



# Multi-modal data integration using deep learning and applications in precision oncology

Dr. Bora Uyar

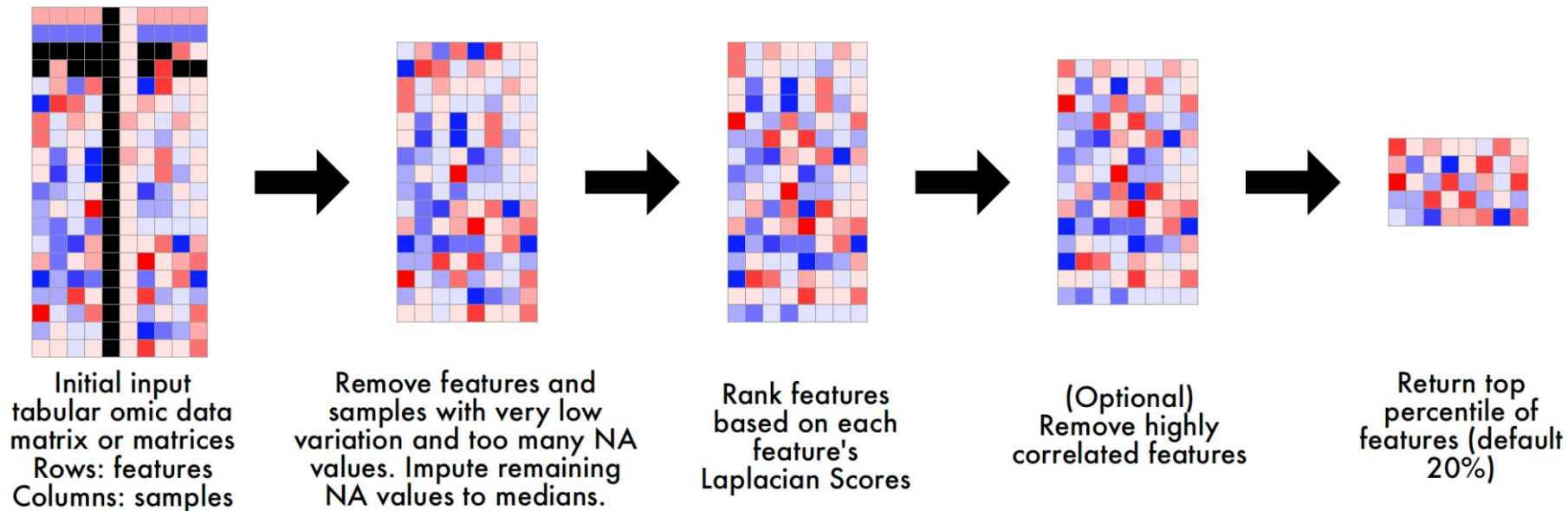
Computational Genomics Workshop

10-16 March 2025



# Data Import

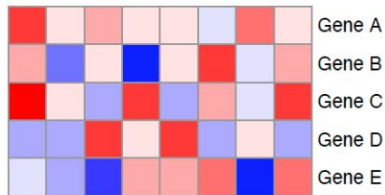
## 1. Data import and cleanup (repeat for all data modalities)



