Unsupervised Domain Adaptation for Semantic Segmentation

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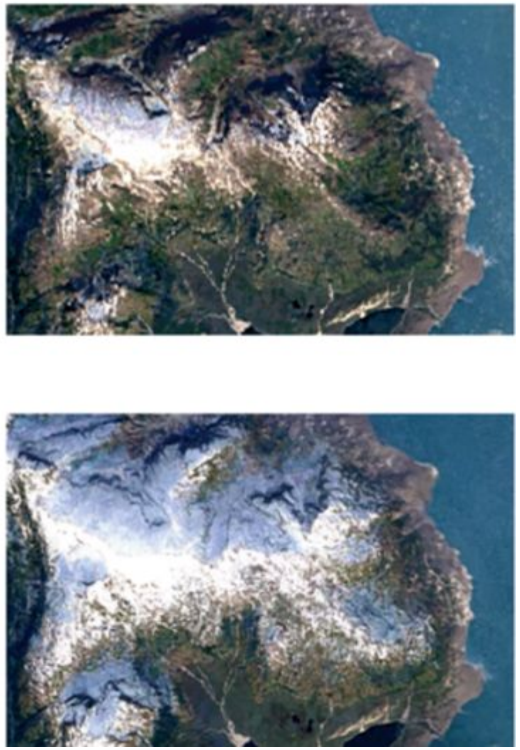
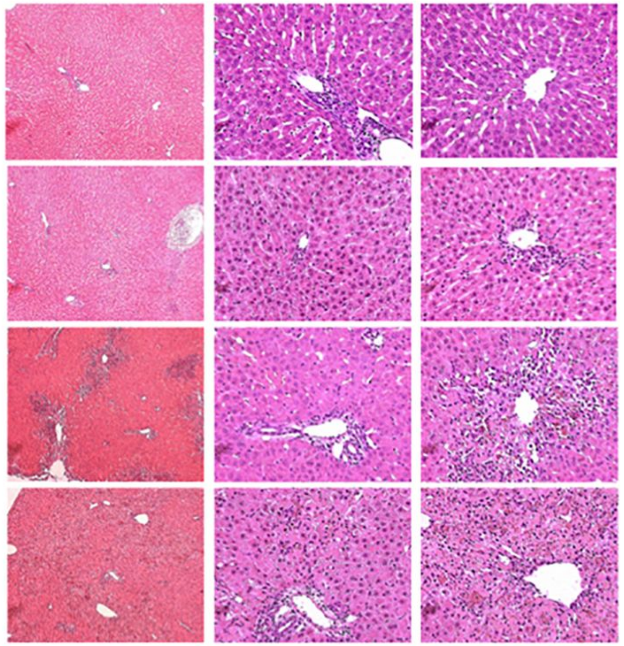
CS 771: Final project presentation

Problem- Distribution Shift



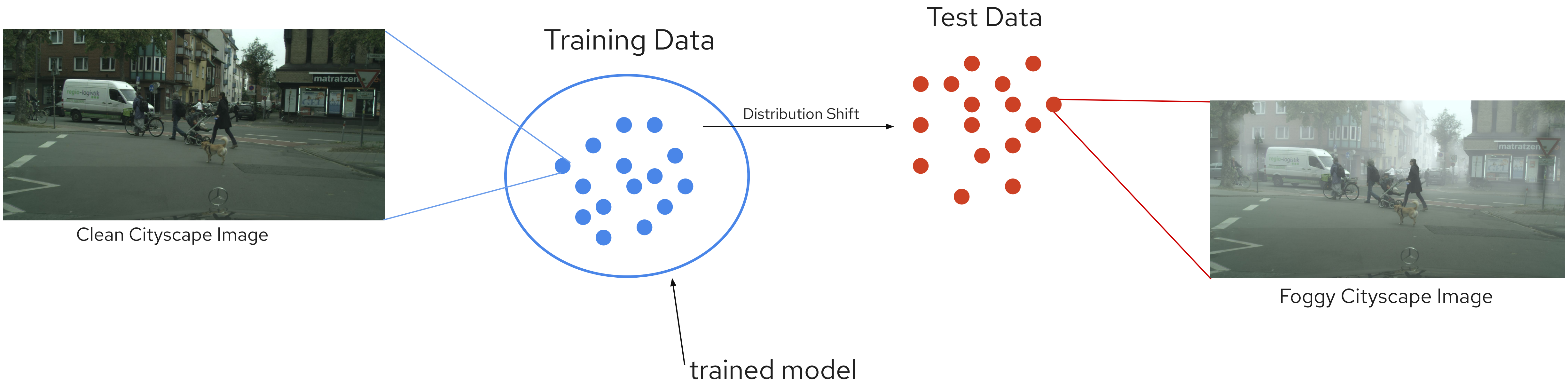
Satellite images
(different seasons)

