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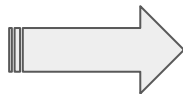
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# Built in Solution to Training

- Train using `model.compile()` and `model.fit()`.
- Specify `optimizer`, `loss` etc in `model.compile()`
- `model.fit()` loops through batches of training data to:
  - Update trainable weights to minimize loss.
  - Achieves the above using chosen optimizer.

# Custom Training Loops

`model.compile()`  
`model.fit()`



Custom Training  
Manage batches  
Calculate loss  
Minimize loss  
Update weights

# Steps to training network

1. **Define** the network
2. **Prepare** the training data
3. **Define** loss and optimizer
4. **Train** the model on training inputs by minimizing loss using custom optimizer.
5. **Validate** the model.

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# 1. Define the Model

```
class Model():  
    def __init__(self):  
        self.w = tf.Variable(5.0)  
        self.b = tf.Variable(0.0)  
  
    def __call__(self, x):  
        return self.w * x + self.b
```

## 2. Prepare Training Data

```
TRUE_w = 3.0
```

```
TRUE_b = 2.0
```

```
NUM_EXAMPLES = 1000
```

```
random_xs = tf.random.normal(shape=[NUM_EXAMPLES])
```

```
ys = (TRUE_w * random_xs) + TRUE_b
```

# Mean Squared Error Loss

$$MSE = \frac{1}{n} \sum_{i=1}^n \left( y_i - y'_i \right)^2$$

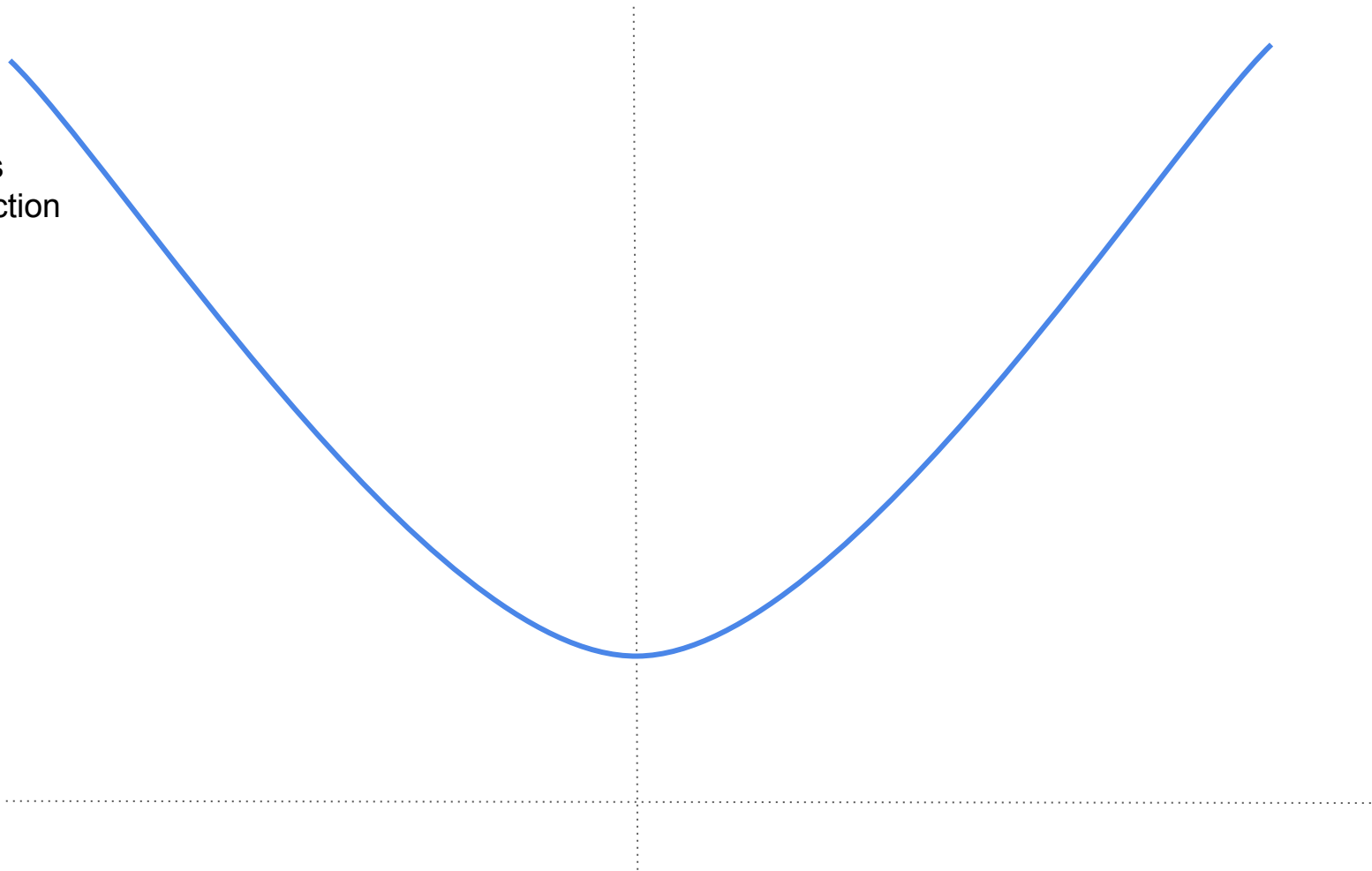


$$MSE = \text{mean} \left( (Y_{true} - Y_{pred})^2 \right)$$

### 3. Mean Squared Error Loss

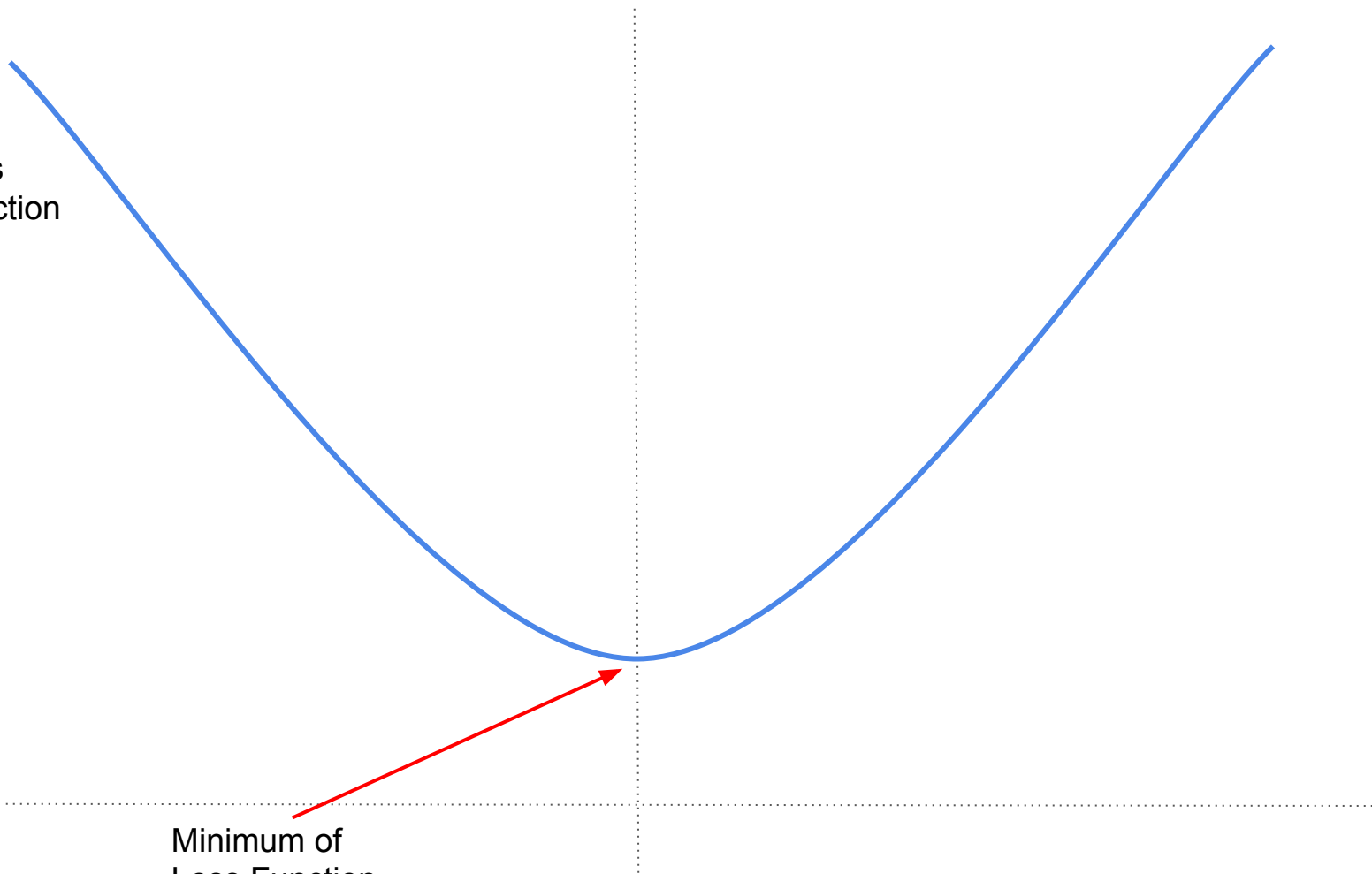
```
def loss(y_true, y_pred):  
    return tf.reduce_mean(tf.square(y_true - y_pred))
```

