Lecture 4. Deep learning architectures

Bayesian Statistical Learning

Ingredients of the Deep Learning framework. Reminder

Data: training set (train the model), validation set (compare models), test set (final evaluation of the model)

Data can be labelled (supervised learning), unlabelled (unsupervised learning), partially labelled (semi-supervised learning) etc.

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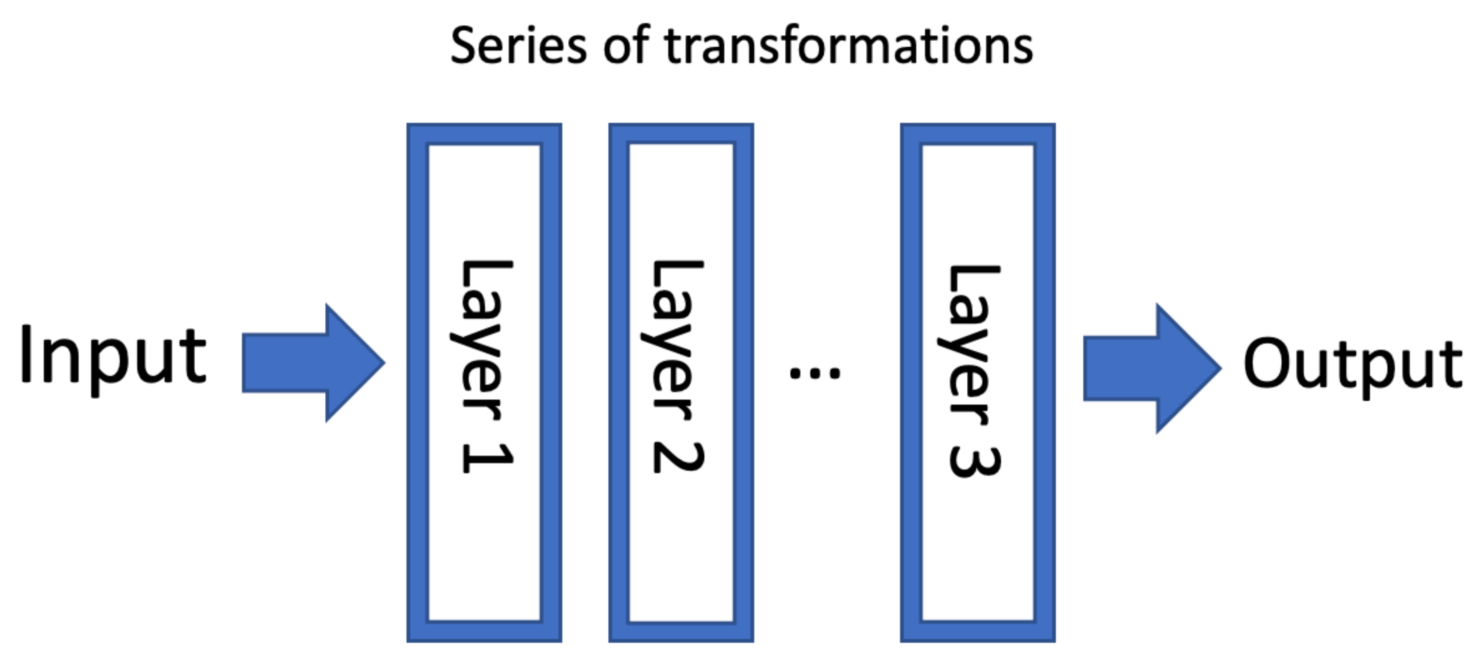
The model:



