



# Deep Learning with Tensorflow in practice

Démarrage à 9h05  
Conférence ENREGISTREE

Vincent Havard,  
Enseignant-chercheur,  
CESI LINEACT,  
Rouen

—  
2022

# Outline

- 1. Neural Networks workflow**
- 2. Deep Learning Metrics**
- 3. Conclusion**

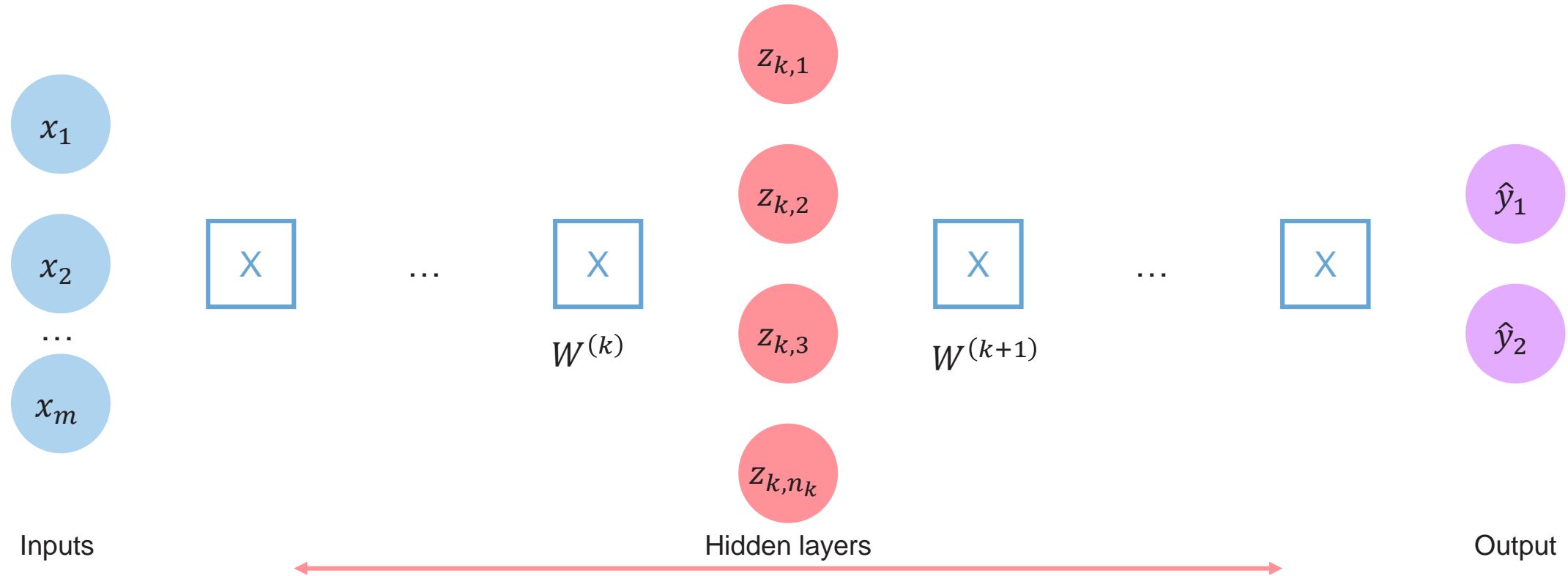




The background is a dark blue field filled with glowing white and light blue lines and dots, resembling a complex network or neural network. Overlaid on this are several horizontal rows of glowing green binary code (0s and 1s). In the center, there is a white rectangular box with a purple L-shaped graphic element on its top-right corner. Inside this box, the text "Neural Networks workflow" is written in a black, sans-serif font.

