



# Exploring Deep Learning Domain Adaptation Performance: From Covariate Shift to Wasserstein and beyond

Encadrement: Étienne Baudrier, Sylvain Faisan, Alexandre Stenger

07/21/2023

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# Esplorando la Performance dell'Adattamento al Dominio nell'Apprendimento Profondo: dallo Spostamento di Covarianza alla Wasserstein e oltre

Supervisione: Étienne Baudrier, Sylvain Faisan, Alexandre Stenger

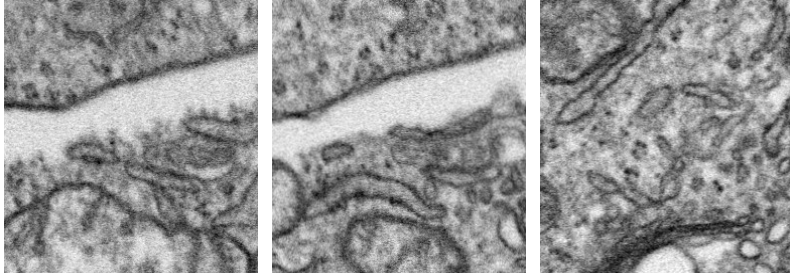
07/21/2023

# Introduzione

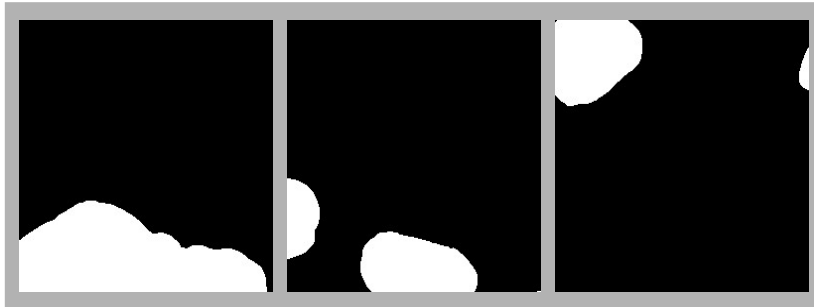
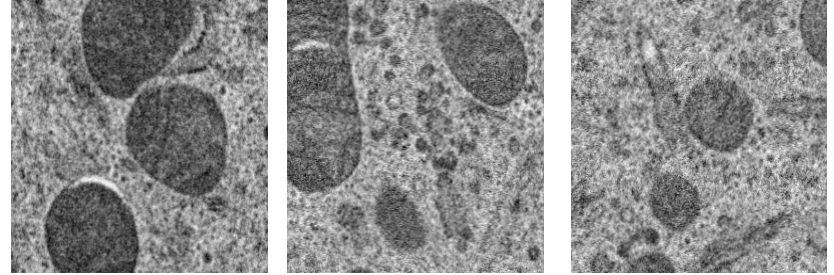


# Introduzione: Spostamento di Covariata

**Dati sorgente** (*fissione chimica*)



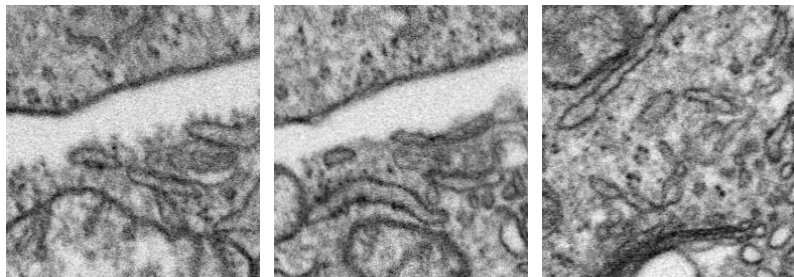
**Dati obiettivo** (*crio-fissione*)



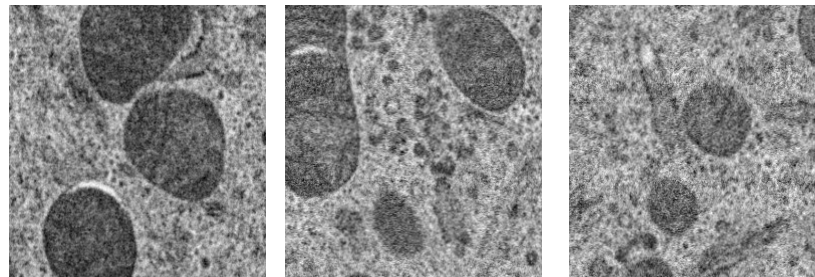
**Spostamento di covariata**

# Introduzione: Spostamento di Covariata

**Dati sorgente**



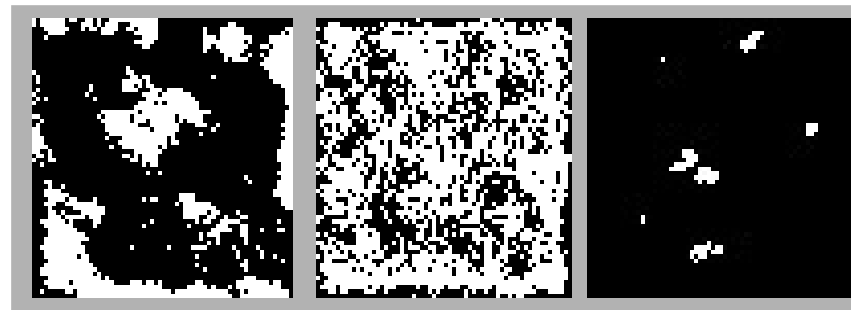
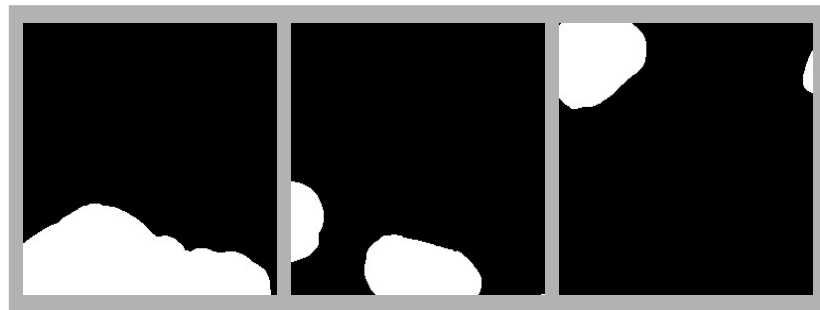
**Dati obiettivo**



