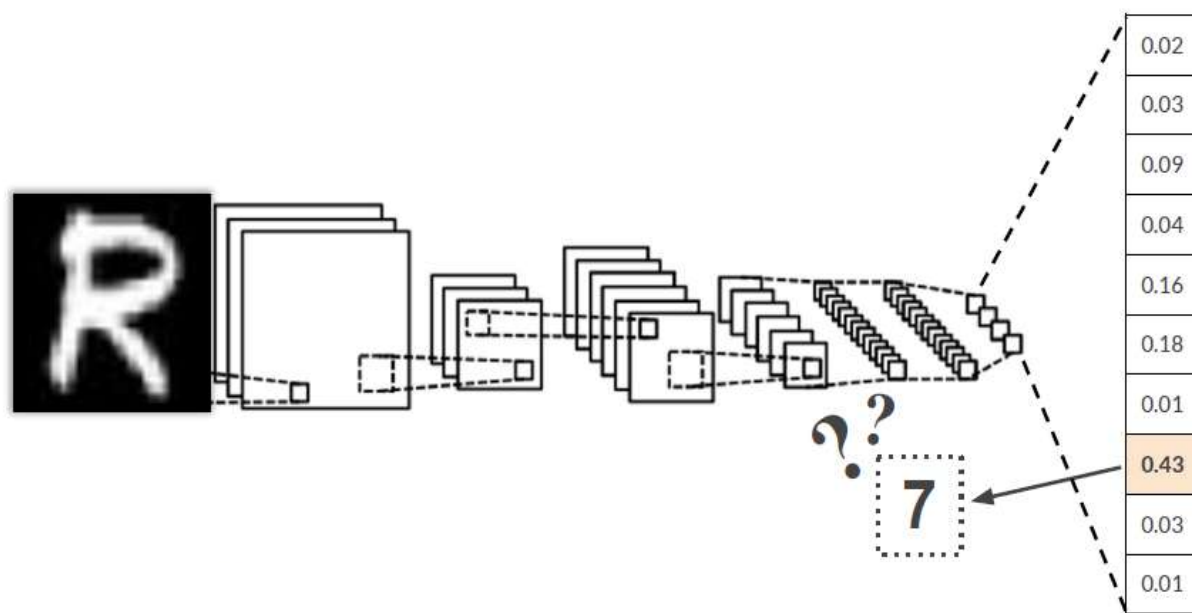
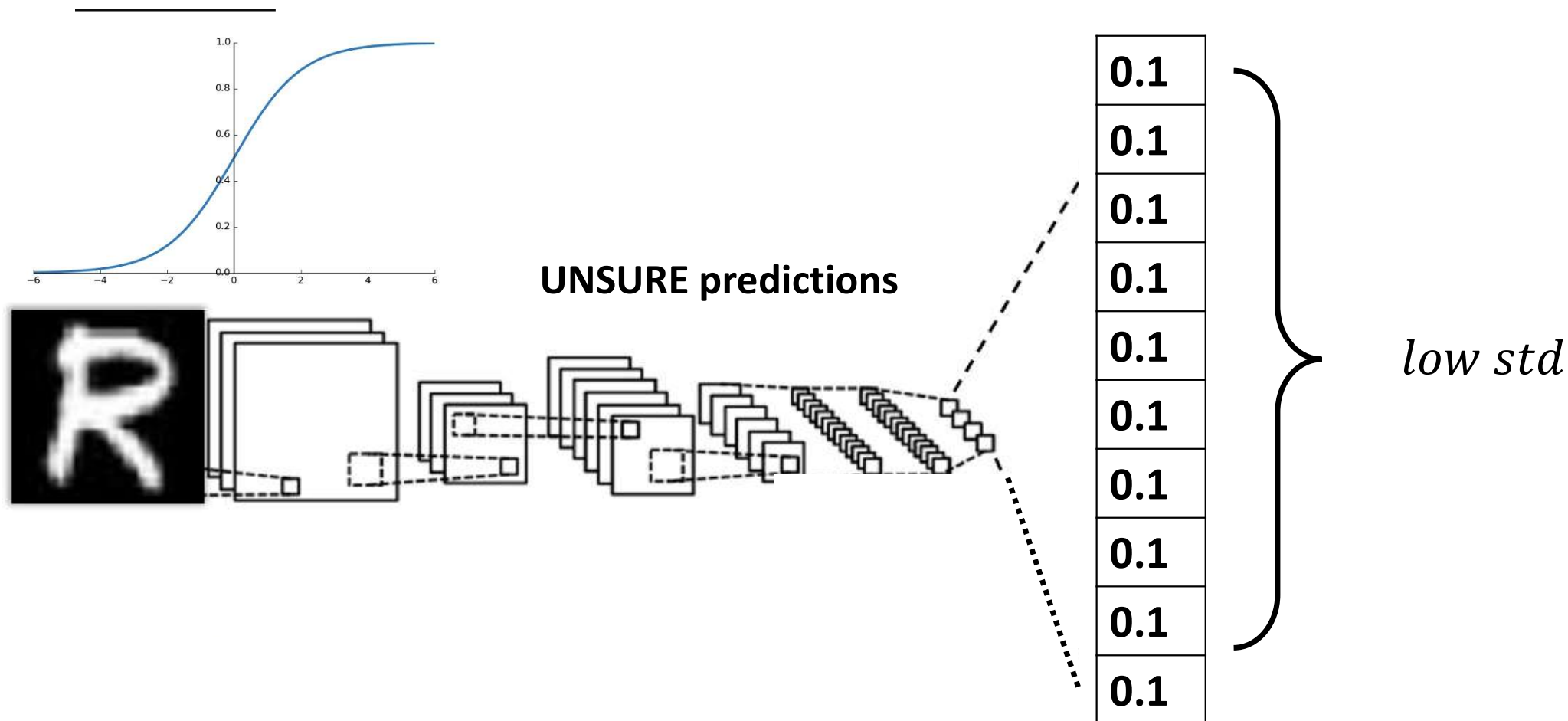


