SINGAPORE INSTITUTE OF TECHNOLOGY

Modern Recommender Systems in Theory and Practice

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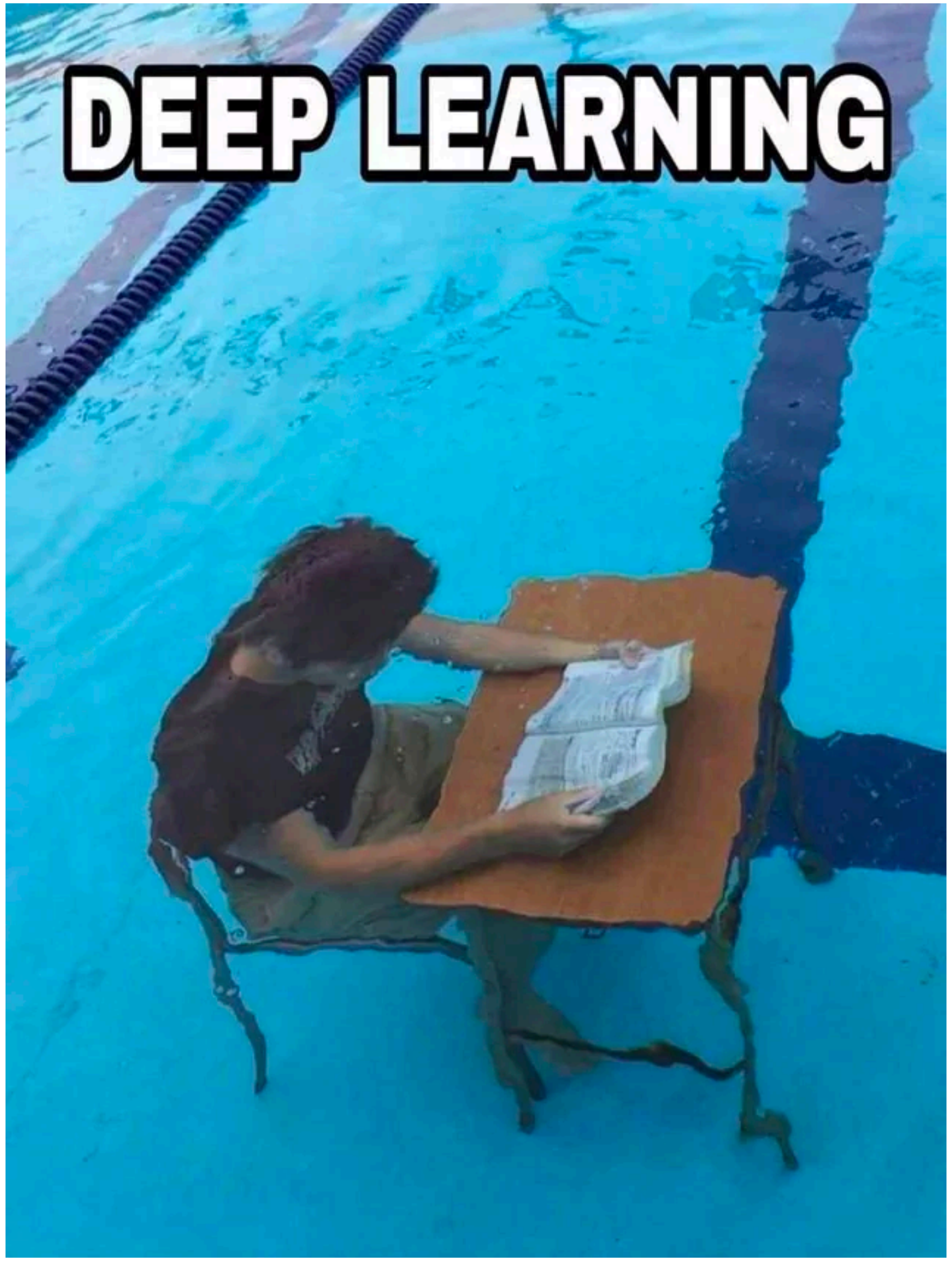
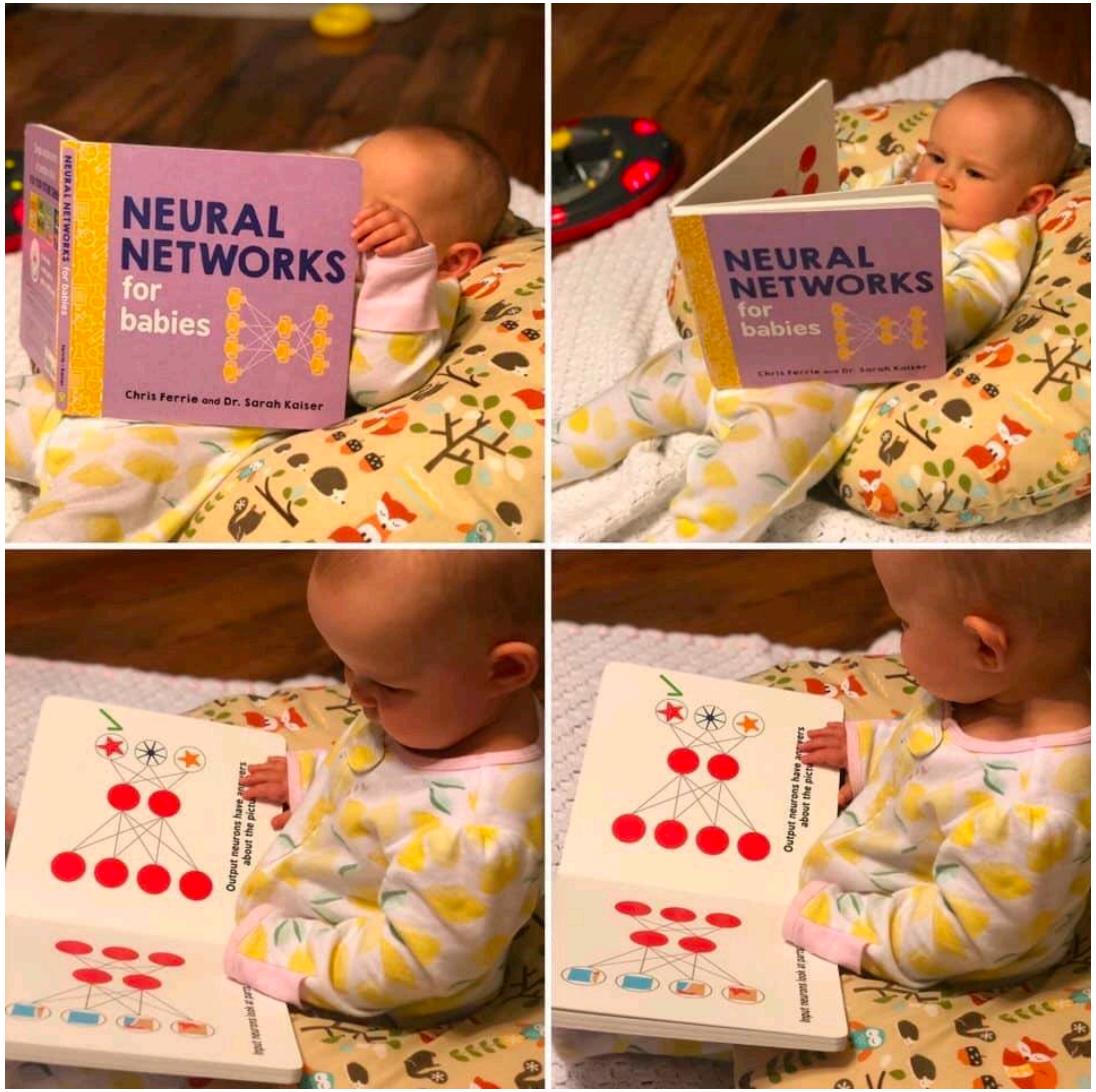
The New Era