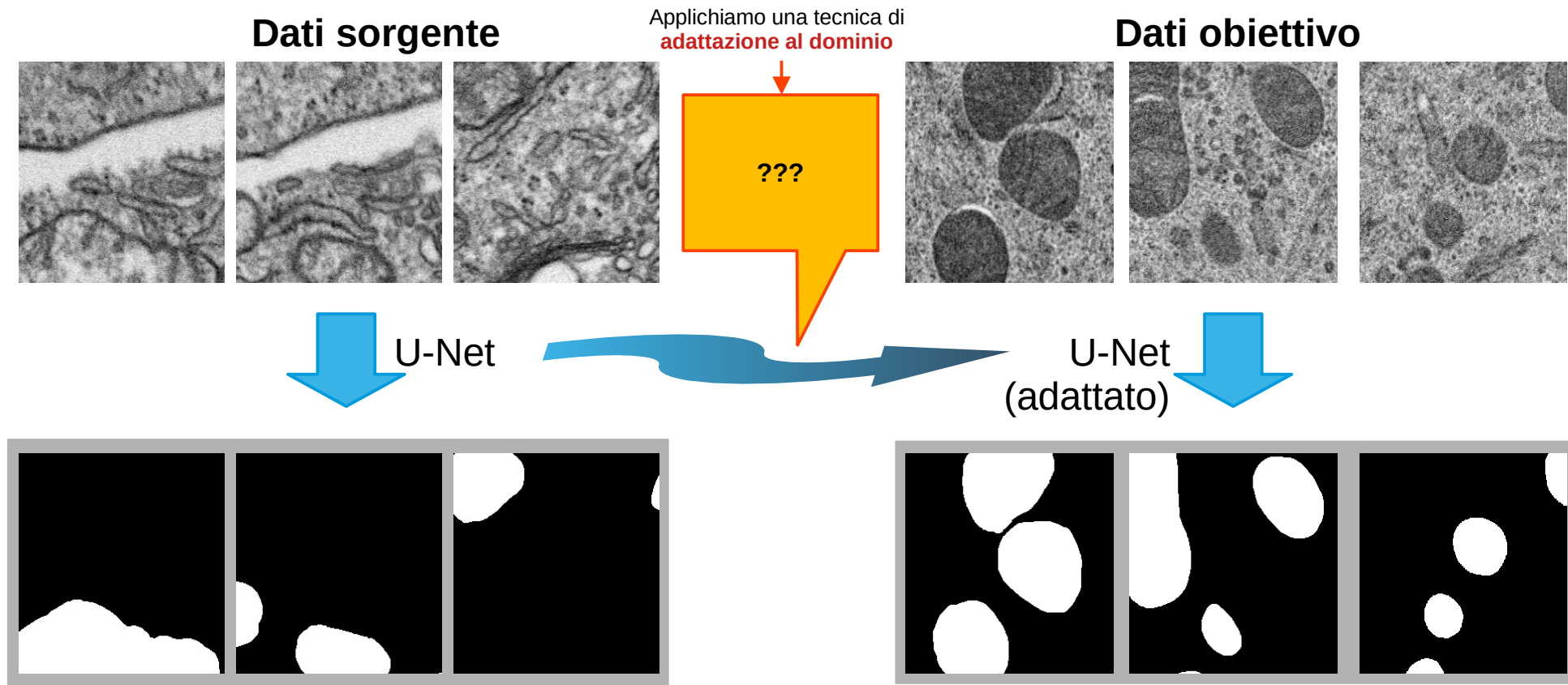
U-Net



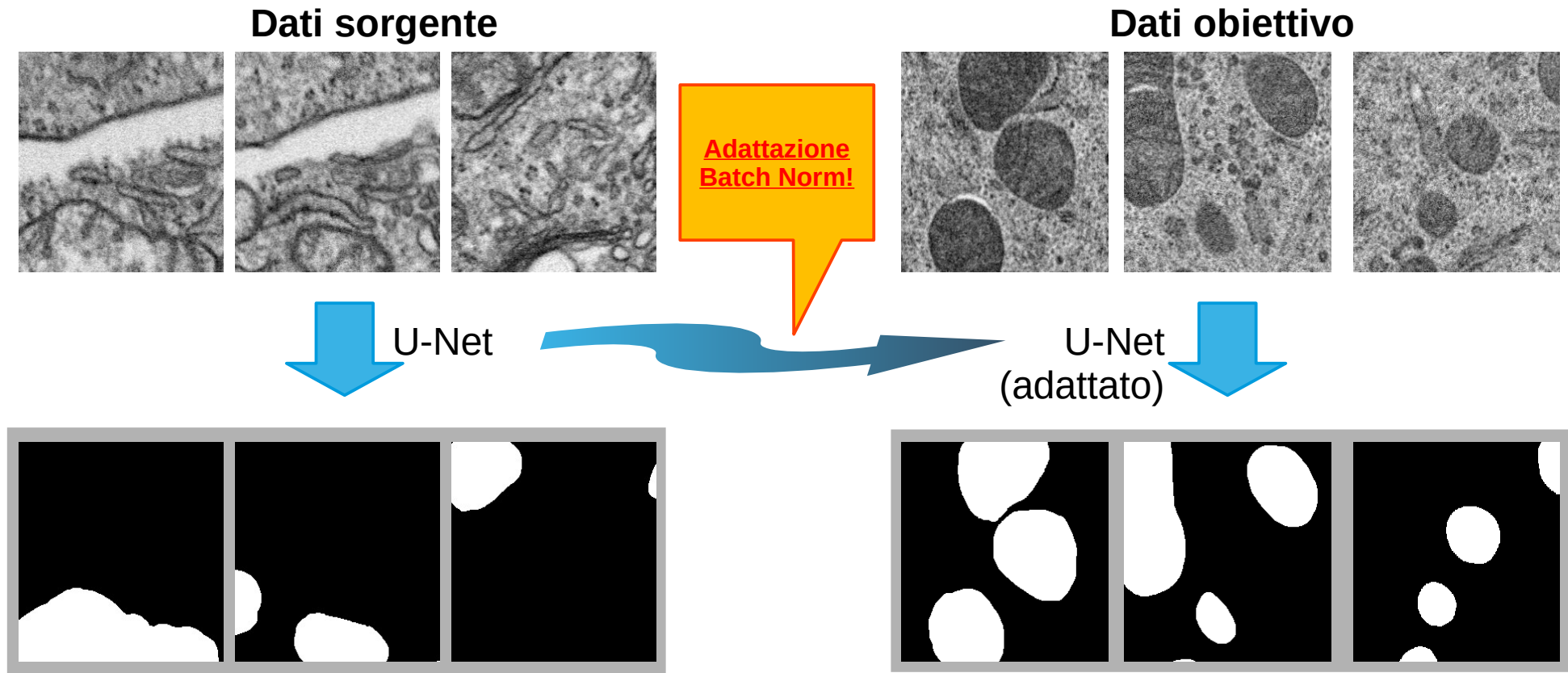
U-Net



# Introduzione: Spostamento di Covariata

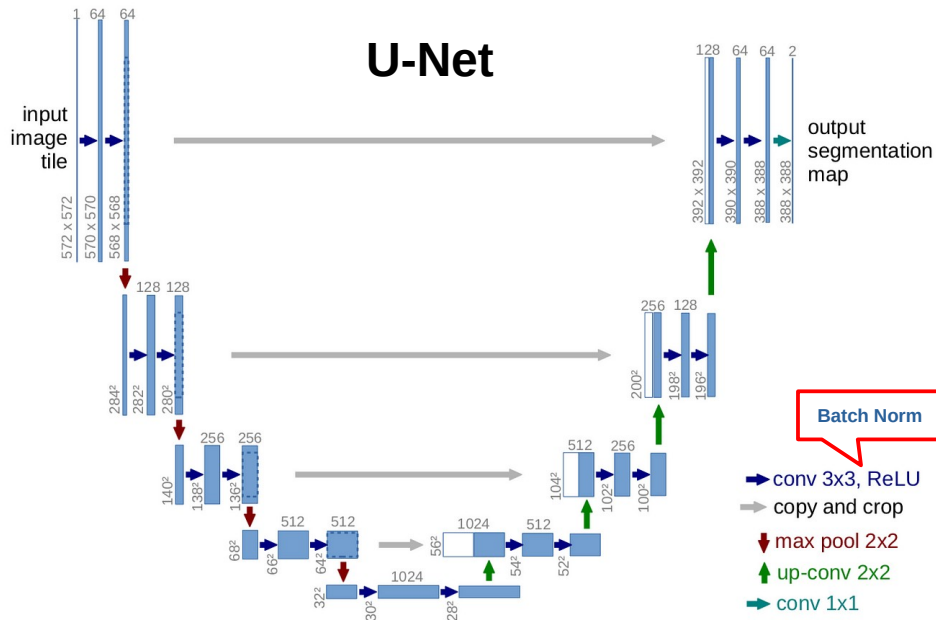


# Introduzione: Spostamento di Covariata



# Introduzione: Adattamento Batch Norm

## Cos'è la Batch Norm?



### Livello Batch Norm

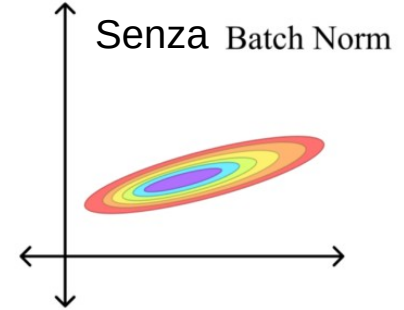
$$\hat{\mu} = \mathbb{E}[x]$$

$$\hat{\sigma} = \sqrt{\text{Var}[x]}$$

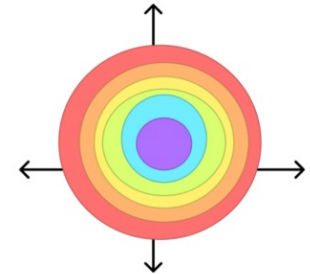
$$y = \frac{x - \hat{\mu}}{\hat{\sigma}} * \gamma + \beta$$

$\gamma, \beta$  imparati durante l'allenamento

Senza Batch Norm



Con Batch Norm





# Introduzione: Adattamento Batch Norm

## Cos'è l'adattamento Batch Norm?

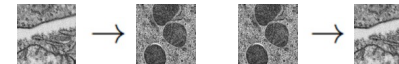
- prendiamo i **dati obiettivo** e li passiamo attraverso la rete, bloccando tutti i parametri ma aggiornando  $\hat{\mu}$  e  $\hat{\sigma}$

# Introduzione: il lavoro della mia équipe



## FAST AND INTERPRETABLE UNSUPERVISED DOMAIN ADAPTATION FOR FIB-SEM CELL SEGMENTATION

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 Étienne Baudrier<sup>†</sup> Benoît Naegel<sup>†</sup>

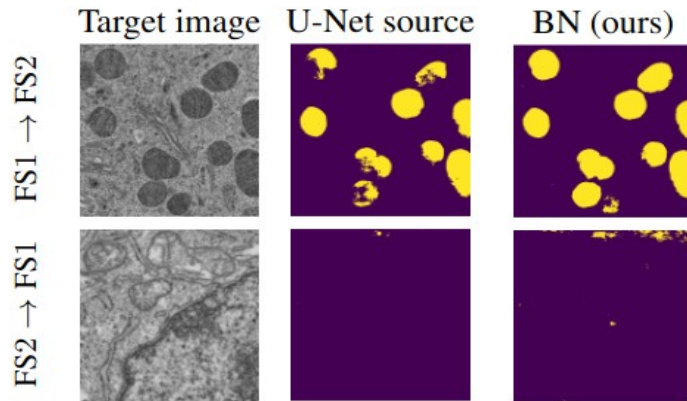


Architecture	FS1 → FS2	FS2 → FS1
U-Net (source trained)	0.556	0.006
Y-Net ([6])	0.614	0.014
CellSegUDA ([4])	0.673	<b>0.041</b>
<b>BatchNorm (ours)</b>	<b>0.736</b>	0.024
U-Net (target trained)	0.881	0.803

