

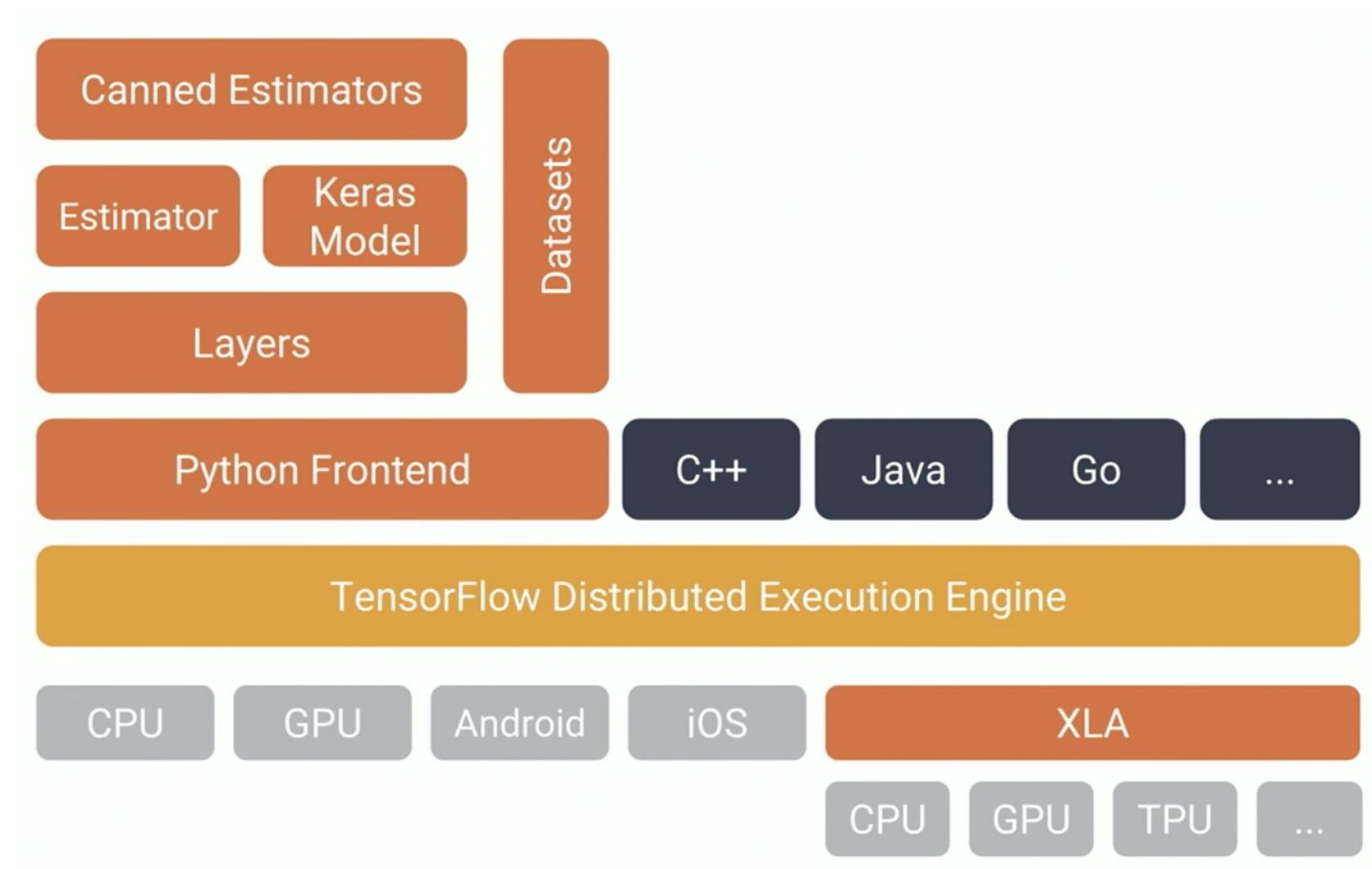
# Introduction to TensorFlow

Lecture 17 for 14-763/18-763

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# TensorFlow Architecture



## Data



`torch.tensor`

`Dataset/DataLoader`

## ML Models

`nn.Module` for building NN models

`backward()` for differentiation



### **Tensor/Dataset**

`tf.Tensor`

`tf.data API`

### **tf.keras High-Level API**

`keras.Sequential()`, `keras.Model` for building models  
`keras.Model.fit()` for training

### **TensorFlow Core**

`tf.Module` for building models  
`tf.GradientTape()` for automatic differentiation

# TensorFlow Architecture

Additional  
tools

## TensorBoard

Tool for Data  
visualization and tuning

## tf.distribute

Allows training across  
multiple GPUs/CPUs on  
multiple machines

## Deployment

TFX for production-level ML  
TensorFlow.js for JavaScript Deployment  
TensorFlowLite for Mobile/Edge

