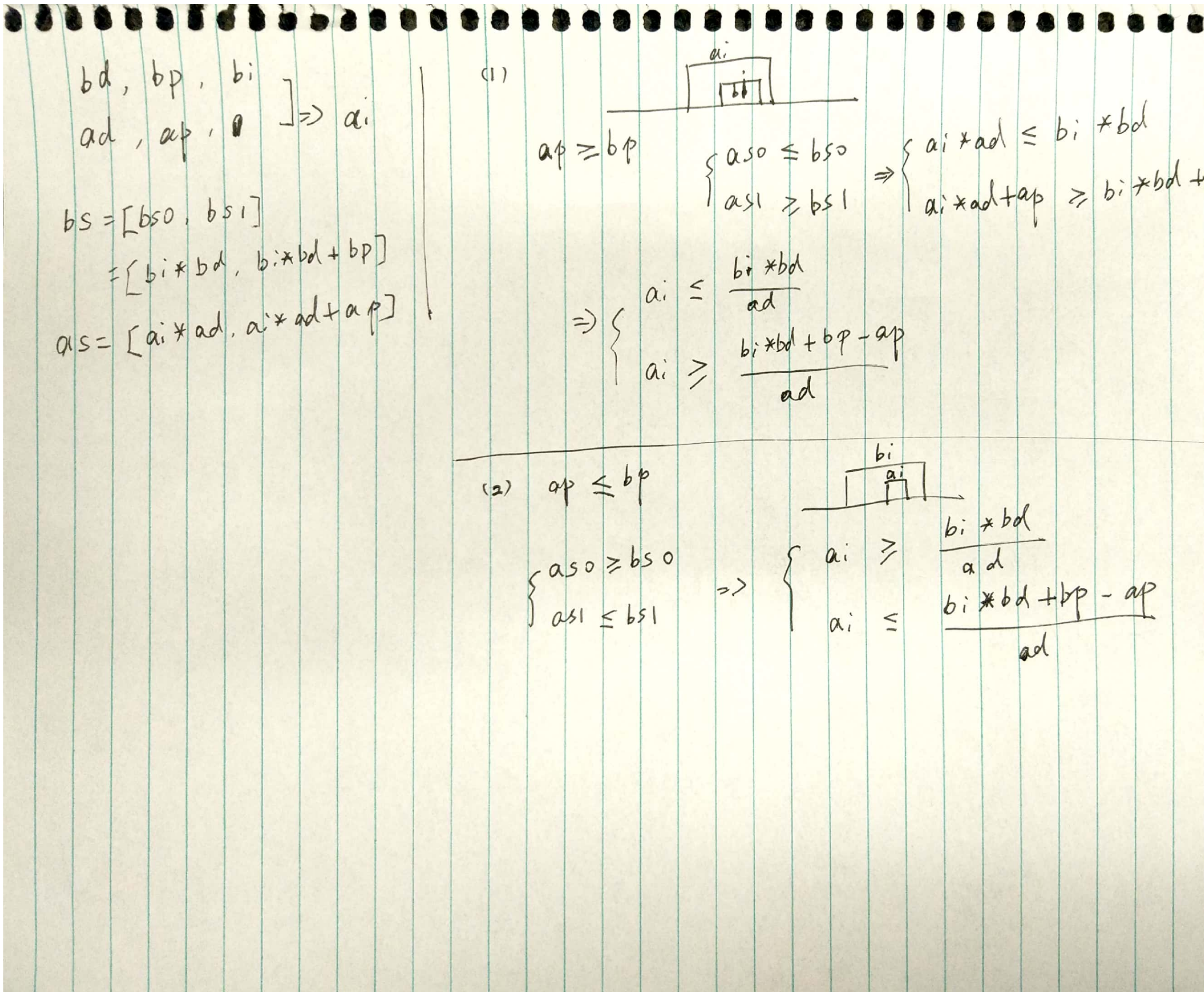
- data augmentation: rotation, different size scale
- data regulation: group norm
- dropout
- combine ShapeNet data
- more powerful network to learn more systematic information:
  1. use large global block size
  2. dynamic sampling
- smaller net

1.2 Important improvements

- Generate bxmh5 online. So the randomly missing part in each epoch is different. This maybe solve the info missing problem for sparse voxel 3d cnn, especially considering that block merging cannot be applied for voxel cnn. However, on line sampling can only solve missing problom of training, test missing still need some tricks to perform block merging.
- Check this: my usage of tf.gather_nd should cost a lot of memory, maybe too much!