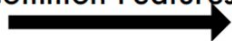
# Data Import

## 2. Harmonize training and testing datasets (repeat for all data modalities)

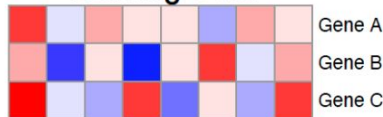
Cleaned up Training Data



Intersect Train and  
Test Data for  
Common Features



Training Data



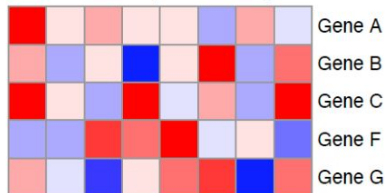
Normalize



Normalize Training Data;  
Learn Scaling Factors



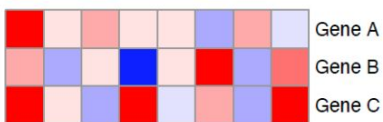
Cleaned up Testing Data



Transform



Transform testing data using  
learned scaling factors



Testing Data

# Important Terms

Neurons/Nodes

Layers: input layer, hidden layers, output layer

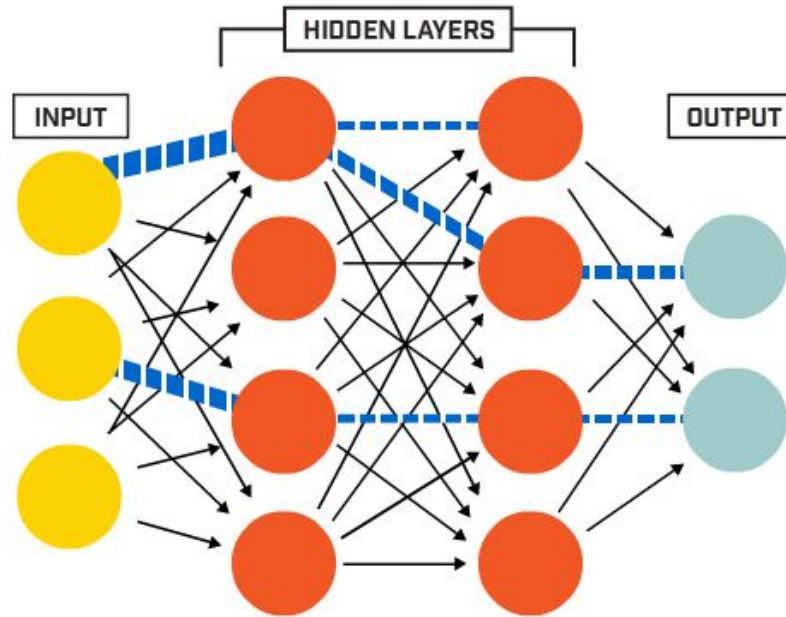
Loss functions

Learning rate

Batch size, batch iterations, epochs

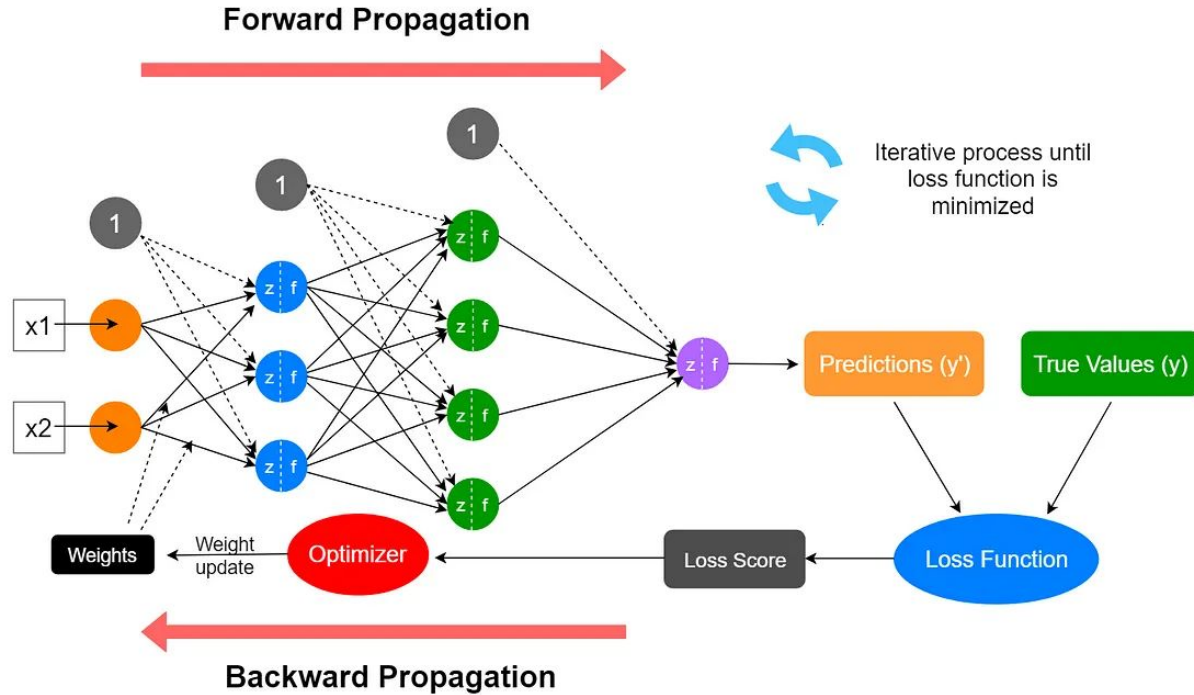
Hyperparameter optimization

# Components of a neural network



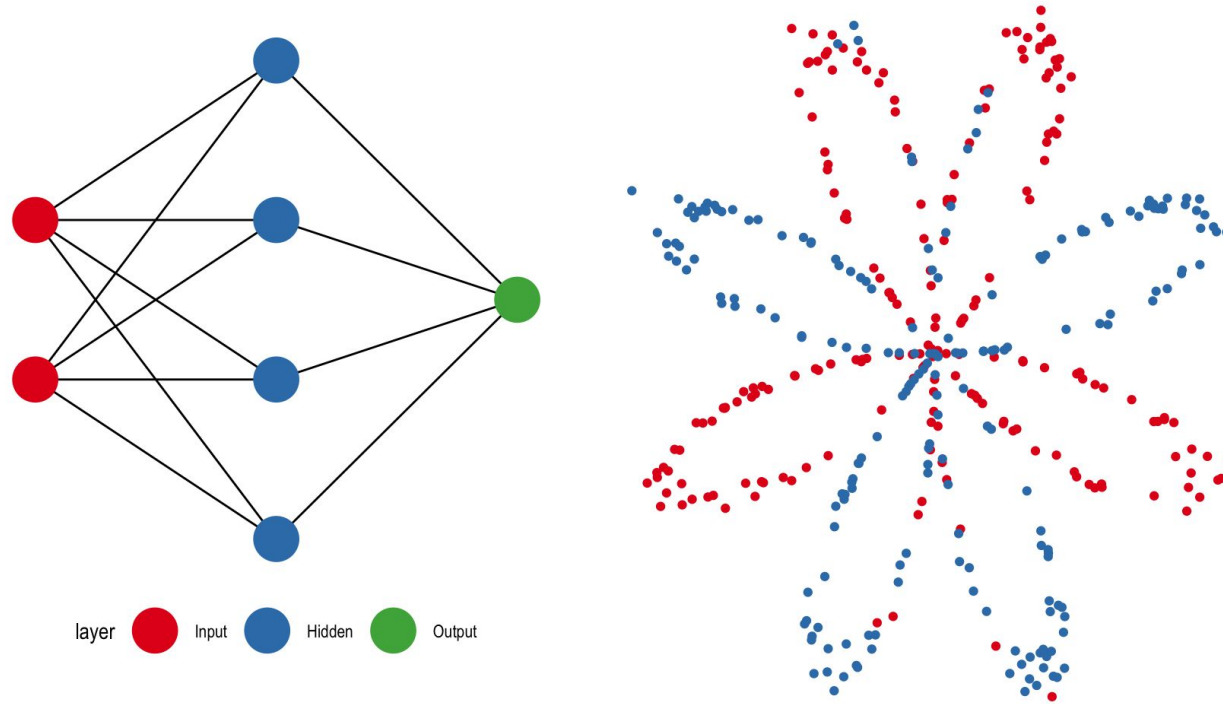
[Introduction to Neural Networks and Their Key Elements  
\(Part-C\) — Activation Functions & Layers | Towards AI](#)