Basics

## Tensor/Dataset

tf.data API

tf.Tensor

## tf.keras High-Level API

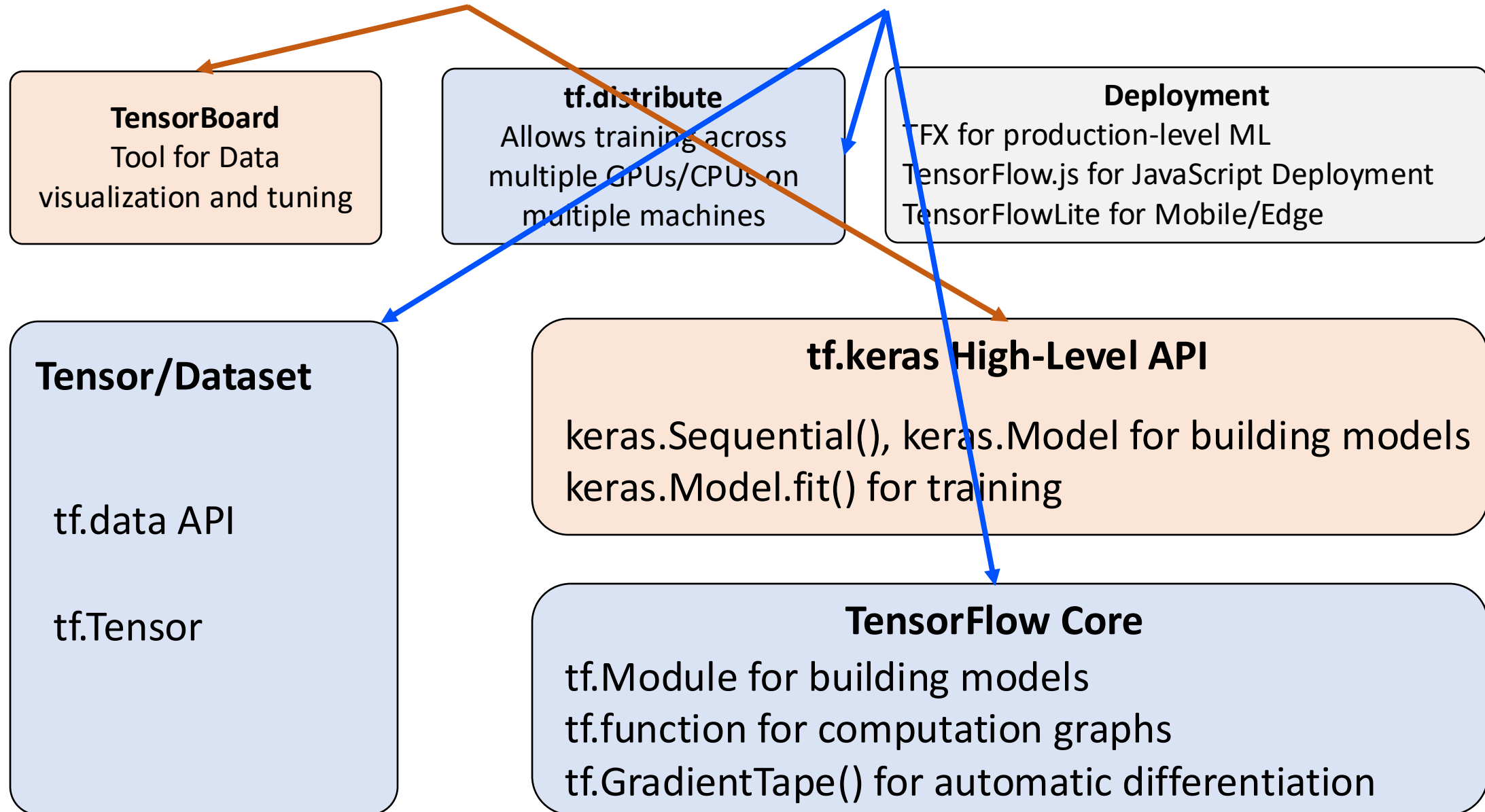
keras.Sequential(), keras.Model for building models  
keras.Model.fit() for training

