Computer Vision 2025

Project 10

Transformer-based Satellite Image and Segmentation Generation for Ground-to-Aerial Image Matching

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Summary

- Introduction
- Dataset
- Proposed methods
- Image Generation (1-4)
- Segmentation (1-2)
- Image Matching
- Experimental results
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Ground-to-aerial image matching

Matching the right satellite image for each streetview images is a very complex task due to **semantic** differences and **domain** adaptation

Streetview

Corresponding satellite

This project aims to **tackle this gap** without the need of more informations (like GPS) but only using the streetview image.

Dataset: CVUSA

The version I used of **Cross-view USA** (CVUSA) contains:

- **Streetview** images
- **Satellite** images
- Satellite **segmentation**
- Polarmap (segmented and not)

The original dataset can be found here, a large dataset containing millions of pairs of ground-level and aerial/satellite images from across the United States.

Proposed architecture

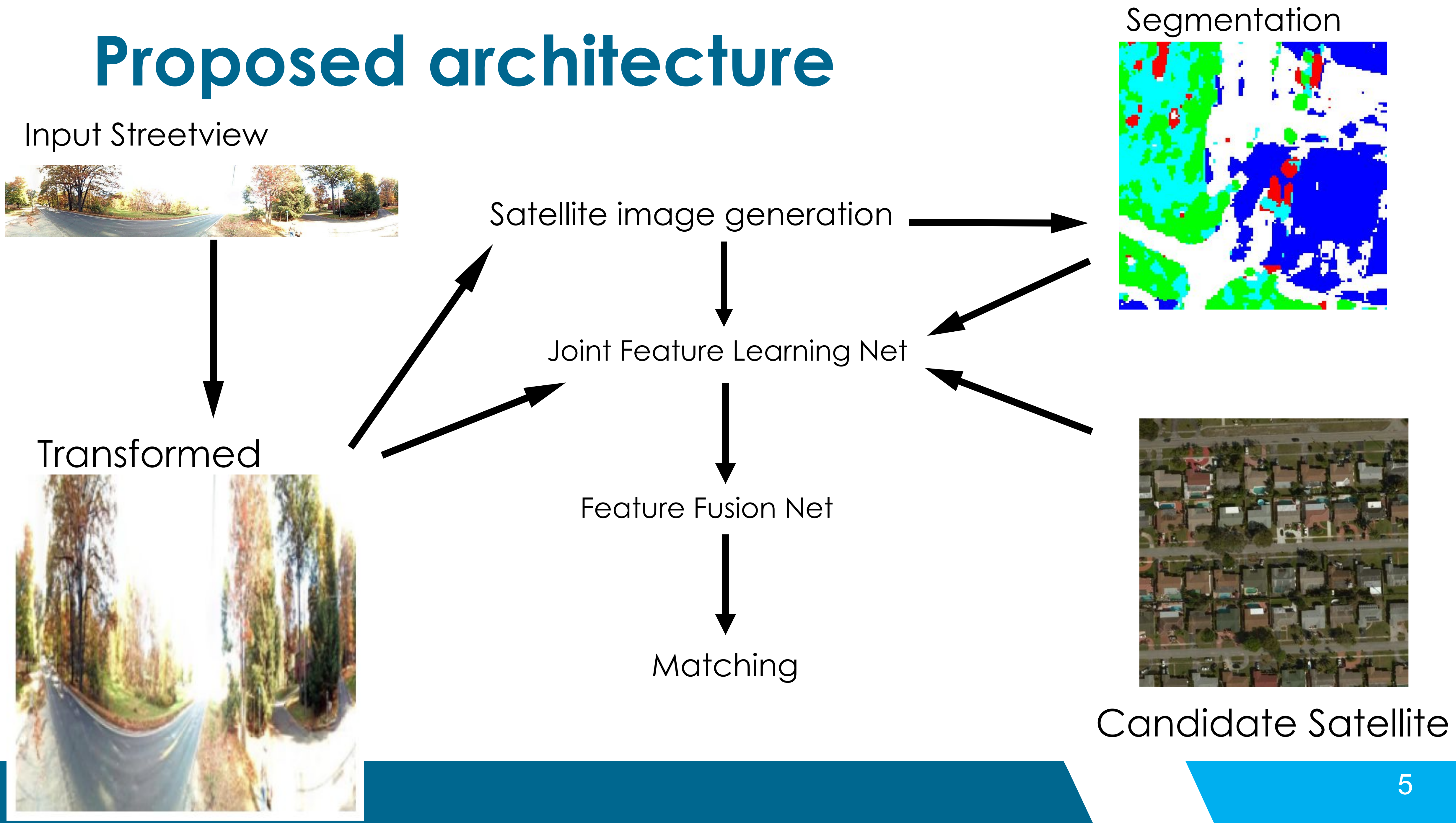


Image Generation (1)

