

Spatial Dependency Networks

Neural Layers for Improved Generative Image Modeling

Đorđe Miladinović, Aleksandar Stanić, Stefan Bauer, Jürgen Schmidhuber & Joachim M. Buhmann

GitHub [@djordjemila](https://github.com/djordjemila)

Twitter [@djordjemila](https://twitter.com/djordjemila)

ETH zürich

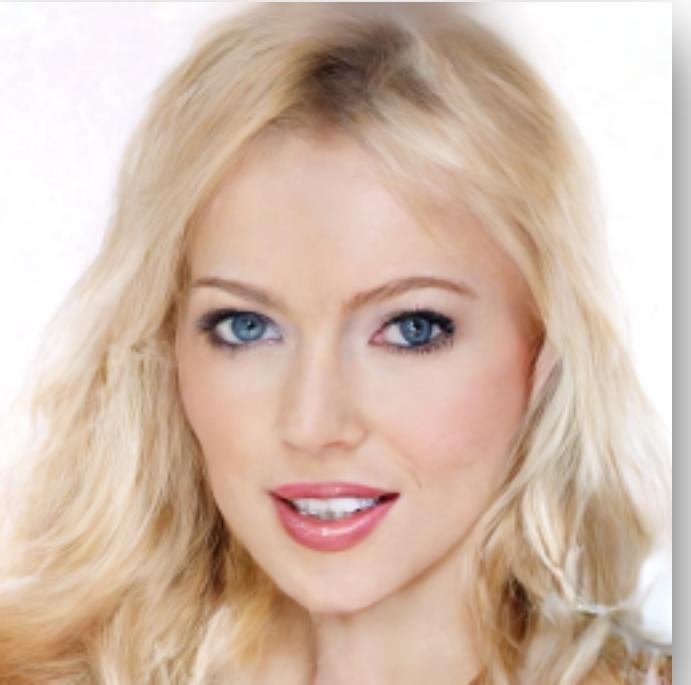
USI/SUPSI
IDSIA
Istituto
Dalle Molle
di studi
sull'intelligenza
artificiale

Università
della
Svizzera
italiana

Max Planck Institute for
Intelligent Systems

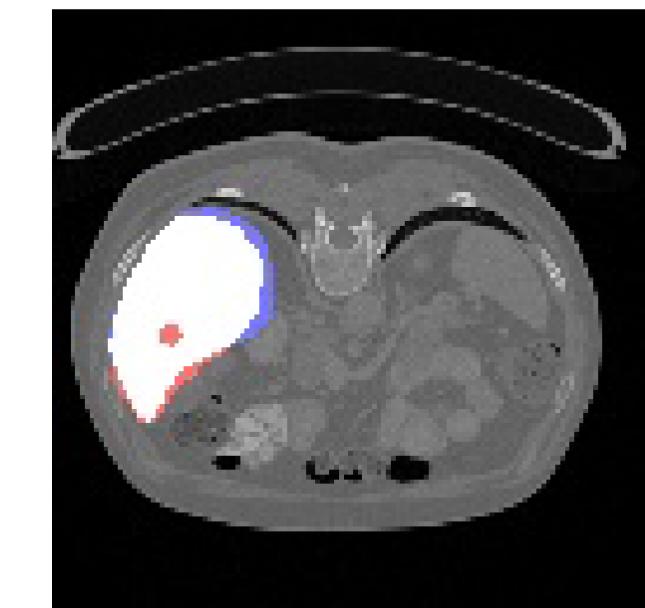
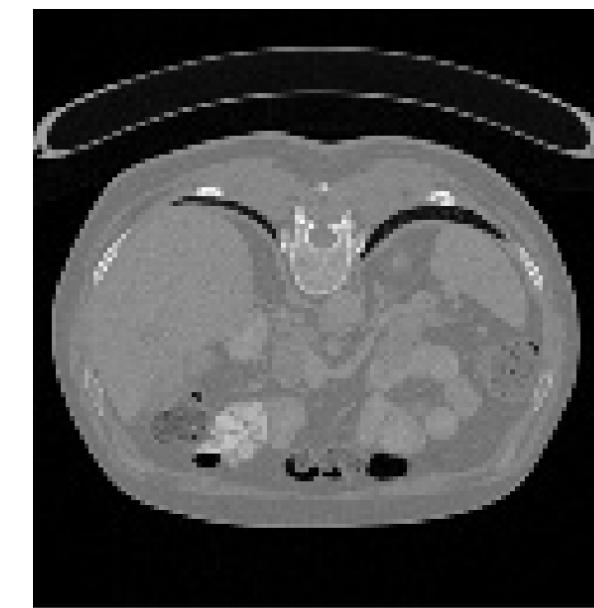
Motivation: Image Generation

Motivation: Image Generation



realistic image synthesis [this work]

Motivation: Image Generation



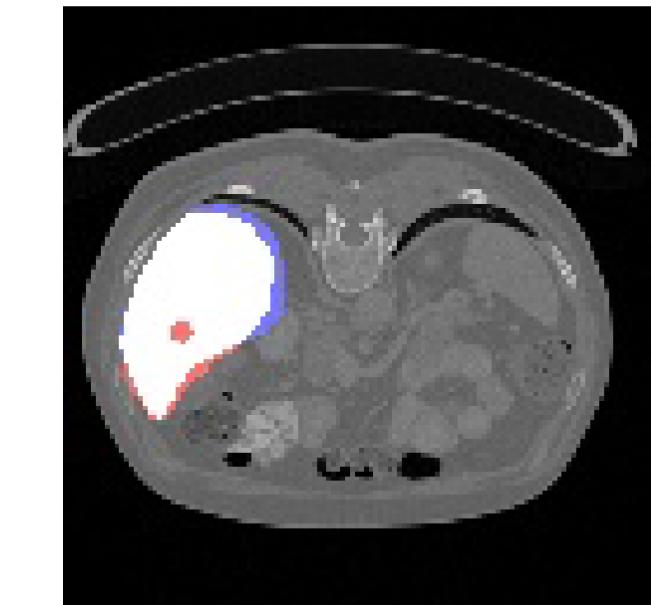
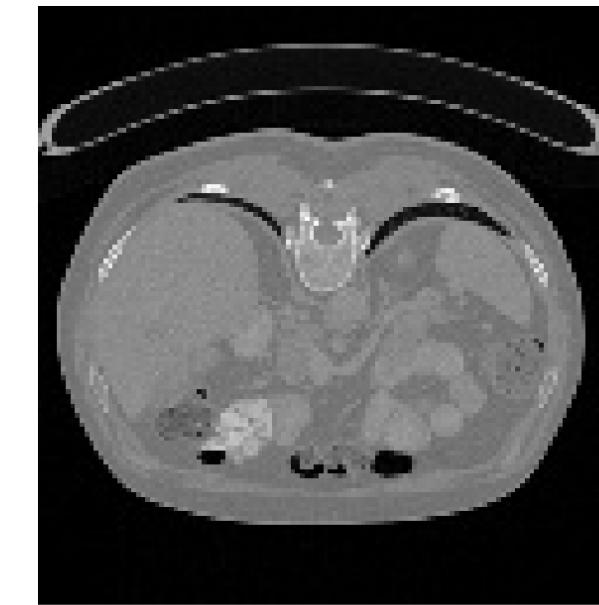
segmentation [Carvalho et al. 2021] [\[follow-up\]](#)

realistic image synthesis [\[this work\]](#)

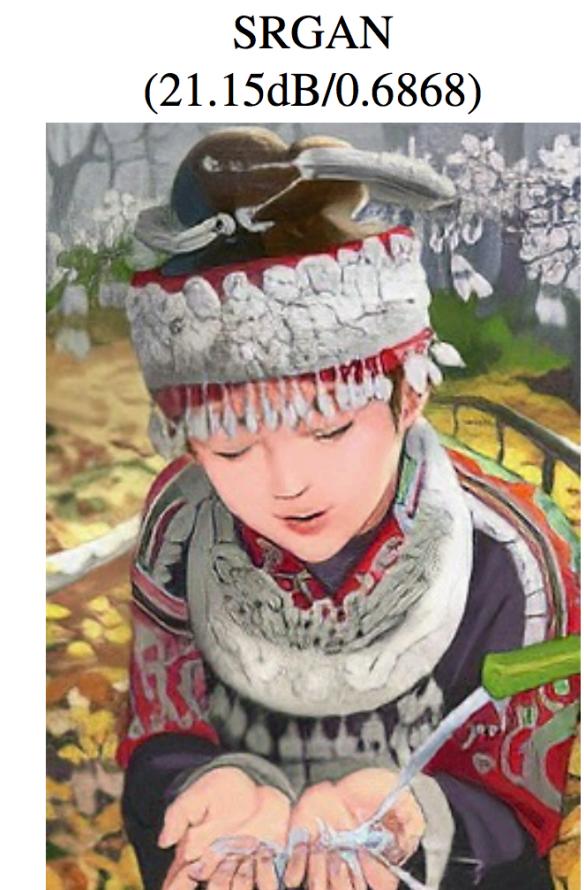
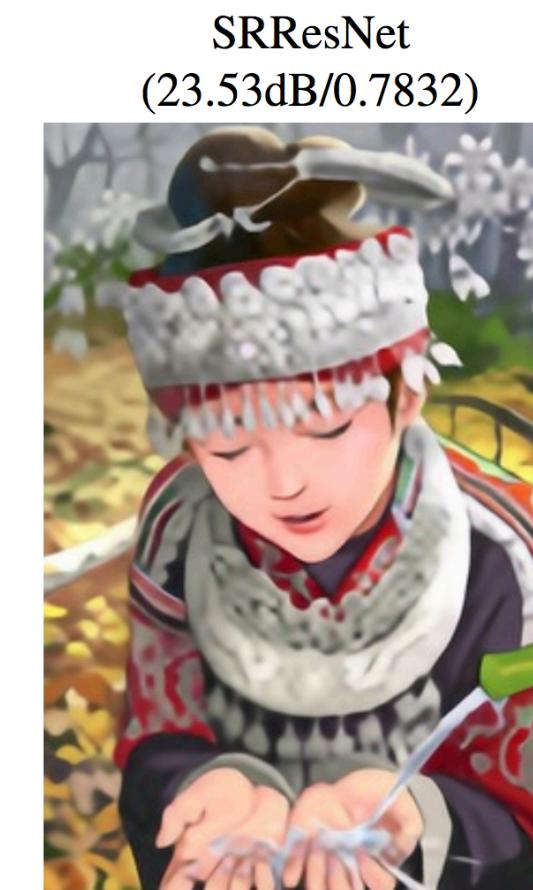
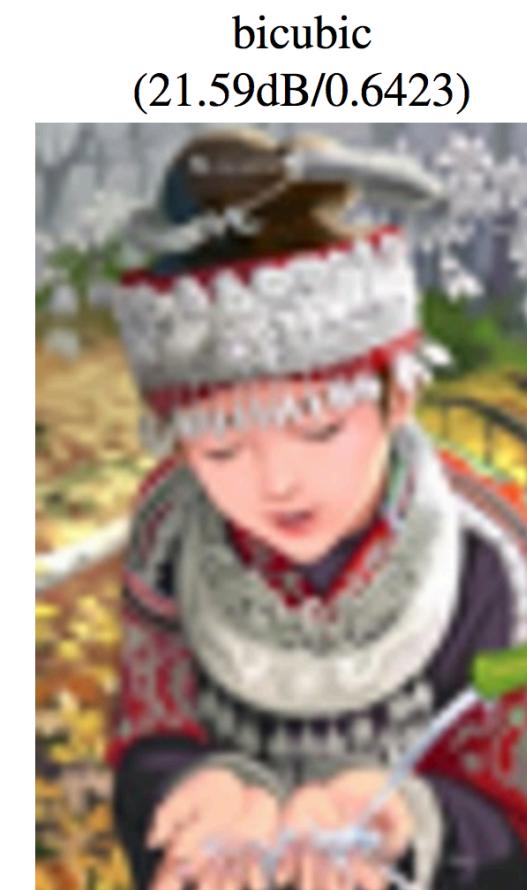
Motivation: Image Generation