## TensorFlow Core

tf.Module for building models  
tf.GradientTape() for automatic differentiation

**We will cover**

**Very similar to PyTorch**



**TensorBoard**  
Tool for Data  
visualization and tuning

**tf.distribute**  
Allows training across  
multiple GPUs/CPUs on  
multiple machines

**Deployment**  
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## Tensor/Dataset

tf.data API

tf.Tensor

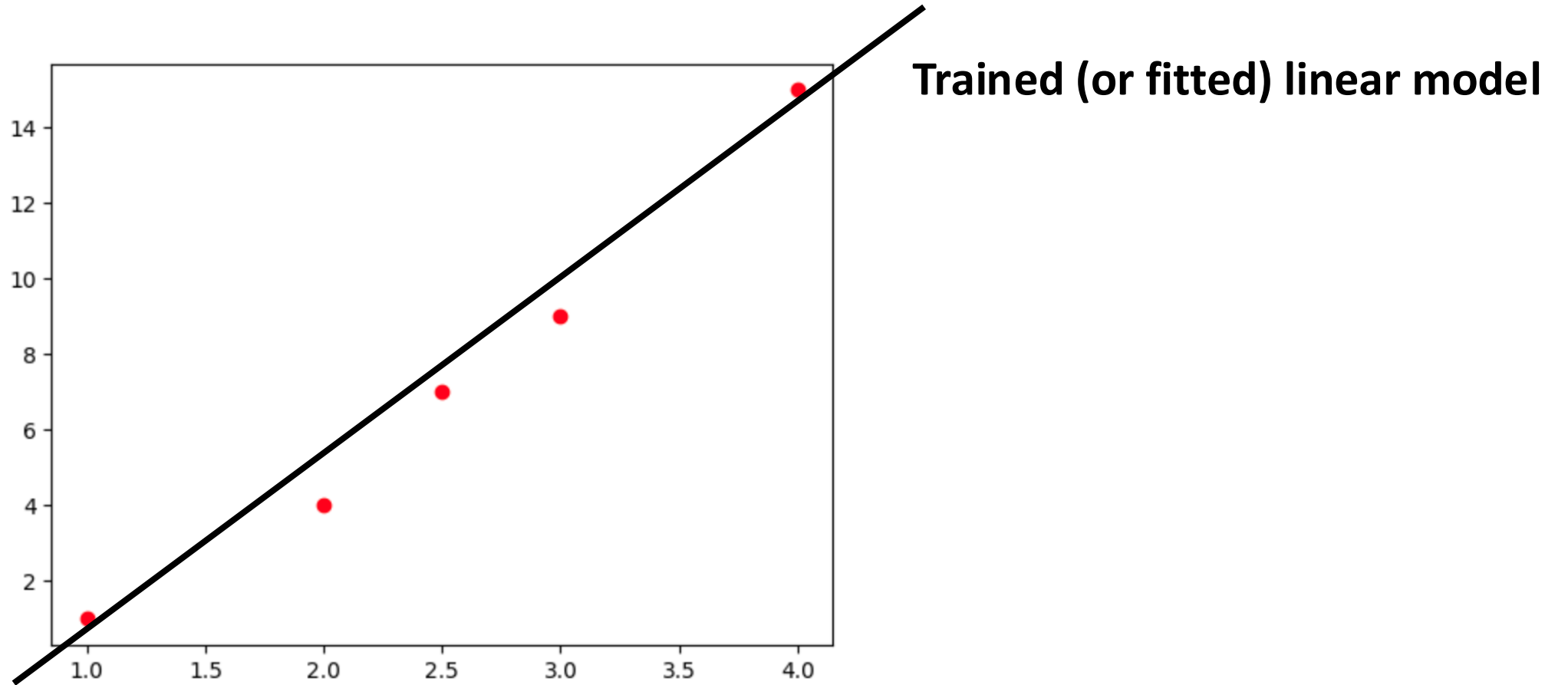
## tf.keras High-Level API

keras.Sequential(), keras.Model for building models  
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## TensorFlow Core

tf.Module for building models  
tf.function for computation graphs  
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# Keras: Linear Regression



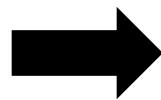
# Keras: Linear Regression

How to create a model with tf.keras?

```
model = keras.Sequential()  
model.add(keras.layers.Dense(1))
```

This layer is a simple linear function with **output dimension 1**  
**No need to specify input dimension**

Input/Feature:  
 $x$



$$y = ax + b$$



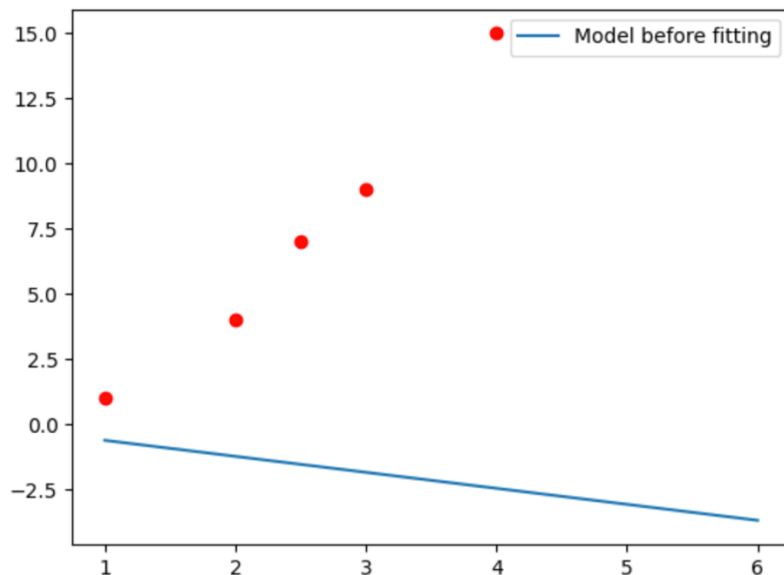
Output/Target  
 $y$



# Keras: Linear Regression

**How does the model look like? (Note: this model is untrained yet)**

```
x_mesh = np.linspace(1,6,100) # generate 100 input values between 1 and 6
x_mesh = tf.constant( x_mesh[:,np.newaxis])
y_pred_mesh = model(x_mesh) # get the output of our model
plt.plot(x, y, 'ro')
plt.plot(x_mesh, y_pred_mesh , label = "Model before fitting")
plt.legend()
```



# Keras: Linear Regression

How does the model look like? (Note: this model is untrained yet)

```
model.summary()
```

