Supplementary Material: Graph-context Attention Networks for Size-varied Deep Graph Matching

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1. Additional experimental results for keypoint matching

Fig. 1 shows some of examples of size-equal graph matching results on some categories of the Pascal VOC dataset, where the nodes of the graph pairs are filtered by applying node intersection filtering. In Tab. 1 and Tab. 2, we demonstrate that the size-equal graph matching accuracy of the proposed approach outperforms the current state-of-the-art on the SPair-71k and Willow ObjectClass datasets respectively, demonstrating its generality. Tab. 3 shows the comparison of different loss functions on all categories of the Pascal VOC dataset with intersection filtering. We can see that our ILP_AL approach achieves the best performance for most categories and overall.

Size-varied graph matching results are visualized in Fig. 2, where all nodes of the graph pairs are used without filtering. We can see that matching graphs may contain different numbers of nodes and outliers in both images, which is closer to the real-world scenario. Our approach has shown superior performance for handling the size-varied graph matching problem.

Table 1. Matching accuracy (%) on Willow ObjectClass dataset with intersection filtering.

method	car	duck	face	m-bike	w-bottle	mean
GMN [1]	67.9	76.7	99.8	69.2	83.1	79.3
PCA-GM [2]	87.6	83.6	**100.0**	77.6	88.4	87.4
IPCA-GM [3]	90.4	88.6	**100.0**	83.0	88.3	90.1
BBGM [4]	96.8	89.9	**100.0**	99.8	99.4	97.2
LCS [5]	91.2	86.2	**100.0**	99.4	97.9	94.9
NGM-v2 [6]	97.4	93.4	**100.0**	98.6	98.3	97.5
NHGM-v2	97.4	93.9	**100.0**	98.6	98.9	97.8
ours	**98.8**	**94.1**	**100.0**	**100.0**	**100.0**	**98.6**

2. Additional experimental results for graph-level matching

Fig. 3 shows unsupervised matching results over training epochs on Pascal VOC dataset with intersection filtering. We can see that node-to-node matching accuracy increases during training. To our knowledge, this is the first work to explore node-to-node matching in an unsupervised way. In Fig. 4, we show unsupervised matching results on the Bosphoros vessel graph dataset [7]. However, different from the previous dataset, the Bosphoros dataset does not provide the node-to-node ground truth, so we can not quantitatively evaluate the proposed approach. We directly show the node-to-node corresponding which is automatically learned via graph-level matching.

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Table 2. Matching accuracy (%) on SPair-71k with intersection filtering.

method	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	dog	horse	mbkie	person	plant	sheep	train	tv	mean
DGMC	54.8	44.8	80.3	70.9	65.5	90.1	78.5	66.7	66.4	73.2	66.2	66.5	65.7	59.1	98.7	68.5	84.9	98.0	72.2
BBGM [4]	66.9	57.7	85.8	78.5	66.9	95.4	86.1	74.6	68.3	78.9	73.0	67.5	**79.3**	73.0	99.1	74.8	75.0	98.6	78.9
NGM-v2 [6]	64.3	57.4	90.0	80.5	**69.5**	94.4	84.2	73.3	70.5	78.3	68.0	**70.9**	77.5	72.6	99.4	80.1	94.6	98.9	79.1
ours	69.4	60.0	**91.7**	77.5	71.0	**97.3**	**90.4**	**73.2**	**73.4**	**83.4**	**74.3**	70.1	78.1	**77.2**	**99.9**	**82.3**	**95.6**	**97.9**	**81.3**

Table 3. Matching accuracy (%) of different loss functions on Pascal VOC Keypoint with intersection filtering.

loss	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbkie	person	plant	sheep	sofa	train	tv	mean
FL [8]	55.7	70.6	74.9	77.3	89.9	93.6	84.7	77.4	53.7	77.9	68.7	77.3	76.4	75.5	56.6	98.3	75.4	79.0	98.2	92.4	77.7
CM [4]	19.8	20.3	27.0	37.0	43.3	66.0	47.8	26.2	27.6	21.9	61.4	27.7	23.8	25.6	16.3	70.5	31.5	33.1	87.0	90.0	40.2
POR [1]	56.7	69.5	76.4	**82.5**	89.2	95.0	86.1	79.2	61.3	78.5	68.2	75.9	77.0	74.5	60.0	98.1	74.5	80.0	98.1	93.7	78.7
BCE [6]	61.7	70.3	**80.6**	81.2	90.4	93.2	**90.6**	78.8	62.1	80.1	87.0	80.6	79.1	**79.0**	65.8	98.1	76.7	80.0	98.2	92.8	81.3
HAL [9]	63.2	**72.3**	80.0	79.2	87.9	94.2	89.0	78.1	60.7	**81.1**	89.7	80.1	78.9	78.7	66.3	**99.4**	**78.7**	73.3	97.9	**94.1**	81.2
ILP_AL	**63.4**	71.2	80.1	81.1	**90.4**	**95.5**	89.5	**80.4**	**65.3**	80.8	**89.9**	**81.4**	**80.6**	78.1	**67.7**	98.2	77.5	**82.6**	**98.4**	93.4	**82.3**

