

UVA CS 4774

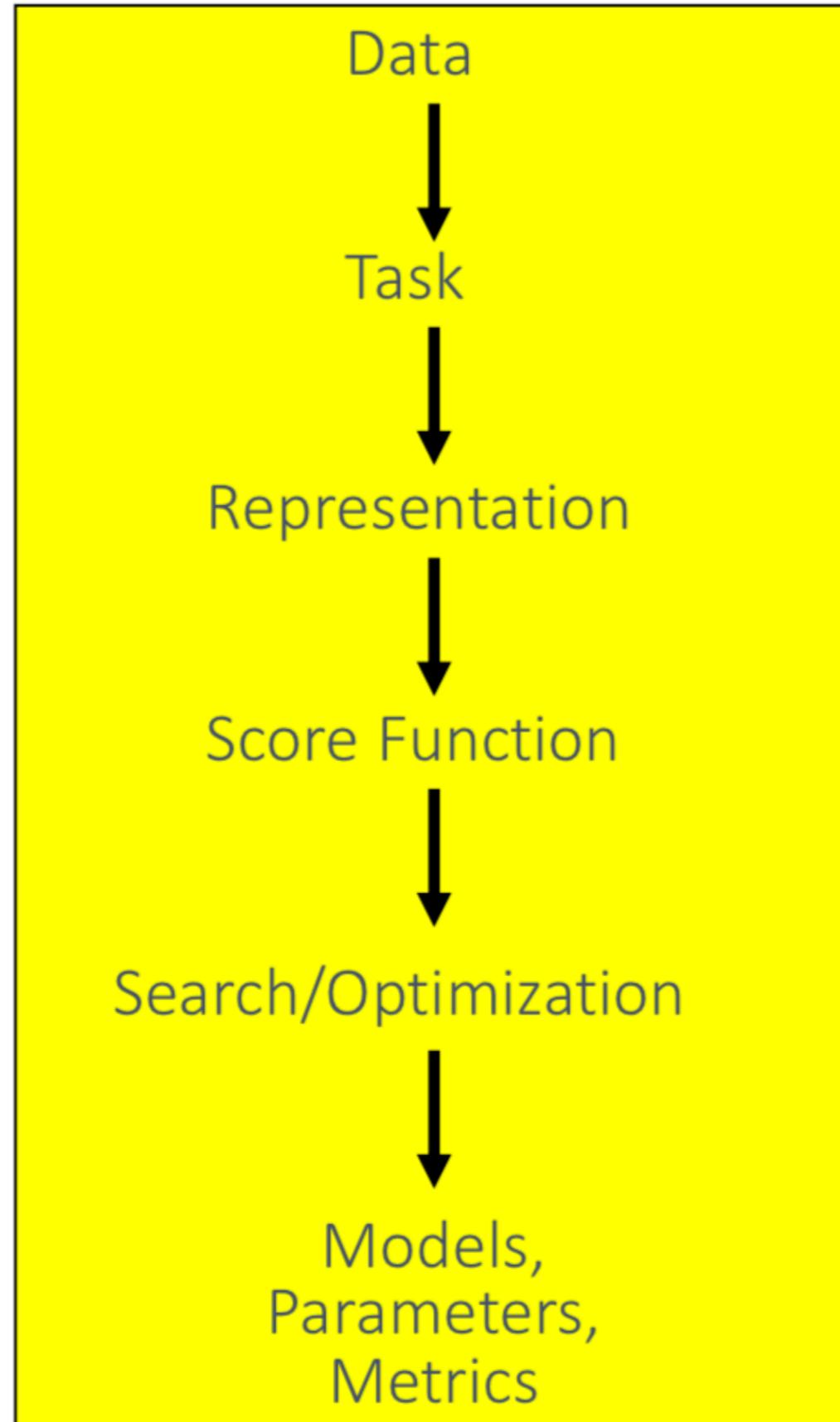
A Brief Introduction to Keras

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Nutshell for the Deep Learning



I: Data

Keras.datasets module provide several toy datasets including MNIST, CIFAR10, CIFAR100, etc.