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(100, 1)	2

Total params: 2

Trainable params: 2

Non-trainable params: 0

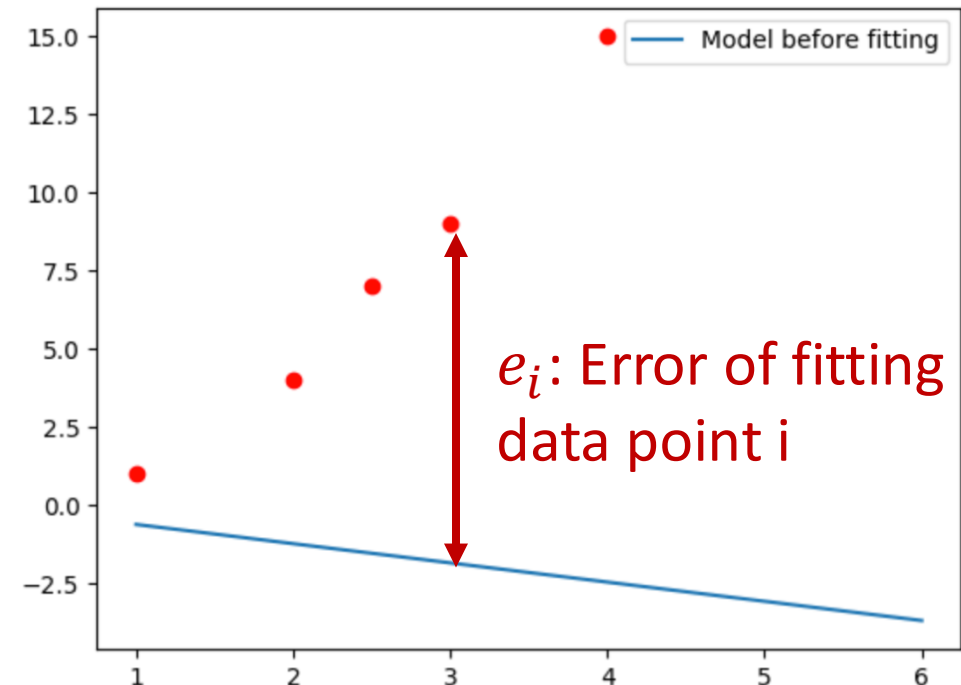
# Keras: Linear Regression

## How to train the model?

```
model.compile(optimizer = keras.optimizers.SGD(), loss = keras.losses.MeanSquaredError())  
model.fit(x,y,epochs=30)
```

Measures how well the model fits the data

$$\text{MeanSquaredError} = \frac{1}{\text{\#number of samples}} \sum_i (e_i)^2$$



# Keras: Linear Regression

## How to train the model?

```
model.compile(optimizer = keras.optimizers.SGD(), loss = keras.losses.MeanSquaredError())  
model.fit(x,y,epochs=30)
```

Choosing the algorithm to find the model weights that minimize the loss.  
SGD, Adam are popular choices, which is similar to PyTorch

# Keras: Linear Regression

## How to train the model?

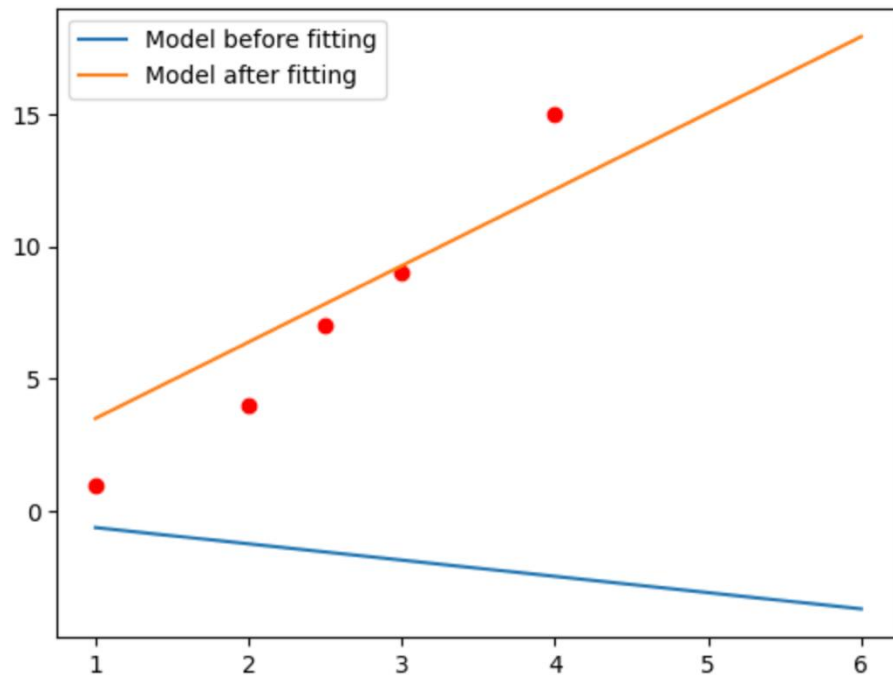
```
model.compile(optimizer = keras.optimizers.SGD(), loss = keras.losses.MeanSquaredError())  
model.fit(x,y,epochs=30)
```

Epochs means how many iterations we go through the data  
(similar to pytorch)

