# Dynamic sampling pointnet notes

xyz

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### 1 Deep 3D Learning Notes

#### 1.1 potential solutions for over fitting

- combine auxiliary tasks:
  - 1. use nxnynz as auxiliary loss 2. boundary
  - 3. planet
- 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



#### 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 different 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 multi-scale classification

#### 1.3.5 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 separate 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 also doesn't matter that it rotates refference or only rotates voxel.

Sparse voxel 3D CNN



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 of the main feature map.

Transform net:

$$(b, n, g_m, 3)$$

$$(b, n, g_m, c_1)$$

$$(b, n, g_m, c_2)$$

$$/$$
  $(b, n, g_m, g_i)$   $/$ 

#### 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\_32-160\_0d1\_step\_0d1\_st

 $32\_12\text{-}0d2\_0d6\text{-}0d2\_0d6$ 

Figure 1: bs=9



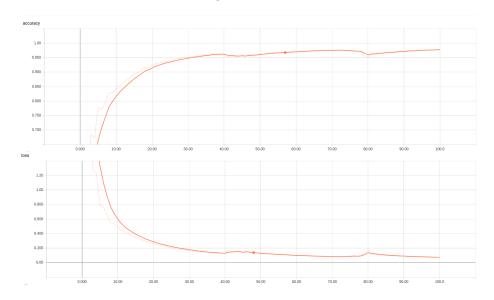
Figure 2: bs=27



### 1.5 feed elements

 $\begin{array}{l} {\rm epoch~num} = 100 \\ {\rm stride\_0d1\_step\_0d1\_bmap\_nh5\_2048\_0d5\_1\_fmn1-160\_32-32\_12-0d2\_0d6-0d2\_0d6} \end{array}$ 

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]

 $\max \text{ epoch} = 500$ 

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

stride_0	$stride\_0d1\_step\_0d1\_bmap\_nh5\_12800\_1d6\_2\_fmn3-512\_64\_24-48\_16\_12-0d2\_0d6\_1d2-0d2\_0d2\_0d6\_1d2-0d2\_0d2\_0d6\_1d2-0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_$							
	$17D\_1LX\_1pX\_29h\_2az$							
model	batch size batch num shuffle	lr ds	data elements	epoch-acc mean-std train/eval				

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-	elements	loss	epoch-pacc-cacc train/eval
		decay		weight	
				in	
				drop	
4bG_111	20/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	110-0.898-0.763
			color_1norm-		160-0.931-0.827
			nxnynz		300-0.967-0.915
4bG_444	15/1083	3-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.729-0.614
			color_1norm-		100-0.857-0.721
			nxnynz		160-0.920-0.834
					260-0.952-0.890
					300-0.958-0.913
4bG_444	15/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.778-0.608
			color_1norm-		100-0.878-0.758
			nxnynz		160-0.930-0.838
					260-0.957-0.901
					300-0.964-0.912
4bG_144	18/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.786-0.637
			color_1norm-		100-0.876-0.767
			nxnynz		160-0.926-0.820
					260-0.959-0.885
					300-0.962-0.906
4bG_114	20/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.772-0.611
			color_1norm-		100-0.874-0.764
			nxnynz		160-0.926-0.851
					260-0.958-0.893 /par 300-0.963-0.904
3aG_444	45/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.893-0.737
			color_1norm-		100-0.908-0.786 /par 160-0.934-0.833
			nxnynz		260-0.950-0.868 /par 300-0.952-0.882
2aG_144	30/1083	2-40	xyz_midnorm_	bl <b>E</b> ck-	60-0.890-0.754
			color_1norm-		100-0.922-0.820 /par 160-0.942-0.858:
			nxnynz		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/

 $bxmh5: \quad stride\_0d1\_step\_0d1\_bxmh5-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_1d6\_2\_fmn4-480\_80\_24-80\_20\_10-12800\_24-80\_20\_10-12800\_24-80\_20\_10-12800\_24-80\_20\_10-12800\_24-80\_20\_10-12800\_24-80\_20\_10-12800\_24-80\_24-80\_20\_24-80_24-80$ 

 $0d2\_0d6\_1d2-0d2\_0d6\_1d2-3A1\\ eval: 17D\_1LX\_1pX\_29h\_2az$ 

	- P						
model	bs/bn	lr-	elements	loss	epoch-pacc-cacc train/eval		
		decay		weight			
				in drop			
4bG_114	20/1080	1-30	xyz midnorm	Е	40-0.784-0.545/0.579-0.451		
			color	N	80-0.883-0.699/0.584-0.439		
			nxnynz		140-0.925-0.795/0.575-0.429		
4bG_111	20/1080	2-30	xyz midnorm	E	40-0.737-0.489/0.587-0.412		
			color	N	80-0.836-0.614/0.582-0.411		
			nxnynz		95-0.867/0.588		
4bG_144	20/1200	2-30	xyz midnorm	E	40-0.761-0.543/0.601-0.416		
			color	N	80-0.864-0.693/0.602-0.426		
			nxnynz		95-0.888/0.597		
Q 1 .					-		