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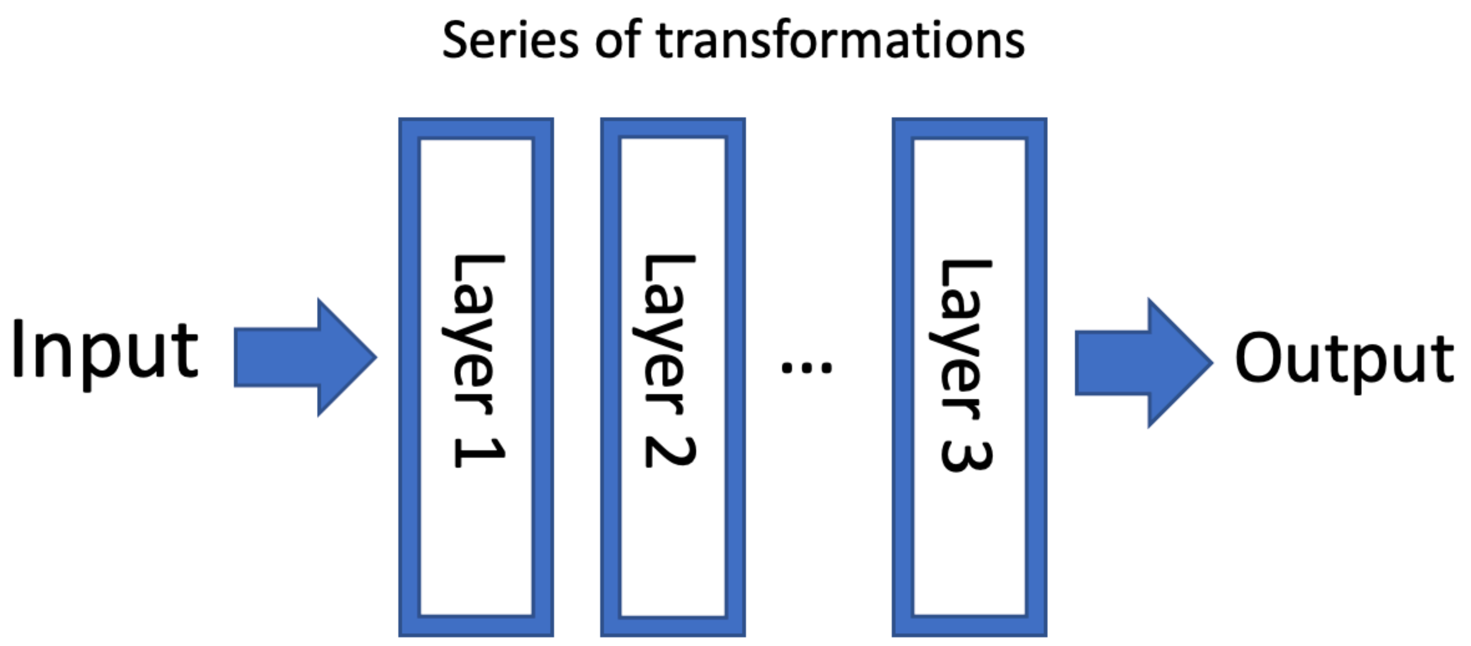

Training: backpropagation, i.e. minimising the given loss function using gradient descent method -> updating the weights of the model

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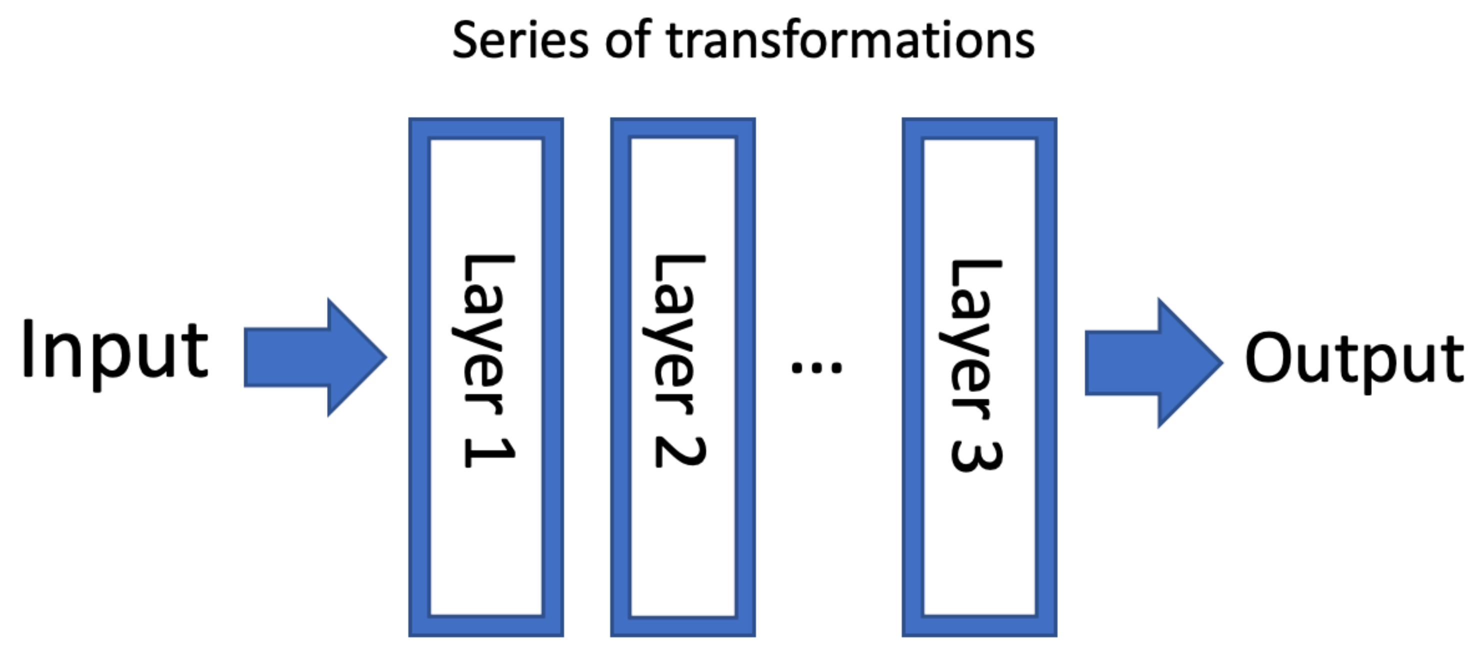