Loss  
Function

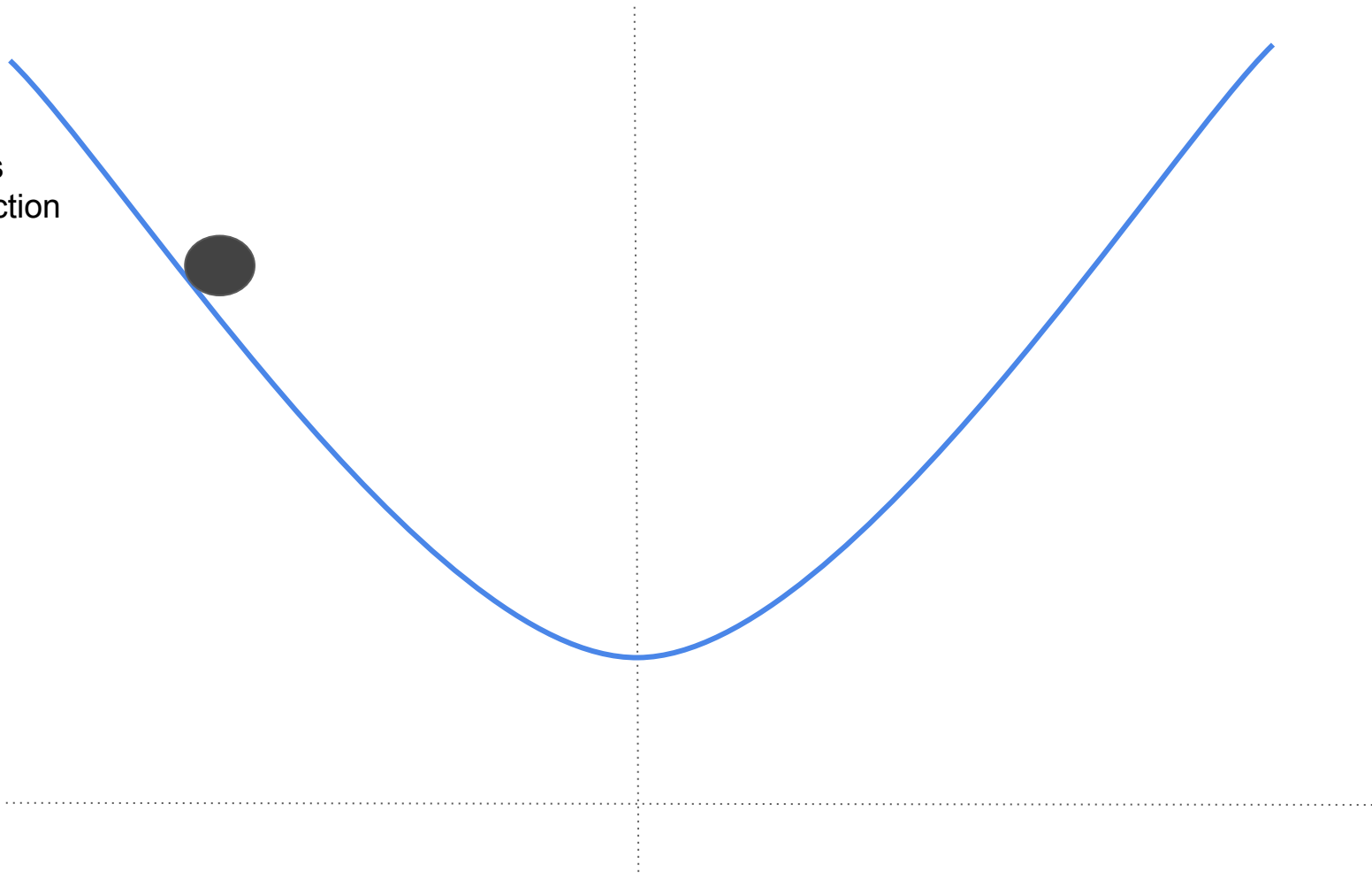


Loss  
Function

Minimum of  
Loss Function



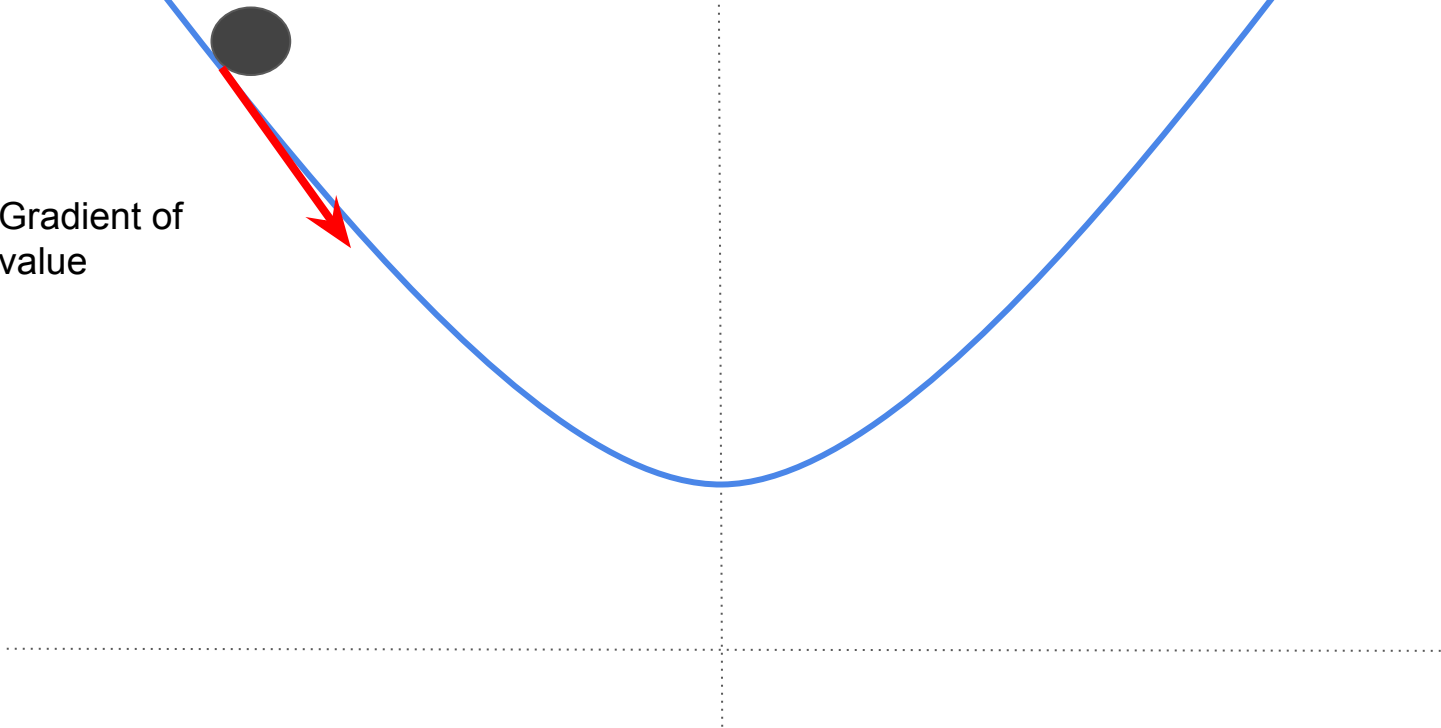
Loss  
Function