# Training Process



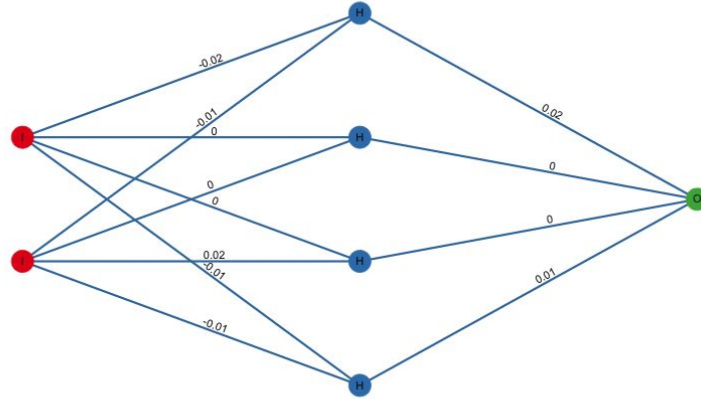
[Decoding Backpropagation and Its Role in Neural Network Learning | ml-articles – Weights & Biases](#)

## Network architecture and the problem

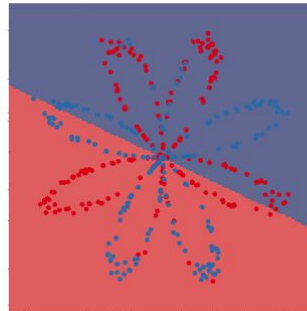


[An animated neuRal net implementation](#)

## Training a neural net at iteration 0



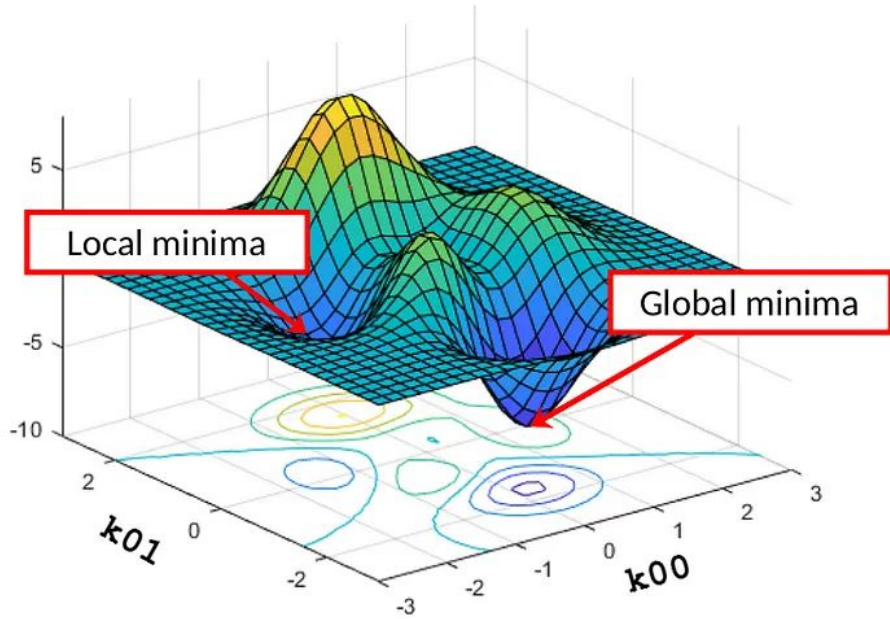
0.7  
•  
0.6  
0.5  
0.4  
0.3



[An animated neuRal net implementation](#)

