Learning Disentangled Geometric Layout Correspondence for Cross-View Geo-localization

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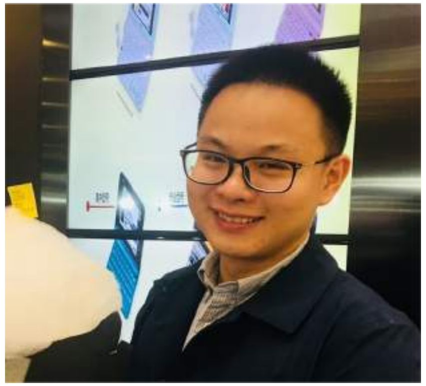

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Information Technology University

Information Technology University, Pakistan

Image geo-localization

Query Image

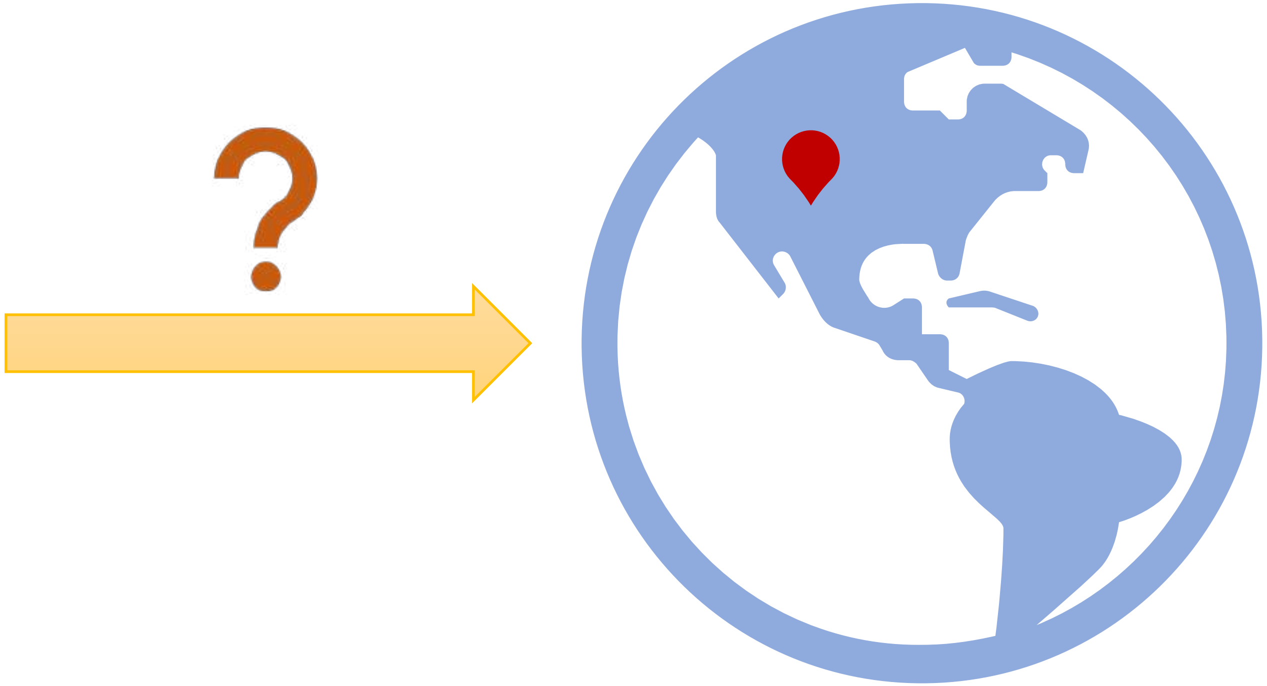

Image and Object Geo-localization

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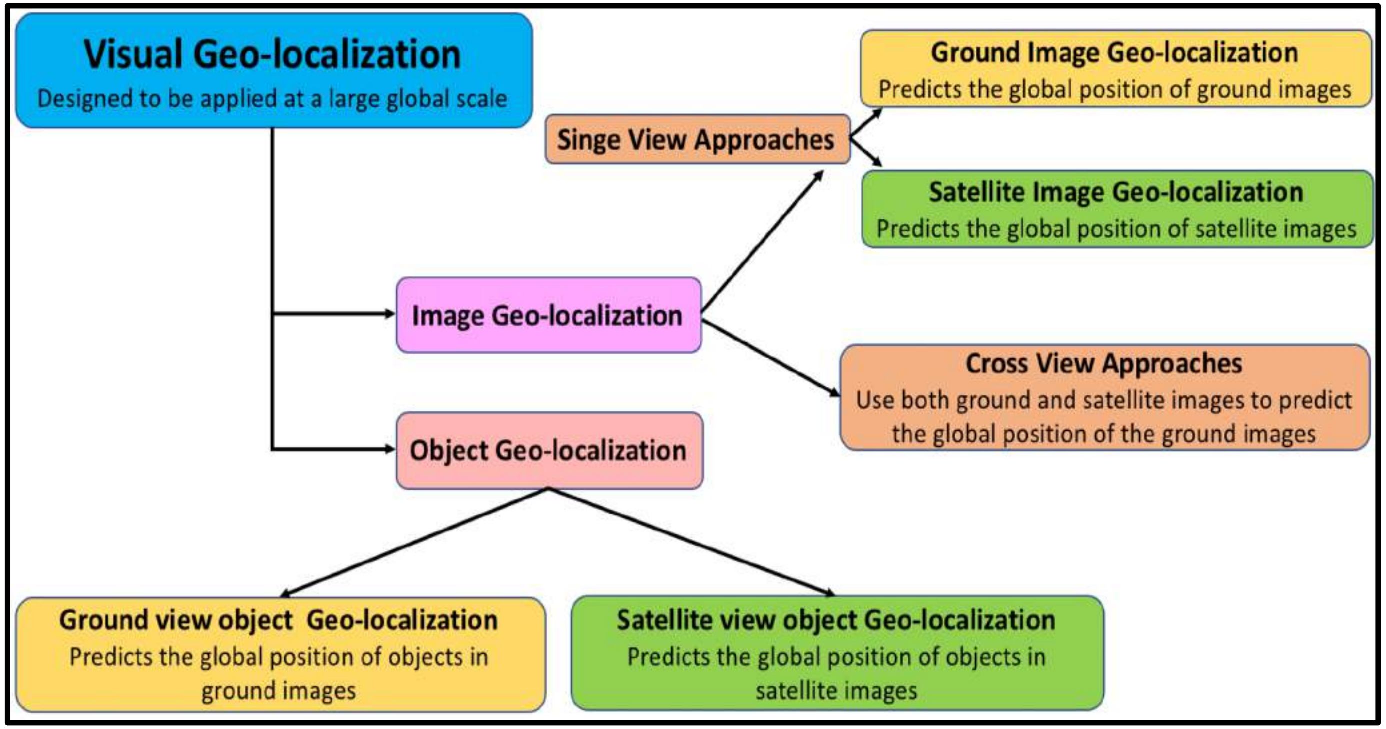
- **Visual Geo-localization**
  Designed to be applied at a large global scale
  - **Image Geo-localization**
    - **Singe View Approaches**
      - **Ground Image Geo-localization**
        Predicts the global position of ground images
      - **Satellite Image Geo-localization**
        Predicts the global position of satellite images
    - **Cross View Approaches**
      Use both ground and satellite images to predict the global position of the ground images
  - **Object Geo-localization**
    - **Ground view object Geo-localization**
      Predicts the global position of objects in ground images
    - **Satellite view object Geo-localization**
      Predicts the global position of objects in satellite images

Daniel Wilson, Xiaohan Zhang, **Waqas Sultani**, Safwan Wshah, "**Visual and Object Geo-localization: A Comprehensive Survey**", arXiv preprint arXiv:2112.15202

Image and Object Geo-localization



Daniel Wilson, Xiaohan Zhang, **Waqas Sultani**, Safwan Wshah, "**Visual and Object Geo-localization: A Comprehensive Survey**", arXiv preprint arXiv:2112.15202

Visual localization

Designed to be applied at a small scale

Object Localization

Predicts position of the object within the image

Camera Pose Estimation

Predicts pose of camera locally

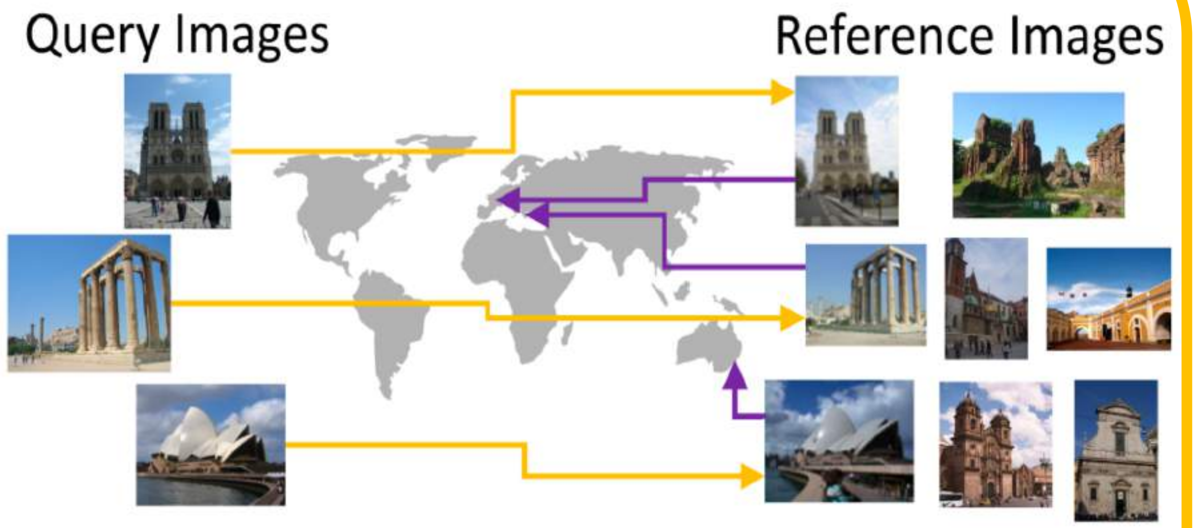
SLAM

Constructs a map of the surrounding environment, typically in real time

Image Geo-localization

Ground-view Geo-localization

Cross-view Geo-localization



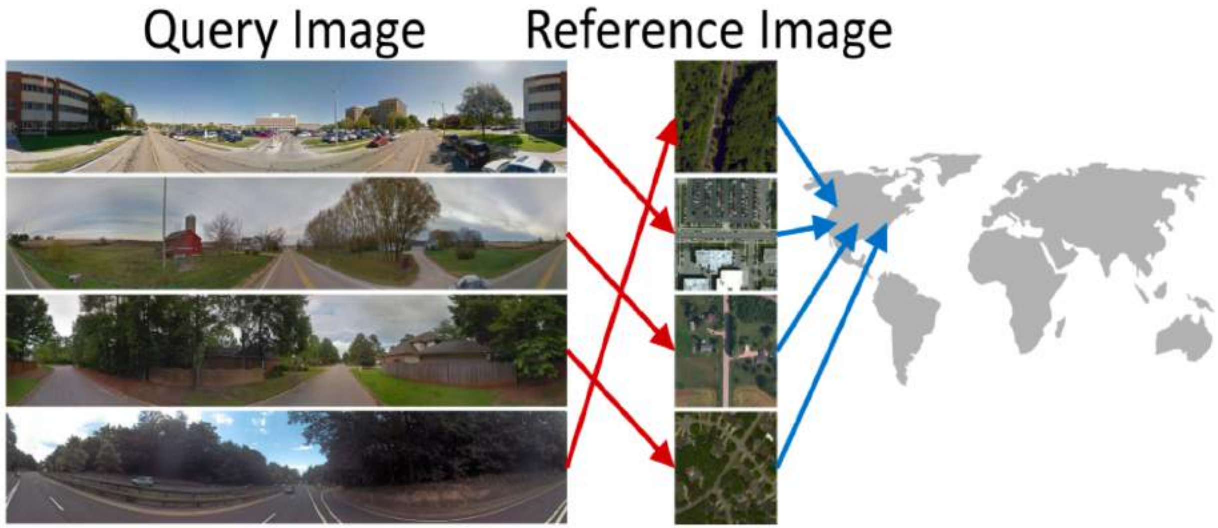
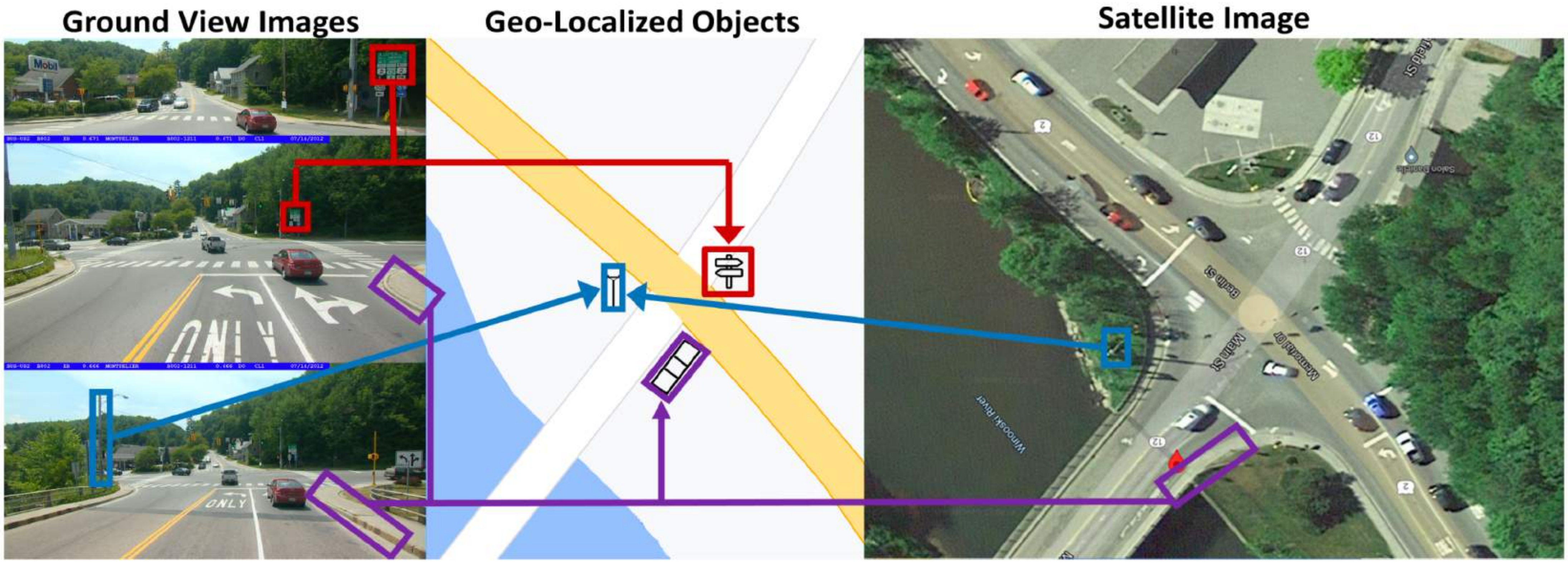


Image Geo-localization

Object Geo-localization



Cross-view image geo-localization

Query Image

Reference database

Challenges in cross-view geo-localization:

- Drastic view changes
- Different capturing time
- Different object resolution

Cross-view image geo-localization

Query Image

Reference database

Challenges in cross-view geo-localization:

- Drastic view changes
- Different capturing time
- Different object resolution

Limitations

- The performance of cross-view geo-localization methods **degrades on cross-area benchmarks**.
- Lack of ability to extract the spatial configuration of visual feature layout.
- Models overfit the low-level details from the training set.