realistic image synthesis [this work]

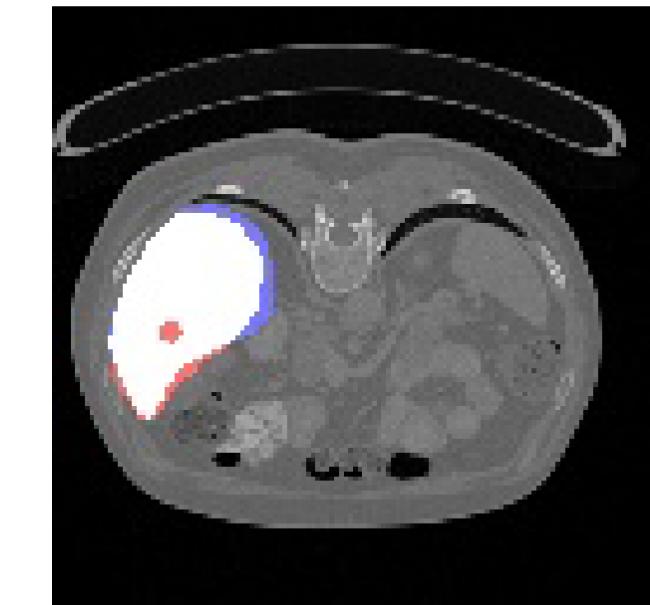
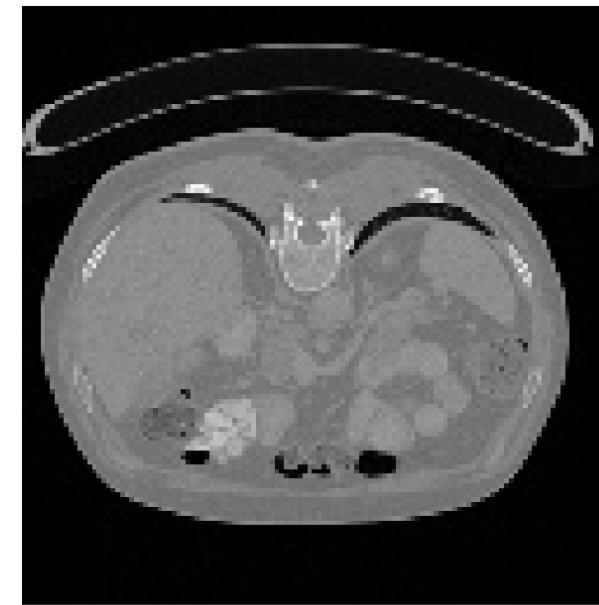


segmentation [Carvalho et al. 2021] [follow-up]

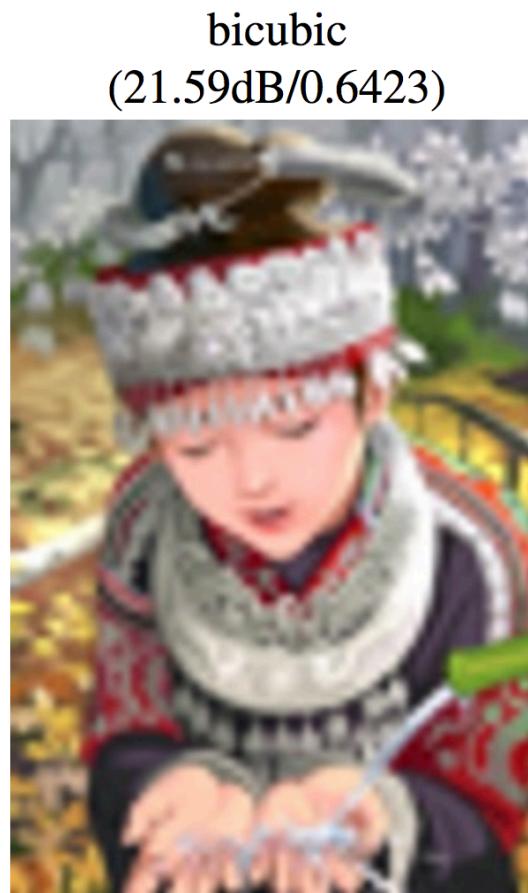


super-resolution [Ledig et al. 2017]

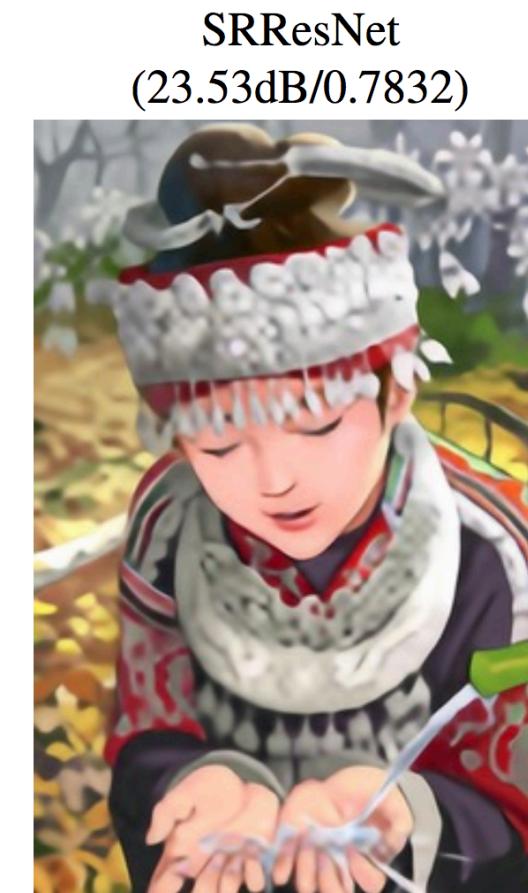
Motivation: Image Generation



segmentation [Carvalho et al. 2021] [follow-up]



bicubic
(21.59dB/0.6423)



SRResNet
(23.53dB/0.7832)



SRGAN
(21.15dB/0.6868)



original

realistic image synthesis [this work]

super-resolution [Ledig et al. 2017]

image-to-image
translation
[Zhu et al. 2017]



(Miladinović et al. 2021)

