Deep Learning Practical Guidance

Getting Started with Image & Text

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Bootcamp Approach

— **Domain**: Image & Text
— **Applied**: Proven & Practical
— **Intuition**: Visualisation & Analogies
— **Code**: Learning by Doing
— **Math**: Attend HackerMath!

Learning Paradigm

Classical Programming Paradigm

Input → $\boxed{f(x)}$ → Output

Create

Learning Paradigm - Machine Learning

Input → $\boxed{\text{Transform}}$ → $\boxed{g(x)}$ → Output

Create features

Learn

Learning Paradigm - Deep Learning

Input → $\boxed{\text{Transform} \rightarrow h(x)}$ → Output

Learn

Learning Types & Applications

— **Supervised**: Regression, Classification, ...

— Unsupervised: Dimensionality Reduction, Clustering, ...

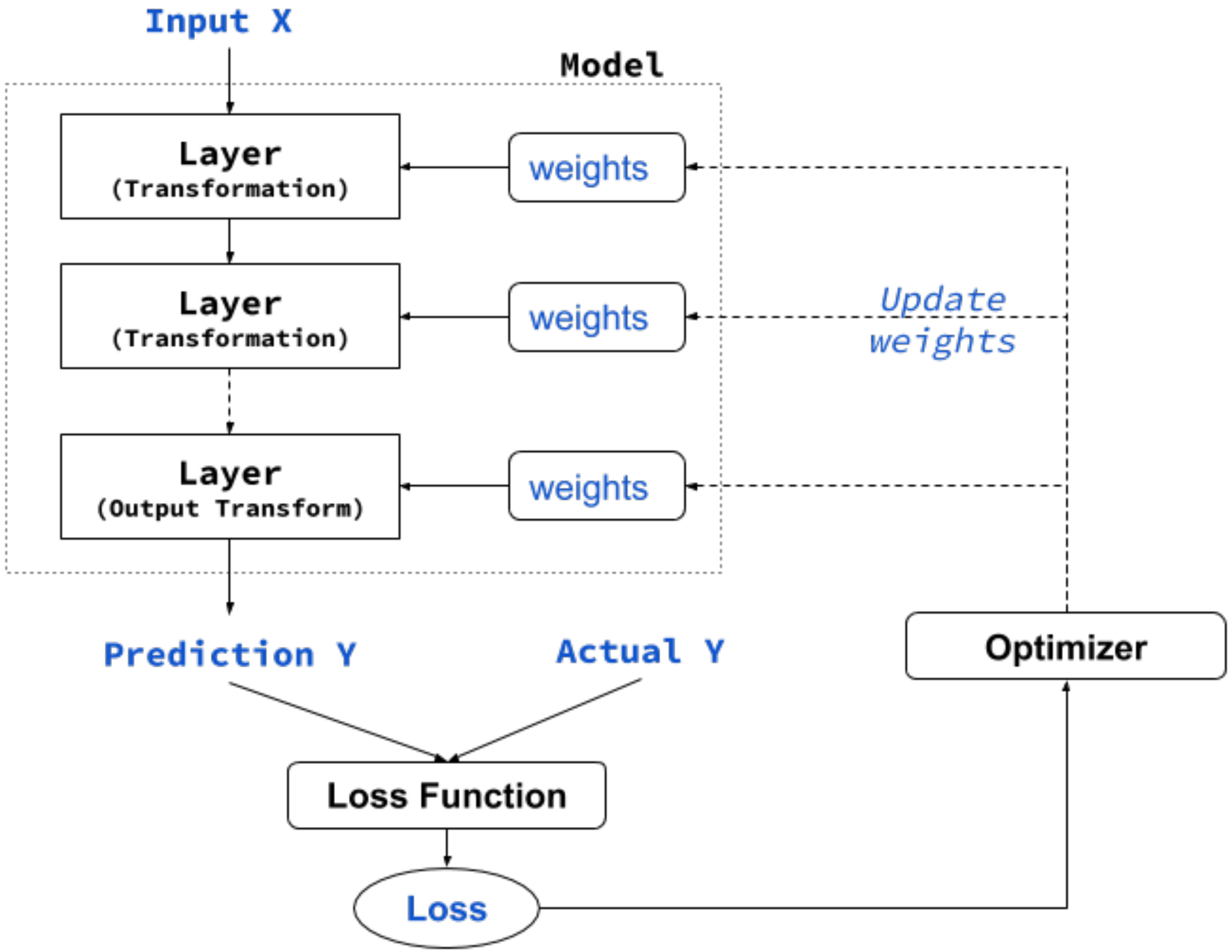
— Self (Semi)-supervised: Auto-encoders, Generative Adversarial Network, ...