[https://publis.icube.unistra.fr/docs/17711/ISBI\\_paper\\_559.pdf](https://publis.icube.unistra.fr/docs/17711/ISBI_paper_559.pdf)

# Introduzione: il lavoro della mia équipe

## Comportamento asimmetrico della BN (adattamento Batch Norm)



*Pro:*

- Facile da implementare
- Estremamente veloce

*Contro:*

- Non sappiamo quando funziona

# L'obiettivo del mio stage

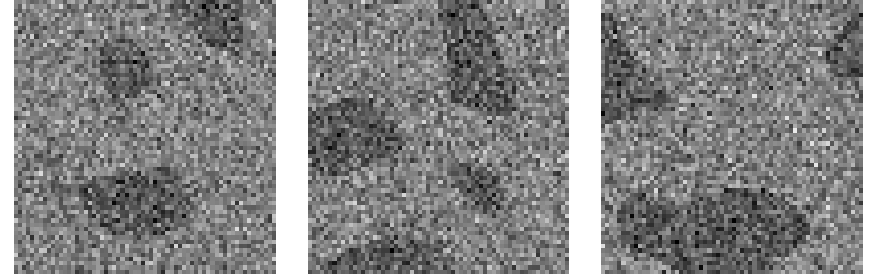
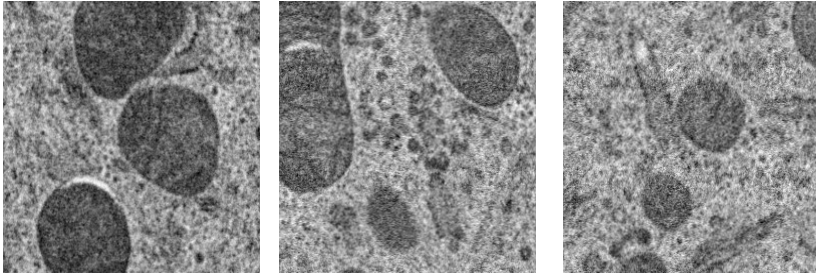
Perché (e quando) funziona l'adattamento Batch Norm?



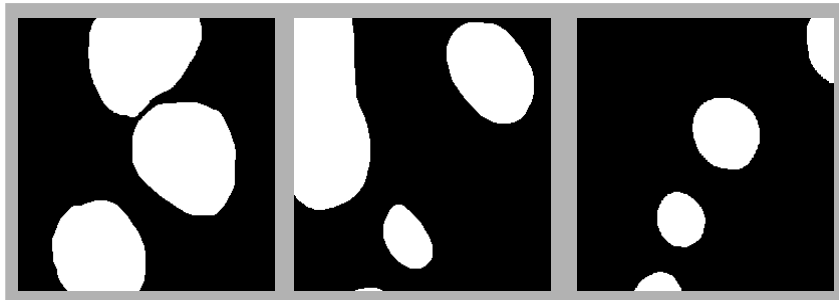
# Generazione dei dati

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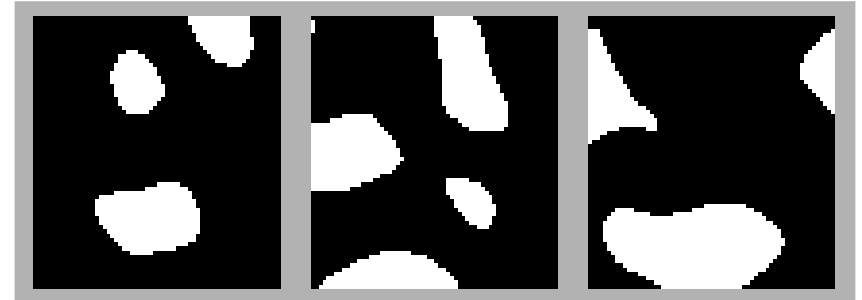
Dati sorgente



Aggiungi  
rumore

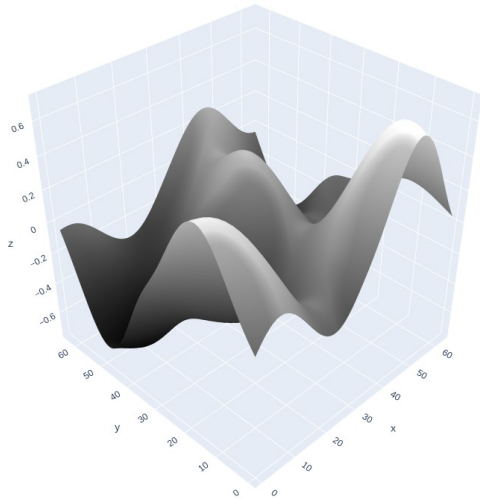


ispirato

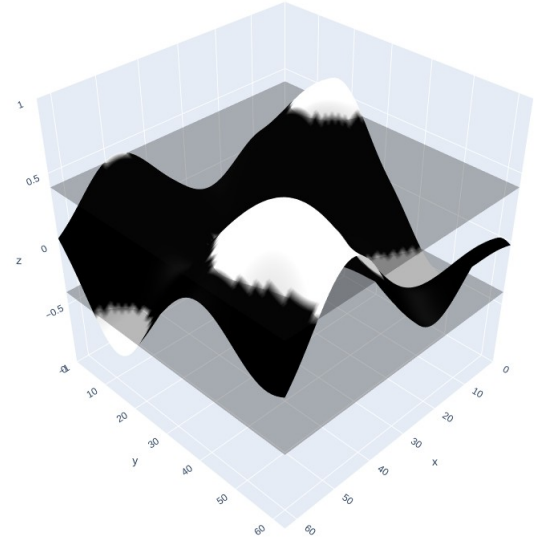


# Generazione dei dati

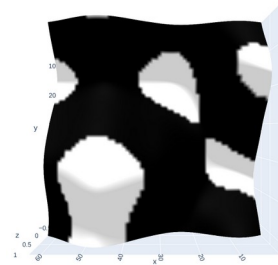
1) Generi un **Rumore di Perlin**



2) definisci una soglia

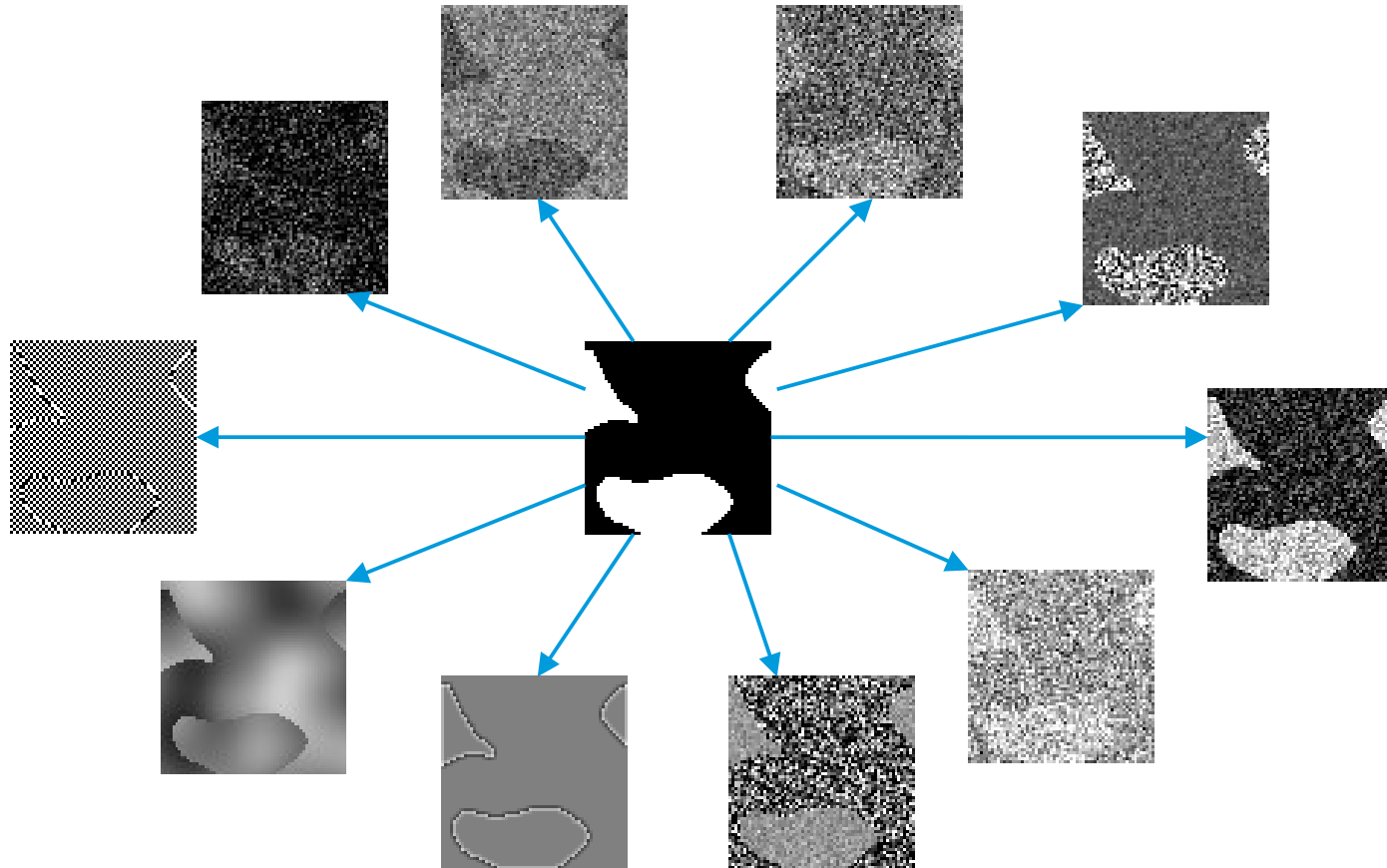


3) “guardi da sopra”