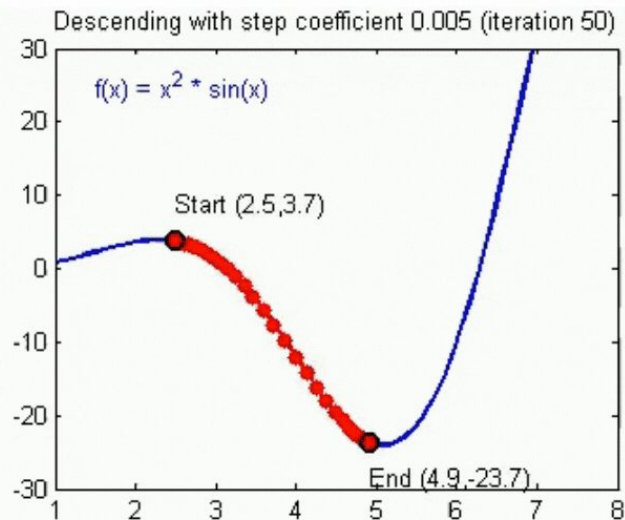


# Gradient Descent

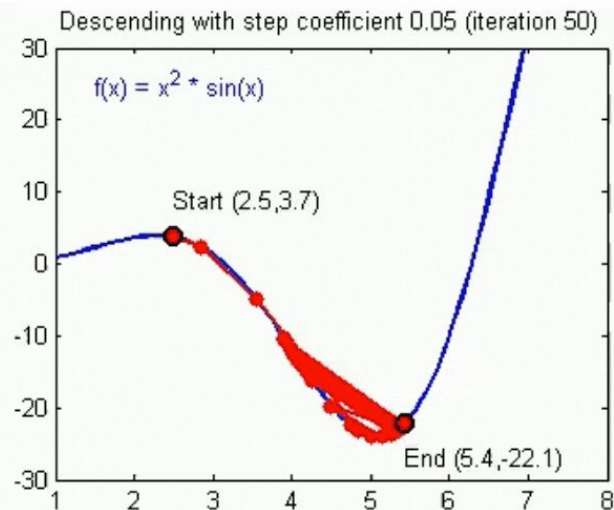


# Impact of the learning rate

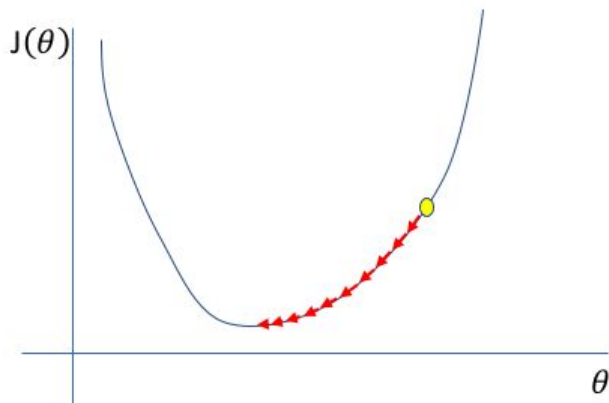
## Convergence



## Divergence

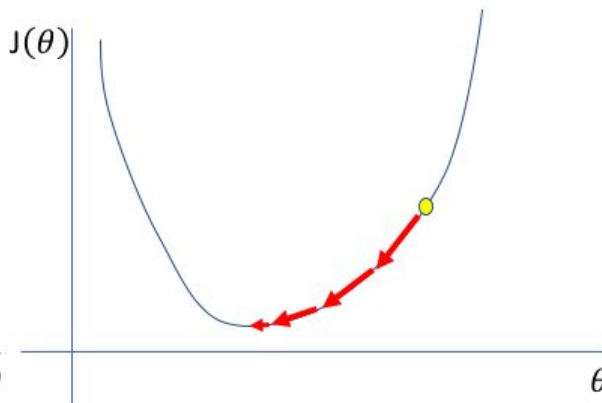


**Too low**



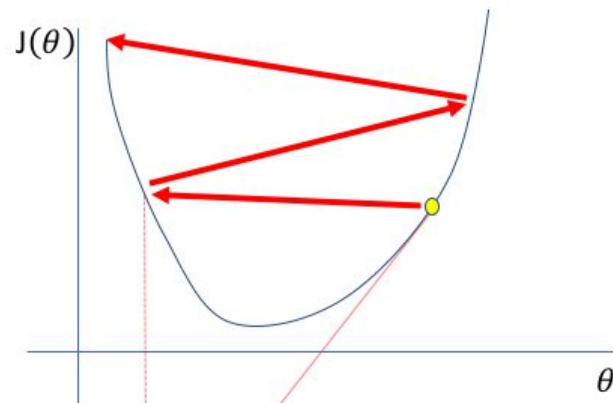
A small learning rate requires many updates before reaching the minimum point

