ByteDance UCF Center for Research in Computer Vision

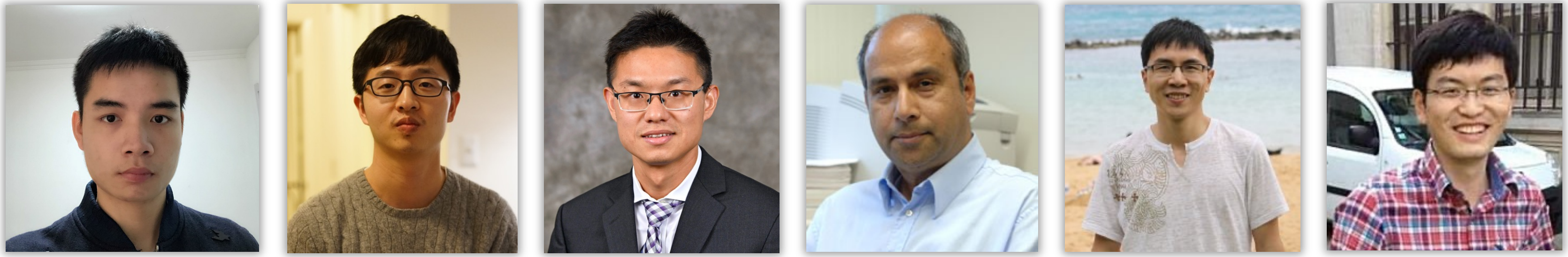
JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

THU-AM-275 Highlight

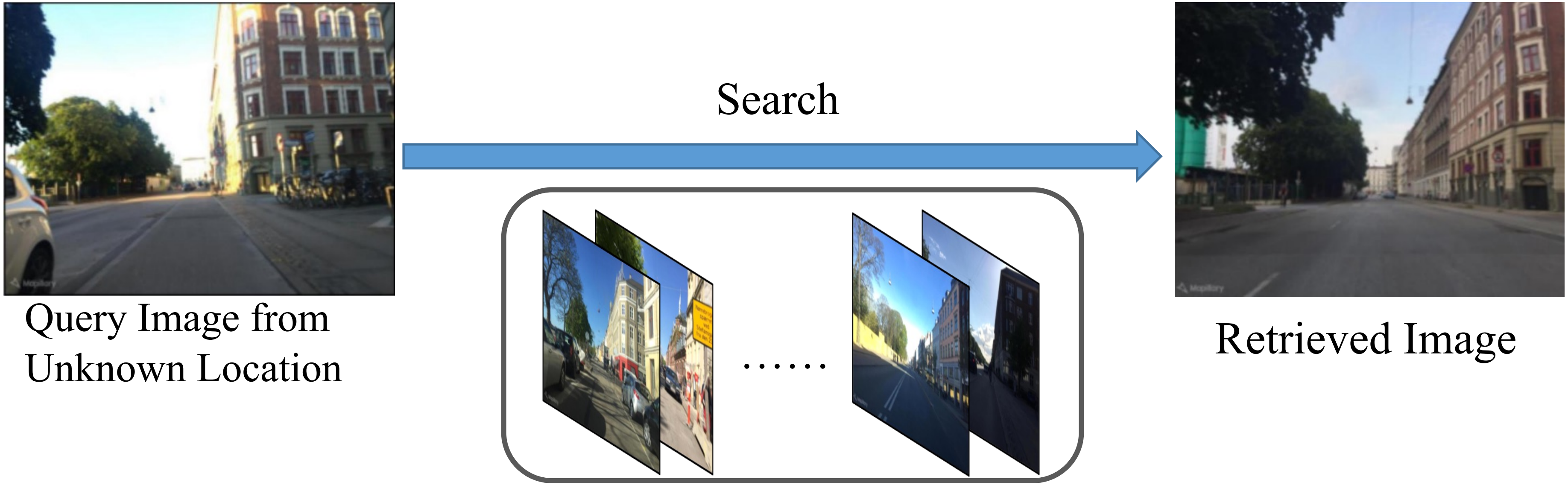
$R^2 Former$: Unified *R*etrieval and *R*eranking Transformer for Place Recognition

Sijie Zhu[1,2], Linjie Yang[1], Chen Chen[2], Mubarak Shah[2], Xiaohui Shen[1], Heng Wang[1]

[1]ByteDance [2]Center for Research in Computer Vision, University of Central Florida



