Deep Learning Explained

Module 3: Multi-layer Perceptron

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Module outline

Application:

OCR using MNIST data

Model:

Recap Logistic Regression

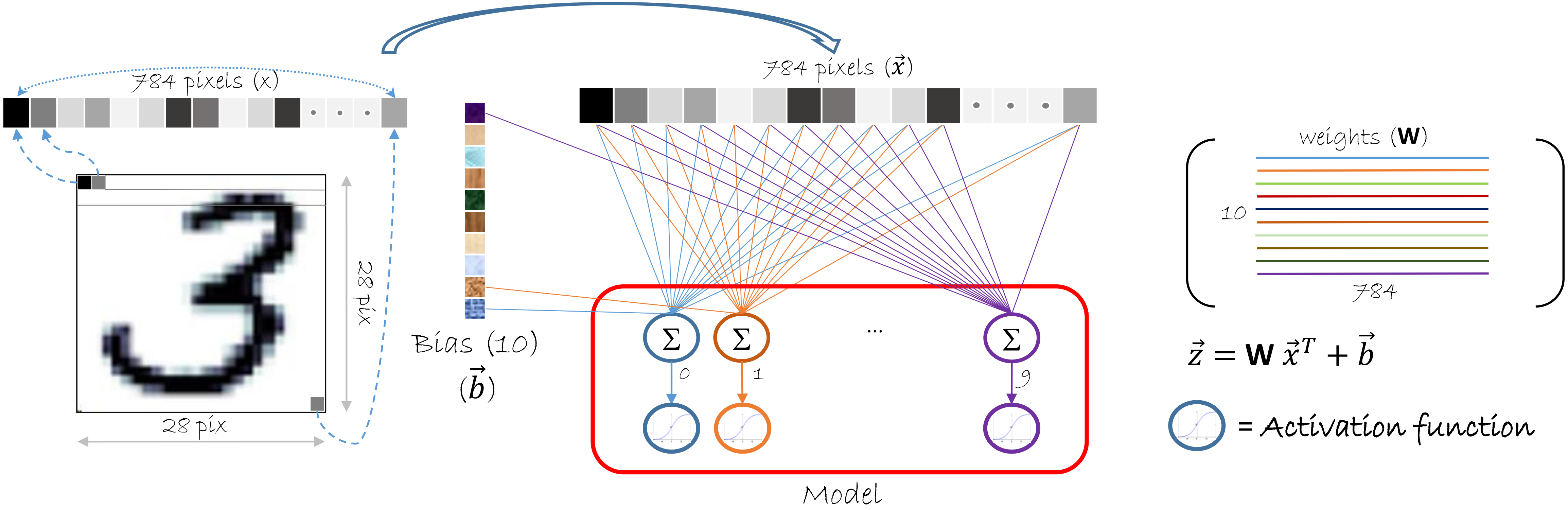
Multi-Layer Perceptron

Concepts:

Activation functions

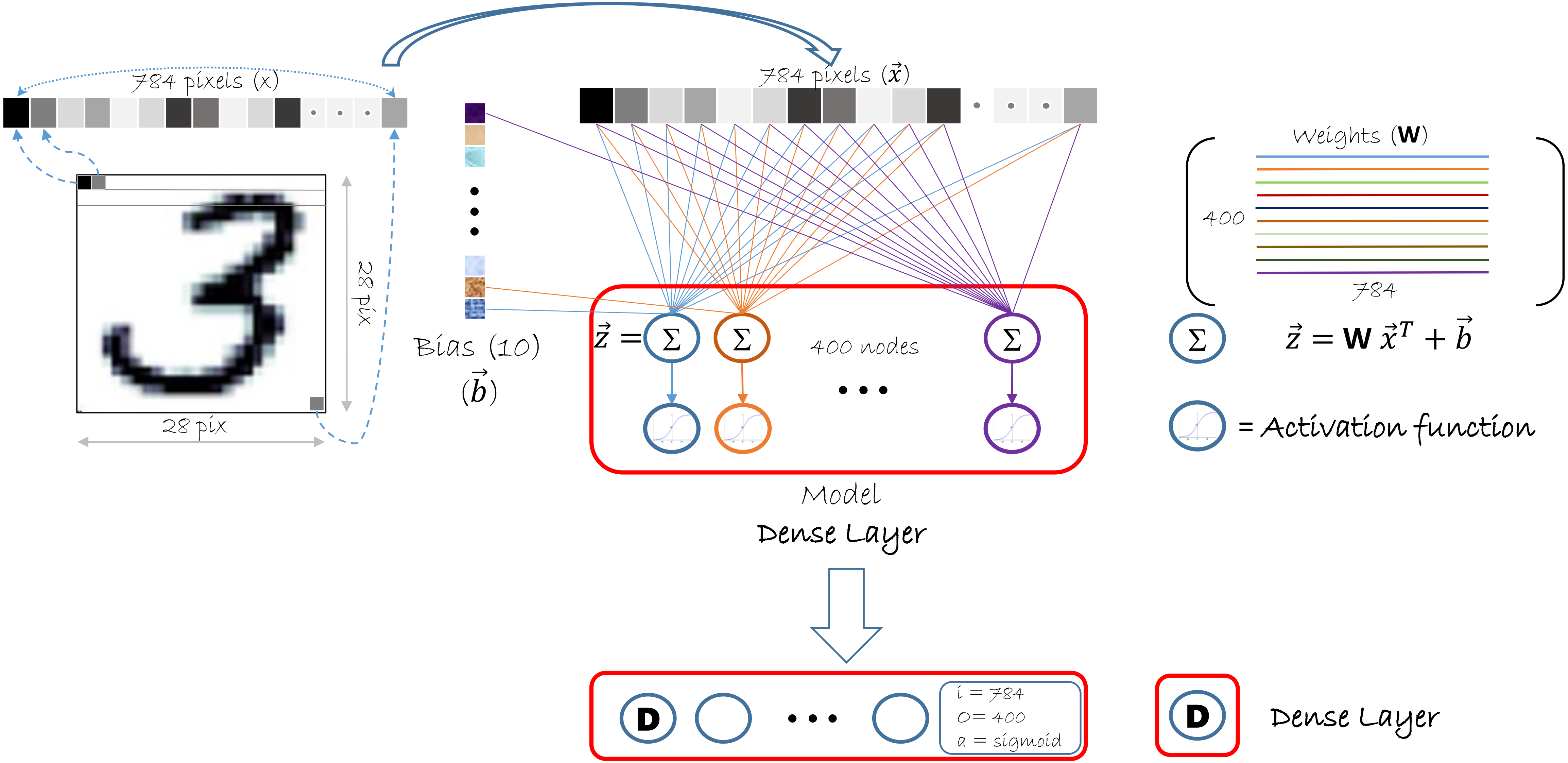
Train-Test-Predict Workflow

Logistic regression



Error rate in detection of MNIST digits with Logistic Regression = 7-8%

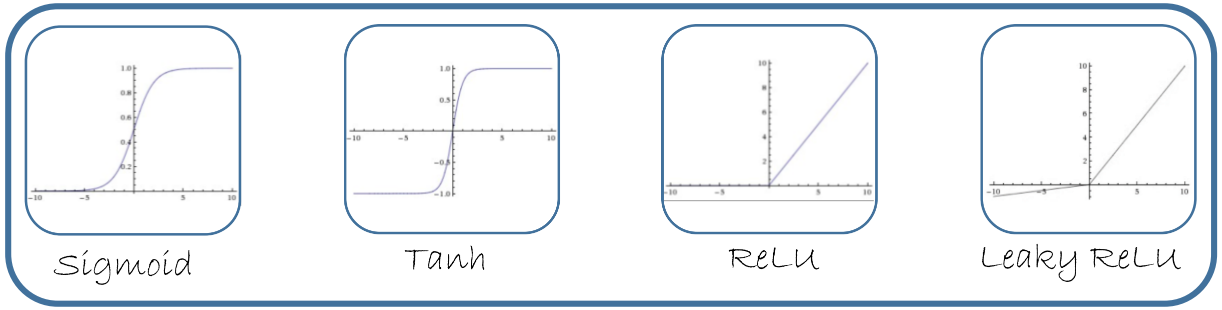
Towards deep networks



Activation functions

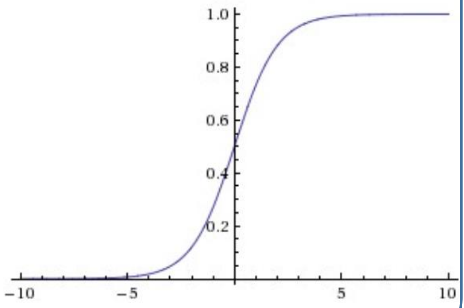
- Activation functions (a.k.a. non-linearity):
  - ✓Take a *single number* and maps it to a *different numerical value*
  - ✓ E.g. *Sigmoid* maps values any numerical value to a *(0,1)* range

- Popular functions:
  - *Sigmoid*
  - *Tanh*
  - *ReLU (Rectified Linear Unit)*
  - *Leaky / Parametric Relu*



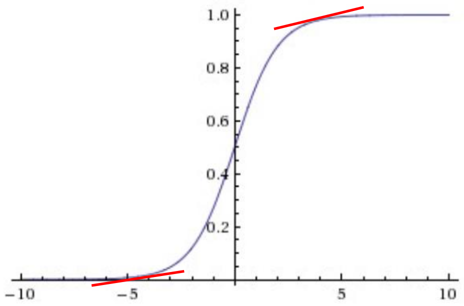
Activation functions

Sigmoid



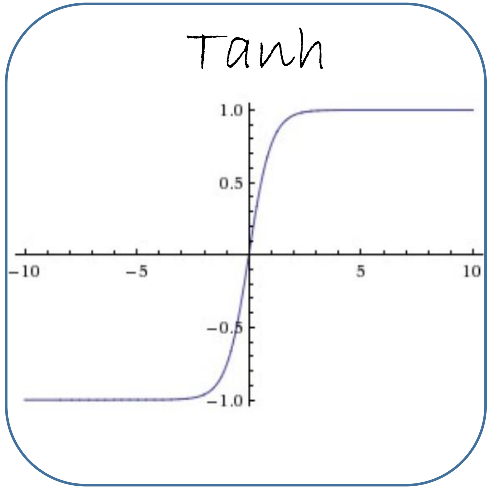
$$\sigma(x) = 1/(1 + e^{-x})$$

- Maps real value number into range 0 – 1
- Historically popular, bears semblance to neurons firing pattern
- Recently its popularity is dipping
  - ✓ Saturation / Vanishing Gradient
    - At either end of the tails, gradients go to zero
    - Caution needed when initializing weights to prevent saturation



  - ✓ Non-zero centered output
    - During optimization, causes zig-zagging dynamics
    - More of inconvenience, less severe than saturation

Activation functions

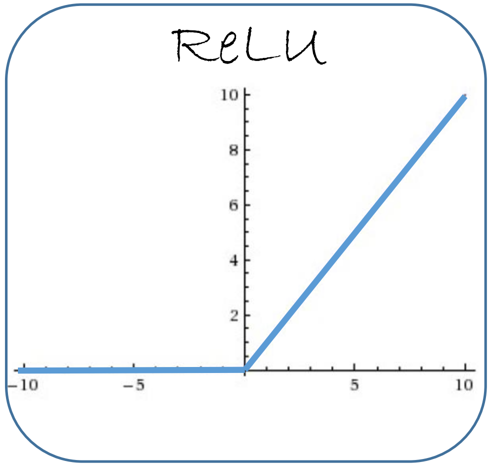


$\tanh(x) = (e^x - e^{-x})/(e^x + e^{-x})$

- Maps real value number into range -1 to 1
- Like *Sigmoid*, its activation also saturates but output is *zero* centered
- *Tanh* is usually preferred over *Sigmoid*
- *Tanh* is a scaled *Sigmoid* function