The main thing I tried were **Diffusion Transformers** I based my work on this paper by Meta

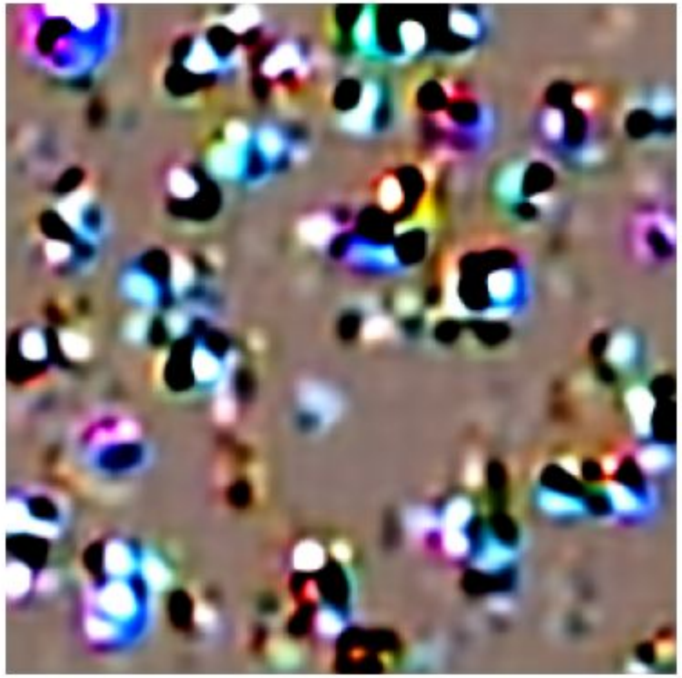
Scalable Diffusion Models with Transformers

William Peebles*
UC Berkeley

Saining Xie
New York University

DiT-XL/2 model, one of the biggest, with **VisualCLIP** and **stability-ai-sd-mse** VAE

Results?
Very **difficult conditioning**, as you can see…



Probably myy main problem was the VAE since it **wasn’t able to decode well its own encodings**

Image Generation (2)

I tried using a **VQGAN** encoder (Taming-Transformers), but the **checkpoints are not available** and I wasn't able to train my own.

Then I tried a **Unet** approach still using Diffusion. I opted for the **Stable Diffusion v1-v4** implementation (pre-trained on LAION-5B).
Reference: huggingface

- VisualCLIP encoding **Openai/clip-vit-base-patch32** (pre-trained on public images)→ 10 epochs for last 2 layers

- **VAE default** of Stable Diffusion → Frozen

- **2 linear layer MLP projection** from CLIP to VAE

Image generation (3)

Pre-trained

Final Result

Original

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- **AdamW**
- **ReduceLrOnPlateau**
- Loss?

Image generation (4)

Losses:

1. Noise loss: **MSE** (1e-5)
2. Clip: 1-**CosineSimilarity** (1e-6)
3. VAE: **lpips**

In my last epoch this were my results:
Noise: 0.1791
Clip: 0.3957
VAE: 0.6177
Total: 1.5882

This means that the hardest task still is conditioning…

- ➔ in fact every time I regenerated an image I got a (substantially) **different output**
- ➔ good denoising but bad conditioning
- ➔ only learning truly **major features** (e.g. color, big roads or houses)