DEEP LEARNING

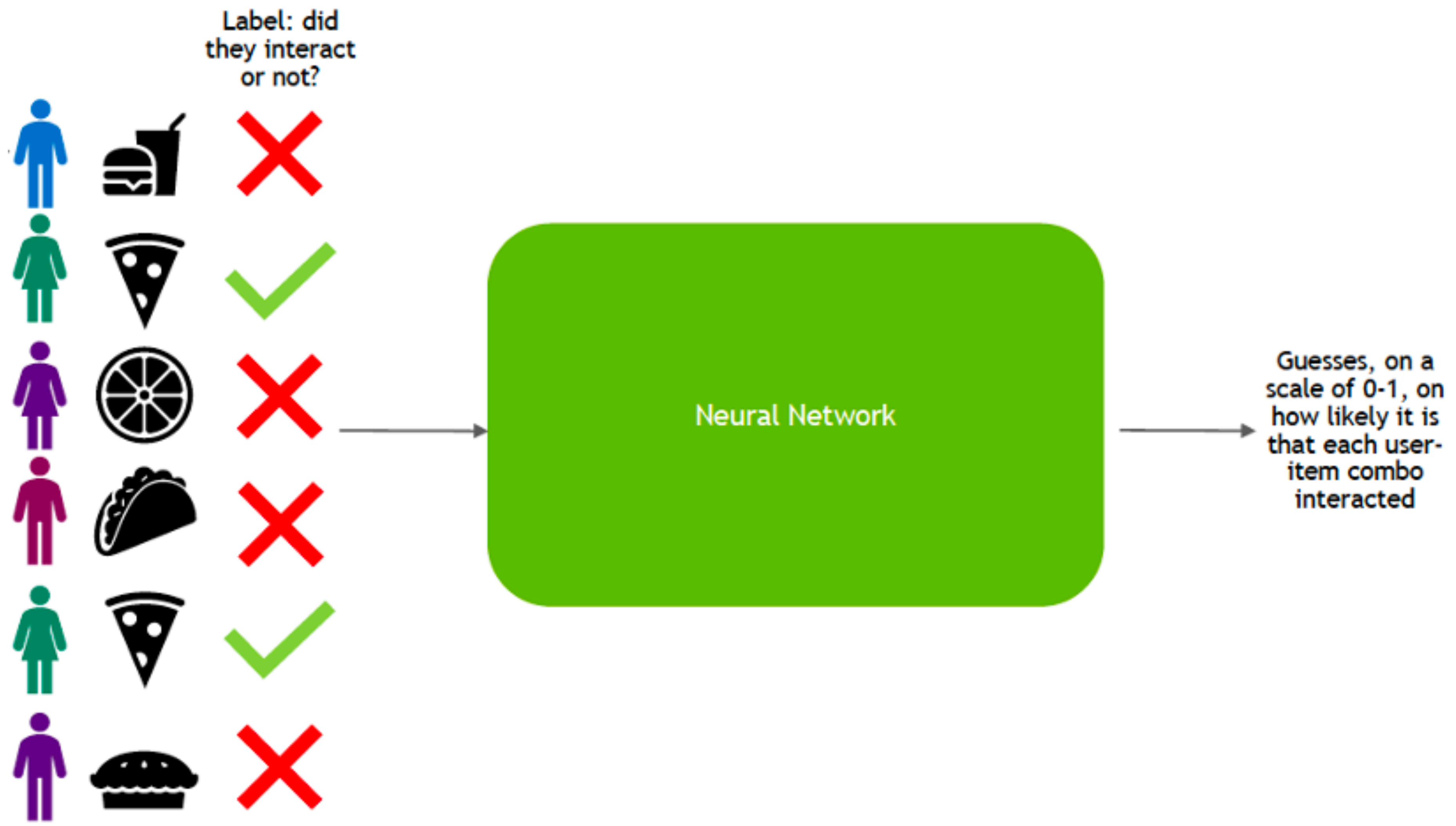

NEURAL NETWORKS
for
babies
Chris Ferrie and Dr. Sarah Kaiser

More Motivations

- More heterogeneous data, more complicated user behaviours, more diverse scenarios, etc.
- For example, short video recommendation
  - What is short video application?
    - User-generated short video clips, usually < 1min
  - Rapid growth of short video applications
    - Number of short video users is 648 millions in China by the end of 2018
    - Number of daily active users is growing at the speed of > 800% each year since 2016

Why Deep Learning?

- Nonlinear Transformation
- Representation Learning
  - Reduce the efforts of hand-craft feature design
  - Heterogeneous content information such as text, images, etc.
- …



Source: Deep learning based recommender system: A survey and new perspectives

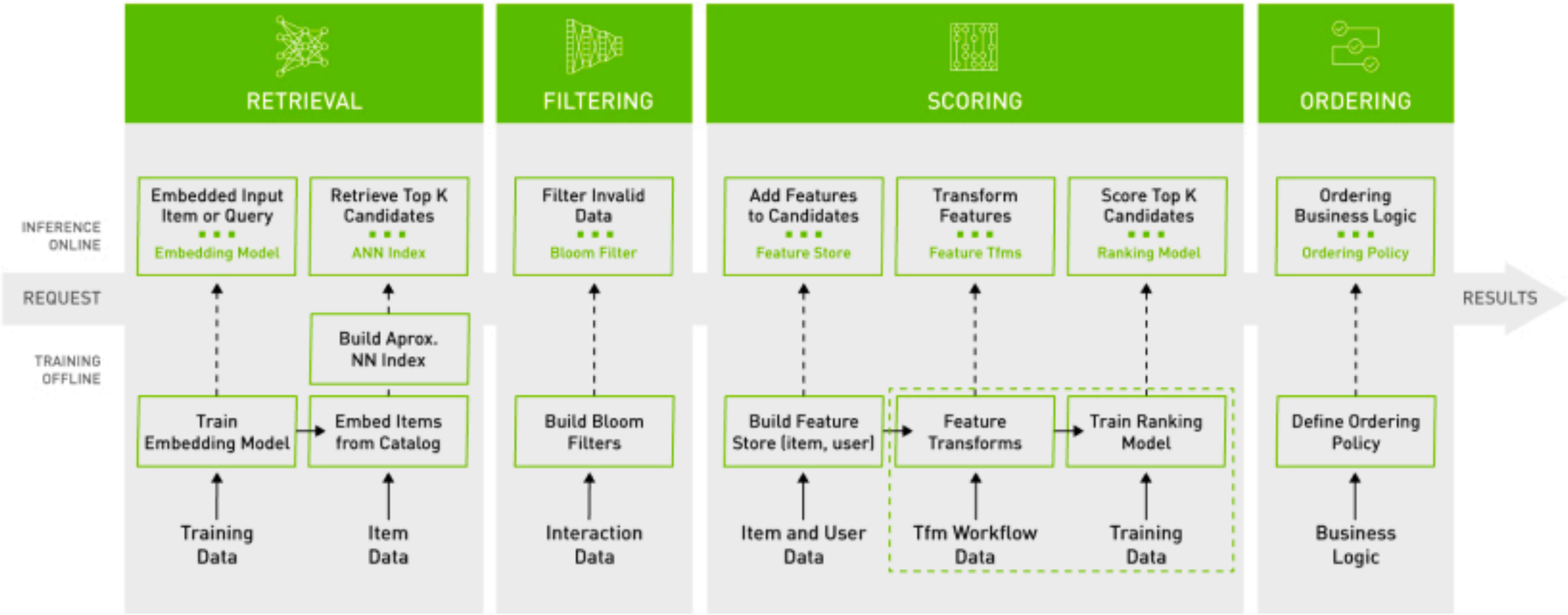
DL empowered RS

tensorflow/
recommenders

TensorFlow Recommenders is a library for building recommender system models using TensorFlow.