$$\tanh(x) = 2\sigma(2x) - 1$$

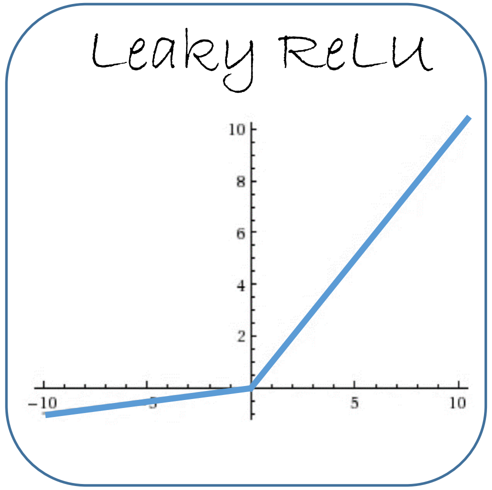
Activation functions



$$f(x) = max(0, x)$$

- ReLU = Rectified Linear Unit
- Very popular and simply thresholds values below 0
- Pros:
  - ✓ Fast convergence
    - — SGD converges much faster compared to sigmoid / tanh
    - — Arguably due to its linear (non saturating form)
  - ✓ Simple implementation
    - — Involves thresholding of activation matrix at zero
- Cons:
  - ✓ Fragile
    - — Irreversibly die when large gradient flows
    - — As much as 40% of network can die if learning rate set is too high

Activation functions (Advanced)



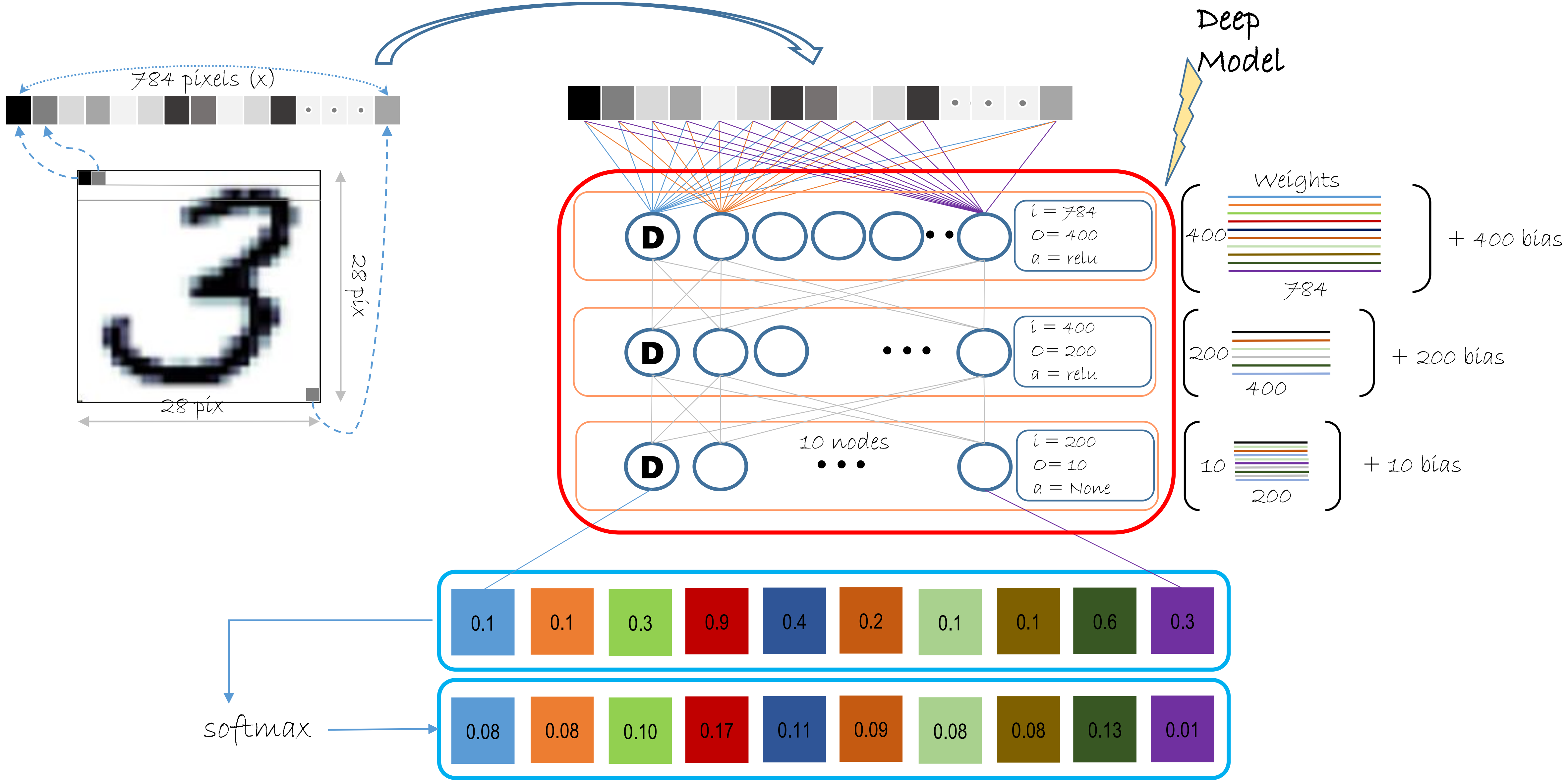
$$f(x) = 1(x < 0)(\alpha x) + 1(x \geq 0)(x)$$

- Aimed to fix "dying ReLU" problem
- For a negative input, instead of zero have a small negative slope (α)
  - ✓ Leaky ReLU has a small fixed slope ($\alpha = 0.1$)
  - ✓ **Parametric Relu** (Param ReLU or PReLU)
    - The slope is prameterized and can be learnt
  - ✓ MaxOut
    - Is applied on the dot product between the weights and the data.