Conclusion:

<sup>(1)</sup> Nein 114 is better than 111

#### 1.10 multi scales & scannet 12887

nh5: stride\_0d1\_step\_0d1\_pl\_nh5-1d6\_2/

 $0d2\_0d6\_1d2-0d2\_0d6\_1d2-3A1$ 

eval: test

evan test	eval. test						
model	bs/bn	lr-	elements	loss	epoch-pacc-cacc train/eval		
		decay		weight			
				in			
				drop			
2aG_144	30/420	2-30	xyz midnorm	Е	40-0.833-0.546/0.686-0.89		
				N	100-0.926-0.727/0.683-0.326		
3aG_144	48/260	2-30	xyz midnorm	Е	40-0.841-0.530/0.668-0.346		
				N	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	Е	60-0.738-0.434/0.706-0.344		
				N	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	60-0.705-0.378/0.684-0.362		
				N			
4bG_144	18-700	2-30	xyz midnorm	Е	40-0.714-0.470/0.6910.433		
				N	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	40-0.775-0.482/0.654-0.304		
				N	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	Е	40-0.819-0.527/0.684-0.333		
				N	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

str	$stride\_0d1\_step\_0d1\_bmap\_nh5\_12800\_1d6\_2\_fmn3-256\_48\_16-56\_8\_8-0d2\_0d6\_1d2-0d2\_0d2\_0d6\_1d2-0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_0d2\_$						
			scar	nnet 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	Е	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	С	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	Е	25/13091 train_300 Y	0.002 80	xyzmid	60-0.765-0.389/0.700-0.252		
1bG	Е	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	Е	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		
Conclusi	on:						
4bG	CN	25/2998- 3521 Y	0.001 40	xyzmid	142-0.726-0.445/0.625-0.242		
4bG	Е	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]
```



 $Figure~4:~17DRP5sb8fy\_1\_2\_a946$ 



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]



 $Figure \ 6: \ qoi\_r1Q\_r47\_rPc\_rqf\_2\_3\_a0d071 \ (raw,gt,pred,err,crt)$ 

### 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/

0d2\_0d6\_1d2-0d2\_0d6\_1d2-3A1 eval: 17D\_1LX\_1pX\_29h\_2az

evai: 17D_	evai: 17D_1LA_1pA_29h_2az						
model	bs/bn	lr-	elements	loss	epoch-pacc-cacc train/eval		
		decay		weight			
				in drop			
5bG_114	6/40	2-30	xyz midnorm	Е	100-0.805-0.645		
			color	N	200-0.865-0.708		
					300-0.880-0.773		
5aG_114	2/140	2-30	xyz midnorm	E	100-0.802-0.619		
			color	N	200-0.873-0.694		
					300-0.895-0.784		
5aG_114	2/140	2-30	xyz midnorm	E	100-0.807-0.687		
			color	idp5	200-0.877-0.729		
					300-0.895-0.778		
Q 1 ·		•			•		

#### Conclusion:

<sup>(1)</sup> Nein 114 is better than 111

### 1.15 Sparse voxel net

#### 1.15.1 90000

nh5: 90000\_gs-3d6\_-6d3/

oxmh5: 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- net aug	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
5VaG_114	7/240	2-40	xyz mid color	Mid Group Norm	Num lw dp:NN5 Y shuffle	40-0.664/0.577 100-0.816-0.586 150-0.869-0.592
5VaG_114	9	2-40	xyz mid color	Rotate Ref	Num lw dp:NN5 Y shuffle	40-0.787-0.620/0.662-0.401 100-0.907-0.755/0.699-0.410 200-0.939-0.816/0.6990.430 300-0.950-0.845/0.691-0.430

