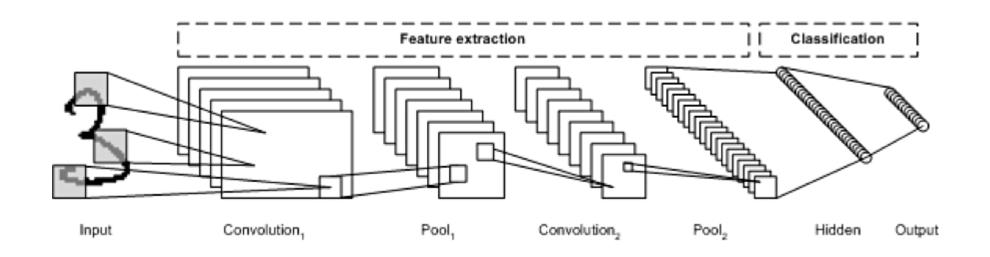
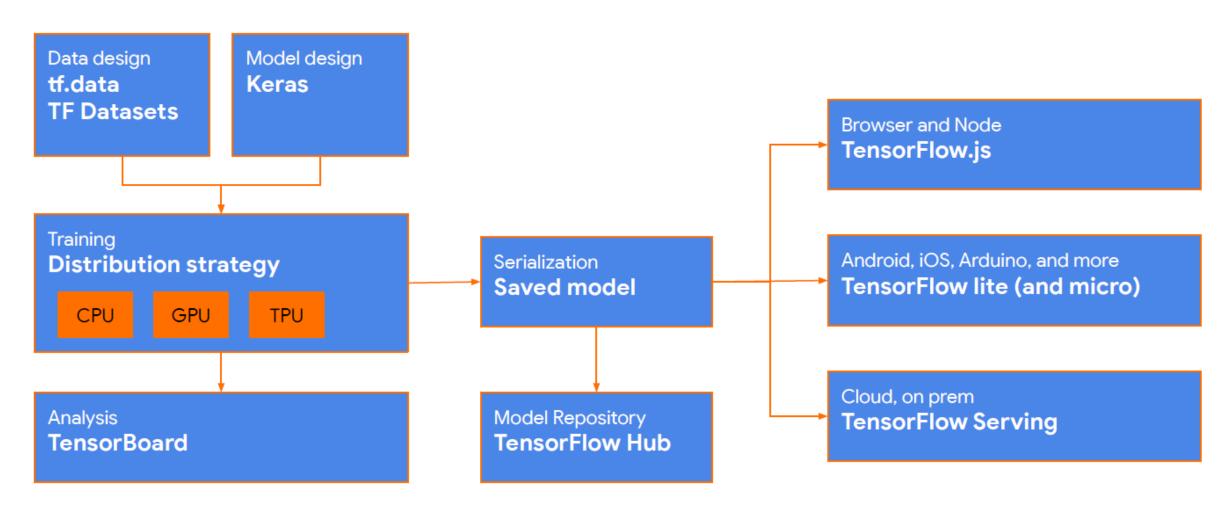
모델서브클래싱



Training

Deployment



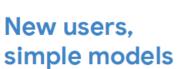
Sequential API + built-in layers Functional API + built-in layers

Functional API

- + Custom layers
- + Custom metrics
- + Custom losses

Subclassing: write everything yourself from scratch







Engineers with standard use cases



Engineers requiring increasing control



Researchers

```
model = keras.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(784,)))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(32, activation='softmax'))
```

Sequential API + built-in layers Functional API + built-in layers **Functional API**

- + Custom layers
- + Custom metrics
- + Custom losses

Subclassing: write everything yourself from scratch







Engineers with standard use cases



Engineers requiring increasing control



Researchers

Visual Question Answering



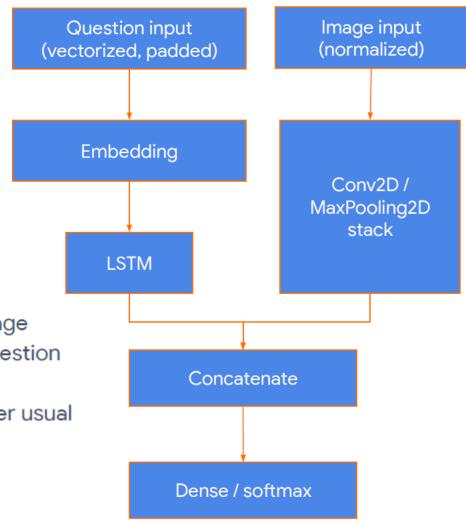
Question: What color is the dog on the right?