~40s per 10.000 immagini

# Generazione dei dati





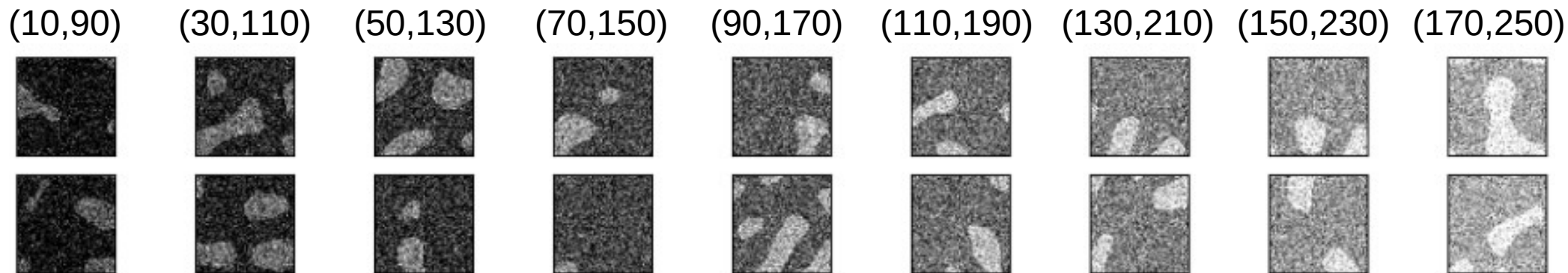
# When does BN adaptation work?

# when does BN adaptation work?

## When BN adaptation works

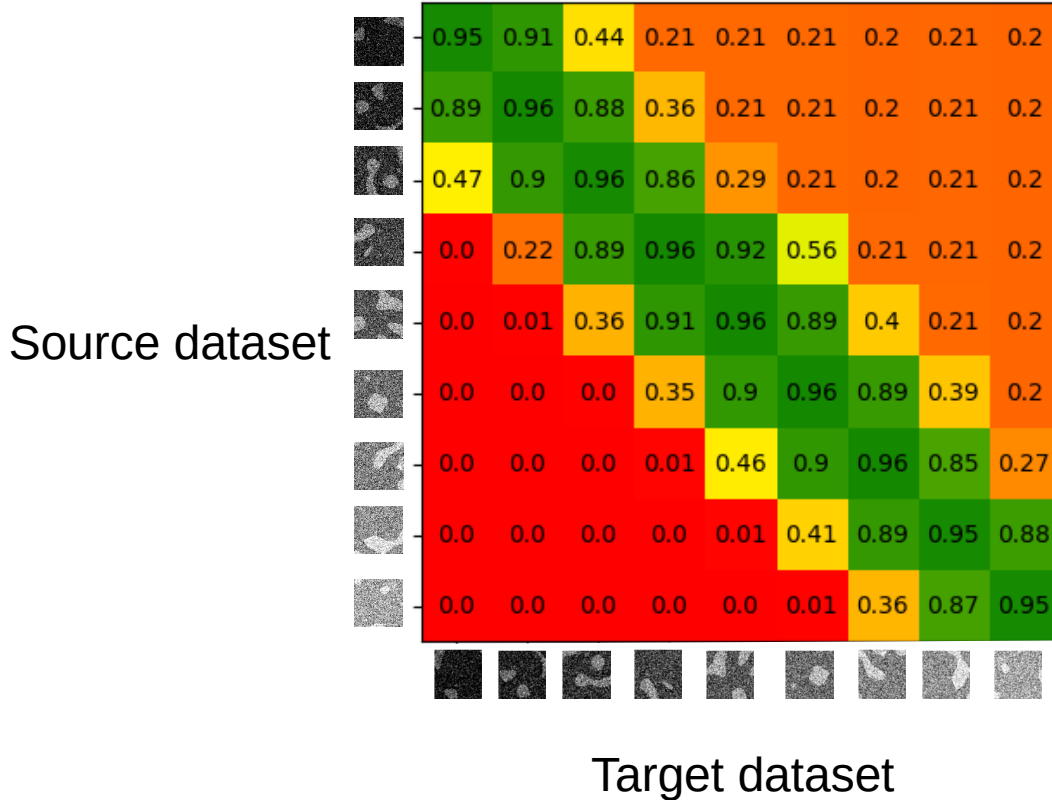
(means of mask and background white noises)

$(\mu_1, \mu_2)$

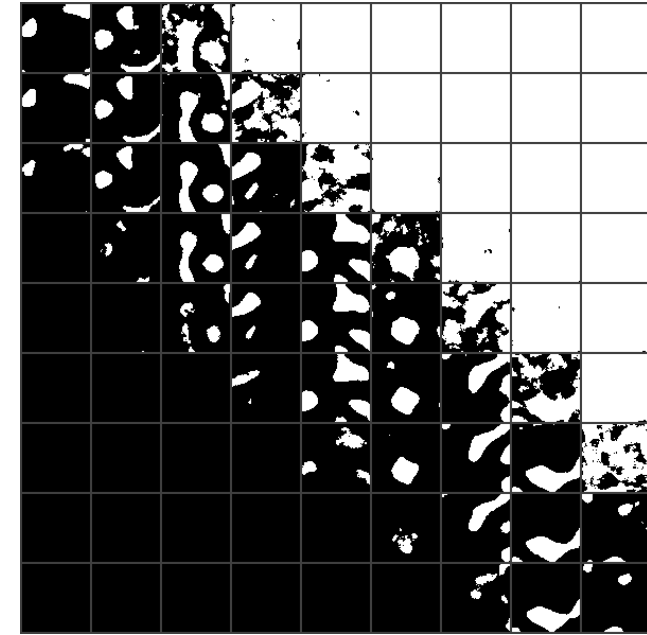


# when does BN adaptation work?

U-Net WITHOUT bn adaptation

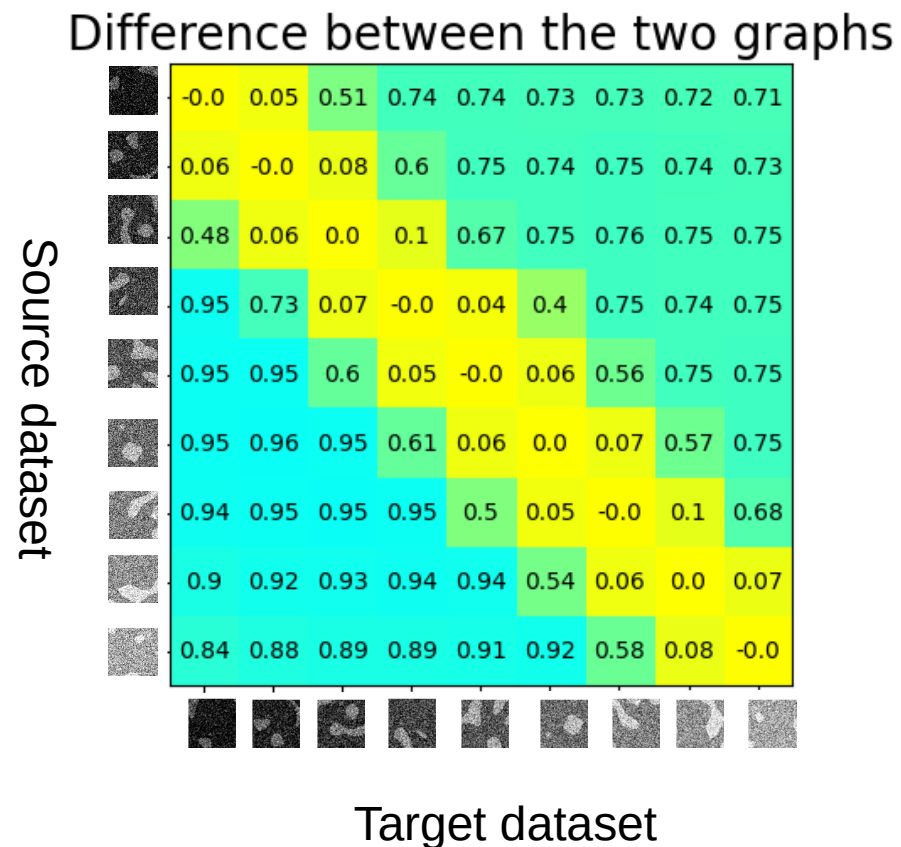
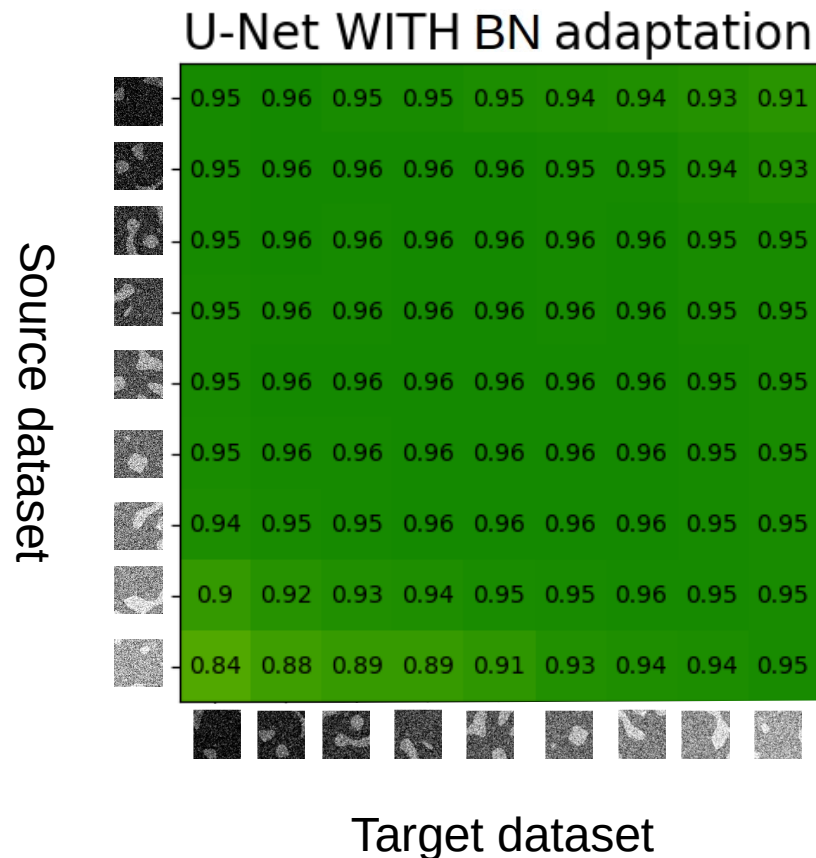