# Keras: Linear Regression

## How does the trained model look like?

```
y_pred_mesh_afterfitting = model(x_mesh)
plt.plot(x, y, 'ro')
plt.plot(x_mesh, y_pred_mesh , label = "Model before fitting")
plt.plot(x_mesh, y_pred_mesh_afterfitting , label = "Model after fitting")
plt.legend()
```



# How to build neural networks?

This is how we build a linear regression model

```
model = keras.Sequential()  
model.add(keras.layers.Dense(1))
```

For each hidden layer, specify  
the width and the activation

To build a neural network, just add more layers

```
model = keras.Sequential()  
  
model.add(keras.layers.Dense(20, activation='relu'))  
model.add(keras.layers.Dense(20, activation='relu'))  
model.add(keras.layers.Dense(20, activation='relu'))  
  
model.add(keras.layers.Dense(1))
```

Add layers  
one-by-one

The output dimension

# Keras: Simple Neural Network

**Equivalent way to create the same neural network**

```
model2 = keras.Sequential(layers=[keras.layers.Dense(20,activation='relu'),  
    keras.layers.Dense(20,activation='relu'),  
    keras.layers.Dense(20,activation='relu'),  
    keras.layers.Dense(1)])
```



# Keras: Simple Neural Network

**Another equivalent way to create the same neural network**

```
input = keras.Input(shape = (1))

intermediate_1 = keras.layers.Dense(20,activation='relu')(input)
intermediate_2 = keras.layers.Dense(20,activation='relu')(intermediate_1)
intermediate_3 = keras.layers.Dense(20,activation='relu')(intermediate_2)

output = keras.layers.Dense(1)(intermediate_3)

model3 = keras.Model(inputs = input,outputs = output)
```

# Neural Network Classification

I have received many questions regarding

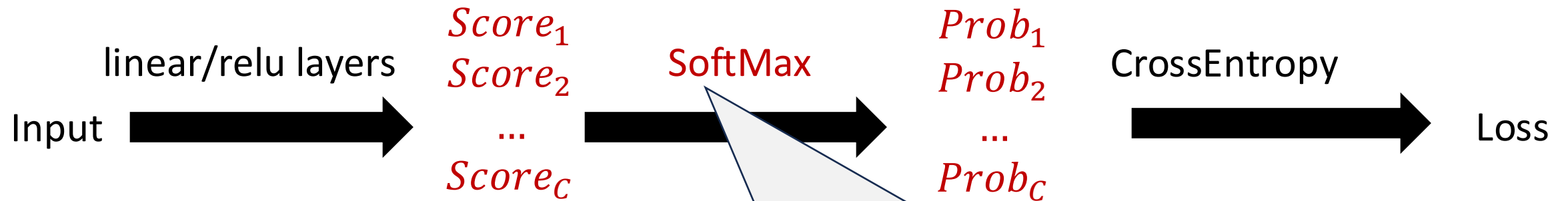
- what should be the input to the cross entropy loss
- what should be the final layer (linear or softmax) of NN.

This can be confusion as PyTorch and tf.keras has different conventions

I would like to clarify this by first presenting the “mathematical” way to compute cross entropy (which is unambiguous), and then present what is the convention for each platform (pytorch/tensorflow).

# Neural Network Classification

Consider a classification problem with  $C$  classes  $1, 2, \dots, C$



$Score_i$  is unnormalized  
(can take values from  $-\infty$   
to  $+\infty$ )

The larger  $Score_i$ , the  
higher the odds of class  $i$

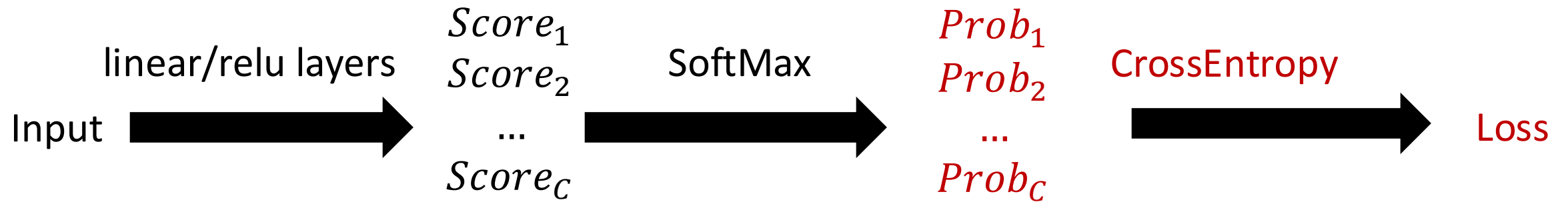
Softmax Function

$$Prob_i = \frac{\exp(Score_i)}{\exp(Score_1) + \exp(Score_2) + \dots + \exp(Score_C)}$$