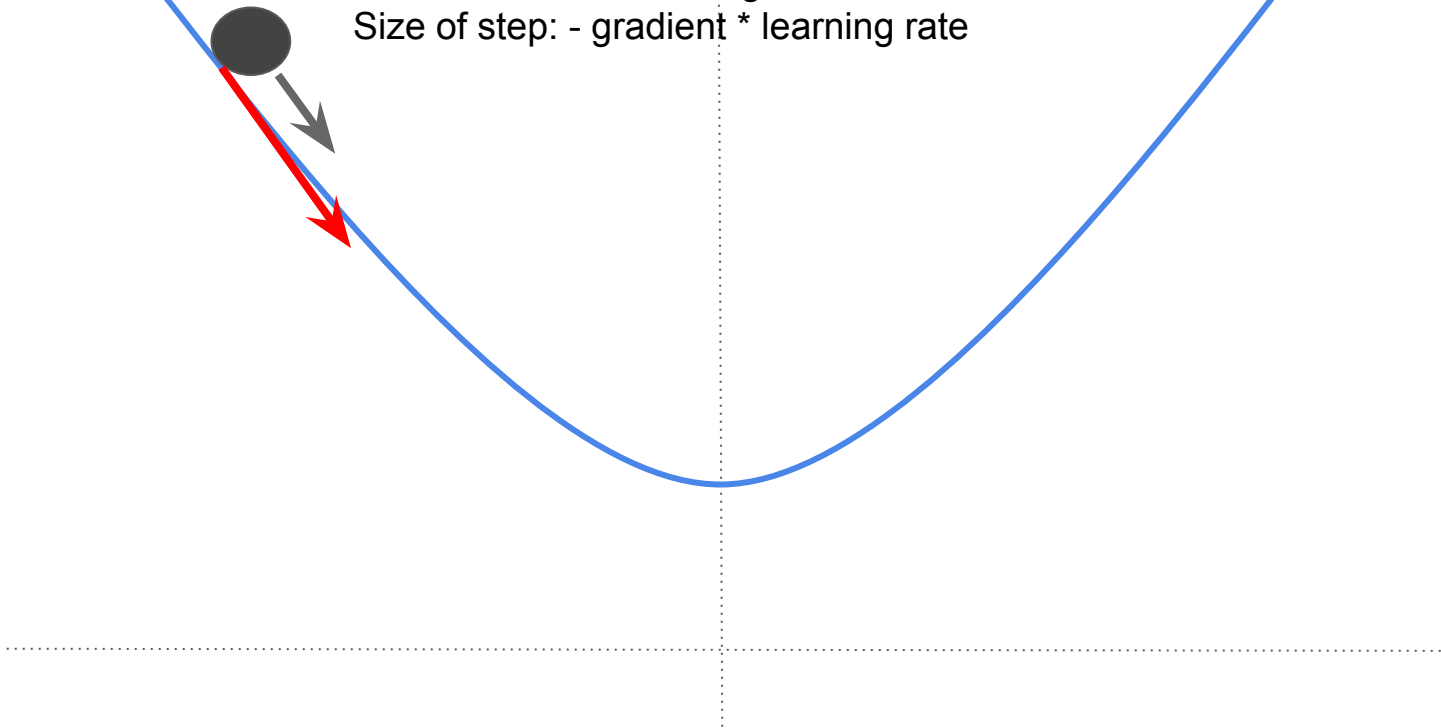
Loss  
Function

Gradient of  
value



Loss  
Function

Move in Direction of Negative of Gradient  
Size of step:  $-\text{gradient} * \text{learning rate}$



