An End-to-End Transformer Model for Crowd Localization

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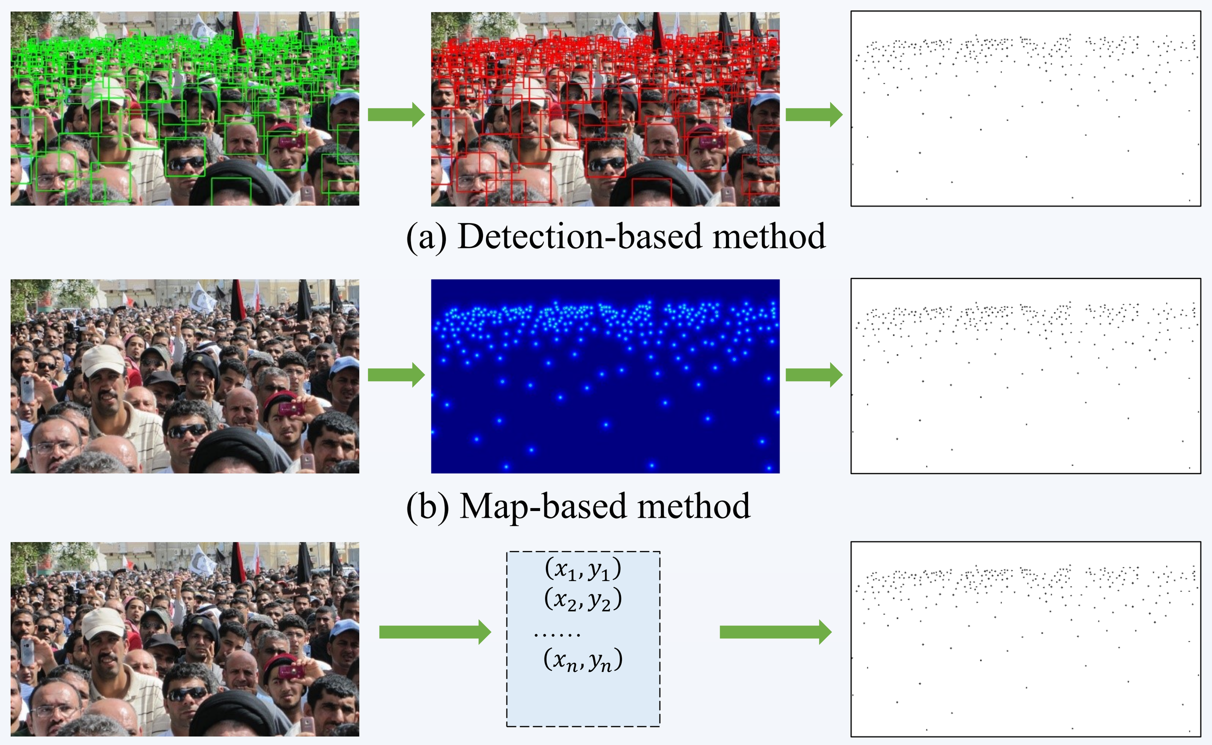
MOTIVATION



(a) Detection-based method

(b) Map-based method

(c) Regression-based method

➢Crowd localization aims to provide the location of each instance.

➢The regression-based methods, directly regressing the coordinates, are more straightforward than the detection-based and map-based methods.

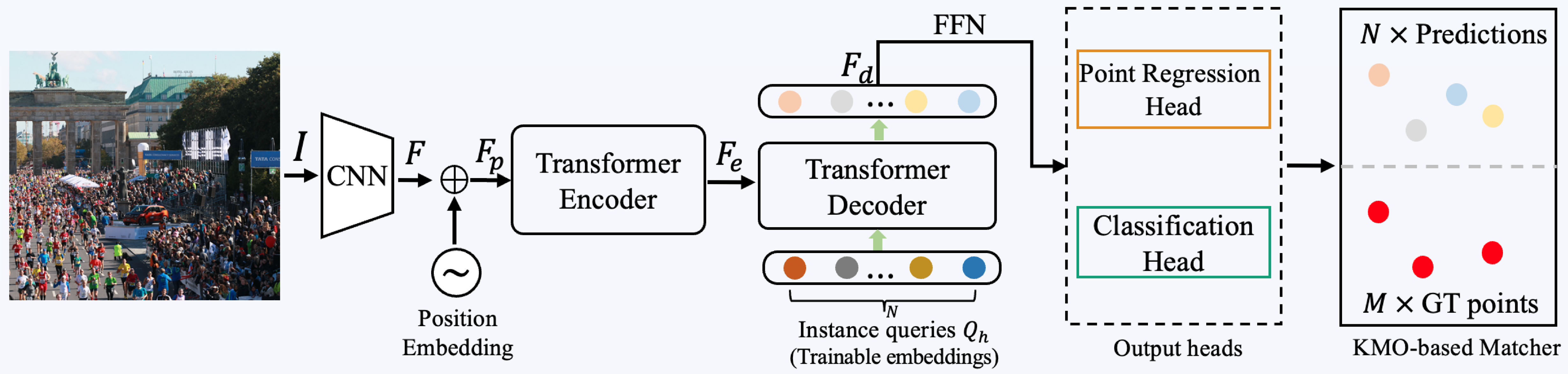
➢DETR shows terrible performance in the crowd localization task, attributed to the intrinsic limitation of the matcher. Due to lack of context, the $L1$ distance easily causes the ambiguous match pair.