Key Idea

- ✓ **Explicitly disentangle geometric information from the raw features**
- ✓ **Learn the spatial correlations among visual features from aerial and ground pairs**

Xiaohan Zhang, Xingyu Li, **Waqas Sultani**, Yi Zhou, Safwan Wshah, “**Learning Disentangled Geometric Layout Correspondence for Cross-View Geo-localization”,** AAAI 2023 (Oral).

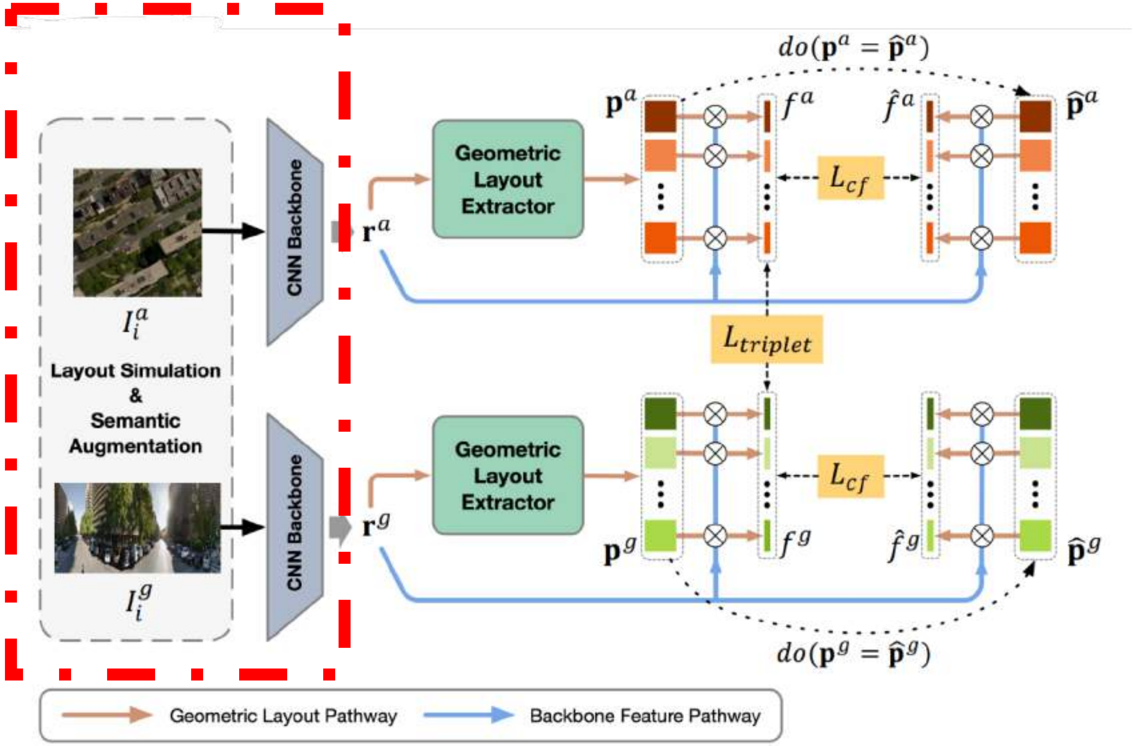
Overview

- ✓ GeoDTR module generates a set of geometric layout descriptors which produce a high quality latent representations.

- ✓ Analysis the effect of data augmentation for improved cross-area cross-view geo-localization performance.

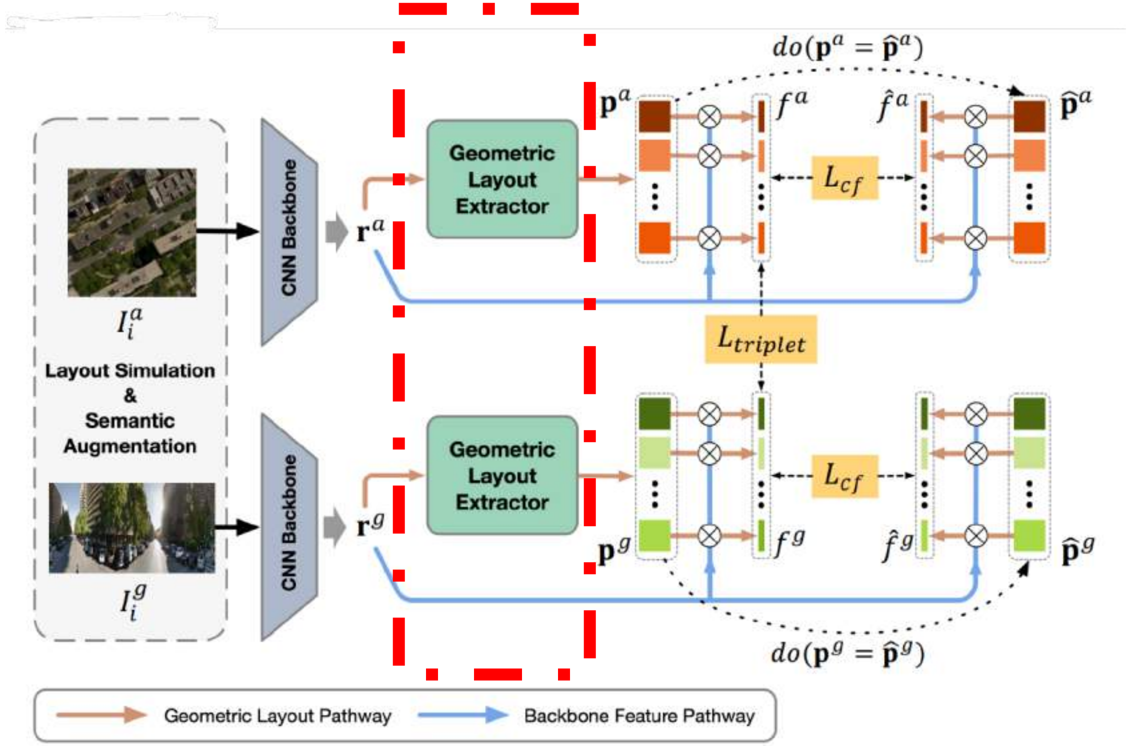
- ✓ To help geometric layout descriptor in exploring spatial information, we propose to employ counterfactual-based learning process.

GeoDTR Overview



1. CNN backbones extract raw features $r^{a(g)}$ from input images $I_i^{a(g)}$ augmented by Layout simulation and Semantic augmentation (LS).

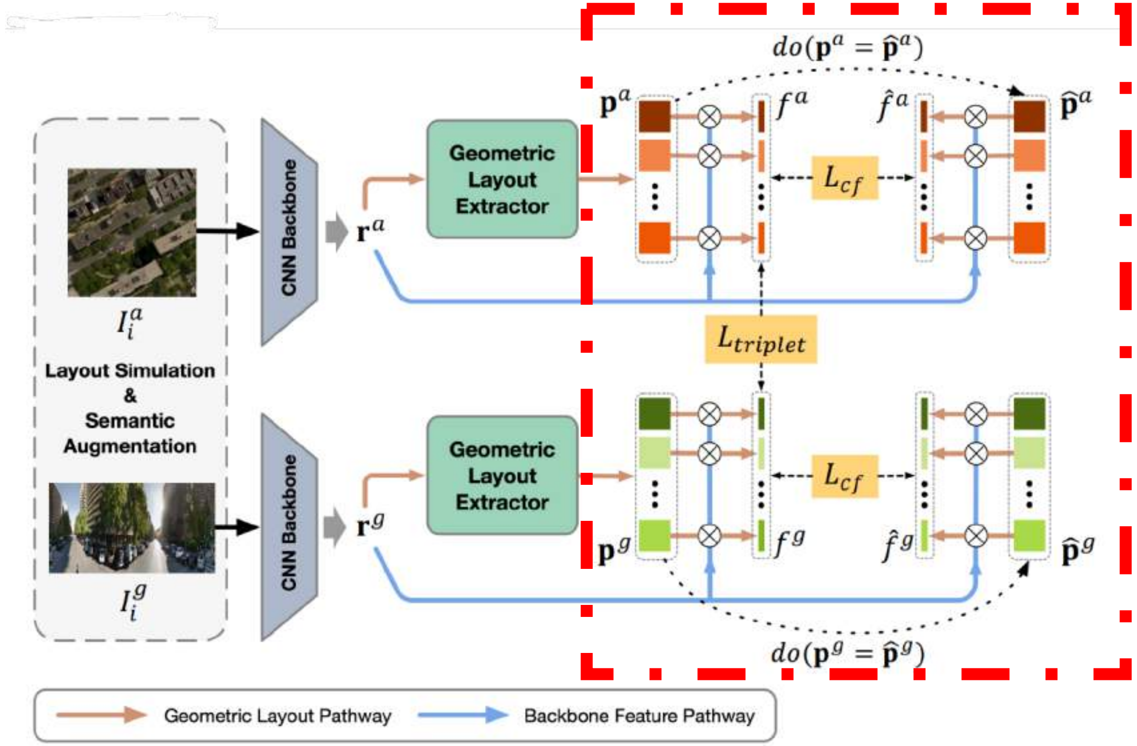
GeoDTR Overview



1. CNN backbones extract raw features $\mathrm{r}^{a(g)}$ from input images $I_i^{a(g)}$ augmented by Layout simulation and Semantic augmentation (LS).

2. $\mathrm{r}^{a(g)}$ are then passed to Geometric Layout Pathway to get layout descriptors $\mathrm{P}^{a(g)}$ and Backbone Feature Pathway to produce latent feature $f^{a(g)}$ by Frobenius product.

GeoDTR Overview



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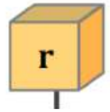
2. $\mathrm{r}^{a(g)}$ are then passed to Geometric Layout Pathway to get layout descriptors $\mathrm{P}^{a(g)}$ and Backbone Feature Pathway to produce latent feature $f^{a(g)}$ by Frobenius product.

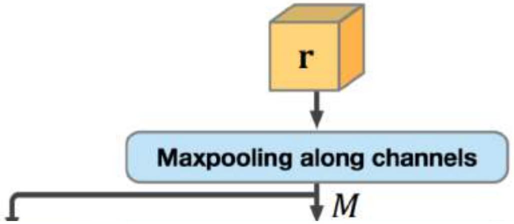
3. A Counterfactual learning paradigm is adopted to generate a counterfactual descriptors $\widehat{\mathrm{P}}^{a(g)}$.

Geometric layout extractor



Geometric Layout Extractor takes raw feature r extracted by backbone as input.

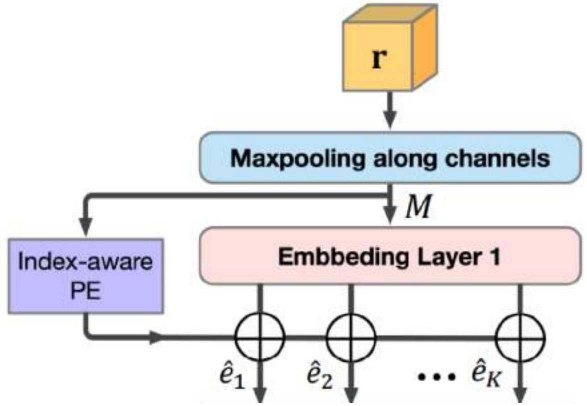
Geometric layout extractor



Geometric Layout Extractor takes raw feature r extracted by backbone as input.

A max pooling layer along channel is applied to obtain Saliency feature map M

Geometric layout extractor

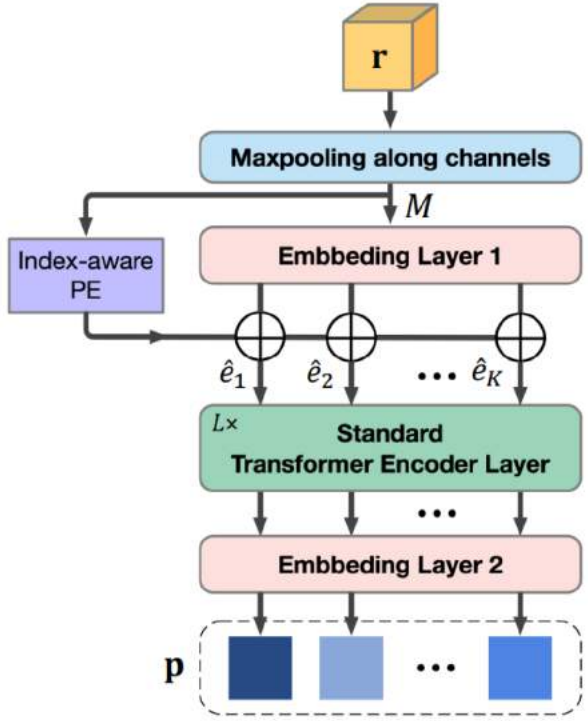


Geometric Layout Extractor takes raw feature r extracted by backbone as input.

A max pooling layer along channel is applied to obtain Saliency feature map M

An embedding layer projects M into K subspaces. Then combined with index-aware position encoding and K embedding vectors to get $\mathrm{E} = [e_1, e_2, \dots e_K]$.

Geometric layout extractor



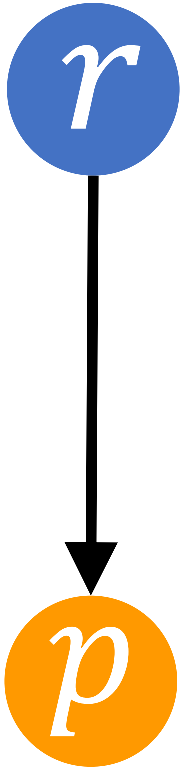
Geometric Layout Extractor takes raw feature r extracted by backbone as input.

A max pooling layer along channel is applied to obtain Saliency feature map M

An embedding layer projects M into K subspaces. Then combined with index-aware position encoding and K embedding vectors to get $\mathrm{E} = [e_1, e_2, \dots e_K]$.