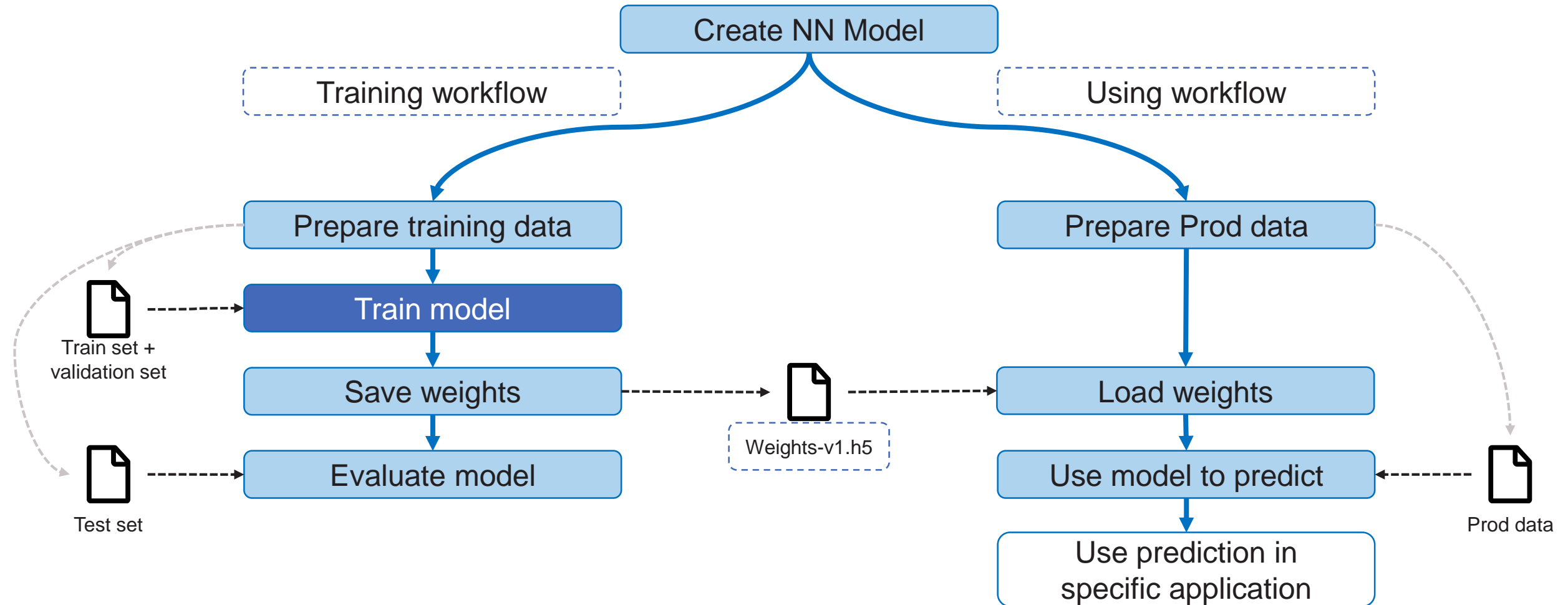
# Neural Networks workflow

# Deep Neural Network

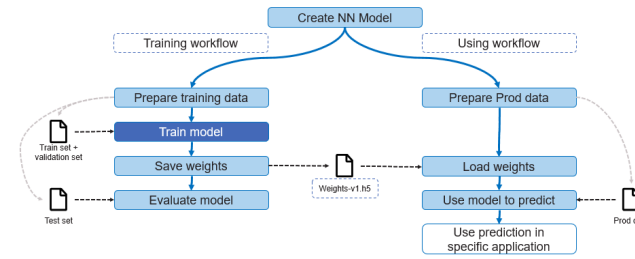


$$z_{k,i} = w_{0,i}^{(k)} + \sum_{j=1}^{d_1} g(z_{k-1,j}) w_{j,i}^{(k)}$$

# Neural networks workflow



# Neural networks workflow



## How to **train** a neural network?

1. Prepare your training data in several sets (*training validation, test*)
2. Create your model
  - Define NN
  - Set the Loss function  
Depends on the problematic to solve
  - Set the optimizer
  - Set the metrics
  - and compile
3. Train the neural network on the training set and please wait...
4. Save the NN weights
5. Evaluate on the test set

## How to **use** a neural network?

1. Prepare your data to use
2. Create the exactly same model
  - Define NN
  - Set the Loss function  
Depends on the problematic to solve
  - Set the optimizer
  - Set the metrics
  - and compile
3. Load the NN weights
4. (*classification only*) transform into probability model
5. Predict on the data given



# Neural networks workflow

## How to train a neural network?

1. Prepare your data in several sets (*training validation, test*)
2. Create your model
  - Define NN
  - Set the Loss function  
Depends on the problematic to solve
  - Set the metrics
  - and compile
3. Train the neural network on the training set and please wait...
4. Save the NN weights\*
5. Evaluate on the test set

\*Save the NN weights during training

[https://www.tensorflow.org/tutorials/keras/save\\_and\\_load#checkpoint\\_callback\\_usage](https://www.tensorflow.org/tutorials/keras/save_and_load#checkpoint_callback_usage)