Visual Geo-localization/Place Recognition



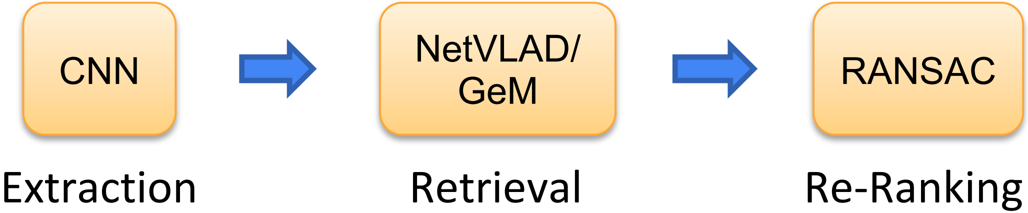
Search

Query Image from
Unknown Location

Retrieved Image

Reference Images from
Known Locations

Retrieval + Reranking



CNN → NetVLAD/ GeM → RANSAC

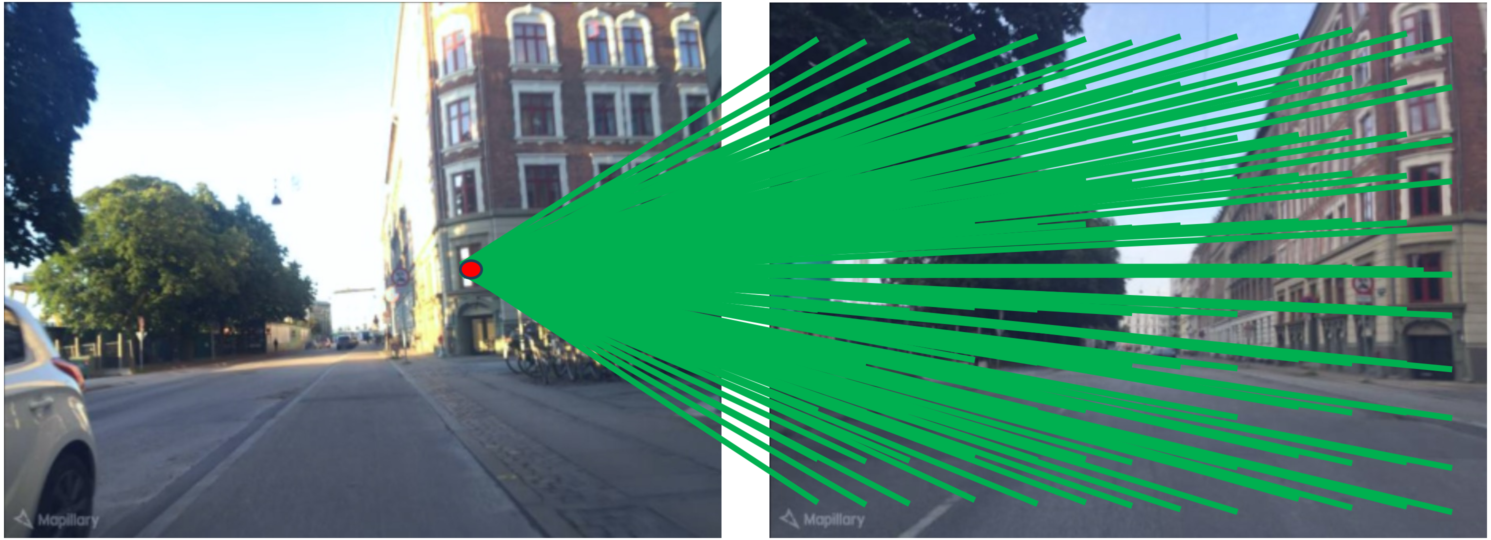
Extraction

Retrieval

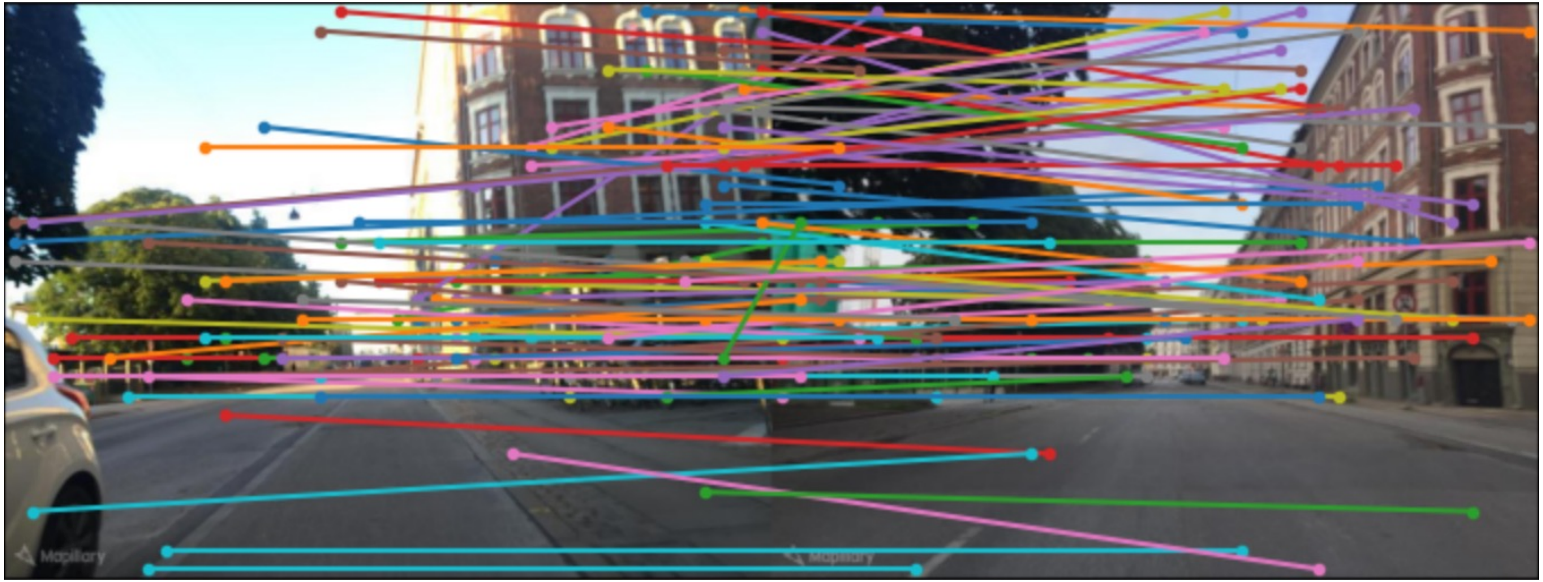
Re-Ranking

MSLS	R@1
ResNet50+GeM	79.6
ResNet50+GeM+RANSAC	84.3

RANSAC



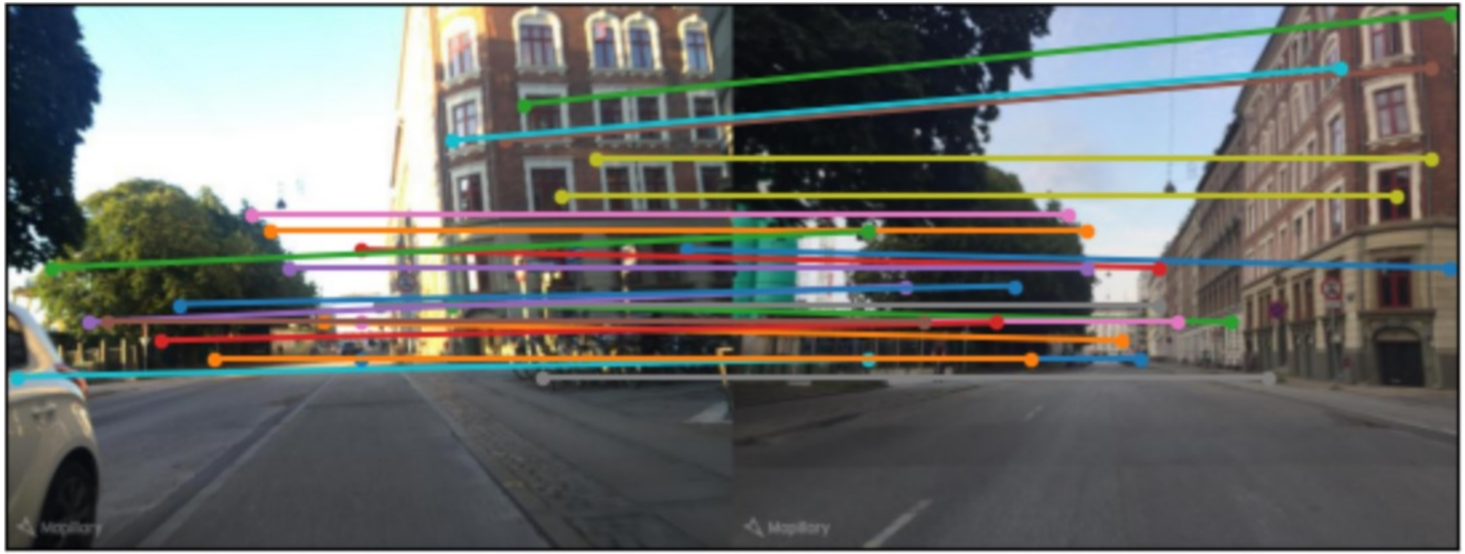
RANSAC



$$\begin{bmatrix} x_1 & y_1 & \widehat{x_1} & \widehat{y_1} \\ \vdots & \vdots & \vdots & \vdots \\ x_n & y_n & \widehat{x_n} & \widehat{y_n} \end{bmatrix}$$