Mask predictions



Source dark, target bright → all white  
Source bright, target dark → all black

# when does BN adaptation work?



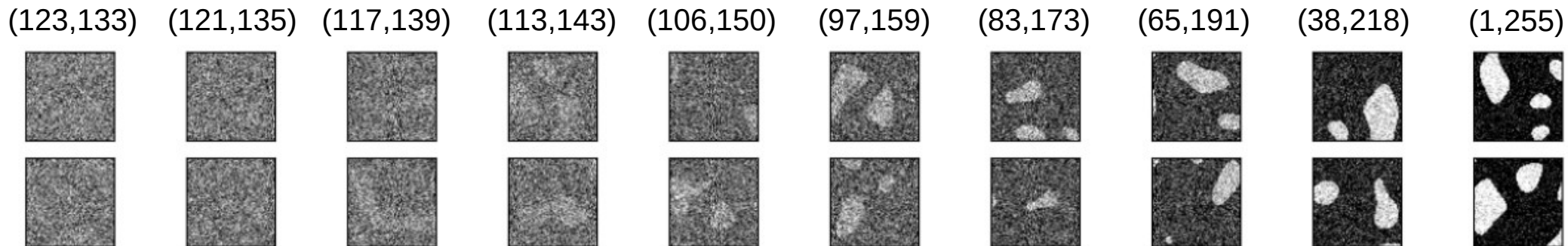


# when does BN adaptation work?

## When BN adaptation ..kinda works?

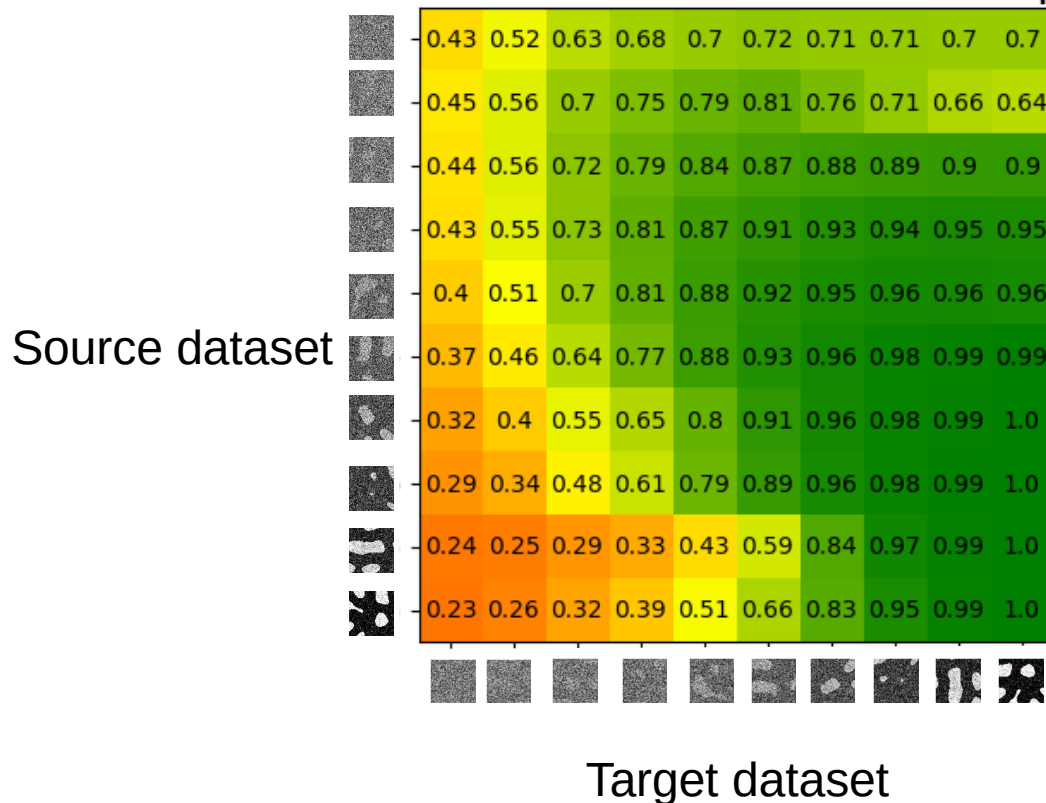
(means of mask and background white noises)