EXPLOITING “UNCERTAIN” DEEP NETWORKS FOR DATA CLEANING IN DIGITALPATHOLOGY

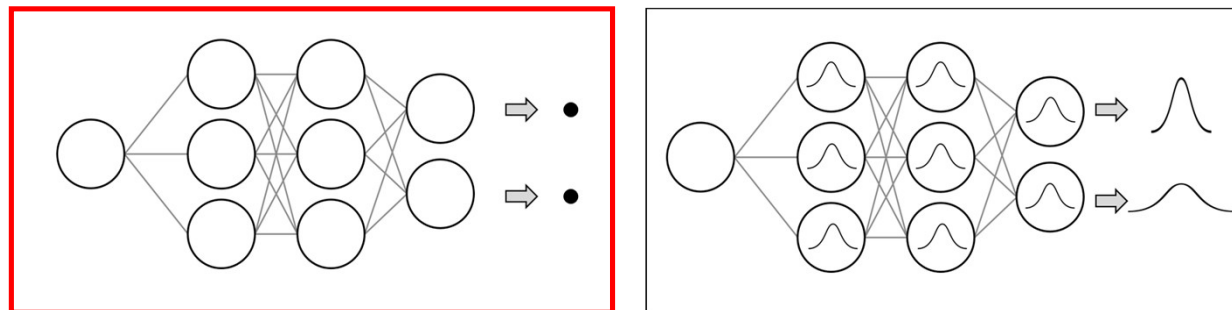
# How to make your CNN say I don't know?