Image Generation requires an Image Decoder/Generator

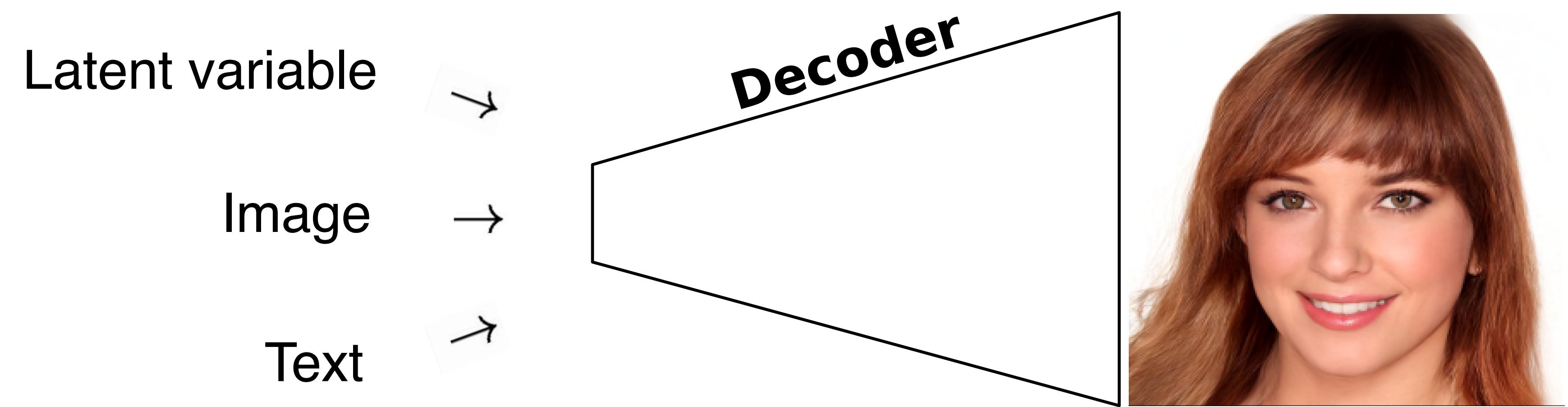
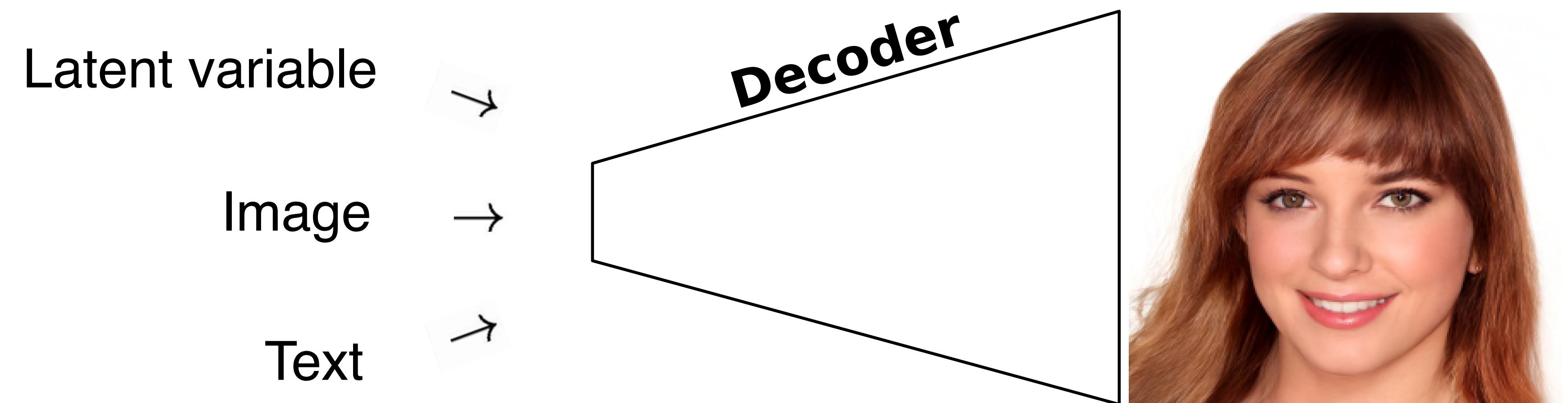
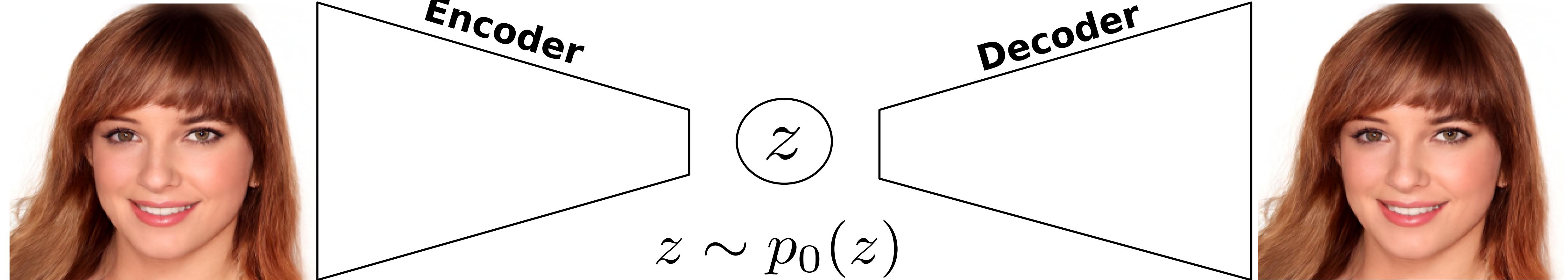


Image Generation requires an Image Decoder/Generator



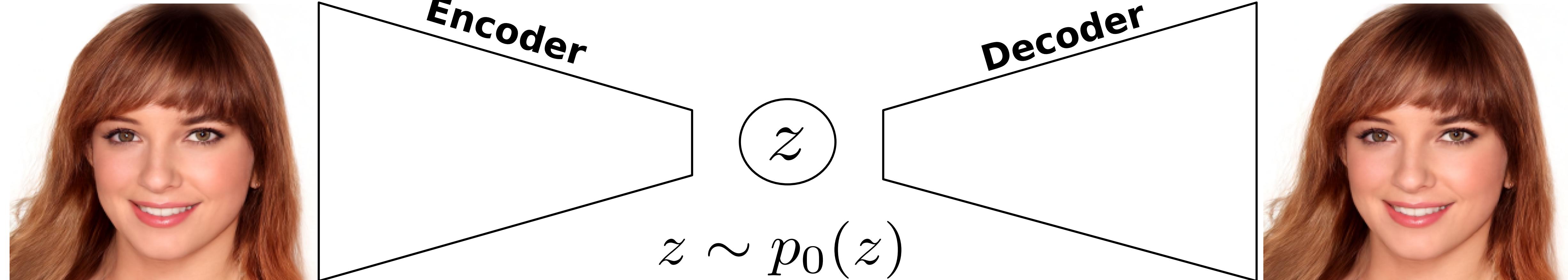
Focus of this paper: **Variational Autoencoders** [Kingma et al. 2013].

Image Generation requires an Image Decoder/Generator



Focus of this paper: **Variational Autoencoders** [Kingma et al. 2013].

Image Generation requires an Image Decoder/Generator

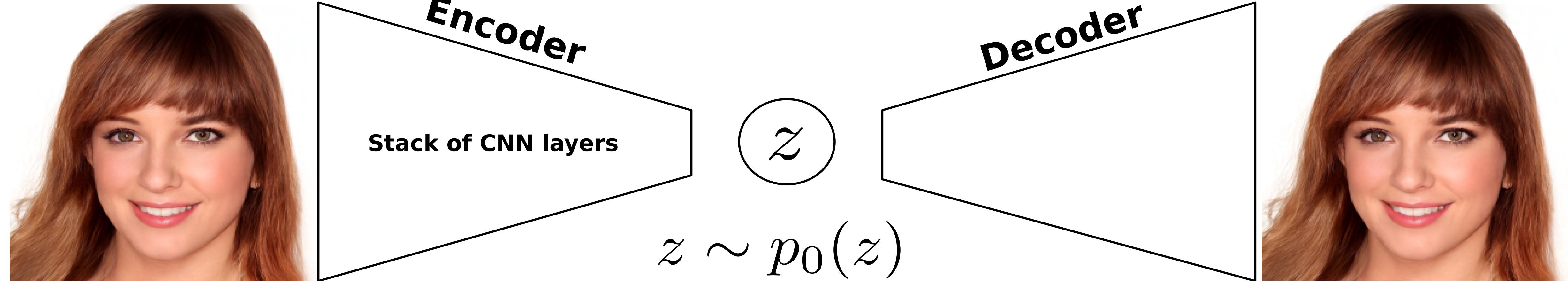


Focus of this paper: **Variational Autoencoders** [Kingma et al. 2013].

Our hypothesis:

- Convolutional network (CNN) – good in extracting patterns from images – encoding.
- **Spatial dependency network (SDN)** – better in synthesizing images – decoding.

Image Generation requires an Image Decoder/Generator

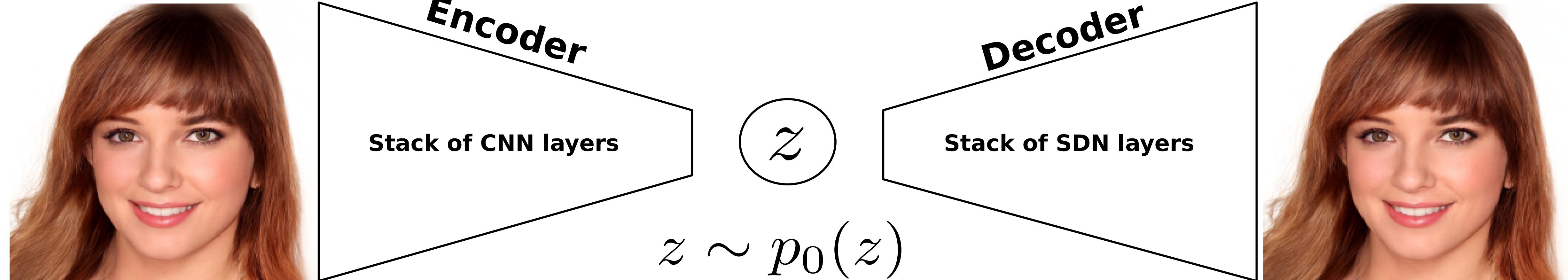


Focus of this paper: **Variational Autoencoders** [Kingma et al. 2013].

Our hypothesis:

- Convolutional network (CNN) – good in extracting patterns from images – encoding.
- **Spatial dependency network (SDN)** – better in synthesizing images – decoding.