32 Contributors | 195 Used by | 2k Stars | 234 Forks

TorchRec



microsoft/
recommenders

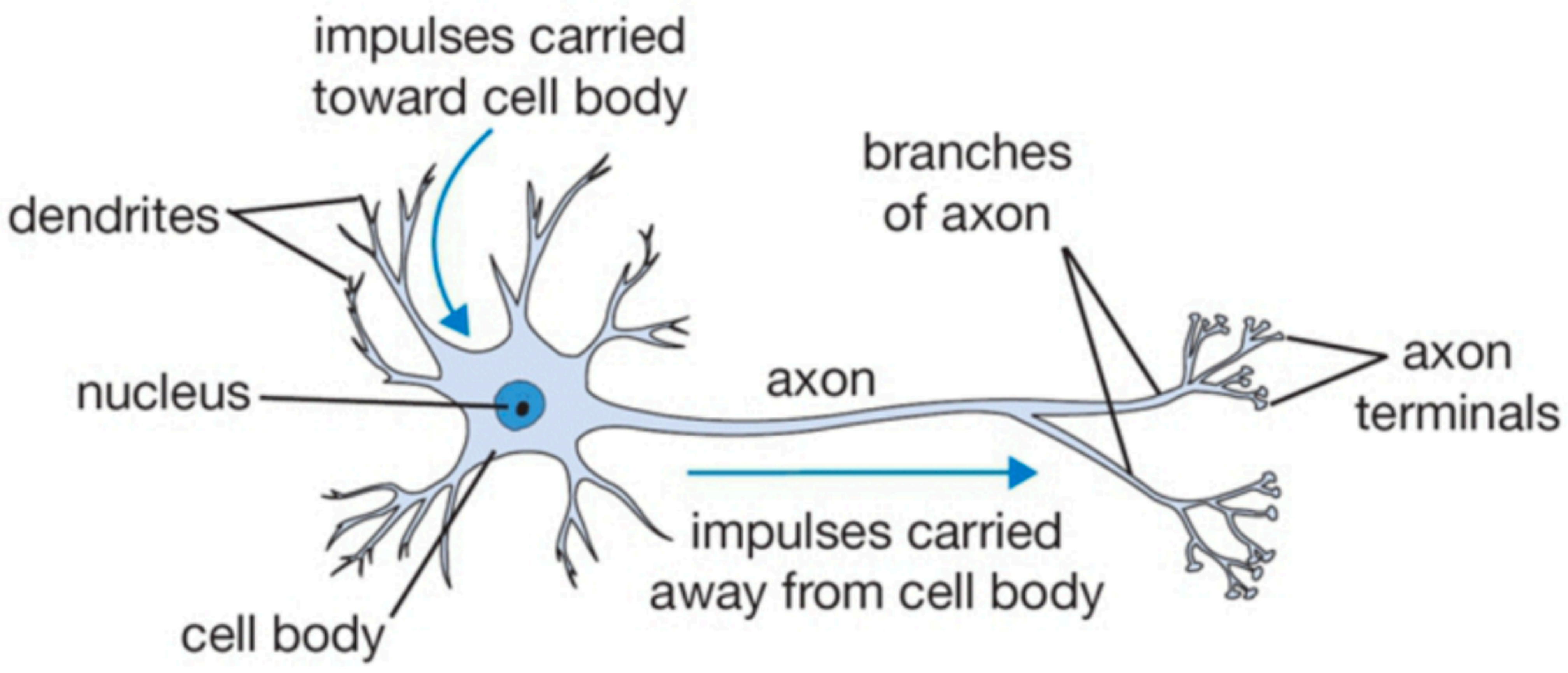
Best Practices on Recommendation Systems

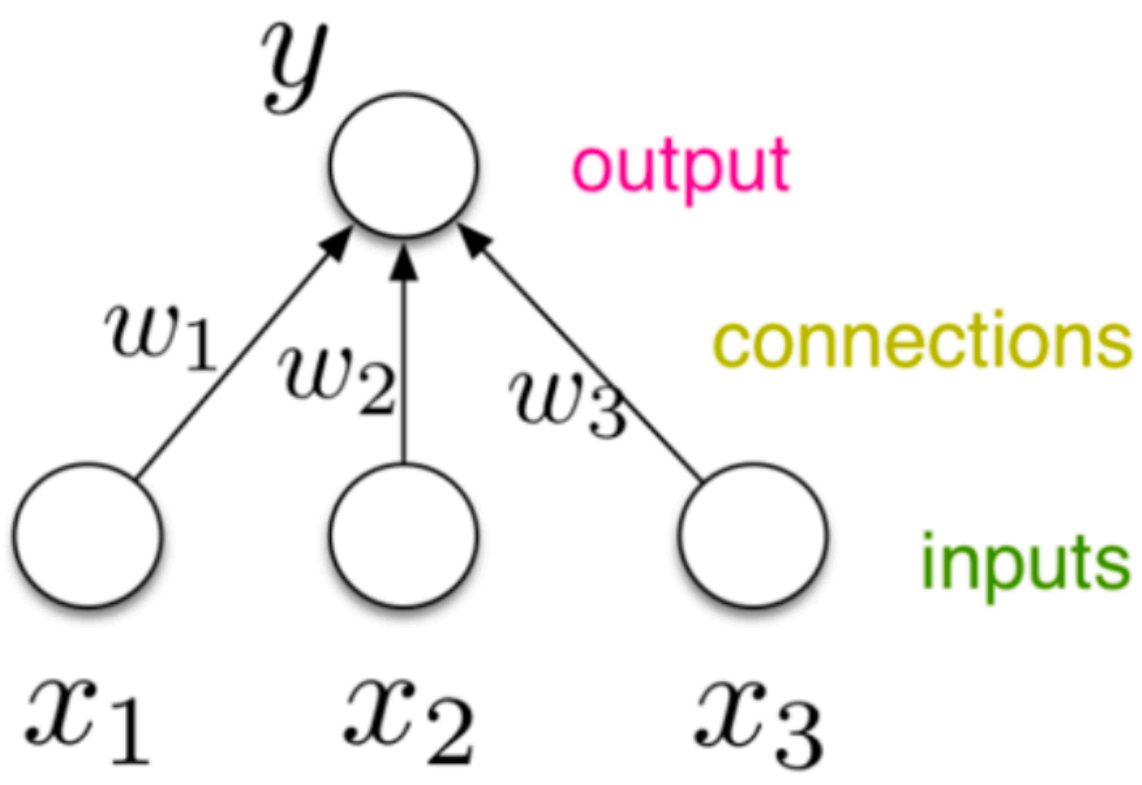
92 Contributors | 59 Used by | 5 Discussions | 15k Stars | 3k Forks