CONTRIBUTION

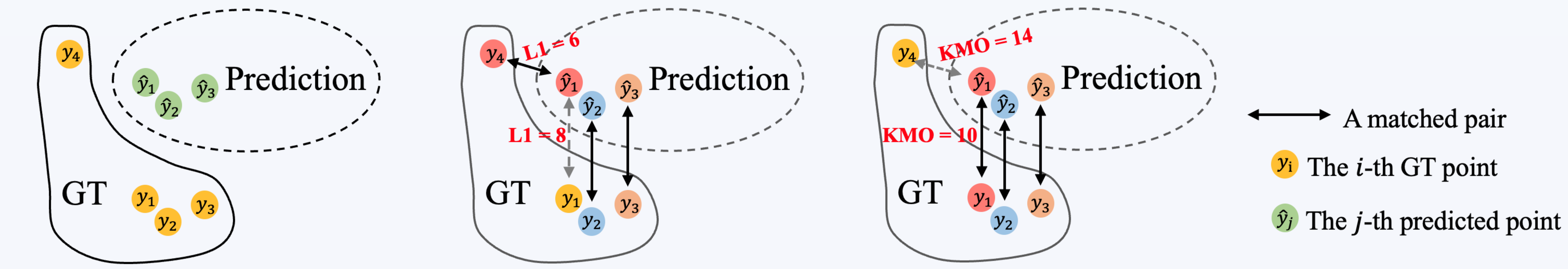
➢We propose an end-to-end Crowd Localization TRansformer framework named CLTR, which formulates the crowd localization as a point set prediction task.

➢We introduce the KMO-based Hungarian bipartite matching, which takes the context from nearby heads as an auxiliary matching cost. As a result, the matcher can effectively reduce the ambiguous points and generate more reasonable matching results.

METHOD



➢The overview of our CLTR. First, the input image I is fed to the CNN-based backbone to extract the features F. Second, the features F are added position embedding, resulting in F_p, fed to the transformer-encoder layers, outputting F_e. Third, we define $N\times$ trainable embeddings Q_h as query, F_e as key, and transformer decoder takes the Q_h and F_e as input to generate the decoded feature F_d. Finally, the F_d can be decoupled to the point coordinate and corresponding confidence score.



(a) A pair of GT and Prediction (b) L1-based Hungarian (c) KMO-based Hungarian

➢(a) A pair of GT and predictions. (b) The $L1$-based Hungarian generate unsatisfactory matching results. (c) The proposed KMO-based Hungarian models the context as the matching cost, generating more reasonable matching results.

$$L_m(y_i, \hat{y}_j) = \left\| y_i^p - \hat{y}_j^p \right\|_1 - \hat{C}_j, i \in M, j \in N,$$

➢Merely taking the $L1$ with confidence will generate unsatisfactory matching results on specific cases.

$$L_m^k(y_i, \hat{y}_j) = \left\| y_i^p - \hat{y}_j^p \right\|_1 + \left\| y_i^k - \hat{y}_j^k \right\|_1 - \hat{C}_j,$$
$$y_i^k = \frac{1}{k}\sum_{k=1}^{k} d_i^k, \quad \hat{y}_j^k = \frac{1}{k}\sum_{k=1}^{k} \hat{d}_j^k,$$

➢The proposed KMO-based matcher, revisiting the label assignment from a context view, turns to find the whole optimum.