$Prob_i$  is “normalized”, i.e. it must lie between 0,1

# Neural Network Classification

Consider a classification problem with  $C$  classes  $1, 2, \dots, C$



Suppose the true label is  $y \in \{1, 2, \dots, C\}$

CrossEntropy for this data point is

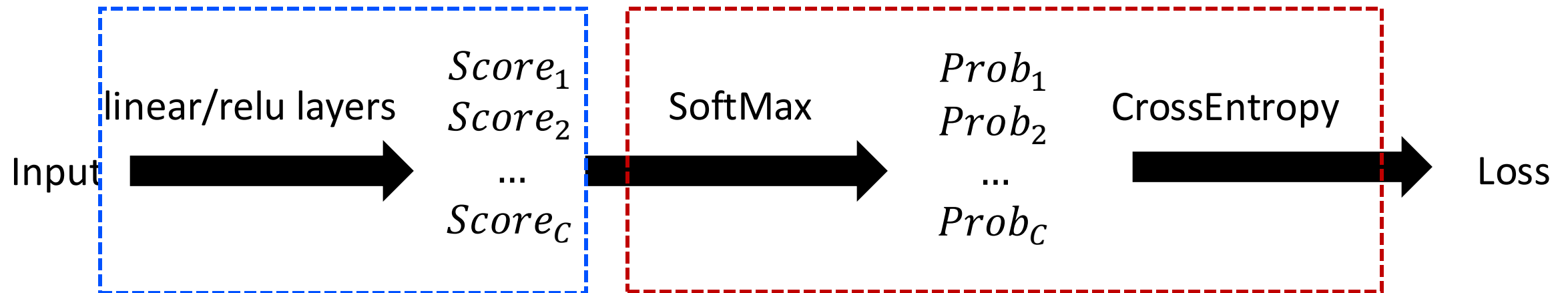
$$-\log Prob_y = \begin{cases} 0 & \text{If } Prob_y = 1 \\ +\infty & \text{If } Prob_y = 0 \end{cases}$$

where  $Prob_y$  is the probability of the correct class

Minimizing cross entropy encourages predicting the true label with larger prob.

# Neural Network Classification

## PyTorch Convention

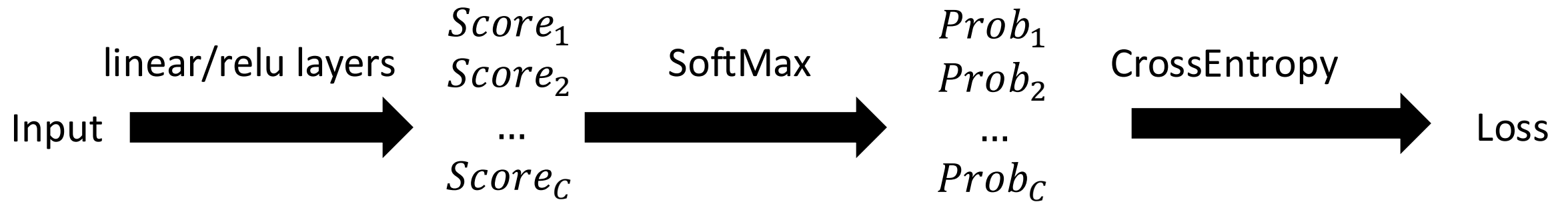


So in PyTorch, neural networks typically don't include softmax as final layer. Typically, linear is the final layer.