Training: backpropagation, i.e. minimising the given loss function using gradient descent method -> updating the weights of the model

/exactly what we did previously when minimising Kullback-Leibler divergence(maximising free energy), but the model is way more complicated/

Variational Autoencoder

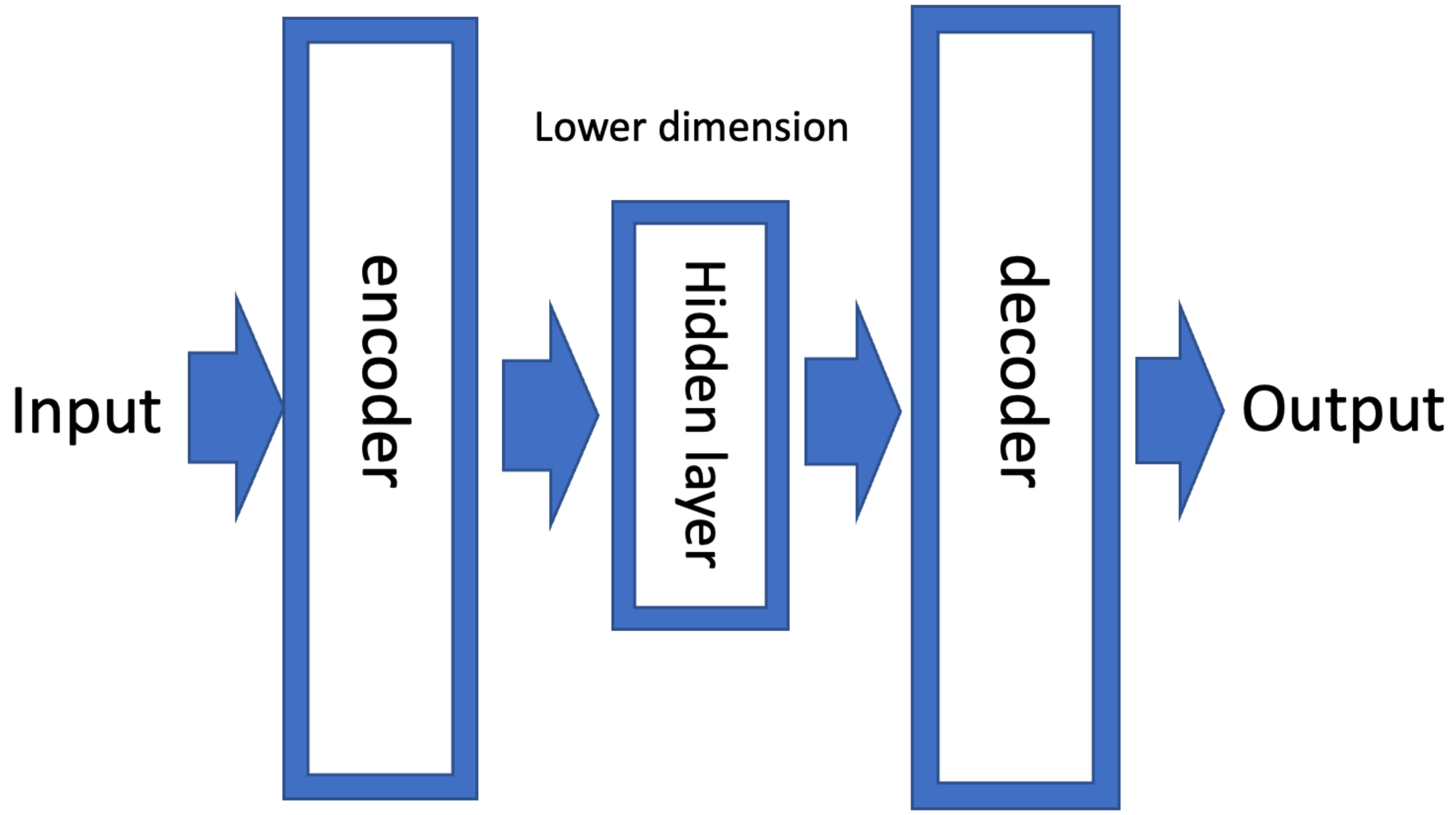
<u>**General autoencoder**</u>: **unsupervised** (no labels),