— Reinforcement Learning: Games, Self-Driving Car, Robotics, ...

Focus: Supervised Learning

— **Classification**: Image, Text, Speech, Translation
— Sequence generation: Given a picture, predict a caption describing it.
— Syntax tree prediction: Given a sentence, predict its decomposition into a syntax tree.
— Object detection: Given a picture, draw a bounding box around certain objects inside the picture.
— Image segmentation: Given a picture, draw a pixel-level mask on a specific object.

Learning Approach



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

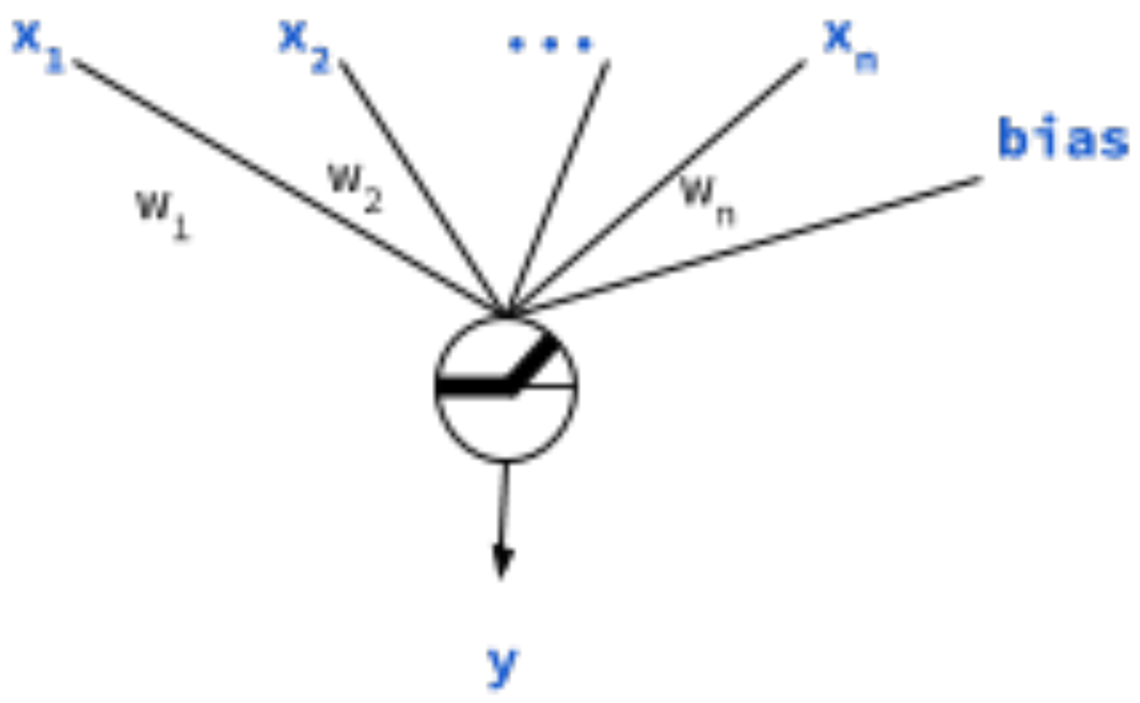
Tensor	Example	Shape
2D	Tabular	(samples, features)
3D	Sequence	(samples, steps, features)
4D	Images	(samples, height, width, channels)
5D	Videos	(samples, frames, height, width, channels)

Learning Unit

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

weights are $w_1 \ldots w_n$ & **activation** is RELU

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



Model Architecture

Basic Model: **Sequential** - A linear stack of layers.

Core Layers
- Dense Layers: Fully connected layer of learning units (Also called Multi-layer Perceptron)
- Flatten

Output y & Loss

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

Guidance for DL

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 **Convoluton 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

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

Learning Process

- **For Overfitting**
  - Get **more training data** (e.g. actual or image augmentation)
  - Reduce **Model Capacity**
  - Add **weight regularisation** (e.g. L1, L2)
  - Add **Dropouts** or use **Batch Normalization**