1.3 Theory

1.3.1 bidxmap



$$\left.\begin{array}{l} bd,\ bp,\ bi \\ ad,\ ap,\ \end{array}\right] \Rightarrow ai$$

$$bs = [bs0, bs1] = [bi * bd,\ bi * bd + bp]$$

$$as = [ai * ad,\ ai * ad + ap]$$

(1) $ap \geq bp$

$$\begin{cases} as0 \leq bs0 \\ as1 \geq bs1 \end{cases} \Rightarrow \begin{cases} ai * ad \leq bi * bd \\ ai * ad + ap \geq bi * bd + \end{cases}$$

$$\Rightarrow \begin{cases} ai \leq \dfrac{bi * bd}{ad} \\ ai \geq \dfrac{bi * bd + bp - ap}{ad} \end{cases}$$

(2) $ap \leq bp$

$$\begin{cases} as0 \geq bs0 \\ as1 \leq bs1 \end{cases} \Rightarrow \begin{cases} ai \geq \dfrac{bi * bd}{ad} \\ ai \leq \dfrac{bi * bd + bp - ap}{ad} \end{cases}$$

1.3.2 group sampling configuration

$$steps = [0.1, 0.3, 0.9, 2.7] + [-6.3]$$

$$strides = [0.1, 0.2, 0.6, 1.8] + [-3.6]$$

$$voxel\ size = [, 3, 4, 4, 3]$$

principles:

(1)Alignment between differert scales:

$$steps[i] = steps[i-1] + strides[i-1] * (k-1) \ (k = voxel\ size)$$

(2)Alignment between voxels on one scale:

$$strides[i]\%steps[i-1] == 0$$

Examples:

$$0.3 = 0.1 + 0.1 * 2 \Rightarrow voxel\ size = 3$$
$$0.2 = 0.1 * 2$$
$$0.9 = 0.3 + 0.2 * 3 \Rightarrow voxel\ size = 4$$
$$0.6 = 0.3 * 2$$

$$6.3 = 2.7 + 1.8 * 2$$
$$3.6 = 1.8 * 2$$

1.3.3 Sparse voxel 3DCNN

1.3.4 Data Augmentation

- (1.1) Rotate corrdinate reference: Rotate both point and voxel box

  Performed by rotating points after sampling and grouping.

  This should only be applied to point position (cascade 0). What if also to features (upper cascades).

- (1.2) Rotae point only, or rotate voxel box only.

  a) It can be performed by rotating points before sampling and grouping.

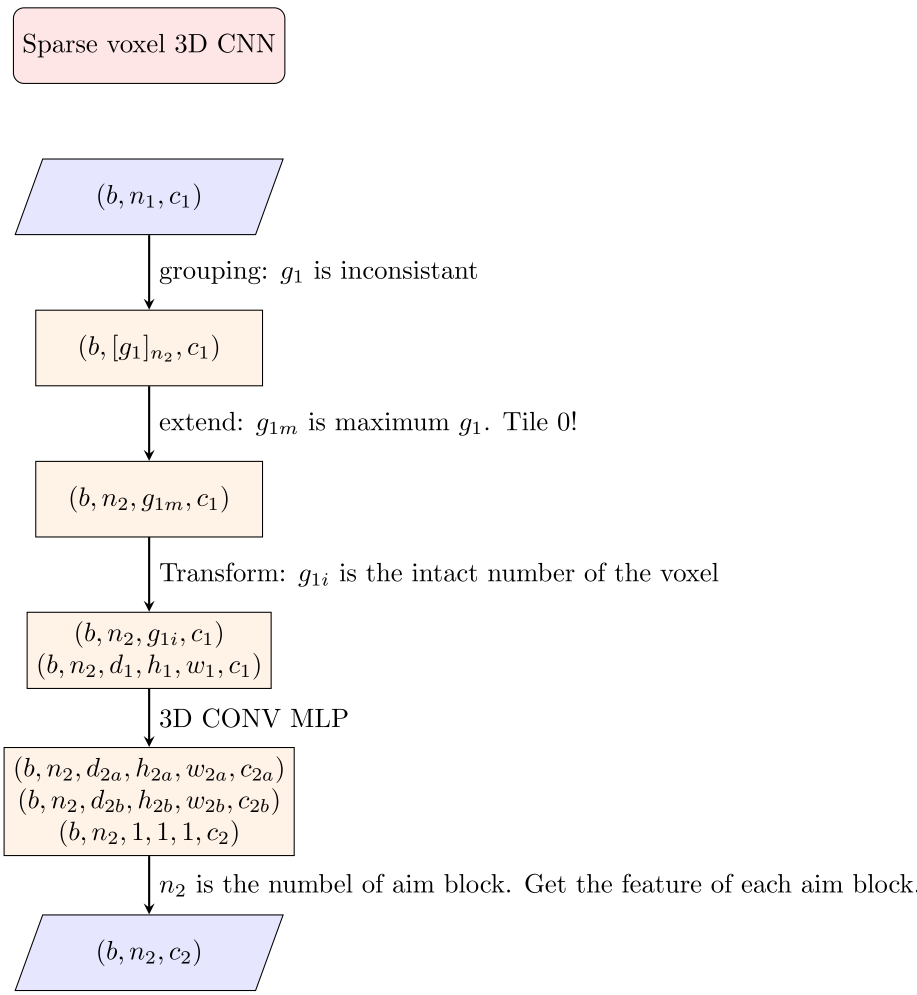
  b) If rotate angle is integral times of pi/2, it can be performed by rotating point indices inside the voxel.

