

# Graphite: GRAPH-Induced feaTure Extraction for Point Cloud Registration

M. Saleh, S. Dehghani, B. Busam, N. Navab, F. Tombari

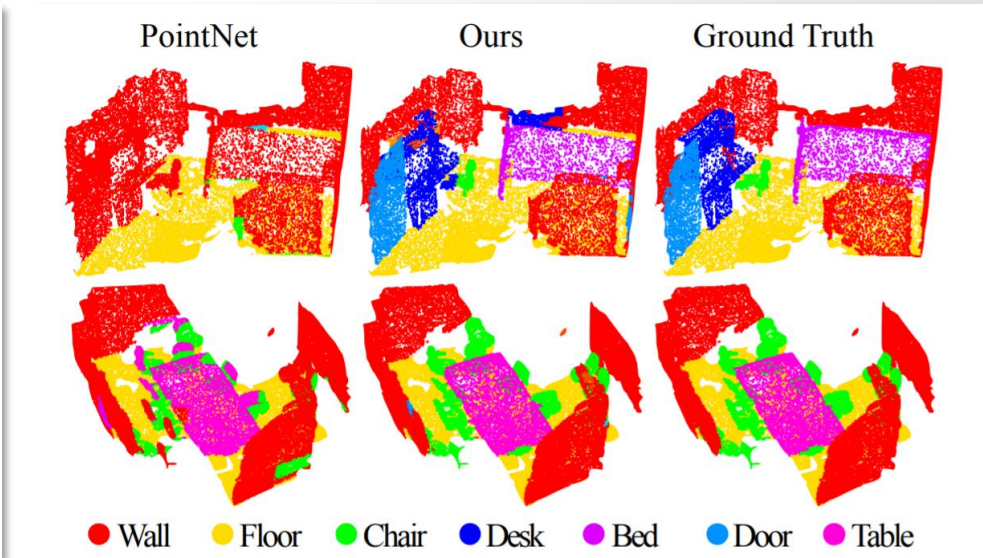
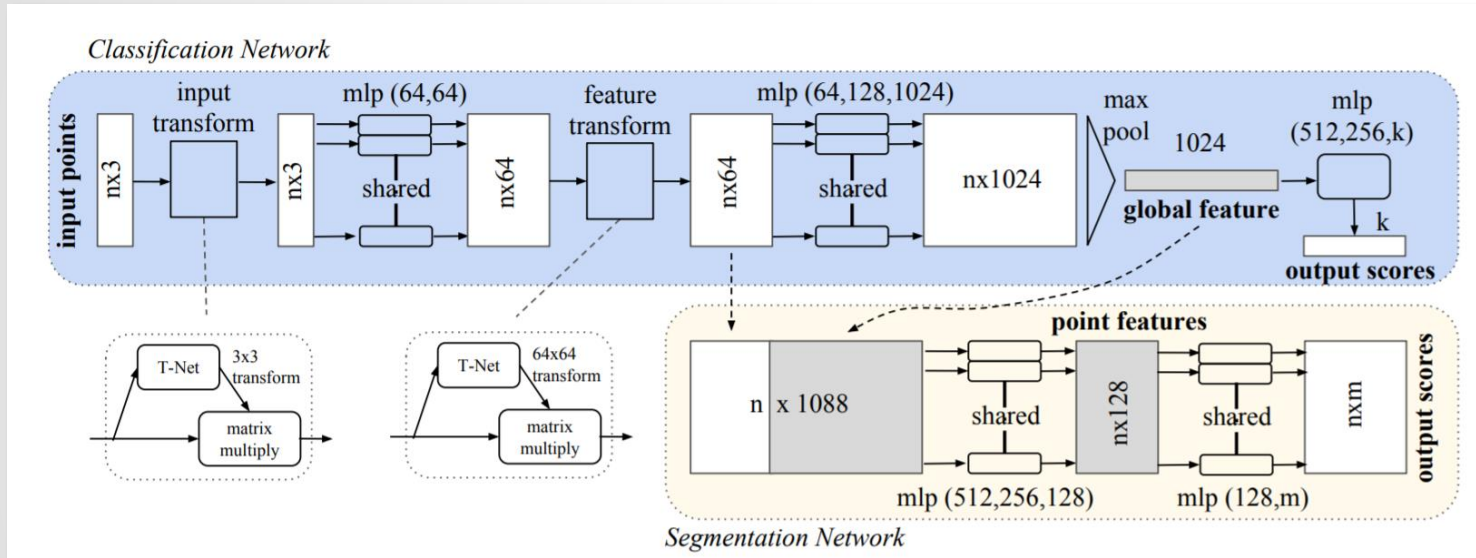
**3DV 2020**



Technische Universität München



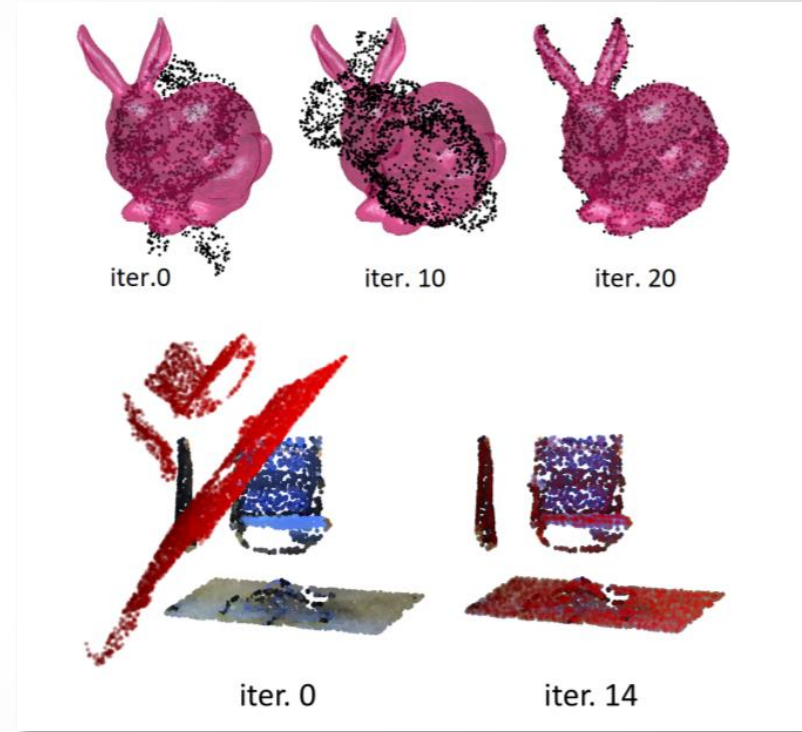
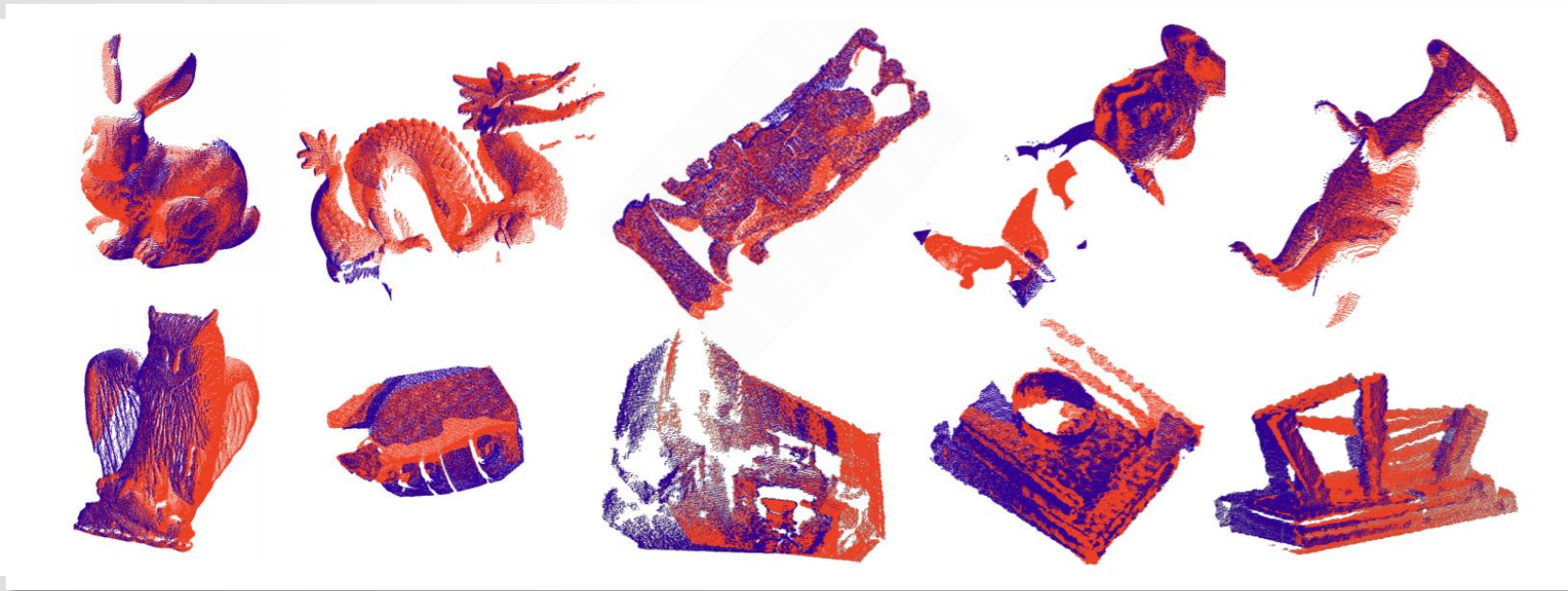
# Point clouds