input features are projected onto a lower dimensional

hidden layer (bottleneck) via **encoder**, and then transformed

back to the original dimension using **decoder**.

The **aim** is to **reconstruct the original input.**



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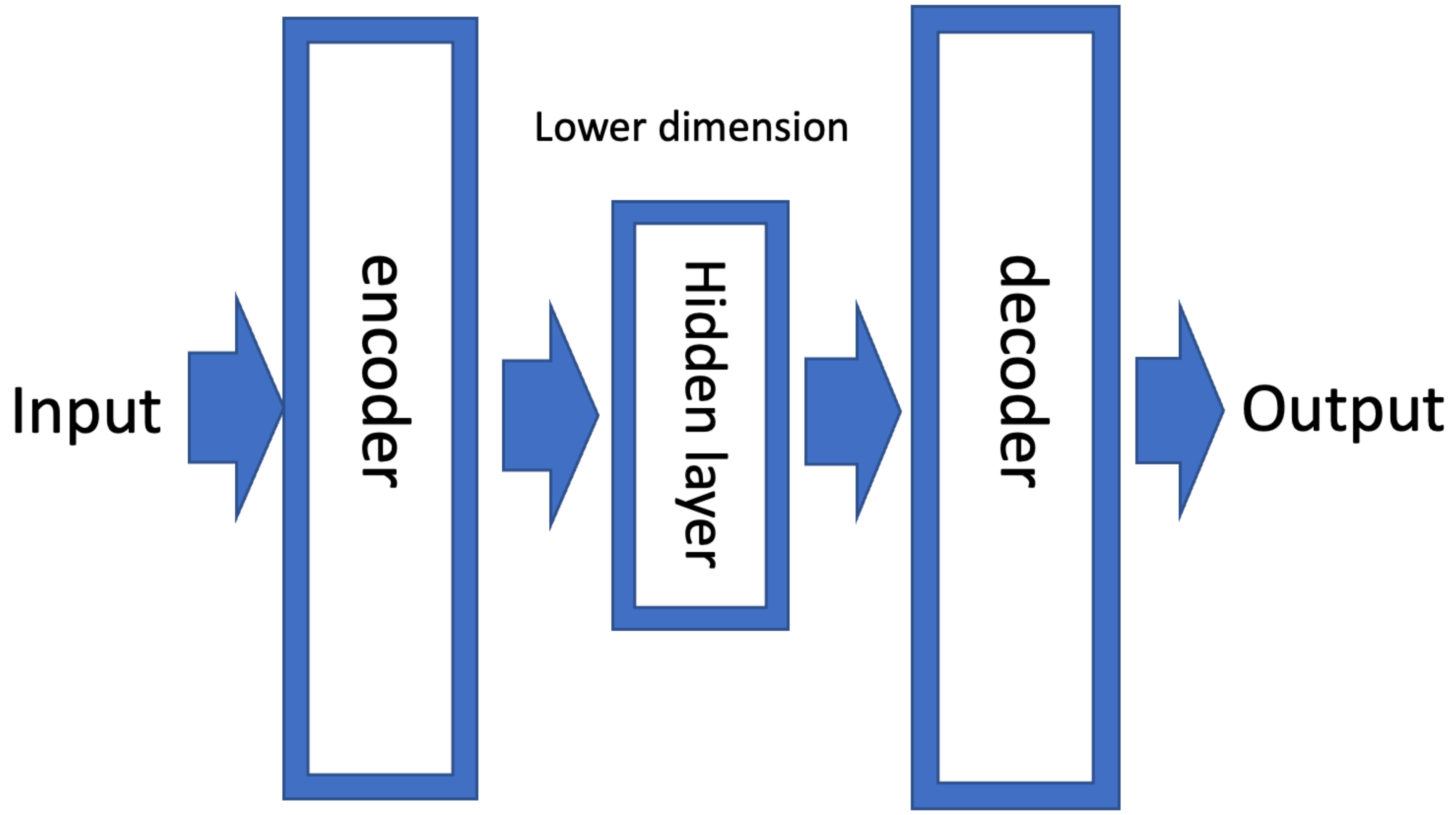
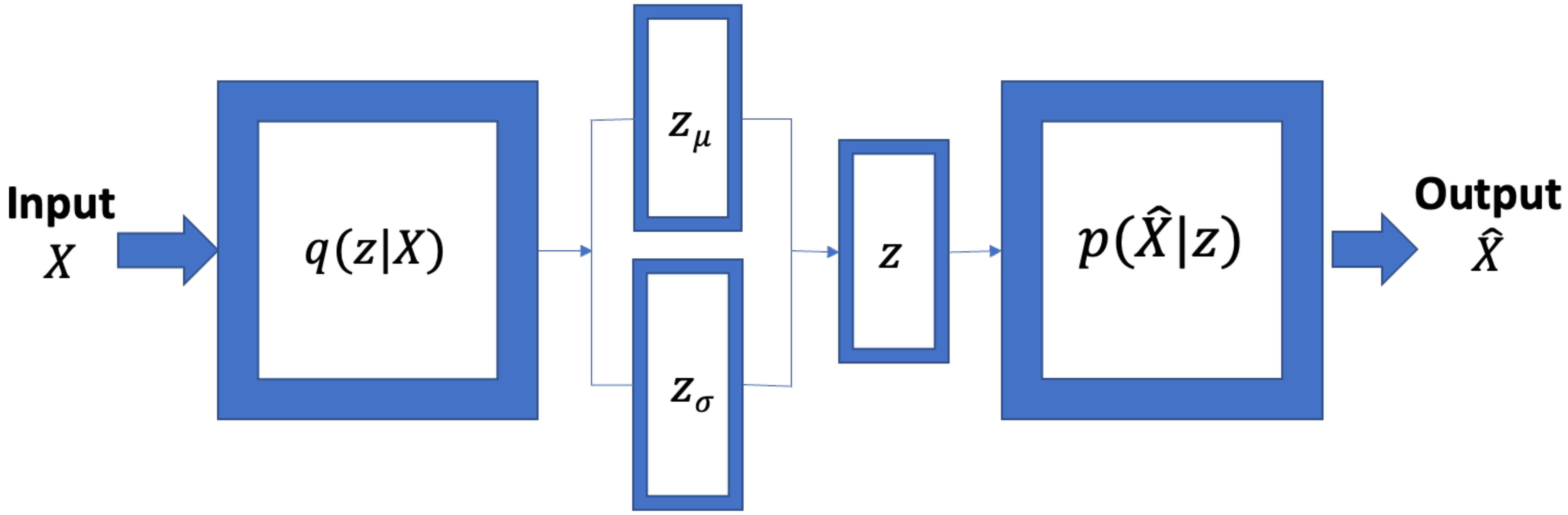


Variational autoencoder: instead of outputting single values onto the hidden layer it outputs a **probability distribution,** thereby forcing the decoder not to take a deterministic values as input but rather to sample from the provided distributions

Variational autoencoder



$z = z_\mu + z_\sigma \varepsilon$, where $\varepsilon \sim N(0,1)$ (good old reparametrisation trick), hence z_μ and z_σ are deterministic layers

