Getting Started with Deep Learning

Basic Concepts & Exercise of Deep Learning

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Deep Learning Basics

— Basic DL Building Blocks

— Guidance on building & training DL models

— **Exercise**: Simple example for DL

Exercise: Simple DL

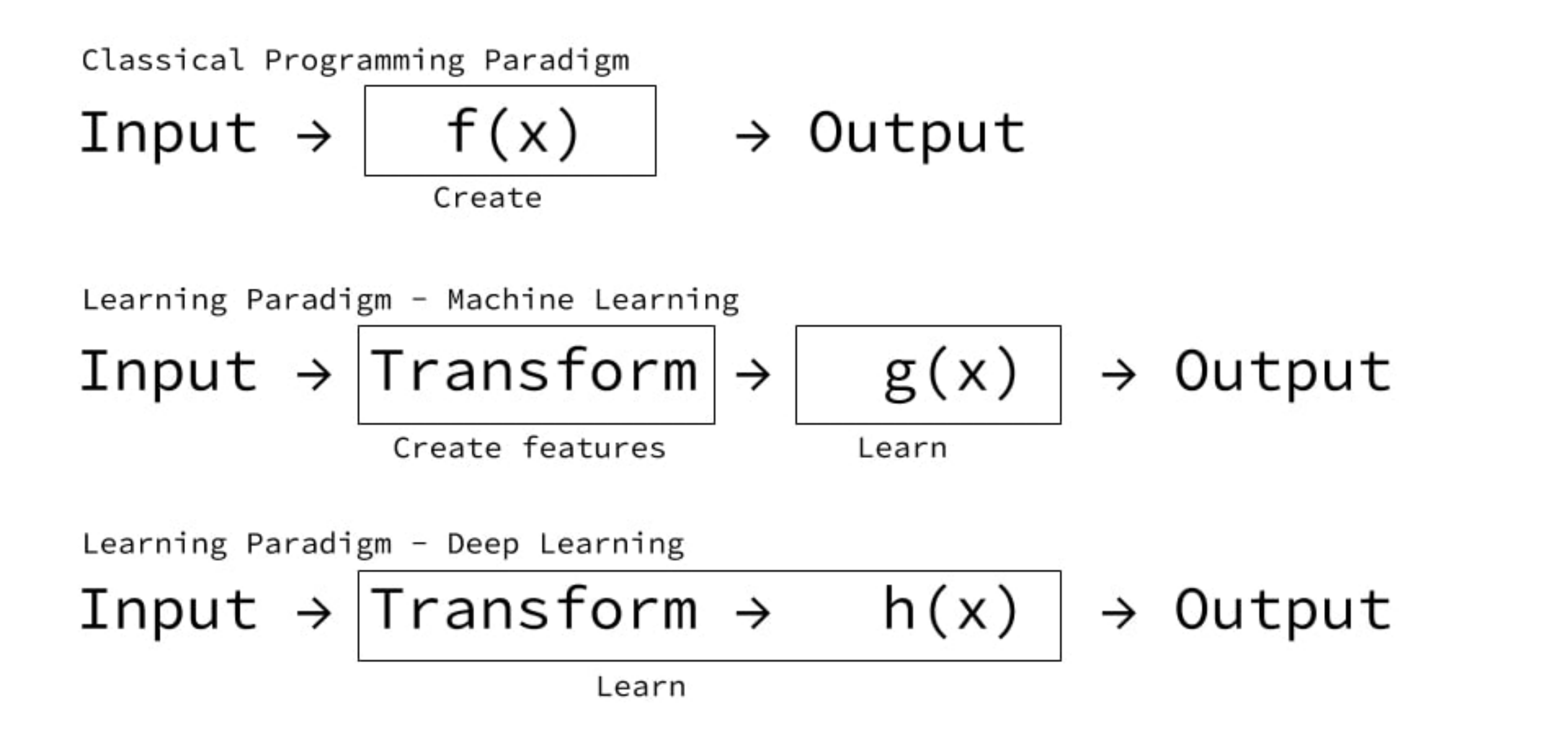
- Introduction to **Keras**: Input, Output, Architecture, Loss, Optimizer
- Build simple DL model: Learning a **Noisy Saddle Curve**

$$Z = 2X^2 - 3Y^2 + 1 + \epsilon$$

Exercise: Simple DL Continued

Experiments with the following:
1. Change activation to linear and see whether you can predict the function or not
2. Change number of layers in the network
3. Change number of learning units in each layer