Qi, Charles R., et al. "Pointnet: Deep learning on point sets for 3d classification and segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2017.

Image from Qi, Charles Ruizhongtai, et al. "Pointnet++: Deep hierarchical feature learning on point sets in a metric space." *Advances in neural information processing systems*. 2017.

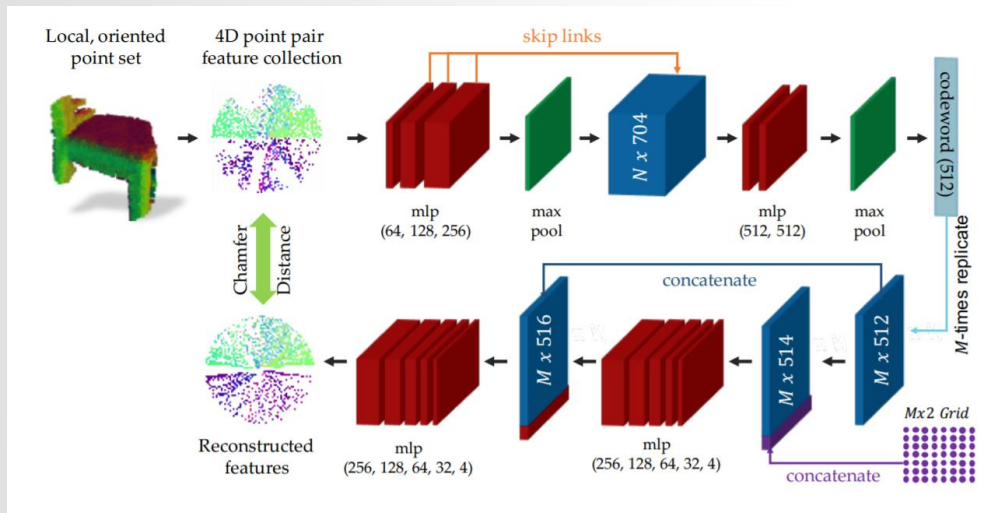
# Global methods



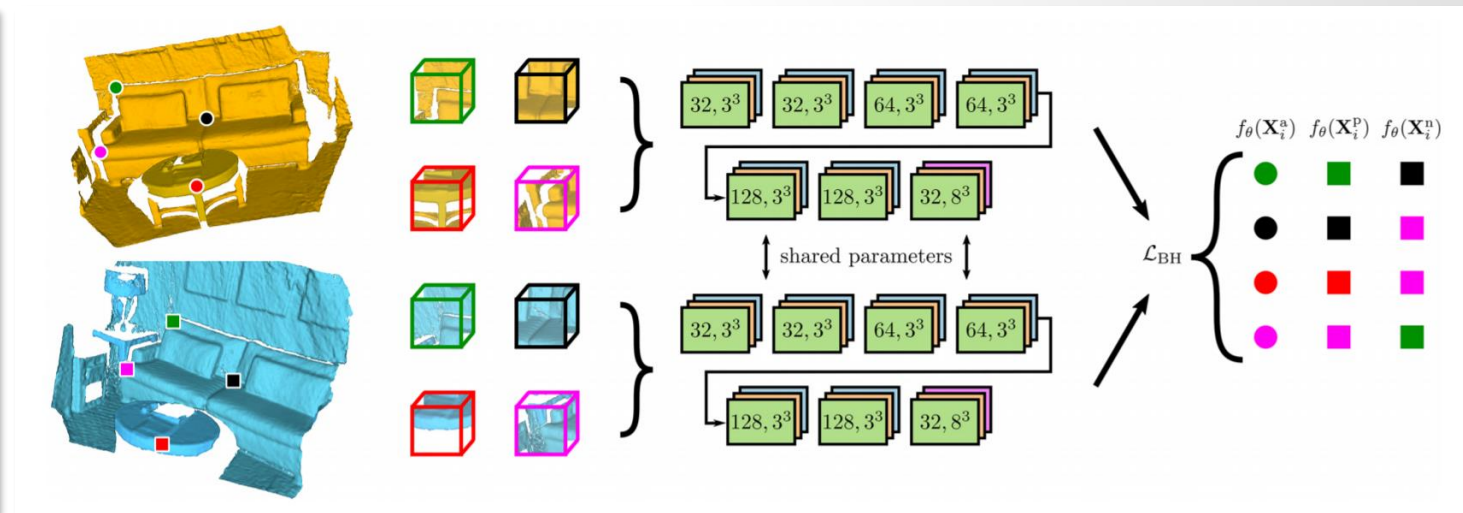
Xiang, Yizhou, et al. "ConGPT: A Global & efficient solution to 3D point-to-point registration." *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2019).  
Kokk, Yizhou, et al. "ConGPT: A Global & efficient solution to 3D point-to-point registration." *IEEE Transactions on Pattern Analysis and Machine Intelligence* (2019).  
2019.