$(\mu_1, \mu_2)$

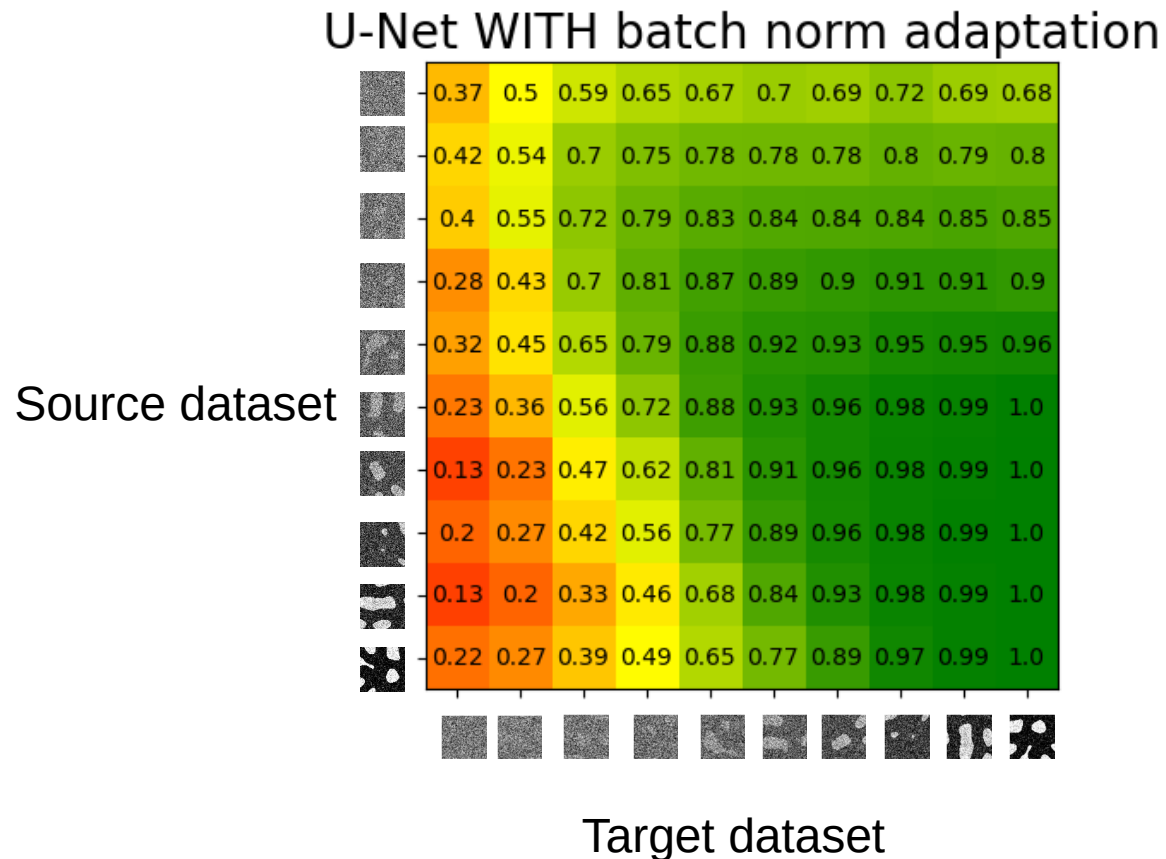


# when does BN adaptation work?

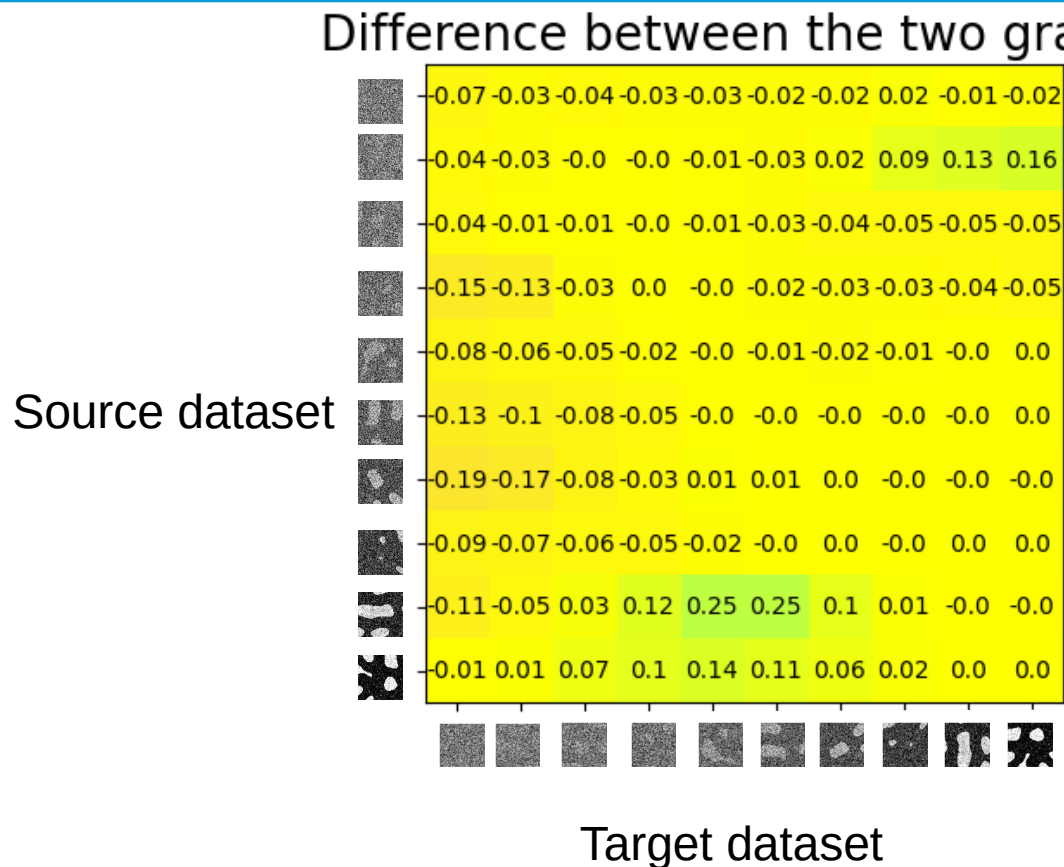
U-Net WITHOUT batch norm adaptation



# when does BN adaptation work?



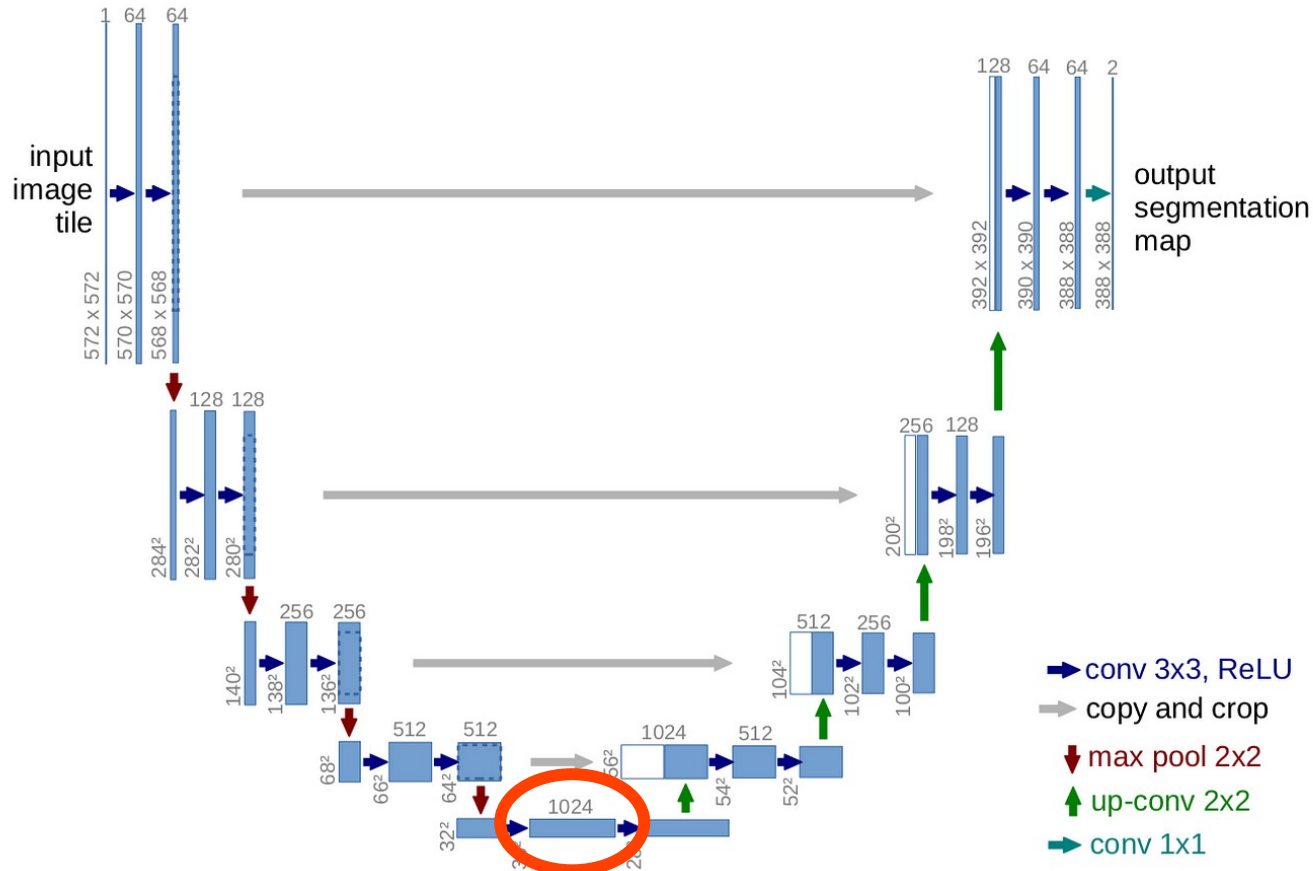
# when does BN adaptation work?



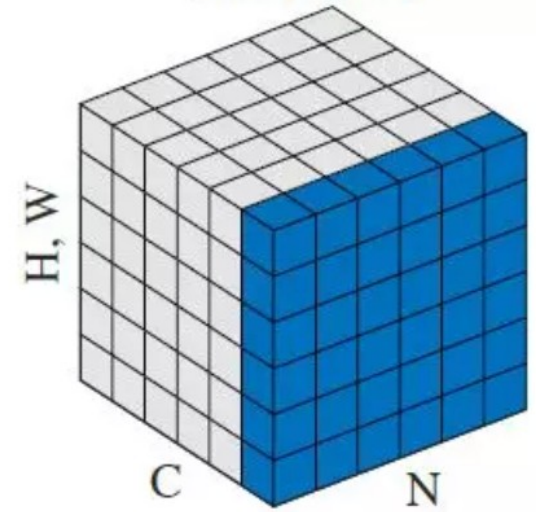


When should we use BN adaptation?

