# Photographic Image Synthesis with Cascaded Refinement Networks

Zejia LV zejialv@zju.edu.cn

5th December 2018

#### Introduction

## Background

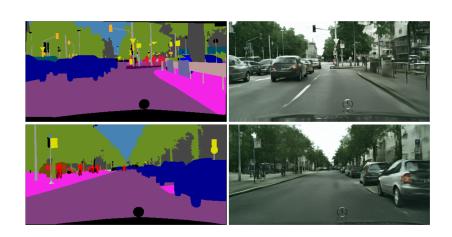
- Given a semantic layout of a novel scene, can an artificial system synthesize an image that depicts this scene and looks like a photograph?
- Mental imagery is believed to play an important role in planning and decision making. Our second source of motivation is the role of mental imagery and simulation in human cognition

#### What we do

Our model is a convolutional network, trained in a supervised fashion on pairs of photographs and corresponding semantic layouts. Such pairs are provided with semantic segmentation datasets.



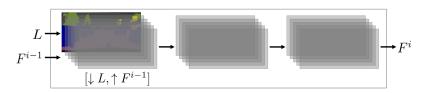
# Introduction



# Algorithms

#### Architecture

The Cascaded Refinement Network(CRN)



# **Algorithms**

For a training pair  $(I, L) \in \mathcal{D}$ , our loss is

$$\mathcal{L}_{I,L}(\theta) = \sum_{l} \lambda_l \|\Phi_l(I) - \Phi_l(g(L;\theta))\|_1$$
 (1)

## Algorithms

Our first version of the modified loss is based on the hindsight loss developed for multiple choice learning

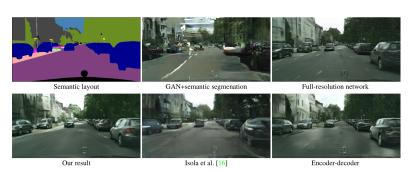
$$\min_{u} \sum_{l} \lambda_{l} \|\Phi_{l}(I) - \Phi_{l}(g_{u}(L;\theta))\|_{1}$$
(2)

We now define a more powerful diversity loss as

$$\sum_{p=1}^{c} \min_{u} \sum_{l} \lambda_{l} \sum_{j} \left\| L_{p}^{l} \odot \left( \Phi_{l}^{j}(I) - \Phi_{l}^{j}(g_{u}(L;\theta)) \right) \right\|_{1}$$
 (3)

## **Experiments**

### Qualitative comparison on the Cityscapes dataset



# **Experiments**

## Qualitative comparison on the NYU dataset



#### **Further**

### Ongoing Optimization

- Encoder-decoder and convolutional network have good performance on image processing.
- This result, while significantly more realistic than the prior state of the art, are clearly not indistinguishabld from real HD images.

#### References

• Qifeng Chen, Vladlen Koltun. Photographic Image Synthesis with Cascaded Refinement Networks