$Loss = reconstruction\ loss + KL(q(z\,|\,X)\,||\,p(z))$, where $p(z) \sim N(0,1)$

Very similar set-up to stochastic variational Bayes! Jupyter notebook var_mod

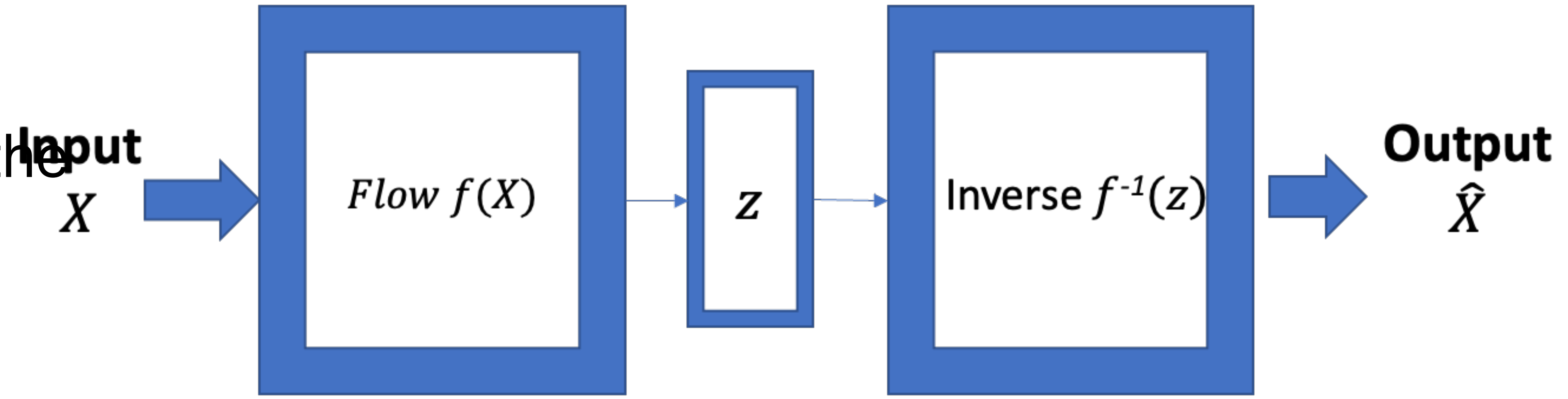
Normalising flows

The major difference compared to VAE:

- Uses **invertible** functions to map onto the latent space z

- For that z has to be the same shape as X

- Given a prior probability density $p_z(z)$ (e.g. normally distributed) and resulting distribution $p_x(x)$ and bijective f



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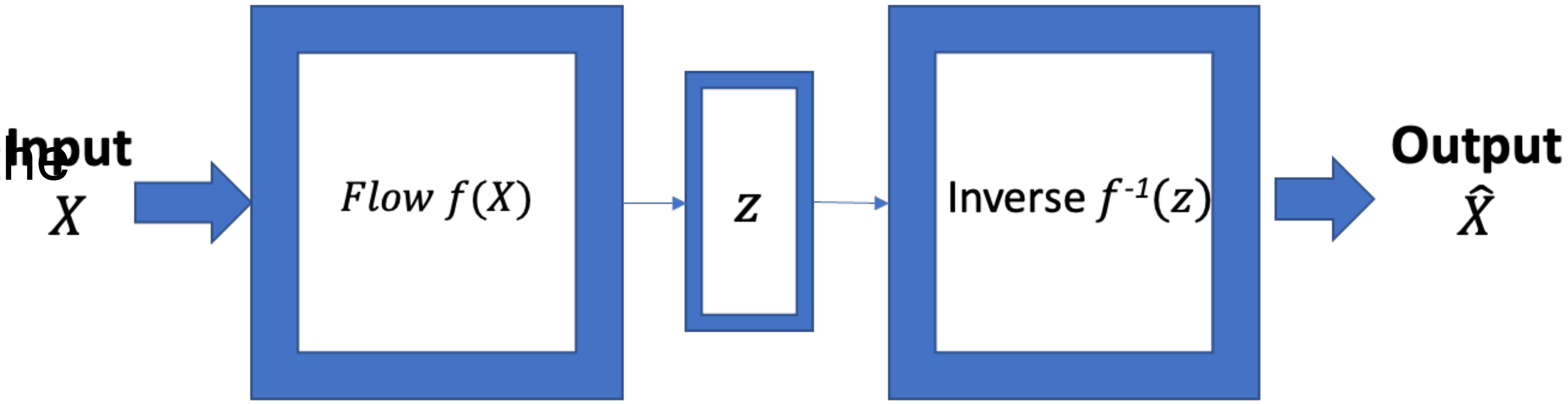