PyTorch `nn.CrossEntropyLoss()`  
Includes BOTH Softmax AND CrossEntropy

# Neural Network Classification

## TensorFlow Keras Convention?

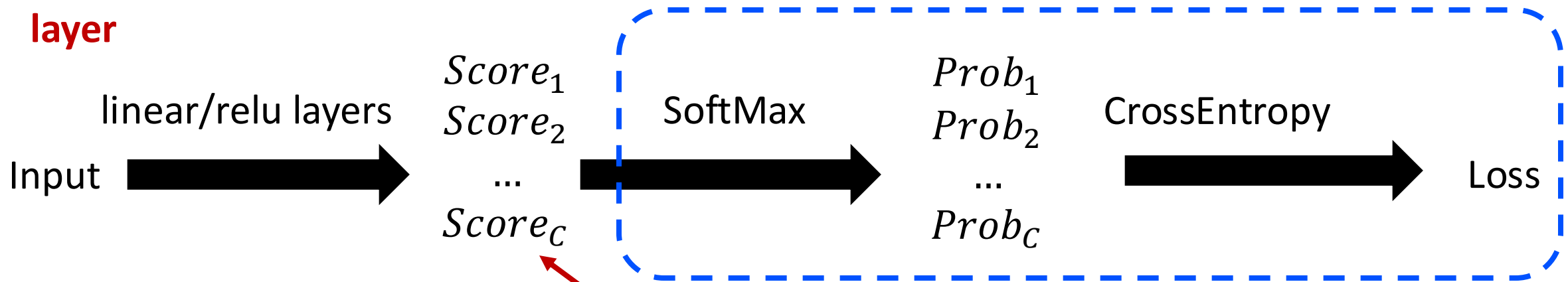


Let's use NSL-KDD as example

# Neural Network Classification

Which means your NN should NOT include softmax as final layer

If From\_logits = true, the SparseCategoricalCrossentropy() will INCLUDE SOFTMAX



NN output are two scores, one for normal and one for attack

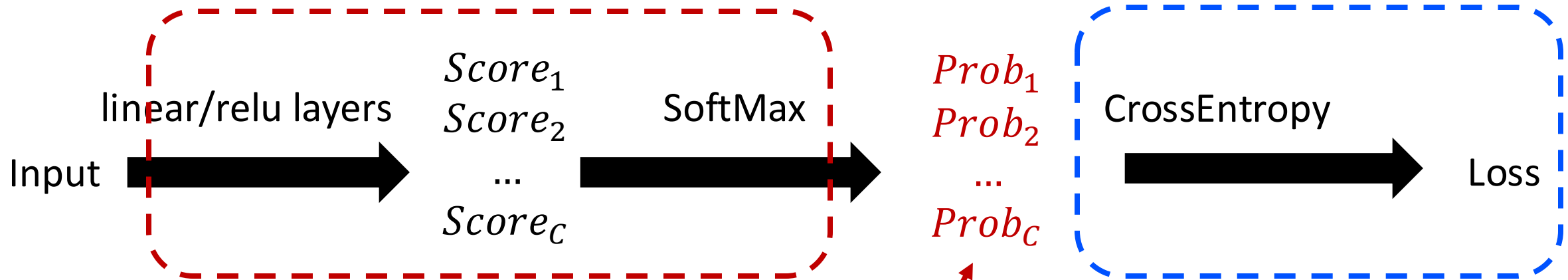
```
model_multiclass = keras.Sequential([keras.layers.Dense(10, activation='relu'),  
                                     keras.layers.Dense(10, activation='relu'),  
                                     keras.layers.Dense(10, activation='relu'),  
                                     keras.layers.Dense(10, activation='relu'),  
                                     keras.layers.Dense(2)] )
```

```
model_multiclass.compile(optimizer = 'sgd',  
                        loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
```

# Neural Network Classification

Which means your NN  
SHOULD INCLUDE softmax

If From\_logits = false, the SparseCategoricalCrossentropy()  
will NOT INCLUDE SOFTMAX



```
model2 = keras.Sequential([keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(2,activation='softmax')])
```

NN output are two probabilities,  
one for normal and one for attack

From\_logits = false assumes NN output is probability

```
model2.compile(optimizer = 'sgd', loss=keras.losses.SparseCategoricalCrossentropy(from_logits=False))
```



# Neural Network Classification

Here we use the `SparseCategoricalCrossentropy` as the loss

- “Sparse” refers to the fact the true label is integer values

## Can also use CategoricalCrossentropy

- In this case, the true label should be onehot encoded

```
model_multiclass.compile(optimizer = 'sgd',  
                        loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
```

# Summary So Far

- Should set `from_logits = True` if NN output is score (last layer linear)
- Should set `from_logits = False` if NN output is probability (last layer softmax)
- NN output dimension should be the same as the number of classes

# Converting DF to tf.Tensor

```
to_array = udf(lambda v: v.toArray().toList(), ArrayType(FloatType()))

nslkdd_df_train = nslkdd_df
nslkdd_df_validate, nslkdd_df_test = nslkdd_df_test.randomSplit([0.5, 0.5])

nslkdd_df_train_pandas = nslkdd_df_train.withColumn('features', to_array('features')).toPandas()
nslkdd_df_validate_pandas = nslkdd_df_validate.withColumn('features', to_array('features')).toPandas()
nslkdd_df_test_pandas = nslkdd_df_test.withColumn('features', to_array('features')).toPandas()
```

```
x_train = tf.constant(np.array(nslkdd_df_train_pandas['features'].values.tolist()))
y_train = tf.constant(np.array(nslkdd_df_train_pandas['outcome'].values.tolist()))

x_validate = tf.constant(np.array(nslkdd_df_validate_pandas['features'].values.tolist()))
y_validate = tf.constant(np.array(nslkdd_df_validate_pandas['outcome'].values.tolist()))

x_test = tf.constant(np.array(nslkdd_df_test_pandas['features'].values.tolist()))
y_test = tf.constant(np.array(nslkdd_df_test_pandas['outcome'].values.tolist()))
```

# Training for NSL-KDD

```
model = keras.Sequential([keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu'),  
                           keras.layers.Dense(10,activation='relu') ,  
                           keras.layers.Dense(2)] )
```

```
model.compile(optimizer = keras.optimizers.SGD(learning_rate=0.02),  
              loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),  
              metrics=[keras.metrics.SparseCategoricalAccuracy()])  
  
model.fit(x_train,y_train, epochs = 5,batch_size = 64, validation_data=(x_validate,y_validate),verbose = 2)
```

# Fit the keras Model

Epoch 1/5

1969/1969 - 1s - loss: 0.1268 - sparse\_categorical\_accuracy: 0.9649 - val\_loss: 0.7386 - val\_sparse\_categorical\_accuracy: 0.7687 - 699ms/epoch - 355us/step

Epoch 2/5

1969/1969 - 1s - loss: 0.0681 - sparse\_categorical\_accuracy: 0.9810 - val\_loss: 0.8911 - val\_sparse\_categorical\_accuracy: 0.7553 - 502ms/epoch - 255us/step

Epoch 3/5

1969/1969 - 1s - loss: 0.0605 - sparse\_categorical\_accuracy: 0.9824 - val\_loss: 1.0256 - val\_sparse\_categorical\_accuracy: 0.7542 - 506ms/epoch - 257us/step

Epoch 4/5

1969/1969 - 1s - loss: 0.0517 - sparse\_categorical\_accuracy: 0.9833 - val\_loss: 1.3345 - val\_sparse\_categorical\_accuracy: 0.7714 - 508ms/epoch - 258us/step