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.

Group norm is poor.

#### 1.15.2 30000

30000\_gs-2d4\_-3d4\_fmn1444-2048\_1024\_128\_24-48\_32\_48\_27-0d1\_0d4\_1\_2d2bxmh5:  $0d1_0d2_0d6_1d2_pd3_mbf_4B1$ eval: test Void point id deleted model lrbs elements norm inloss epoch-pacc-cacc train/eval decay net weight in drop aug 5VaG\_114 2-40 xyz mid Rotate Num lw 20-0.749/0.645 color Ref dp:5N530-0.810/0.705 Y shuffle 40-0.870/0.744 80-0.917-0.737/0.7540.422  $120 \hbox{-} 0.929 \hbox{-} 0.765$  $200 \hbox{-} 0.953 \hbox{-} 0.774$ 300-0.962/0.774 train[200-280] t(d,c):[4.1 25.5 79.6] loss: 0.337 acc: 0.954-0.041 acc histgram: [0.000e+00 0.000e+00 0.000e+00 0.000e+00 3.084e-04 1.850e-03 8.973e-02 8.668e-01 4.009e-02]
weighted class pre/rec/IOU: 0.962 0.954 0.918 N=97.290000M points ave/std: 0.954 0.041
class ave pre/rec/IOU: 0.825/ 0.948/ 0.799
class\_pre: -0.00, 0.98, 0.98, 0.92, 0.89, 0.83, 0.91, 0.88, 0.88, 0.76, 0.81, 0.76, 0.79, 0.79, 0.77, 0.71, 0.80, 0.84, 0.57, 0.84, class\_rec: -0.00, 0.90, 0.93, 0.96, 0.91, 0.94, 0.98, 0.98, 0.95, 0.92, 0.98, 0.96, 0.97, 0.94, 0.96, 0.94, 0.97, 0.96, 0.94, 0.98, 0.96, 0.97, 0.94, 0.90, 0.91, 0.90, 0.84, 0.81, 0.91, 0.88, 0.86, 0.72, 0.80, 0.76, 0.78, 0.76, 0.76, 0.76, 0.69, 0.78, 0.82, 0.56, 0.80, number(K): 0,34786,31997, 5563, 4131, 1808, 2598, 1901, 3002, 278, 272, 223, 880, 631, 2163, 815, 113, 462, 432, 2761, classname: unann, wall,floor,chair,table, desk, bed,books, sofa, sink,batht,toile,curta,count, door,windo,showe,refri,pictu,cabin,o eval[200-79] t(d,c):[4.0 11.6 81.8] loss: 22.747 acc: 0.774-0.179 acc histgram: [0.007 0.007 0.011 0.015 0.038 0.064 0.141 0.207 eval[200-79] t(d,c):[4.0 11.6 81.8] loss: 22.747 acc: 0.772-0.178 acc histgram: [0.005 0.006 0.012 0.013 0.042 0.072 0.148 0.207 weighted class pre/rec/IOU: 0.822 0.772 0.703 N=28.290000M points ave/std: 0.772 0.178 class ave pre/rec/IOU: 0.429/ 0.344/ 0.278 class pre: -0.00, 0.82, 0.94, 0.68, 0.58, 0.45, 0.60, 0.43, 0.57, 0.37, 0.44, 0.52, 0.11, 0.42, 0.20, 0.07, 0.28, 0.33, 0.03, 0.4 class\_rec: -0.00, 0.88, 0.92, 0.68, 0.52, 0.30, 0.51, 0.38, 0.55, 0.20, 0.36, 0.38, 0.03, 0.30, 0.06, 0.00, 0.15, 0.16, 0.00, 0.3 class\_IOU: -0.00, 0.74, 0.88, 0.54, 0.43, 0.24, 0.43, 0.27, 0.41, 0.16, 0.28, 0.30, 0.02, 0.22, 0.05, 0.00, 0.11, 0.13, 0.00, 0.2 number(K): 0,10626, 8669, 1584, 1231, 587, 725, 460, 888, 66, 47, 62, 222, 243, 675, 100, 16, 94, 54, classname: unann, wall,floor,chair,table, desk, bed,books, sofa, sink,batht,toile,curta,count, door,windo,showe,refri,pictu,cabi Model saved in file: model.ckpt-200

Conclusion:

# 1.16 Charles Point++, fast distance sampling

#### 1.16.1 MODELNET40

config	epoch-train acc/eval acc-eval cls
	acc
batch_size=32, decay_rate=0.7, decay_step=200000,	4-0.746/0.819-0.748
learning_rate=0.001, log_dir='log', max_epoch=251,	10-0.802/0.848-0.788
model='pointnet2_cls_ssg', momentum=0.9, nor-	40-0.886/0.875-0.858
mal=False, num_gpus=2, num_point=1024, opti-	60-0.916/0.892-0.859
mizer='a dam	·
aug=True, batch_size=32, decay_rate=0.7, de-	10-0.806/0.853-0.817
