Surveillance Problem with Deep Learning

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Surveillance Problem

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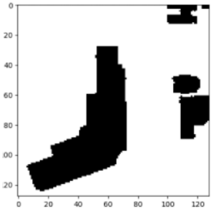

Problem Statement

- Consider a domain $\Omega \subset \mathbb{R}^n$. Let the domain be partitioned as $\Omega = \Omega_{\text{free}} \cup \Omega_{\text{obs}}$
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- An implicit assumption: the sensor range is larger than the area of the environment

Greedy Algorithm

- Can use a greedy algorithm based on choosing subsequent x_{k+1} that maximize information gain. Let the gain function be

$$g(x;\Omega_k) := |\mathcal{V}_x \cup \Omega_k| - |\Omega_k|$$

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- However, this is very costly to compute

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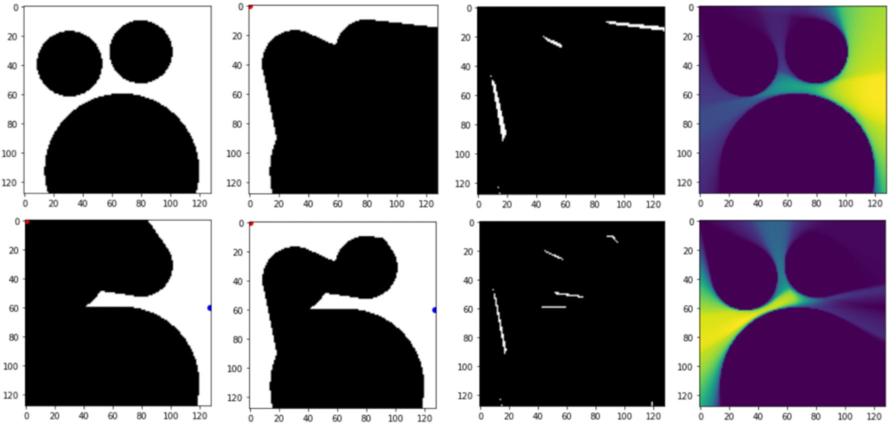
- Let the learned function be

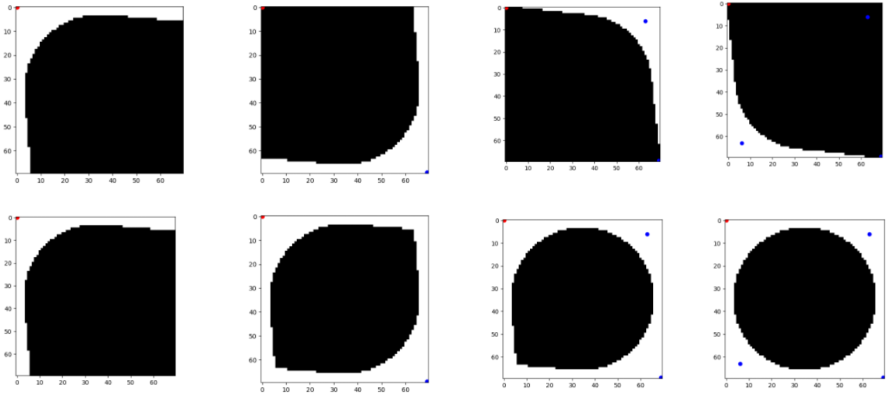
$$g_\theta(x; \Omega_k, B_k)$$

  where B_k is the part of $\partial\Omega_k$ that might be in Ω_{free} (i.e., $B_k = \partial\Omega_k \setminus \Omega_{\text{obs}}$)

Cumulative Visibility, Frontiers, and Gain Function



Example Results



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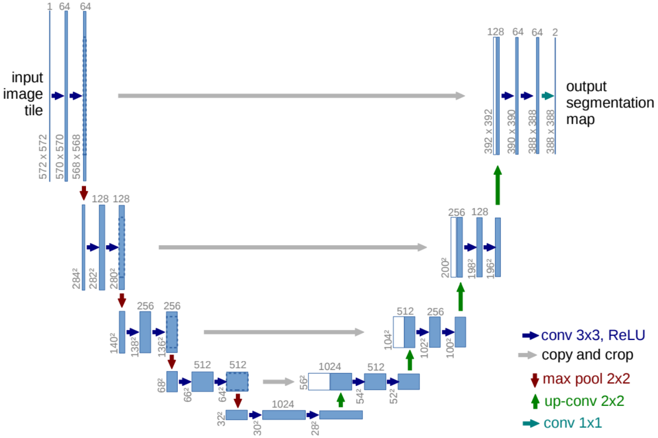
U-Net