Answer: Golden

Workflow

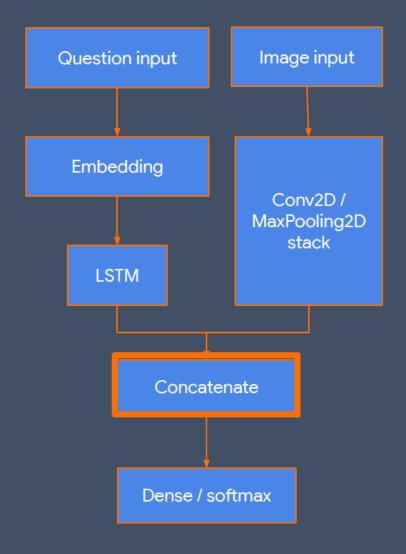
A multi-input model

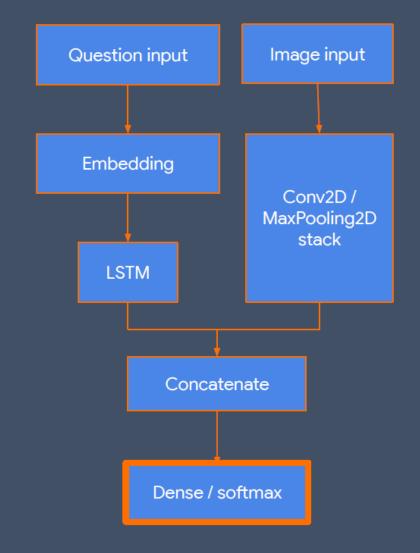
- Use a CNN to embed the image
- 2. Use a LSTM to embed the question
- 3. Concatenate
- 4. Classify with Dense layers, per usual



```
# A vision model.
                                                             Question input
                                                                            Image input
# Encode an image into a vector.
vision_model = Sequential()
vision_model.add(Conv2D(64, (3, 3),
                                                              Embedding
                           activation='relu',
                                                                             Conv2D /
                                                                           MaxPooling2D
                           input_shape=(224, 224, 3)))
                                                                              stack
vision_model.add(MaxPooling2D())
                                                                LSTM
vision_model.add(Flatten())
# Get a tensor with the output of your vision model
                                                                    Concatenate
image_input = Input(shape=(224, 224, 3))
encoded_image = vision_model(image_input)
                                                                   Dense / softmax
```

```
# A language model.
                                                                              Image input
                                                               Question input
# Encode the question into a vector.
question_input = Input(shape=(100,),
                          dtype='int32',
                                                                Embedding
                          name="Question")
                                                                               Conv2D /
                                                                             MaxPooling2D
                                                                                stack
embedded = Embedding(input_dim=10000,
                                                                  LSTM
                        output_dim=256,
                        input_length=100)(question_input)
                                                                      Concatenate
encoded_question = LSTM(256)(embedded_question)
                                                                     Dense / softmax
```





outputs=output)

Sequential API + built-in layers Functional API + built-in layers **Functional API**

- Custom layers
- Custom metrics
- + Custom losses

Subclassing: write everything yourself from scratch



New users, simple models



Engineers with standard use cases





Researchers

```
class MyModel(tf.keras.Model):
    def __init__(self, num_classes=10):
        super(MyModel, self).__init__(name='my_model')
        self.dense_1 = layers.Dense(32, activation='relu')
        self.dense_2 = layers.Dense(num_classes,activation='softmax')

def call(self, inputs):
    # Define your forward pass here
    x = self.dense_1(inputs)
    return self.dense_2(x)
```

```
class MyModel(tf.keras.Model):
    def __init__(self, num_classes=10):
        super(MyModel, self).__init__(name='my_model')
        self.dense_1 = layers.Dense(32)
        self.dense_2 = layers.Dense(num_classes,activation='softmax')

def call(self, inputs):
    # Define your forward pass here
    x = self.dense_1(inputs)
    x = tf.nn.relu(x)
    return self.dense_2(x)
```