  Rotate voxel can be applied to all cascades.

- (2.1) Rotate the global block by the same angle

- (2.2) Rotate each voxel by seperate angle in each scale.

  Since the features are calculated independently in each voxel, it should be fine to apply different rotatio angle for each voxel. It doesn't matter that the rotation center is voxel center or global block center. It alos doesn't matter that it rotates refference or only rotates voxel.



Two main obstacles for performing 3D convolution on point cloud are: (1) there are too many vacant points, (2) the position of points are not aligned. The key idea of sparse voxel is to perform 3DCONV on cascades from the second. Because the positions are actually almost aligned. At the same time, the vacant rate within a small block is acceptably large. Above all, it may be possible to do apply 3D-CONV within a small block.

Centres of blocks in cascades other than first one are actually aligned to the grid. So it is possible to perform 3d convolution directly. However, the average position of points inside these blocks are not aligned. Thus it is also maybe beneficial to utilise a transform net to align them.

On the other hand, there are many vacant points in the block. I am wondering if it is beneficial to set the features of vacant points by a T-net from around existing points.

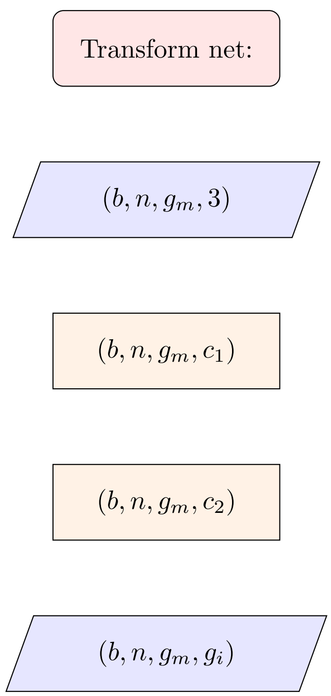
Purpose of T-Net: fix number + align + till

There are some interesting problems for Transform net:

- Only depend on position or feature.
- Should be resolution invariant.
- If it should be constant for all channels.
- If it should be constant for all local aim blocks.

Reasons that we do not need the T-Net:

- 3d-conv can till features of the vacant points.
- If the base-points are not strictly aligned, add the position to feature map. Or get a special feature of positions within the block and then add ot the main feature map.



1.4 batch size

1.4.1 bs=27 vs bs=81

batch size: 9,27,81
data: xyz-color_1norm
model: 1AG
sampling & grouping: stride_0d1_step_0d1_bmap_nh5_2048_0d5_1_fmn1-160_32-32_12-0d2_0d6-0d2_0d6