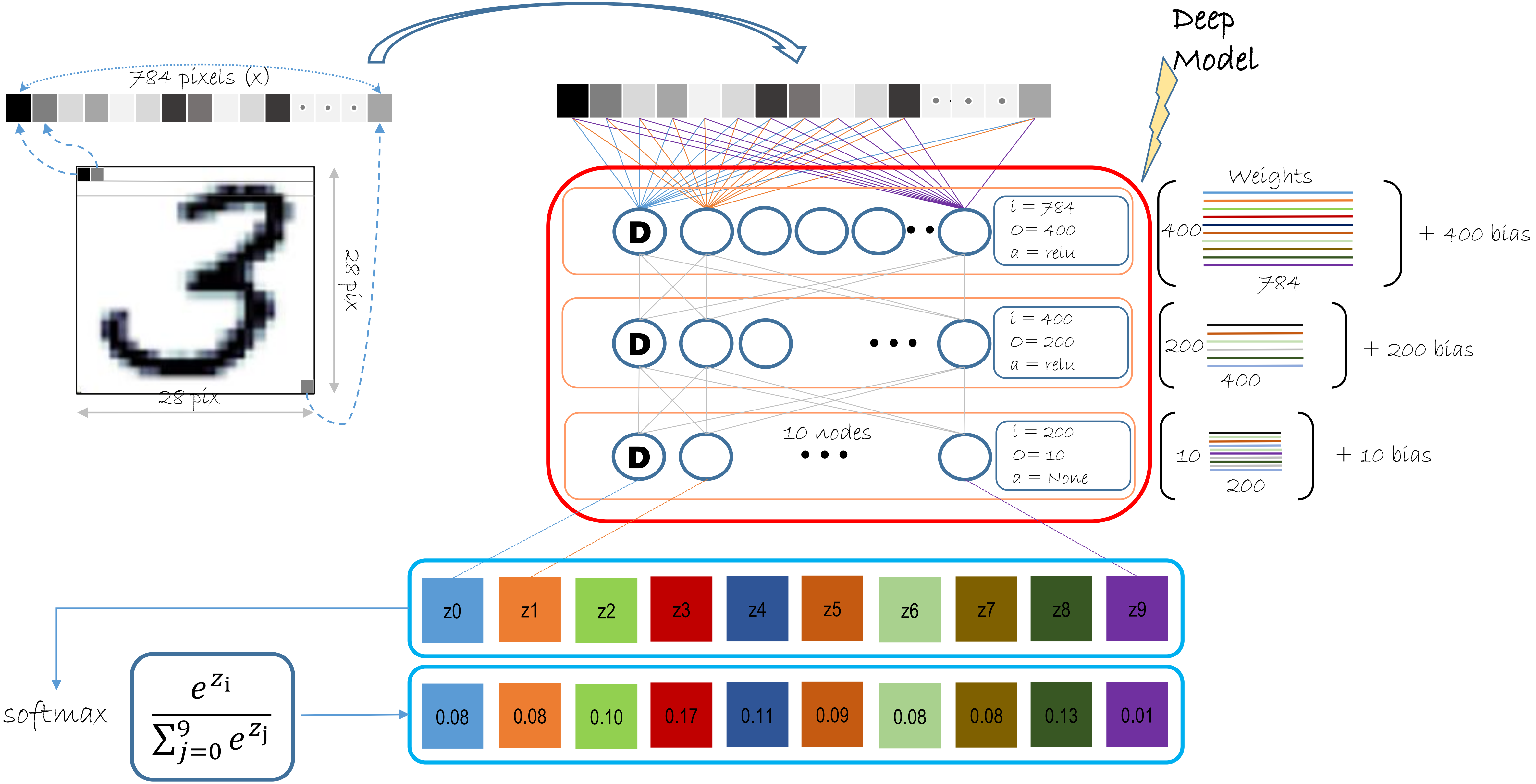
$$f(x) = \max(a_1^T x + c_1, a_2^T x + c_2)$$

    - **ReLU**, **LeakyReLU** and **Param ReLU** are special case of **Maxout**
    - Enjoys benefit of all, except number of parameters double