First load the dataset:

```
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data(path="mnist.npz")
```

Preprocessing:

```
x_train = x_train.astype("float32") / 255 # Scale pixel values to [0, 1]
x_train = np.expand_dims(x_train, -1) # Size of x_train = [60000, 28, 28, 1], for CNN.
x_train = x_train.reshape(-1, 784) # Size of x_train = [60000, 784], for MLP.
```

```
y_train = keras.utils.to_categorical(y_train, num_classes) # (60000, ) to (60000, 10)
y_test = keras.utils.to_categorical(y_test, num_classes)
```

II: Model

Two ways to build your model: sequential and functionals

Sequential:

```
input_shape = (28, 28, 1)
model = keras.Sequential(
    [
        keras.Input(shape=input_shape),
        layers.Conv2D(32, kernel_size=(3, 3), activation="relu"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(64, kernel_size=(3, 3), activation="sigmoid"),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Flatten(),
        layers.Dropout(0.5),
        layers.Dense(num_classes, activation="softmax"),
    ]
)
```

model.summary()

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d (MaxPooling2D)	(None, 13, 13, 32)	0
conv2d_1 (Conv2D)	(None, 11, 11, 64)	18496
max_pooling2d_1 (MaxPooling2D)	(None, 5, 5, 64)	0
flatten (Flatten)	(None, 1600)	0
dropout (Dropout)	(None, 1600)	0
dense (Dense)	(None, 10)	16010

Total params: 34,826
Trainable params: 34,826
Non-trainable params: 0

Functional:

```
class MyModel(keras.Model):  
  
    def __init__(self):  
        super(MyModel, self).__init__()  
        self.dense1 = keras.layers.Dense(4, activation='relu')  
    def call(self, inputs):  
        x = self.dense1(inputs)  
        return x  
  
model = MyModel()
```

Print out your model:

```
model = MyModel()  
model.build(input_shape=(None,784))  
model.summary()
```

Model: "my_model"

Layer (type)	Output Shape	Param #
dense_1 (Dense)	multiple	3140

Total params: 3140

Trainable params: 3140

Non-trainable params: 0

II: Define your optimizer

```
my_opt = keras.optimizers.Adam(learning_rate=1e-3) # Adam, SGD, Adagrad, RMSprop, etc.
```

III: Define your loss function

```
my_loss = keras.losses.CategoricalCrossentropy(  
    label_smoothing=0,  
    name="categorical_crossentropy",  
)
```

IV: Compile your model: configures the model for training

```
model.compile(loss=my_loss, optimizer=my_opt, metrics=["accuracy"])
```

Or, simply calling:

```
model.compile(loss="categorical_crossentropy", optimizer="adam", metrics=["accuracy"])
```

VI: Start your training

```
history = model.fit(x_train, y_train, batch_size=batch_size, epochs=epochs, validation_split=0.1, shuffle=True)
```