## How to train a neural network?

1. Prepare your data in several sets (*training set, validation set, test set*)

```
[18]: mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

2. Create your model

- Define NN
- Set the Loss function (*It depends on the problematic to solve*)
- Set the metrics for evaluation
- and compile

```
[16]: def create_model(summary=False, loss_fn_to_use =
      tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)):
    model = tf.keras.models.Sequential([
        tf.keras.layers.Flatten(input_shape=(28, 28)),
        tf.keras.layers.Dense(128, activation='relu'),
        tf.keras.layers.Dropout(0.2),
        tf.keras.layers.Dense(10)
    ])
    if summary:
        model.summary()
    # Set loss function to use with the model
    loss_fn = loss_fn_to_use

    # and compile
    model.compile(optimizer='adam', loss=loss_fn, metrics=['accuracy',
        tf.keras.metrics.SparseCategoricalAccuracy()])

    return model
```

3. Train the neural network on the training set ...*and please wait*

it is possible to save the NN weights during training see [https://www.tensorflow.org/tutorials/keras/save\\_and\\_load#checkpoint\\_callback\\_usage](https://www.tensorflow.org/tutorials/keras/save_and_load#checkpoint_callback_usage)

4. Save the Neural Network weights
5. Evaluate on the test set

```
[17]: # Create your model
model = create_model(summary=True)
# Training from a few minutes to days
model.fit(x_train, y_train, epochs=5) # *you can save NN weights during training

# Save weights after training
model.save_weights('./mnist_model_0.98.h5')

# evaluate training on test set
model.evaluate(x_test, y_test, verbose=2)
```

# Neural networks workflow

## How to use a neural network?

1. Prepare your data to use
2. Create the exactly same model
  - Define NN
  - Set the Loss function  
Depends on the problematic to solve
  - Set the metrics
  - and compile
3. Load the NN weights
4. (classification only) transform into probability model
5. Predict on the data given



## How to use a neural network?

1. prepare your data

```
[29]: mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

2. Create your model

- Define NN
- Set the Loss function (It depends on the problematic to solve)
- Set the metrics for evaluation
- and compile

3. Load the NN weights

```
[ ]: model = create_model(summary=False)
# Load weights trained
model.load_weights('./mnist_model_0.98.h5')
# evaluate to check the model is well loaded
model.evaluate(x_test, y_test, verbose=2)
```

4. (classification only) transform into probability model

5. Predict on the data given

```
[ ]: # probability model
probability_model = tf.keras.Sequential([model, tf.keras.layers.Softmax()])
```

```
[44]: # Prepare the data given
im_to_test = x_test[0]
# only when testing on 1 unique sample
im_to_test = np.expand_dims(im_to_test, axis=0)

# NOT UNDERSTANDABLE approach
model_output = model.predict(im_to_test)
model_output_class = np.argmax(model_output)
print(model_output)
print(model_output_class)

# UNDERSTANDABLE approach
prob_model_output = probability_model.predict(im_to_test)
prob_model_output_class = np.argmax(prob_model_output)
print(prob_model_output)
print(prob_model_output_class)

[[ -6.098753  -13.523815  -4.2792406  1.8365132 -20.36935  -3.3478541
 -22.223114  13.569721  -5.958574  -1.6038301]]
7
[[2.8713529e-09 1.7116818e-12 1.7712962e-08 8.0228556e-06 1.8215655e-15
 4.4955883e-08 2.8534189e-16 9.9999166e-01 3.3034322e-09 2.5716190e-07]]
7
```