cay_step=200000, gpu=1, indrop=True, learn-	60-0.939/0.8946/0.868
ing_rate=0.001, log_dir='log', max_epoch=251,	100-0.971/0.9036-0.883
model='pointnet2_cls_ssg', momentum=0.9, nor-	
mal=True, num_point=8 192, optimizer='adam',	
shuffle=True	

# 1.17 MODELNET40, My point++

After fix shuffle problem

### 1.17.1 3m

model	$\frac{\text{merging. R}}{\text{bs}}$	lr	elements	norm in-	loss	epoch-pacc-cacc train/eval
model	DS	bn de-	group pos	net	weight	cpoch-pace-cace train/evar
		cay	group pos	aug	in drop	
3m	36	1-30	xyzg	Rotate	E, NN5	1-0.707/0.775
0111	00	7-7	bc	Ref	2, 11110	2-0.744/0.804
		' '	BC	1001		4-0.785/0.817
						10-0.831/0.826
						30-0.906/0.857
						60-0.967/0.852
3m	36	1-30	xyzg	Rotate	E, NN5	1-0.704/0.754
9111		7-7	mean	Ref	2, 11110	2-0.747/0.781
		' '	Incan	1001		4-0.783/0.810
						10-0.839/0.835
						60-0.969/0.865
3m	36	1-30	xyzrsg	Rotate	E, NN5	10-0.844/0.830
J111	33	7-7	mean	Ref	2, 1110	60-0.978/0.868
$3\mathrm{m}$	36	1-30	xyzrsg,	Rotate	E, NN5	10-0.887/0.881
OIII	00	7-7	nxnynz	Ref	2, 11110	60-0.985/0.890
			mean	Teci		00 0.309/ 0.030
1 1- 1- 7 - 4	006 2 2 f	1444 1004	1	10 014 011 0	10 12 OMO	
				d2_0d4-0d1_0	uz-pus-zm2	
	merging. R		1	D	TO NINIE	1.0.000/0.705
3m	28	1-30	xyzg	Rotate	E, NN5	1-0.698/0.795
		7-7 mear	mean	Ref		10-0.834/0.853
0	90	1.20		D	TO NINIE	60-0.962/0.874
$3 \mathrm{m}$	28	1-30	xyzg	Rotate	E, NN5	1-0.703/0.786
		7-7	bc	Ref		10-0.832/0.847
0	20	1.00		D	TO NINTE	60-0.957/0.867
$3 \mathrm{m}$	28	1-30	xyzrsg	Rotate	E, NN5	1-0.695/0.764
		7-7	mean	Ref		10-0.840/0.847
0	20	1.00		D	E NINE	60-0.976/0.880
$3 \mathrm{m}$	28	1-30	xyzrsg,	Rotate	E, NN5	1-0.747/0.814
		7-7	nxnynz	Ref		10-0.882/0.879
			mean			60-0.985/0.897
						160-0.998/0.905
	096 -mgs 1 -gs	2_2_fmn14_n	$nvp1-1024_24$	0_1-48_27_160	0-0d2_0d4-0	$d1_0d2$ -pd3-mbf-neg-
2M2p						
017	FA	1 00	T	<b>.</b>	T- 3737~	1 0 7 10 /0 007
3Vm	58	1-30	xyzrsg	Rotate	E, NN5	1-0.549/0.635
		5-5	nxnynz	Ref		10-0.852/0.812
			mean			30-0.961/0.840
						60-0.984/0.837
		1	1			100-0.994/0.828
				_		
3Vm	58	1-30	xyzrsg	Rotate	E, 3N5	1-0.543/0.614
3Vm	58	1-30 5-5	xyzrsg nxpynz	Rotate Ref	E, 3N5	10-0.852/0.798
3Vm	58				E, 3N5	10-0.852/0.798 20-0.926/0.825
3Vm		5-5	nxaynz mean	Ref	, i	10-0.852/0.798 20-0.926/0.825 27-0.955/0.800
	58	5-5	nxaynz		E, 3N5 E, NN5	10-0.852/0.798 20-0.926/0.825 27-0.955/0.800 10-9.763/0.803
3Vm		5-5	nxaynz mean	Ref	, i	10-0.852/0.798 20-0.926/0.825 27-0.955/0.800

<sup>(0)</sup> The performance of pointnet++ based on farest distance sampling is better. The reason may be on

#### 1.17.2 4m

 $bxmh5:4096\_mgs1\_gs2\_2d2\_fmn1444\_mvp1-3200\_1024\_48\_1-18\_24\_56\_56-0d1\_0d2\_0d6-0d0\_0d1\_0d4-pd3-mbf-neg-3M1$ 

model	bs	lr	elements	aug	loss	epoch-pacc-cacc train/eval
		bn de-	group pos		weight	
		cay			in drop	
4m	16	1-30	xyzrsg-	RotateRef	Е	10-0.688/0.755
			nxnynz		NN5	60-0.845/0.859
						100-0.873/0.875
						200-0.914/0.880
4m	16	1-30	xyzg	RotateRef	E	10-0.635/0.680
					NN5	60-0.784/0.807
						120-0.837/0.830
						241-0.878/0.846