**Just right**



The optimal learning rate swiftly reaches the minimum point

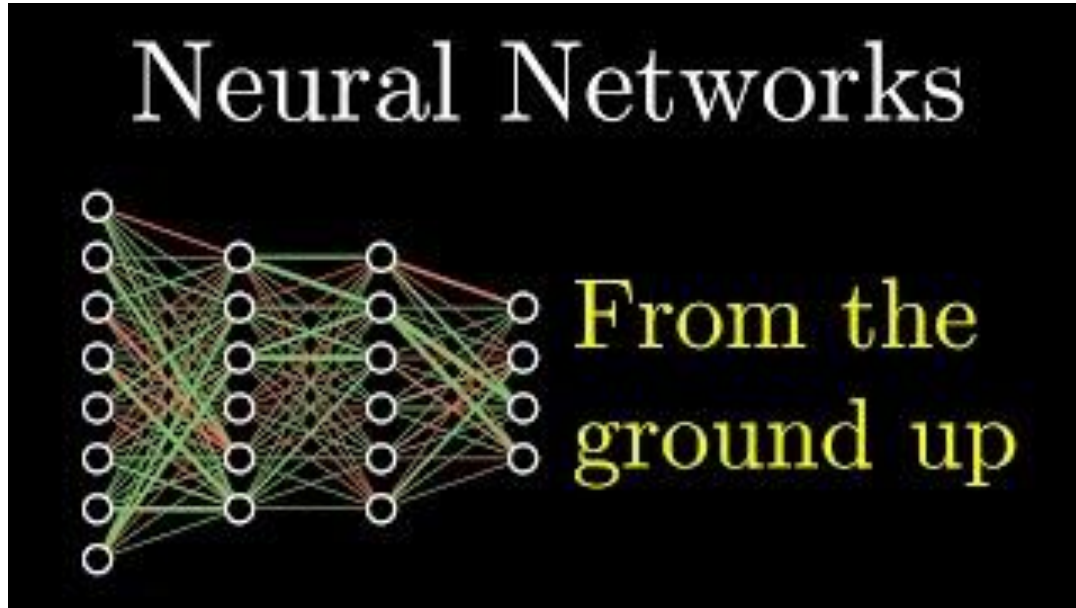
**Too high**



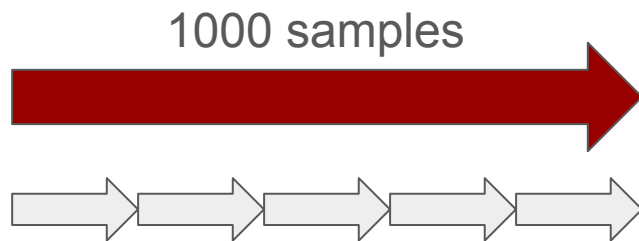
Too large of a learning rate causes drastic updates which lead to divergent behaviors

[Setting the learning rate of your neural network.](#)

Recommended:



# Batch iterations, epochs, HPO iterations



batch size: 200

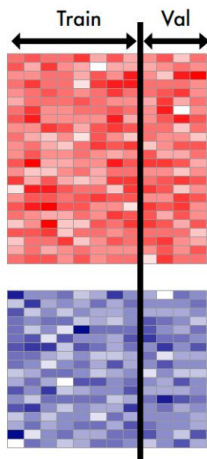
5 batch iterations = 1 Epoch

Batch iteration < Epoch < HPO iteration

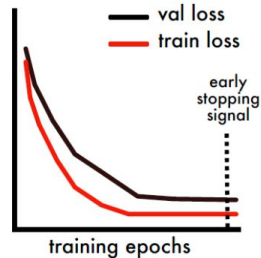
# Hyperparameter Tuning

## Sequential Bayesian Hyper-parameter Optimization (HPO)

Split Training Dataset for training/validation



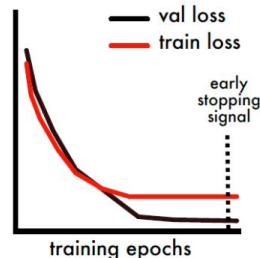
Randomly initialize hyperparameters and train the model



Learning Rate	0.001
Batch Size	32
Hidden Units	256
Embedding Units	64
...	...

HPO-1

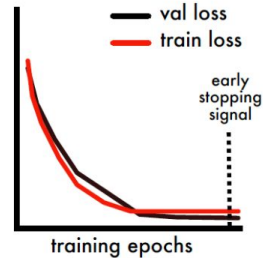
Suggest new parameters based on previous validation loss and train the model



Learning Rate	0.0001
Batch Size	64
Hidden Units	512
Embedding Units	32
...	...