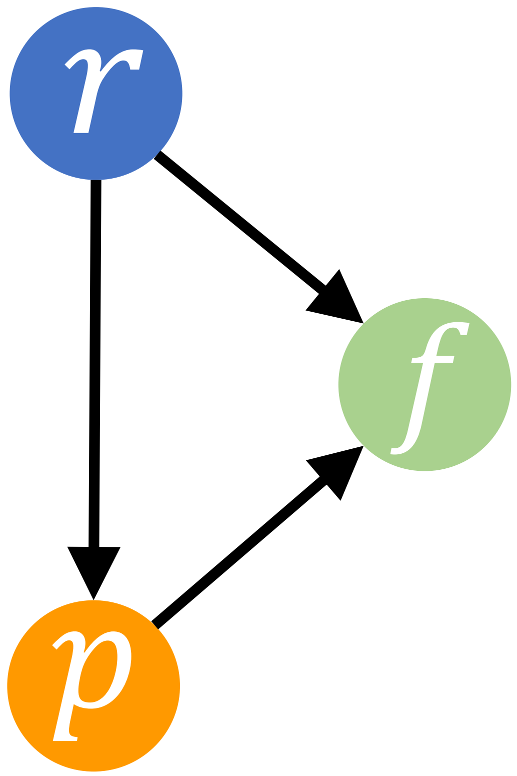
Finally, a transformer is applied to explore correlations in E. After the transformer, another embedding layer produces geometric layout descriptors P.

Counterfactual-based learning process



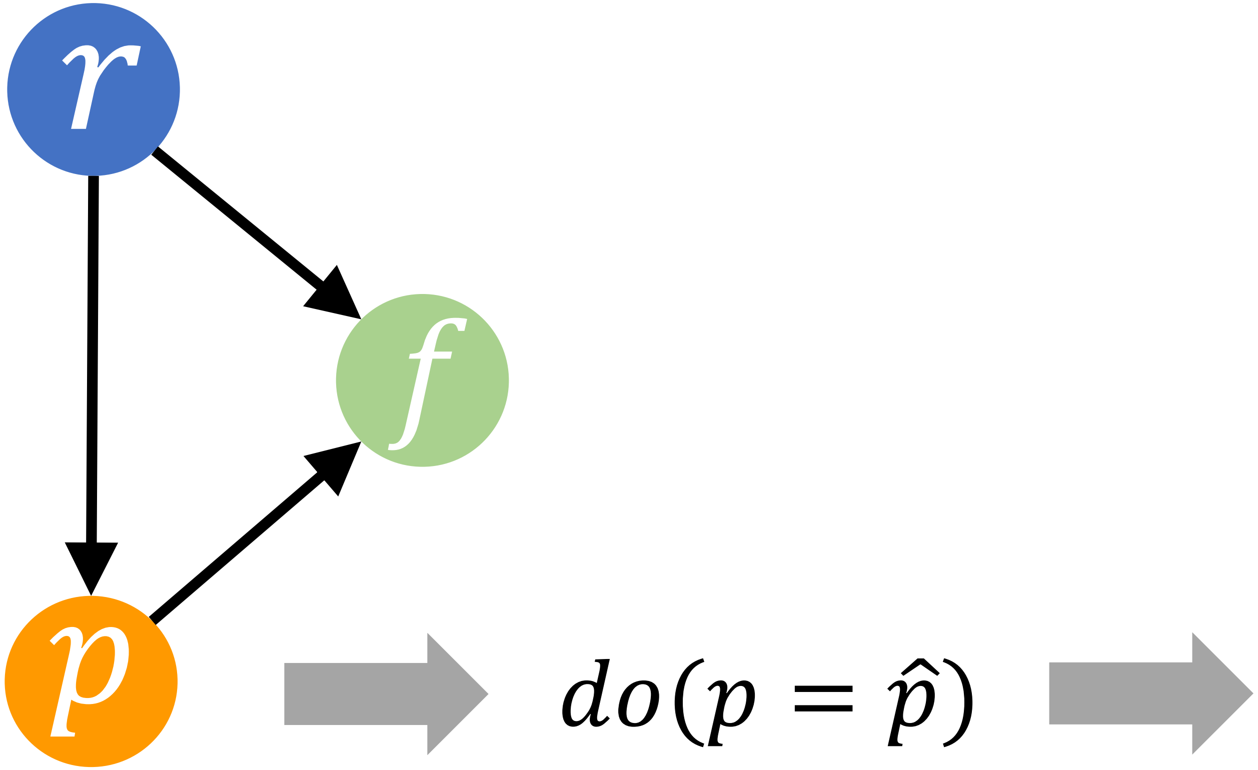
$\boldsymbol{p}$ is obtained from $\boldsymbol{r}$ by geometric layout extractor

Counterfactual-based learning process



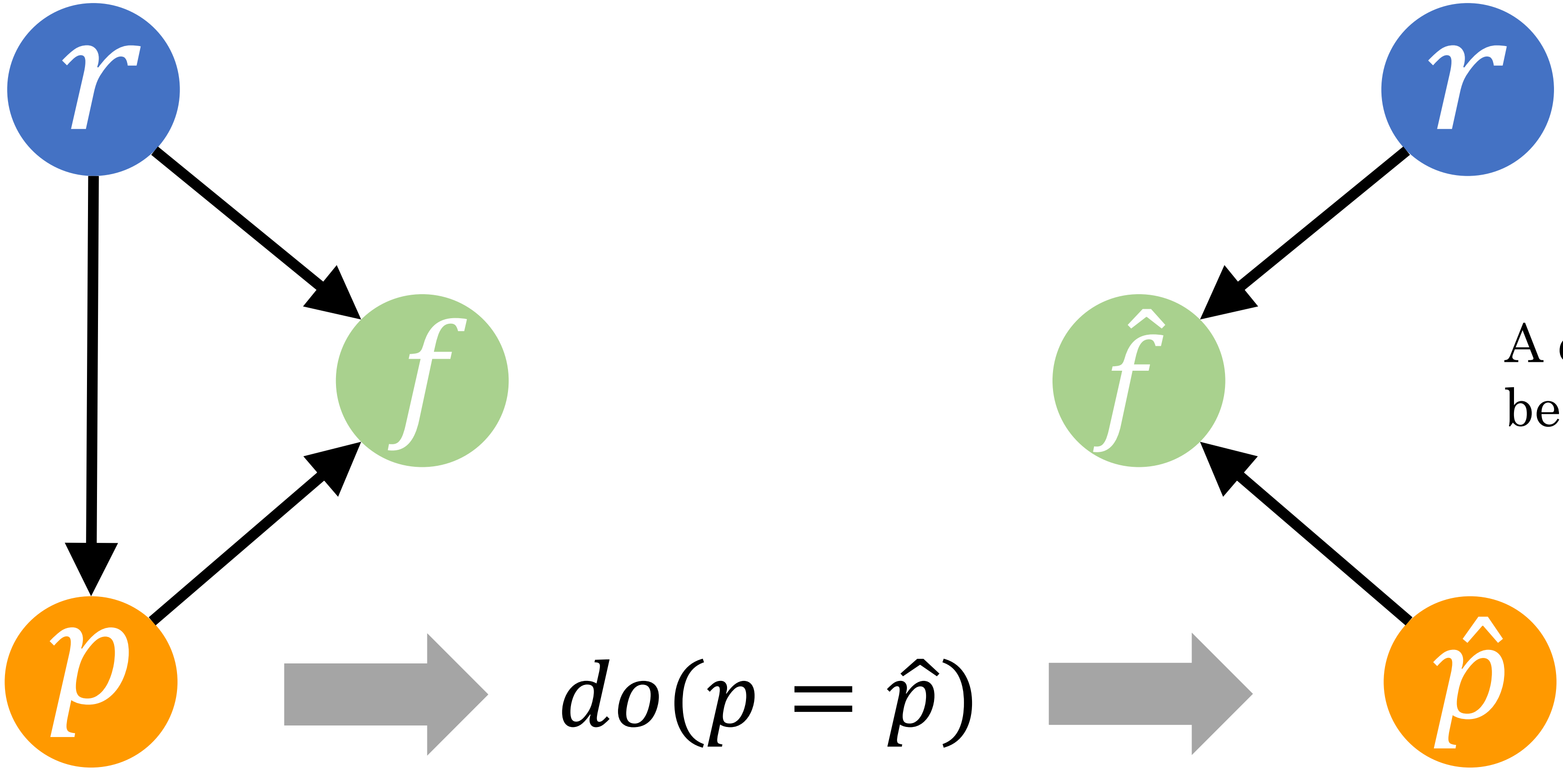
$\boldsymbol{f}$ is the Frobenius product of $\boldsymbol{r}$ and $\boldsymbol{p}$.

Counterfactual-based learning process



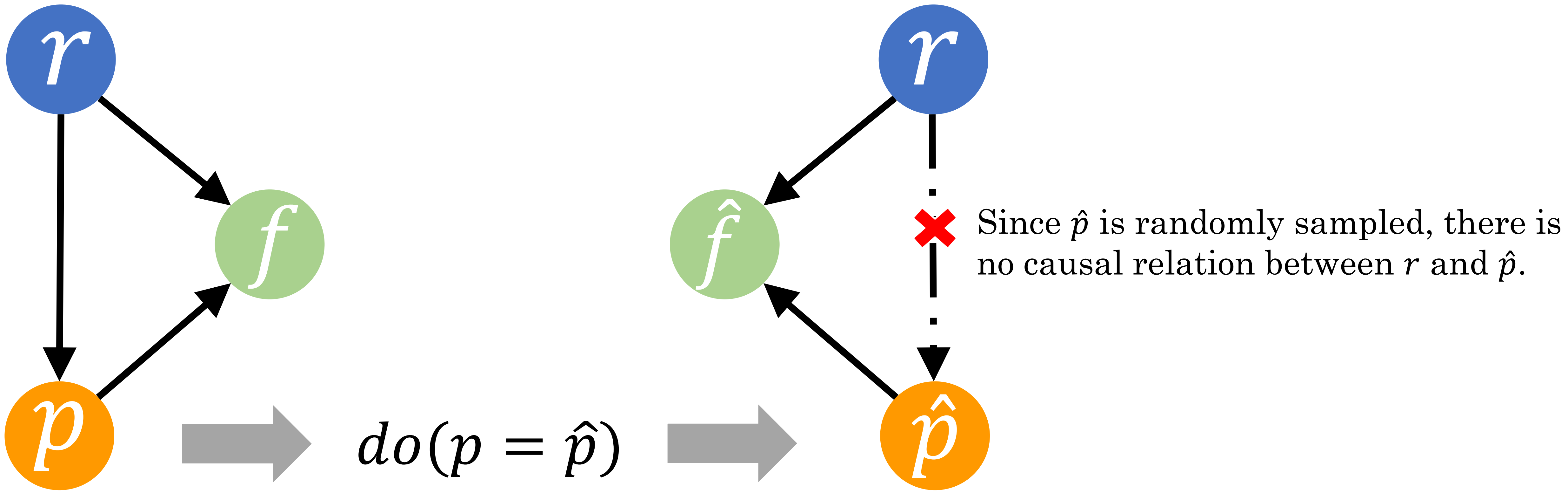
An intervention $\boldsymbol{do}(\boldsymbol{p} = \widehat{\boldsymbol{p}})$ is applied on $\boldsymbol{p}$ which replaces $\boldsymbol{p}$ into randomly sampled vectors $\widehat{\boldsymbol{p}}$.

Counterfactual-based learning process

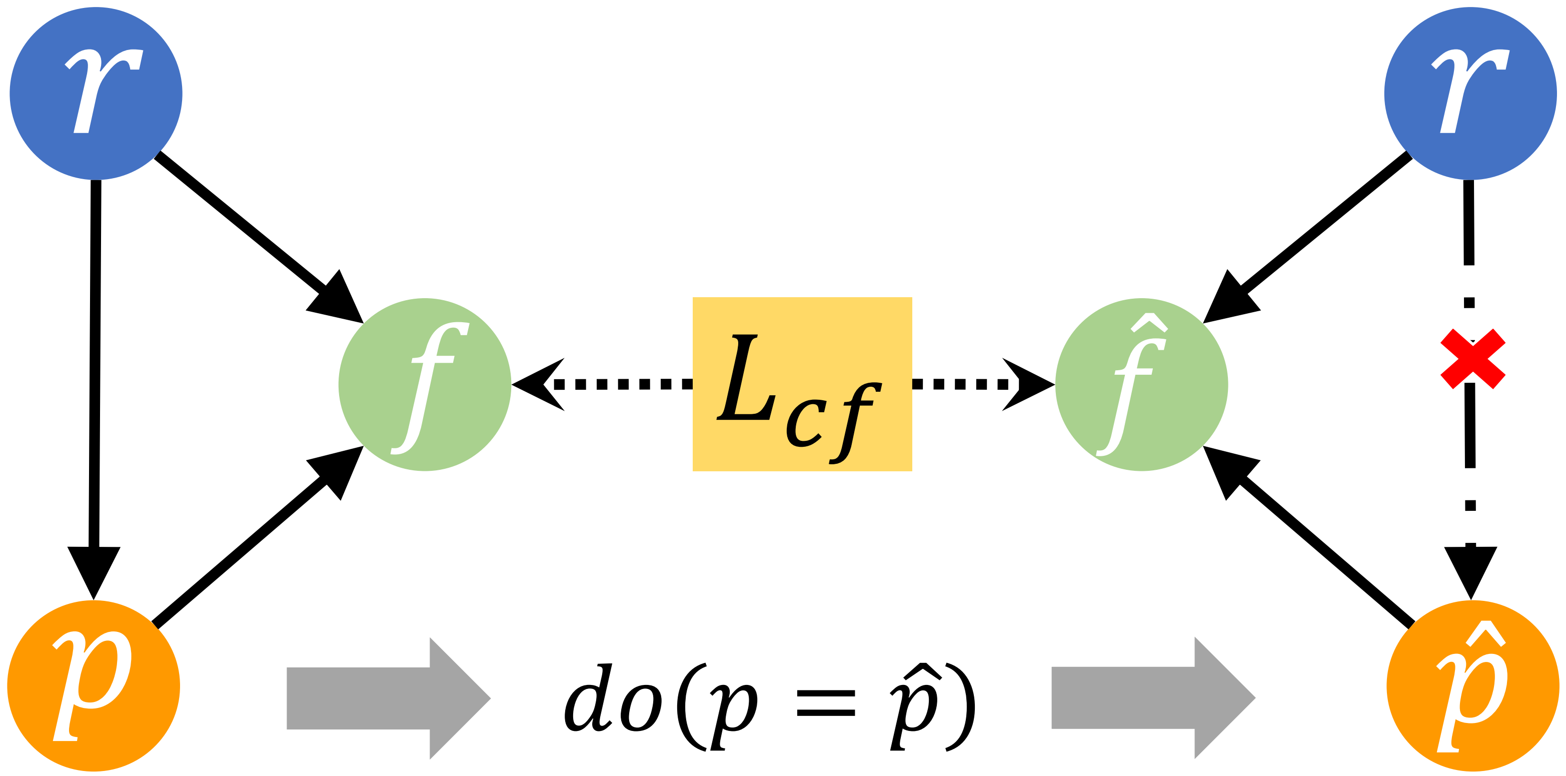


A counterfactual latent feature $\hat{f}$ can be produced via r and $\hat{p}$.