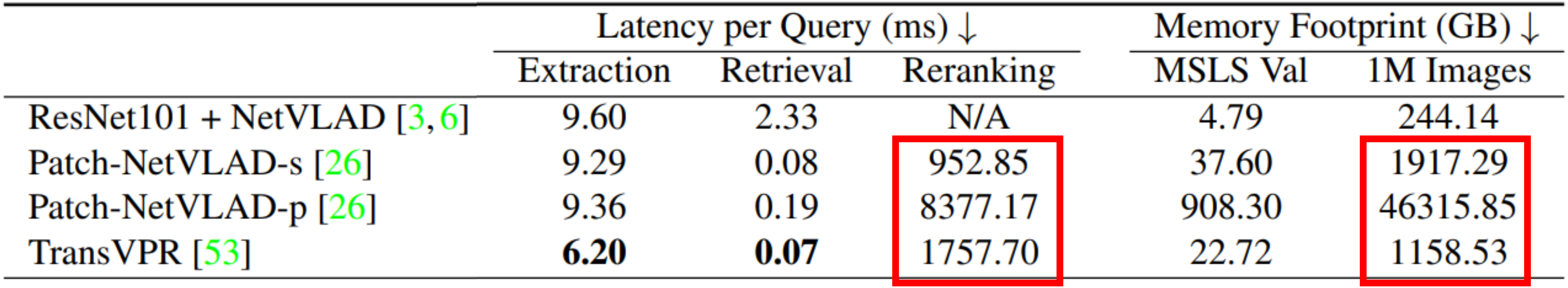
Only take x,y coronates as input. (Geometric Information)

RANSAC is not optimal for reranking



Correlation/similarity and attention information are not considered.

RANSAC is not optimal for reranking

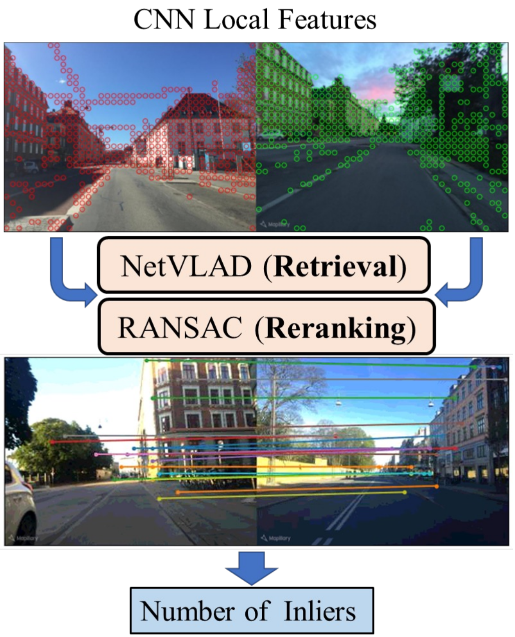


	Latency per Query (ms) ↓			Memory Footprint (GB) ↓	
	Extraction	Retrieval	Reranking	MSLS Val	1M Images
ResNet101 + NetVLAD [3,6]	9.60	2.33	N/A	4.79	244.14
Patch-NetVLAD-s [26]	9.29	0.08	952.85	37.60	1917.29
Patch-NetVLAD-p [26]	9.36	0.19	8377.17	908.30	46315.85
TransVPR [53]	**6.20**	**0.07**	1757.70	22.72	1158.53