Autonomous driving
(different weather)

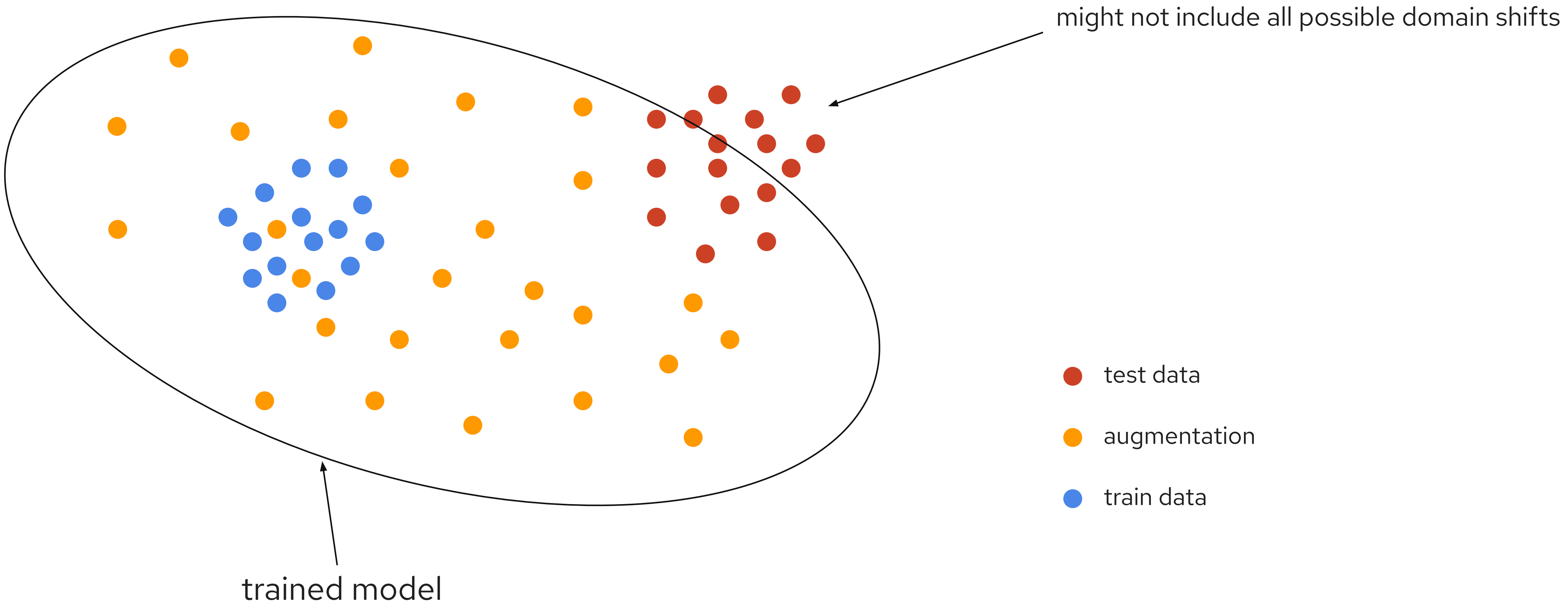


Medical images
(different stains)