# Local methods

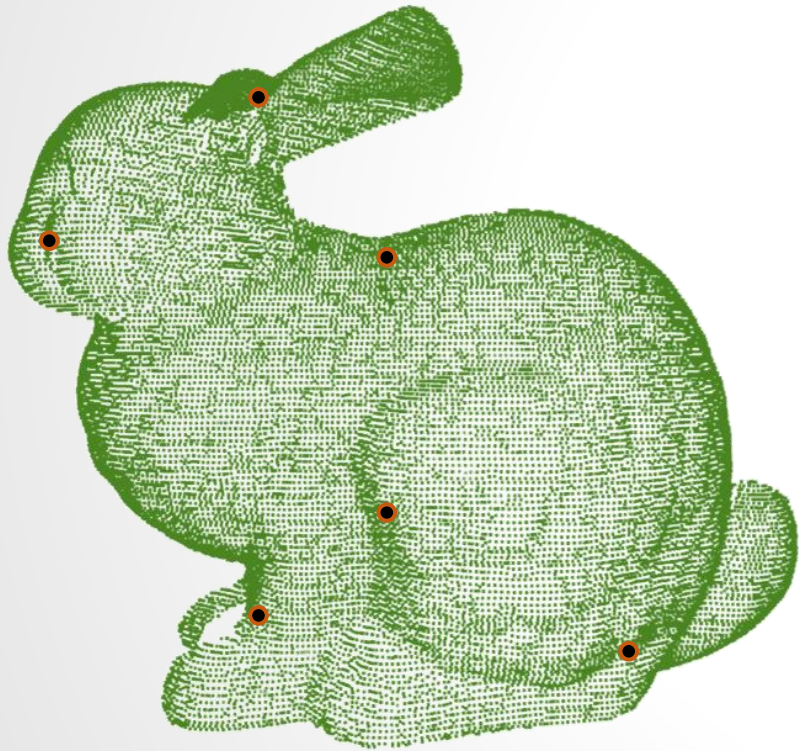


Deng, Haowen, Tolga Birdal, and Slobdan Ilic. "Ppf-foldnet: Unsupervised learning of rotation invariant 3d local descriptors." *Proceedings of the European Conference on Computer Vision (ECCV)*. 2018.

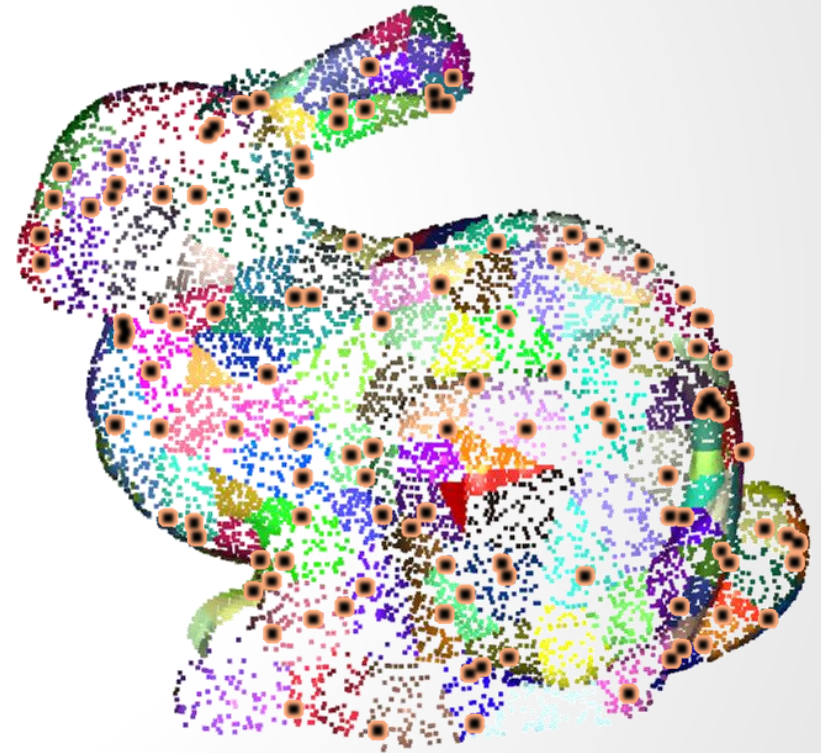


Zeng, Andy, et al. "3dmatch: Learning local geometric descriptors from rgb-d reconstructions." *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2017.

# Graphite

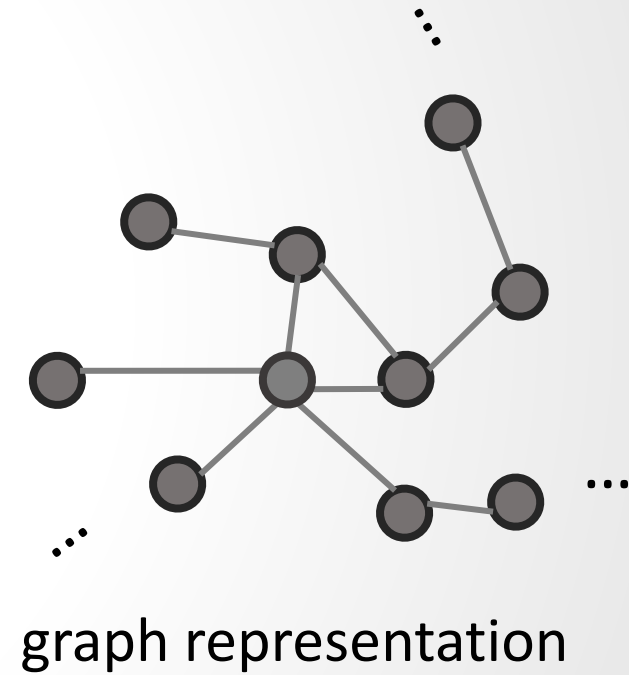
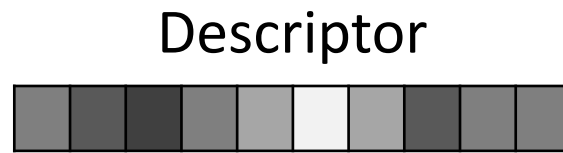
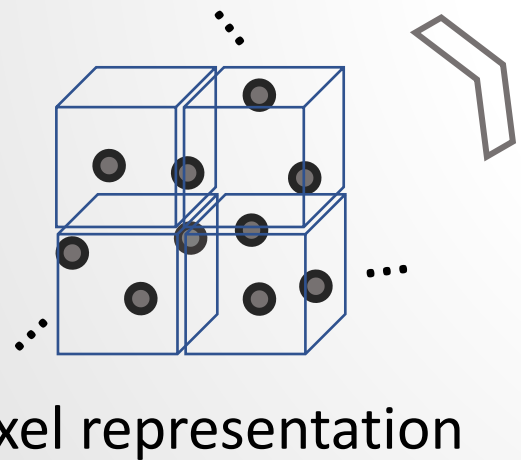
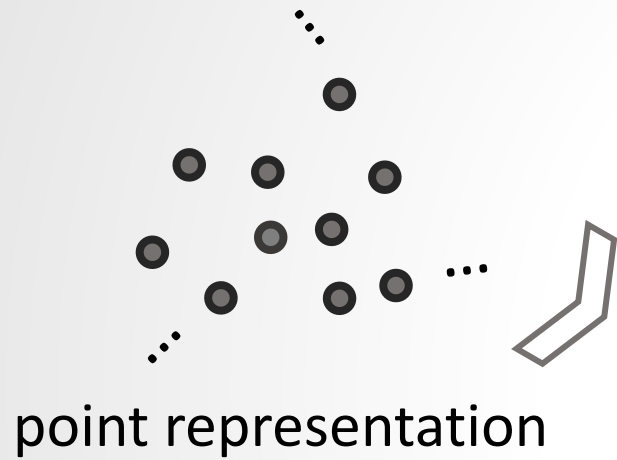