4m	16	1-30	xyzrsg-	RotateRef	E	10-0.623/0.671
			nxnynz		3N5	60-0.766/0.793
						120-0.821/0.810
4m	16	1-30	xyzg-	RotateRef	E	10-0.691/0.726
			nxnynz		NN5	60-0.840/0.853
						1100-0.874/0.862
						120-0.886/0.861
4Vm	56	1-30	xyzg-	RotateRef	E	10-0.894/0.817
			nxnynz		NN5	60-0.993/0.834
						79-0.997/0.842

	0 0		444_mvp1-32	200_1024_48_1-	18_24_56_	56-0d1_0d2_0d6-
	.0d4-pd3-neg	g-3M1				
No Block	k Merging					
4m	16	1-30	xyzg-	RotateRef	E	10-0.711/0.705
			nxnynz		NN5	60-0.878/0.850
						100-0.912/0.869
4m	16	1-30	xyzg	RotateRef	E	10-0.644/0.682
					NN5	60-0.778/0.802
						100-0.816/0.827
4m	16	1-30	xyzs	RotateRef	E	10-0.637/0.676
					NN5	60-0.784/0.792
						100-0.821/0.828
4m	16	1-30	xyzr	RotateRef	E	10-0.658/0.698
					NN5	60-0.801/0.821
						70-0.815/0.819
4Vm	30	1-30	xyzg-	RotateRef	E	10-0.890/0.830
			nxnynz		NN5	51-0.992/0.841
						100-0.999/0.847
						113-0.999/0.853
						129-0.999/0.847
4Vm	30	1-30	xyzg-	RotateRef	E	10-0.846/0.796
			nxnynz		575	49-0.982/0.841
4Vm	30	1-30	xyzg-	RotateRef	E	10-0.848/0.824
			nxnynz		N75	60-0.989/0.831
4Vm	28	1-30	xyzg	RotateRef	E	10-0.884/0.821
					NN5	60-0.994/0.838
						80-0.996/0.842
4Vm	30	1-30	xyzg	RotateRef	Е	10-0.752/0.663
			nxnynz	RotateVox	NN5	60-0.949/0.828
						79-0.969/0.814

#### Conclusion:

- (1) Input drop out increase overfitting here. This is not reasonable!
- (2) Learns much slower than 3m?
- (3) The variance is greater, maybe because of small bacth size.
- (4) Block merge is a little bit helpful for pointnet++ (5) xyzs is a little bit better than xyzg for pointnet++

bxmh5:409	06_mgs1_gs2_2	2d2_fmn14	444_mvp1-320	00_1024_48_1-	18_24_56_56-	·0d1_0d2_0d6-
	d4-pd3-neg-3	M1				
No Block I	Merging					
4Vm-S2	30	3-30	xyzs	RotateRef	E	10-0.885/0.815
				RotateVox	NN5	30-0.979/0.847
						40-0.982/0.855
4Vm-S2	30	3-30	xyzs	RotateRef	E	10-0.889/0.843
			nxnynz	RotateVox	NN5	30-0.980/0.843
						60-0.995/0.848
4Vm-S3	30	3-30	xyzs	RotateRef	Е	10-0.894/0.838
			nxnynz	RotateVox	NN5	30-0.981/0.851
						60-0.996/0.853
4Vm-S4	30	3-30	xyzs	RotateRef	E	10-0.888/0.862
			nxnynz	RotateVox	NN5	30-0.976/0.865
						48-0.989/0.850
4Vm-S3	50	1-20	xyzg	RotateRef	Е	10-0.930/0.829
normal				RotateVox	NN5	30-0.983/0.841
label						50-0.991/0.847
						69-0.998/0.861
						80-0.998/0.855
4Vm-S3	50	1-20	xyzrsg	RotateRef	E	10-0.923/0.847
normal				RotateVox	NN5	30-0.981/0.837
label						52-0.996/0.865
						53-0.993/0.856
4Vm-	29	1-30	xyzs	RotateRef	Е	10-0.900/0.841
S2L2			nxnynz	RotateVox	NN5	30-0.981/0.838
						60-0.996/0.851
4Vm-	29	1-30	xyzs	RotateRef	Е	10-0.899/0.841
S3L3			nxnynz	RotateVox	NN5	30-0.992/0.847
						60-0.996-0.854
Conclusion	1:					
bymh5·400	06 mgs1 gs9 9	2d2 fmp1/	144 myn1-396	00 1024 48 1-	18 24 56 56-	·0d1_0d2_0d6-
	d4-pd3-neg-3			00_1024_40_1-	10_41_00_00	041_042_040
No Block		.,				
4Vm1	24	1-10	xyzs	RotateIn	Е	10-0.862/0.859
477 4 60	24	1.10	nxnynz	D I		10.0.074/0.007
4Vm1-S3	24	1-10	xyzs	RotateIn	Е	10-0.874/0.867
			nxnynz			11-0.883/0.873
						20-0.952/0.868
						40-0.990/0.862