HPO-2

Final HPO Step



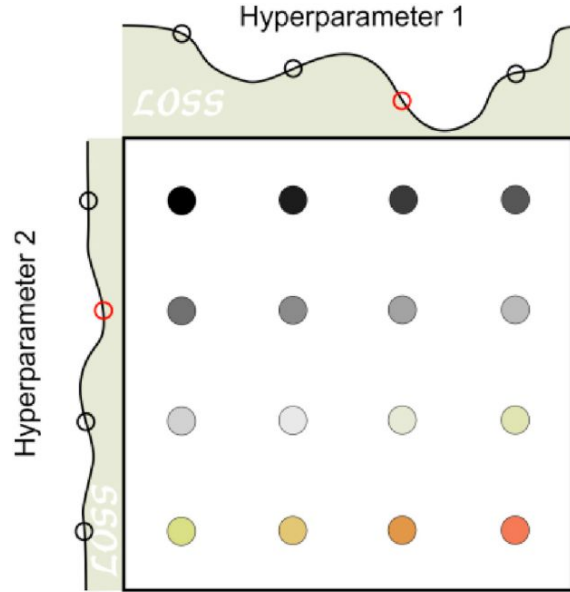
Learning Rate	0.01
Batch Size	16
Hidden Units	128
Embedding Units	24
...	...

HPO-N

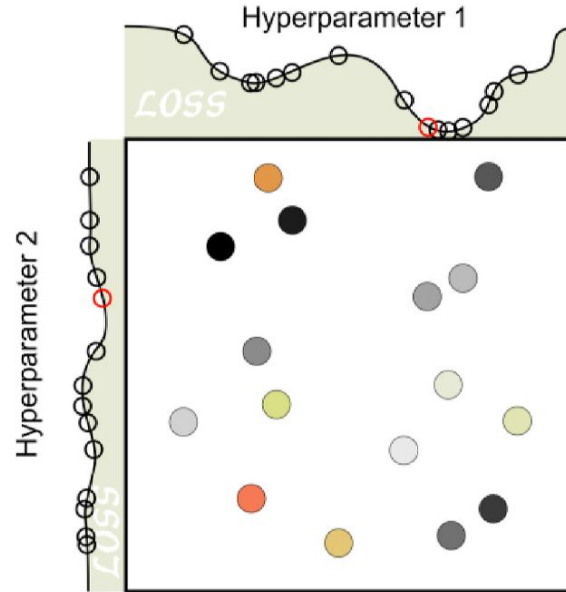
After HPO is finished:

1. Pick the best performing model hyper-parameters based on validation loss
2. Evaluate the best model's performance on the testing (holdout) dataset