Image Generation requires an Image Decoder/Generator

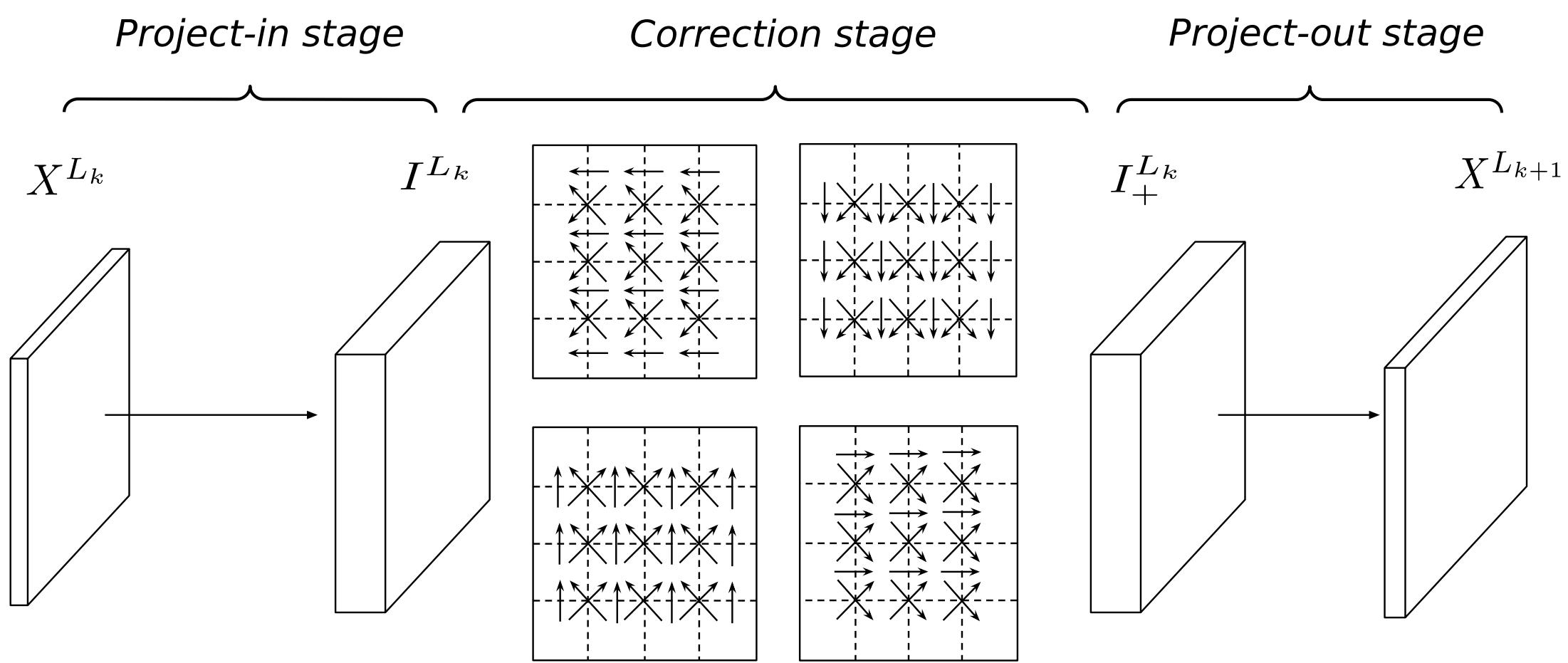


Focus of this paper: **Variational Autoencoders** [Kingma et al. 2013].

Our hypothesis:

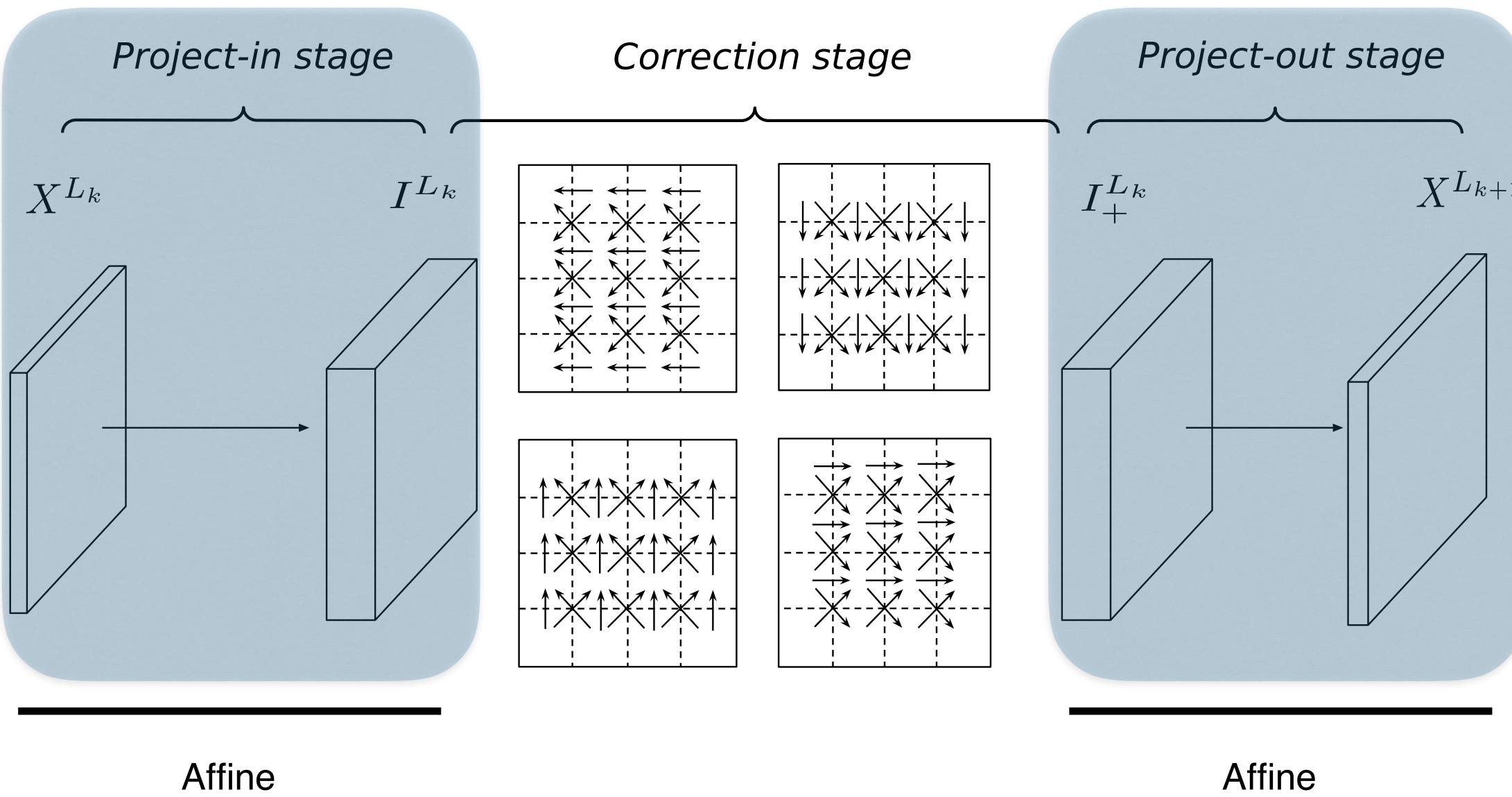
- Convolutional network (CNN) – good in extracting patterns from images – encoding.
- **Spatial dependency network (SDN)** – better in synthesizing images – decoding.

Spatial Dependency Network (SDN)



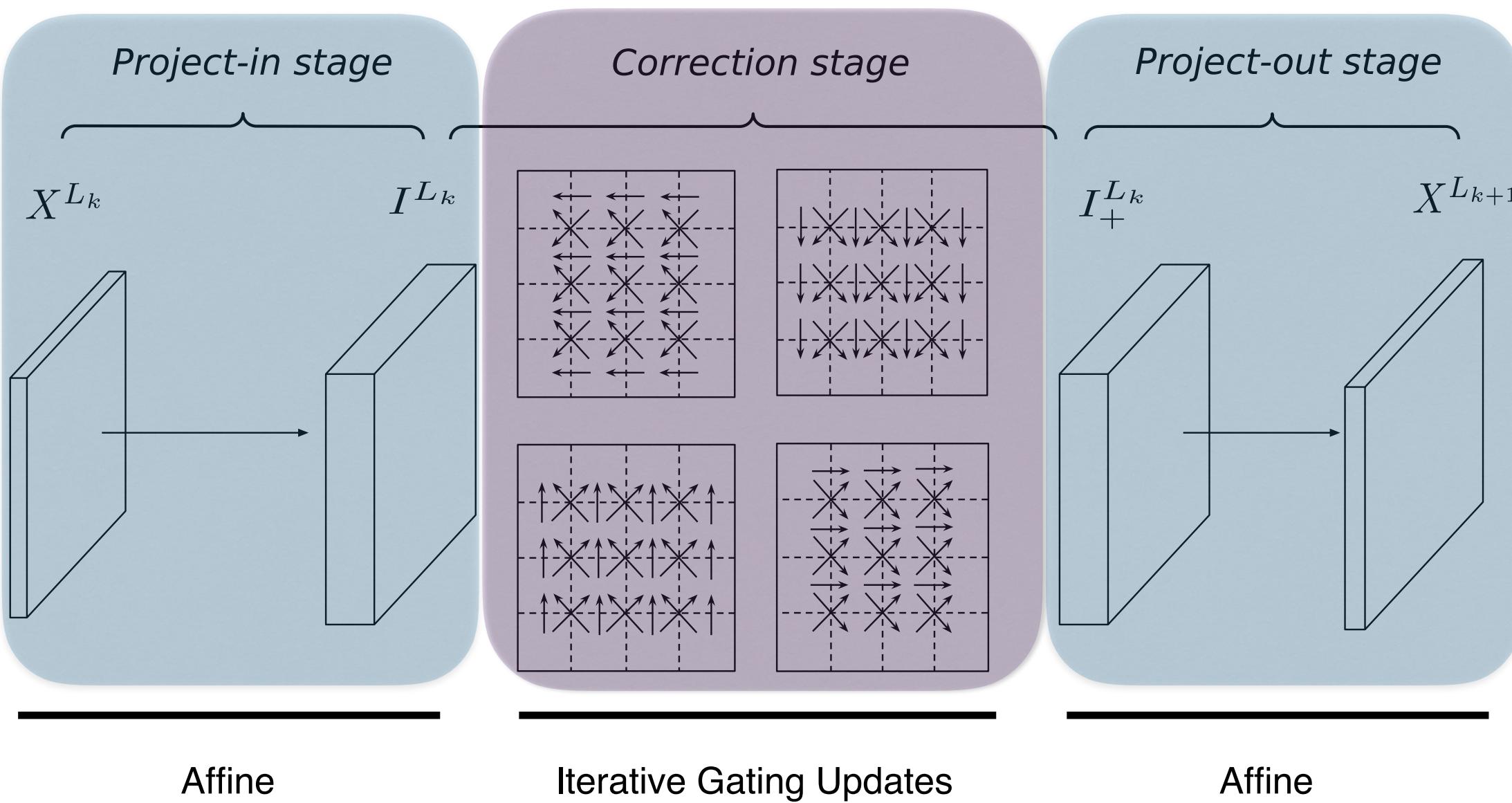
Computational flow of an SDN layer.