Figure 1: bs=9

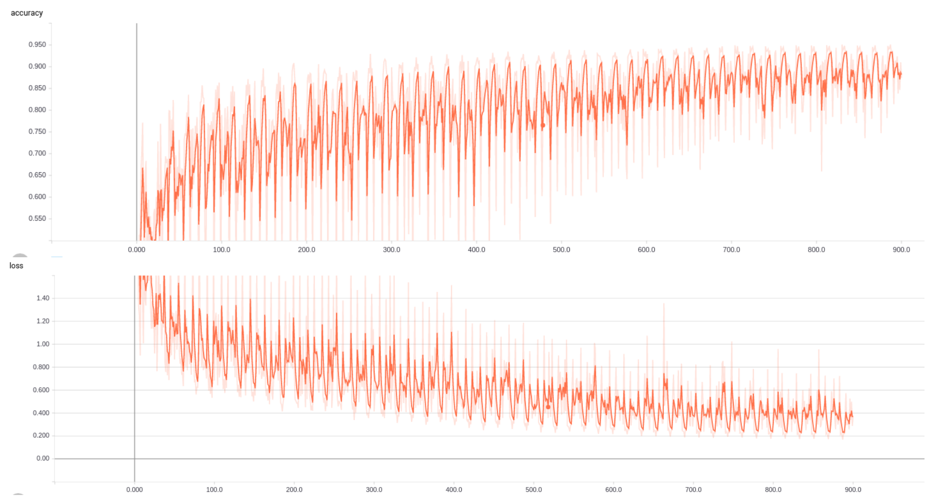


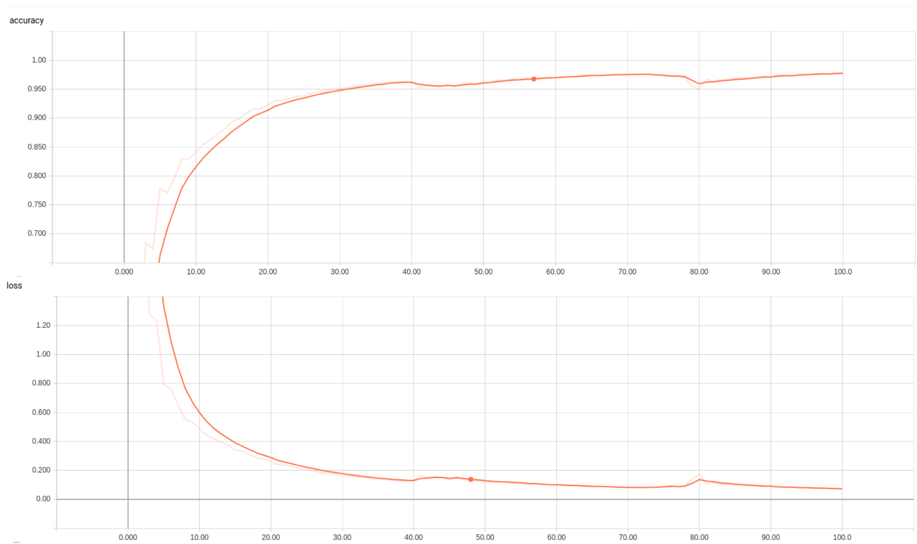
Figure 2: bs=27

1.5 feed elements

epoch num = 100

stride_0d1_step_0d1_bmap_nh5_2048_0d5_1_fmn1-160_32-32_12-0d2_0d6-0d2_0d6

Figure 3: bs=81



model	batch size	data elements	acc	loss
1AG	9	xyz color	0.890	0.356
1AG	27	xyz color	0.920	0.240
3AG	27	xyz color	0.912	0.273
2A	27	xyz color	0.908	0.294
2AG	27	xyz color	0.902	0.293
1A	27	xyz color	0.883	0.351
1AG	81	xyz color	0.978	0.072
1AG	9	xyz	0.861	0.427
1AG	27	xyz	0.907	0.257
1AG	81	xyz	0.975	0.078
1A	27	xyzmid color	0.889	0.357
3AG	27	xyzmid color	0.933	0.193
2A	27	xyzmid color	0.939	0.177
2AG	27	xyzmid color	0.929	0.208
3AG	27	xyz xyzmid color	0.924	0.230
2A	27	xyz xyzmid color	0.898	0.317
2AG	27	xyz xyzmid color	0.908	0.280
1A	27	xyz xyzmid color	0.910	0.281
1AG	27	xyz xyzmid color	0.944	0.163
1AG	81	xyz xyzmid color	0.976	0.078
2A	81	xyz xyzmid color	0.942	0.173
3AG	81	xyz xyzmid color	0.949	0.147

1. large batch size is better
2. $1AG(0.92) > 3AG(0.912) > 2A(0.908) > 2AG(0.902) > 1A(883)$

   1AG is much better than 1A

   1AG is a bit better than 3AG ???
3. xyz-color is only a bit better than xyz
4. xyzmid-color is much better than xyz-color
5. **xyzmid-color is normally much better than xyz-xyzmid-color ???**

1.6 model

batch size: 50

data: xyz_midnorm_block-color_1norm

epoch_num = 600

sampling & grouping: stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn3-600_64_24-60_16_12-0d2_0d6_1d2-0d2_0d6_1d2

model	acc	loss
3A	0.909	0.248
3AG	0.913	0.231
4AG	0.912	0.232

batch size: 32

data: xyz_midnorm_block-color_1norm

sampling & grouping: stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn6-2048_256_64-32_32_16-0d2_0d6_1d2-0d1_0d3_0d6

matterport3d

feed_data_elements:['xyz_midnorm_block', 'color_1norm']

feed_label_elements:['label_category', 'label_instance']

train data shape: [362 12800 6]

test data shape: [384 12800 6]

max epoch = 500

model	acc	loss
1AG	0.944/0.431	0.161/4.633
4AG	0.835/0.401	0.520/3.644

1.7 integration: matterport3d

<table>
<tr><td colspan="5">stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn3-512_64_24-48_16_12-0d2_0d6_1d2-0d2_0d6_1d2
17D_1LX_1pX_29h_2az</td></tr>
<tr><td>model</td><td>batch size
batch num
shuffle</td><td>lr
ds</td><td>data elements</td><td>epoch-acc mean-std
train/eval</td></tr>
</table>