Counterfactual-based learning process



Counterfactual-based learning process



A counterfactual loss is applied on f and $\hat{f}$ to maximize the distance as follow,

$$L_{cf} = \log(1 + e^{-\beta[|f,\hat{f}|_2]})$$

Data augmentation

- Usually break the correspondence between aerial-ground pairs and incapable to provide diverse layout.

Aerial image

Ground image

Data augmentation

- Usually break the correspondence between aerial-ground pairs and incapable to provide diverse layout.

- No sufficient attention on the low-level details.

Aerial image

Ground image (Cropped)

Data augmentation

- ✓ Layout simulation
- ✓ Semantic augmentation

LS techniques

Layout simulation

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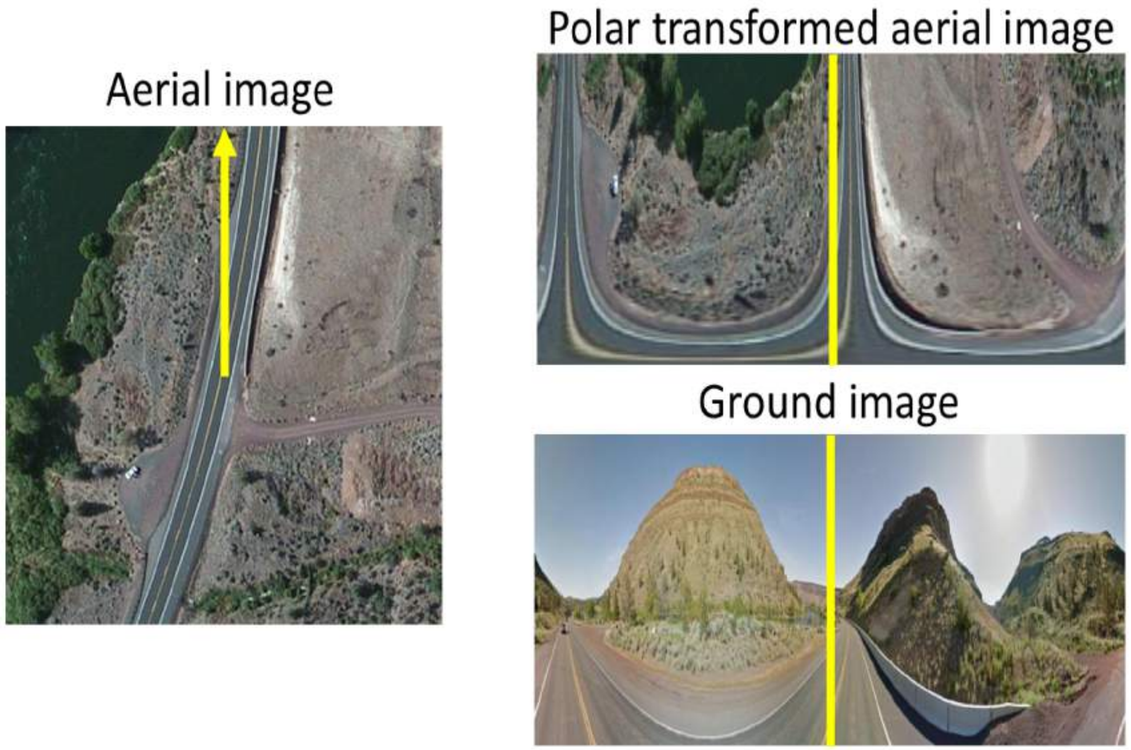
- Layout simulation aims to generate aerial-ground pairs **with unseen layouts** by using geometric transformations that satisfy the following requirements:

I. The generated aerial-ground pairs should **keep the correspondence**.

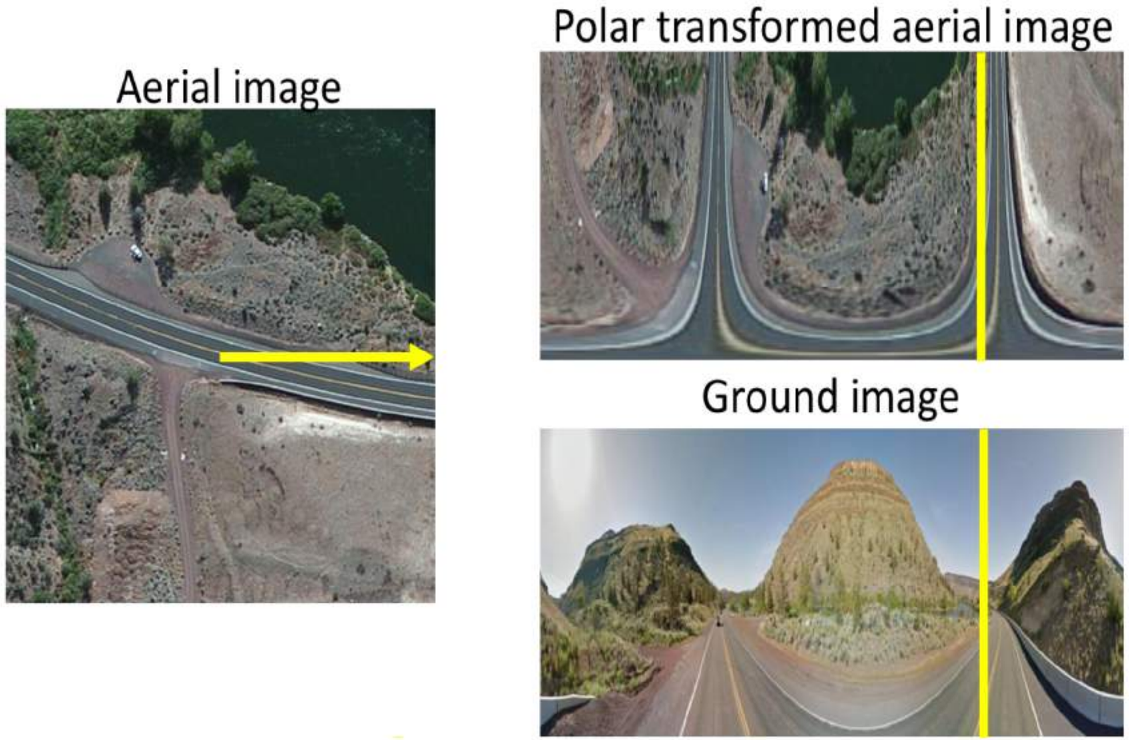
II. The generation process must **maintain the low-level details**.

Layout simulation



Rotation

Layout simulation



Rotation

Layout simulation

Aerial image

Polar transformed aerial image

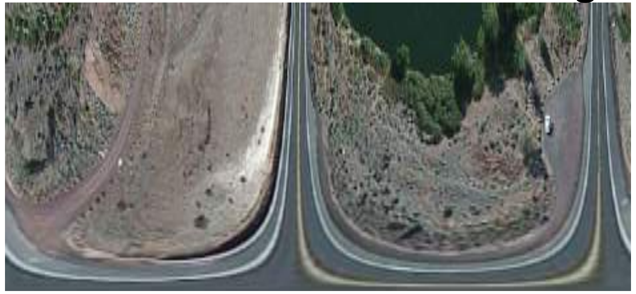
Ground image

FLIP

Layout simulation

Aerial image

Polar transformed aerial image

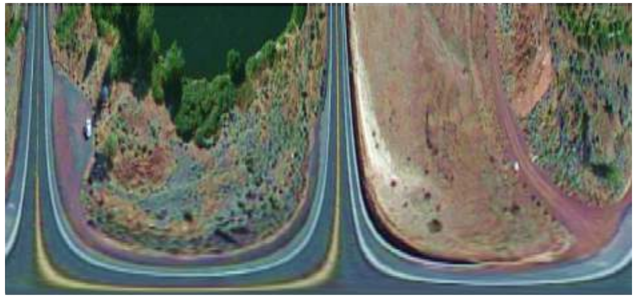


Ground image

FLIP

Semantic augmentation

- Semantic augmentation modifies the low-level features in aerial and ground images ***separately*** by randomly adjusting or applying:
- Brightness
- Contrast
- Saturation
- Gaussian blur
- Image grayscale



Semantic augmentation

- Semantic augmentation modifies the low-level features in aerial and ground images ***separately*** by randomly adjusting or applying:
- Brightness
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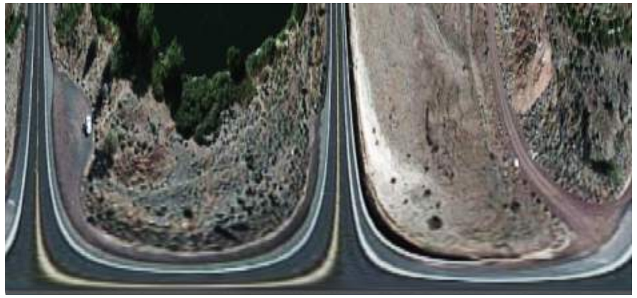
- Image grayscale
- Image posterizing



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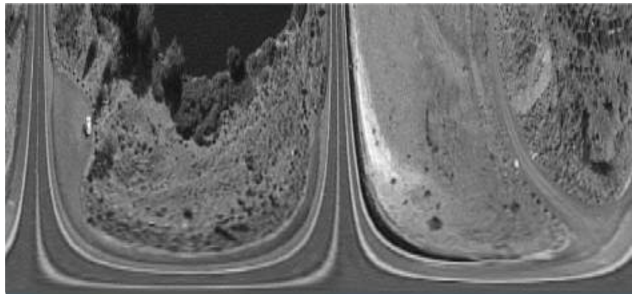

Training objectives

1. Counterfactual loss :

$$L_{cf}^{a(g)} = \log(1 + e^{-\beta[|f^{a(g)}, \hat{f}^{a(g)}|_2]})$$

2. Soft margin triplet loss :

$$L_{triplet} = \log(1 + e^{\alpha[|f_i^g, f_i^a|_2 - |f_i^g, f_j^a|_2]})$$

3. Total loss :

$$L = L_{triplet} + L_{cf}^{a(g)}$$

Implementation details

- A ResNet-34 is employed as backbone.
- α and β are set to 10 and 5 respectively.
- The model is trained on a single Nvidia V100 GPU for 200 epochs with an AdamW optimizer.
- The number of descriptors K is set to 8.
- Our code can is open-sourced at *https://gitlab.com/vail-uvm/geodtr*

Experiments Setup

CVUSA:

- 35,532 training pairs
- 8,884 testing pairs.

CVACT :

- 35,532 training pairs
- 8,884 validation pairs (CVACT_val).
- 92,802 testing pairs (CVACT_test).

Evaluation Metrics:

Similar to existing methods, we choose to use recall accuracy at top K ($R@K$) for evaluation purposes.

We use $R@1$, $R@5$, $R@10$, and $R@1\%$.

Experiment – CVUSA same-area

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Method	R@1	R@5	R@10	R@1%
FusionGAN	48.75%	-	81.27%	95.98%
CVFT	61.43%	84.69%	90.49%	99.02%
SAFA	81.15%	94.23%	96.85%	99.49%
SAFA†	89.84%	96.93%	98.14%	99.64%
DSM†	91.93%	97.50%	98.54%	99.67%
CDE†	92.56%	97.55%	98.33%	99.57%
L2LTR	91.99%	97.68%	98.65%	99.75%
L2LTR†	94.05%	98.27%	98.99%	99.67%
TransGeo	94.08%	98.36%	99.04%	99.77%
SEH†	**95.11%**	98.45%	99.00%	99.78%
Ours w/ LS	93.76%	**98.47%**	**99.22%**	**99.85%**
Ours w/ LS†	**95.43%**	**98.86%**	**99.34%**	**99.86%**

Experiment – CVACT same-area

Method	CVACT_val				CVACT_test			
	R@1	R@5	R@10	R@1%	R@1	R@5	R@10	R@1%
CVFT	61.05%	81.33%	86.52%	95.93%	26.12%	45.33%	53.80%	71.69%
SAFA	78.28%	91.60%	93.79%	98.15%	-	-	-	-
SAFA†	81.03%	92.80%	94.84%	98.17%	55.50%	79.94%	85.08%	94.49%
DSM†	82.49%	92.44%	93.99%	97.32%	35.63%	60.07%	69.10%	84.75%
CDE†	83.28%	93.57%	95.42%	98.22%	61.29%	85.13%	89.14%	98.32%
L2LTR	83.14%	93.84%	95.51%	**98.40%**	58.33%	84.23%	88.60%	95.83%
L2LTR†	84.89%	94.59%	95.96%	98.37%	60.72%	85.85%	89.88%	96.12%
TransGeo	84.95%	94.14%	95.78%	98.37%	-	-	-	-
SEH†	84.75%	93.97%	95.46%	98.11%	-	-	-	-
Ours w/ LS	**85.43%**	**94.81%**	**96.11%**	98.26%	**62.96%**	**87.35%**	**90.70%**	**98.61%**
Ours w/ LS†	**86.21%**	**95.44%**	**96.72%**	**98.77%**	**64.52%**	**88.59%**	**91.96%**	**98.74%**