Model training

model.fit() model.fit() model.train_on_batch(), Custom training loop +callbacks + callbacks with GradientTape **Quick experiment Customize your** Custom training loop Complete control training loop using built-in e.g. new optimization Add checkpointing, optimizers and losses algorithm; easily modify early stopping, e.g. GANs gradients as you go. **TensorBoard** monitoring, send Slack notifications...

```
model.compile(optimizer=Adam(),
              loss=BinaryCrossentropy(),
              metrics=[AUC(), Precision(), Recall()])
model.fit(data,
          epochs=10,
          validation_data=val_data,
          callbacks=[EarlyStopping()
                      TensorBoard(),
                     ModelCheckpoint()])
```

...or write your own callbacks!

Model training

model.fit()

model.fit() +callbacks model.train_on_batch(), + callbacks

Custom training loop with GradientTape









Customize your training loop Add checkpointing, early stopping, TensorBoard monitoring, ... Custom training loop using built-in optimizers and losses e.g. GANs e.g. new optimization algorithm; easily modify gradients as you go.

Graphs with one LOC

```
@tf.function
def train_step(features, labels):
    with tf.GradientTape() as tape:
        logits = model(features, training=True)
        loss = loss_fn(labels, logits)

    grads = tape.gradient(loss, model.trainable_variables)
    optimizer.apply_gradients(zip(grads, model.trainable_variables))
    return loss
```

Gradients

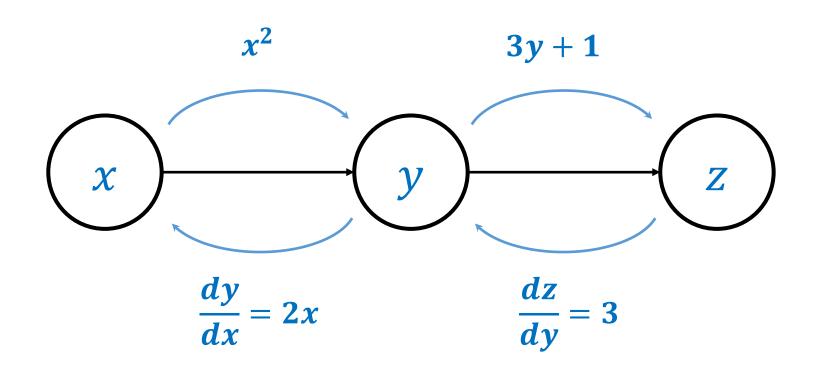
```
x = tf.constant(3.0)
with tf.GradientTape() as g:
    g.watch(x)
    y = x * x
dy_dx = g.gradient(y, x) # 6.0
```

Variables are automatically tracked

```
dense1 = tf.keras.layers.Dense(32)
dense2 = tf.keras.layers.Dense(32)
```

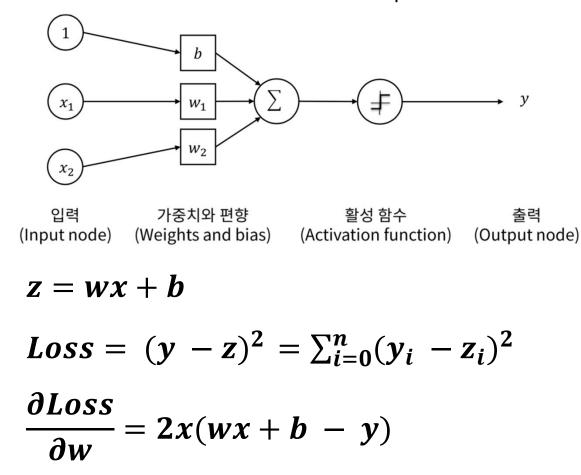
```
with tf.GradientTape() as tape:
    result = dense2(dense1(tf.zeros([1, 10])))
    tape.gradient(result, dense1.variables)
```

계산그래프(Computational Graph)