Loss  
Function

End up here



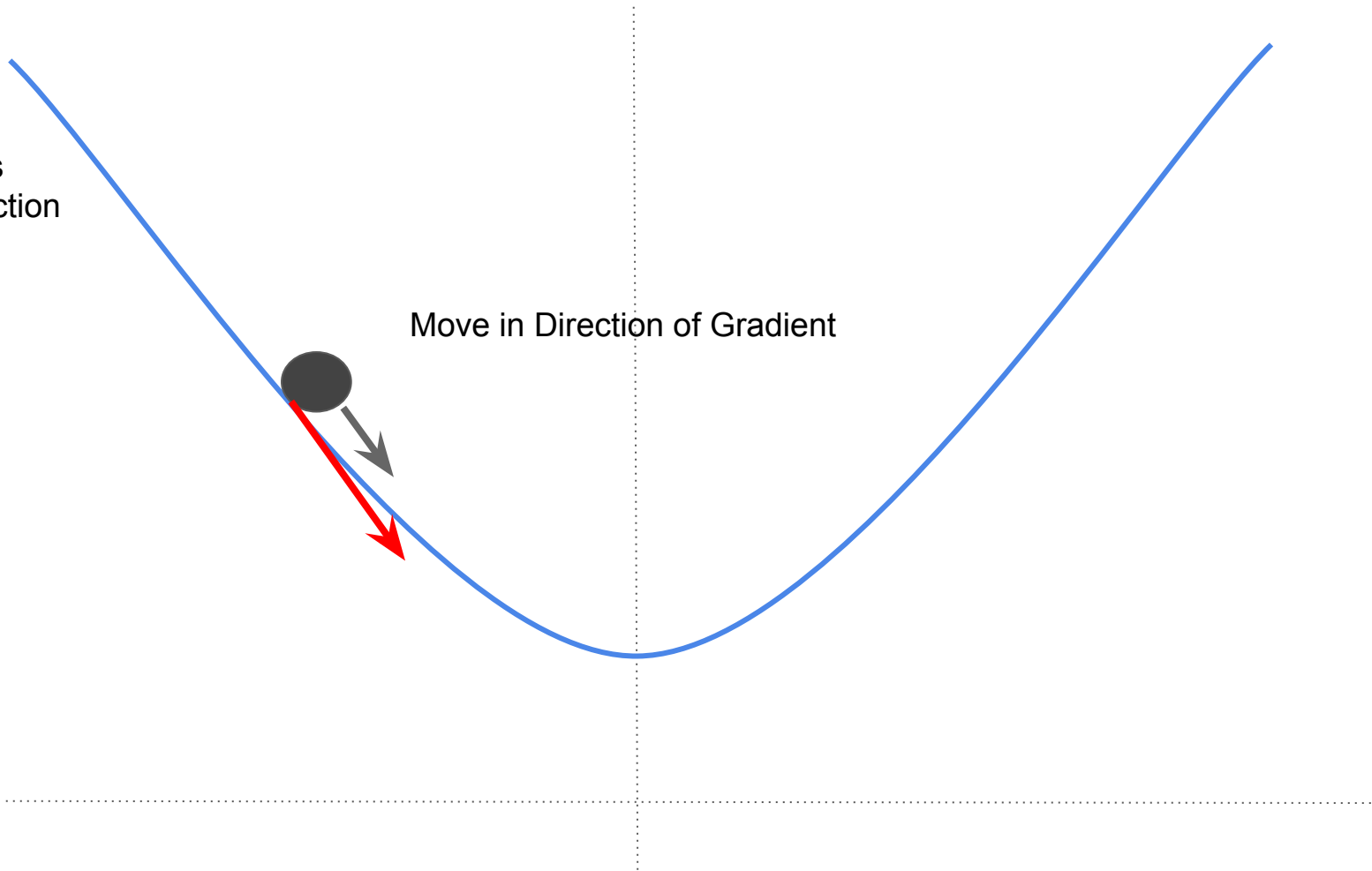
Loss  
Function

Get the gradient



Loss  