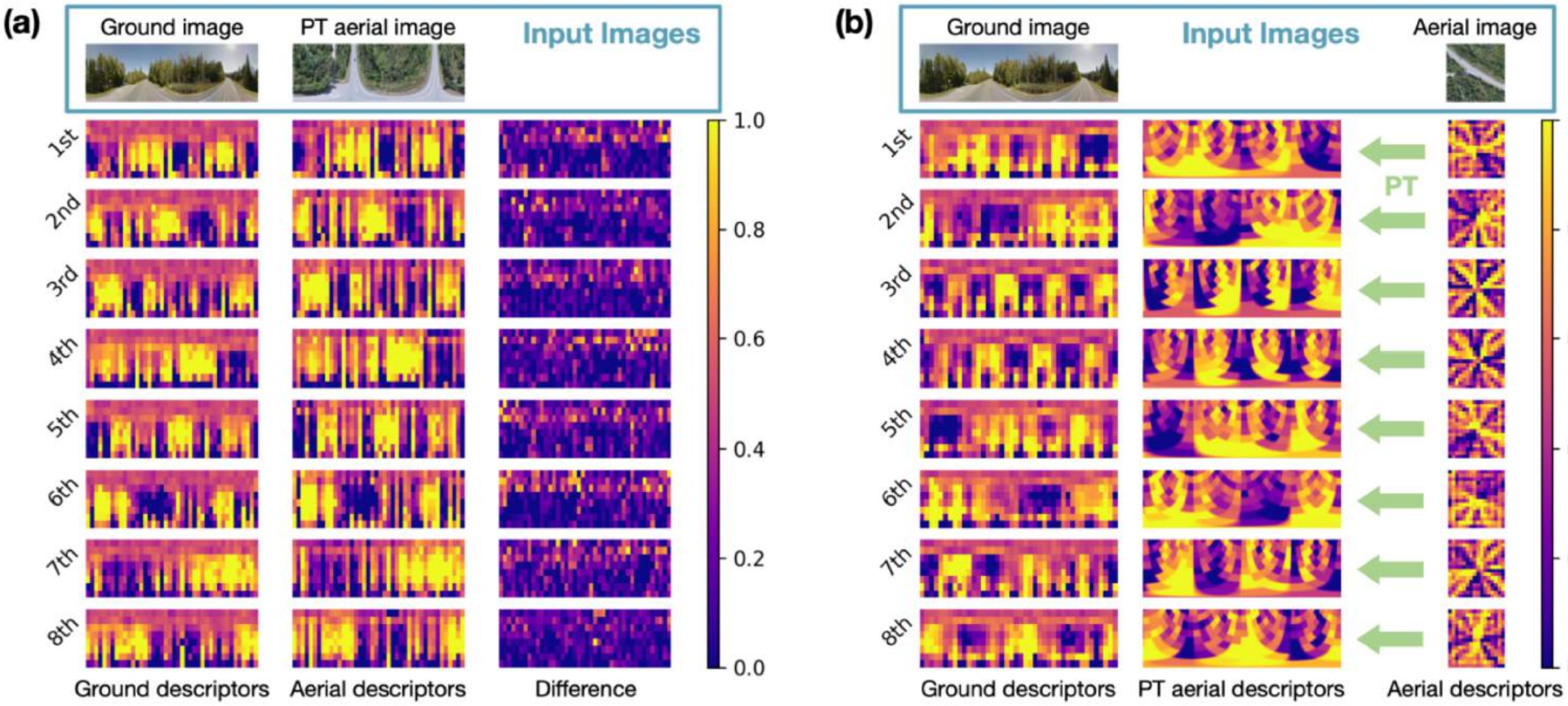
Experiment – Cross-area

Model	Task	R@1	R@5	R@10	R@1%
SAFA†	CVUSA → CVACT	30.40%	52.93%	62.29%	85.82%
DSM†		33.66%	52.17%	59.74%	79.67%
L2LTR†		**47.55%**	**70.58%**	**77.39%**	91.39%
TransGeo		37.81%	61.57%	69.86%	89.14%
Ours w/ LS		43.72%	66.99%	74.61%	**91.83%**
Ours w/ LS†		**53.16%**	**75.62%**	**81.90%**	**93.80%**
SAFA‡	CVACT → CVUSA	21.45%	36.55%	43.79%	69.83%
DSM†		18.47%	34.46%	42.28%	69.01%
L2LTR†		**33.00%**	**51.87%**	**60.63%**	**84.79%**
TransGeo		18.99%	38.24%	46.91%	88.94%
Ours w/ LS		29.85%	49.25%	57.11%	82.47%
Ours w/ LS†		**44.07%**	**64.66%**	**72.08%**	**90.09%**

Experiment – LS on other methods

LS + other methods	Configuration	Same-area R@1	Same-area R@5	Same-area R@10	Same-area R@1%	Cross-area R@1	Cross-area R@5	Cross-area R@10	Cross-area R@1%
Trained on CVUSA	SAFA	89.84%	96.93%	98.14%	99.64%	30.40%	52.93%	62.29%	85.82%
	SAFA w/ LS	88.19%	96.48%	98.20%	99.74%	37.15%	60.31%	69.20%	89.15%
	L2LTR	94.05%	98.27%	98.99%	99.67%	47.55%	70.58%	77.52%	91.39%
	L2LTR w/ LS	93.62%	98.46%	99.03%	99.77%	52.58%	**75.81%**	**82.19%**	93.51%
	GeoDTR w/o LS	95.23%	98.71%	99.26%	99.79%	47.79%	70.52%	77.52%	92.20%
	GeoDTR w/ LS	**95.43%**	**98.86%**	**99.34%**	**99.86%**	**53.16%**	75.62%	81.90%	**93.80%**
Trained on CVACT	SAFA	81.03%	92.80%	94.84%	98.17%	21.45%	36.55%	43.79%	69.83%
	SAFA w/ LS	79.88%	92.84%	94.71%	97.96%	25.42%	42.30%	50.36%	76.49%
	L2LTR	84.89%	94.59%	95.96%	98.37%	33.00%	51.87%	60.63%	84.79%
	L2LTR w/ LS	83.49%	94.93%	96.44%	98.68%	37.69%	57.78%	66.22%	89.63%
	GeoDTR w/o LS	**87.42%**	95.37%	96.50%	98.65%	29.13%	47.86%	56.21%	81.09%
	GeoDTR w/ LS	86.21%	**95.44%**	**96.72%**	**98.77%**	**44.07%**	**64.66%**	**72.08%**	**90.09%**

Learned descriptors visualization

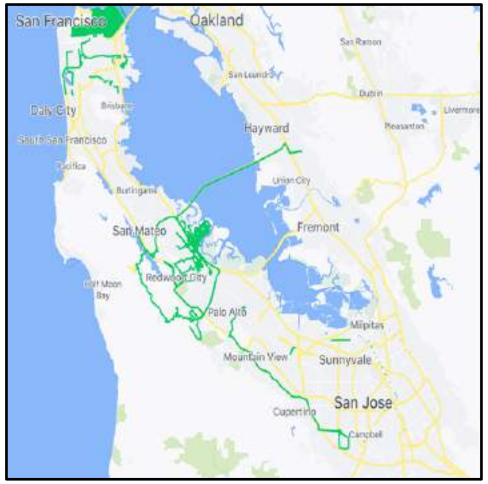


Summary

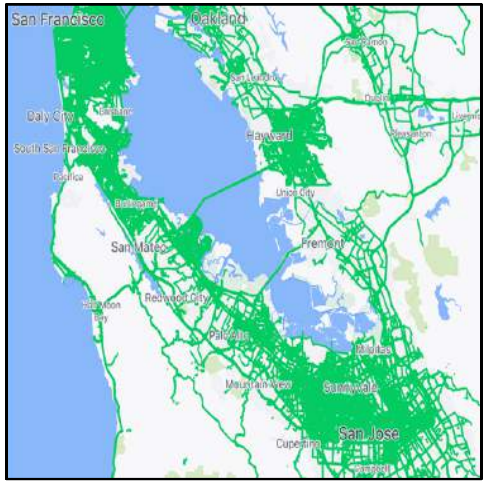
1. **GeoDTR** disentangles geometric information from raw features to better captures the correspondence between aerial and ground images.
2. **Layout simulation and semantic augmentation (LS)** techniques improve the performance of GeoDTR (as well as other existing models) on cross-area experiments.
3. A novel **counterfactual-based learning schema** guides GeoDTR to better grasp the spatial configurations and therefore produce better latent feature representations.

Limitations

- Cross-view image geo-localization heavily rely on panoramic query images.
- Limited field-of-view (FOV) images are more common than panoramas.



(a) Panoramic images coverage



(b) Limited FOV images coverage

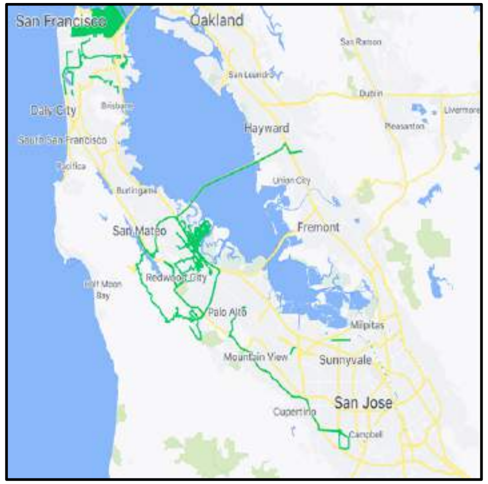
Cross-View Image Sequence Geo-localization



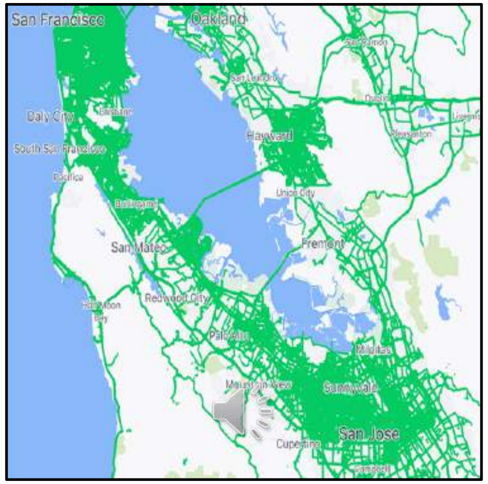
Xiaohan Zhang, **Waqas Sultani**, Safwan Wshah , **Cross-View Image Sequence Geo-localization,** WACV 2023

Motivation

- Cross-view image geo-localization heavily rely on panoramic query images.
- Limited field-of-view (FOV) images are more common than panoramas.
- Sequence of limited FOV images expands the range of visibility of a single limited FOV image.
- We propose to geo-locate sequences of limited FOV images instead of panoramas.



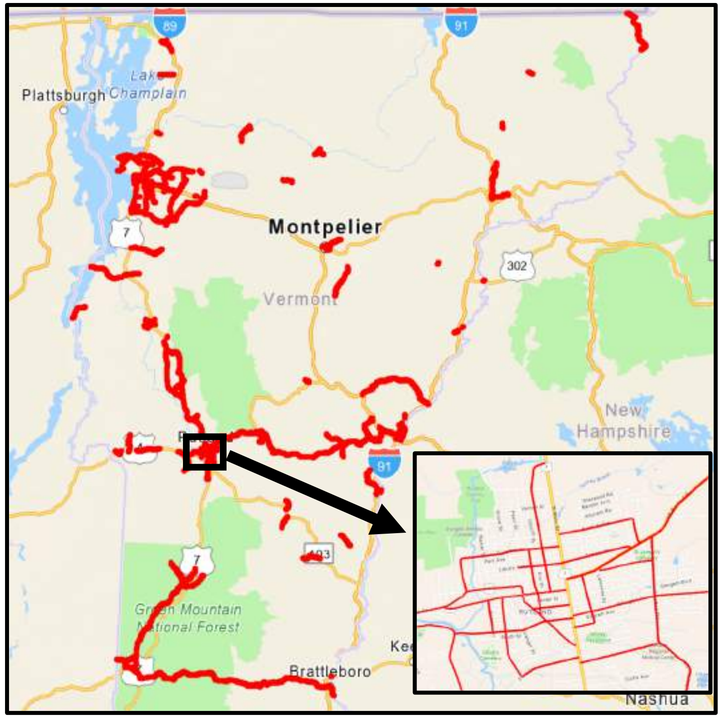
(a) Panoramic images coverage



(b) Limited FOV images coverage

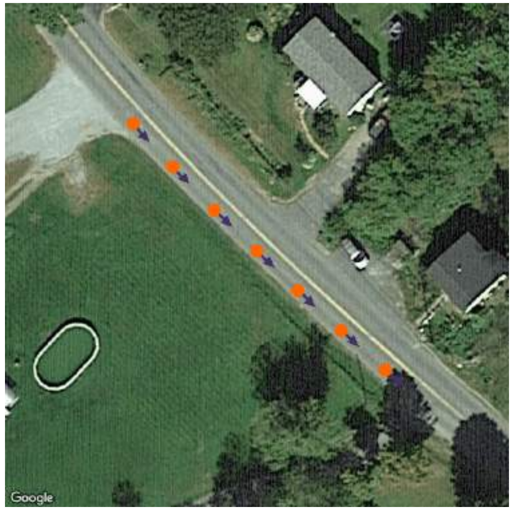
Dataset

- Covers more than *500 km of road* in Vermont, USA.
- Various coverage area, urban, suburban, highway, etc.
- Dataset contains *118,549* ground images and forms *38,863* satellite-sequence pairs.
- The dataset does not contain panoramic images.