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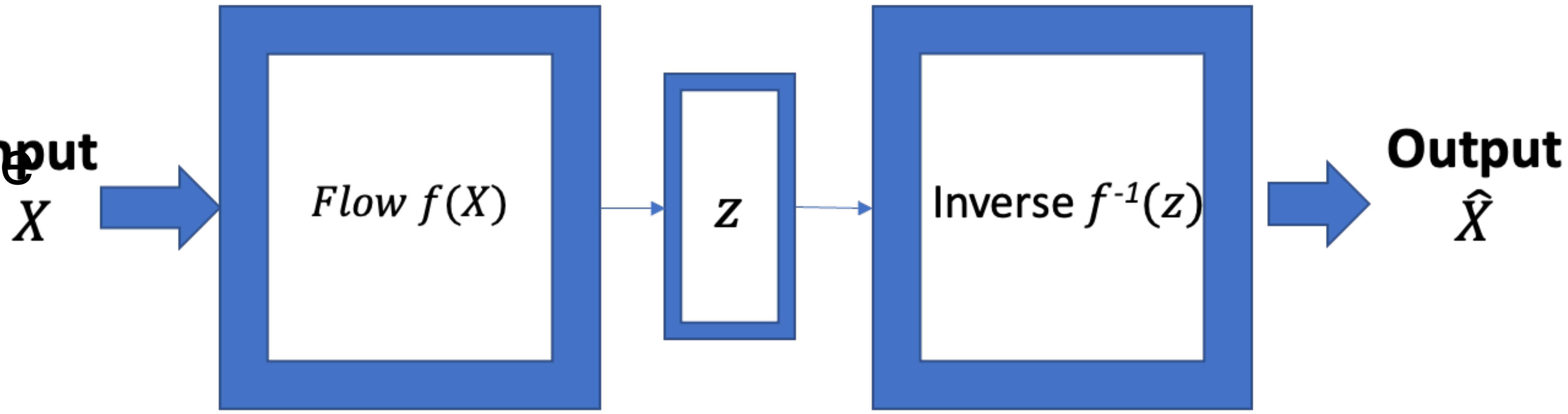

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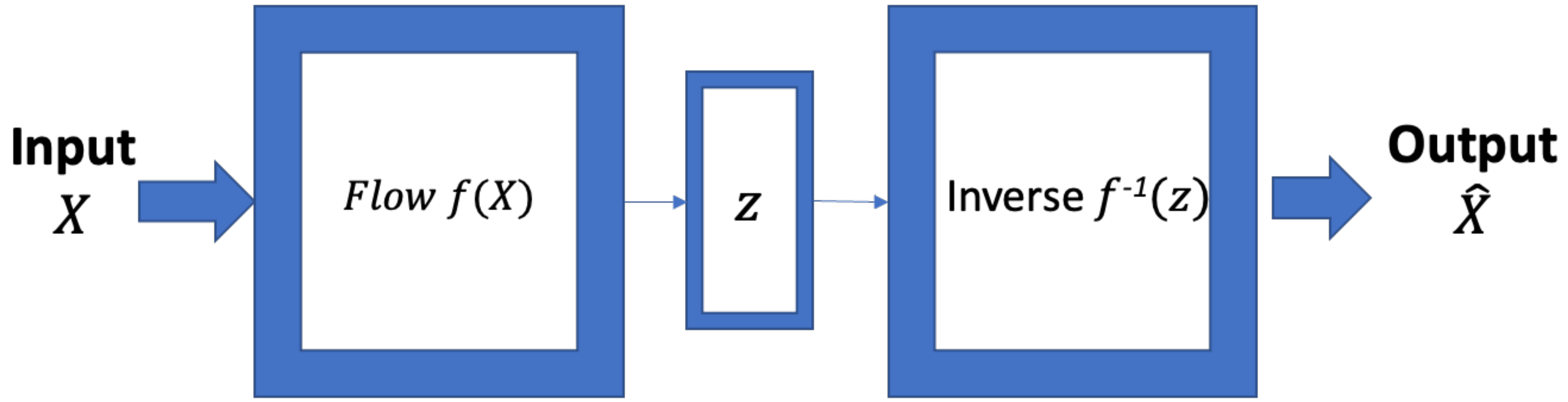