>1 s

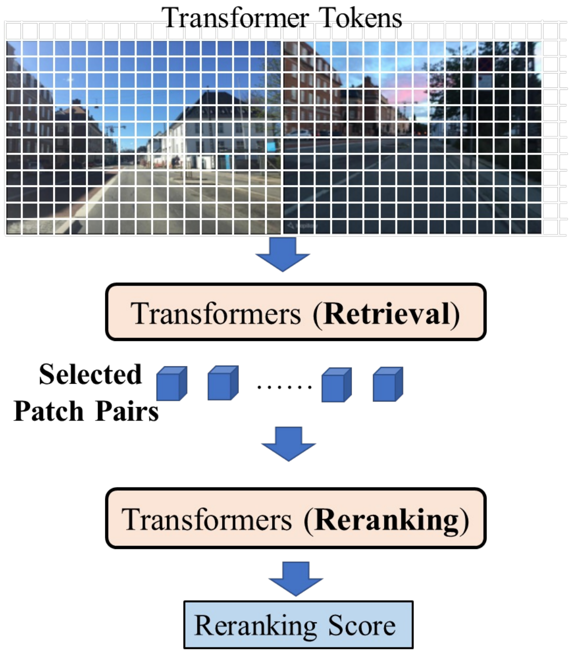
>1000GB

A Unified Solution with Only Transformers

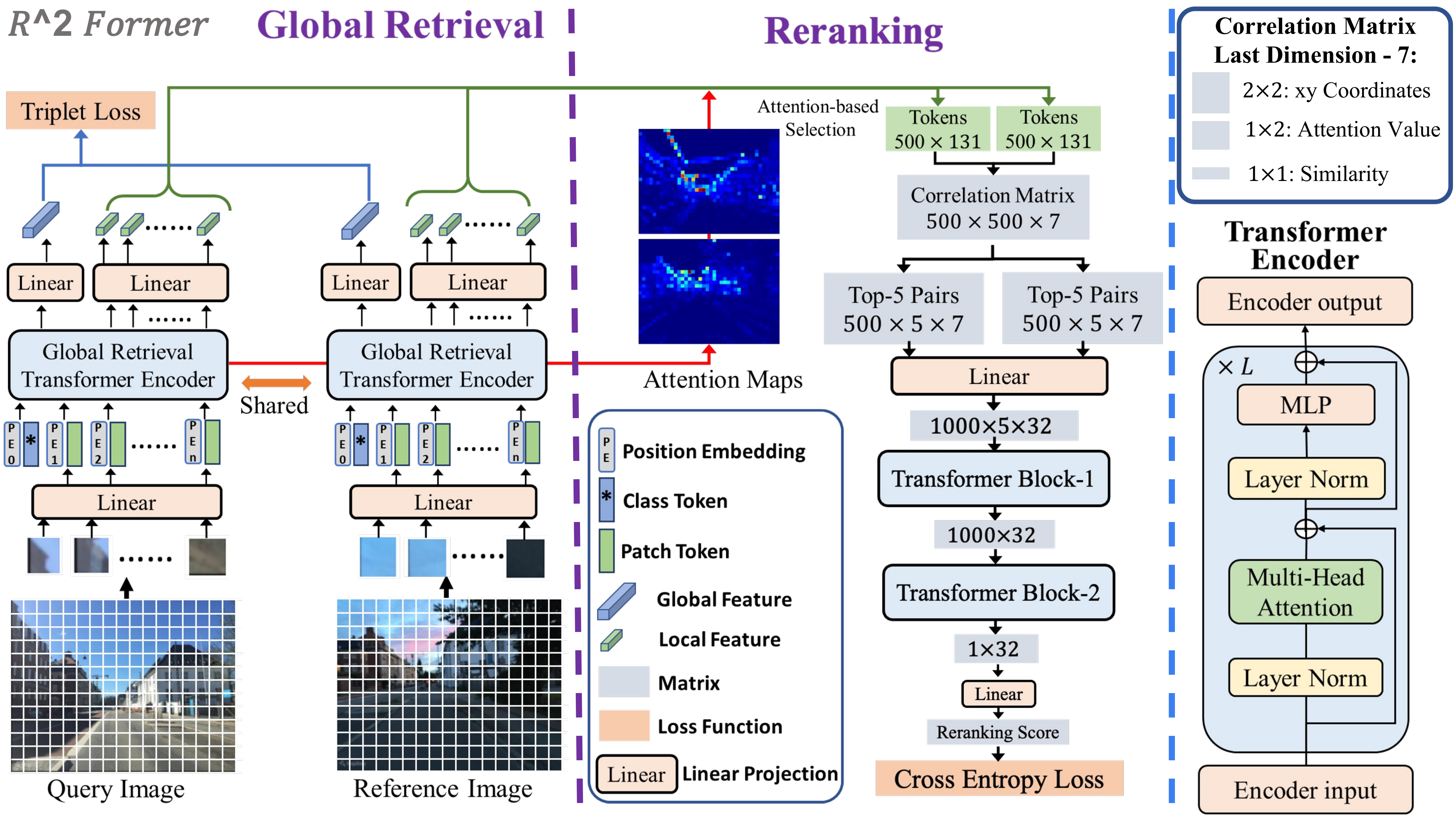


(a) Conventional Pipeline

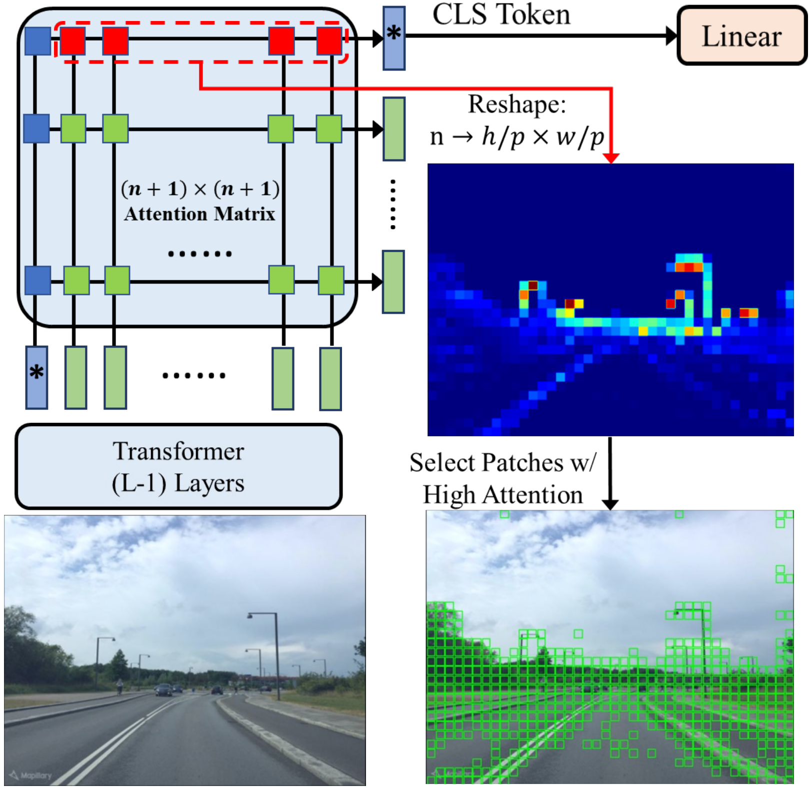
- ✗ End-to-end Learnable ✓
- ✗ Beyond Geometry ✓
- ✗ Real-time Deployment ✓