1aG	30/60	0.005	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	250-0.981
1DSaG	30/60	0.001-40	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.914-0.775
1DSaG	30/60	0.001-40	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.914-0.775
1DSaG kp0.5	30/60	0.001-80 300-3e-4	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.942-0.842
1DSaG kp0.2	30/60	0.001-80 300-3e-4	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.928-0.797
1DSaG kp0.5	30/60	0.005-80 300-1.7e-3	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.970-0.916
1DSaG kp0.2	30/60	0.005-80 300-1.7e-3	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.966-0.924
1DSaG kp0.8	30/60	0.005-80 300-1.7e-3	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	300-0.976-0.933 500-0.984-0.954
1aG	30/1083	0.003	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	200-0.947
1aG	30/1083	0.01	'xyz_midnorm_block', 'color_1norm'	200-0.783 500-0.791
1aG	30/1083	0.003/30 300-0.00012	'xyz_midnorm_block', 'color_1norm'	200-0.903 300-0.921
1bG	25/1083	0.001-30 100-3e-4 300-4e-5	'xyz_midnorm_block'	100-0.854 200-0.918 300-0.936
1bG	25/1083	0.001-30 100-3e-4 300-4e-5	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	100-0.914 200-0.957 300-0.966
1bG	25/1083	0.02	'xyz_midnorm_block', 'color_1norm'	200-0.655 300-0.718
1bG	25/1083	0.02	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	200-0.772 300-0.823
1bG	25/1083	0.001	'xyz'	200-0.772 90-0.553-0.210

4bG	25/1083	0.001-30 100-3e-4 200-1e-4 300-4e-5	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	100-0.752 200-0.816 300-0.832
2 1DSaG	30/1083	0.002-80	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	200-0.930-0.830/0.450 460-0.952-0.881/0.471
1aG	30/19755	0.001-30 50-7e-4 100-3e-4	'xyz_midnorm_block', 'color_1norm','nxnynz'	50-0.752/0.580 100-0.843/0.574 (NoShuf) 102-0.806/0.570 (Shufle)
1bG	25/19755	0.001-30	'xyz_midnorm_block', 'color_1norm','nxnynz'	38-0.719/0.587 80-0.823/0.583 (NoShuf) 81-0.782/0.587 (Shufle)
1aG	30/19755	0.02	'xyz_midnorm_block', 'color_1norm'	56-0.562
1aG	30/19755	0.02 127-0.00483	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	87-0.616 127-0.686
1bG	25/18737	0.001 N	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	24-0.682/0.509 70-0.858/0.509
1bG	25/18737	0.001 Y	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	24-0.738/0.573 70-0.876/0.563 90-0.897 /0.561
4bG	25/18737	0.001 Y	'xyz_midnorm_block', 'nxnynz'	24-0.576/0.545
4bG	25/18737	0.001 Y	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	24-0.594/0.569
1DSaG	30/18737	0.002-80 Y	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	20-0.688-0.394/0.428-0.224 36-0.742/0.395
1DSaG	30/18737	0.007-80 Y	'xyz_midnorm_block', 'color_1norm', 'nxnynz'	20-0.725-0.453/0.435-0.206 38-0.783/0.396
Conclusion: 1: nxnynz helps a lot 2: 1bG is much deeper than 1aG, why worse than 1aG 3: learning rate is important, cannot be too large				

1.8 multi scales & mat 1083

nh5: stride_0d1_step_0d1_pl_nh5-1d6_2/17D_1LX_1pX_29h_2az bxmh5: stride_0d1_step_0d1_bxmh5-12800_1d6_2_fmn4-480_80_24-80_20_10-0d2_0d6_1d2-0d2_0d6_1d2-3A1					
model	bs/bn	lr-decay	elements	loss weight in drop	epoch-pacc-cacc train/eval
4bG_111	20/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	110-0.898-0.763 160-0.931-0.827 300-0.967-0.915
4bG_444	15/1083	3-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.729-0.614 100-0.857-0.721 160-0.920-0.834 260-0.952-0.890 300-0.958-0.913
4bG_444	15/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.778-0.608 100-0.878-0.758 160-0.930-0.838 260-0.957-0.901 300-0.964-0.912
4bG_144	18/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.786-0.637 100-0.876-0.767 160-0.926-0.820 260-0.959-0.885 300-0.962-0.906
4bG_114	20/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.772-0.611 100-0.874-0.764 160-0.926-0.851 260-0.958-0.893 /par 300-0.963-0.904
3aG_444	45/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.893-0.737 100-0.908-0.786 /par 160-0.934-0.833 260-0.950-0.868 /par 300-0.952-0.882
2aG_144	30/1083	2-40	xyz_midnorm_block-color_1norm-nxnynz	E	60-0.890-0.754 100-0.922-0.820 /par 160-0.942-0.858: 260-0.957-0.897 /par 300-0.960-0.911