Sparse description



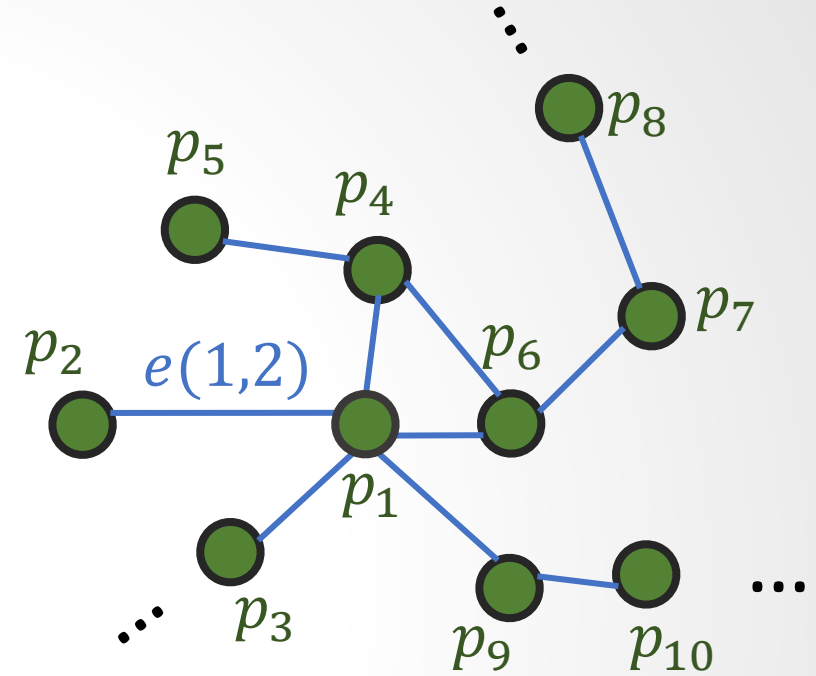
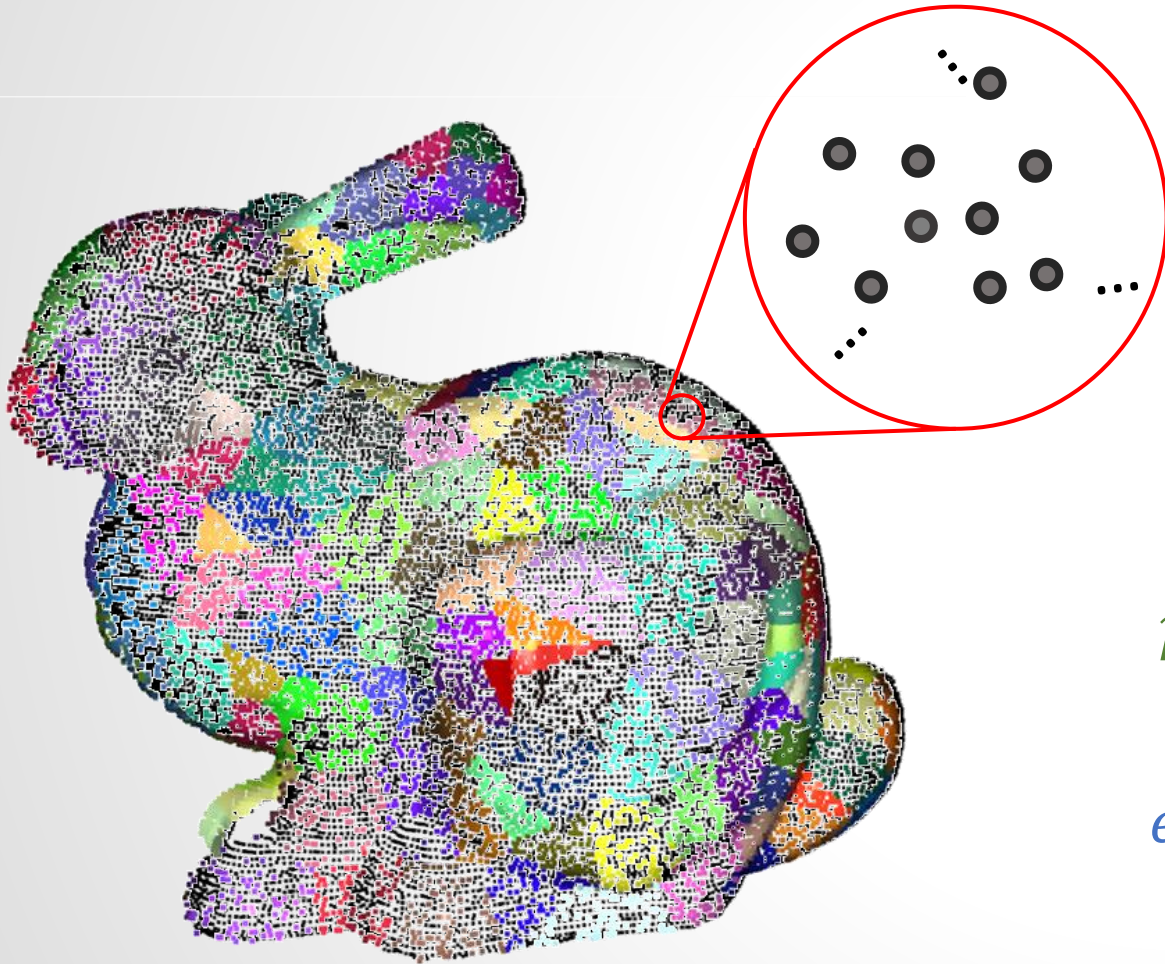
Dense description and  
keypoint per patch

# Graphite





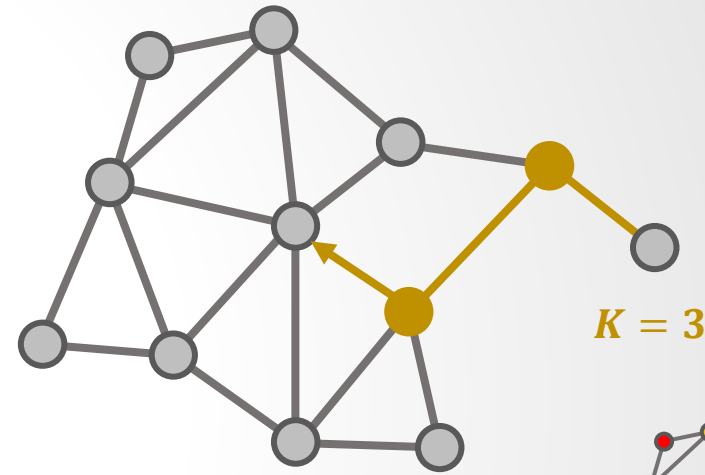
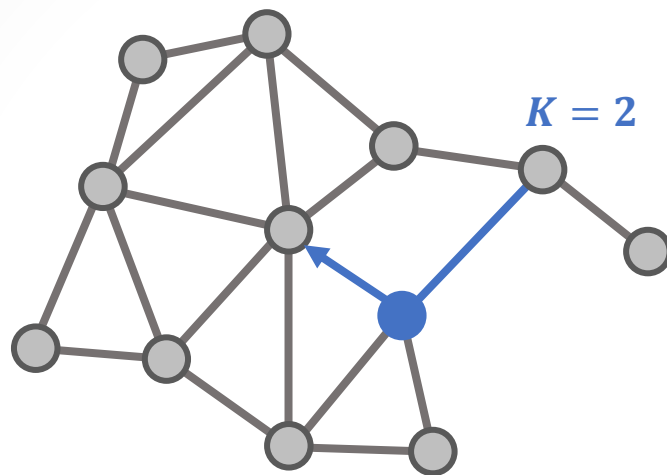
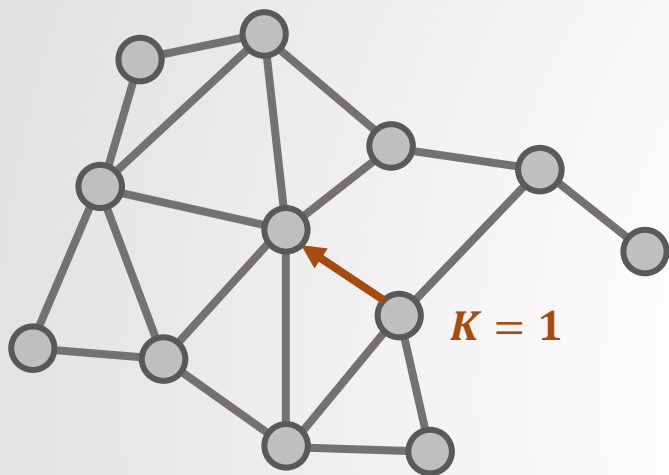
# Graph construction