RESULTS

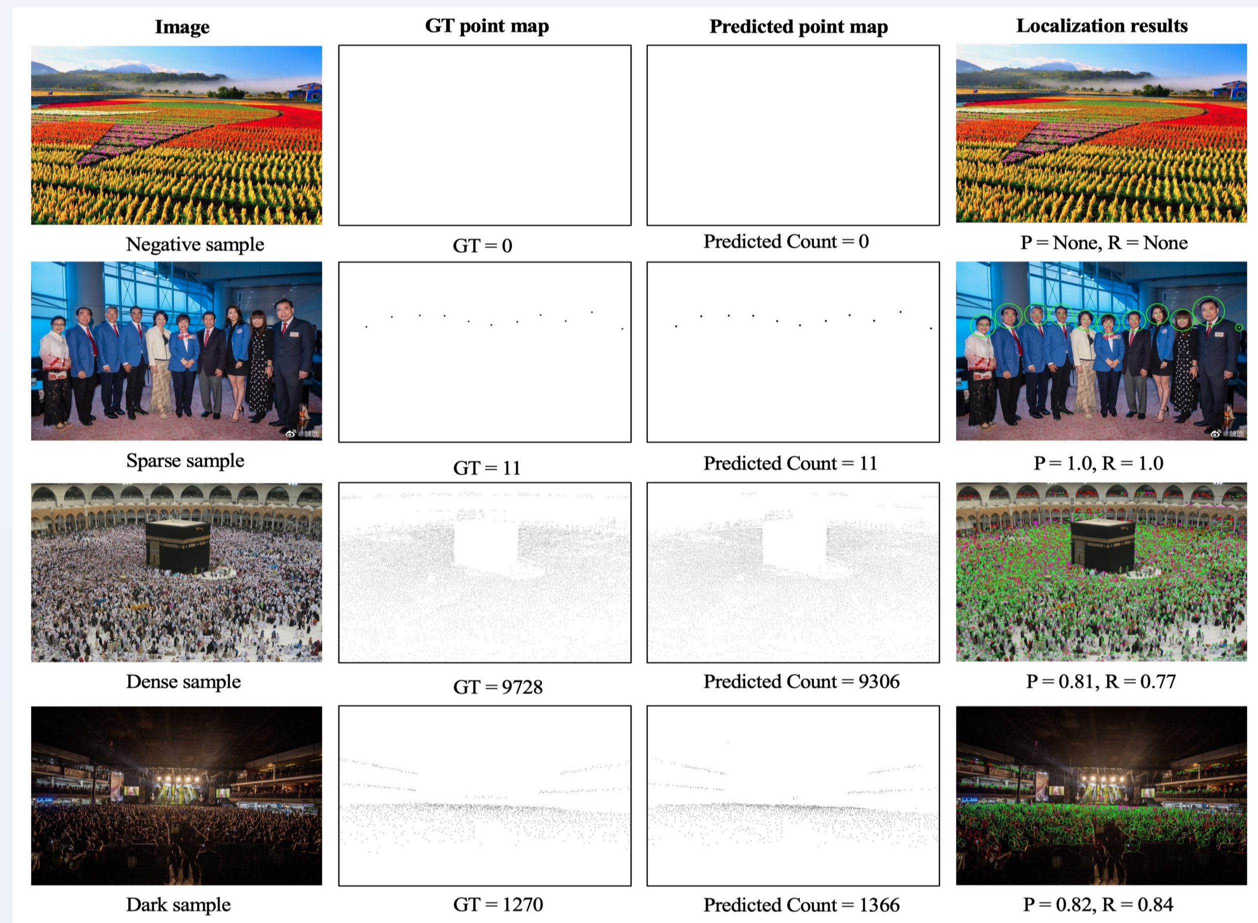
Method	Validation set P(%)	Validation set R(%)	Validation set F(%)	Test set P(%)	Test set R(%)	Test set F(%)
Faster RCNN* [29]	**96.4%**	3.8%	7.3%	**95.8%**	3.5%	6.7%
TinyFaces* [11]	54.3%	**66.6%**	**59.8%**	52.9%	61.1%	56.7%
TopoCount* [1]	-	-	-	69.5%	**68.7%**	**69.1%**
GPR [7]	61.0%	52.2%	56.3%	55.8%	49.6%	52.5%
RAZ_Loc [19]	69.2%	56.9%	62.5%	66.6%	54.3%	59.8%
AutoScale_loc [46]	70.1%	63.8%	66.8%	67.3%	57.4%	62.0%
Crowd-SDNet [44]	-	-	-	65.1%	62.4%	63.7%
GL [39]	-	-	-	**80.0%**	56.2%	66.0%
CLTR (**ours**)	**73.9%**	**71.3%**	**72.6%**	69.4%	**67.6%**	**68.5%**

Localization performance on NWPU dataset.

Method	Output Position Information	Validation set MAE	Validation set MSE	Test set MAE	Test set MSE
MCNN [48]	✗	218.5	700.6	232.5	714.6
CSRNet [16]	✗	104.8	433.4	121.3	387.8
CAN [22]	✗	93.5	489.9	106.3	**386.5**
SCAR [9]	✗	81.5	397.9	110.0	495.3
BL [27]	✗	93.6	470.3	105.4	454.2
SFCN [43]	✗	95.4	608.3	105.4	424.1
DM-Count [41]	✗	**70.5**	**357.6**	**88.4**	388.6
RAZ_loc [19]	✔	128.7	665.4	151.4	634.6
AutoScale_loc [46]	✔	97.3	571.2	123.9	515.5
TopoCount [1]	✔	-	-	107.8	438.5
GL [39]	✔	-	-	79.3	346.1
CLTR (**ours**)	✔	**61.9**	**246.3**	**74.3**	**333.8**

Counting performance on NWPU dataset.

VISUALIZATIONS



Some examples from the NWPU dataset. From left to right, there are images, GT points, predicted points, and localization results.

ACKNOWLEDGEMENT

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