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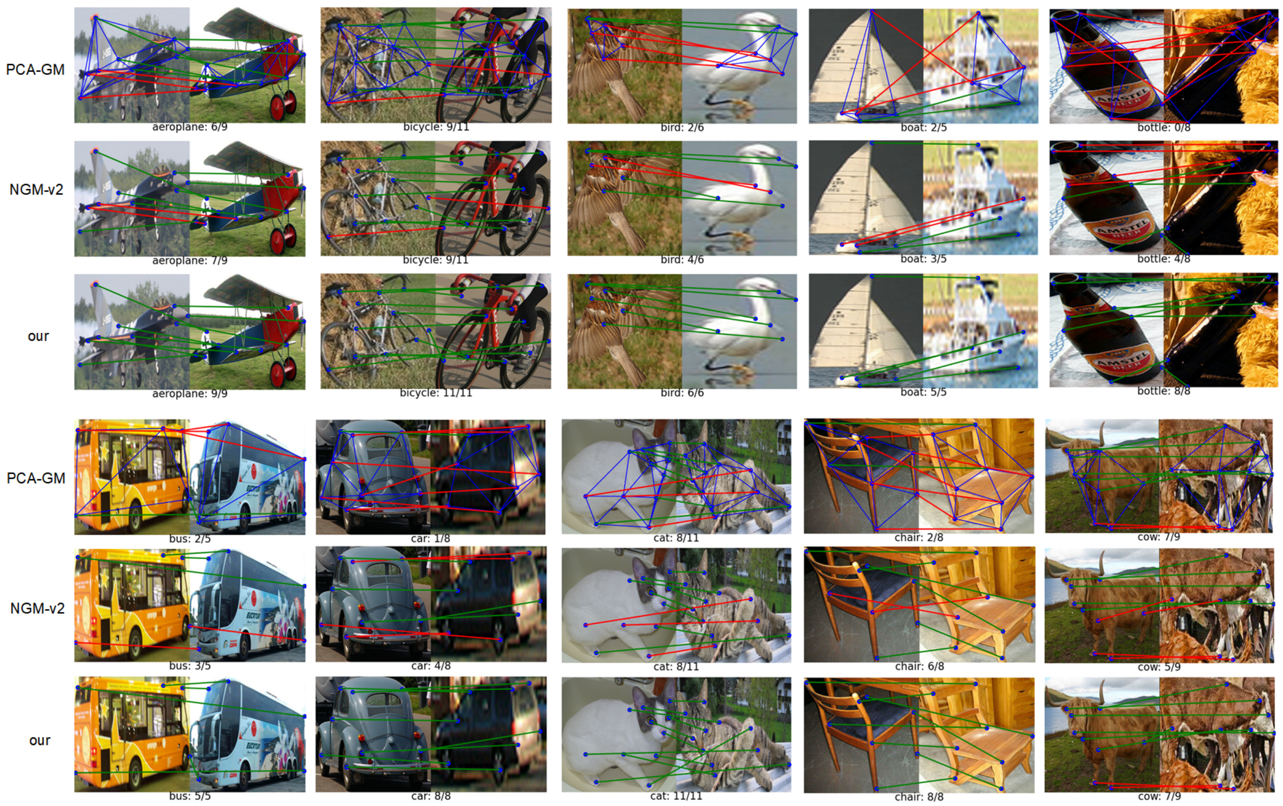

Figure 1. Visualization of size-equal graph matching results on some categories of Pascal VOC dataset. The pair graphs of the images contain the same size of nodes (shown in blue solid circles). Green and red indicates correct and incorrect predictions, respectively. We only show graphs in the first row images for better visualization.