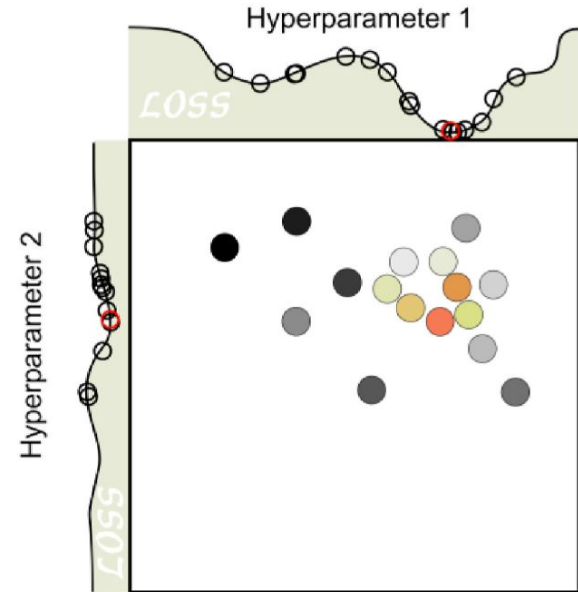
# Hyperparameter tuning



Grid Search



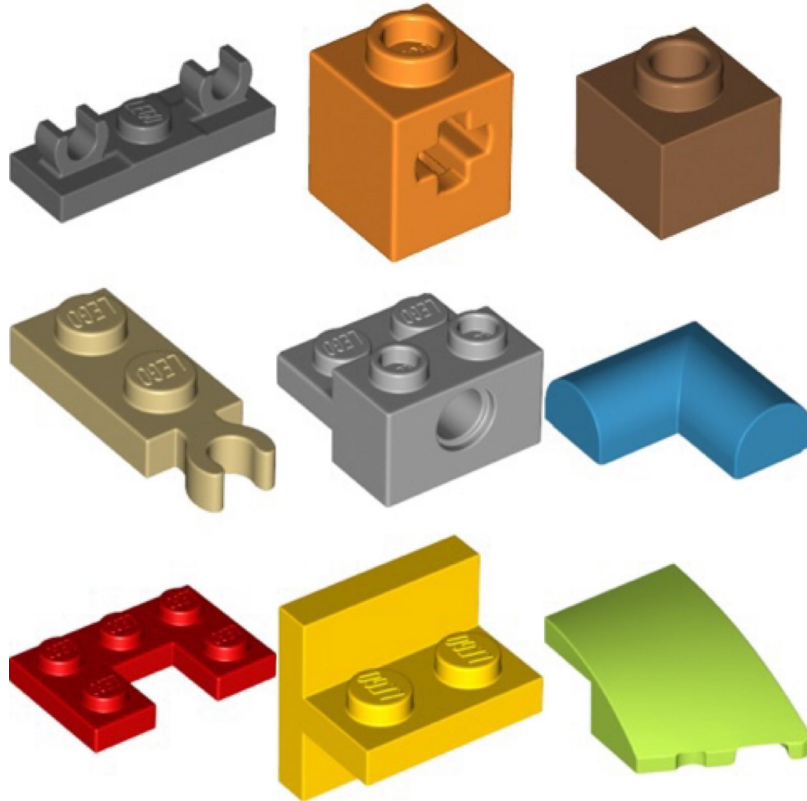
Random Grid Search



Bayesian Optimization

[A tutorial on automatic hyperparameter tuning of deep spectral modelling for regression and classification tasks - ScienceDirect](#)

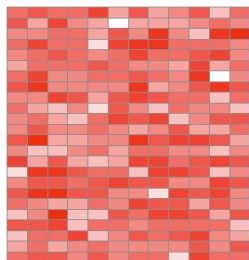
Neural Network Layers can be combined like Lego pieces



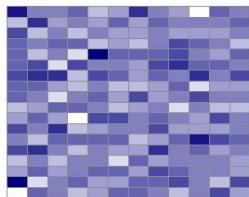


# DirectPred: Standard Fully Connected Networks

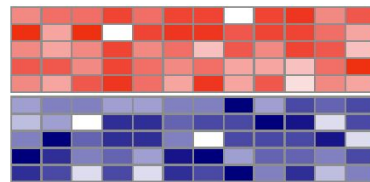
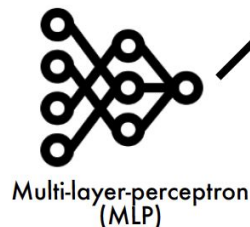
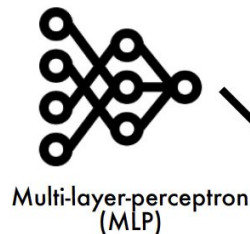
## 1.INPUT (Multi)-modal data matrices



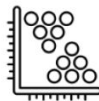
■  
■  
■



## 2.ENCODING Derive sample embeddings



Use sample  
embeddings for  
clustering



## 3.PREDICTION Connect sample embeddings to one or more supervisor MLPs

Mean Squared  
Error Loss (MSE) for  
Numerical Variables



Cross-Entropy Loss  
for Categorical  
Variables



Cox Proportional  
Hazards Loss for  
Survival Variables



# Homework

[https://github.com/BIMSBbioinfo/compgen\\_course\\_2025\\_module3/tree/main/homeworks/hw2](https://github.com/BIMSBbioinfo/compgen_course_2025_module3/tree/main/homeworks/hw2)