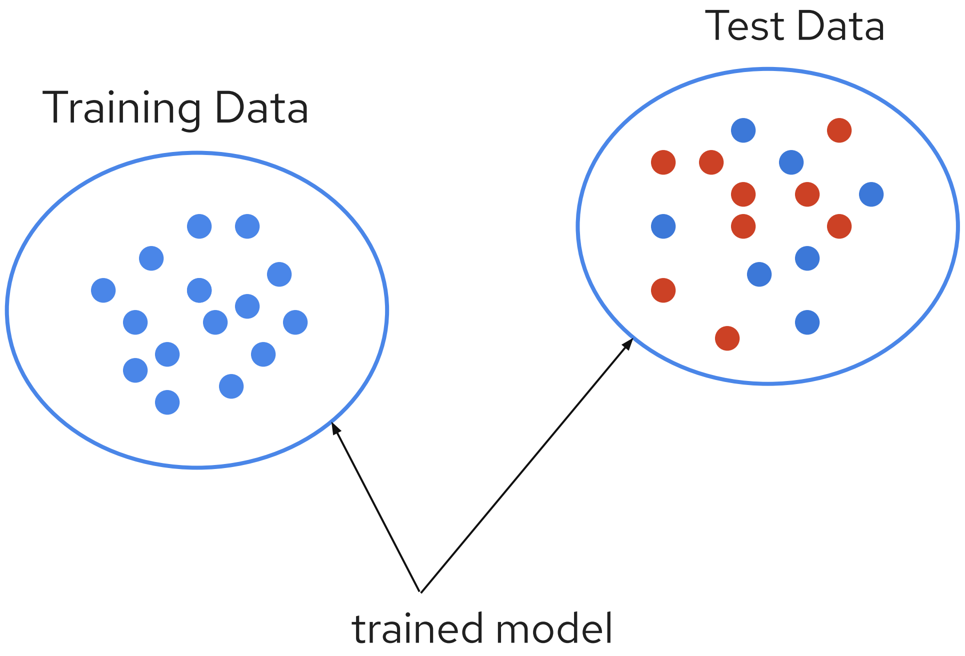
Problem- Distribution Shift



Solution 1 – Augmentation



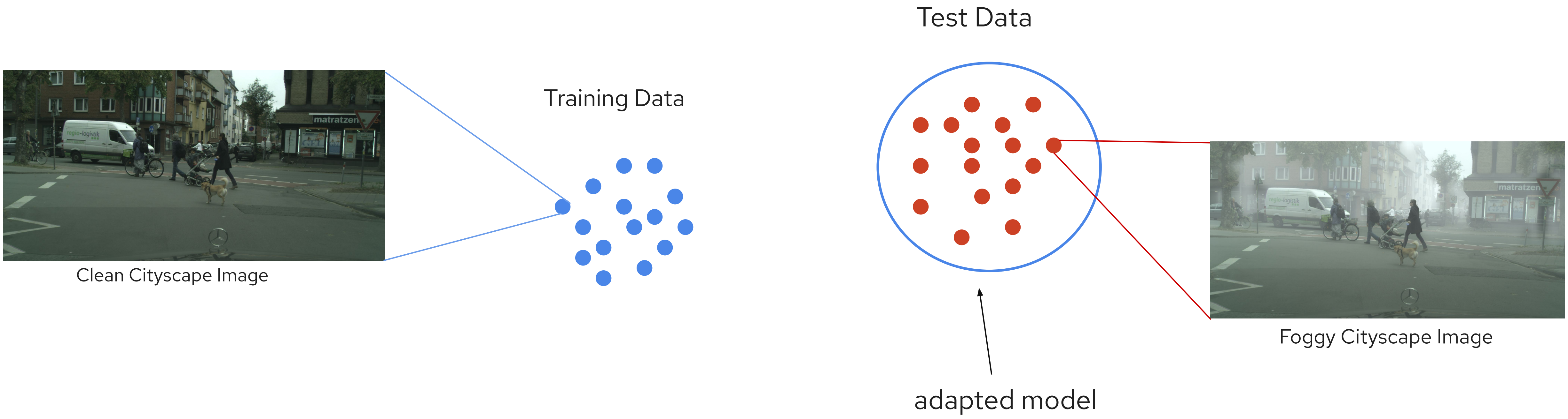
Solution 2 - Add Data from that Distribution