MLP based

- Neural extension of Traditional RS (e.g., MF)
  - Neural Collaborative Filtering (NCF)
- Feature Representation Learning with MLP
  - Wide and Deep (WideDeep)
- And many more…

MLP based



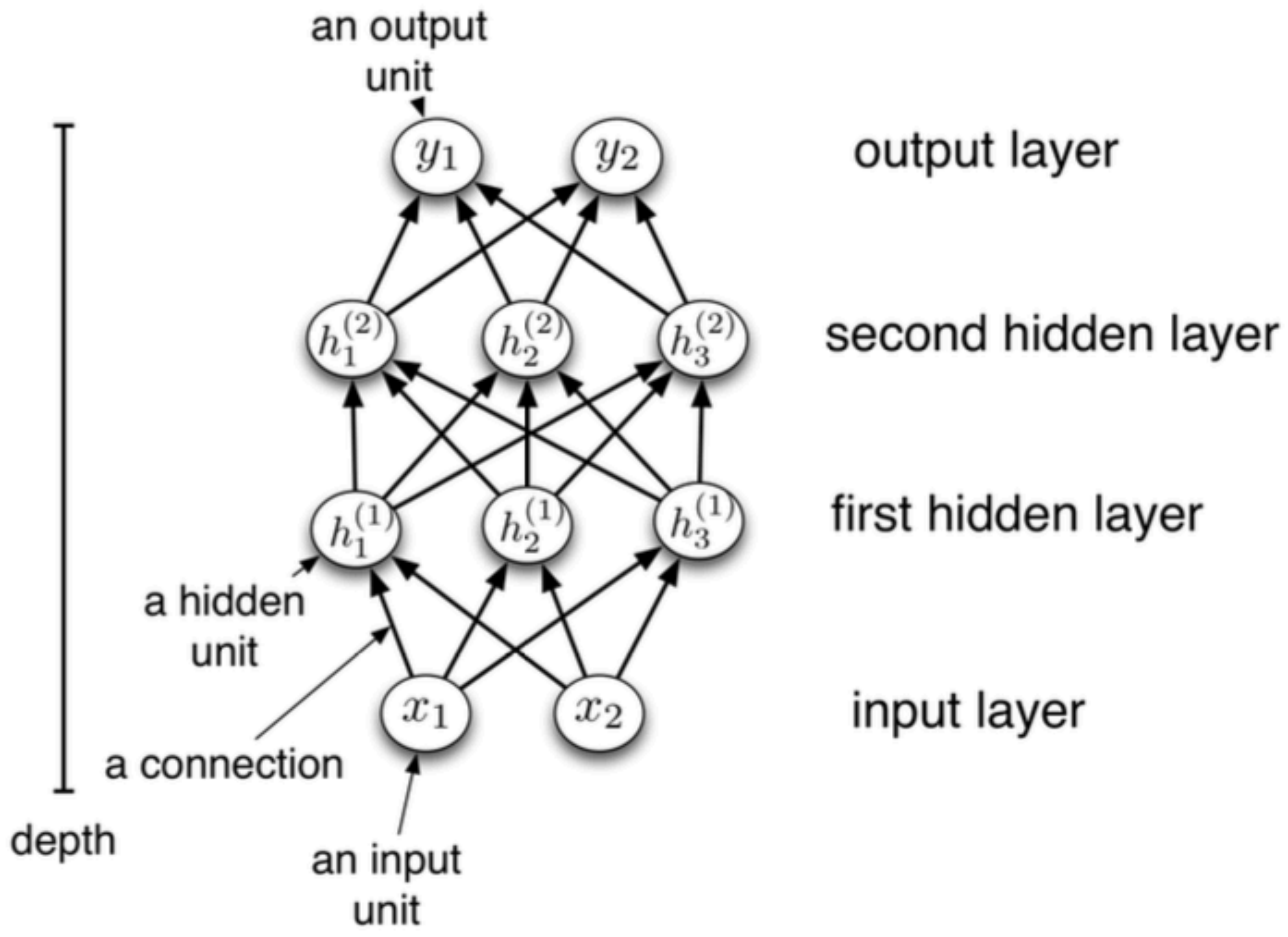


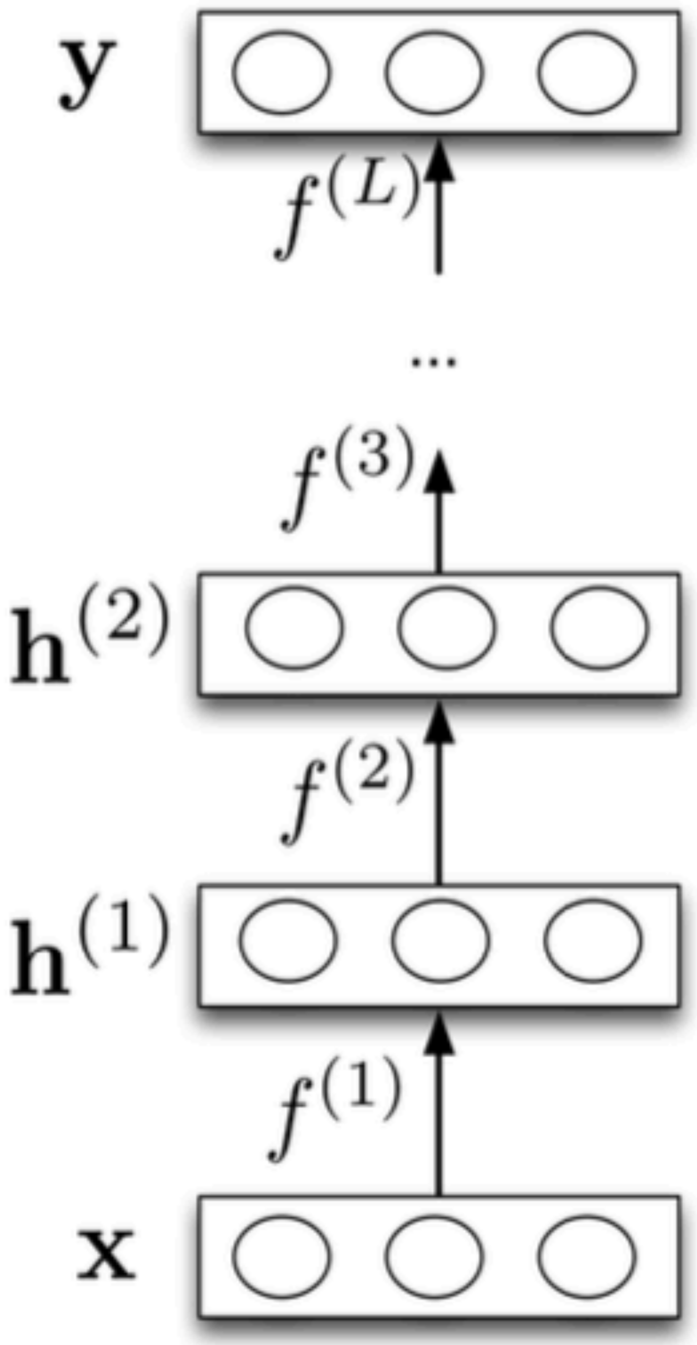
output weights bias

$$y = \phi\left(\mathbf{w}^\top \mathbf{x} + b\right)$$