# Why Bayesian Convolutional Neural Networks (B-CNNs)?

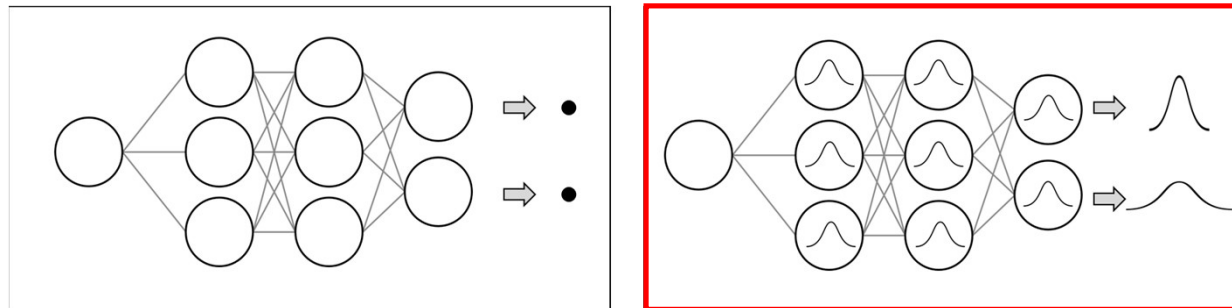
- Bayesian modelling: the **weights’** distribution.



**Standard CNNs: weights are  
POINT ESTIMATE VALUES**

# Why Bayesian Convolutional Neural Networks (B-CNNs)?

- Bayesian modelling: the **weights’** distribution.



**B-CNNs: weights described by  
PDFs computed as BAYESIAN  
POSTERIORS [1]**

[1] Dropout as a Bayesian Approximation: Representing Model Uncertainty in Deep Learning (Gal et al., 2016)



# Why Bayesian Convolutional Neural Networks (B-CNNs)?

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- We use Bayesian inference to estimate weights' PDFs
- Given a prior over the weights  $\mathbf{W}$  of the CNN, the objective of Bayesian inference is to find a posterior distribution over all model's parameters  $\mathbf{W}$

$$p(\mathbf{W}|X, Y) = \frac{p(Y|X, \mathbf{W})p(\mathbf{W})}{p(Y|X)}$$

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Prior: prior beliefs we have on the parameters

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Intractable for CNNs

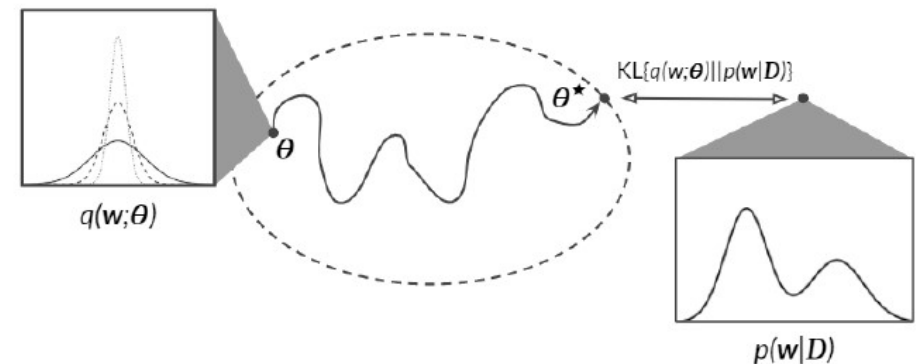
# Why Bayesian Convolutional Neural Networks (B-CNNs)?

- We need a way to approximate the real Bayesian posterior for weights  $\mathbf{W}$
- Variational inference
  - i. We minimize the KL divergency between the posterior and a generic distribution easier which is to work with
  - ii. Minimizing KL divergence is known to be equivalent to maximizing the so-called evidence lower bound (ELBO)
- Variational inference turns the integration problem into an optimization one

$$KL\{q_{\theta}(\omega)||p(\omega|X, Y)\} = \int_{\Omega} q_{\theta}(\omega) \log \frac{q_{\theta}(\omega)}{p(\omega|X, Y)} d\omega \quad (i)$$