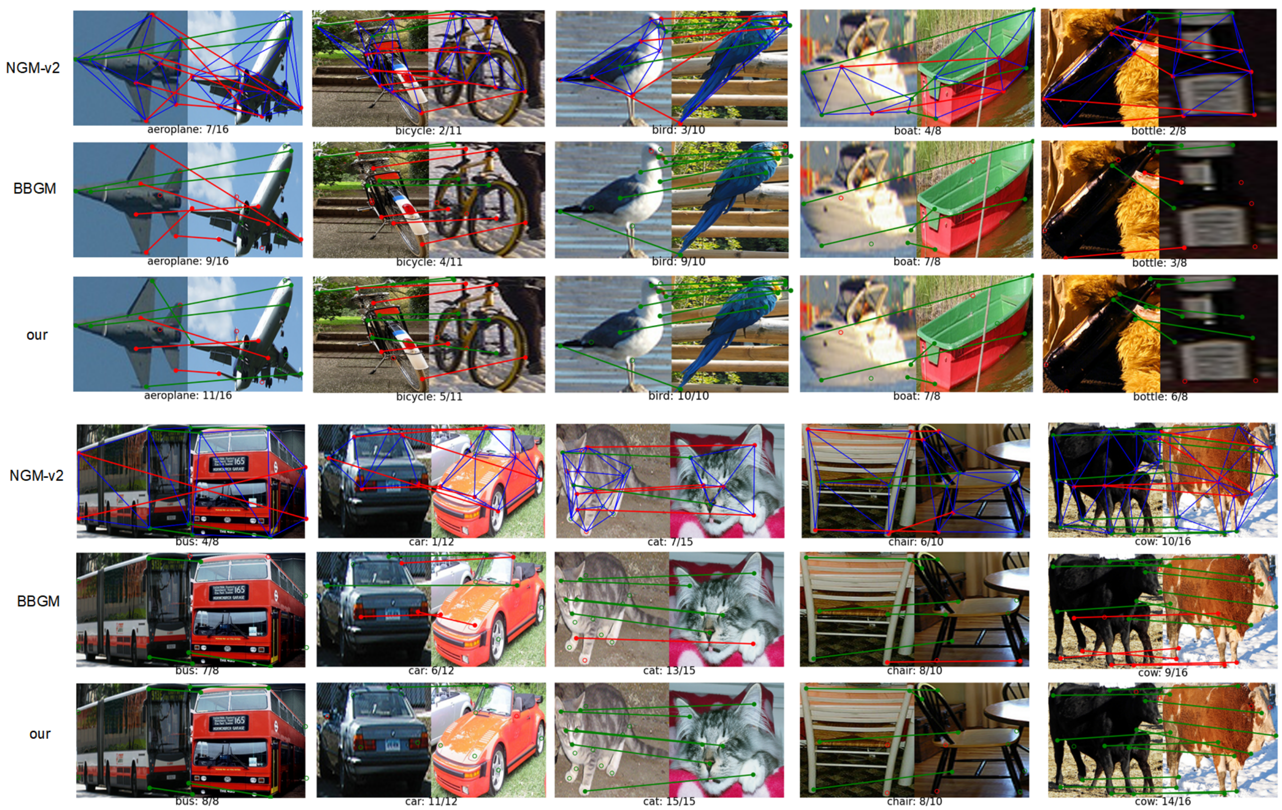

Figure 2. Visualization of size-varied graph matching results on some categories of Pascal VOC dataset. The pair graphs of the images may contain different size of nodes, where predicted matched points and unmatched points are shown in soid circles and empty circles respectively. Green and red indicates correct and incorrect predictions, respectively. We only show graphs in the first row images for better visualization.