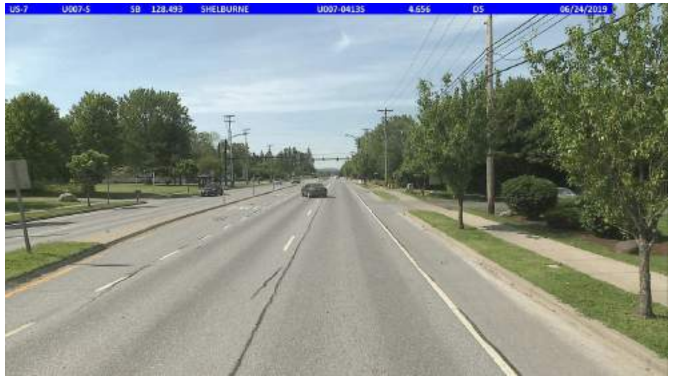


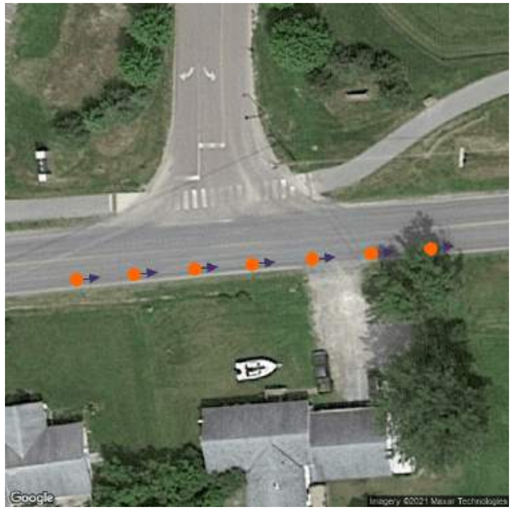
Dataset coverage area

Samples from our dataset



Samples from our dataset





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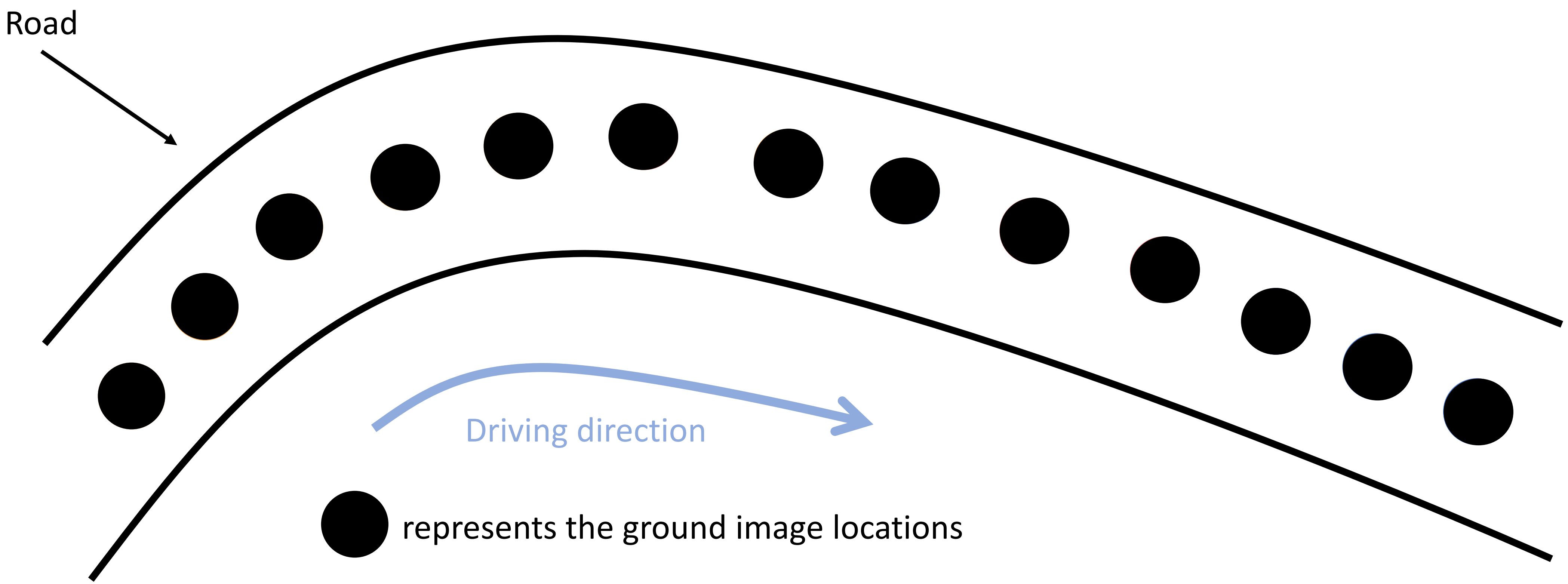
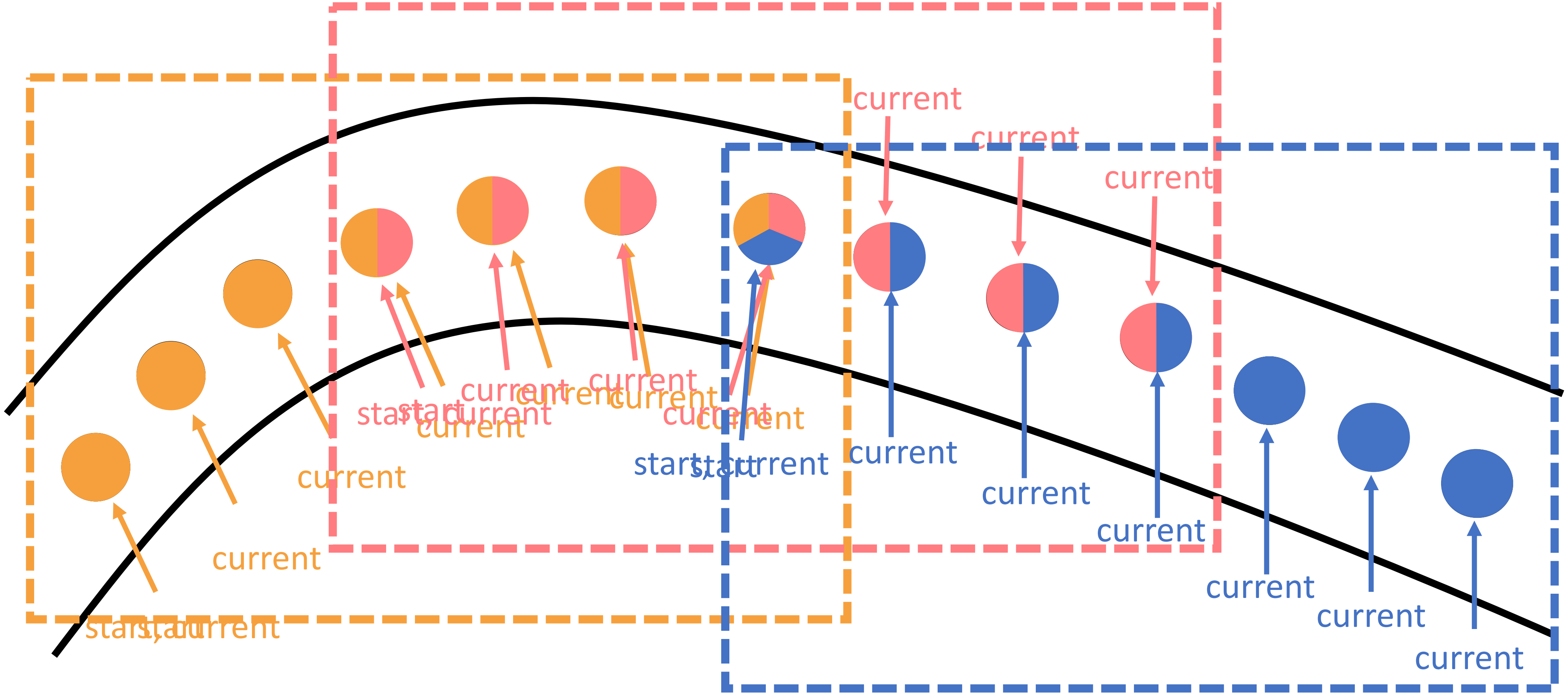
Sequence Formation