- Base the model on U-Net because we want the value predicted at each pixel to depend on a neighborhood



Source: https://arxiv.org/pdf/1505.04597.pdf

Dataset

- Used two types of environments
  - Circle: 64×64 pixel environments consisting of 2 to 6 circles
  - City: 128×128 pixel aerial city blocks cropped from INRIA Aerial Image Labeling Dataset

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- Generated training data using the greedy algorithm
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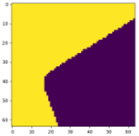
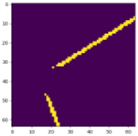
- Got ∼50,000 data pairs for Circle, and ∼20,000 data pairs for City

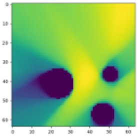
Inputs and Targets (Circle)



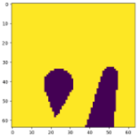
(a) Cumulative Visibility 1



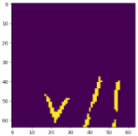
(b) Frontier 1



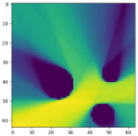
(c) Gain 1



(d) Cumulative Visibility 2



(e) Frontier 2



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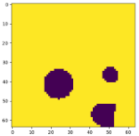
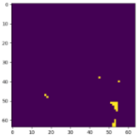
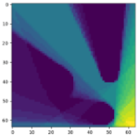


(g) Cumulative Visibility 3



(h) Frontier 3



(i) Gain 3

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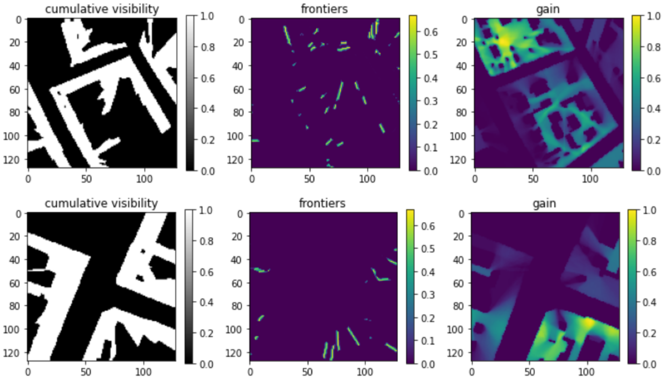

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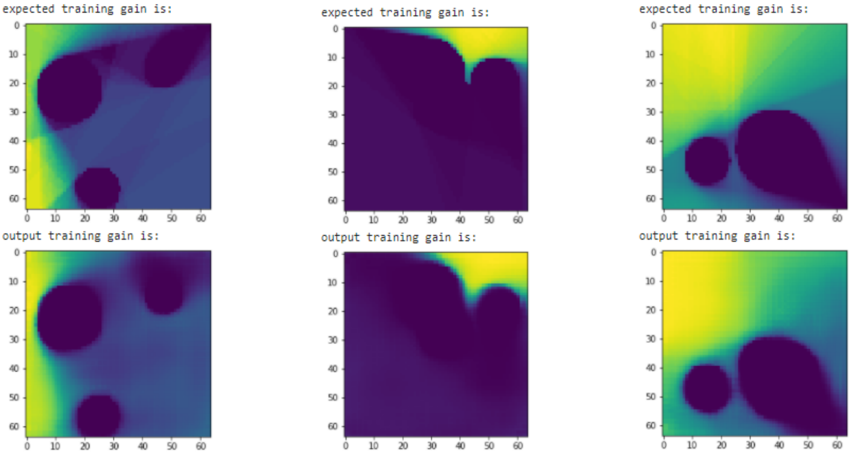