Spatial Dependency Network (SDN)



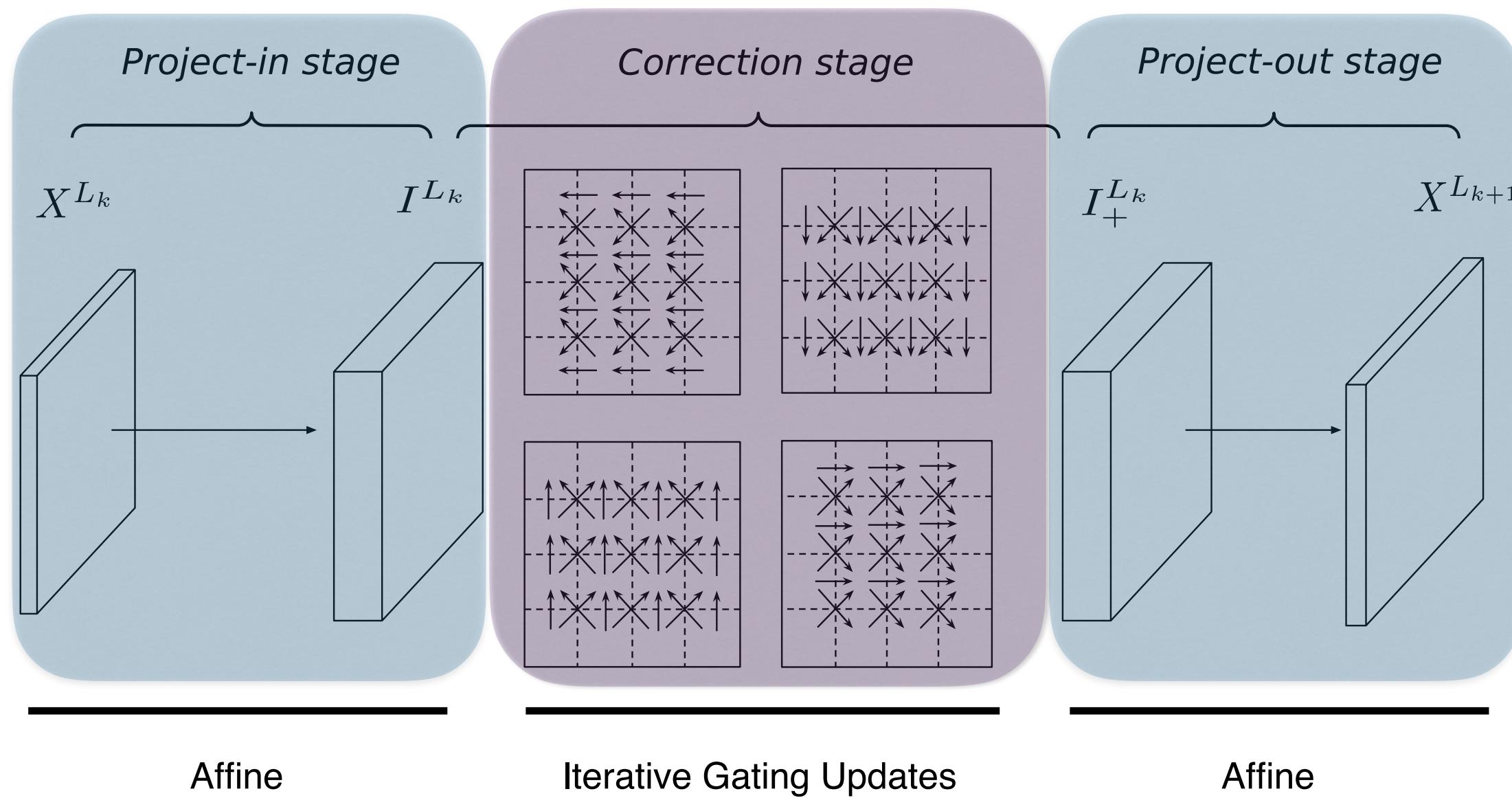
Computational flow of an SDN layer.

Spatial Dependency Network (SDN)



Computational flow of an SDN layer.

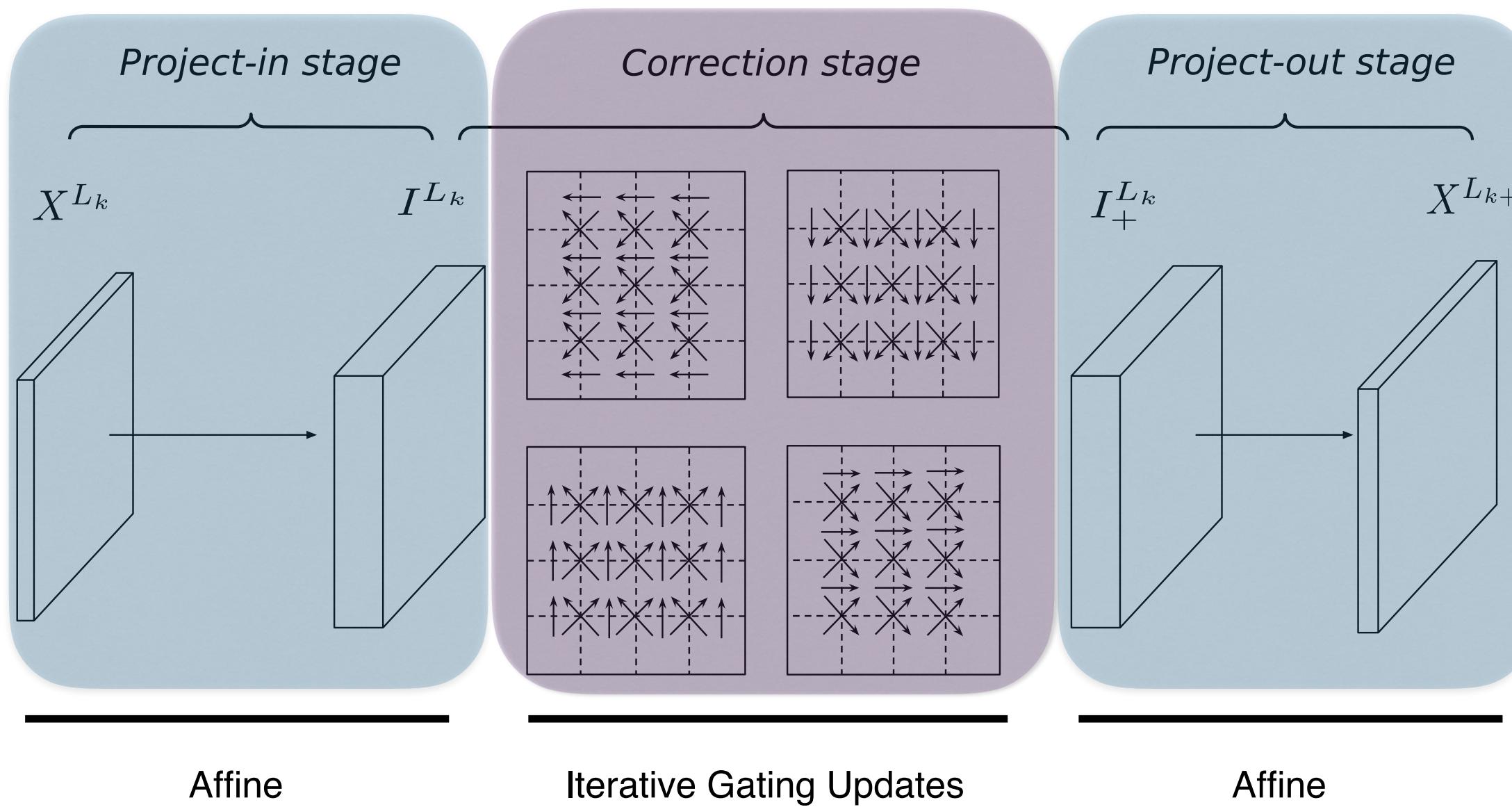
Spatial Dependency Network (SDN)



Computational flow of an SDN layer.

SDN layers:

Spatial Dependency Network (SDN)

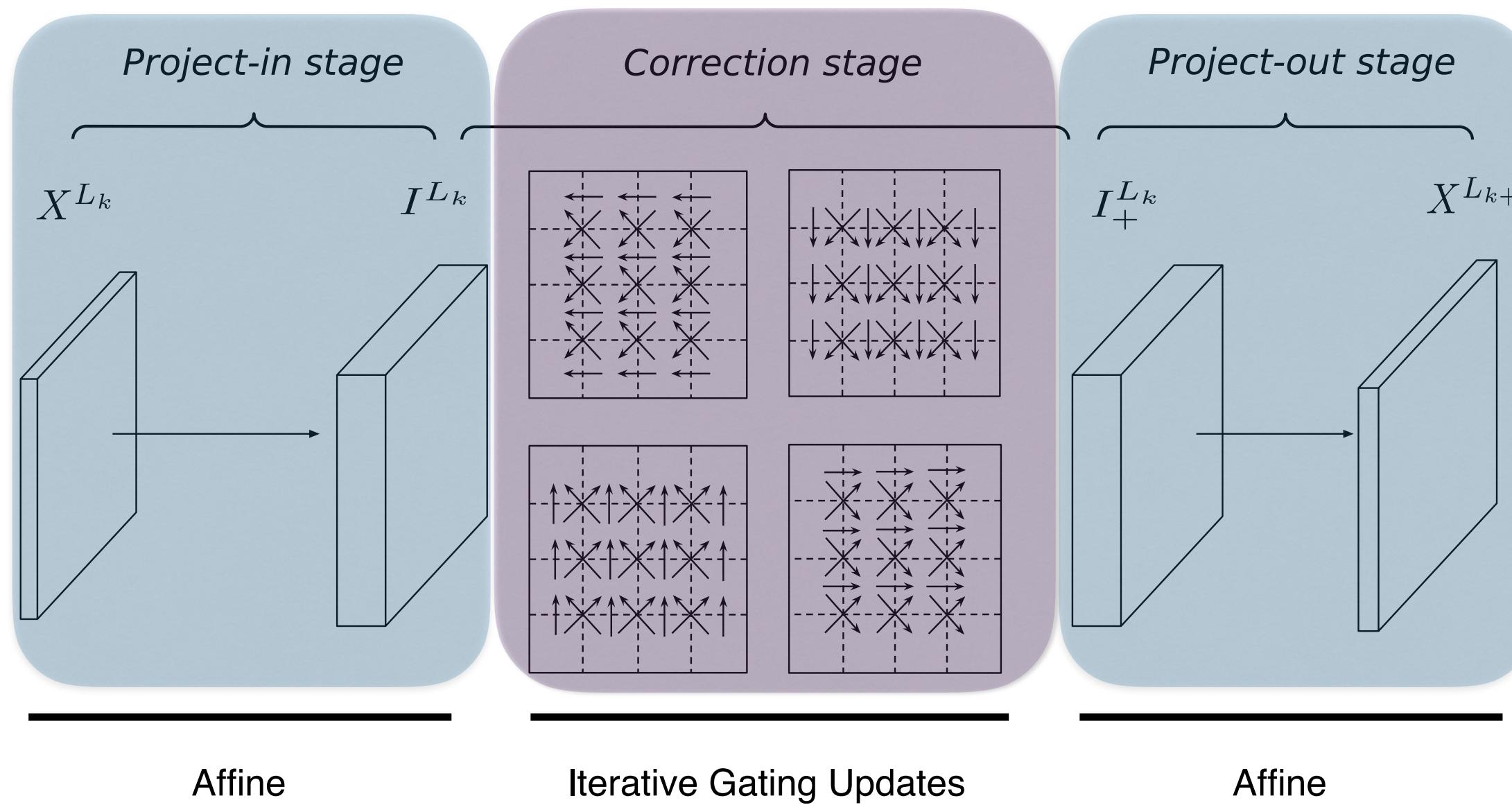


Computational flow of an SDN layer.