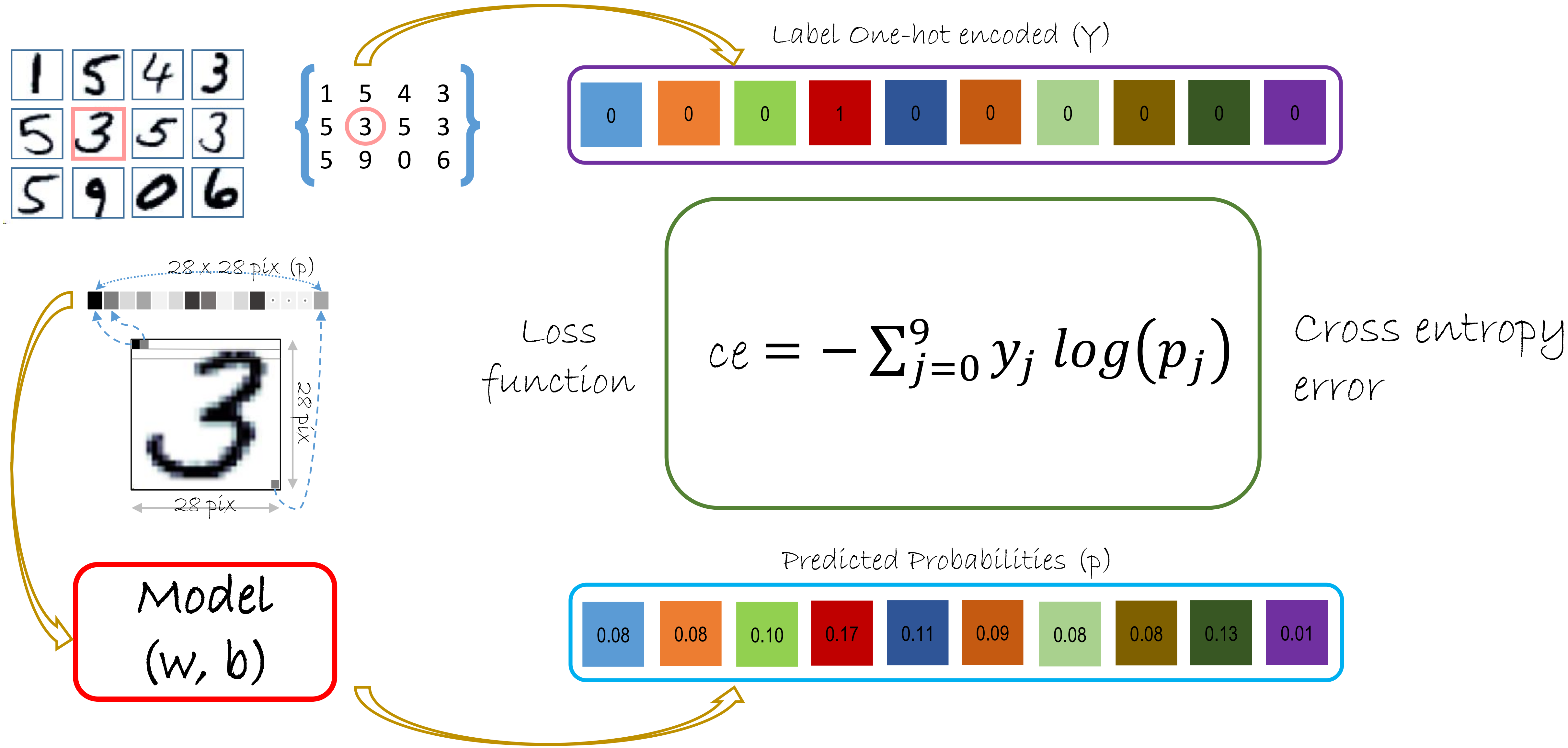
Our first deep network



Multi-layer perceptron

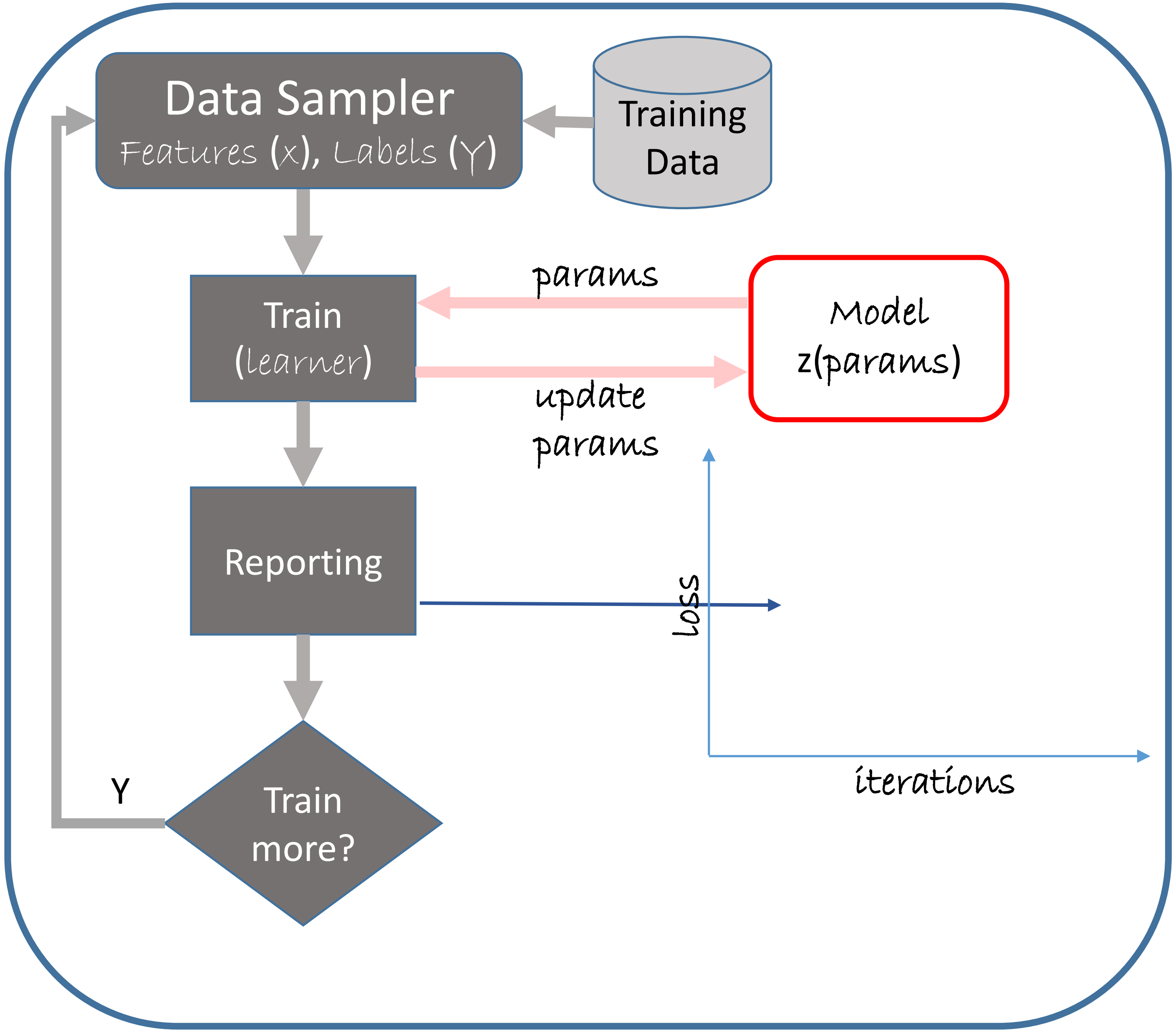


Loss function

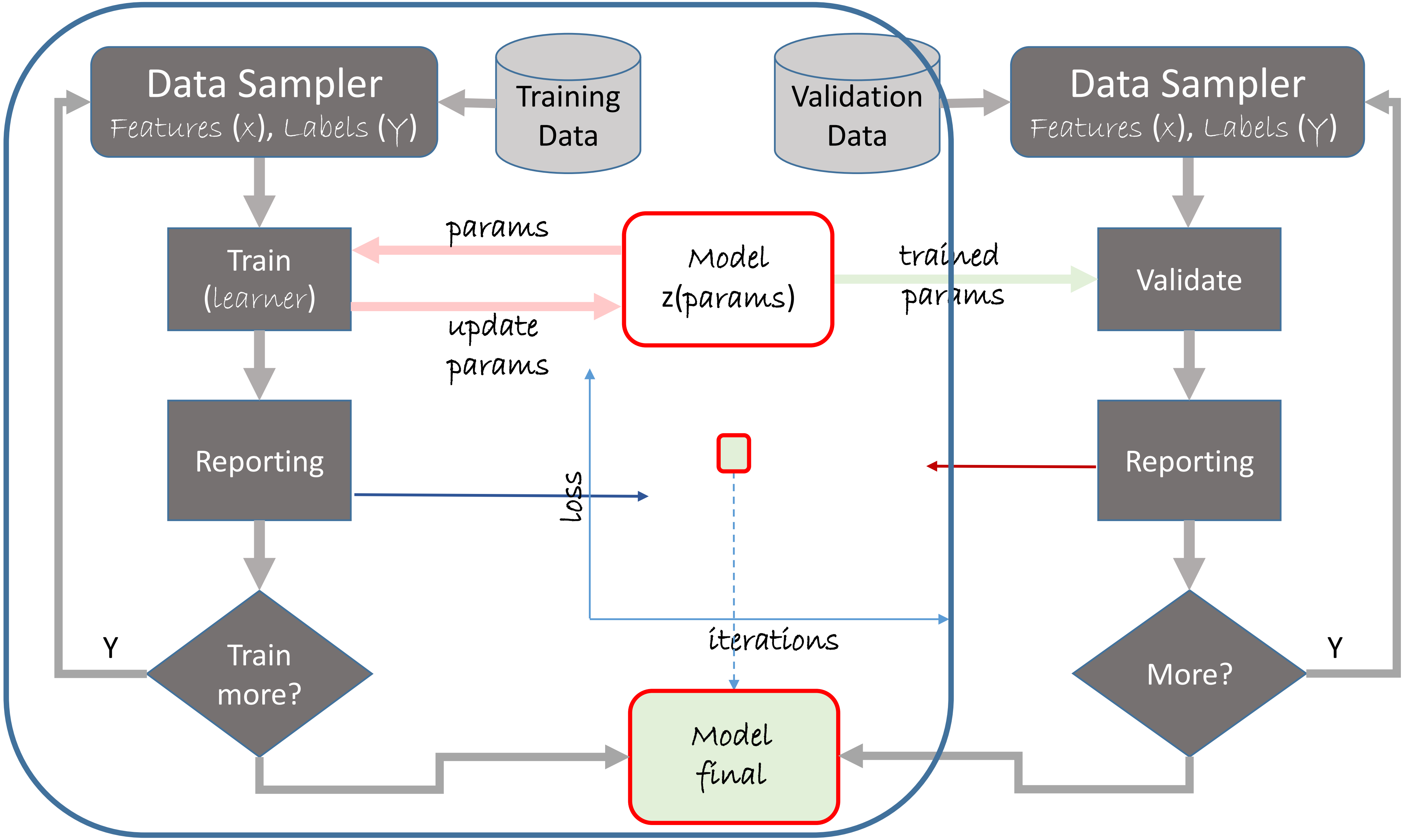