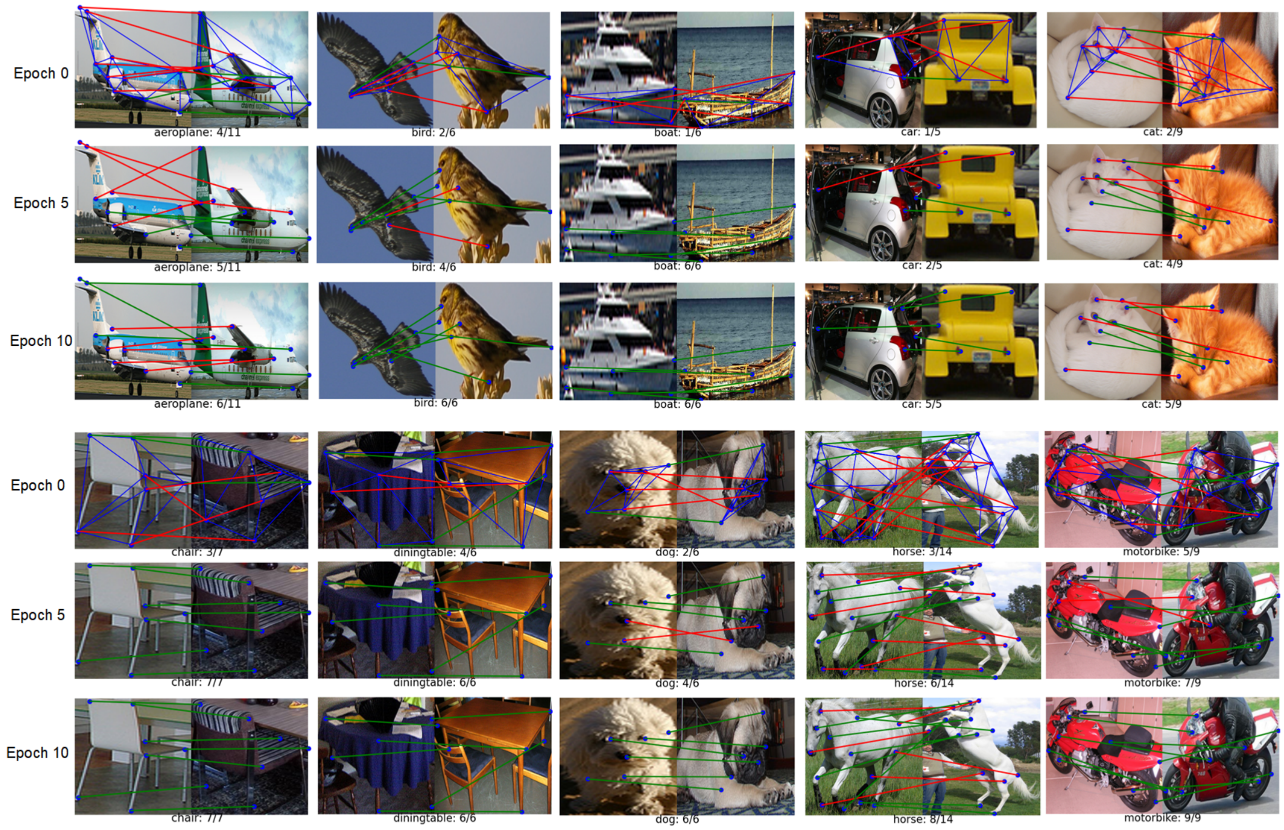

Figure 3. Visualization of unsupervised matching results over training epochs on Pascal VOC dataset with intersection filtering.

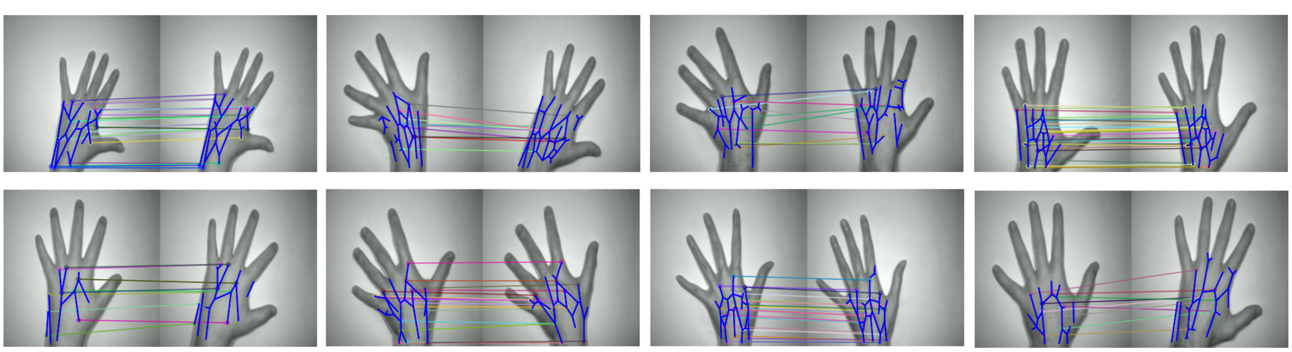

Figure 4. Visualization of unsupervised matching results on Bosphoros vessel graph dataset. Since this dataset does not provide the node-to-node ground truth, we can not compute the matching accuracy of the proposed approach on it. Here we do not show the node-to-node corresponding with low confidence.