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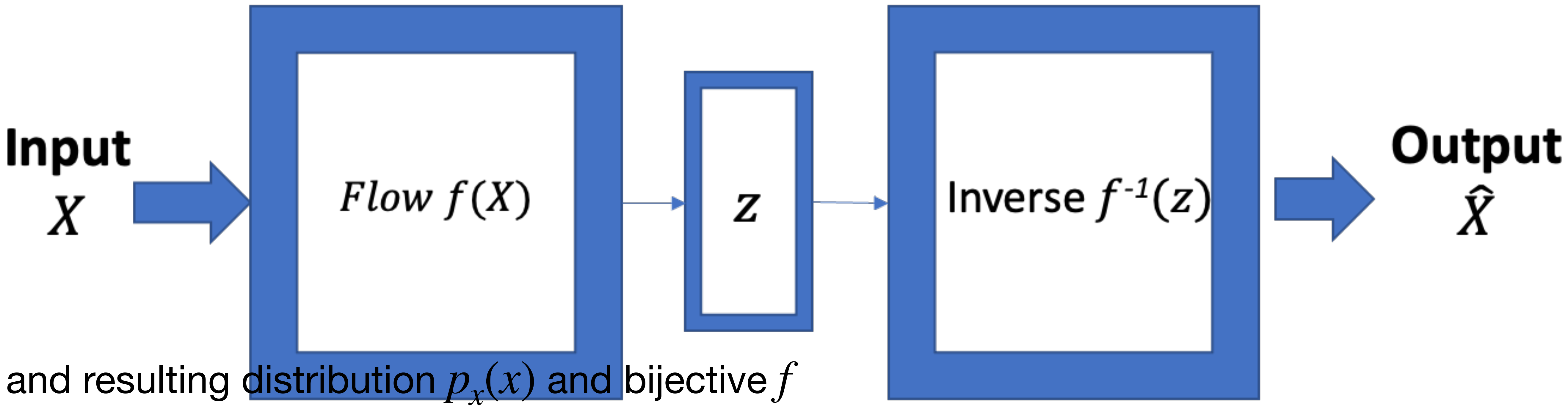

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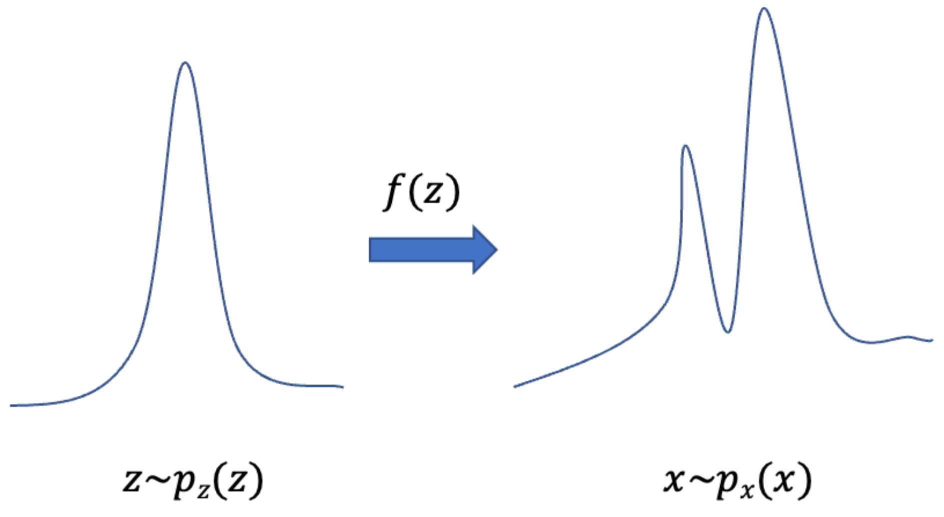
Visually:



Jupyter notebook flows