Function

Move in Direction of Gradient

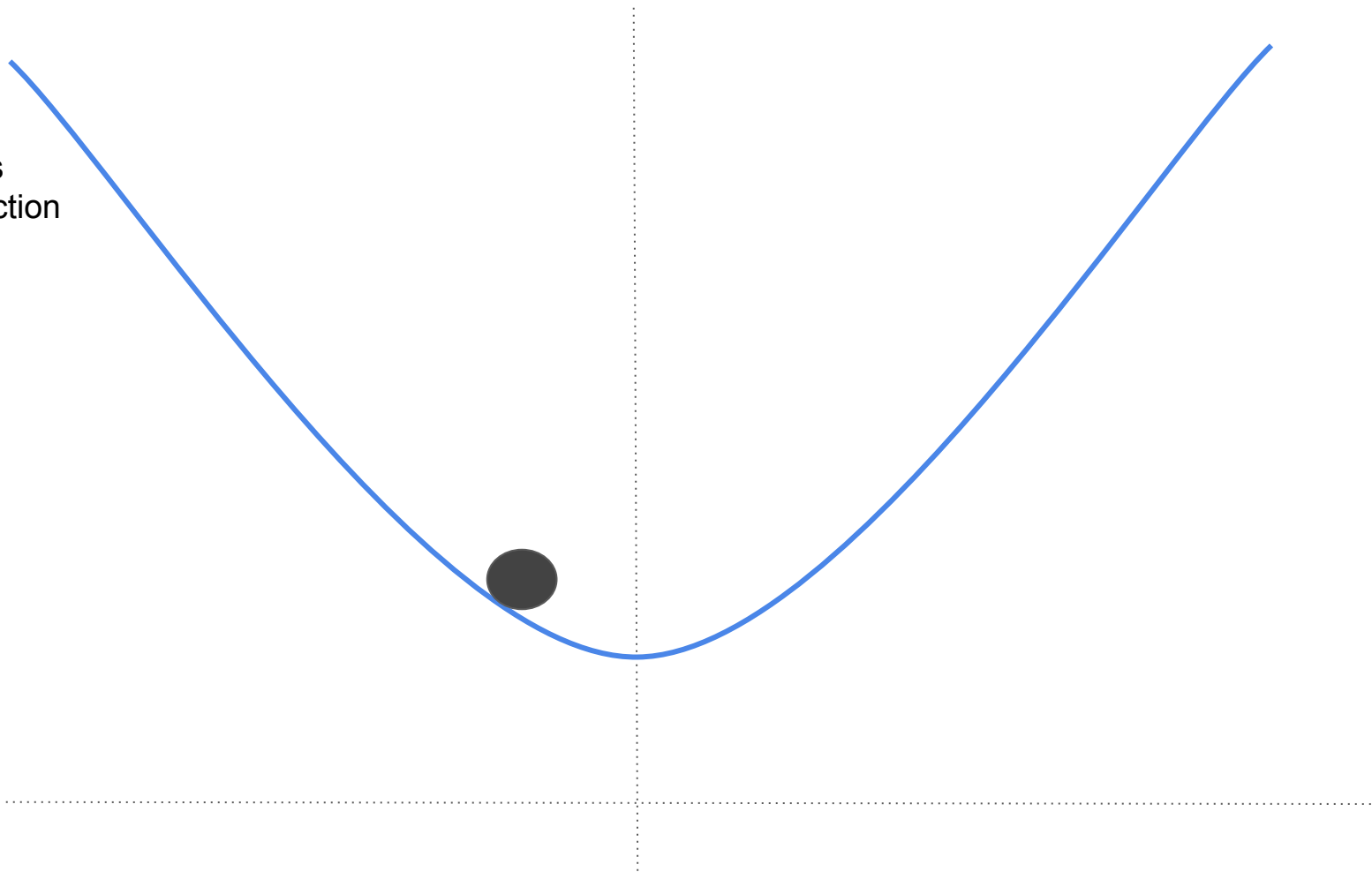


Loss  
Function