# One hot Encoding label for classification

One-hot encoding is a way to represent label for classification

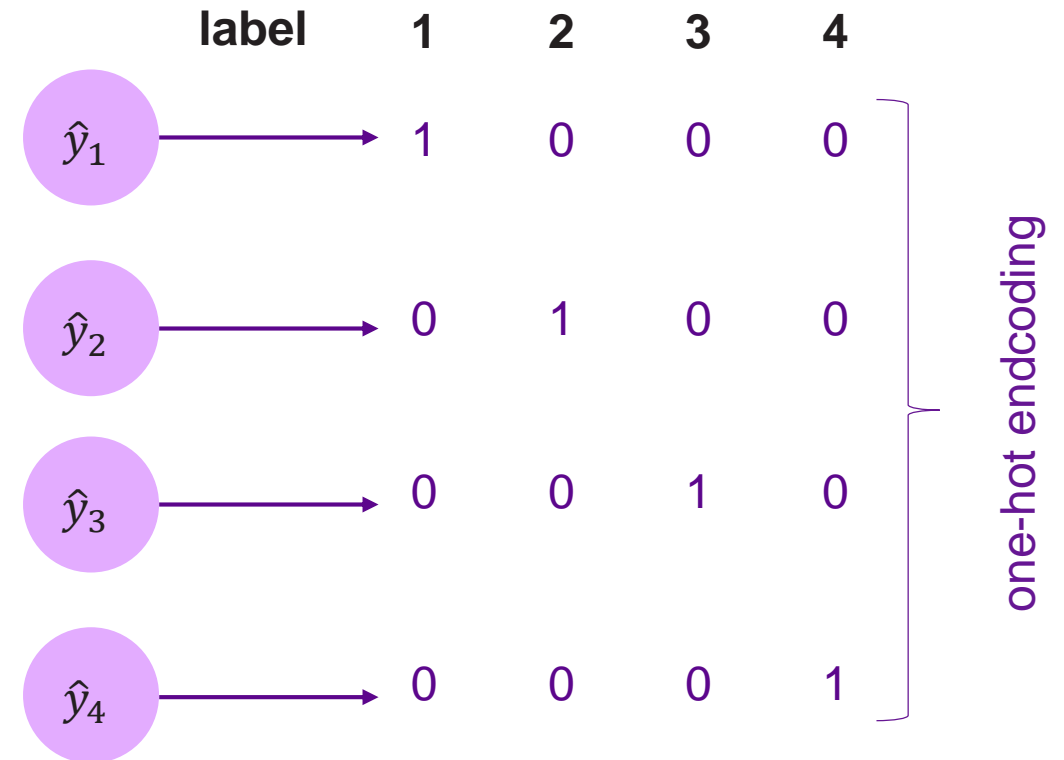
In tensorflow, when you use:

- **CategoricalCrossEntropy**: the label must be encoded in one-hot representation

`y_true = [1,2,3,4,4,2,1, ...]`

- **SparseCategoricalCrossEntropy**: the label must be in integer and it is automatically converted into one-hot encoding

```
y_true = [[1,0,0,0],  
          [0,1,0,0],  
          [0,0,1,0],  
          [0,0,1,0],  
          [0,0,0,1],  
          [0,1,0,0],  
          [1,0,0,0]]
```