### 1.17.3 5m

1 1 2 4 4	1 17 10000 0 0 17 6 1111 1 0 000 1001 00 10 10 00 10 00 10 017 11						
$bxmh5:10000\_gs3\_3d5\_fmn1444\_mvp1-2560\_1024\_80\_16\_1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_48-0d0\_0d2\_0d5\_1d1-24\_32\_48\_27\_0d0\_0d2\_0d5\_1d1-24\_32\_0d0\_0d2\_0d5\_0d0\_0d2\_0d5\_0d0\_0d2\_0d0\_0d0\_0d0\_0d0\_0d0\_0d0\_0d0\_0d0$							
0d0_0d1_0d3_0d6-pd3-mbf-neg-4M1							
	•	Ü					
model	bs	lr	elements	aug	loss	epoch-pacc-cacc train/eval	
		bn de-	group pos		weight	,	
		cay			in drop		
5m1	32	1-30	xyzg	RotateRef	E	60-0.956/0.843	
						200-0.998/0.845	
$5\mathrm{m}$	48	1-30	xyzrsg-	RotateRef	E	60-0.852/0.837	
			nxnyznz			100-0.894/0.866	
						119-0.923-0.878	
						150-0.938-0.867	
5Vm	32	1-30	xyzr	N	E	10-0.853/0.802	
						60-0.985/0.829	
						160-0.998/0.831	
Conclusio	n:						
(0)							

# $2 \quad res3d$

### 2.1 learning rate and batch norm decay

odel bs feed aug lr0 bnd optimizer filters0	train/eval
l34m 64 xyzg-nxnynz none 0.01 0.5 adam 32	0-?/0.12
V	5-0.337/0.175
	10-0.425/0.368
	30-0.544/0.625
ol34m 64 xyzg-nxnynz none 0.01 0.997 adam 32	0-?/0.033
	5-0.073/0.048
	10-0.056/0.044
	20-0.099/0.119
ol34m 64 xyzg-nxnynz none 0.001 0.5 adam 32	0-?/0.580
	5-0.781/0.756
	15-0.854/0.818
ol34m 64 xyzg-nxnynz none 0.001 0.997 adam 32	0-?/0.041
	5-0.491/0.687
	10-0.712/0.503
	20-0.973/0.853
ol34m 64 xyzg-nxnynz all 0.001 0.7 adam 32	0-0.090/0.110
	24-0.557/0.524
ol34m 32 xyzg-nxnynz none 0.001 0.7 adam 32	0-0.016/0.516
	24-0.815/0.823
ol34m 64 xyzg-nxnynz none 0.0001 0.7 adam 32	0-0.037/0.417
	24-0.935/0.812
ol34m 64 xyzg-nxnynz none 0.001 0.7 adam 32	0-0.047/0.560
	24-0.897/0.825
ol34m 64 xyzg-nxnynz none 0.001 0.9 adam 32	0-0.029/0.464
	24-0.883/0.821
ol34m 64 xyzg-nxnynz all 0.001 0.7 momentum 32	0-0.055/0.078
V	24-0.577/0.472
ol34m 64 xyzg-nxnynz none 0.0001 0.7 momentum 32	0-4.177/3.609-0.015/0.164
v	30-0.640/1.087-0.911/0.775
ol34m 64 xyzg-nxnynz none 0.001 0.7 momentum 32	0-0.022/0.478
· · ·	24-0.987/0.829
ol34m 64 xyzg-nxnynz none 0.001 0.9 momentum 32	0.058/0.547
v	24-0.980/0.833
ol34m 32 xyzg-nxnynz none 0.001 0.7 momentum 32	0-0.045/0.608
	24-0.965/0.849

- (0)Learning rate too high leads to no convergence
- (1)Batch norm decay seems always better. Especially can allow high learning rate.
- ()bnd 0.5, 0.997 doesnt work ()lr 0.001 > 0.01

### 2.2 aug none and all

#### 2.2.1 voxel

$ \begin{tabular}{ll} Merged\_tfrecord/6\_mgs1\_gs2\_2-mbf-neg\_fmn14\_mvp1-1024\_240\_1-6\\ 2M2pp \end{tabular} $	4_27_256-0d2_0d4-0d1_0d2-pd3-
model bs feed aug lr0 bnd optimizer filters0	train/eval
rs34V 48 xyzg-nxnynz all 0.001 0.9 adam 32	0-113.598/2.431-0.084/0.448
	9-1.675/1.232-0.687/0.755
	35-0.341/1.007-0.980/0.850
rs34V 48 xyzg-nxnynz f 0.001 0.9 adam 32	0-7.958/2.025-0.027/0.581
rs34V 48 xyzg-nxnynz none 0.0001 0.9 adam 32	0-4.220/1.459-0.059/0.712
	15-0.481/1.612-0.976/0.803
rs34V 48 xyzg-nxnynz none 0.001 0.9 adam 32	0-7.067/3.760-0.052/0.509
	9-0.732/1.176-0.890/0.812
	25-0.365/1.026-0.974/0.844
	6-0.307/1.025-0.993/0.870 7615
	40-0.180/1.284-0.999/0.860