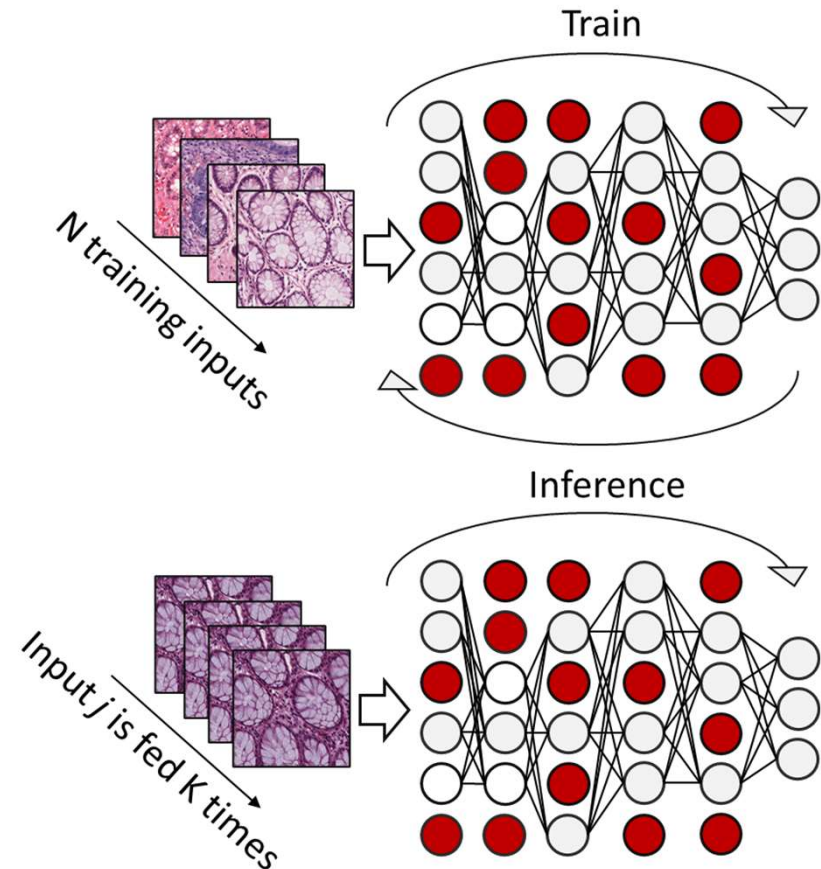
$$\int_{\Omega} q_{\theta}(\omega) \log p(y|x, \omega) d\omega - KL\{q_{\theta}(\omega)||p(\omega)\} \quad (ii)$$