SDN layers:

1. **enforce spatial coherence** — the similarity of neighboring feature vectors.

Spatial Dependency Network (SDN)

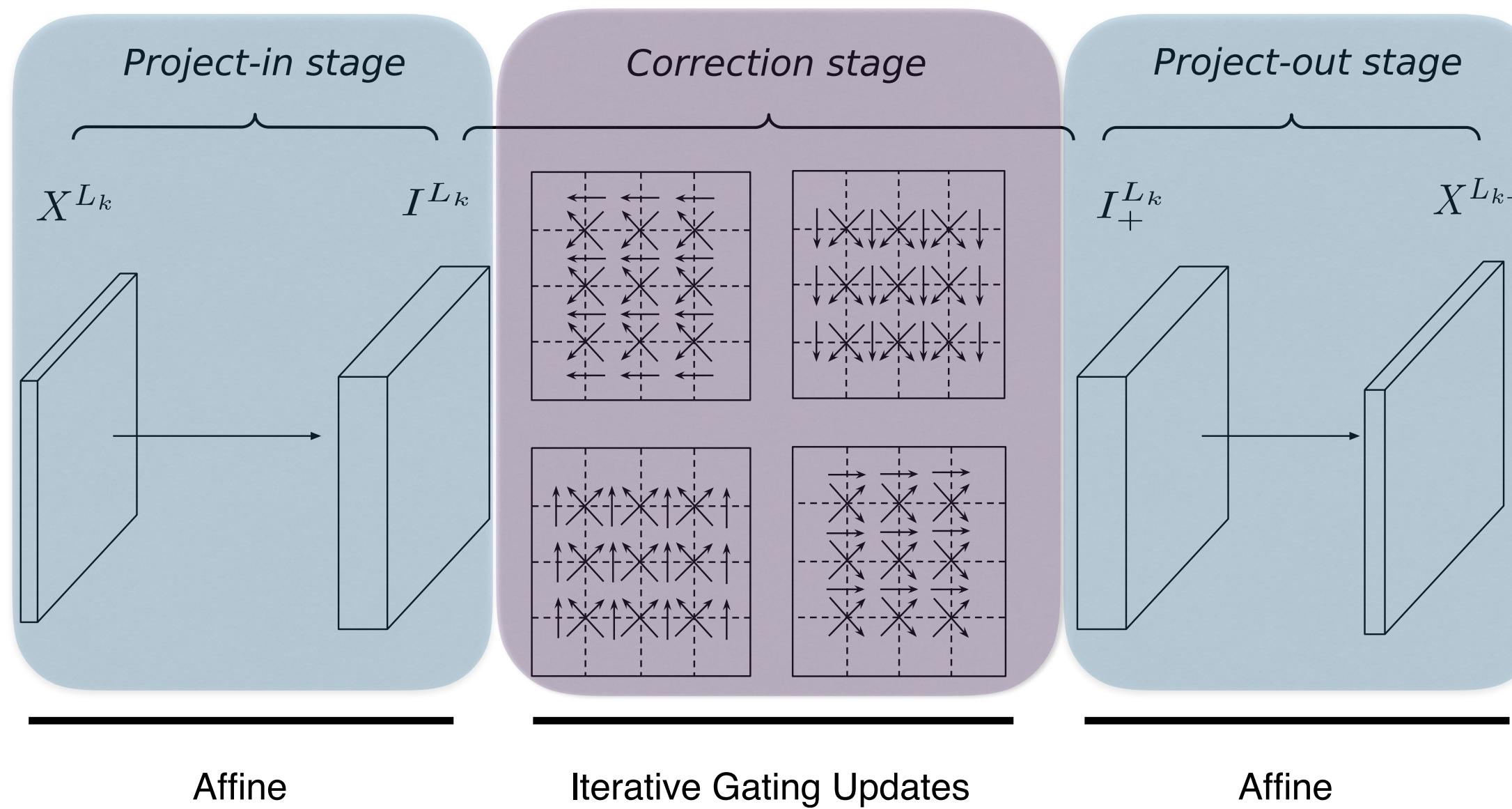


Computational flow of an SDN layer.

SDN layers:

1. **enforce spatial coherence** — the similarity of neighboring feature vectors.
2. **model long-range spatial dependencies** at each level of a NN.

Spatial Dependency Network (SDN)

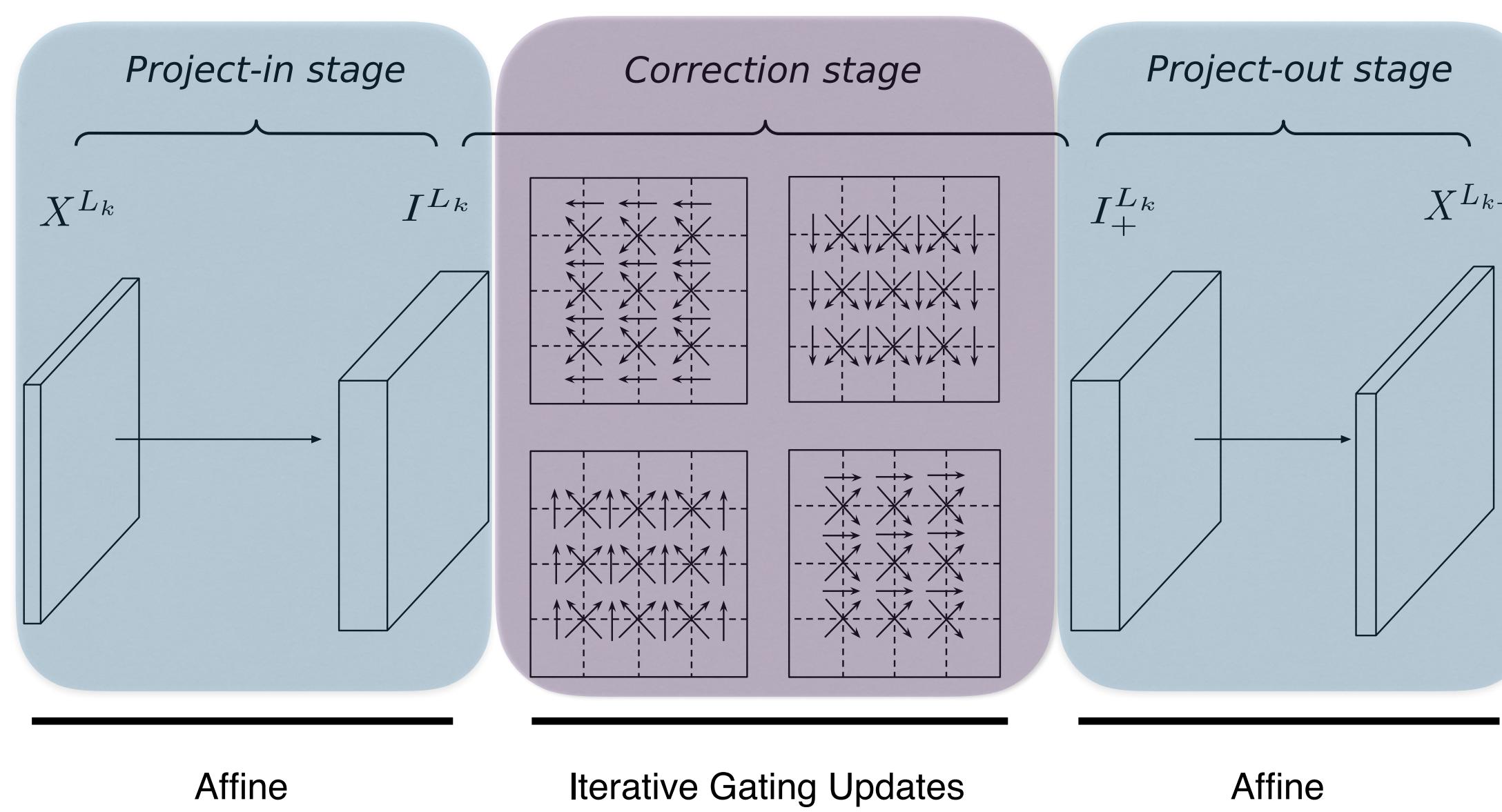


Computational flow of an SDN layer.