	16041
rs34V 48 xyzg-nxnynz r 0.001 0.9 adam 32	0-8.119/2.267-0.011/0.486
	9-0.842/0.982-0.864/0.819
	40-0.275/1.147-0.990/0.852
rs34V 48 xyzg-nxnynz s 0.001 0.9 adam 32	0-43.883/2.201-0.047/0.585
	9-0.710/1.168-0.893/0.790
	40-0.229/1.042-0.994/0.876
Conclusion:	
(0)s > r	

### 2.2.2 Pointnet++ residual

	4_240_1-64_27_256-0d2_0d4-0d1_0d2-pd3-
model bs feed aug lr0 bnd optimizer filters0	train/eval
rs34m 16 xyzg-nxnynz none 0.001 0.9 adam 32	625-4.059/1.490-0.041/0.671 6160-0.558/1.032-0.949/0.832
rs34m 48 xyzg-nxnynz none 0.0001 0.9 adam 32	19075-0.418/0.937-0.991/0.878 8220-0.402/1.013-1.000/0.837
rs34m 48 xyzg-nxnynz none 0.01 0.9 adam 32	0-26.717/1.521-0.016/0.703 215 9-0.665/1.004-0.902/0.816 2060 35-0.303/0.758-0.998/0.894 30-0.149/0.678-1.000/0.897 13950
rs34m 96 xyzg-nxnynz none 0.001 0.9 adam 32	0-4.485/1.356-0.035/0.721 112 9-0.530/1.044-0.958/0.832 1030 35-0.382/0.966-1.000/0.876 3682

# 2.3 No aug, no drop: xyzg vs xyzs, Learning rate, Batch size

$Merged\_tfrecord/6\_mgs1\_gs2\_2-mbf-neg\_fmn14\_mvp1-1024\_240\_1-64\_27\_256-0d2\_0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2$					
2M2pp	_				
model bs feed aug lr0 bnd optimizer filters0	train/eval				
rs34m 32 xyzg none 0.001 0.9 adam 32	1 4.053/1.774-0.083/0.621				
	10 0.743/1.197-0.882/0.783				
	25 0.494/1.205-0.963/0.814				
	40 0.397/1.064-0.998/0.846				
rs34m 64 xyzg none 0.001 0.9 adam 32	1 4.251/1.741-0.034/0.644				
	10 0.678/1.145-0.913/0.791				
	40 0.385/1.064-1.000/0.852				
rs34m 32 xyzs none 0.001 0.9 adam 32	1 4.067/1.980-0.054/0.579				
	10 0.674/1.242-0.914/0.771				
	25 0.517/1.245-0.961/0.804				
	40 0.391/1.158-1.000/0.837				
rs $34$ m $32$ xyzs none $0.01$ $0.9$ adam $32$	1 10.757/1.779-0.016/0.623				
	0.796/1.124-0.859/0.771				
	25 0.658/0.981-0.880/0.819				
	35 0.270/0.879-0.999/0.860				
rs34m 64 xyzs none 0.01 0.9 adam 32	1 42.370/2.499-0.014/0.428				
	10 0.963/1.149-0.824/0.774				
	40 0.277/1.076-0.999/0.846				
	60 0.192/0.983-0.996/0.852				
rs34m 64 xyzs none 0.001 0.9 adam 32	1 4.133/1.766-0.016/0.620				
	10 0.582/1.199-0.945/0.808				
	25 0.454/1.501-0.980/0.774				
	40 0.389/1.187-1.000/0.838				

# 2.4 aug rotation

Merged_tfrecord/6_mgs1_gs2_2-mbf-neg_fmn14_mvp1-1024_240_1-64_27_256-0d2_0d4-0d1_0d2-pd3-		
2M2pp		
model bs feed aug lr0 bnd optimizer filters0	train/eval	
rs34m 64 xyzs r-360_0_0 0.01 0.9 adam 32	1 48.100/2.417-0.014/0.440	
	10 1.038/1.276-0.796/0.731	
	25 0.705/1.248-0.868/0.743	
	40 0.318/0.979-0.986/0.839	
rs34m 64 xyzs r-360_30_30 0.01 0.9 adam 32	1 51.557/3.245-0.013/0.246	
	40 0.342/2.055-0.994/0.615	
rs34m 64 xyzs r-0_0_360 0.01 0.9 adam 32	1 53.404/2.661-0.009/0.375	
	10 1.302/1.431-0.719/0.688	
	40 0.350/1.410-0.991/0.776	
rs34m 64 xyzs r-0_360_0 0.01 0.9 adam 32	1 44.500/3.347-0.009/0.246	
	9 1.481/1.560-0.696/0.668	
	41 0.327/1.488-0.996/0.787	
rs34m 32 xyzs r-360_0_0 0.01 0.9 adam 32	$1\ 10.584/2.093 – 0.015/0.512$	
	7 1.293/1.255-0.715/0.739	