Epoch 5/5

1969/1969 - 0s - loss: 0.0389 - sparse\_categorical\_accuracy: 0.9868 - val\_loss: 1.4130 - val\_sparse\_categorical\_accuracy: 0.7617 - 497ms/epoch - 253us/step

# Evaluate it on the test data

```
✓ model.evaluate(x_test,y_test, verbose = 2)
```

```
| ✓ 0.1s
```

```
179/179 - 0s - loss: 1.3673 - sparse_categorical_accuracy: 0.7626 - 93ms/epoch - 518us/step
```

## Up Next

### **TensorBoard**

Tool for Data  
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### **tf.distribute**

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# TensorBoard

- TensorBoard is an interactive interface that allows you to
  - Track “scalar” metrics, like train/validation loss, auc, accuracy, across different epochs
  - Visualize the structure of neural network
  - Hyper-Parameter Tuning



# Let's try TensorBoard

```
import datetime

model = keras.Sequential([keras.layers.Dense(10, activation='relu'),
                           keras.layers.Dense(10, activation='relu'),
                           keras.layers.Dense(10, activation='relu'),
                           keras.layers.Dense(10, activation='relu'),
                           keras.layers.Dense(2)])

model.compile(loss=keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=[keras.metrics.SparseCategoricalAccuracy(name='Accuracy')])

log_dir = "logs14763/myfirstlog/" + datetime.datetime.now().strftime("%Y%m%d-%H%M%S")
tensorboard_callback = tf.keras.callbacks.TensorBoard(log_dir=log_dir, histogram_freq=1)

model.fit(x=x_train, y=y_train,
        epochs=20, verbose=2,
        validation_data=(x_validate, y_validate),
        callbacks=[tensorboard_callback])
```

Create a callback object and specify log directory

Pass the callback to Model.fit(), which will run the callback to write all necessary info to the log directory

# How to launch TensorBoard?

Launch TensorBoard within notebook

```
%load_ext tensorboard  
%tensorboard --logdir logs14763/myfirstlog/
```

Launch TensorBoard in terminal

- Use the following command: `tensorboard --logdir logs14763/myfirstlog/`
- The terminal will then prompt a URL, typically <http://localhost:6006>
- Use your browser to enter that URL

# Hyper Parameter Tuning with TensorBoard

- We have kept using a Neural Network with 3 hidden layers, each with 20 neurons.
- There is no fixed rule in how we should choose these numbers, and let's tune it!

# Hyper Parameter Tuning with TensorBoard

```
from tensorboard.plugins.hparams import api as hp
```

```
HP_WIDTH = hp.HParam('NN_width', hp.Discrete([20,30]))
```

```
HP_DEPTH = hp.HParam('NN_depth', hp.Discrete([4,6]))
```

Create two hyper parameters and pick several values

```
with tf.summary.create_file_writer('logs14763/hparam_tuning') as default():
```

```
    hp.hparams_config(
```

```
        hparams=[HP_WIDTH, HP_DEPTH],
```

```
        metrics=[hp.Metric('Accuracy')],
```

```
    )
```

Configure the hyper-parameter panel - two hyperparameters to tune, with the metric

Create NN model with given depth and width

```
def train_test_model(hparams, logdir):  
    model = keras.Sequential()  
    for _ in range(hparams[HP_DEPTH]):  
        model.add(keras.layers.Dense(hparams[HP_WIDTH], activation='relu'))  
    model.add(keras.layers.Dense(2))  
    model.compile(  
        optimizer=keras.optimizers.SGD(),  
        loss = keras.losses.SparseCategoricalCrossentropy(from_logits=True),  
        metrics=[keras.metrics.SparseCategoricalAccuracy(name="Accuracy_epochs")]  
    )  
    history = model.fit(x_train, y_train, epochs=5, verbose = 2,  
        callbacks=[tf.keras.callbacks.TensorBoard(log_dir=logdir, histogram_freq=1)],  
        validation_data = (x_validate, y_validate))  
    accuracy = np.max(history.history["val_Accuracy_epochs"])  
    return accuracy
```

Calculate the largest accuracy across different epochs

```

for hp_width in HP_WIDTH.domain.values:
    for hp_depth in (HP_DEPTH.domain.values):

```

Go through all combinations of hyper-parameters

```

    hparams = {
        HP_WIDTH: hp_width,
        HP_DEPTH: hp_depth,
    }

```

```

    run_name = f"run-WIDTH{int(hparams[HP_WIDTH])}-DEPTH{hparams[HP_DEPTH]}"
    print('--- Starting trial: %s' % run_name)
    print({h.name: hparams[h] for h in hparams})

```

```

    run_dir = 'logs14763/hparam_tuning/' + run_name

```

Train our model and get Accuracy

```

    accuracy = train_test_model(hparams, run_dir)

```

```

    with tf.summary.create_file_writer(run_dir).as_default():
        hp.hparams(hparams) # record the values used in this trial
        tf.summary.scalar("Accuracy", accuracy, step=1)

```

Record the hyper-parameter value, Accuracy to the log directory

# Hyper Parameter Tuning with TensorBoard