Deep Learning Paradigm

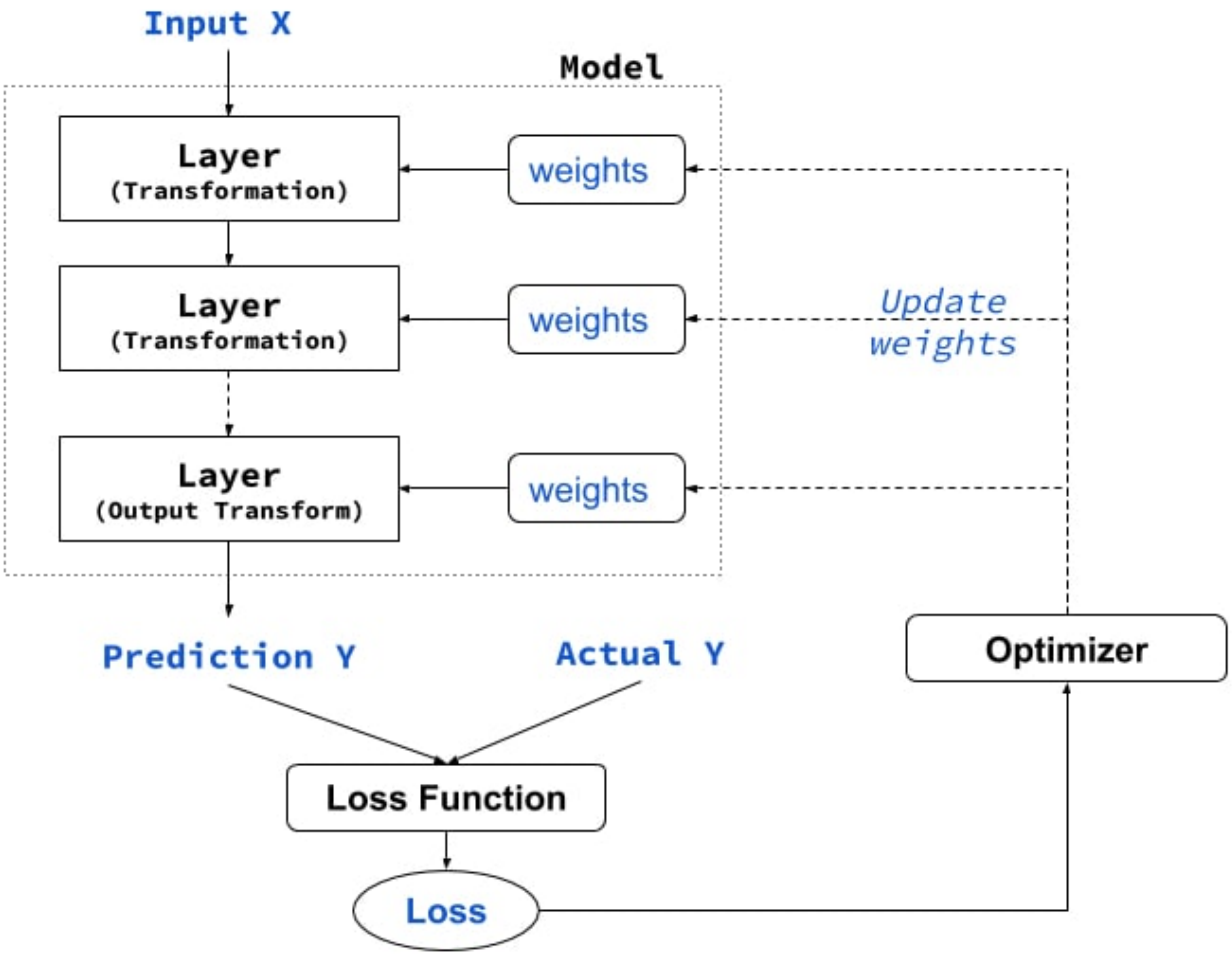


Learning Types & Applications

- **Supervised**: Regression, Classification, ...
- **Unsupervised**: Dimensionality Reduction, Clustering, ...
- **Self (semi)-supervised**: Auto-encoders, Generative Adversarial Network, ...
- **Reinforcement Learning**: Games, Self-Driving Car, Robotics, ...

Deep Learning Build Blocks

- **Input**: X
- **Architecture**: Layers, Learning Units, Weights
- **Output**: $Y_{predicted}$
- **Loss Function**:$Loss\,f(Y_{predicted}, Y_{actual})$
- **Optimizer Function**


Input X
Model
Layer
(Transformation)
weights
Layer
(Transformation)
weights
Update
weights
Layer
(Output Transform)
weights
Prediction Y
Actual Y
Optimizer
Loss Function
Loss

Data Representation: Tensors

- Numpy arrays (aka Tensors)
- Generalised form of matrix (2D array)
- Attributes
  - Axes or Rank: `ndim`
  - Dimensions: `shape` e.g. (5, 3)
  - Data Type: `dtype` e.g. `float32`, `uint8`, `float64`

Tensor Types

- **Scalar**: 0D Tensor
- **Vector**: 1D Tensor
- **Matrix**: 2D Tensor
- **Higher-order**: 3D, 4D or 5D Tensor

Input X

Tensor	Type	Examples	Shape
2D	Tabular	Spreadsheets	(samples, features)
3D	Sequence	TimeSeries, Text	(samples, steps, features)
4D	Spatial	Images	(samples, height, width, channels)
5D	Spatial + Sequence	Video	(samples, frames, height, width, channels)