$$ce = -\sum_{j=0}^{9} y_j \, log(p_j)$$

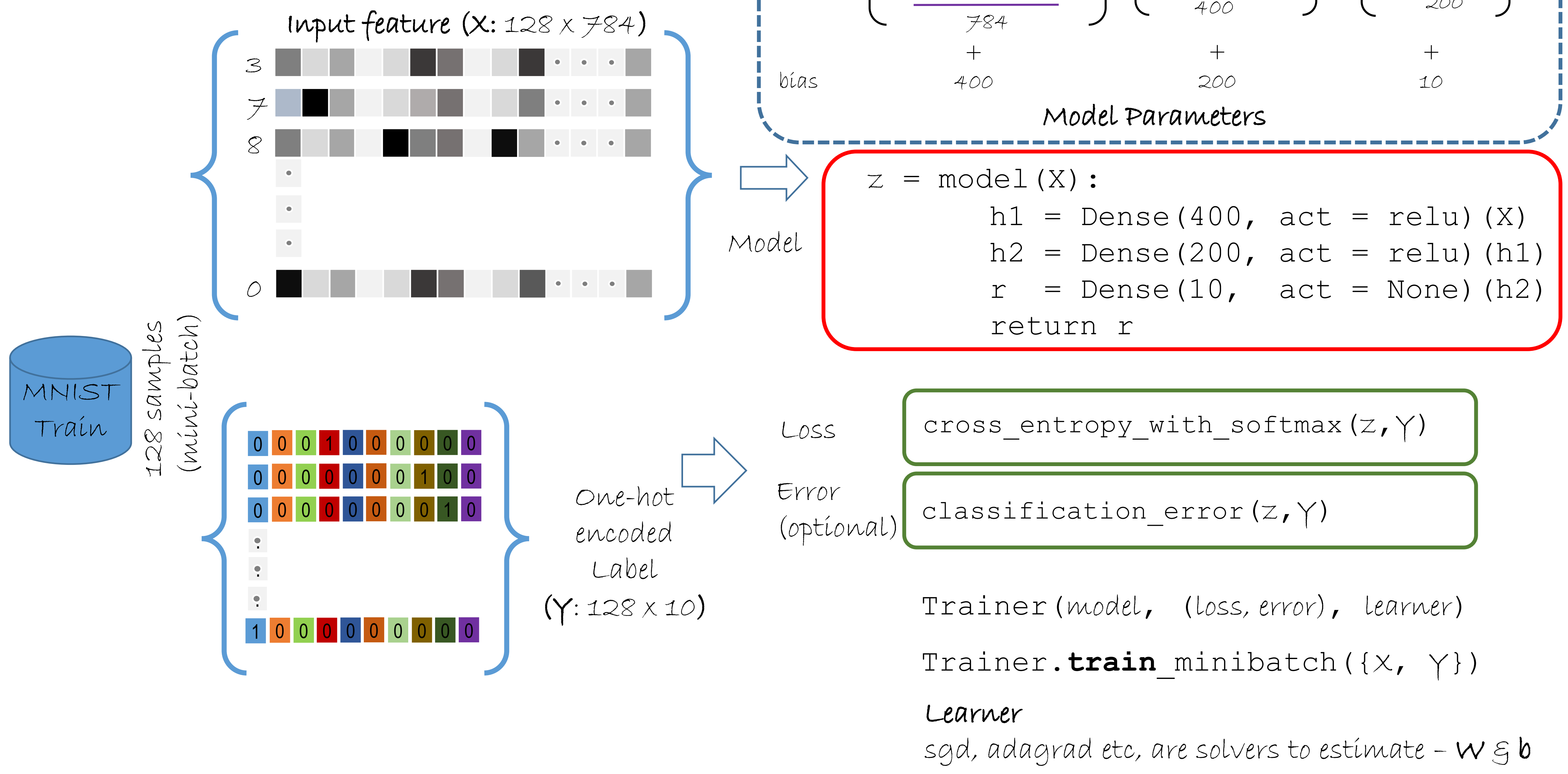
Train workflow



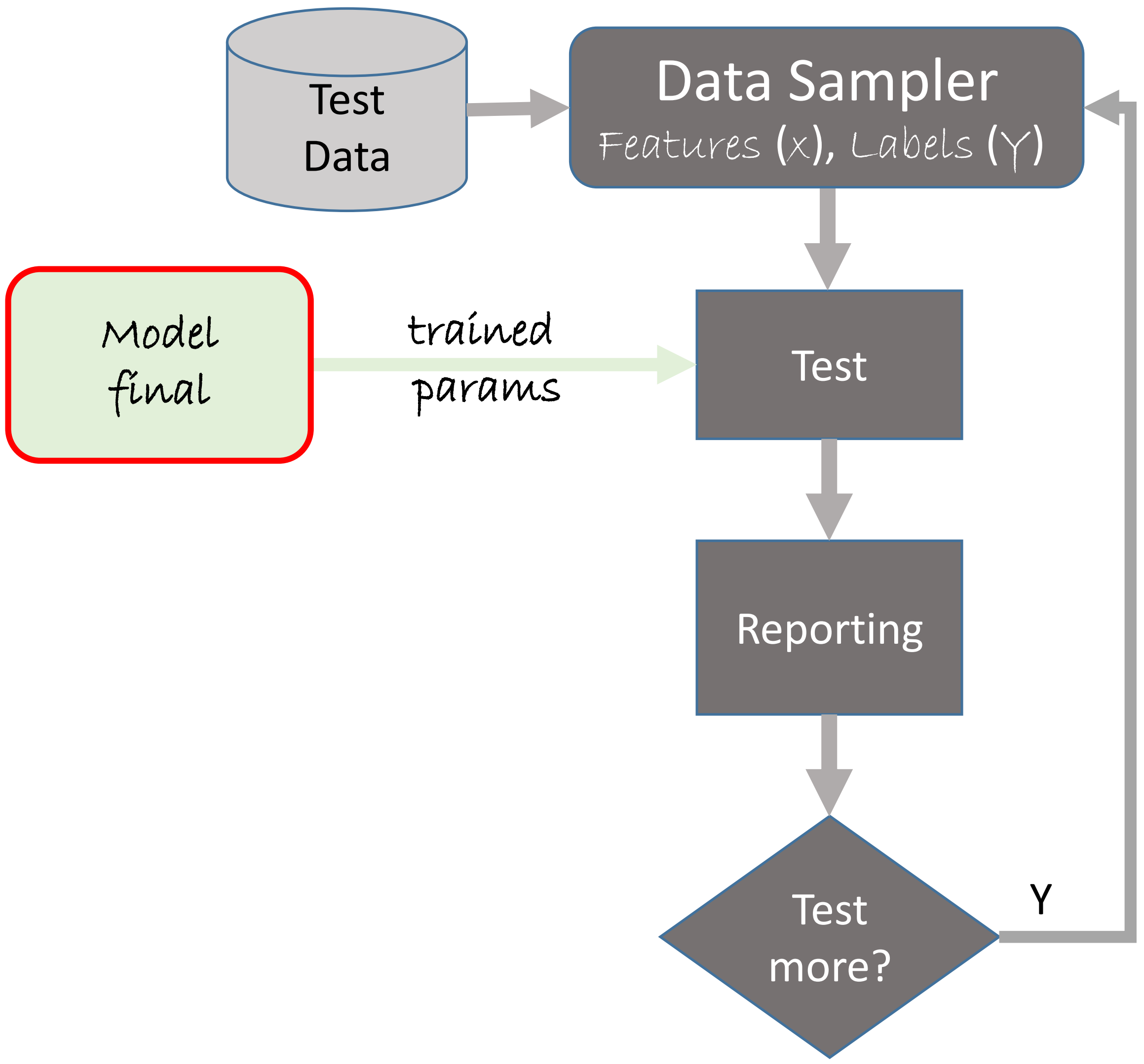
Validation workflow