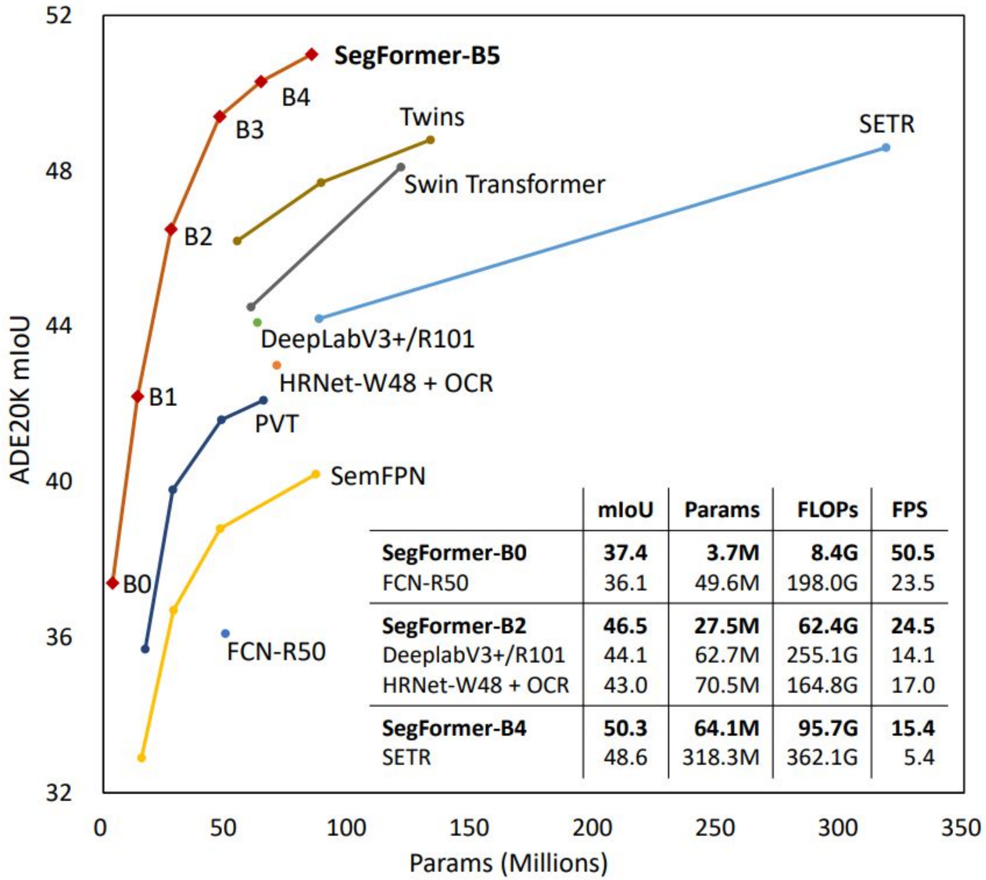
Segmentation (1)

I used **SegFormer** because there are available checkpoints pre-trained on Ade20K which has many spatial informations and domain closer to urban and aerial image.

The chosen model was SegFormerB3.

It makes a significant **improvement** from B2 model **without having too many parameters** and it's quite close to B4 and B5 with much less parameters.

Reference

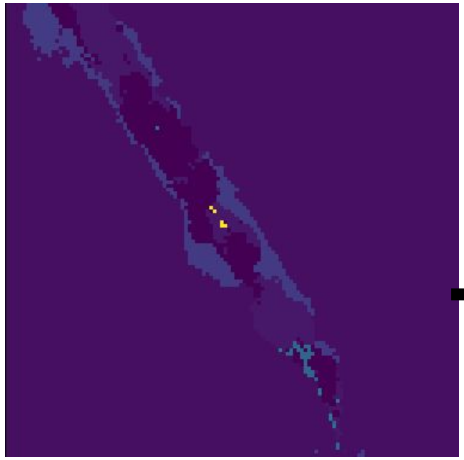


	mIoU	Params	FLOPs	FPS
SegFormer-B0	**37.4**	**3.7M**	**8.4G**	**50.5**
FCN-R50	36.1	49.6M	198.0G	23.5
SegFormer-B2	**46.5**	**27.5M**	**62.4G**	**24.5**
DeeplabV3+/R101	44.1	62.7M	255.1G	14.1
HRNet-W48 + OCR	43.0	70.5M	164.8G	17.0
SegFormer-B4	**50.3**	**64.1M**	**95.7G**	**15.4**
SETR	48.6	318.3M	362.1G	5.4

Segmentation (2)