# 2.5 aug sfj

$Merged\_tfrecord/6\_mgs1\_gs2\_2-mbf-neg\_fmn14\_mvp1-1024\_240\_1-64\_27\_256-0d2\_0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2$		
2M2pp		
model bs feed aug lr0 bnd optimizer filters0	train/eval	
rs34m 64 xyzs s 0.01 0.9 adam 32	1 57.040/2.343-0.013/0.472	
	30 1.213/0.906-0.797/0.853	
	60 0.229/0.992-0.995/0.848	
rs34m 64 xyzs f 0.01 0.9 adam 32	1 49.818/2.240-0.010/0.477	
	10 1.026/1.086-0.807/0.797	
	40 0.330/0.836-0.984/0.869	
	60 0.264/0.834-0.977/0.867	
rs34m 64 xyzs j 0.01 0.9 adam 32	1 63.166/2.140-0.024/0.502	
	10 0.870/1.077-0.843/0.789	
	40 0.280/0.963-0.995/0.859	
	60 0.206/0.882-0.989/0.852	

# 2.6 dropout

$Merged\_tfrecord/6\_mgs1\_gs2\_2-mbf-neg\_fmn14\_mvp1-1024\_240\_1-64\_27\_256-0d2\_0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d4-0d1\_0d2-pd3-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2$		
2M2pp		
model bs feed aug lr0 bnd optimizer filters0	train/eval	
rs34m 64 xyzs none 0_0_3 0.01 0.9 adam 32	1 39.920/1.931-0.012/0.615	
	10 0.906/1.066-0.837/0.798	
	30 0.671/0.893-0.906/0.860	
	60 0.245/1.006-0.997/0.851	
rs34m 32 xyzs none $0\_0\_5$ $0.01$ $0.9$ adam 32	1 5.472/1.770-0.009/0.596	
	10 0.940/1.022-0.829/0.802	
	30 0.540/0.770-0.919/0.863	
	60 0.228/0.948-0.996/0.860	
rs34m 64 xyzs none 0_0_5 0.01 0.9 adam 32	1 40.743/1.985-0.012/0.544	
	10 0.871/1.064-0.857/0.795	
	30 0.712/0.919-0.905/0.848	
	40 0.441/0.956-0.981/0.856	
	61 0.272/0.961–1.000/0.858	
rs34m 64 xyzs none 0_0_7 0.01 0.9 adam 32	1 24.039/1.855-0.014/0.604	
	10 1.064/1.094-0.802/0.787	
	30 0.860/0.890-0.861/0.853	
	60 0.326/0.943-0.977/0.857	

# 2.7 integration

$Merged\_tfrecord/6\_mgs1\_gs2\_2-mbf-neg\_fmn14\_mvp1-1024\_240\_1-64\_27\_256-0d2\_0d4-0d1\_0d2-pd3-0d2-0d4-0d1-0d2-pd3-0d2-0d4-0d1-0d2-pd3-0d2-0d4-0d1-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2-0d2$	
2M2pp	
model bs feed aug lr0 bnd optimizer filters0	train/eval
pl34m 32 xyzs rsfj-360_0_0 0_0_5 0.001 0.5 adam 32	1 4.594/3.275-0.070/0.195
	10 1.714/1.682-0.584/0.595
	60 0.963/1.080-0.802/0.767
	120 0.902/1.069-0.825/0.774
pl34m 32 xyzs sf j $0\_0\_5$ 0.001 $0.5$ adam 32	1 4.756/2.999-0.099/0.265
	60 0.745/0.909-0.861/0.824
	120 0.705/0.913-0.878/0.821
rs34m 32 xyzs rsfj-360_0_0 0_0_5 0.001 0.5 adam 32	1 5.085/2.686-0.098/0.352
	10 1.519/1.538-0.666/0.664
	60 0.861/1.027-0.848/0.815
rs34m 32 xyzs sf j $0\_0\_5$ 0.001 0.5 adam 32	1 5.775/2.230-0.138/0.478
	40 0.669/0.905-0.908/0.845
	60 0.631/0.894-0.922/0.848
rs34m 64 xyzg sfj 0_0_5 0.001 0.5 adam 32	1 5.064/1.906-0.247/0.574
	40 0.626/0.847-0.923/0.858
	60 0.568/0.846-0.938/0.859
	$100\ 0.532/0.845 - 0.952/0.856$
rs34m 32 xyzg sf j $0\_0\_5$ 0.01 $0.5$ adam 32	1 7.503/1.544-0.149/0.662
	45 0.432/0.680-0.933/0.876
rs34m 64 xyzg rsfj-360_0_0 0_0_5 0.001 0.5 adam 32	1 4.950/2.256-0.163/0.463
	40 0.893/0.977-0.841/0.823
	$100\ 0.794/0.939 – 0.866/0.828$
rs34m 32 xyzg rsfj-360_0_0 0_0_5 0.01 0.5 adam 32	1 8.848/2.317-0.152/0.424
	40 0.640/0.759-0.870/0.840
	100 0.492/0.706-0.912/0.855
rs34m 32 xyzg rsfj-360_0_0 0_0_5 0.001 0.5 adam 32	1 6.015/2.569-0.109/0.406
	10 1.417/1.428-0.698/0.697