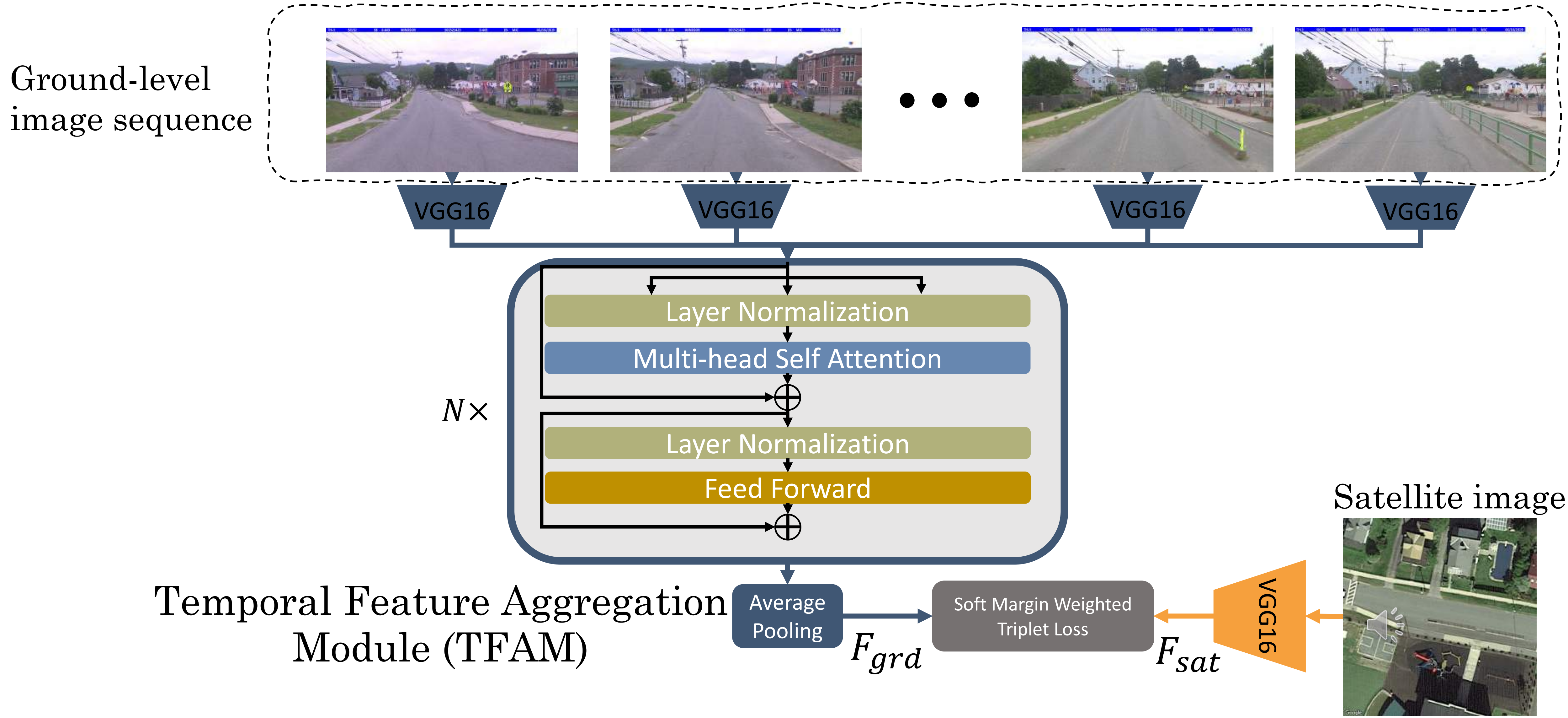


Sequence Formation

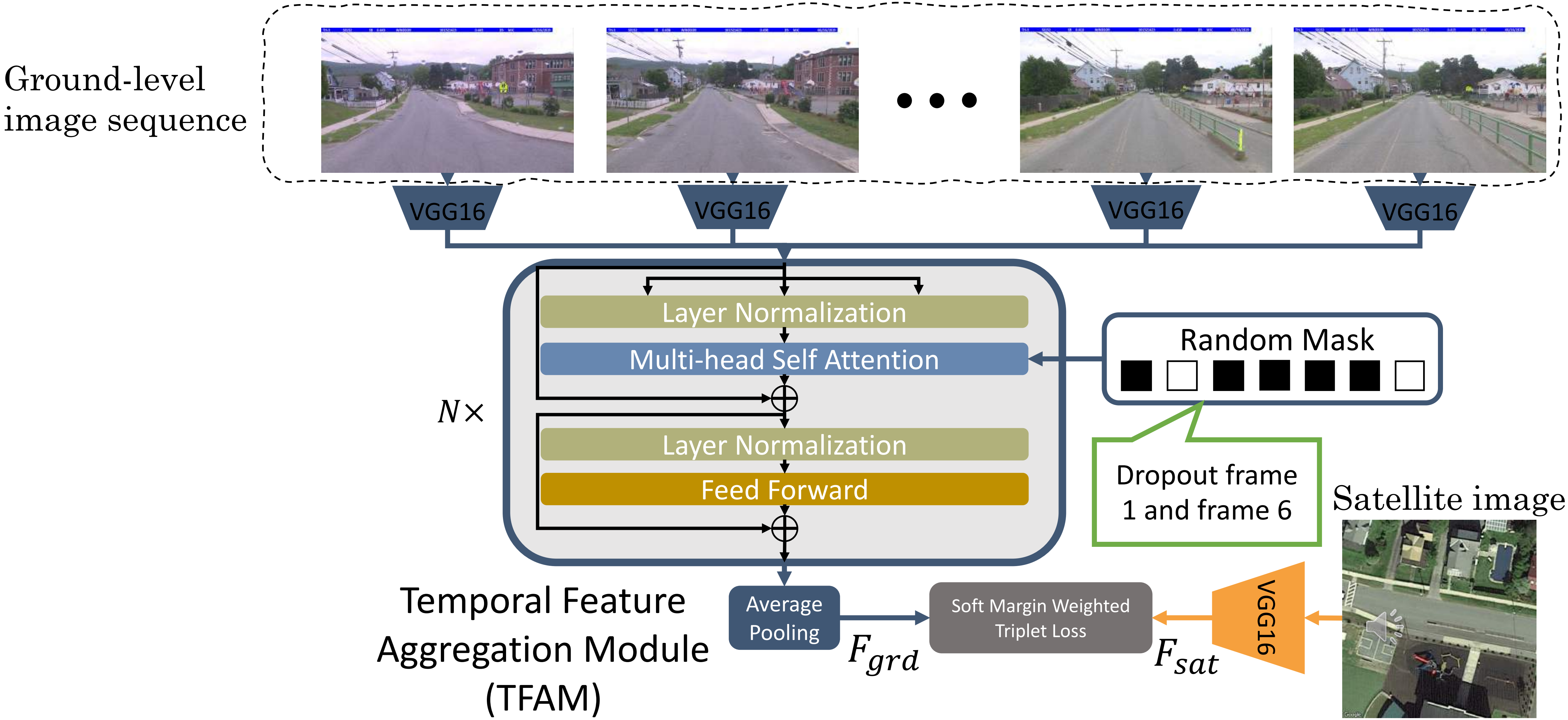


$$distance(start, current) > \Delta$$

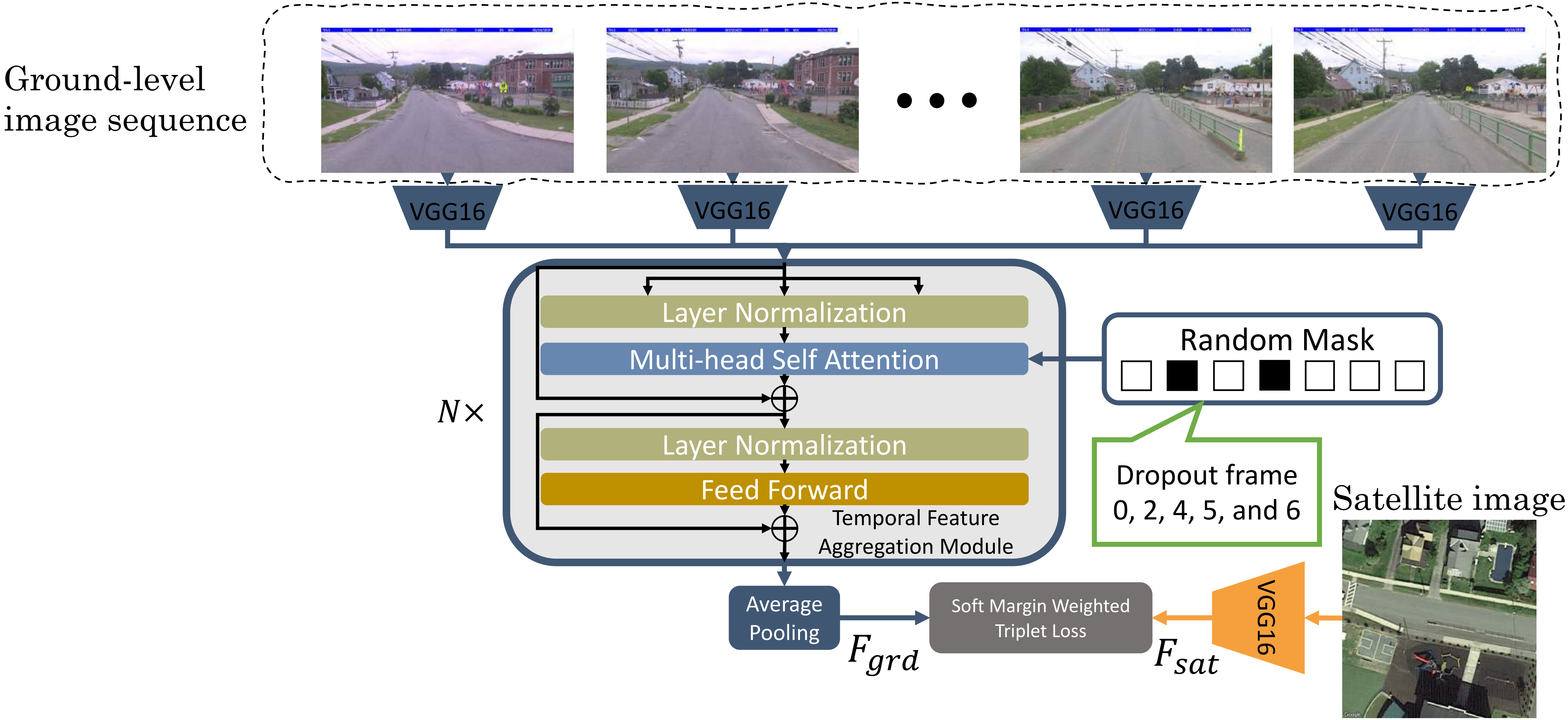
Proposed Model



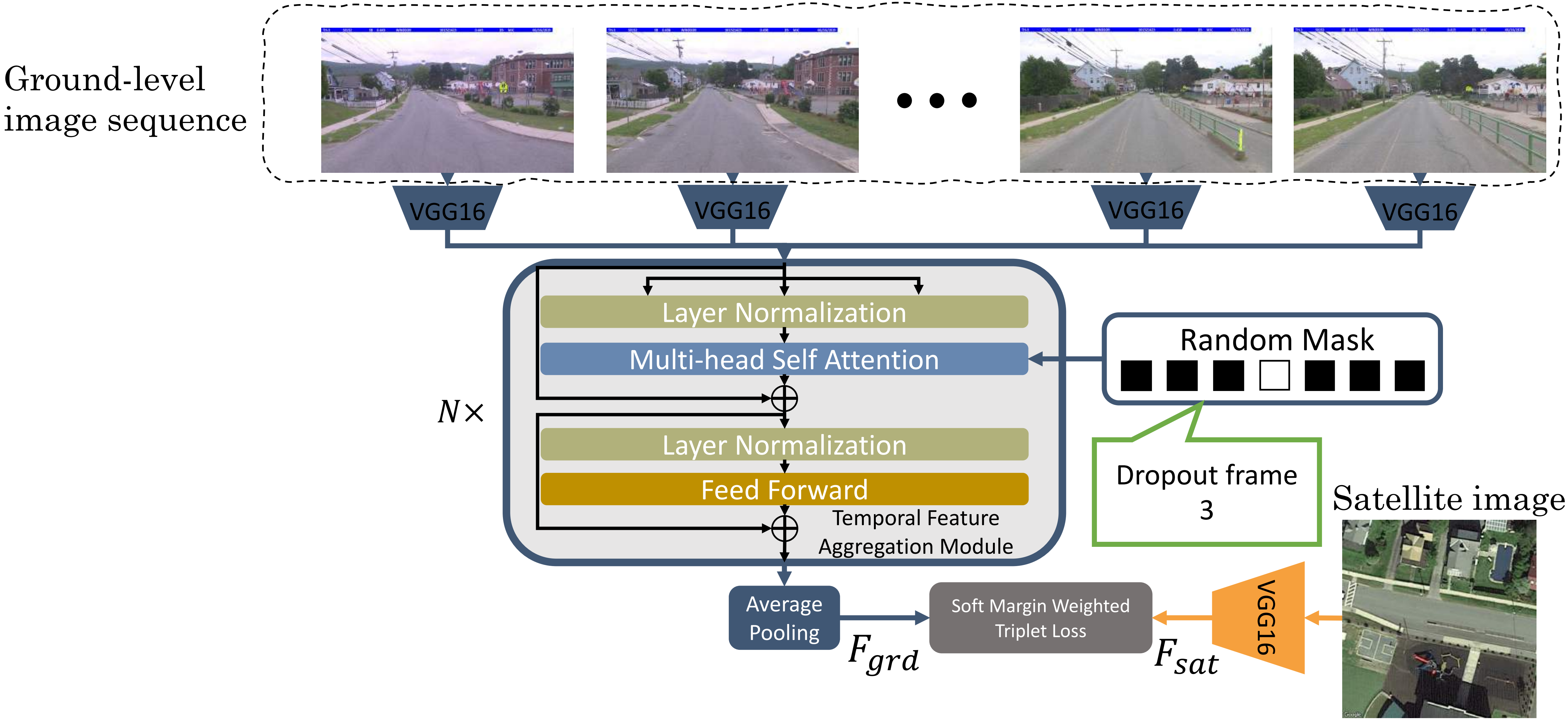
Sequential Dropout



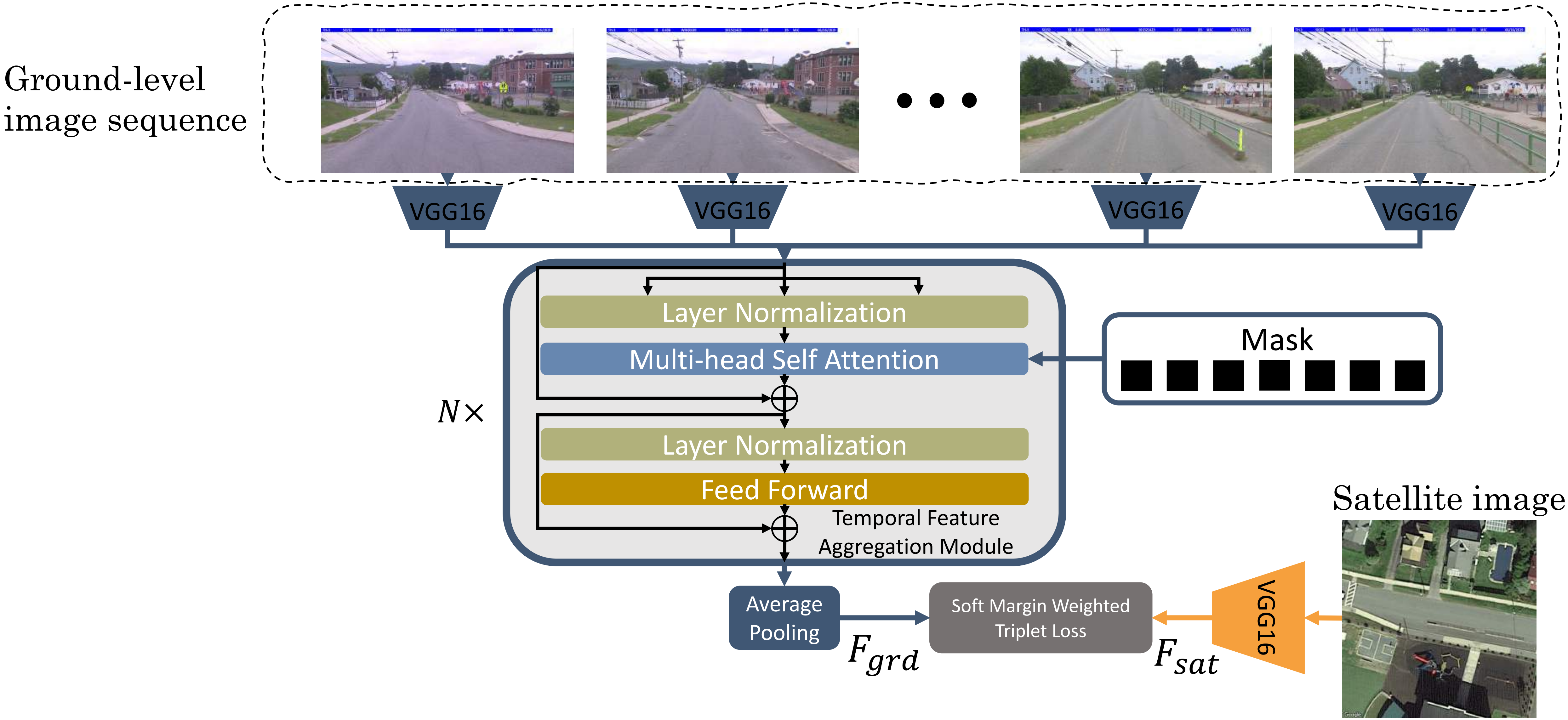
Sequential Dropout



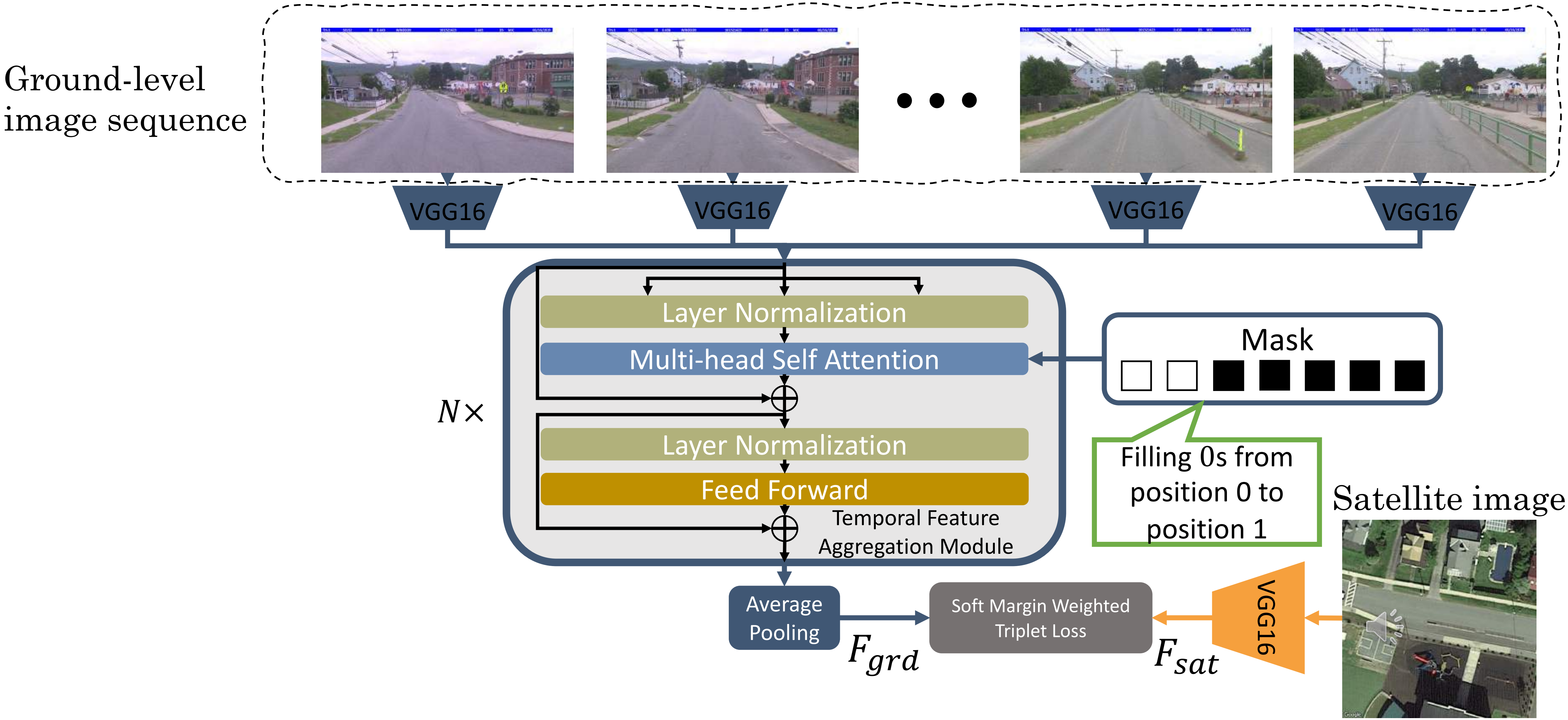
Sequential Dropout



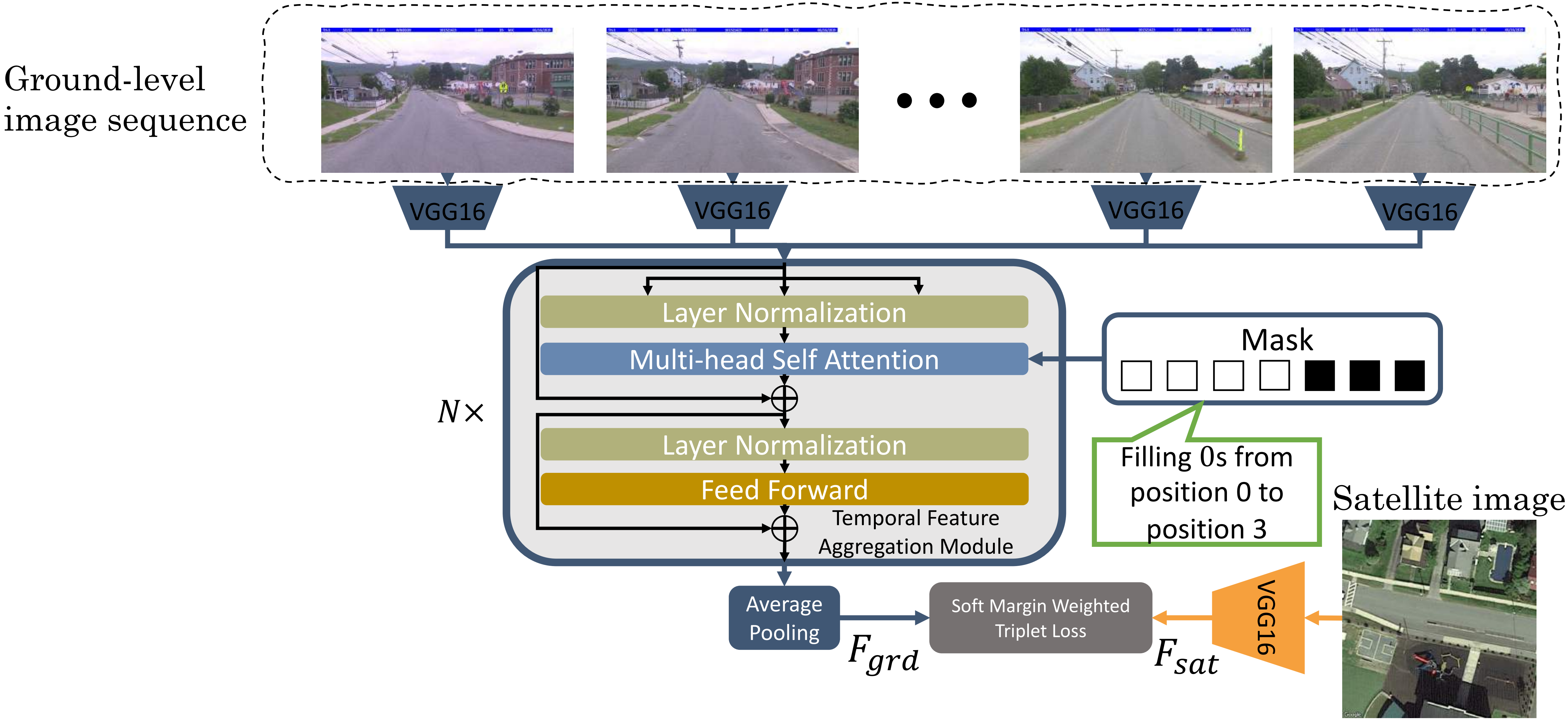
Testing – using the full sequence



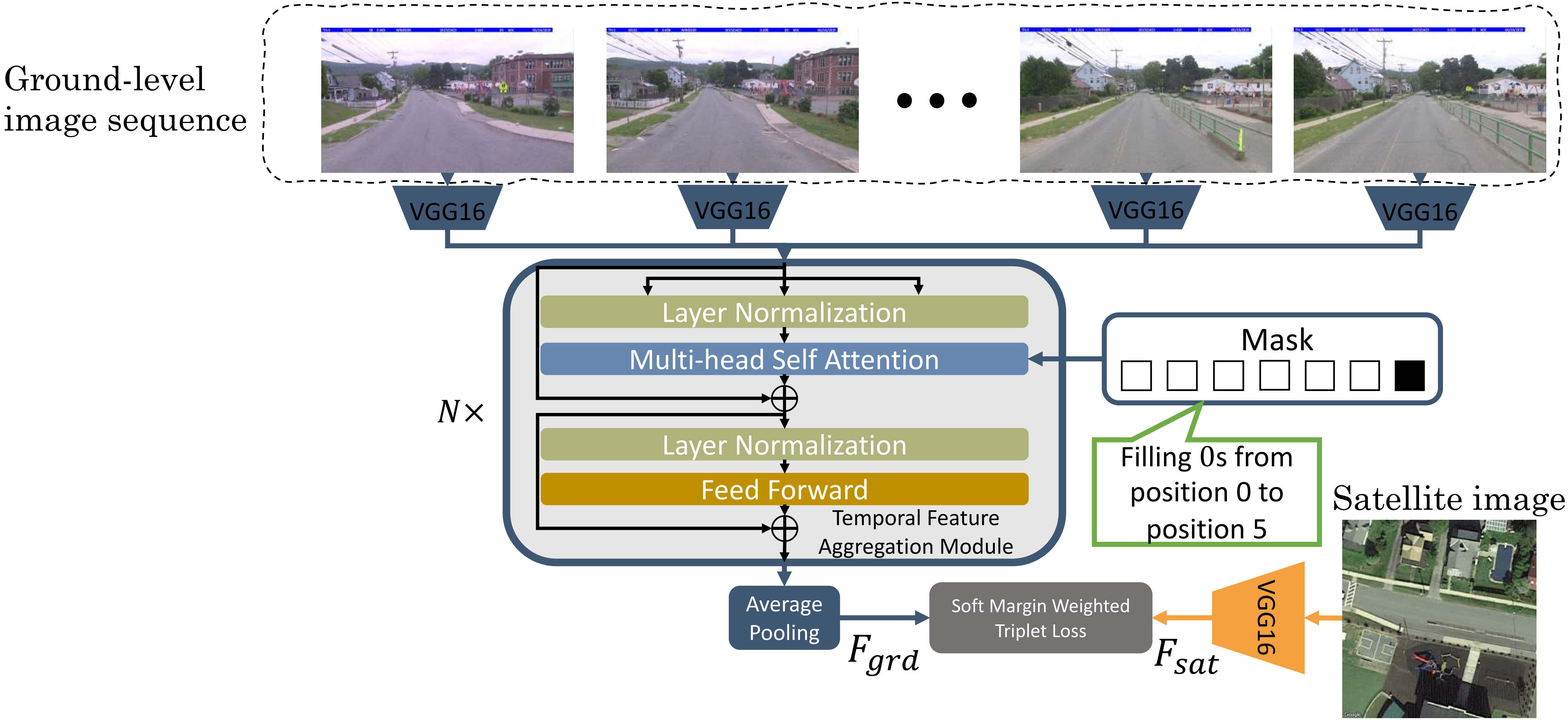
Inferencing



Testing – simulating sequence length=3



Testing – simulating sequence length=1



Experiments

Baseline Methods:

- SAFA (center) : Training on using center image as query and testing on query center image only.
- SAFA (sequence) : Training on using center image as query and testing on query sequence by feature averaging.
- VIGOR: Training on a query sequence in which center image is considered as "positive" and other images are "semi-positive".

Evaluation Metric:

We choose to use recall accuracy at top K ($R@K$) for evaluation purpose.

$R@K$ measures the probability of the ground truth aerial image ranking within the first K predictions given a query image. In the experiments,

We evaluate for:

$R@1, R@5, R@10,$ and $R@1\%$.

Experiments

	R@1	R@5	R@10	R@1%
VIGOR	0.54%	2.52%	4.48%	18.55%
SAFA(center image as query)	0.68%	2.92%	5.06%	21.81%
SAFA(sequence as query)	0.63%	2.83%	5.03%	21.51%