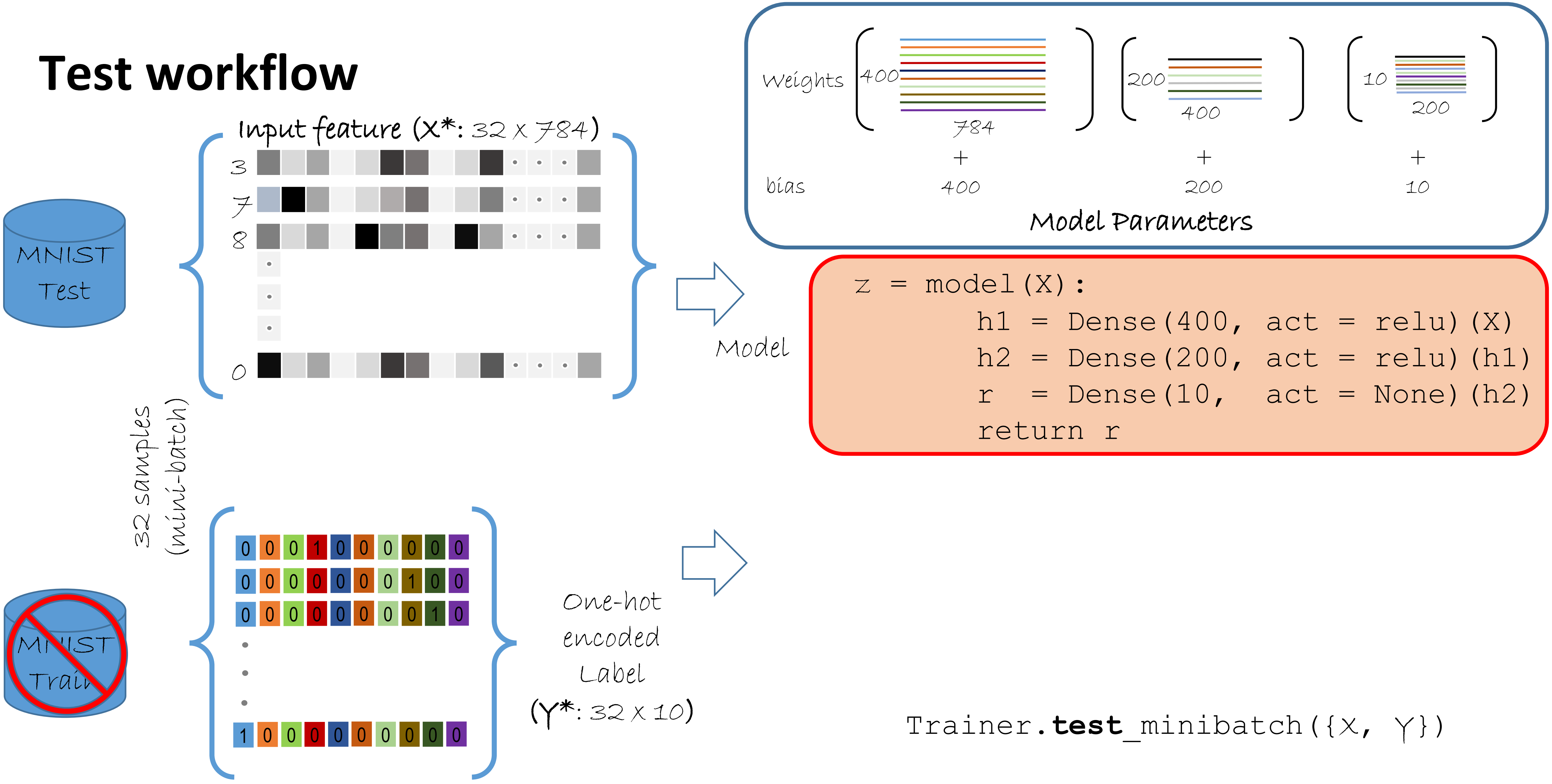
Train workflow



Test workflow



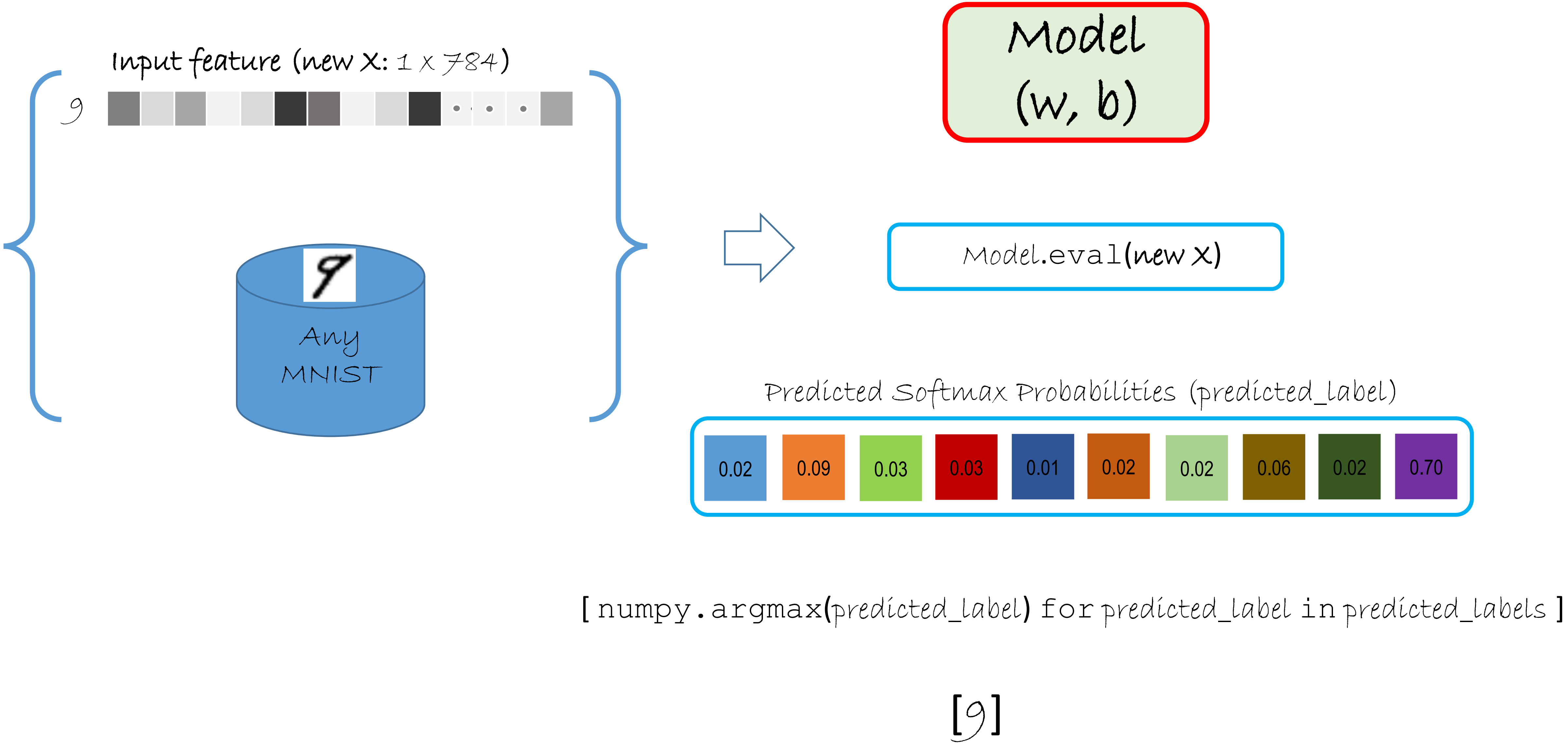
Test workflow




```
z = model(X):
        h1 = Dense(400, act = relu)(X)
        h2 = Dense(200, act = relu)(h1)
        r  = Dense(10,  act = None)(h2)
        return r
```

```
Trainer.test_minibatch({X, Y})
```

Prediction workflow



Prediction workflow