1.9 multi scales & mat 21826

nh5: stride_0d1_step_0d1_pl_nh5-1d6_2/ bxmh5: stride_0d1_step_0d1_bxmh5-12800_1d6_2_fmn4-480_80_24-80_20_10-0d2_0d6_1d2-0d2_0d6_1d2-3A1 eval: 17D_1LX_1pX_29h_2az					
model	bs/bn	lr-decay	elements	loss weight in drop	epoch-pacc-cacc train/eval
4bG_114	20/1080	1-30	xyz midnorm color nxnynz	E N	40-0.784-0.545/0.579-0.451 80-0.883-0.699/0.584-0.439 140-0.925-0.795/0.575-0.429
4bG_111	20/1080	2-30	xyz midnorm color nxnynz	E N	40-0.737-0.489/0.587-0.412 80-0.836-0.614/0.582-0.411 95-0.867/0.588
4bG_144	20/1200	2-30	xyz midnorm color nxnynz	E N	40-0.761-0.543/0.601-0.416 80-0.864-0.693/0.602-0.426 95-0.888/0.597
Conclusion: (1) Nein 114 is better than 111					

1.10 multi scales & scannet 12887

nh5: stride_0d1_step_0d1_pl_nh5-1d6_2/
bxmh5: stride_0d1_step_0d1_bxmh5-12800_1d6_2_fmn4-480_80_24-80_20_10-0d2_0d6_1d2-0d2_0d6_1d2-3A1
eval: test

model	bs/bn	lr-decay	elements	loss weight in drop	epoch-pacc-cacc train/eval
2aG_144	30/420	2-30	xyz midnorm	E N	40-0.833-0.546/0.686-0.89 100-0.926-0.727/0.683-0.326
3aG_144	48/260	2-30	xyz midnorm	E N	40-0.841-0.530/0.668-0.346 100-0.924-0.709/0.673-0.327 200-0.949-0.782/0.673-0.332 **300-0.955-0.802/0.671-0.330**
4bG_111	22-580	2-30	xyz midnorm	E N	60-0.738-0.434/0.706-0.344 100-0.796-0.506/0.699-0.315 180-0.863-0.589/0.695-0.308
4bG_111	22-580	7-30	xyz midnorm	E N	60-0.705-0.378/0.684-0.362
4bG_144	18-700	2-30	xyz midnorm	E N	40-0.714-0.470/0.6910.433 100-0.794-0.481/0.682-0.393 160-0.849-0.582/0.676-0.362
4aG_1a4	55-220	2-30	xyz midnorm	CN N	40-0.775-0.482/0.654-0.304 100-0.877-0.637/0.661-0.298 160-0.901-0.690/0.660-0.311 220-0.908-0.707/0.655-0.334
4aG_1a4	55-220	2-30	xyz midnorm	E N	40-0.819-0.527/0.684-0.333 100-0.923-0.706/0.681-0.304

Conclusion:
(1) 3aG is much better than 4bG. Potential reasons:(a) 4bG is too wide and deep, so that needs more time to train. (b) The batch size of 4bG is too small
(2) nein 144 seems is not better than 111
(3)Learning rate 0.002 is better than 0.007
(4)Loss weight CN does not help

1.11 integration: scannet

stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn3-256_48_16-56_8_8-0d2_0d6_1d2-0d2_0d6_1d2 scannet train					
model	loss: E,N,C input drop (No)	batch size batch num shuffle	lr ds	data elements	epoch-point ac-class ac train/eval
1bG	E	25/12887 test Y	0.001 40	xyzmid	23-0.732-0.326/0.664-0.260 25-0.746-0.340/0.669-0.273
1bG	N	25/12887 Y	0.001 40	xyzmid	25-0.733-0.390/0.666-0.252
1bG	C	25/12887 Y	0.001 40	xyzmid	25-0.703-0.356/0.655-0.252
1bG	CN	25/12887 Y	0.001 40	xyzmid	25-0.681-0.366/0.611-0.237
1DSaG	E idp9	30/12887 Y	0.003 80	xyzmid	40-0.738-0.376/0.513-0.228 90-0.832/0.496
1bG	E	25/13091 train_300 Y	0.002 80	xyzmid	60-0.765-0.389/0.700-0.252
1bG	E	25/13091 Y	0.003 80	xyzmid	10-0.646/0.689 60-0.753-0.349/0.691-0.234 100-0.833-0.480/0.672-0.261
1bG	CN	25/13091 Y	0.002 80	xyzmid	60-0.738-0.409/0.670-0.237
1bG	E idp9	25/13091 Y	0.003 80	xyzmid	10-0.641/0.585 16-0.646/0.633
1DSaG	E	30/13091 Y	0.003 80	xyzmid	40-0.794-0.456/0.420-0.154 100-0.872-0.602/0.417-0.153
Conclusion:					
4bG	CN	25/2998-3521 Y	0.001 40	xyzmid	142-0.726-0.445/0.625-0.242
4bG	E	25/2998-3521 Y	0.001 40	xyzmid	145-0.792-0.506/0.656-0.257