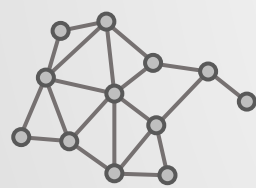
$$p_i = (x_i, y_i, z_i, a_i, b_i, c_i)$$

$$e(j, k) = \begin{cases} \frac{r}{r + \|p_j - p_k\|} & , \text{if } \|p_j - p_k\| < r \\ 0 & , \text{otherwise} \end{cases}$$

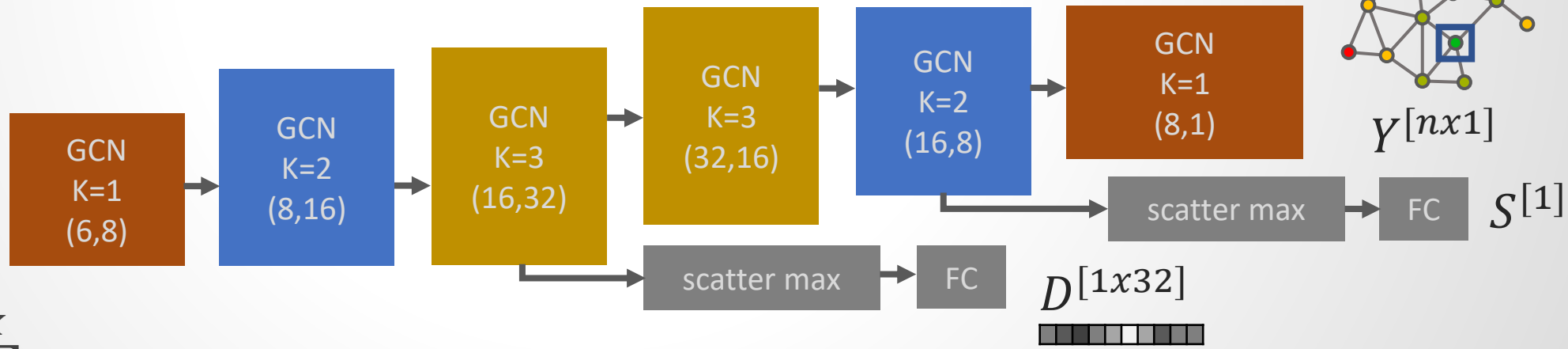
# Architecture



Input Patch



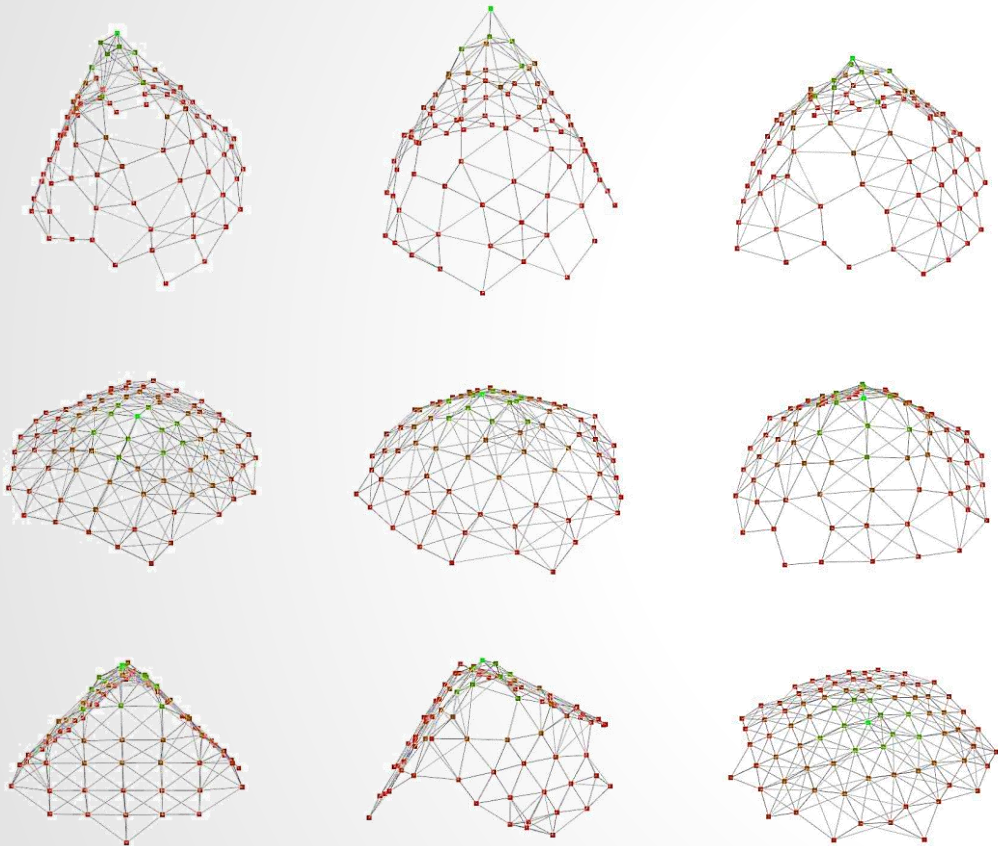
$X[n \times 6]$   
 $A[n \times n]$



$$X'_i = \sum_{k=0}^K D'^{-1/2} A^k D'^{-1/2} X_i \Theta_k$$



# Training datasets



Anchor

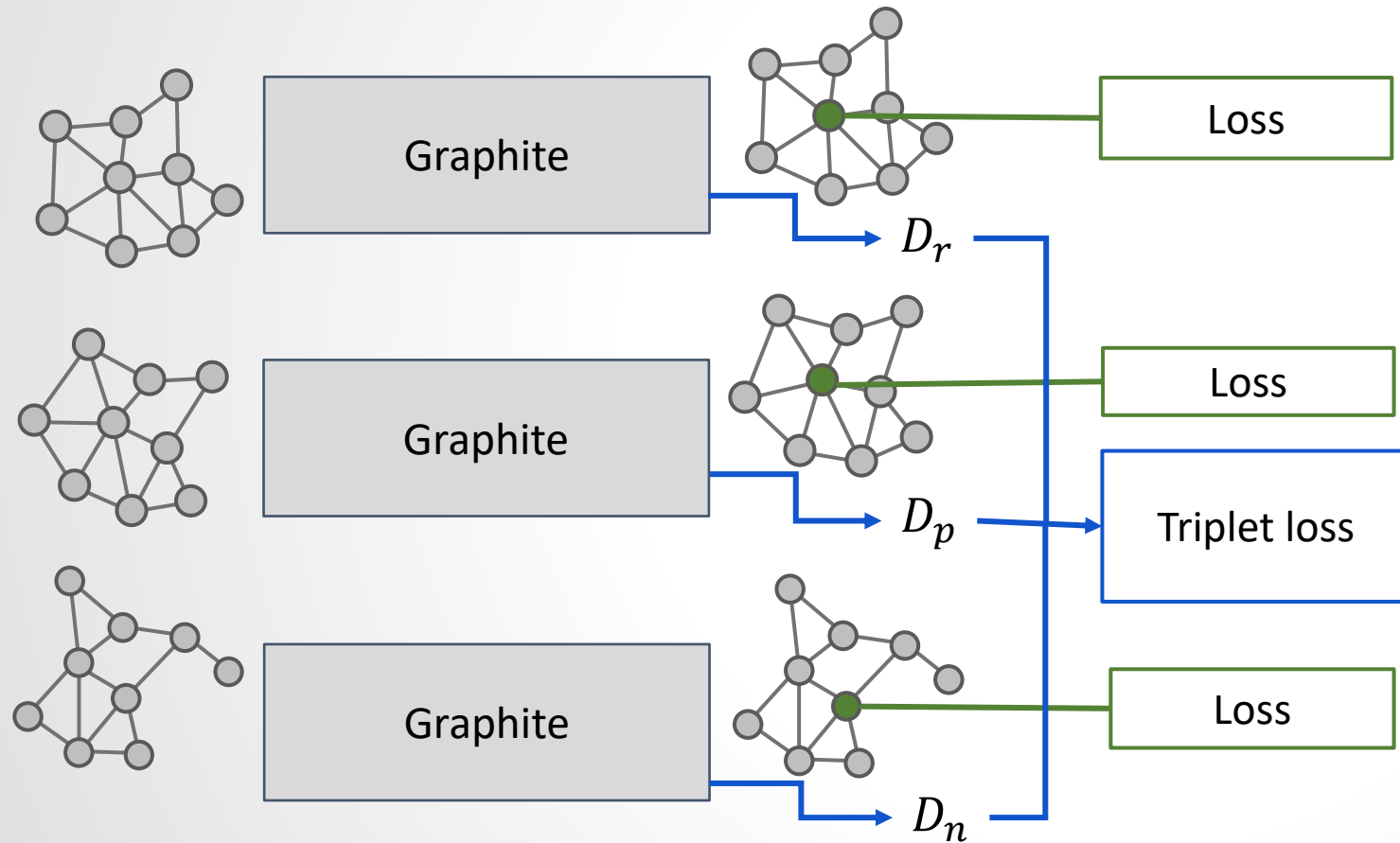
Positive

Negative



ModelNet40 registration pair and patches

# Initialization

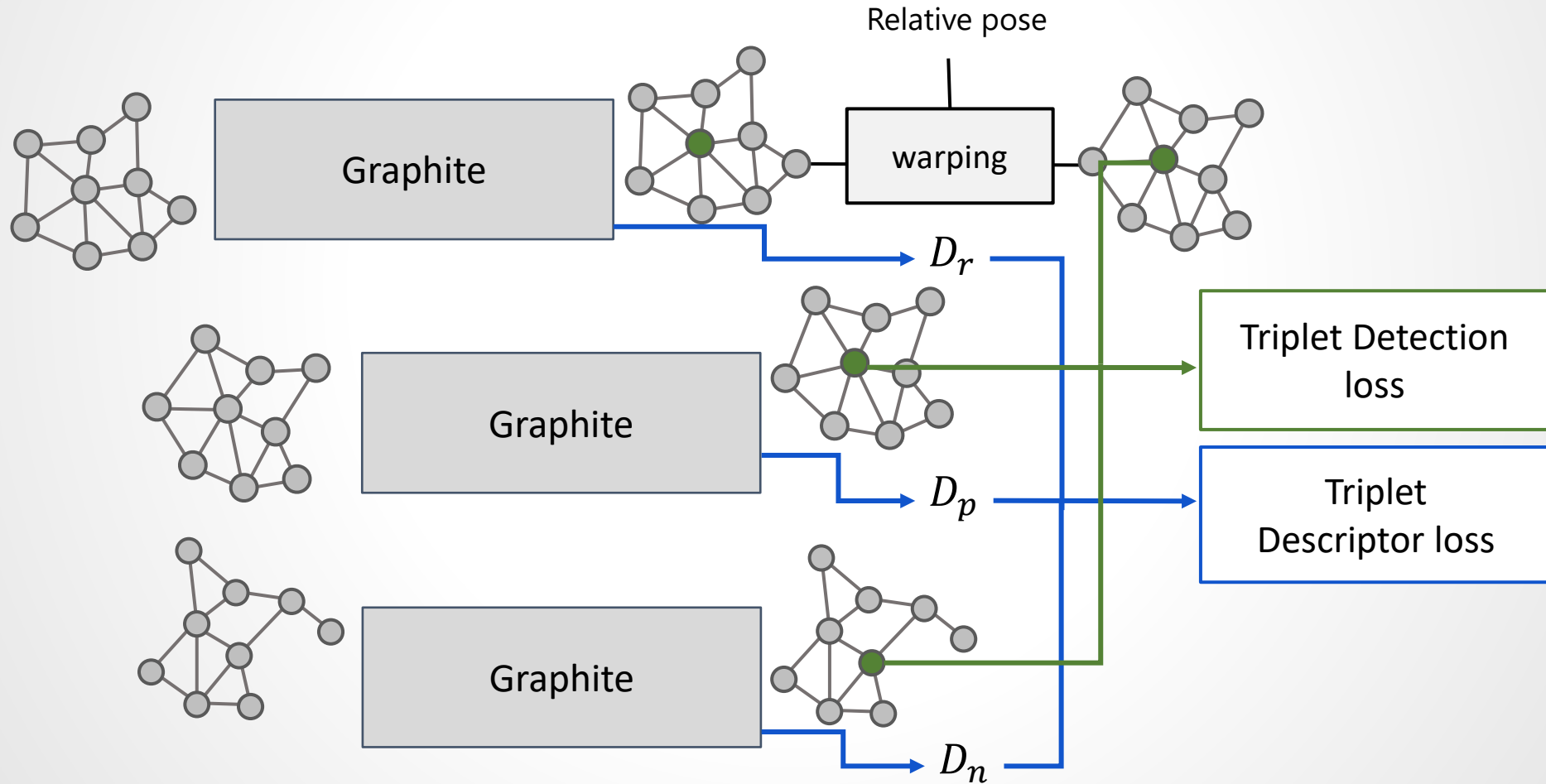


$$L_S = (Y - \hat{Y})^2$$

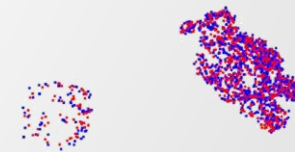
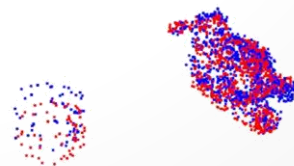
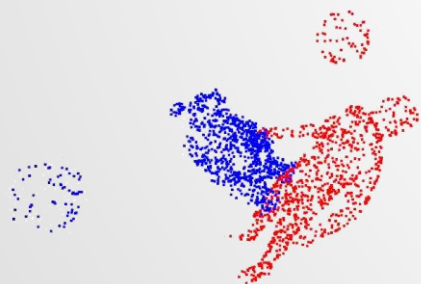