activation function inputs

MLP based





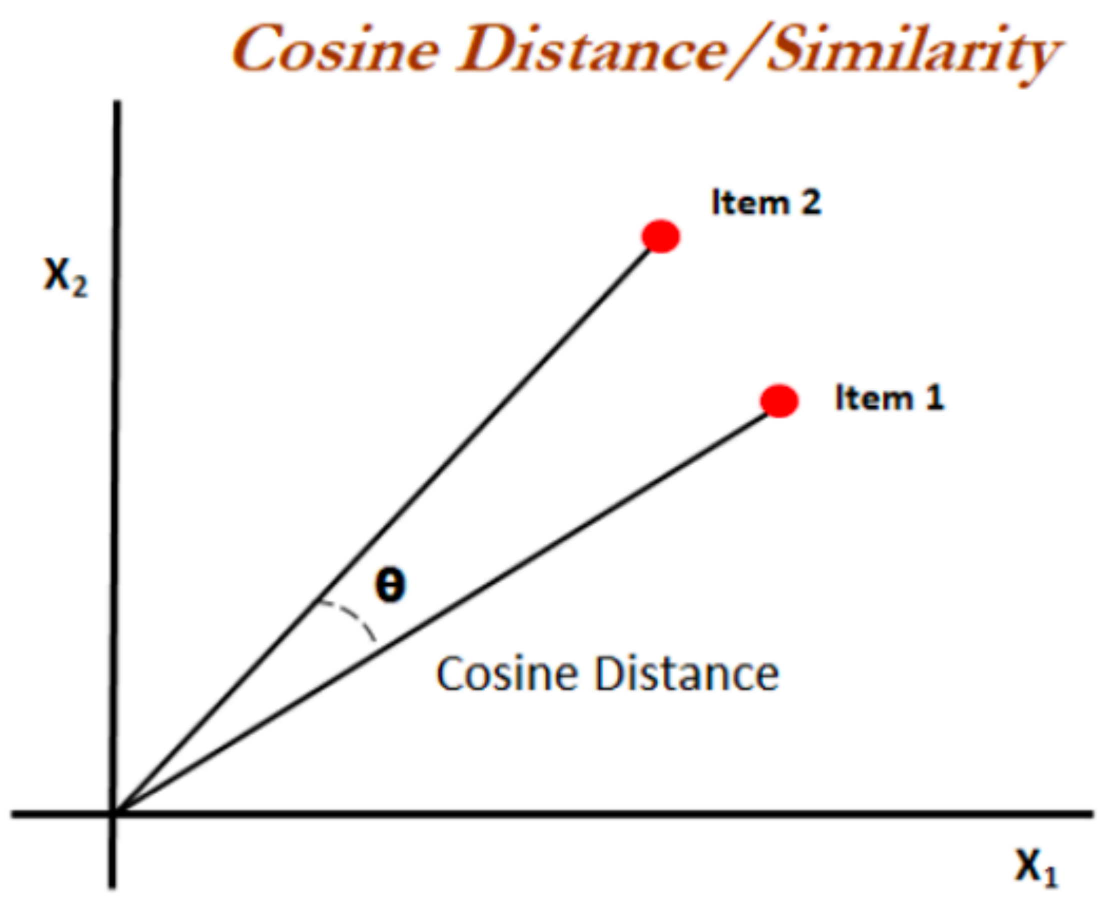
$$
\begin{aligned}
h^{(1)} &= f^{(1)}\Big(\sum_j w_{ij}^{(1)} x_j + b_i^{(1)}\Big) \\
h^{(2)} &= f^{(2)}\Big(\sum_j w_{ij}^{(2)} h_j^{(1)} + b_i^{(2)}\Big) \\
y_i &= f^{(3)}\Big(\sum_j w_{ij}^{(3)} h_j^{(2)} + b_i^{(3)}\Big)
\end{aligned}
$$