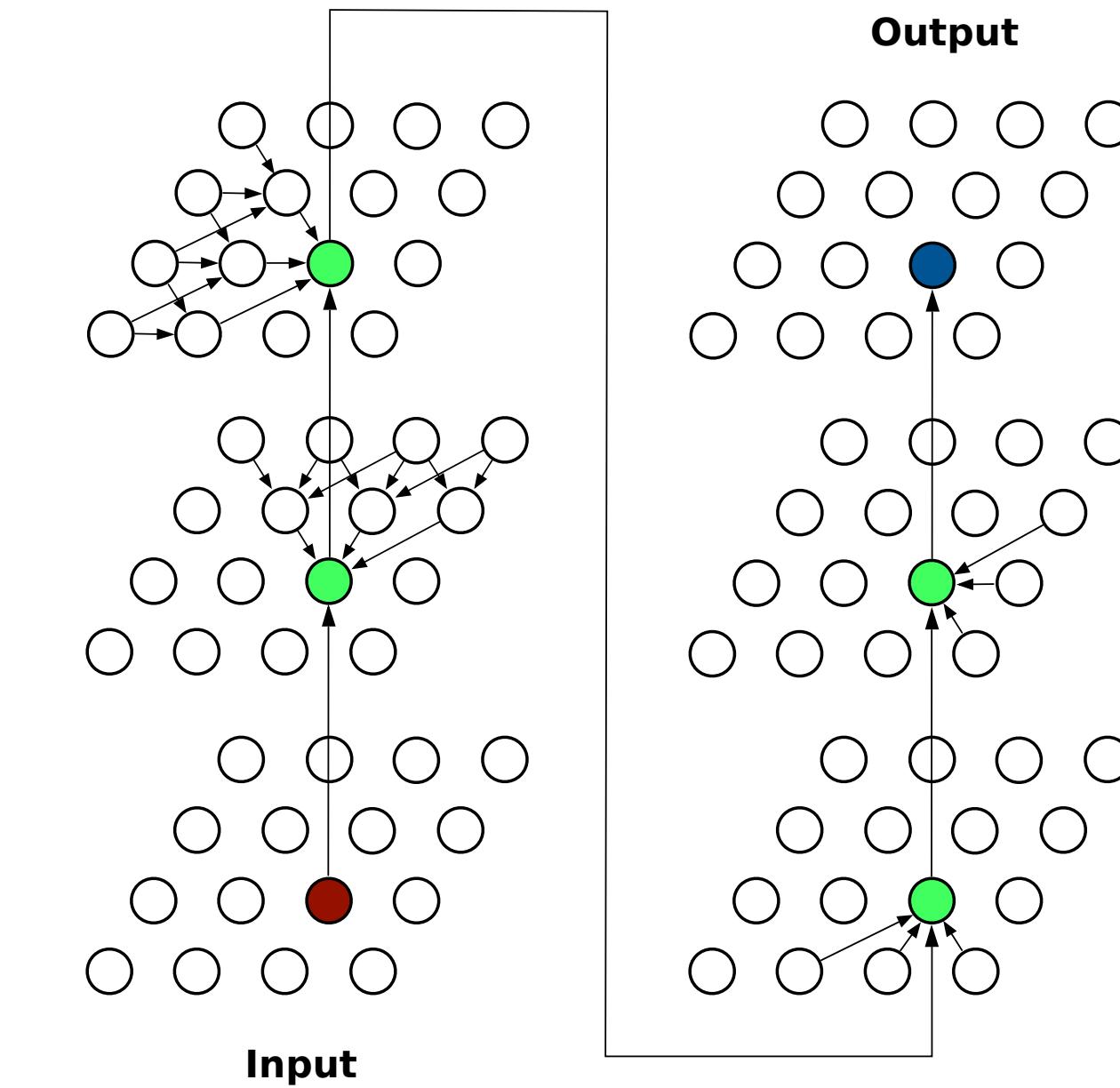
SDN layers:

1. **enforce spatial coherence** — the similarity of neighboring feature vectors.
2. **model long-range spatial dependencies** at each level of a NN.
3. **achieve equivariance to translation** through parameter sharing.

Spatial Dependency Network (SDN)



Computational flow of an SDN layer.

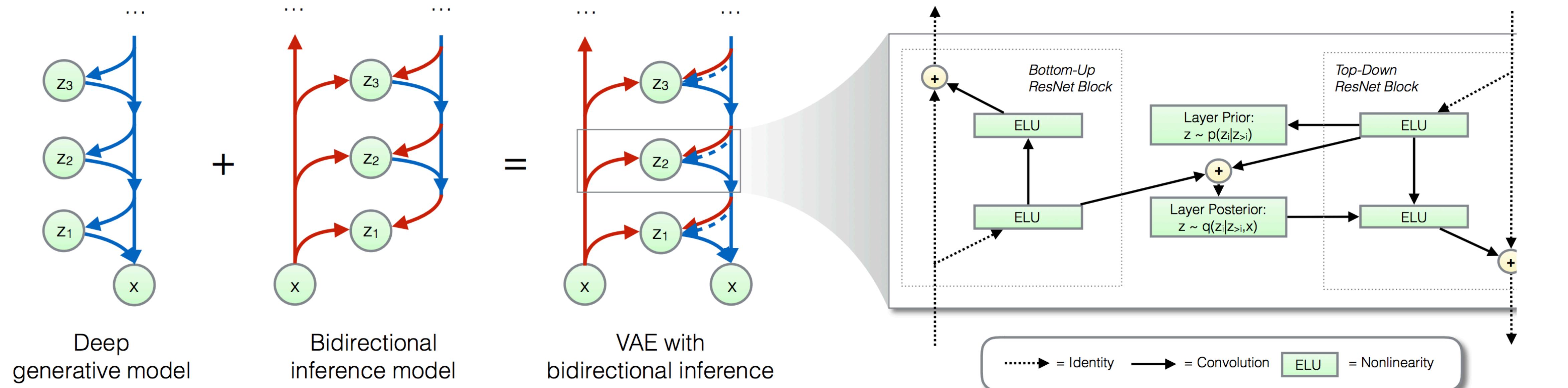


Graphical model of an SDN layer.

SDN layers:

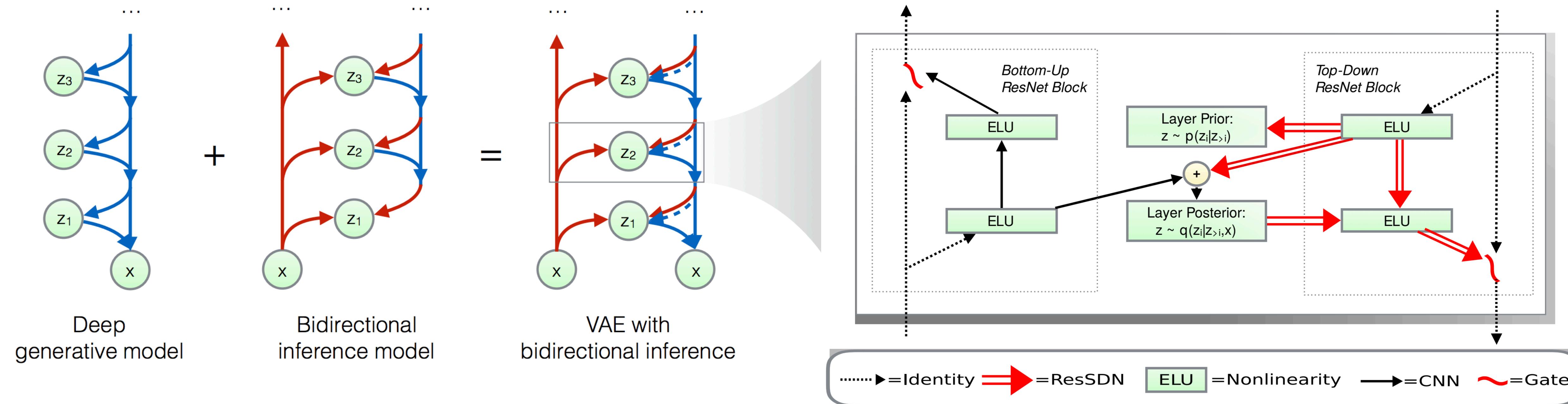
1. **enforce spatial coherence** — the similarity of neighboring feature vectors.
2. **model long-range spatial dependencies** at each level of a NN.
3. **achieve equivariance to translation** through parameter sharing.

SDN-VAE: IAF-VAE enhanced with SDN layers



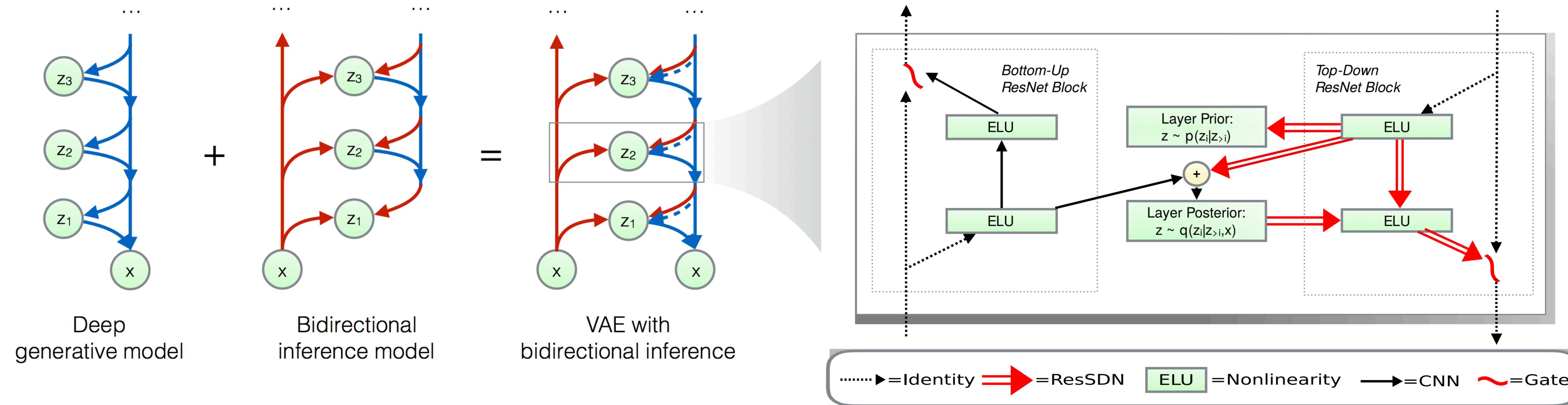
IAF-VAE: Hierarchical (Ladder) VAE [Sønderby et al. 2016] with ResNet blocks [Kingma et al. 2017]

SDN-VAE: IAF-VAE enhanced with SDN layers



IAF-VAE: Hierarchical (Ladder) VAE [Sønderby et al. 2016] with ResNet blocks [Kingma et al. 2017]