(b) Our Unified Framework


R^2 Former
Global Retrieval
Reranking
Triplet Loss
Linear
Linear
Linear
Linear
Global Retrieval Transformer Encoder
Global Retrieval Transformer Encoder
Shared
P E 0
*
P E 1
P E 2
P E n
Linear
Linear
Query Image
Reference Image
Attention-based Selection
Attention Maps
Tokens 500 × 131
Tokens 500 × 131
Correlation Matrix 500 × 500 × 7
Top-5 Pairs 500 × 5 × 7
Top-5 Pairs 500 × 5 × 7
Linear
1000×5×32
Transformer Block-1
1000×32
Transformer Block-2
1×32
Linear
Reranking Score
Cross Entropy Loss
P E
Position Embedding
*
Class Token
Patch Token
Global Feature
Local Feature
Matrix
Loss Function
Linear
Linear Projection
Correlation Matrix Last Dimension - 7:
2×2: xy Coordinates
1×2: Attention Value
1×1: Similarity
Transformer Encoder
Encoder output
× L
MLP
Layer Norm
Multi-Head Attention
Layer Norm
Encoder input

Attention Map



CLS Token

Linear

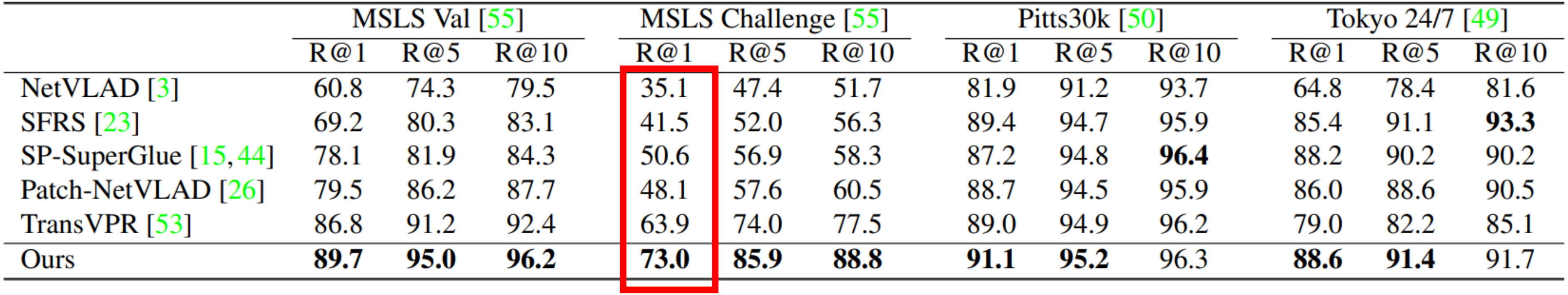
Reshape:
n → $h/p \times w/p$

$(n+1) \times (n+1)$
Attention Matrix

Transformer
(L-1) Layers

Select Patches w/
High Attention

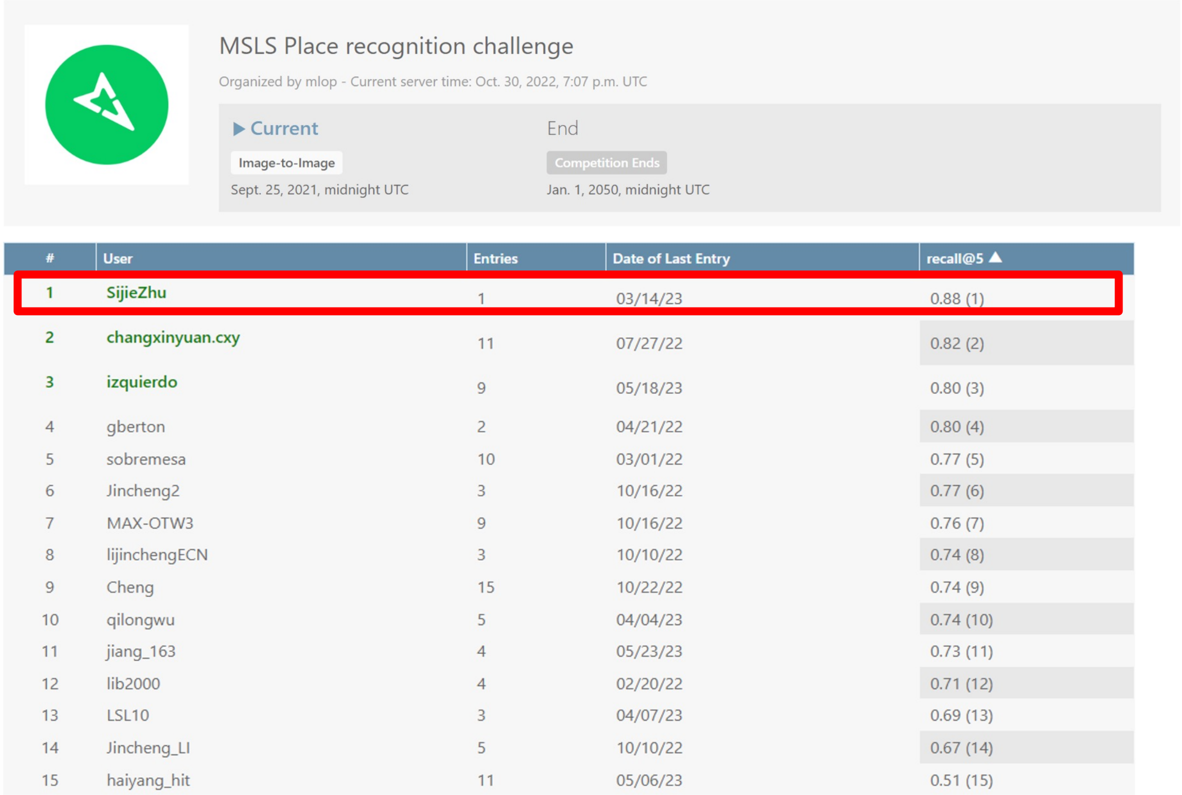
Performance on Major Datasets



	MSLS Val [55]			MSLS Challenge [55]			Pitts30k [50]			Tokyo 24/7 [49]		
	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10	R@1	R@5	R@10
NetVLAD [3]	60.8	74.3	79.5	35.1	47.4	51.7	81.9	91.2	93.7	64.8	78.4	81.6
SFRS [23]	69.2	80.3	83.1	41.5	52.0	56.3	89.4	94.7	95.9	85.4	91.1	**93.3**
SP-SuperGlue [15, 44]	78.1	81.9	84.3	50.6	56.9	58.3	87.2	94.8	**96.4**	88.2	90.2	90.2
Patch-NetVLAD [26]	79.5	86.2	87.7	48.1	57.6	60.5	88.7	94.5	95.9	86.0	88.6	90.5
TransVPR [53]	86.8	91.2	92.4	63.9	74.0	77.5	89.0	94.9	96.2	79.0	82.2	85.1
Ours	**89.7**	**95.0**	**96.2**	**73.0**	**85.9**	**88.8**	**91.1**	**95.2**	96.3	**88.6**	**91.4**	91.7