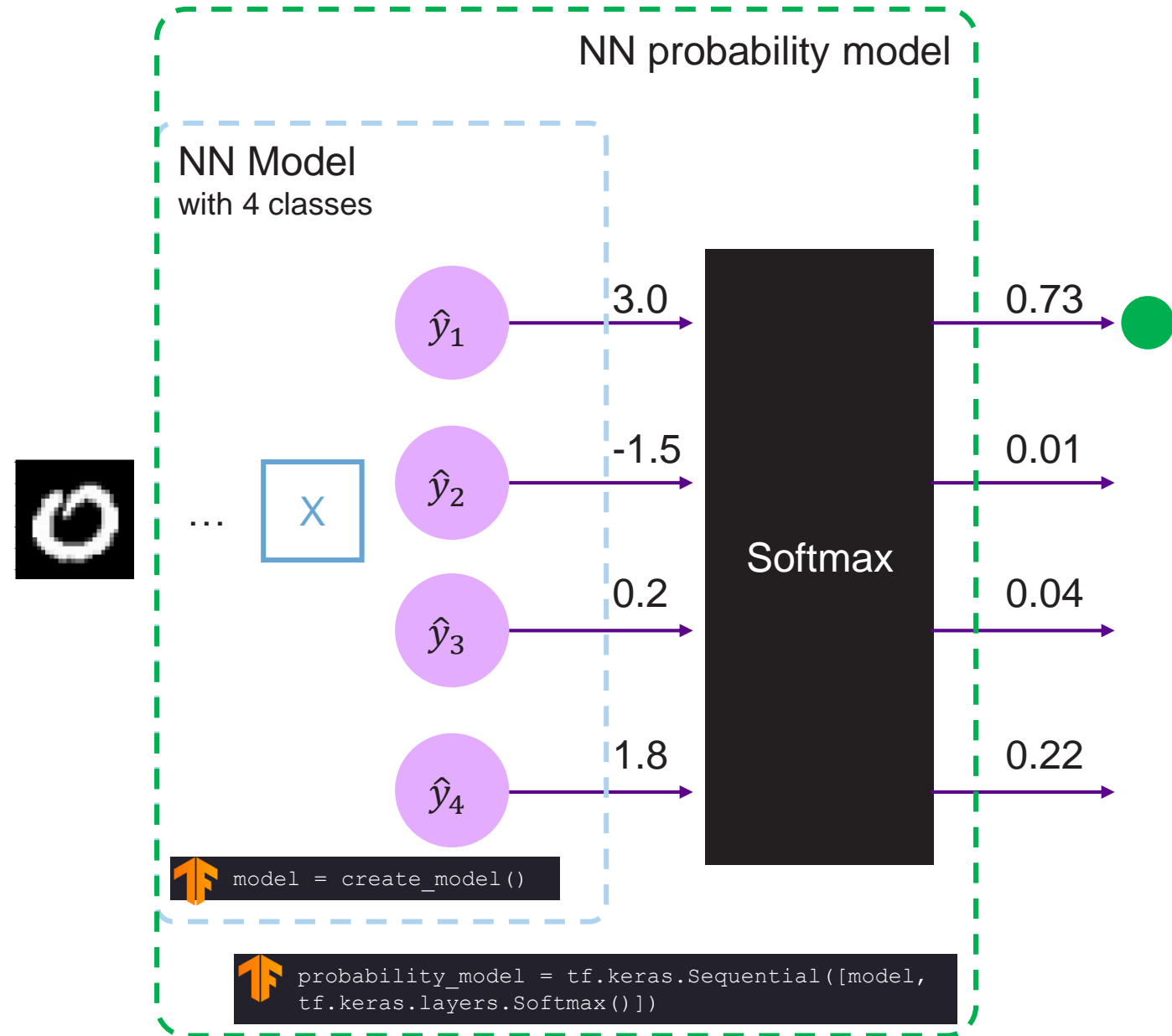


# What is a softmax layer?

It transforms a vector of value into a vector of probability value.

For a Neural network with K classes, it is.

$$\text{softmax}(z)_i = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}, \text{ for } i = 1 \dots K$$





# Neural Networks metrics

# Binary classification metrics

		Predicted		
		Predicted positive	Predicted negative	
Ground truth	Ground truth positive	True positive <i>TP</i>	False negative <i>FN</i> Error Type II	Recall / sensitivity