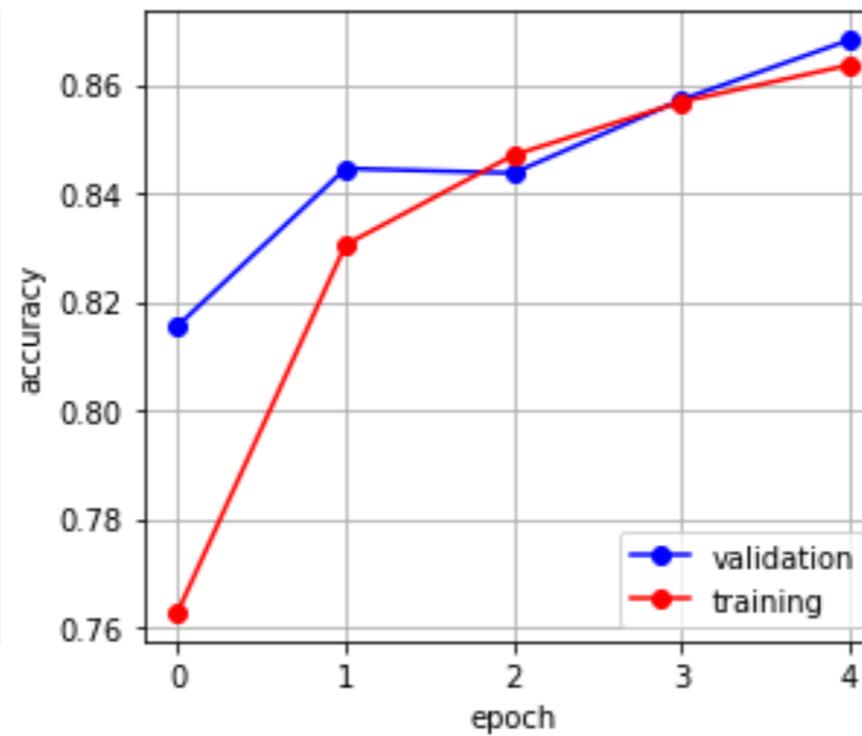
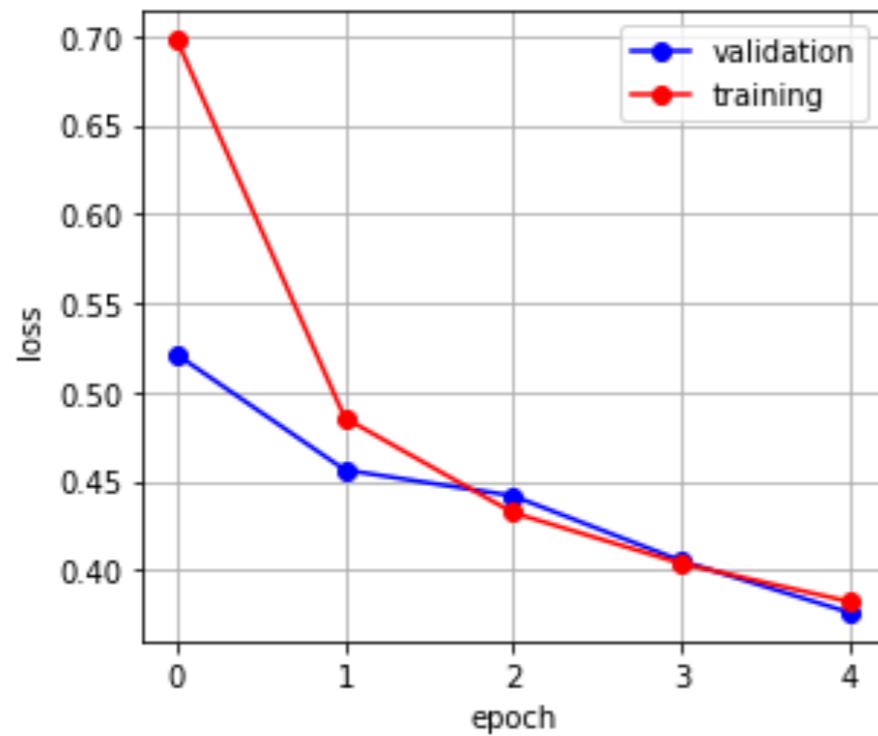
```
Epoch 1/5  
422/422 [=====] - 48s 114ms/step - loss: 0.3594 - accuracy: 0.8901 - val_loss: 0.0810 - val_accuracy: 0.9772  
Epoch 2/5  
422/422 [=====] - 42s 100ms/step - loss: 0.1094 - accuracy: 0.9663 - val_loss: 0.0552 - val_accuracy: 0.9845  
Epoch 3/5  
422/422 [=====] - 33s 78ms/step - loss: 0.0824 - accuracy: 0.9742 - val_loss: 0.0508 - val_accuracy: 0.9860  
Epoch 4/5  
422/422 [=====] - 33s 78ms/step - loss: 0.0691 - accuracy: 0.9789 - val_loss: 0.0446 - val_accuracy: 0.9880  
Epoch 5/5  
422/422 [=====] - 30s 72ms/step - loss: 0.0593 - accuracy: 0.9815 - val_loss: 0.0429 - val_accuracy: 0.9892
```

VII: Start your evaluation

```
model.evaluate(x_test, y_test) # Returns the loss value & metrics values for the model in test mode.
```

VIII: Start your analysis and visualize your metric

```
train_loss_history = history.history['loss']  
val_loss_history = history.history['val_loss']  
  
train_acc_history = history.history['accuracy']  
val_acc_history = history.history['val_accuracy']
```



Extra:

1: Custom data generator: https://www.tensorflow.org/api_docs/python/tf/keras/utils/Sequence

2: Data augmentation: <https://keras.io/api/preprocessing/image/>

3: Custom layer: https://keras.io/guides/making_new_layers_and_models_via_subclassing/

4: Custom metric: [https://github.com/borundev/ml_cookbook/blob/master/Custom%20Metric%20\(Confusion%20Matrix\)%20and%20train_step%20method.ipynb](https://github.com/borundev/ml_cookbook/blob/master/Custom%20Metric%20(Confusion%20Matrix)%20and%20train_step%20method.ipynb)