1.12 Semantic segmentation expamples

1.12.1 good: 1083, train, 0.946

log: log-model_1bG-gsbb_3B1-bs25-lr1-ds_30-xyz_midnorm_block-color_1norm-nxnynz-12800-mat_1083

model: 1bG

sampling & grouping:

stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn3-512_64_24-48_16_12-0d2_0d6_1d2-0d2_0d6_1d2

batch size: 25

learning rate: 0.001000

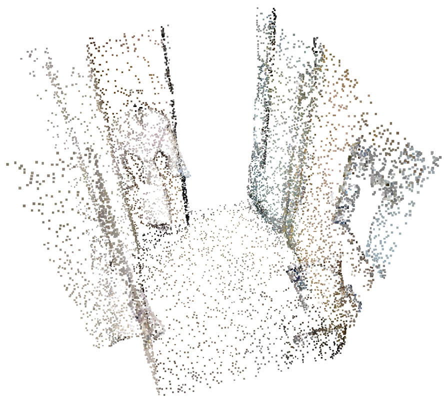
decay_epoch_step: 30

matterport3d

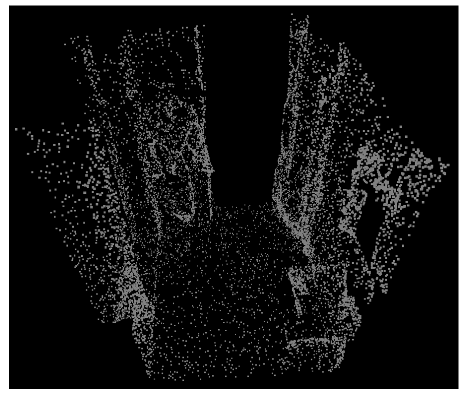
feed_data_elements:['xyz_midnorm_block', 'color_1norm', 'nxnynz']

feed_label_elements:['label_category', 'label_instance']

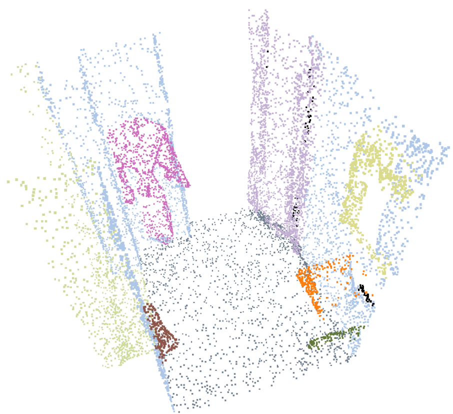
train data shape: [1083 12800 9]



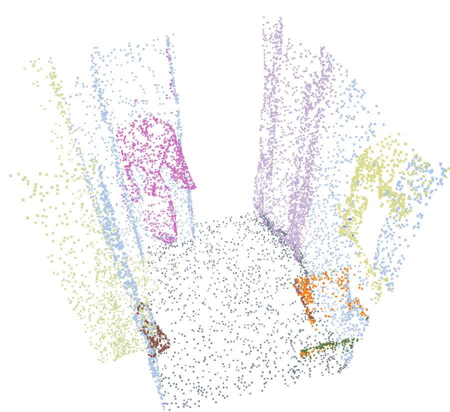
(a) colorized point cloud



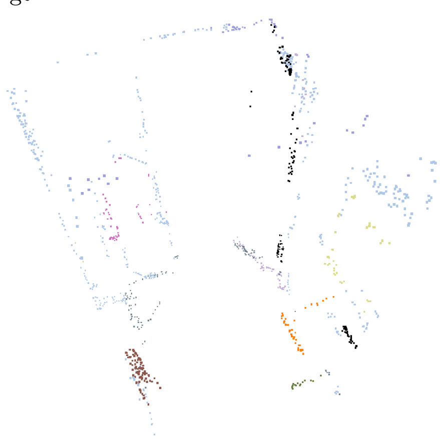
(b) raw point cloud



(c) gt

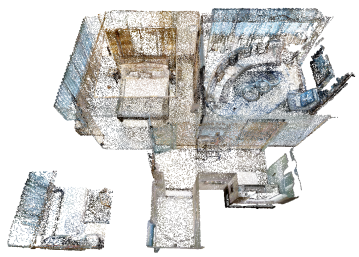


(d) pred

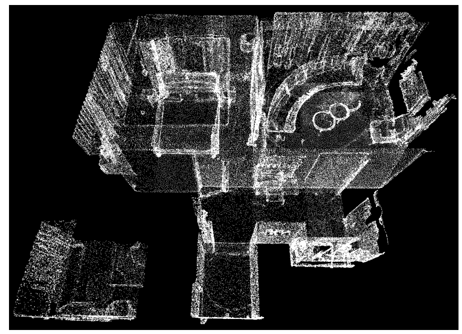


(e) err

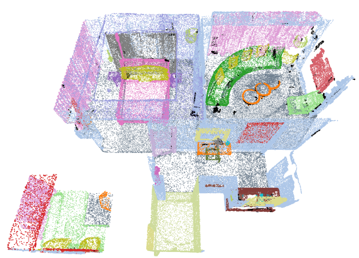
Figure 4: 17DRP5sb8fy_1_2_a946



(a) colorized point cloud



(b) raw point cloud



(c) gt

(d) pred

(e) err

Figure 5: 17DRP5sb8fy_0_25_a946

1.12.2 bad: 18737,eval 0.071

model: 1bG

sampling & grouping: stride_0d1_step_0d1_bmap_nh5_12800_1d6_2_fmn3-512_64_24-48_16_12-0d2_0d6_1d2-0d2_0d6_1d2