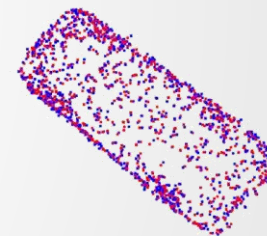
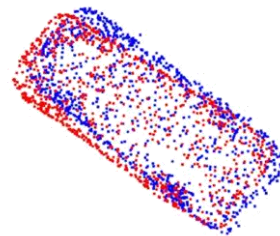
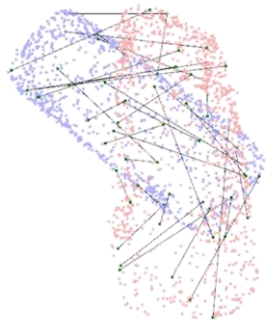
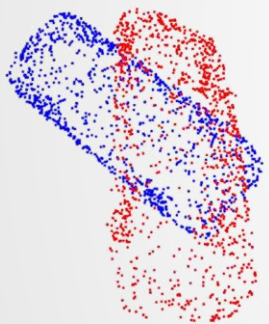
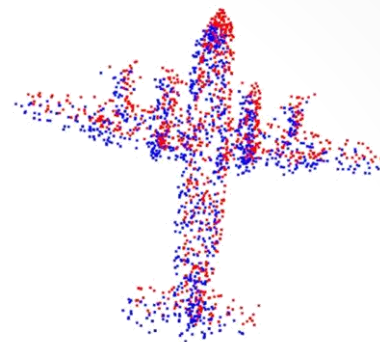
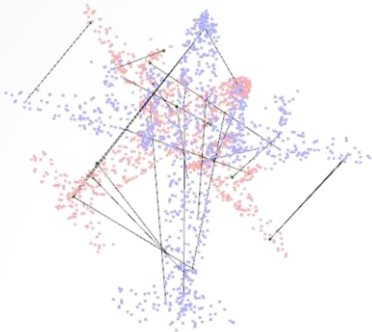
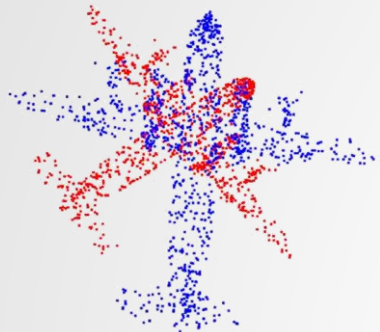
$$L_S = (S - \hat{S})^2$$

$$L_D = \frac{|D_r - D_p|}{|D_r - D_p| + m \cdot |D_r - D_n|}$$

# Training with pose variations



# ModelNet40 registration



Original pair

Keypoint matches

Graphite

Graphite + ICP



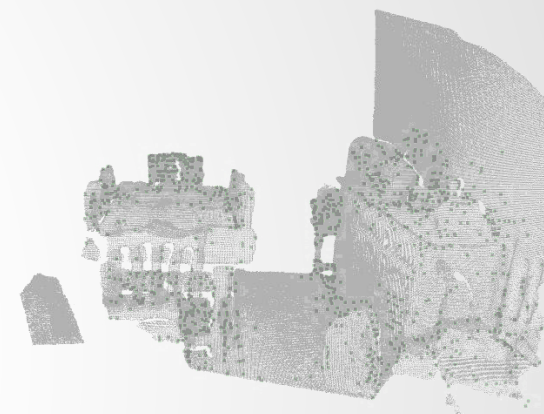
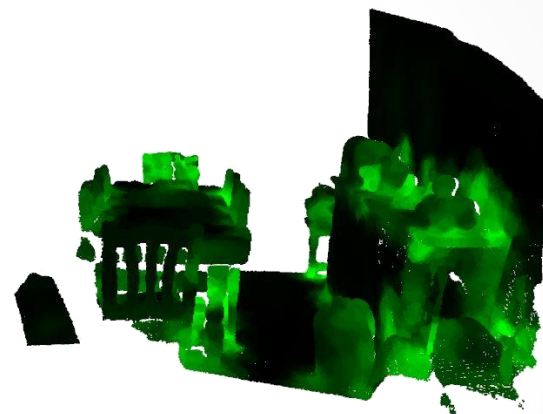
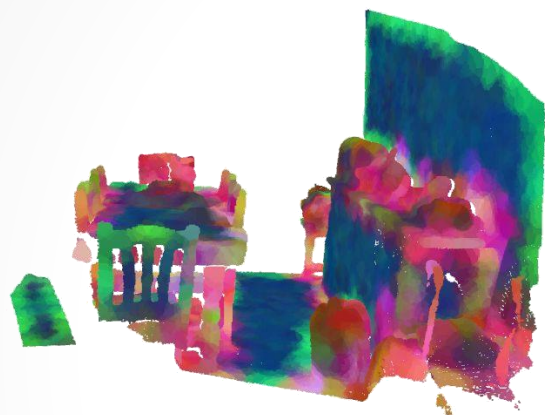
# ModelNet40 registration

Method		MSE	RMSE	MAE
ICP	R	892.60	29.88	23.63
	t	8.60	2.93	2.52
Go-ICP	R	192.26	13.87	2.91
	t	0.05	0.22	0.06
FGR	R	97.00	9.85	1.45