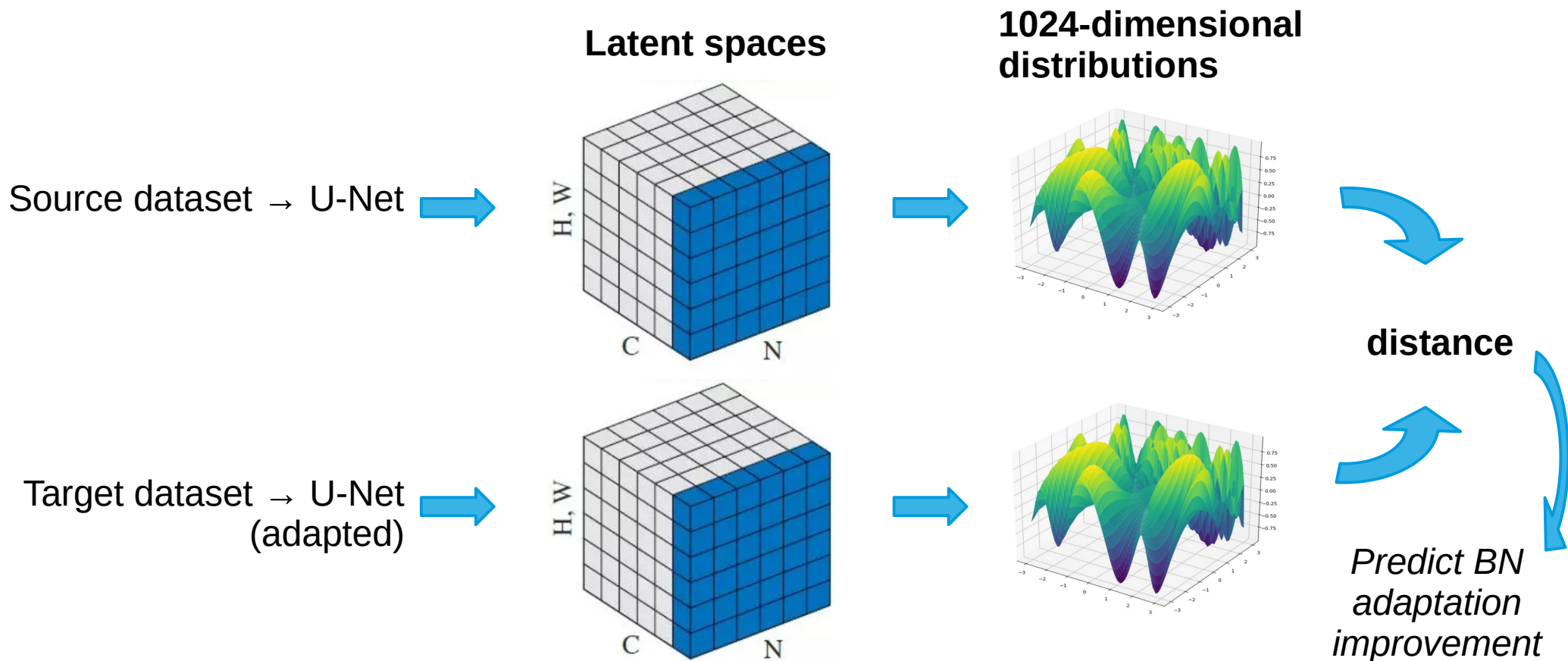
# When should we use BN adaptation?



Latent space

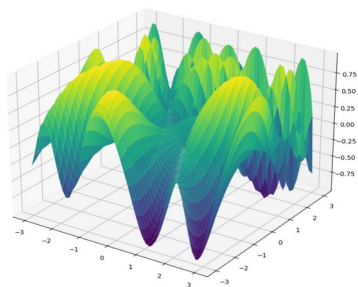


# When should we use BN adaptation?

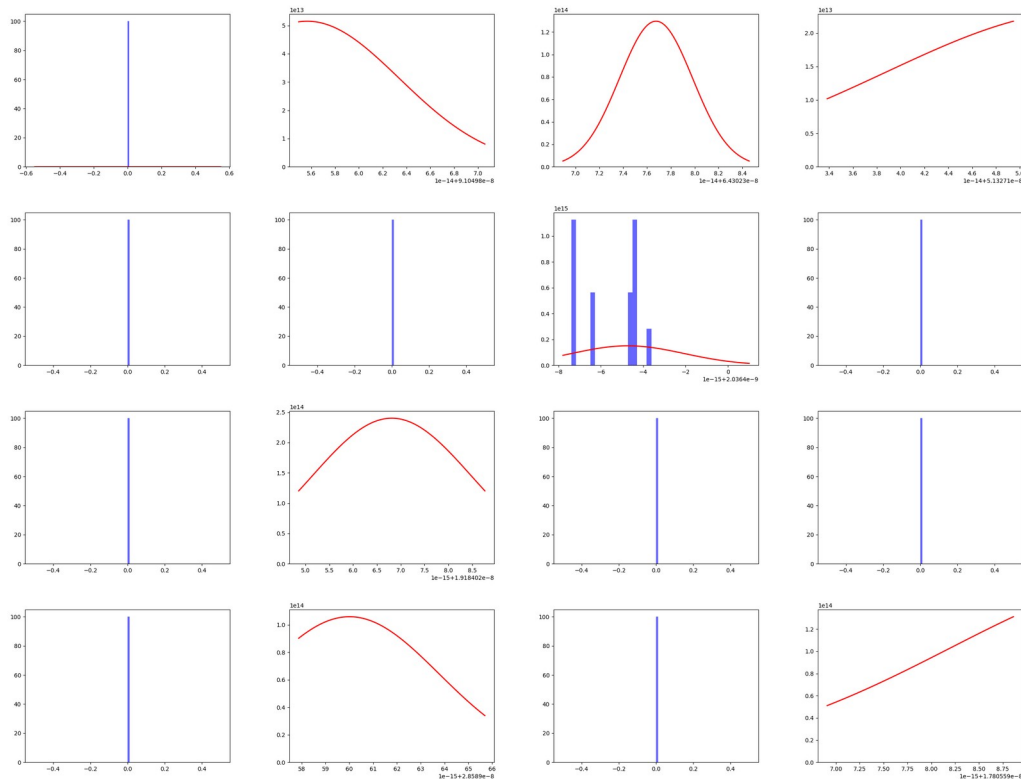


# When should we use BN adaptation?

1024-dimensional  
distributions



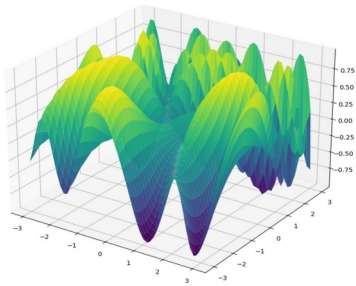
Projection  
per-dimension



What is going on???

# When should we use BN adaptation?

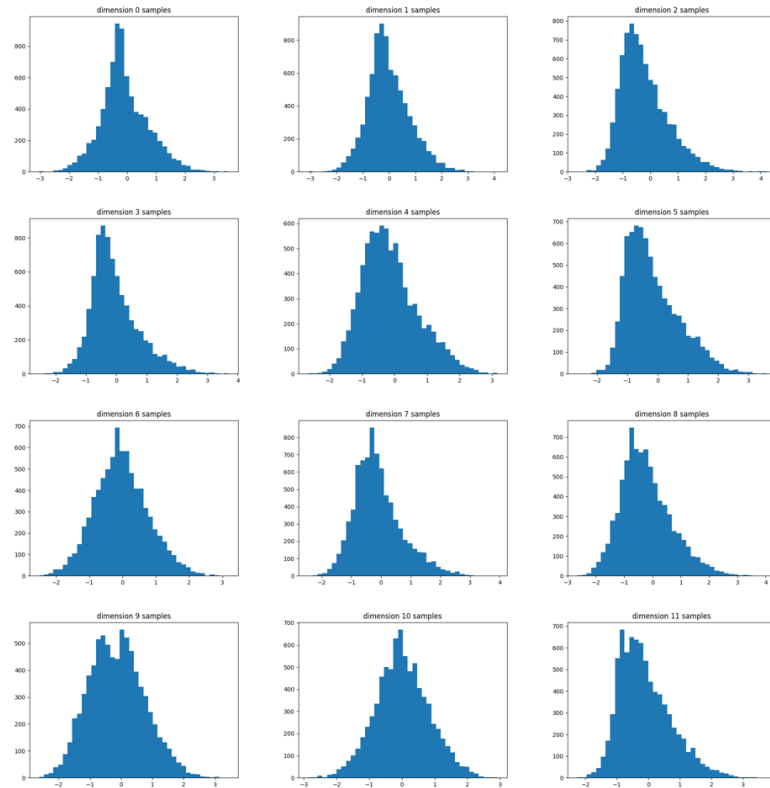
1024-dimensional  
distributions



*Removed  
weight decay +  
Before ReLU*



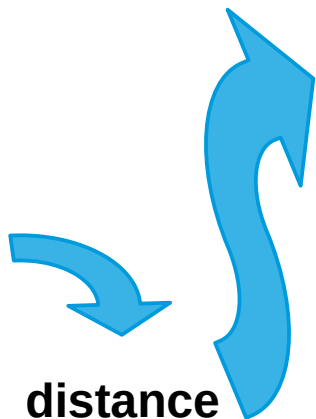
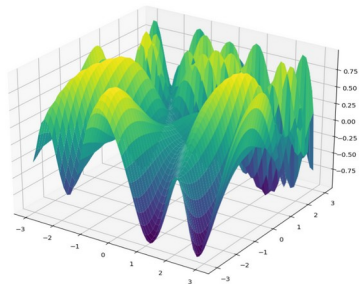
Projection  
per-dimension



We can work with this!