Gradient 계산

- 텐서플로는 자동미분(automatic difference)을 지원합니다.
- 중첩된 함수의 그레이디언트를 계산하기 위해 연쇄법칙(Chain Rule)을 구현한 것으로 생각할 수 있습니다.
- 텐서플로는 계산그래프안에서 Tensor의 Gradient를 계산하는 기능을 제공합니다.
- Gradient 를 계산하려면 tf.GradientTape을 통해 계산을 기록해야 합니다.



```
import tensorflow as tf
    w = tf.Variable(1.0)
   b = tf.Variable(0.5)
    print(w.trainable, b.trainable)
    x = tf.convert to tensor([1.4])
    y = tf.convert to tensor([2.1])
    with tf.GradientTape() as tape:
        z = tf.add(tf.multiply(w, x), b)
11
        loss = tf.reduce sum(tf.square(y - z))
13
14
15
    dloss_dw = tape.gradient(loss, w)
    tf.print('dL/dw : ', dloss_dw)
```



model_subclassing.ipynb

Conv 3

3x3, 16개

MaxPool(2,2)

ReLU

nv 3x3, 32개

MaxPool(2,2)
ReLU

Conv 3x3, 64개

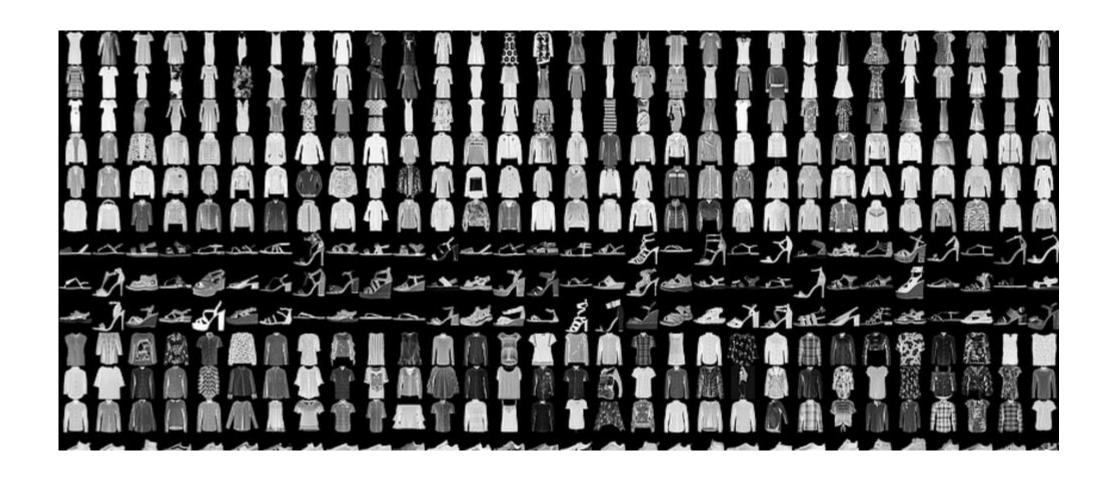
Flatten

ReLU

FC, 10

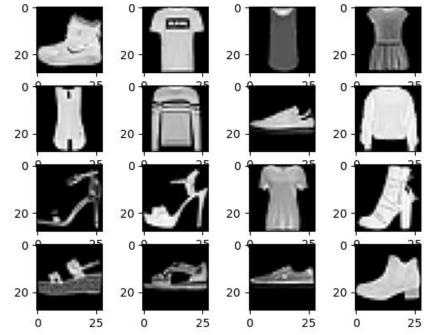
Softmax

- Fashion MNIST 데이터셋은 운동화, 셔츠, 샌들과 같은 작은 이미지들의 모음입니다.
- 기본 MNIST 데이터셋과 같이 열 가지로 분류될 수 있는 28×28 픽셀의 이미지 70,000개로 이루어져 있습니다.



```
import matplotlib.pyplot as plt
    import tensorflow as tf
    from tensorflow.keras.datasets import fashion mnist
    from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
 6
   # load fashion mnist data
    (x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
 9
10
   # adjusting to 0 ~ 1.0
    x_{train} = x_{train} / 255.0
   x \text{ test} = x \text{ test} / 255.0
14
    print(x_train.shape, x_test.shape)
```

```
17  # reshaping
18  x_train = x_train.reshape(-1,28,28,1)
19  x_test = x_test.reshape(-1,28,28,1)
20
21  # plotting
22  plt.figure()
23  for c in range(16):
24     plt.subplot(4,4,c+1)
25     plt.imshow(x_train[c].reshape(28,28), cmap='gray')
26  plt.show()
```



```
class MyModel(tf.keras.Model):
        def init (self):
29
            super(MyModel, self). init ()
30
31
            self.conv1 = Conv2D(kernel_size=(3,3), filters=16, activation='relu')
            self.conv2 = Conv2D(kernel_size=(3,3), filters=32, activation='relu')
32
            self.conv3 = Conv2D(kernel_size=(3,3), filters=64, activation='relu')
33
34
            self.pool = MaxPooling2D((2, 2))
            self.flatten = Flatten()
35
            self.d1 = Dense(32, activation='relu')
36
            self.d2 = Dense(10, activation='softmax')
37
38
39
       def call(self, x):
            x = self.conv1(x)
40
41
            x = self.pool(x)
            x = self.conv2(x)
42
43
            x = self.pool(x)
44
            x = self.conv3(x)
            x = self.flatten(x)
45
            x = self.d1(x)
46
            return self.d2(x)
47
```

```
model = MyModel()
50