	Ground truth Negative	False positive <i>FP</i> Error Type I	True negative <i>TN</i>	Specificity

Precision

$$\text{Accuracy} = \frac{TP+TN}{ALL}$$

$$\text{precision} = \frac{TP}{Pred\ positive} = \frac{TP}{TP+FP}$$

$$\text{TPR} = \text{recall} = \text{sensitivity} = \frac{TP}{GT\ positive} = \frac{TP}{TP+FN}$$

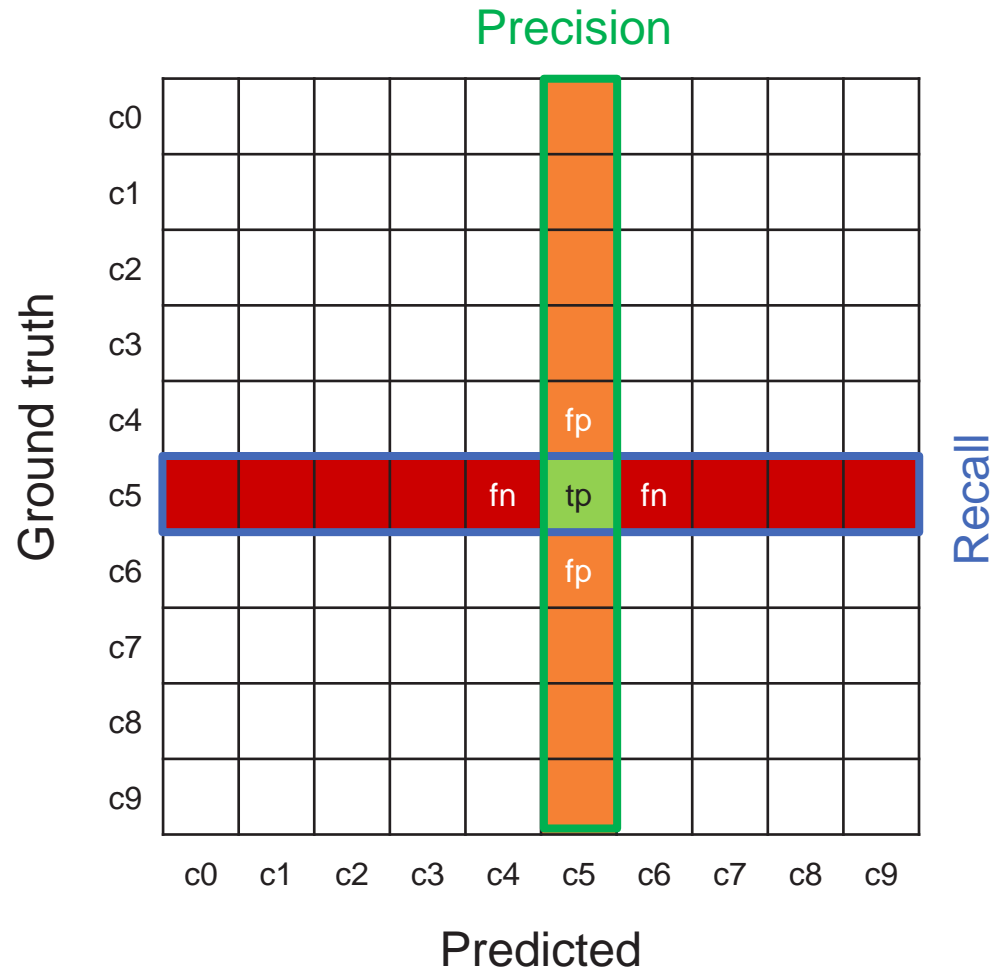
$$\text{specificity} = \frac{TN}{GT\ negative} = \frac{TN}{FP+TN}$$