# When should we use BN adaptation?

1024-dimensional  
distributions

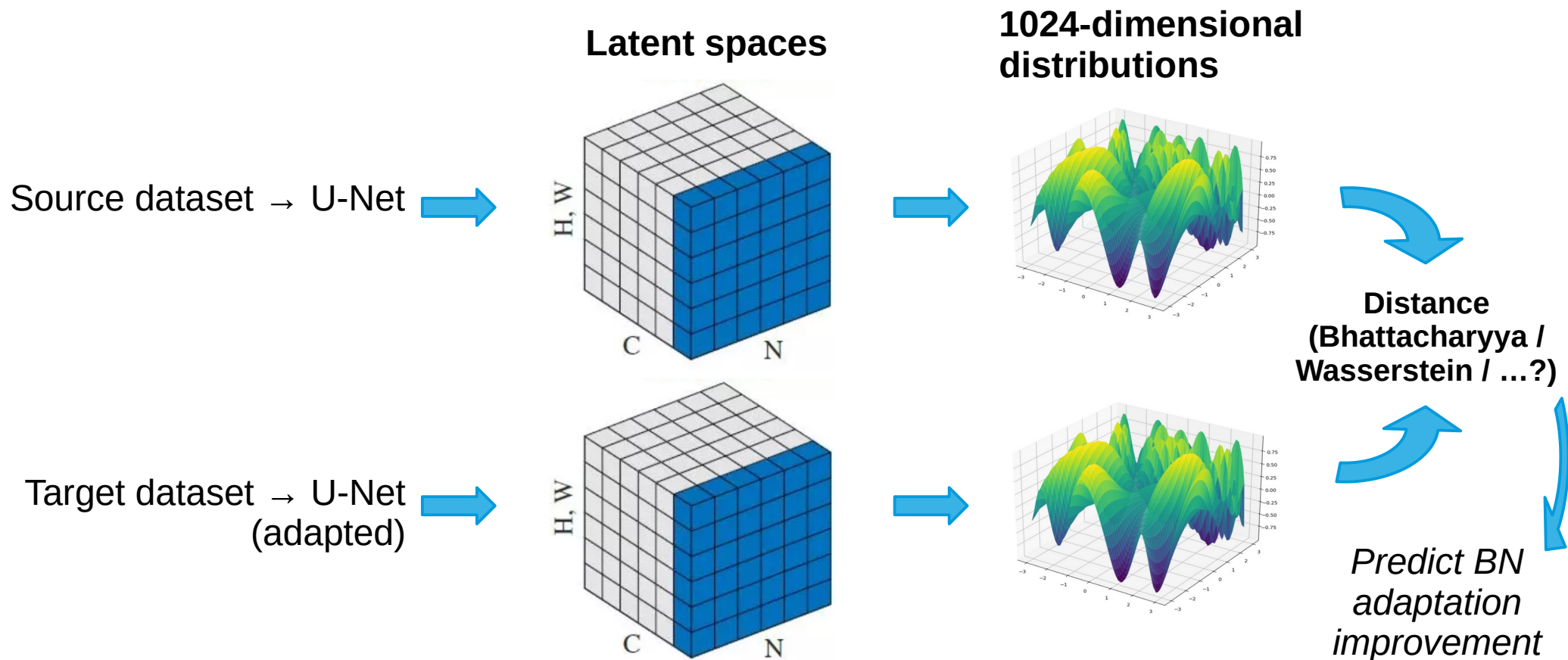


distance



	WASSERSTEIN	SLICED WASSERSTEIN	BHATTACHARYYA
Accounts for	full distribution	projections	projections
Assumptions	Gaussianity	-	-
Sparsity of data	causes less issues	causes issues	causes issues
Computations	Rounding errors	[?]	manageable

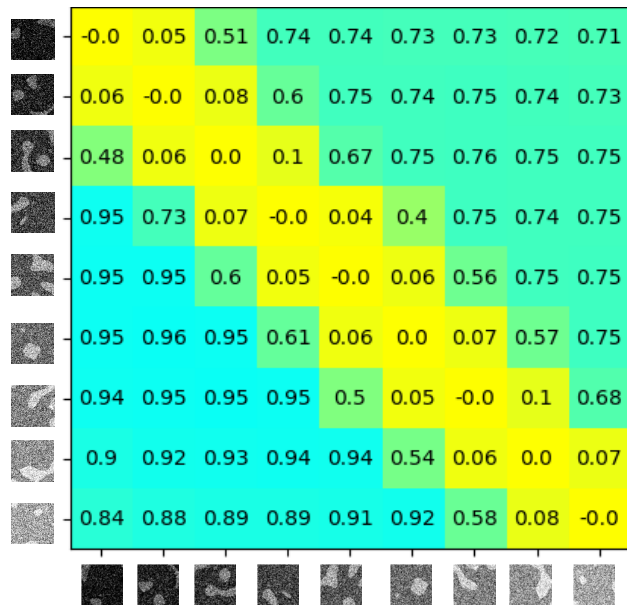
# When should we use BN adaptation?



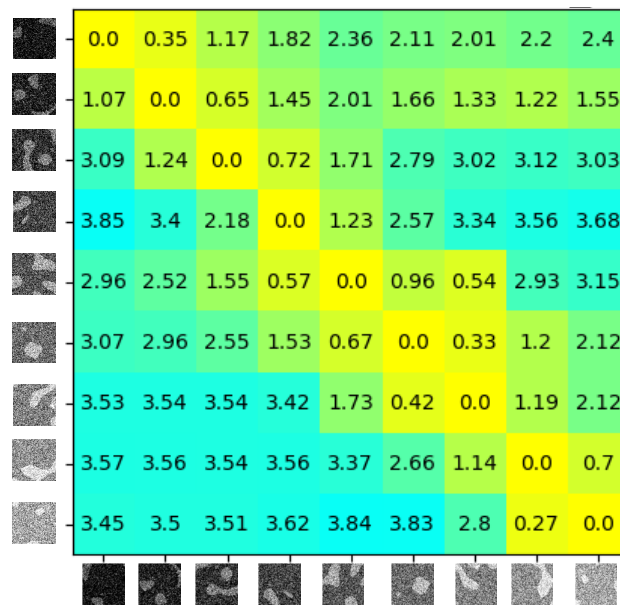


# When should we use BN adaptation?

**BN adaptation  
improvement**



**Bhattacharyya**



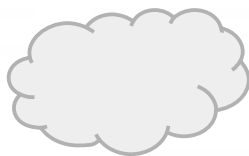
*Close! But not there yet ...*

# Synthesis and future ideas

# Synthesis



- BN adaptation works well with brightness shifts
- it can correct irregular training

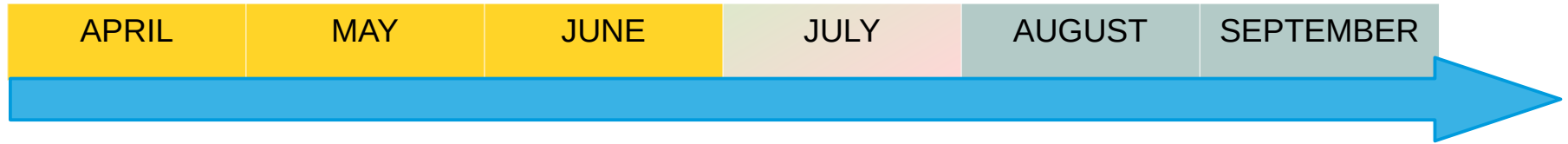


- We need more experiments to find a good predictor for the improvement!



- in some cases it does not improve the performance


# Future ideas



*What is the plan for my next 2 months?*

## **What I'm working on**

- keep experimenting with different datasets combinations
- test on all latent spaces of UNet
- test different distance measures (e.g. sliced Wasserstein)
- test for different image transformations (cropping, affine transformations, deformations, brightness, contrast, hue, ...)

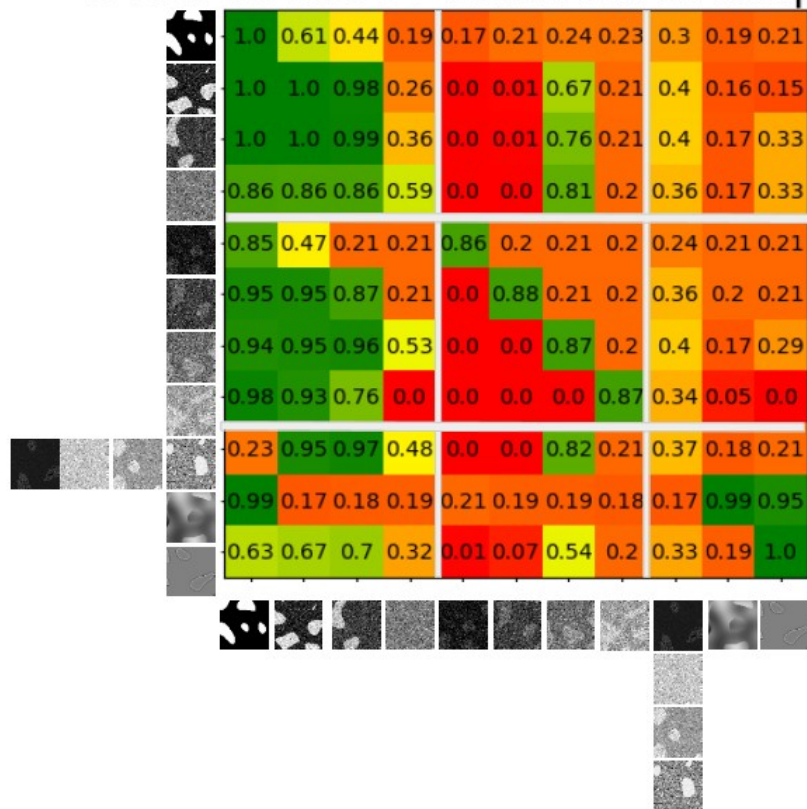


**Thanks for your attention!**

- extra slides -

# EXTRA

U-Net WITHOUT batch norm adaptation



U-Net WITH batch norm adaptation