+9.1%

Top-1 Result on MSLS Challenge



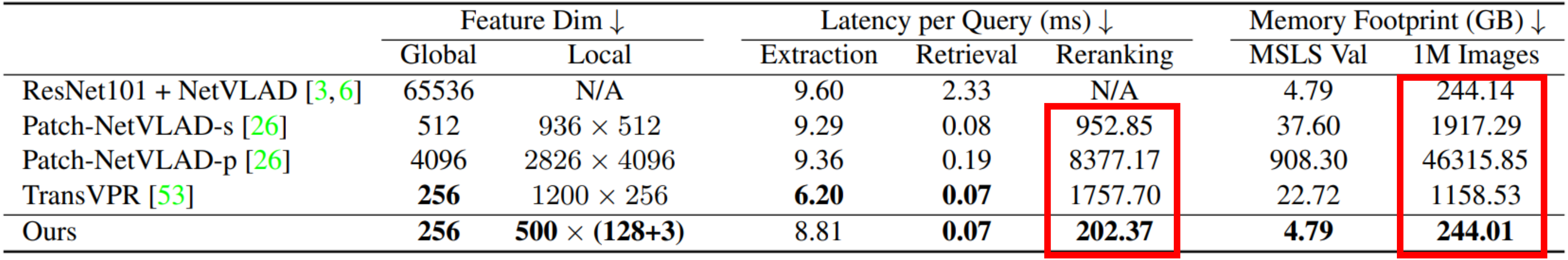
MSLS Place recognition challenge

Organized by mlop - Current server time: Oct. 30, 2022, 7:07 p.m. UTC

▶ Current	End
Image-to-Image	Competition Ends
Sept. 25, 2021, midnight UTC	Jan. 1, 2050, midnight UTC

#	User	Entries	Date of Last Entry	recall@5 ▲
1	SijieZhu	1	03/14/23	0.88 (1)
2	changxinyuan.cxy	11	07/27/22	0.82 (2)
3	izquierdo	9	05/18/23	0.80 (3)
4	gberton	2	04/21/22	0.80 (4)
5	sobremesa	10	03/01/22	0.77 (5)
6	Jincheng2	3	10/16/22	0.77 (6)
7	MAX-OTW3	9	10/16/22	0.76 (7)
8	lijinchengECN	3	10/10/22	0.74 (8)
9	Cheng	15	10/22/22	0.74 (9)
10	qilongwu	5	04/04/23	0.74 (10)
11	jiang_163	4	05/23/23	0.73 (11)
12	lib2000	4	02/20/22	0.71 (12)
13	LSL10	3	04/07/23	0.69 (13)
14	Jincheng_LI	5	10/10/22	0.67 (14)
15	haiyang_hit	11	05/06/23	0.51 (15)

Computational Efficiency

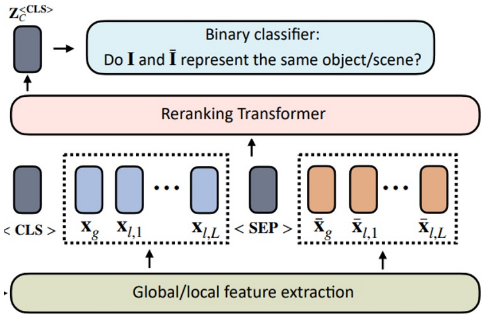


	Feature Dim ↓		Latency per Query (ms) ↓			Memory Footprint (GB) ↓	
	Global	Local	Extraction	Retrieval	Reranking	MSLS Val	1M Images
ResNet101 + NetVLAD [3,6]	65536	N/A	9.60	2.33	N/A	4.79	244.14
Patch-NetVLAD-s [26]	512	936 × 512	9.29	0.08	952.85	37.60	1917.29
Patch-NetVLAD-p [26]	4096	2826 × 4096	9.36	0.19	8377.17	908.30	46315.85
TransVPR [53]	**256**	1200 × 256	**6.20**	**0.07**	1757.70	22.72	1158.53
Ours	**256**	**500 × (128+3)**	8.81	**0.07**	**202.37**	**4.79**	**244.01**

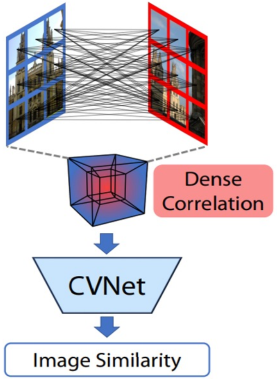
×4.7 Faster

22% Cost

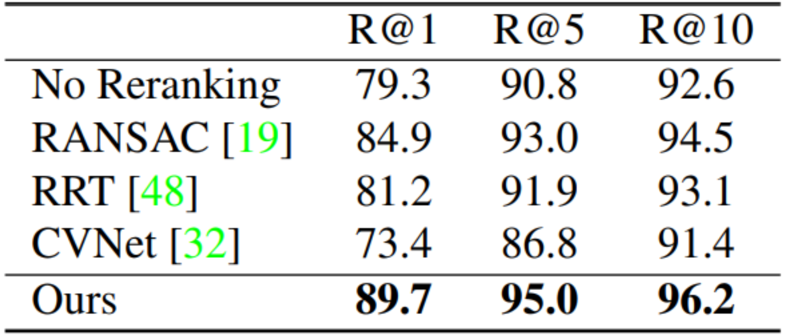
Comparison with Other Reranking Methods



RRT (Reranking Transformer)