$$\text{FPR} = \frac{FP}{GT\ negative} = \frac{FP}{FP + TN}$$

$$\text{F1}_{score} = \frac{2 \cdot \text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$



# Multi classes classification metrics – Confusion matrix



True positive, false positive and false negative on confusion matrix on **c5** class

tp: true positive

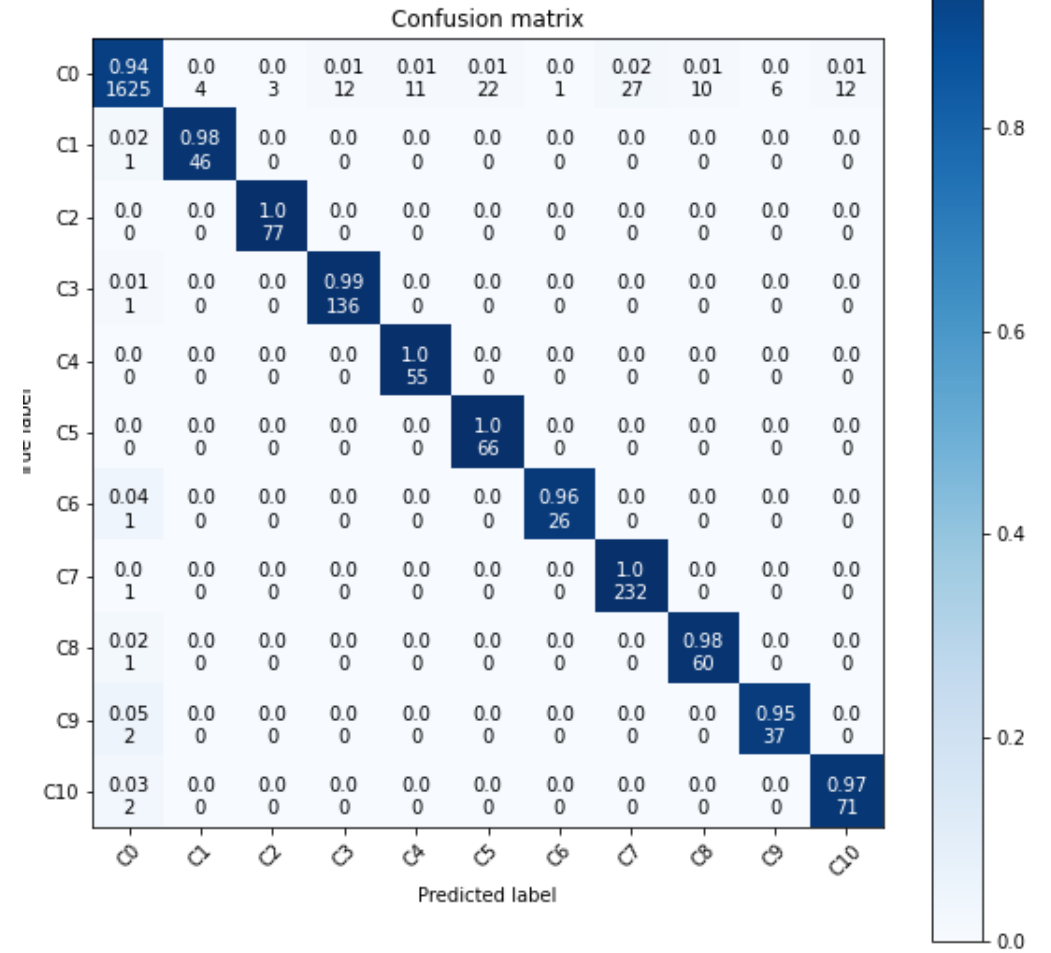
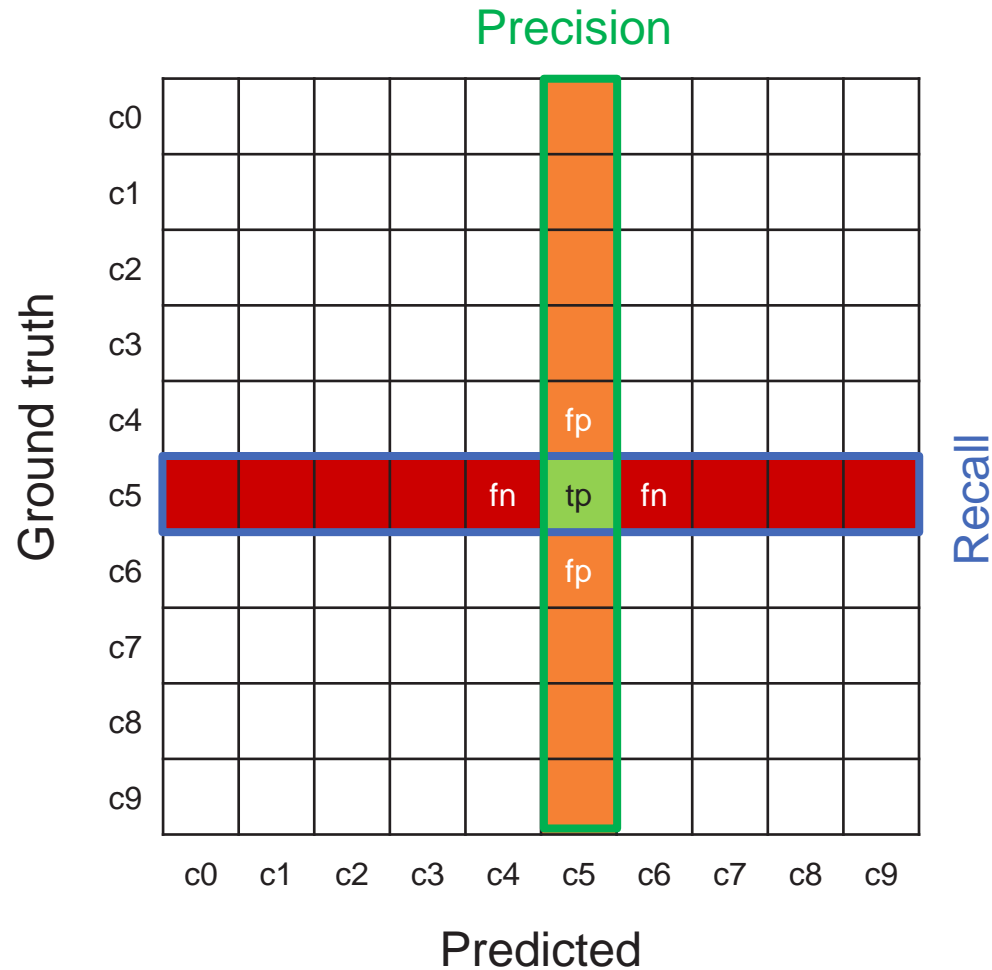
fp: false positive

fn: false negative

tn: true negative

True negative is not computable with this representation.