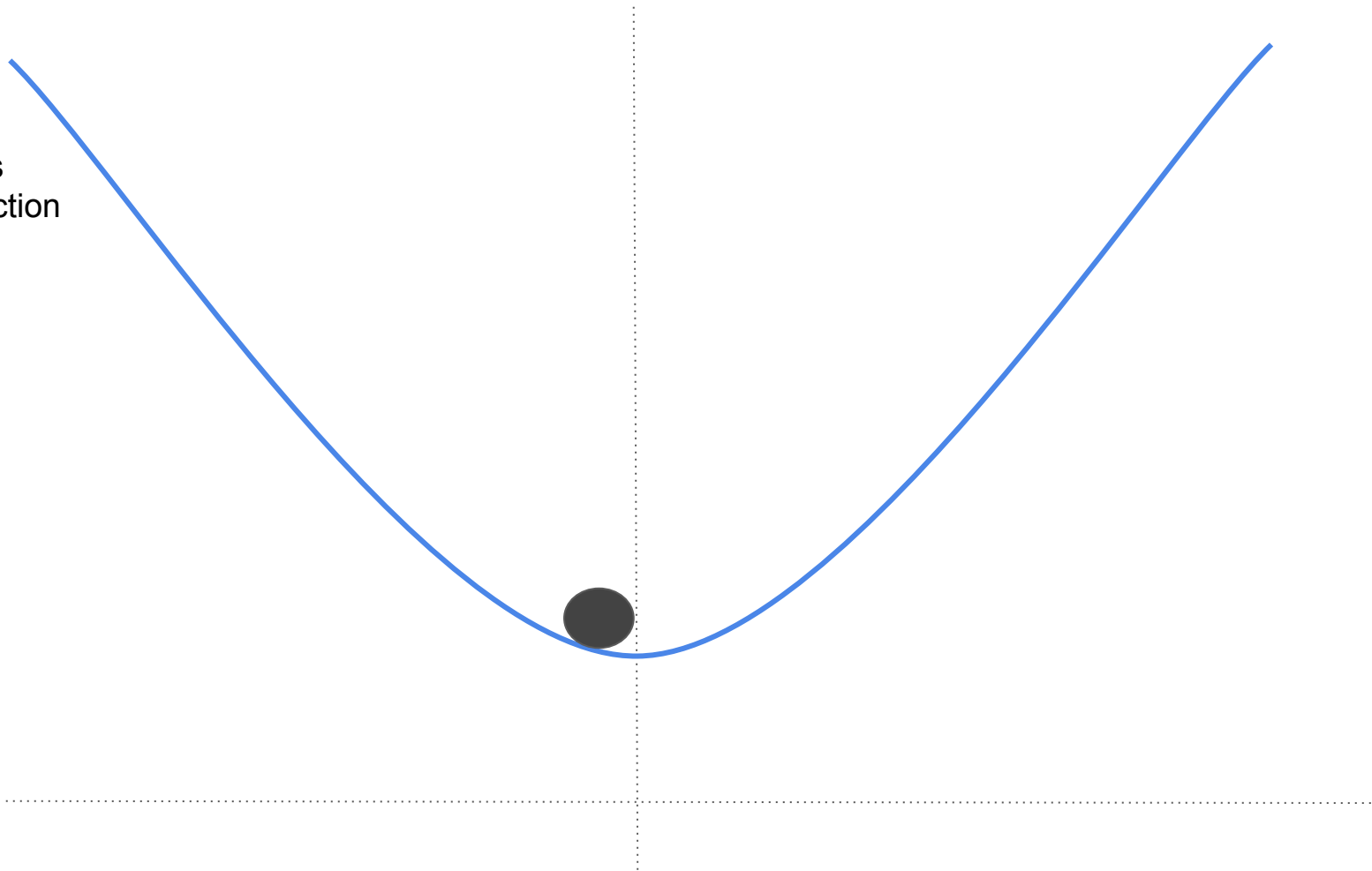
End Up here



Loss  
Function

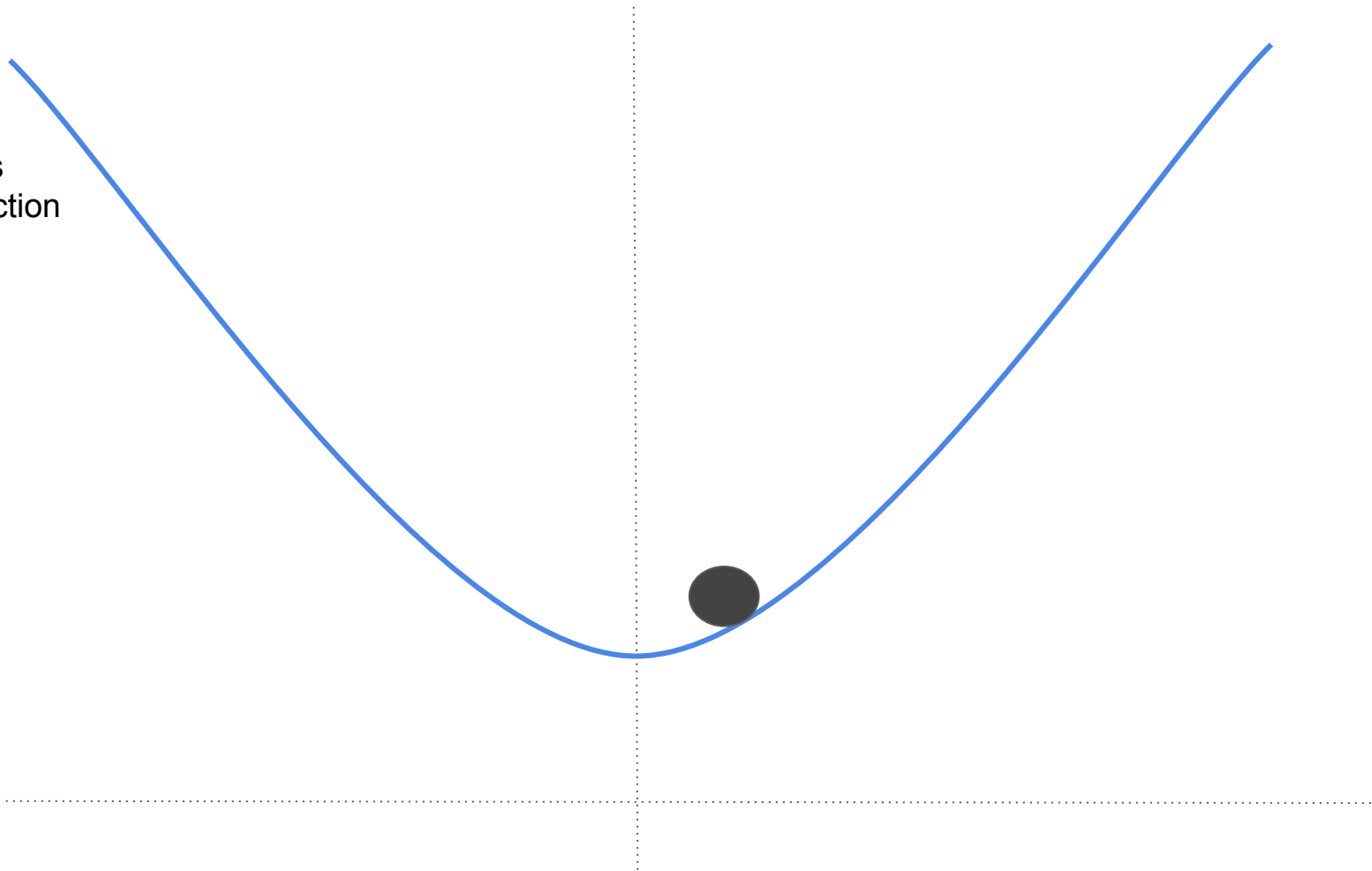


Loss  