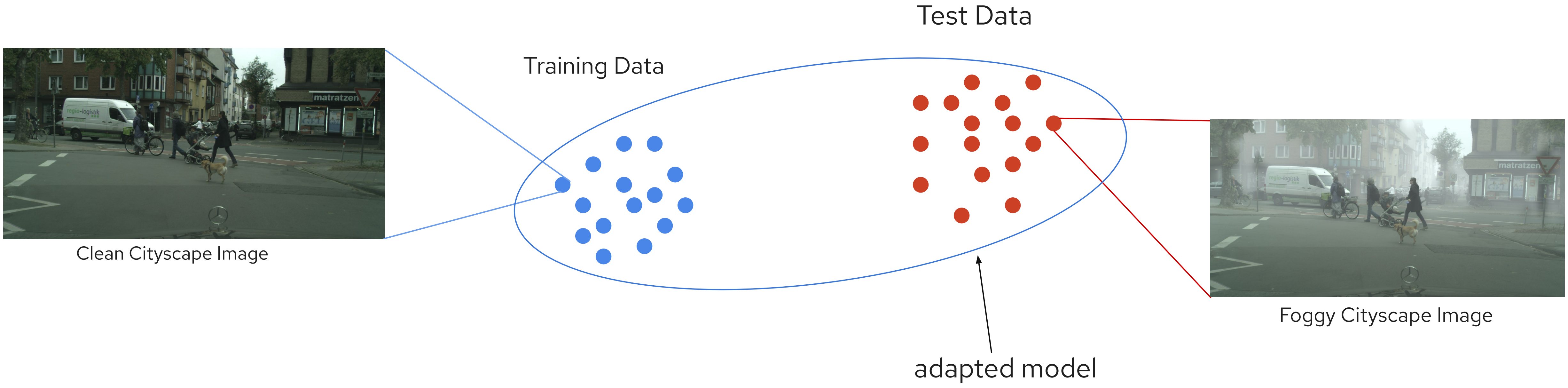
Drawback:

- Retraining Needed
- Annotation Effort

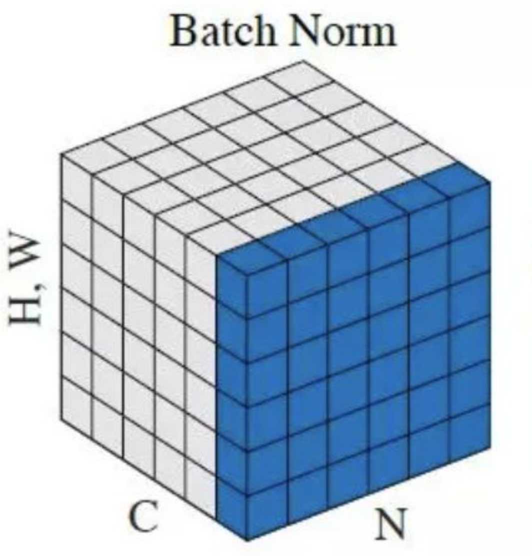
Solution 3 - Test Time Adaptation



Solution 3 – Test Time Adaptation



Batch Normalization



Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1...m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