batch size: 25

learning rate: 0.001000

decay_epoch_step: 50

epoch 0 train IsShuffleIdx: True

epoch 0 train IsShuffleIdx: True
matterport3d
feed_data_elements:['xyz_midnorm_block', 'color_1norm', 'nxnynz']
feed_label_elements:['label_category', 'label_instance']
train data shape: [18737 12800 9]
test data shape: [4172 12800 9]

Figure 6: qoi_r1Q_r47_rPc_rqf_2_3_a0d071 (raw,gt,pred,err,crt)

1.13 point++

1.13.1 scannet seg

each room as a block, total 40 block			
batch size batch num	lr ds	data elements	epoch-point ac-class ac train/eval/eval whole scene
30/40	0.001	xyzmid	200-0.675/0.757-0.54/0.799-0.52
25	0.001	xyzmid	200-0.689/0.787-0.556/0.815-0.517i

1.14 whole room global block & multi scales & scan 305

nh5: stride_0d1_step_0d1_pl_nh5-1d6_2/ bxmh5: stride_0d1_step_0d1_bxmh5-12800_1d6_2_fmn4-480_80_24-80_20_10-0d2_0d6_1d2-0d2_0d6_1d2-3A1 eval: 17D_1LX_1pX_29h_2az					
model	bs/bn	lr-decay	elements	loss weight in drop	epoch-pacc-cacc train/eval
5bG_114	6/40	2-30	xyz midnorm color	E N	100-0.805-0.645 200-0.865-0.708 300-0.880-0.773
5aG_114	2/140	2-30	xyz midnorm color	E N	100-0.802-0.619 200-0.873-0.694 300-0.895-0.784
5aG_114	2/140	2-30	xyz midnorm color	E idp5	100-0.807-0.687 200-0.877-0.729 300-0.895-0.778
Conclusion: (1) Nein 114 is better than 111					

1.15 Sparse voxel net

nh5: 90000_gs-3d6_-6d3/
bxmh5: 90000_gs-3d6_-6d3_fmn1444-6400_2400_320_32-32_16_32_48-0d1_0d3_0d9_2d7-0d1_0d2_0d6_1d8-pd3-mbf-4A1
eval: test

model	bs/bn	lr-decay	elements	norm in sub block	loss weight in drop	epoch-pacc-cacc train/eval
5VaG_114	16/113	1-50	xyz mid	No	Num lw dp:3N5 N shuffle	20-0.764-0.556/0.645-0.362 40-0.864-0.695/0.675-0.351 100-0.935-0.842/0.682-0.380 200-0.961-0.897/0.671-0.374 300-0.969-0.920/0.676-0.360
5VaG_114	30/40	2-40	xyz mid color	No	Num lw dp:466 Y shuffle	20-0.605-0.443/0.577-0.381 40-0.668-0.490/0.544-0.372 100-0.795-0.581/0.653-0.384 120-0.805-0.594/0.676-0.377
5VaG_114	30/40	2-40	xyz mid color	No	Num lw dp:4N6 Y shuffle	20-0.677-0.520/0.607-0.373 40-0.801-0.624/0.659-0.373 100-0.906-0.754/0.687-0.368 120-0.911-0.776/0.692-0.421
5VaG_114	30/40	2-40	xyz mid color	No	Num lw dp:N66 Y shuffle	20-0.614-0.457/0.566-0.344 40-0.685-0.500/0.552-0.356 60-0.741-0.552/0.650-0.357 80-0.770-0.564/0.649-0.392 98-0.797-/0.675
5VaG_114	30/40	2-40	xyz mid color	Mid	Num lw dp:555 Y shuffle	100-0.746/0.649 300-0.823-0.608/0.682-0.377
5VaG_114	39/40	2-40	xyz mid color	Mid	Num lw dp:5N5 Y shuffle	40-0.839-0.649/0.656-0.353 100-0.918-0.771/0.681-0.381
5VaG_114	36/40	1-40	xyz mid color	Mid	Num lw dp:NN5 Y shuffle	40-0.833-0.655/0.628-0.329 100-0.916-0.772/0.682-0.339 178-0.941/0.686

Conclusion:
Mid norm in sub block seems worse than no.
The infuence of input drop seems not obvious.
Dropout of cnn (0.5) makes the net really hard to train. Seems no good for overfitting.