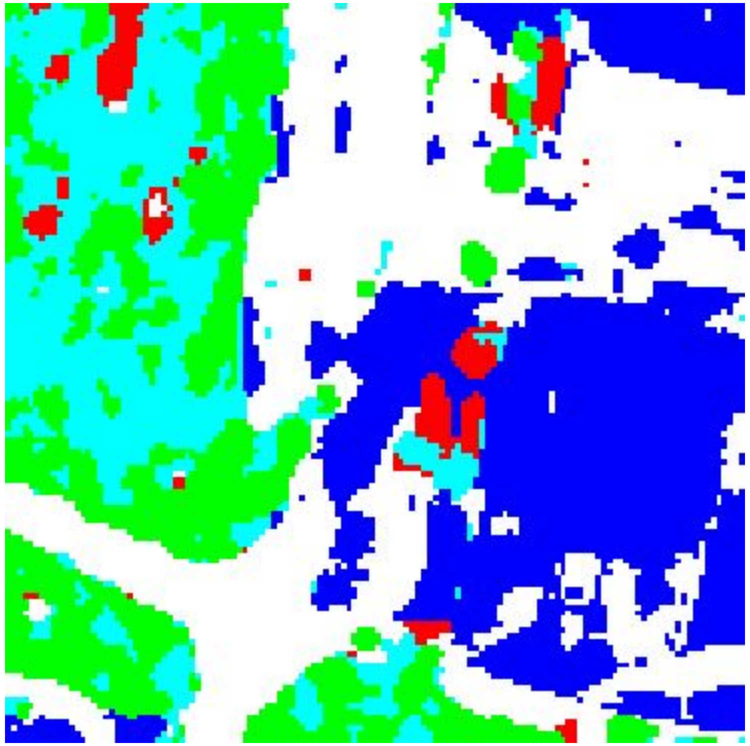
- **CrossEntropyLoss**
- **AdamW**
- **ReduceLrOnPlateau** (lr=3e-5)

Pre-trained

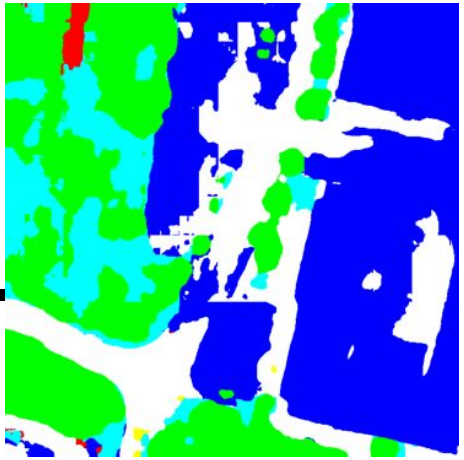


SegFormerB3 on Ade20K:
mIoU = 0.49

Fine-tuned



Original



Fine-tuned on CVUSA:
mIoU = 0.39

Feature extraction

JointFeatureLearningNet:

- 4 pre-trained VGG16 (Ground, Synthetic, Seg Syntethic, Candidate)

  ⟶ Joint representation

FeatureFusionNet:

- 1 FFN trained from scratch

  ⟶ Concatenate

- **Triplet Loss**
- **AdamW** (different lr for VGG and FFN)

Last epoch's loss: **0.15**

Metrics

Base accuracy: 51%
With 10 competitors:
Top1: 9%
Top5: 49%

For comparison (with more competitors)
ALCOR LAB's SAN (with 360 FOV)
Top1: 77%
Top5: 92%

Regmi and Shah FFN
Top1: 49%

It clearly is unfair to compare my task with those results but that's the **baseline** at the moment. My task of course was broader but nonetheless these are the results.

Conclusion

What's the take away from this experiment?

- Synthetic Satellite generation is a complex task, especially with bigger architectures like transformers
- The technique works but needs **more experimenting**
- It was **interesting and fun** to experiment with it
- Will be much **easier and more effective** in the future

Future Developments

Having more hardware capabilities (and time):

- Try again with **Diffusion Transformers** either fine-tuning the **VAE** or training it from scratch
- More fine-tuning on **VisualClip**
- More training on **SegFormer3**
- Adding **segmap** to the JointFeatureLearningNet
- Try with **polarmaps**
- **More complex training loop** for FFN and VGG
- Would be nice to see it reversed (**from satellite to streetview**, maybe embedding it in a satellite?)

Thanks for your attention