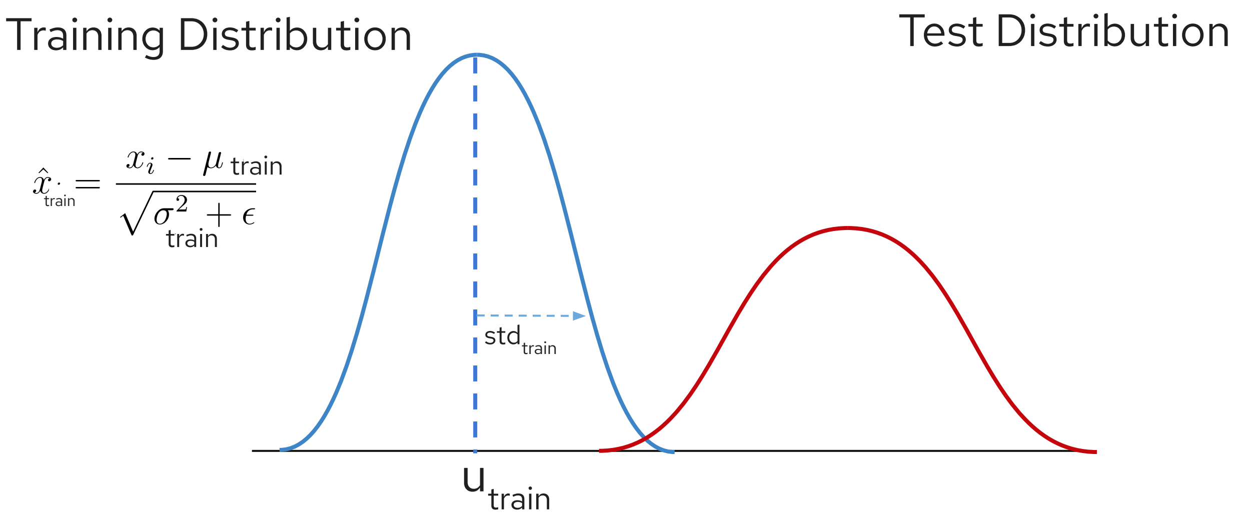
$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

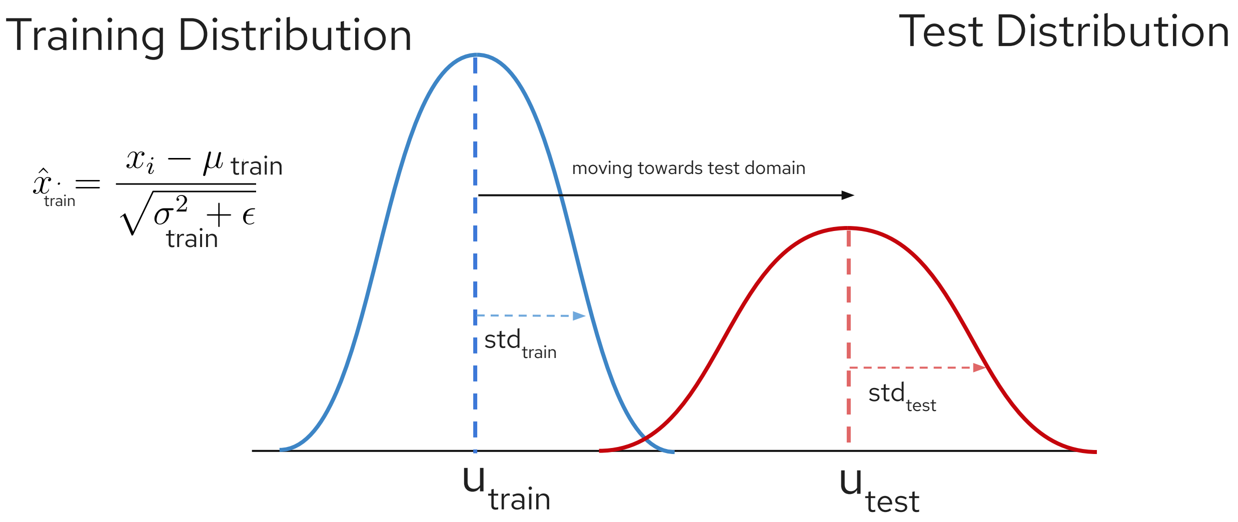
$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

Adaptive Batch Normalization (AdaBN)



Adaptive Batch Normalization (AdaBN)