Ours w/o Sequential Dropout	1.39%	6.50%	10.45%	32.42%
Ours	**1.80%**	**6.45%**	**10.36%**	**34.38%**

Comparison between our proposed method and SOTA methods on the proposed dataset

Ablation Studies

# of TFAMs	# of Heads	R@1	R@5	R@1%
0	0	0.91%	4.49%	26.69%
2	2	1.45%	6.22%	31.84%
4	2	1.40%	6.34%	32.97%
4	4	1.51%	6.27%	32.93%
6	4	1.59%	6.02%	32.14%
6	8	1.80%	6.45%	34.38%

Ablation study on # of TFAM and # of attention heads

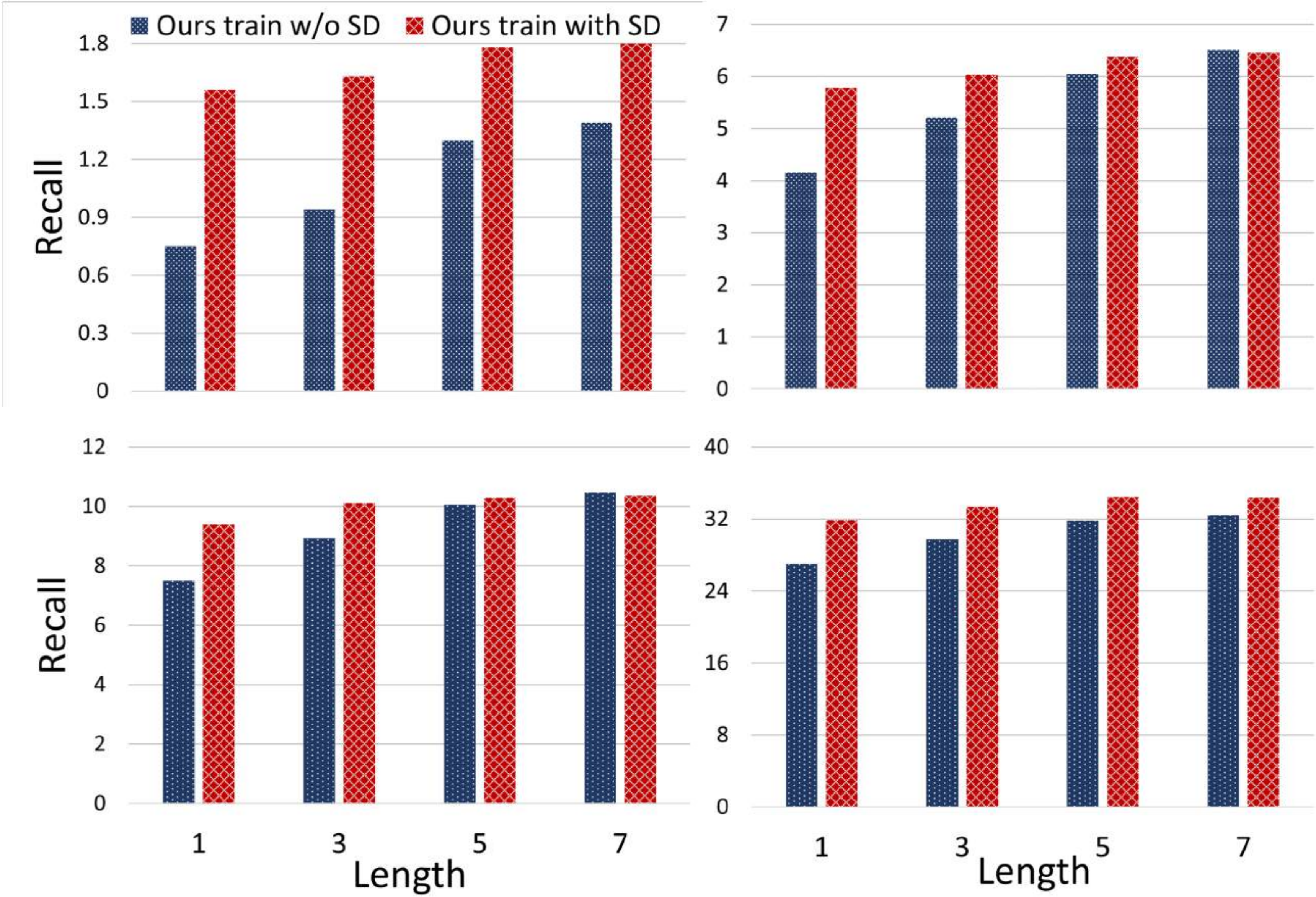
# of dropout images	R@1	R@5	R@1%
1	1.40%	6.08%	31.89%
3	1.51%	6.64%	34.34%
5	1.63%	6.41%	34.40%
6	1.80%	6.45%	34.38%

Ablation study on # of dropout images in the ground sequence

Variant Sequence Lengths

Recall@1

Recall@5



Recall@10

Recall@1%

Qualitative Results

Query sequence

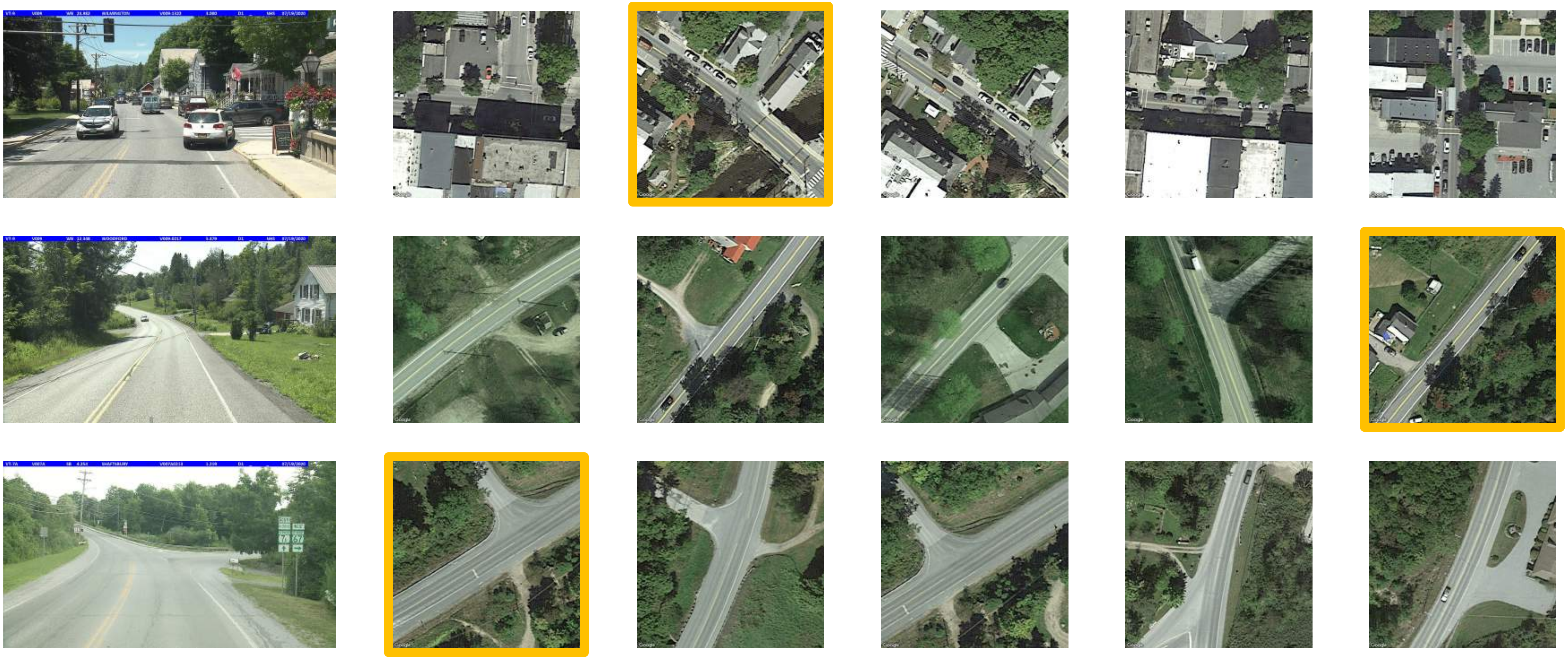
Top-5 predictions

Blue boarder indicates ground truth

Sample results

Query sequence

Top-5 predictions



Blue boarder indicates ground truth

Summary

1. A new end-to-end approach for cross-view image sequence geo-localization.

2. Put forward a novel large-scale cross-view image sequence geo-localization dataset.

3. Propose a new sequential dropout technique to regularize the model to predict coherent features on sequences of different lengths.

Code and dataset are available at https://gitlab.com/vail-uvm/seqgeo

Codes

- https://zxh009123.github.io/
- https://gitlab.com/vail-uvm/geodtr
- https://gitlab.com/vail-uvm/seqgeo

Thanks