	t	0.02	0.14	0.02
PointNetLK	R	306.32	17.50	5.28
	t	0.08	0.28	0.07
DCP-v1	R	19.20	4.38	2.68
	t	< <b>0.01</b>	0.05	0.04
DCP-v2	R	9.92	3.15	2.01
	t	< <b>0.01</b>	<b>0.05</b>	<b>0.03</b>
<b>Ours</b>	R	7.44	2.73	1.49
	t	0.31	0.56	0.38
<b>Ours + ICP</b>	R	<b>0.75</b>	<b>0.86</b>	<b>0.11</b>
	t	0.09	0.30	0.07

# Registration under noise

Method		MSE	RMSE	MAE
ICP	R	882.56	29.71	23.56
	t	8.45	2.91	2.49
Go-ICP	R	131.18	11.45	2.53
	t	0.05	0.23	0.042
FGR	R	607.69	24.65	10.06
	t	1.19	1.09	0.27
PointNetLK	R	256.16	16.00	4.60
	t	0.047	0.216	0.057
DCP-v1	R	6.93	2.63	1.52
	t	<b>&lt;0.01</b>	<b>0.02</b>	0.02
DCP-v2	R	<b>1.17</b>	<b>1.08</b>	0.74
	t	<b>&lt;0.01</b>	<b>0.02</b>	<b>0.01</b>
<b>Ours</b>	R	17.76	4.21	2.35
	t	0.39	0.63	0.44
<b>Ours + ICP</b>	R	4.03	2.01	<b>0.31</b>
	t	0.10	0.31	0.08