   # compile and train
   model.compile(optimizer='adam',
53
                  loss='sparse categorical crossentropy',
                  metrics=['accuracy'])
54
55
56
   history = model.fit(x_train, y_train,
        epochs=10, validation split=0.25)
58
59
   plt.figure(figsize=(10,4))
  plt.subplot(1,2,1)
  plt.plot(history.history['loss'], 'b-', label='loss')
  plt.plot(history.history['val_loss'], 'r-', label='val_loss')
  plt.xlabel('epoch')
   plt.legend()
```

Gradient 및 자동 미분 실습



https://www.tensorflow.org/guide/autodiff?hl=ko



model_subclassing_gt.ipynb

Loss Function 정의

```
[12] loss_function = SparseCategoricalCrossentropy()
```

Optimizer 정의

```
[13] optimizer = Adam()
```

Metric 정의

```
[14] train_loss = Mean()
    train_acc = SparseCategoricalAccuracy()
    test_loss = Mean()
    test_acc = SparseCategoricalAccuracy()
```

Train step 함수

```
[15] @tf.function
     def train_step(images, labels):
         with tf.GradientTape() as tape:
            # 1. 예측(Prediction)
            predictions = model(images)
            # 2. Loss 계산
             loss = loss function(labels, predictions)
         # 3. Gradients 계산
         gradients = tape.gradient(loss, model.trainable_variables)
         # 4. 오차역전파(Backpropagation) - weight 업데이트
         optimizer.apply_gradients(zip(gradients, model.trainable_variables))
         # loss와 accuracy를 업데이트 합니다.
         train_loss(loss)
         train_acc(labels, predictions)
```

Test step 함수

```
[16] @tf.function
    def test_step(images, labels):
        # 1. 예측(Prediction)
        predictions = model(images)
        # 2. Loss 계산
         loss = loss_function(labels, predictions)
        # Test셋에 대해서는 gradient를 계산 및 backpropagation 하지 않습니다.
        # loss와 accuracy를 업데이트
        test_loss(loss)
        test_acc(labels, predictions)
```

모델 훈련

```
[17] EPOCHS = 10
     for epoch in range(EPOCHS):
         for train_images, train_labels in train_ds:
             train_step(train_images, train_labels)
         for test_images, test_labels in test_ds:
            test_step(test_images, test_labels)
         template = 'Epoch : {}, Train Loss : {:.5f}, 정확도: {:.2f}%, 테스트 손실: {:.5f}, 테스트
         print (template.format(epoch+1.
                               train_loss.result().
                               train_acc.result()*100,
                               test loss.result().
                               test_acc.result()*100))
```

Epoch : 1, Train Loss : 0.57843, 정확도: 78.79%, 테스트 손실: 0.42673, 테스트 정확도: 84.77% Epoch : 2, Train Loss : 0.46914, 정확도: 82.85%, 테스트 손실: 0.39928, 테스트 정확도: 85.69%

Thank you