Architecture

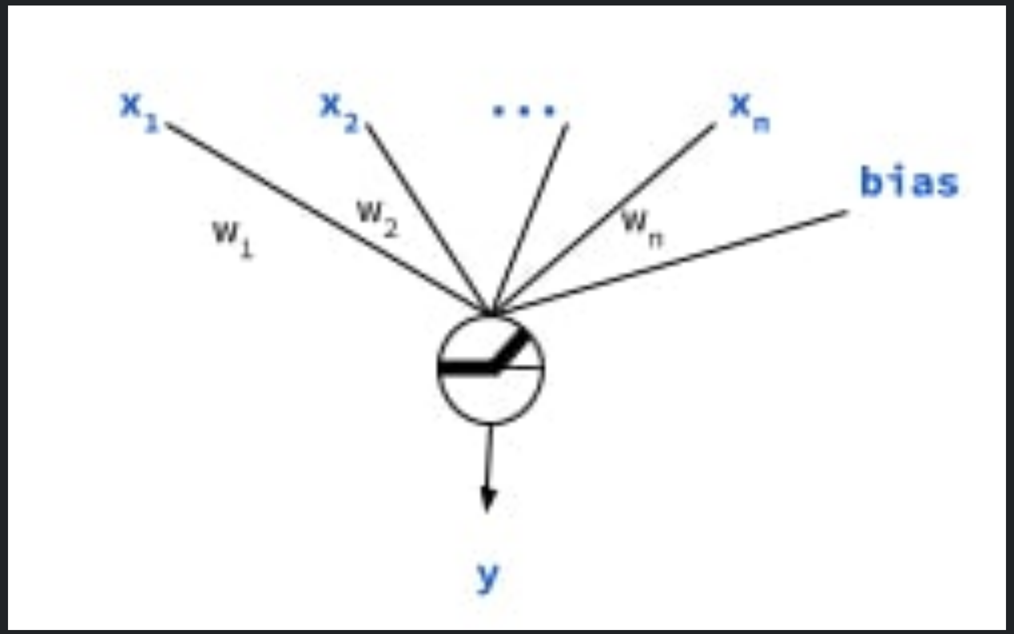
Model
Sequential: A linear stack of layers, learnt in a feed-forward manner

Layers
- Dense Layers: Fully connected layer of learning units (also called Multi-Layer Perceptron)
- Basic Layers: Layers that support basic computation e.g. Flatten, Add, Multiply, DotProduct

Learning Unit

$$y = RELU(dot(w, x) + bias)$$

weights are $w_1 \ldots w_n$ & **activation** is RELU $f(z) = max(z, 0)$



Output Y & Loss

y	**Last Layer Activation**	**Loss Function**
Regression	None	Mean Square Error
Regression (0-1)	sigmoid	MSE or Binary Cross Entropy
Binary-Class	sigmoid	Binary Cross Entropy
Multi-Class	softmax	Categorical Cross Entropy
Multi-Class & Multi-Label	sigmoid	Binary Crossentropy

Optimizers

- **SGD**: Excellent but requires tuning learning-rate decay, and momentum parameters
- **RMSProp**: Good for RNNs
- **Adam**: Adaptive momentum optimiser, generally a good starting point.

Deep Learning Guidance

General guidance on building and training neural networks.

Treat them as heuristics (derived from experimentation) and as good starting points for your own explorations.

Pre-Processing

- **Normalize** / **Whiten** your data (Not for text!)
- **Scale** your data appropriately (for outlier)
- Handle **Missing Values** - Make them 0 (Ensure it exists in training)
- Create **Training & Validation Split**
- **Stratified** split for multi-class data
- **Shuffle** data for non-sequence data. Careful for sequence!!

General Architecture

- Use **ADAM** Optimizer (to start with)
- Use **RELU** for non-linear activation (Faster for learning than others)
- Add **Bias** to each layer
- Use **Xavier** or **Variance-Scaling** initialisation (Better than random initialisation)
- Refer to output layers activation & loss function guidance for tasks

Dense / MLP Architecture

- No. of units reduce in deeper layer
- Units are typically 2^n
- Don't use more than 4 - 5 layers in dense networks

CNN Architecture (for Images)

- Increase **Convolution filters** as you go deeper from 32 to 64 or 128 (Max)
- Use **Pooling** to subsample: Makes image robust from translation, scaling, rotation
- Use **pre-trained models** as feature extractors for similar tasks
- Progressively **train n-last layers** if the model is not learning
- **Image Augmentation** is key for small data and for faster learning

RNN / CNN Architecture (for NLP)

- **Embedding** layer is critical. **Words** are better than **Characters**
- Learn the embedding with the task or use pre-trained embedding as starting point
- Use BiLSTM / LSTM vs Simple RNN. Remember, RNNs are really slow to train
- Experiment with 1D CNN with larger kernel size (7 or 9) than used for images.
- MLP can work with bi-grams for many simple tasks.

Learning Process

- **Validation Process**
  - Large Data: Hold-Out Validation
  - Smaller Data: K-Fold (Stratified) Validation
- **For Underfitting**
  - Add more layers: **go deeper**
  - Make the layers bigger: **go wider**
  - Train for more epochs: **go longer**

Learning Process

- **For Overfitting**
  - Get **more training data** (e.g. actual/augmentation)
  - Reduce **model capacity**
  - Add **weight regularisation** (e.g. L1, L2)
  - Add **dropouts** or use **batch normalization**