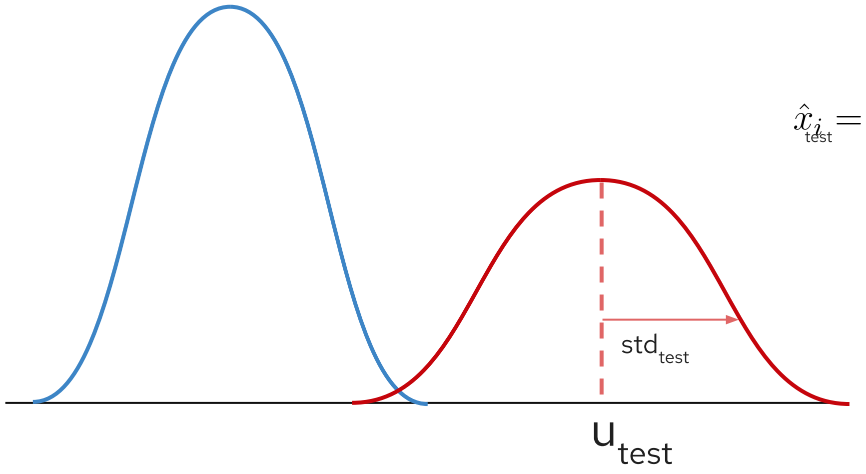
Learning mean and variance from test data



Adaptive Batch Normalization (AdaBN)

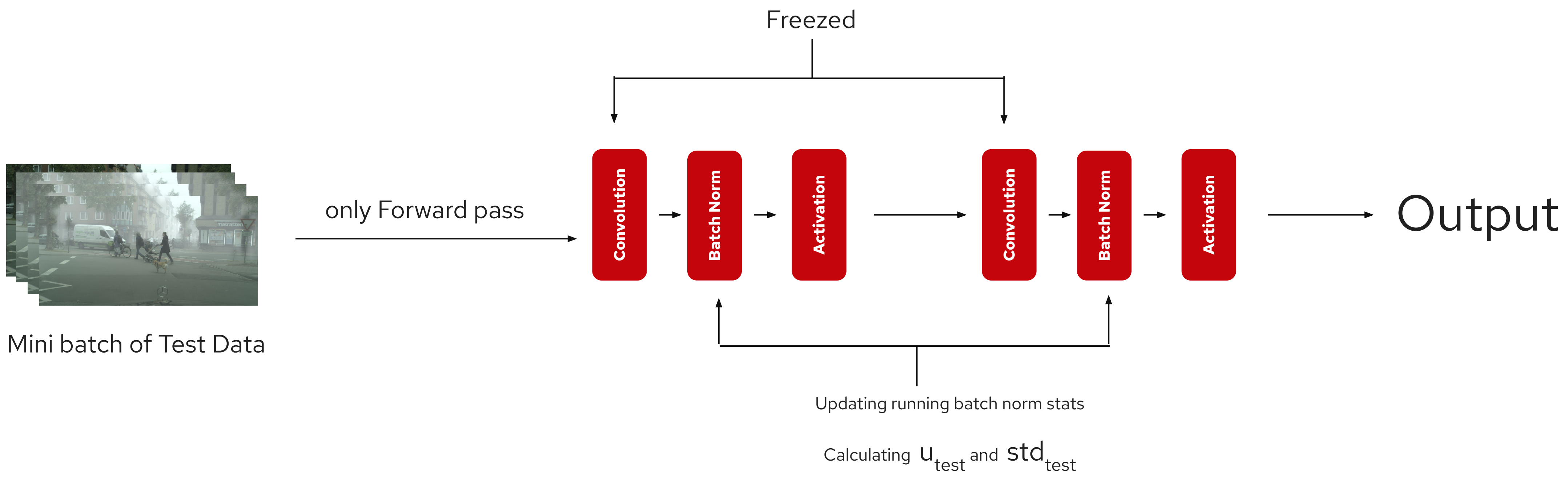
Test Distribution

$$\hat{x}_{i_{\text{test}}} = \frac{x_i - \mu_{\text{test}}}{\sqrt{\sigma^2_{\text{test}} + \epsilon}}$$