# 3dmatch registration



3DMatch seed points

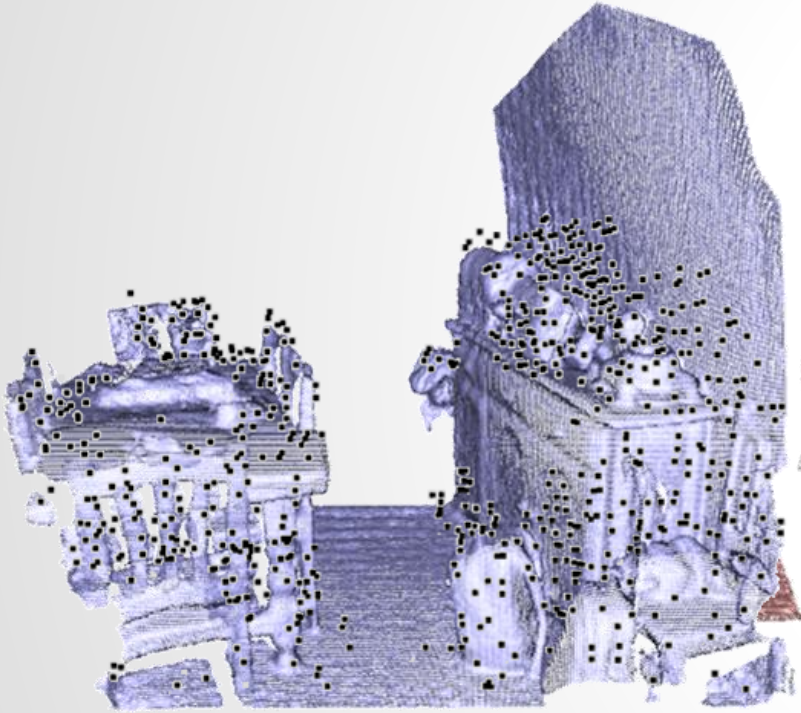
Descriptor visualisation

Keypoint scores

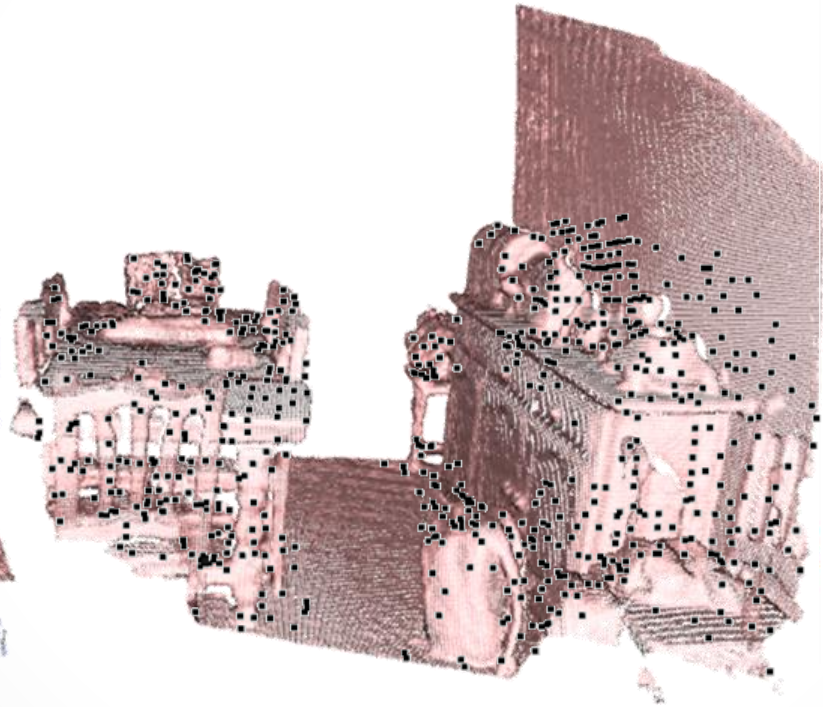
Validated keypoints



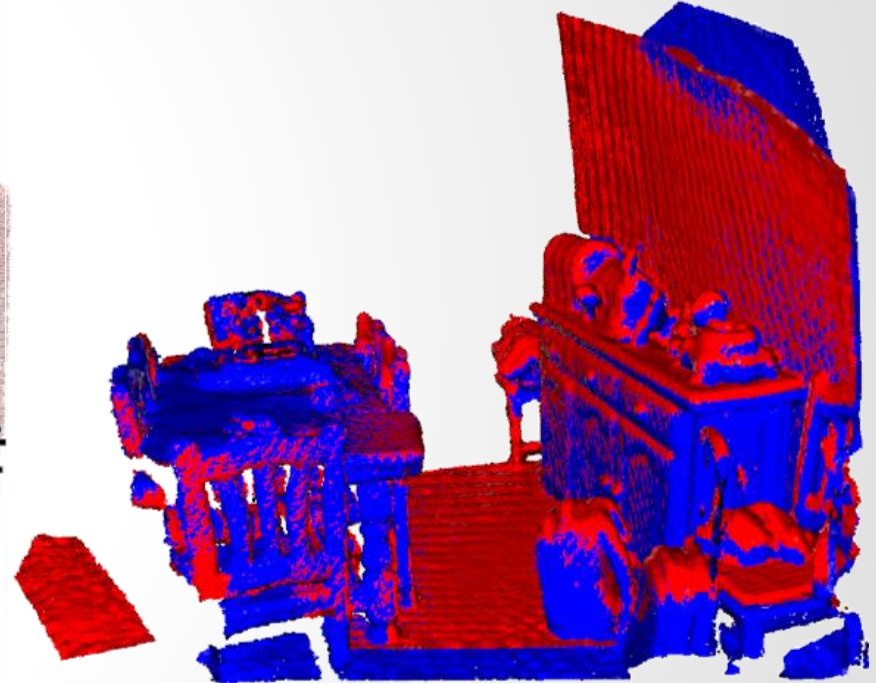
# 3dmatch registration



Scene 1 + Keypoints



Scene 2 + Keypoints



Registered with Graphite



# Geometric registration benchmark

Method	Handcrafted		Trained on 3DMatch				CGF (32 dim)	Graphite (32 dim)	
	FPFH (33 dim)	SHOT (352 dim)	3DMatch (512 dim)	PPFNet (64 dim)	PPF-FoldNet (512 dim)	Perfect-Match (16 dim)			Perfect-Match (32 dim)
Kitchen	43.1	74.3	58.3	89.7	78.7	93.1	97.0	60.3	64.82
Home 1	66.7	80.1	72.4	55.8	76.3	93.6	95.5	71.1	83.97
Home 2	56.3	70.7	61.5	59.1	61.5	86.5	89.4	56.7	68.26
Hotel 1	60.6	77.4	54.9	58.0	68.1	95.6	96.5	57.1	80.77
Hotel 2	56.7	72.1	48.1	57.7	71.2	90.4	93.3	53.8	80.53
Hotel 3	70.4	85.2	61.1	61.1	94.4	98.2	98.2	83.3	96.29
Study	39.4	64.0	51.7	53.4	62.0	92.8	94.5	37.7	82.53
MIT Lab	41.6	62.3	50.7	63.6	62.3	92.2	93.5	45.5	76.62
Average	54.3	73.3	57.3	62.3	71.8	92.8	94.7	58.2	79.22
STD	11.8	7.7	7.8	11.5	9.9	3.4	2.7	14.2	9.10

# Conclusion

- We describe patches using our lightweight graph-based model
- Our model is trained with minimum supervision
- It also extracts salient interest points, keypoints
- Keypoints can be used to downsample the original point cloud to a uniformly distributed set
- For registration a combination of keypoint and descriptor can be used
- Although trained on synthetic point clouds, our model generalizes well with real depth scans

# Graphite: GRAPH-Induced feaTure Extraction for Point Cloud Registration

Paper ID 2

Official Code and pretrained models

[github.com/mahdi-slh/Graphite](https://github.com/mahdi-slh/Graphite)