# Neural Networks evaluation on classification task with confusion matrix representation



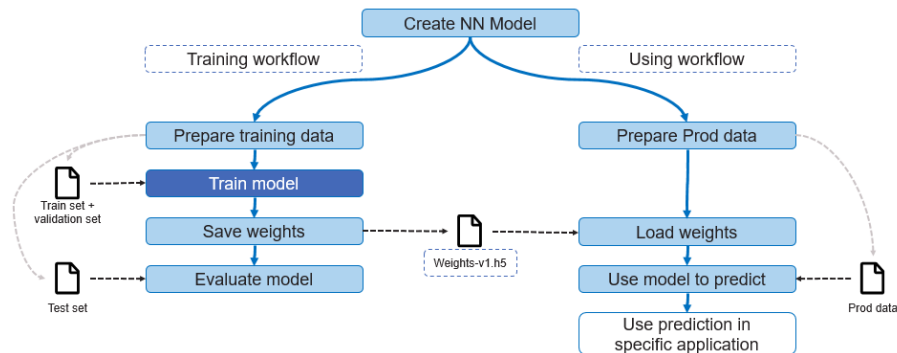
The background is a dark blue field filled with glowing white and light blue lines that form a complex network, resembling a globe or a data mesh. Overlaid on this are several horizontal lines of binary code (0s and 1s) in a light blue, monospace font. A large, white, L-shaped graphic element is positioned in the center, framing the text.

# Conclusion

# Conclusion

## Neural Networks creation workflow

- **Prepare** your data
- **Create** your model
- **Train** the neural network
- **Save** the NN weights
- **Evaluate** on the test set



## Evaluating Neural Networks

- Accuracy
- Precision
- Recall = sensitivity
- Specificity
- F1 score

		Predicted		
		Predicted positive	Predicted negative	
Ground truth	Ground truth positive	True positive <i>TP</i>	False negative <i>FN</i> Error Type II	Recall / sensitivity
	Ground truth Negative	False positive <i>FP</i> Error Type I	True negative <i>TN</i>	Specificity
		Precision		



# References

---

© Alexander Amini and Ava Soleimany, MIT 6.S191: Introduction to Deep Learning

Van Veen, F. & Leijnen, S. (2019). The Neural Network Zoo. Retrieved from <https://www.asimovinstitute.org/neural-network-zoo>

A. Khan, A. Sohail, U. Zahoor, and A. S. Qureshi, “A Survey of the Recent Architectures of Deep Convolutional Neural Networks,” *Artif Intell Rev*, vol. 53, no. 8, pp. 5455–5516, Dec. 2020, doi: [10.1007/s10462-020-09825-6](https://doi.org/10.1007/s10462-020-09825-6).

"Anatomy and Physiology" by the US National Cancer Institute's Surveillance, Epidemiology and End Results (SEER) Program . Neuron description, Licence [CC BY-SA 3.0](https://creativecommons.org/licenses/by-sa/3.0/)

H. Li, Z. Xu, G. Taylor, C. Studer, and T. Goldstein, “Visualizing the Loss Landscape of Neural Nets,” in *Advances in Neural Information Processing Systems*, 2018, vol. 31, pp. 6389–6399, [Online]. Available: <https://proceedings.neurips.cc/paper/2018/file/a41b3bb3e6b050b6c9067c67f663b915-Paper.pdf>.

Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). *Deep learning* (Vol. 1, No. 2). Cambridge: MIT press.

# References

---

## Datasets:

- A. Kuznetsova, H. Rom, N. Alldrin, J. Uijlings, I. Krasin, J. Pont-Tuset, S. Kamali, S. Popov, M. Mallocci, A. Kolesnikov, T. Duerig, and V. Ferrari. The Open Images Dataset V4: Unified image classification, object detection, and visual relationship detection at scale. *IJCV*, 2020.
- R. Benenson, S. Popov, and V. Ferrari. Large-scale interactive object segmentation with human annotators. *CVPR*, 2019.
- Olga Russakovsky\*, Jia Deng\*, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg and Li Fei-Fei. (\* = equal contribution) **ImageNet Large Scale Visual Recognition Challenge**. *IJCV*, 2015
- J. Carreira, E. Noland, C. Hillier, and A. Zisserman, *A Short Note on the Kinetics-700 Human Action Dataset*. 2019.
- Ambika Choudhury, 10 Open Datasets You Can Use For Computer Vision Projects, available at <https://analyticsindiamag.com/10-open-datasets-you-can-use-for-computer-vision-projects/>
- J. Fritsch, T. Kuehnl, and A. Geiger, “A New Performance Measure and Evaluation Benchmark for Road Detection Algorithms,” 2013.
- A. Geiger, P. Lenz, and R. Urtasun, “Are we ready for Autonomous Driving? The KITTI Vision Benchmark Suite,” 2012.
- M. Menze and A. Geiger, “Object Scene Flow for Autonomous Vehicles,” 2015.
- A. Geiger, P. Lenz, C. Stiller, and R. Urtasun, “Vision meets Robotics: The KITTI Dataset,” *International Journal of Robotics Research (IJRR)*, 2013.
- Google Research, available at <https://research.google/tools/datasets/>, access on Nov. 10, 2019