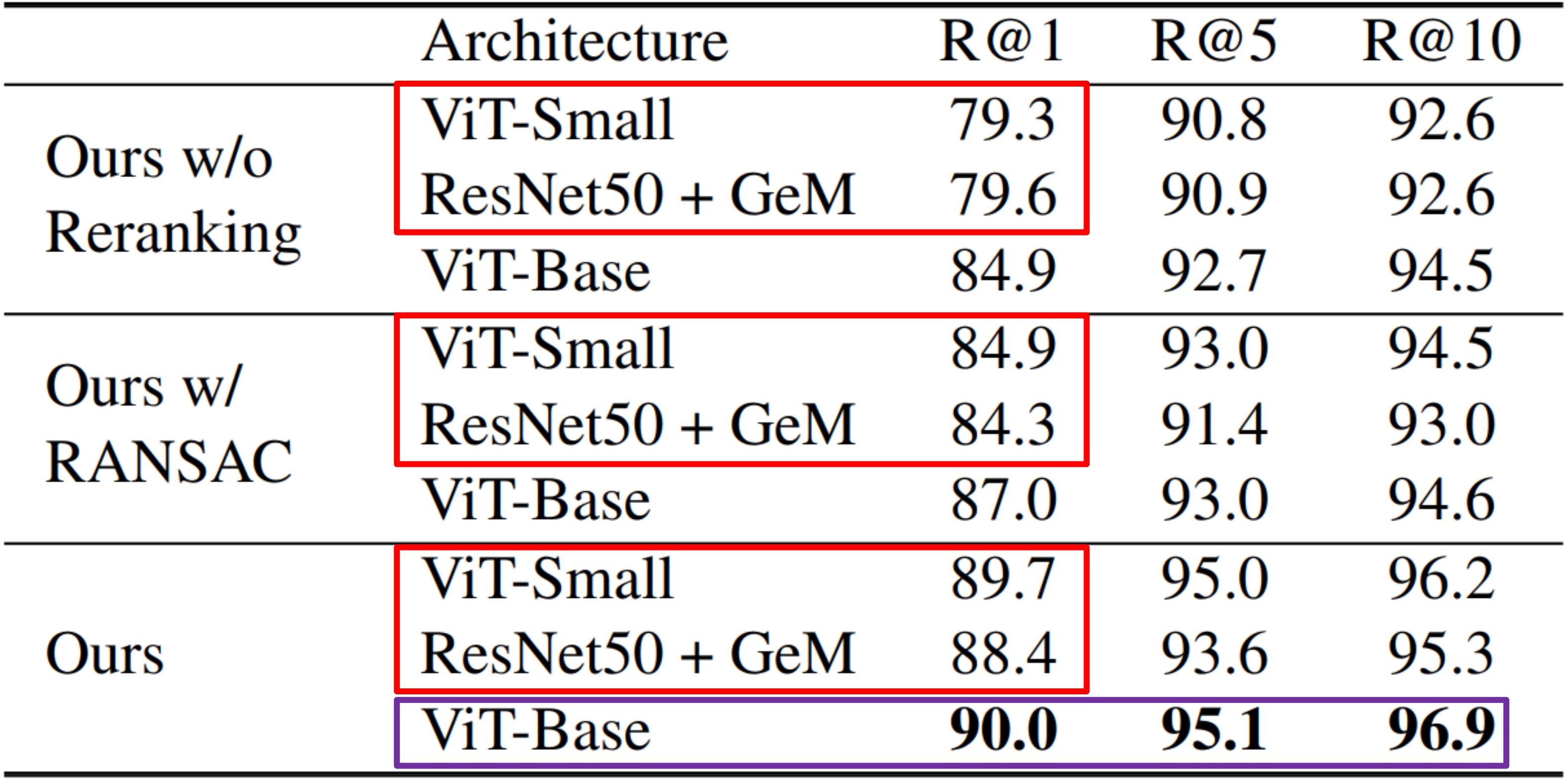


CVNet (Correlation Verification)



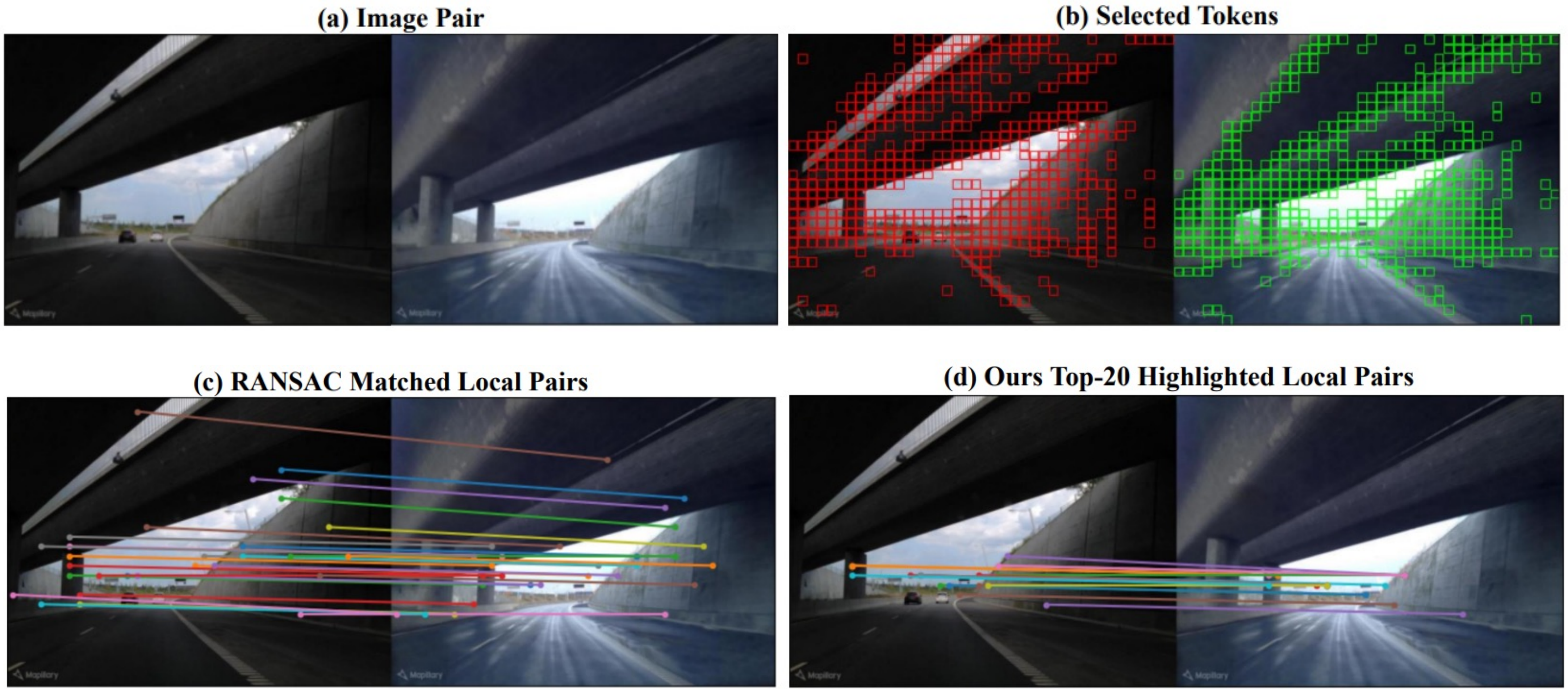
	R@1	R@5	R@10
No Reranking	79.3	90.8	92.6
RANSAC [19]	84.9	93.0	94.5
RRT [48]	81.2	91.9	93.1
CVNet [32]	73.4	86.8	91.4
Ours	**89.7**	**95.0**	**96.2**

