

## Motivation & Contributions

### ➤ Motivation

- Hand-crafted 3D keypoint feature descriptors are unstable and difficult to adapt to new scenes.
- Supervised deep learning based 3D keypoint feature extraction methods require huge amounts of point-level annotated data for training, while annotating training data is labor- and time-consuming.

### ➤ Contributions

- Present a KeyPoint Siamese Network (KPSNet) to simultaneously detect 3D keypoints and learn their feature representations.
- Design an alignment module to generate pairs of training samples and label them on-the-fly, do not require manually annotating 3D keypoints.

## Method

- Keypoint detector learns to discriminate whether a candidate is a keypoint or not.
- Feature extractor learns to extract the keypoints' features.
- The required labels for training is generated by the Alignment Module.
- **Alignment Module**
- Label each candidate as 0/1 for keypoint detector.
- Generate pairs of samples for feature extractor, as well as labeling them as positive/negative.

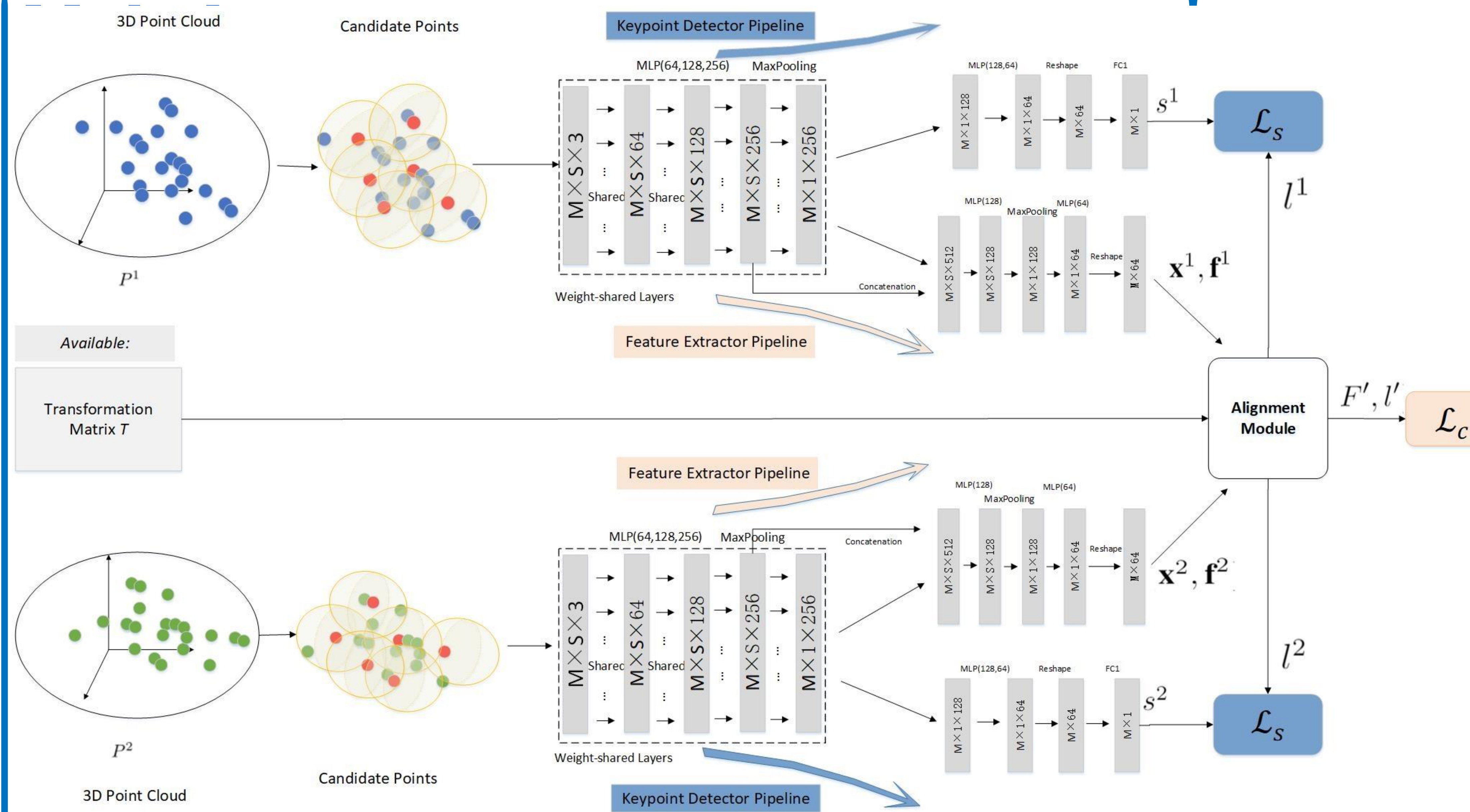


Fig.1 Overview of our KPSNet

### ➤ Joint Optimization

- we introduce the following multitask loss:

$$\mathcal{L}(\{K^1, K^2\}) = \alpha \mathcal{L}_c(F', l') + \beta \mathcal{L}_s^1(s^1, l^1) + \beta \mathcal{L}_s^2(s^2, l^2) \quad (1)$$

$$\mathcal{L}_c(F', l') = \frac{\sum_{n=1}^N l'_n \|\mathbf{f}_n^1 - \mathbf{f}_n^2\|^2}{2N_{pos}} + \frac{\sum_{n=1}^N (1 - l'_n) \max(0, \delta - \|\mathbf{f}_n^1 - \mathbf{f}_n^2\|)^2}{2N_{neg}} \quad (2)$$

$$\mathcal{L}_s^m(s^m, l^m) = -\frac{\gamma \sum_{n=1}^N l_n^m \log s_n^m + 1}{N_{pos} + 1} \quad (3)$$

## Results

Table 1. Our evaluations on the 3D-match benchmark

	Spin Images		SHOT		FPFH		USC		KPSNet(ours)	
	recall	prec.	recall	prec.	recall	prec.	recall	prec.	recall	prec.
Red Kitchen	0.27	0.49	0.21	0.44	0.36	0.52	0.52	0.60	0.58	<b>0.72</b>
Home 1	0.56	0.14	0.37	0.13	0.56	0.16	0.35	0.16	0.54	<b>0.23</b>
Home 2	0.35	0.10	0.30	0.11	0.43	0.13	0.47	<b>0.24</b>	0.40	0.19
Hotel 1	0.37	0.29	0.28	0.29	0.29	0.36	0.53	0.46	0.50	<b>0.53</b>
Hotel 2	0.33	0.12	0.24	0.11	0.36	0.14	0.20	0.17	0.40	<b>0.23</b>
Hotel 3	0.32	0.16	0.42	0.12	0.61	<b>0.21</b>	0.38	0.14	0.38	0.17
Study Room	0.21	0.07	0.14	0.07	0.31	0.11	0.46	<b>0.17</b>	0.52	0.15
MIT Lab	0.29	0.06	0.22	0.09	0.31	0.09	0.49	<b>0.19</b>	0.36	0.13
Average	0.34	0.18	0.27	0.17	0.40	0.21	0.43	0.27	0.46	<b>0.30</b>



Fig.2 Visualization of estimated transformations