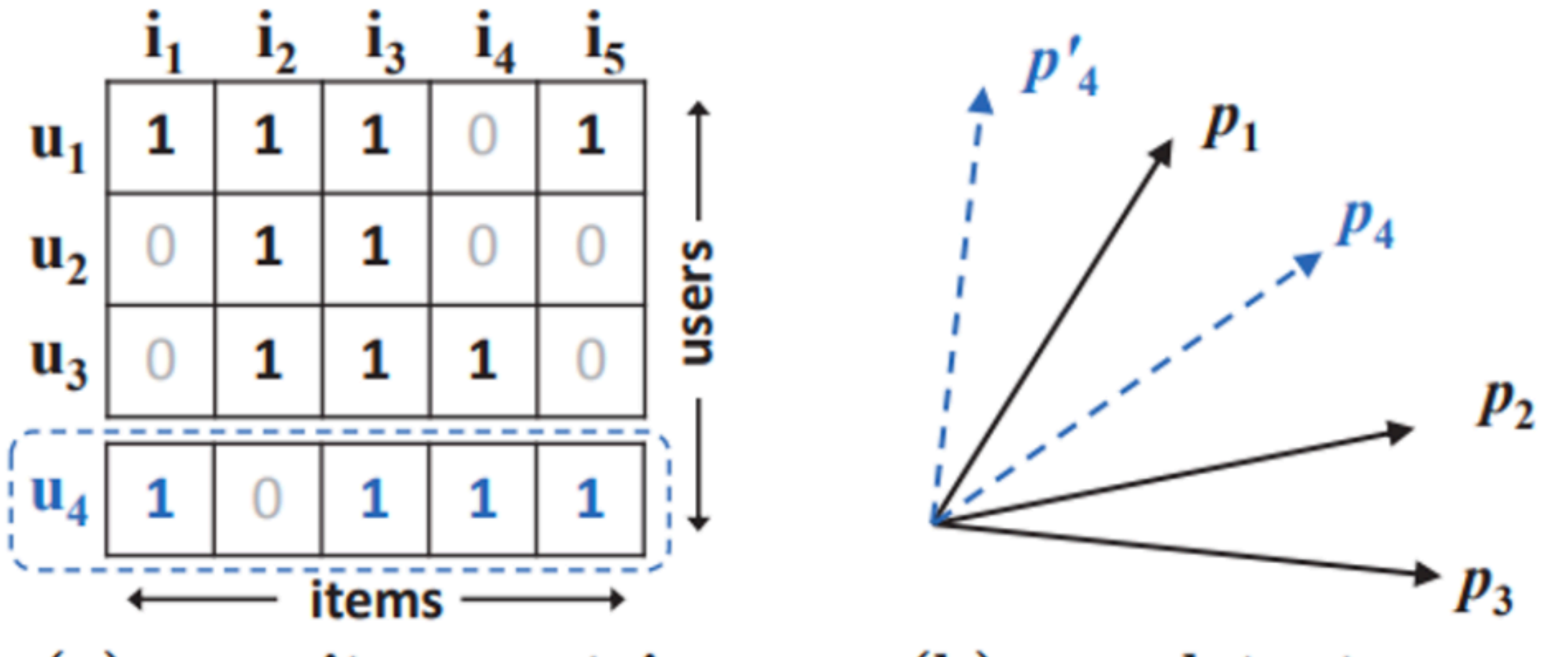
$$\Downarrow$$

$$
\begin{aligned}
\mathrm{h}^{(1)} &= f^{(1)}(\mathrm{W}^{(1)}(x) + \mathrm{b}^{(1)}) \\
\mathrm{h}^{(2)} &= f^{(2)}(\mathrm{W}^{(2)}\mathrm{h}^{(1)} + \mathrm{b}^{(2)}) \\
\mathrm{y} &= f^{(3)}(\mathrm{W}^{(3)}\mathrm{h}^{(2)} + \mathrm{b}^{(3)})
\end{aligned}
$$

MLP based

Neural Collaborative Filtering (NCF)