Transformer Token vs CNN Local Feature



	Architecture	R@1	R@5	R@10
Ours w/o Reranking	ViT-Small	79.3	90.8	92.6
	ResNet50 + GeM	79.6	90.9	92.6
	ViT-Base	84.9	92.7	94.5
Ours w/ RANSAC	ViT-Small	84.9	93.0	94.5
	ResNet50 + GeM	84.3	91.4	93.0
	ViT-Base	87.0	93.0	94.6
Ours	ViT-Small	89.7	95.0	96.2
	ResNet50 + GeM	88.4	93.6	95.3
	ViT-Base	**90.0**	**95.1**	**96.9**

Interpretability



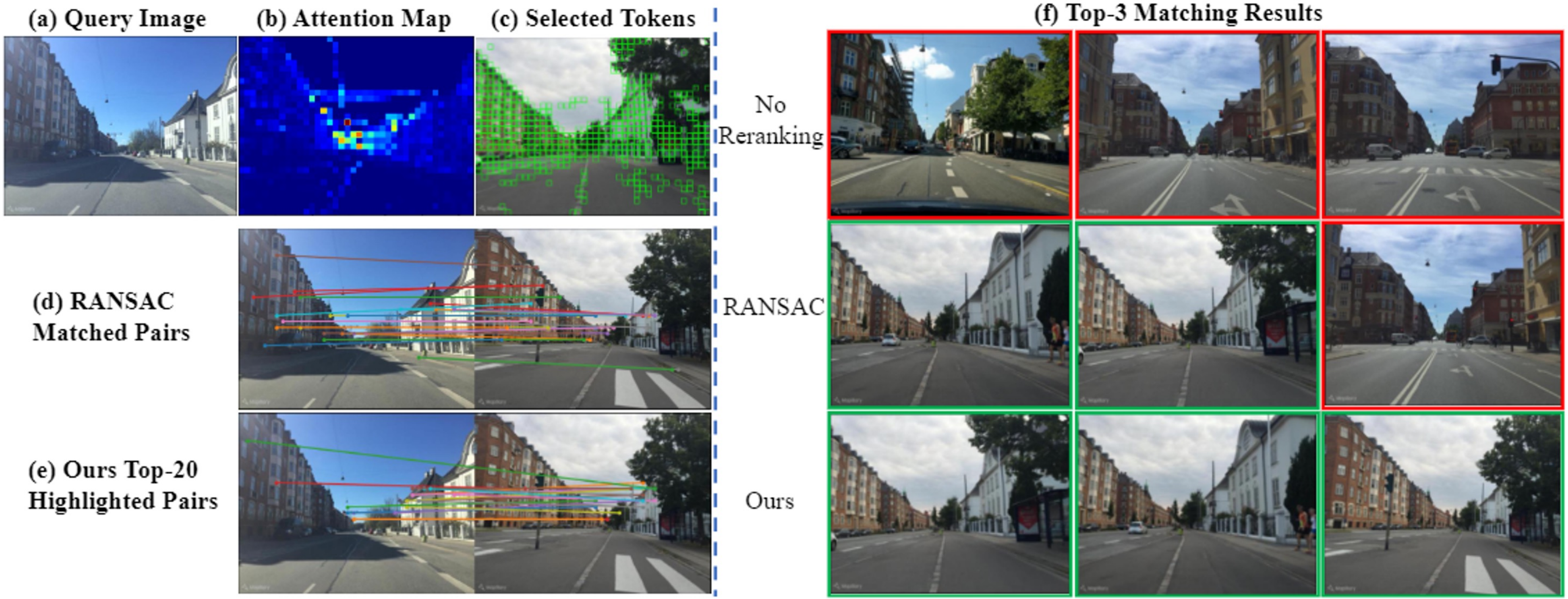
(a) Image Pair

(b) Selected Tokens

(c) RANSAC Matched Local Pairs

(d) Ours Top-20 Highlighted Local Pairs

Case Study


(a) Query Image
(b) Attention Map
(c) Selected Tokens
(f) Top-3 Matching Results
No Reranking
(d) RANSAC Matched Pairs
RANSAC
(e) Ours Top-20 Highlighted Pairs
Ours

Summary

- A unified retrieval and reranking framework for place recognition employing only transformers, which demonstrates that vision transformer tokens are comparable and sometimes better than CNN local features in terms of reranking or local matching.

- A novel transformer-based reranking module that learns to attend to the correlation of informative local feature pairs. It can be combined with either CNN or transformer backbones with better performance and efficiency than other reranking methods, e.g. RANSAC.

- Code: https://github.com/Jeff-Zilence/R2Former

Thank You!

UCF