Ideally is 0

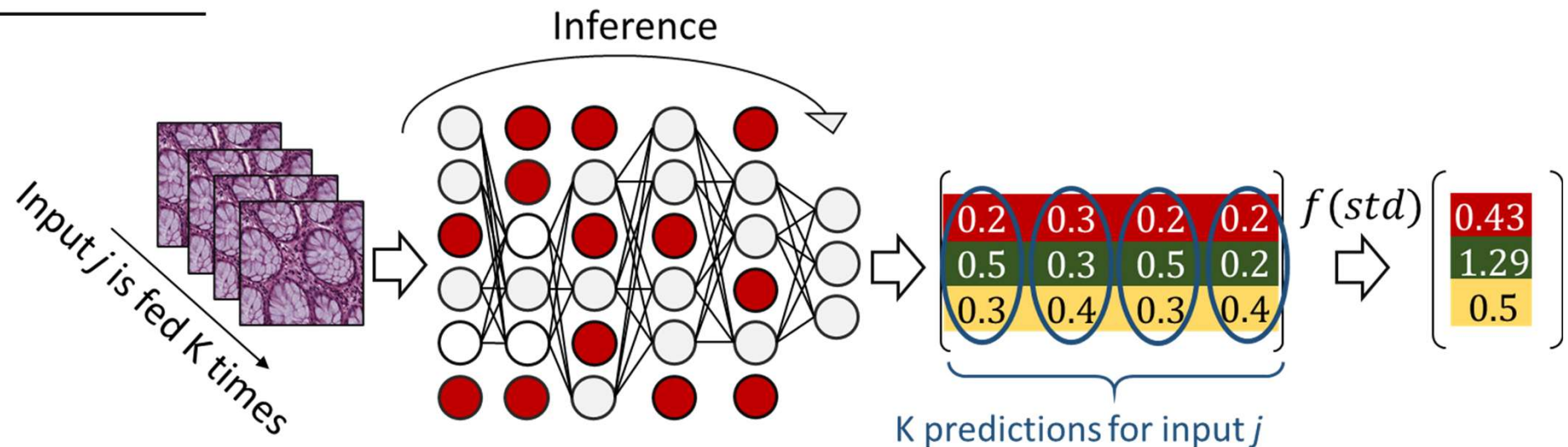


# Why Bayesian Convolutional Neural Networks (B-CNNs)?

- We need a way to approximate the real Bayesian posterior for weights  $\mathbf{W}$
- Variational dropout method
- Consists in applying dropout before each trainable layer in a deep network, also at inference time
- This has been shown to be equivalent to gaussian distributions for the weights [1]

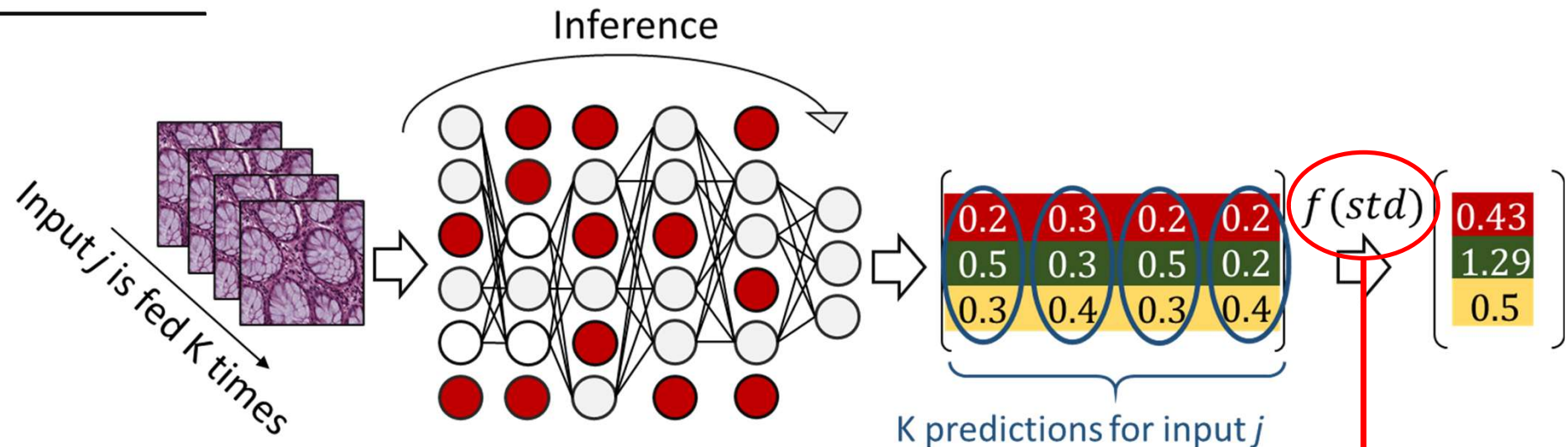


# Why Bayesian Convolutional Neural Networks (B-CNNs)?



- At inference time, for the **same input  $j$**  we get  **$K$  different outputs** because the model uses different parameters every time
- From the prediction's distribution, an **uncertainty measure based on standard deviation** can be retrieved

# Why Bayesian Convolutional Neural Networks (B-CNNs)?



- Uncertainty formula [2]:

$$\frac{1}{T} \sum_{t=1}^T \text{diag}(\hat{p}_t) - \hat{p}_t^{\otimes 2} + \frac{1}{T} \sum_{t=1}^T (\hat{p}_t - \bar{p})^{\otimes 2}$$

[2] Uncertainty quantification using Bayesian neural networks in classification: Application to biomedical image segmentation (Kwon et al., 2019) 13