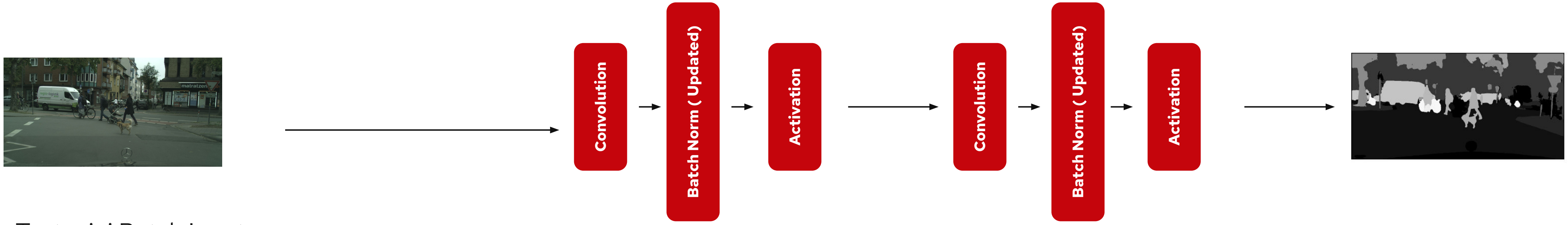
Adaptive Batch Normalization (AdaBN)

Iteratively Forward feed mini batches of Test Data



Adaptive Batch Normalization (AdaBN)

Inferring on test data



Test mini Batch Input

Experimental setup

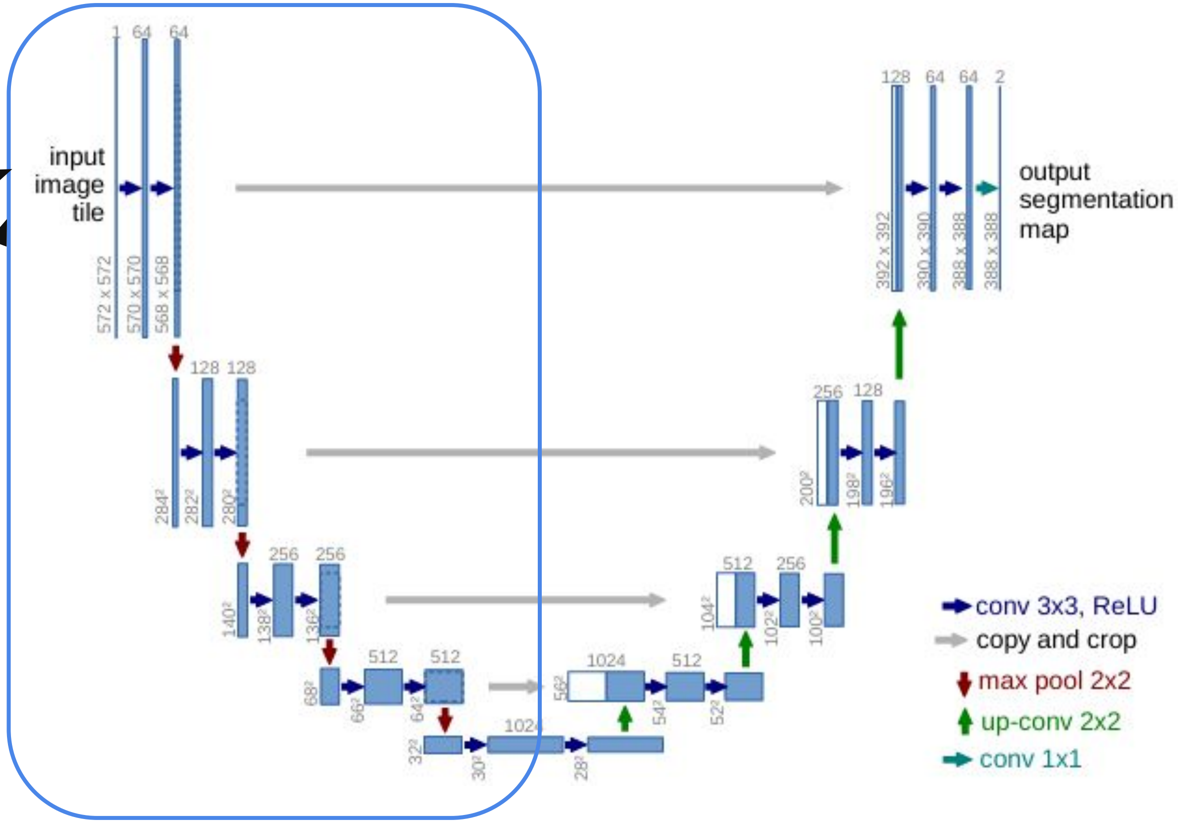
2 baseline models:

1. Normal cityscape

2. Augmented cityscape

(flip, rotate, color, gamma distortions)

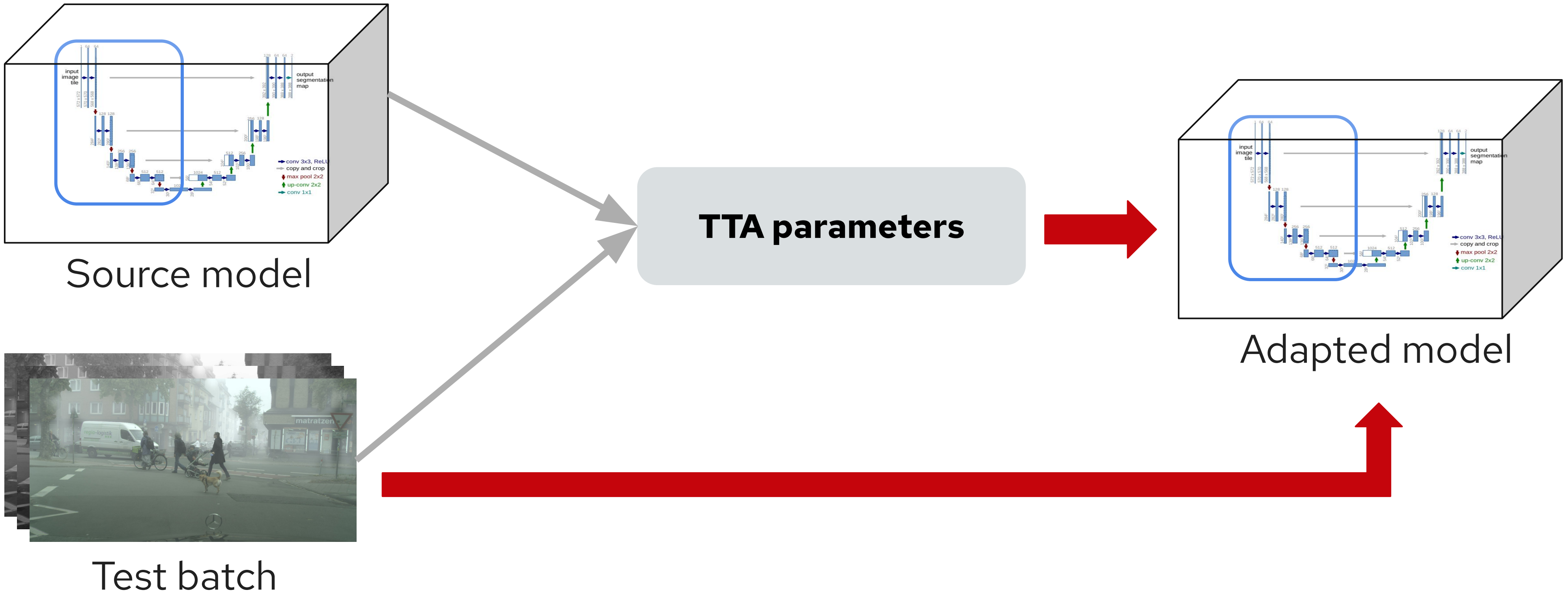
U-net architecture



Encoder : Resnet50

Loss = $L_{CE} + L_{DICE}$

Experimental setup



Baseline Model Results

	Normal	Fog 0.005	Fog 0.01	Fog 0.02
w/o Aug	0.7	0.68	0.64	**0.55**
w/ Aug	0.72	0.7	0.67	**0.62**

Normal CityScape

Foggy CityScape

After TTN Results

Fog 0.02, Batch size 8

Test:Train	No mix	0.2	0.5	1	Baseline
w/o aug	0.645	**0.645**	0.639	0.631	**0.55**
w/ Aug	0.689	**0.693**	0.691	0.682	**0.62**

Baseline model **After TTN**

Weakness and Shortcomings

- Recomputing statistics during inference introduces additional computational costs, which may not be ideal for time-sensitive applications

- For substantial domain shifts, recalibrating the statistics may not be sufficient