SDN-VAE: IAF-VAE enhanced with SDN layers



IAF-VAE: Hierarchical (Ladder) VAE [Sønderby et al. 2016] with ResNet blocks [Kingma et al. 2017]

with additional modifications:

- Mixed-precision [Micikevicius et al. 2017]
- Gated “highway” residual [Srivastava et al. 2015]
- Discretized Mixture of Logistics [Salimans et al. 2017]

SDN-VAE: Density Estimation

Type	Method	CIFAR-10	ImageNet32	CelebAHQ256
VAE-based	SDN-VAE (ours)	2.87	3.85	0.70
	IAF-VAE+ (ours)	3.05	4.00	0.71
	IAF-VAE (Kingma et al., 2016)	3.11	X	X
	BIVA (Maaløe et al., 2019)	3.08	X	X
	NVAE (Vahdat & Kautz, 2020)	2.91	3.92	0.70
Flow-based	GLOW (Kingma & Dhariwal, 2018)	3.35	4.09	1.03
	FLOW++ (Ho et al., 2019)	3.08	3.86	X
	ANF (Huang et al., 2020)	3.05	3.92	0.72
	SurVAE (Nielsen et al., 2020)	3.08	4.00	X
Autoregressive*	PixelRNN (Van Oord et al., 2016)	3.00	3.86	X
	PixelCNN (Van den Oord et al., 2016)	3.03	3.83	X
	PixelCNN++ (Salimans et al., 2017)	2.92	X	X
	PixelSNAIL (Chen et al., 2018)	2.85	3.80	X
	SPN (Menick & Kalchbrenner, 2018)	X	3.85	0.61
	IT (Parmar et al., 2018)	2.90	3.77	X

Negative test log-likelihood.

SDN-VAE: Density Estimation

Type	Method	CIFAR-10	ImageNet32	CelebAHQ256
VAE-based	SDN-VAE (ours)	2.87	3.85	0.70
	IAF-VAE+ (ours)	3.05	4.00	0.71
	IAF-VAE (Kingma et al., 2016)	3.11	X	X
	BIVA (Maaløe et al., 2019)	3.08	X	X
Flow-based	NVAE (Vahdat & Kautz, 2020)	2.91	3.92	0.70
	GLOW (Kingma & Dhariwal, 2018)	3.35	4.09	1.03
	FLOW++ (Ho et al., 2019)	3.08	3.86	X
	ANF (Huang et al., 2020)	3.05	3.92	0.72
Autoregressive*	SurVAE (Nielsen et al., 2020)	3.08	4.00	X
	PixelRNN (Van Oord et al., 2016)	3.00	3.86	X
	PixelCNN (Van den Oord et al., 2016)	3.03	3.83	X
	PixelCNN++ (Salimans et al., 2017)	2.92	X	X
	PixelSNAIL (Chen et al., 2018)	2.85	3.80	X
	SPN (Menick & Kalchbrenner, 2018)	X	3.85	0.61
	IT (Parmar et al., 2018)	2.90	3.77	X

Negative test log-likelihood.

CNN vs SDN

SDN-VAE: Density Estimation

SotA !!

Type	Method	CIFAR-10	ImageNet32	CelebAHQ256
VAE-based	SDN-VAE (ours)	2.87	3.85	0.70
	IAF-VAE+ (ours)	3.05	4.00	0.71
	IAF-VAE (Kingma et al., 2016)	3.11	X	X
	BIVA (Maaløe et al., 2019)	3.08	X	X
	NVAE (Vahdat & Kautz, 2020)	2.91	3.92	0.70
	GLOW (Kingma & Dhariwal, 2018)	3.35	4.09	1.03
Flow-based	FLOW++ (Ho et al., 2019)	3.08	3.86	X
	ANF (Huang et al., 2020)	3.05	3.92	0.72
	SurVAE (Nielsen et al., 2020)	3.08	4.00	X
Autoregressive*	PixelRNN (Van Oord et al., 2016)	3.00	3.86	X
	PixelCNN (Van den Oord et al., 2016)	3.03	3.83	X
	PixelCNN++ (Salimans et al., 2017)	2.92	X	X
	PixelSNAIL (Chen et al., 2018)	2.85	3.80	X
	SPN (Menick & Kalchbrenner, 2018)	X	3.85	0.61
	IT (Parmar et al., 2018)	2.90	3.77	X

Negative test log-likelihood.

CNN vs SDN

SDN-VAE: Image Synthesis



temperature



temperature



SDN-VAE: Image Manipulation

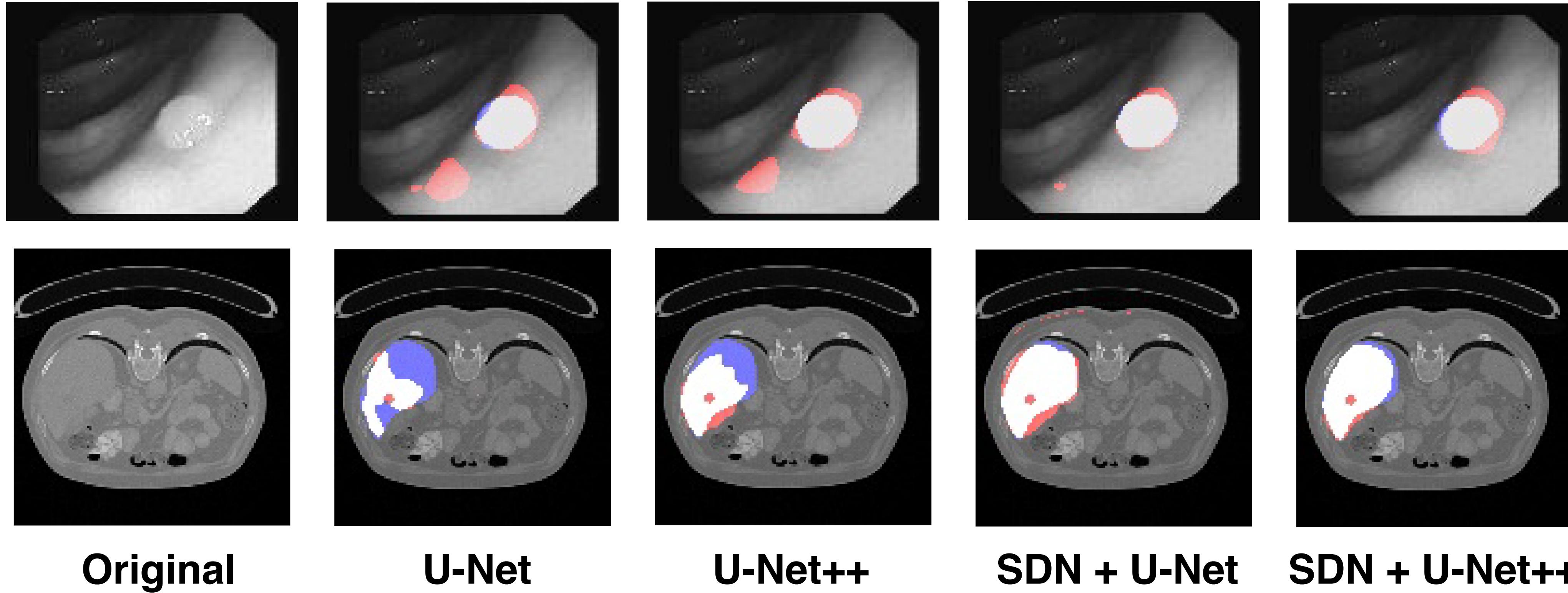


temperature



SDU-Nets for Medical Image Segmentation

SDN + U-Net [Carvalho et al. 2021]



(see the paper for quantitative results)

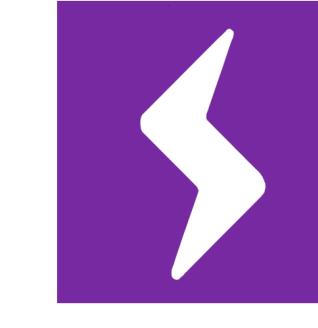
False Positives

False Negatives

Correct

Implementation & Other Information

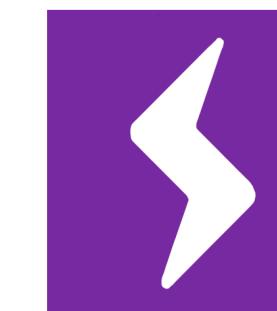
 PyTorch

 PyTorch
Lightning



<https://github.com/djordjemila/sdn>

Implementation & Other Information



PyTorch
Lightning



<https://github.com/djordjemila/sdn>

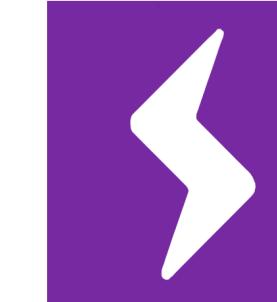
```
from torch.nn import Conv2d
img_decoder = nn.Sequential(
    ...
    Conv2d(in_ch, out_ch, 4, 2, 1),
    nn.ReLU(True),
    ...
)
```

From CNN to SDN layer
in just one line of code !



```
from sdnlib.nn import SDNLayer
img_decoder = nn.Sequential(
    ...
    SDNLayer(in_ch, out_ch, num_features, 4, 2, 1),
    nn.ReLU(True),
    ...
)
```

Implementation & Other Information



PyTorch
Lightning



<https://github.com/djordjemila/sdn>

```
from torch.nn import Conv2d
img_decoder = nn.Sequential(
    ...
    Conv2d(in_ch, out_ch, 4, 2, 1),
    nn.ReLU(True),
    ...
)
```

From CNN to SDN layer
in just one line of code !



```
from sdnlib.nn import SDNLayer
img_decoder = nn.Sequential(
    ...
    SDNLayer(in_ch, out_ch, num_features, 4, 2, 1),
    nn.ReLU(True),
    ...
)
```

arXiv link for the SDN paper: <https://arxiv.org/abs/2103.08877>

arXiv link for the follow-up, SDU-Net paper: <https://arxiv.org/abs/2103.11713>

Make sure you are up to date on Twitter ! Follow: <https://twitter.com/djordjemila>