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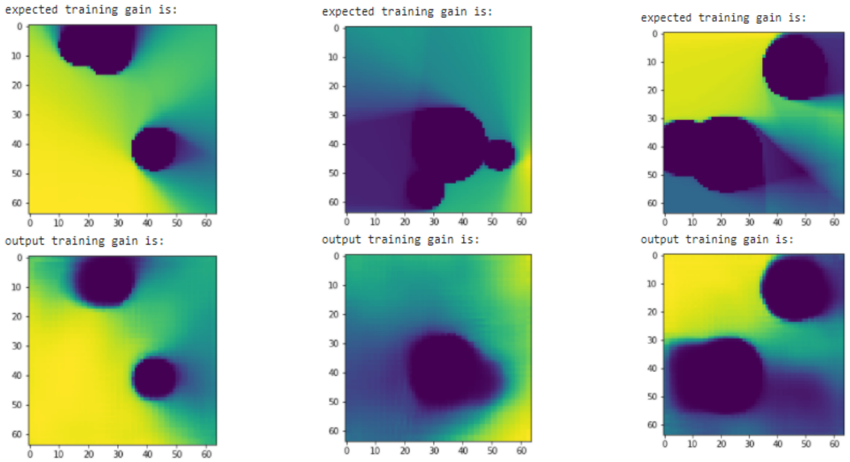
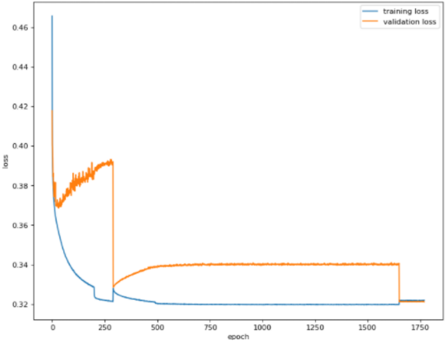
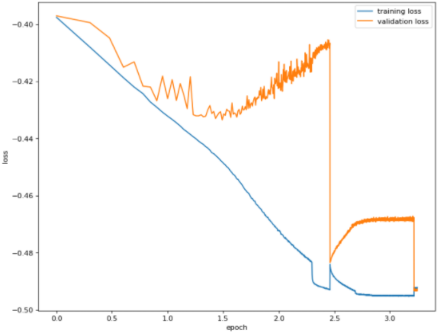


Results: Circular Environments Losses





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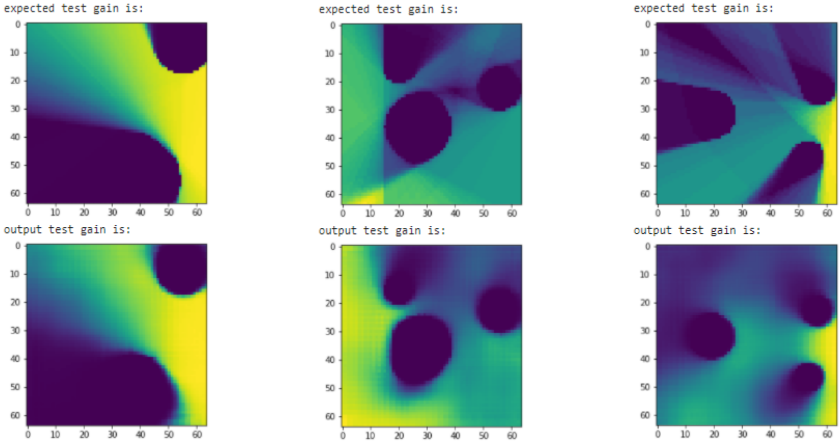
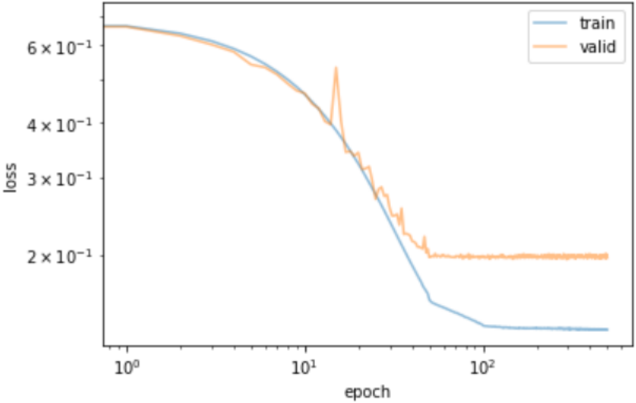