(a) user–item matrix (b) user latent space

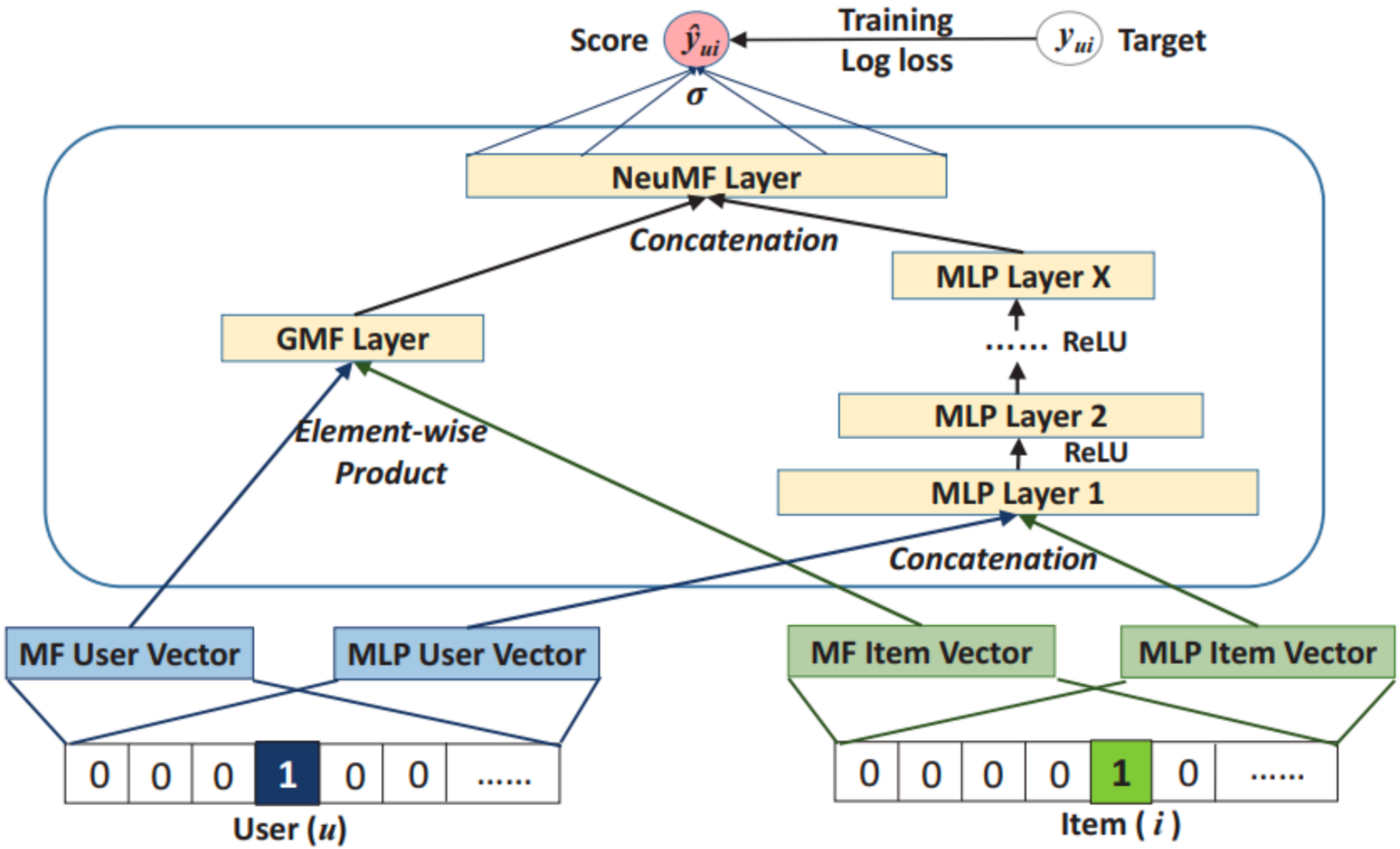
p1 = [1,1,1,0,1]
p2 = [0,1,1,0,0]
p3 = [0,1,1,1,0]
p4 = [1,0,1,1,1]

Sim(23) = 2/3 = 0.67
Sim(12) = 2/4 = 0.5
Sim(13) = 2/5 = 0.4

Sim(41) = 3/5 = 0.6
Sim(42) = 1/5 = 0.2
Sim(43) = 2/5 = 0.4

MLP based

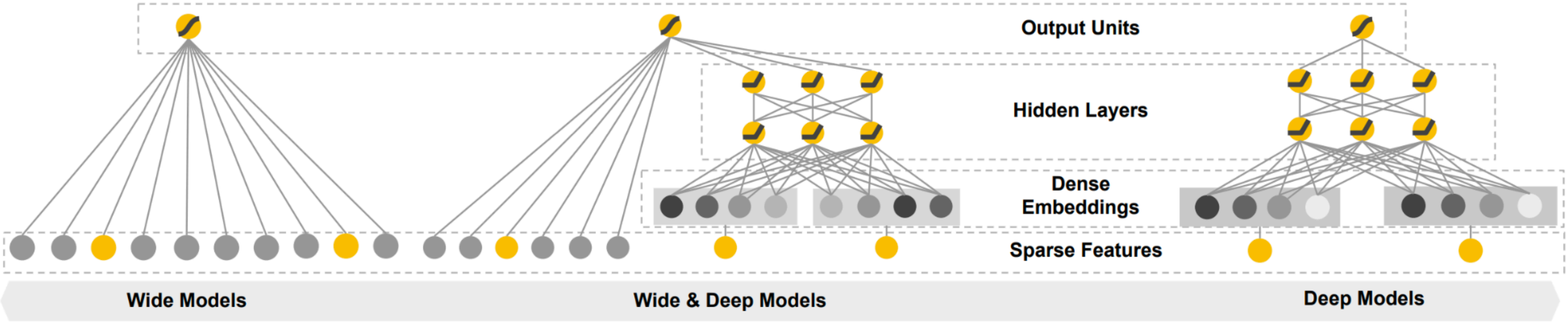
Neural Collaborative Filtering (NCF)



MLP based

Wide and Deep

- Wide component: a cross-product transformation is used to capture the interactions between binary features (e.g., AND(gender=female, language=en) is 1 if “gender is female” and “language=en”, 0 otherwise)
- Deep component: each of these sparse, high-dimensional categorical features are first converted into a low-dimensional and dense real-valued vector; then fed into MLP



Autoencoder based