Results: City Environments

- Loss vs Epoch for 500 epochs



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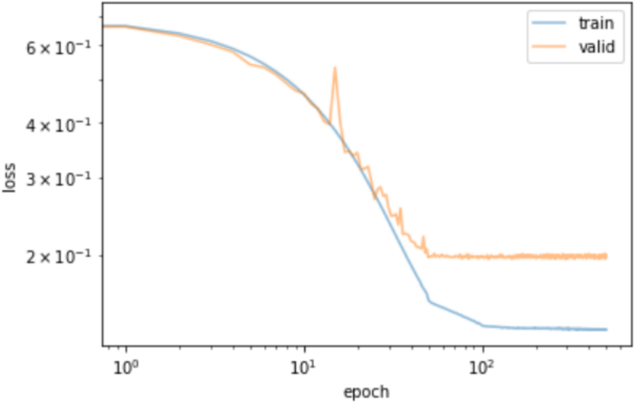
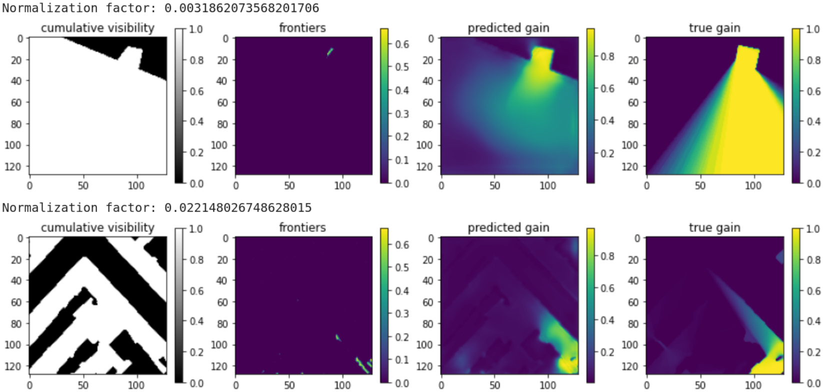


- Learning rate was decreased by a factor of 10 at epoch 50, 100, 150, resulting in slowed down decreases in losses
- The model doesn't generalize well on validation set

- Prediction on validation set
  - Good examples



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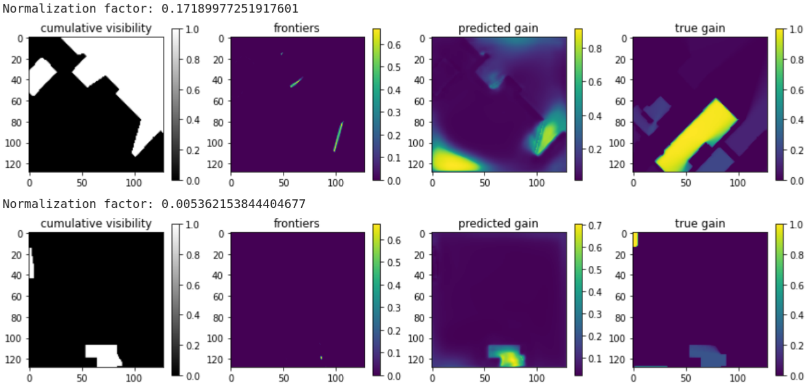

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  - Can improve this by giving the network more direct information of the map, e.g., using cumulative visibility and obstacles as input, rather than using cumulative visibility and frontier

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- Build a model to learn the “true” (unnormalized) gain function
  - Option 1: train the “true” gain function with MSE loss, with ReLU as the final layer
  - Option 2: create an additional module, MLP for example, connecting the bottom layer of the current Unet to a single output for the normalization factor

References

- Olaf Ronneberger and Philipp Fischer and Thomas Brox, U-Net: Convolutional Networks for Biomedical Image Segmentation
- Louis Ly thesis