Function

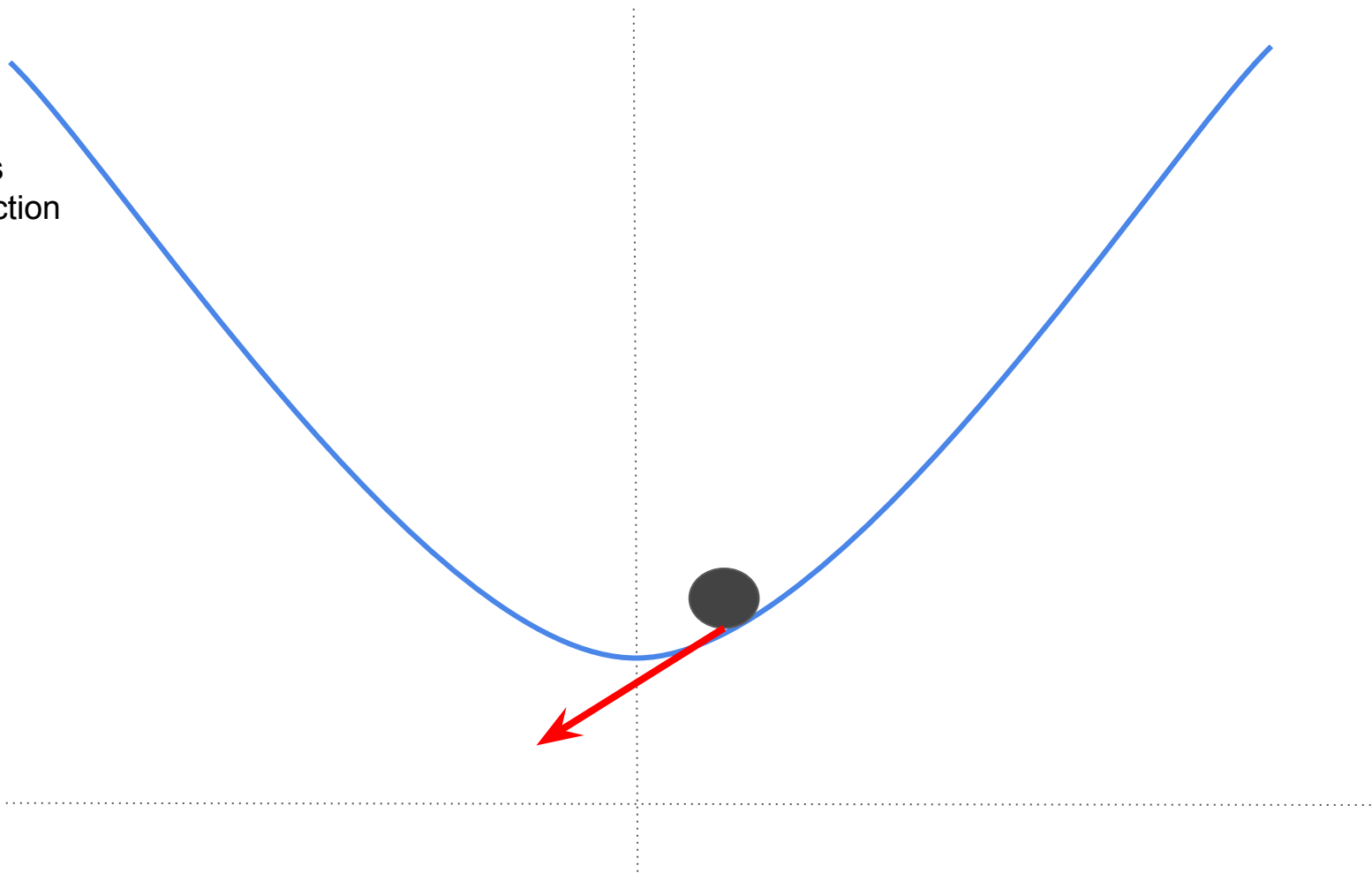




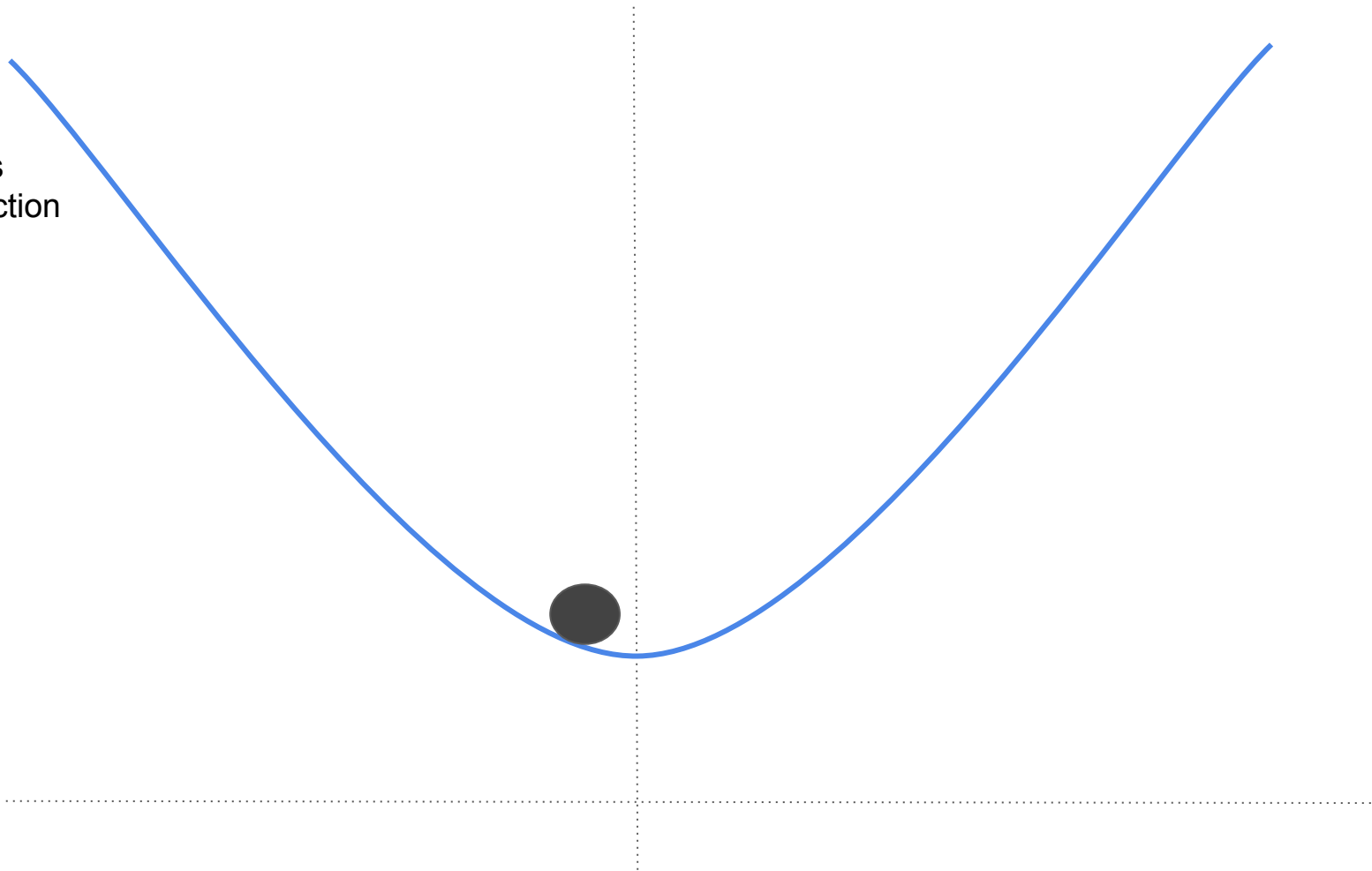
Loss  
Function



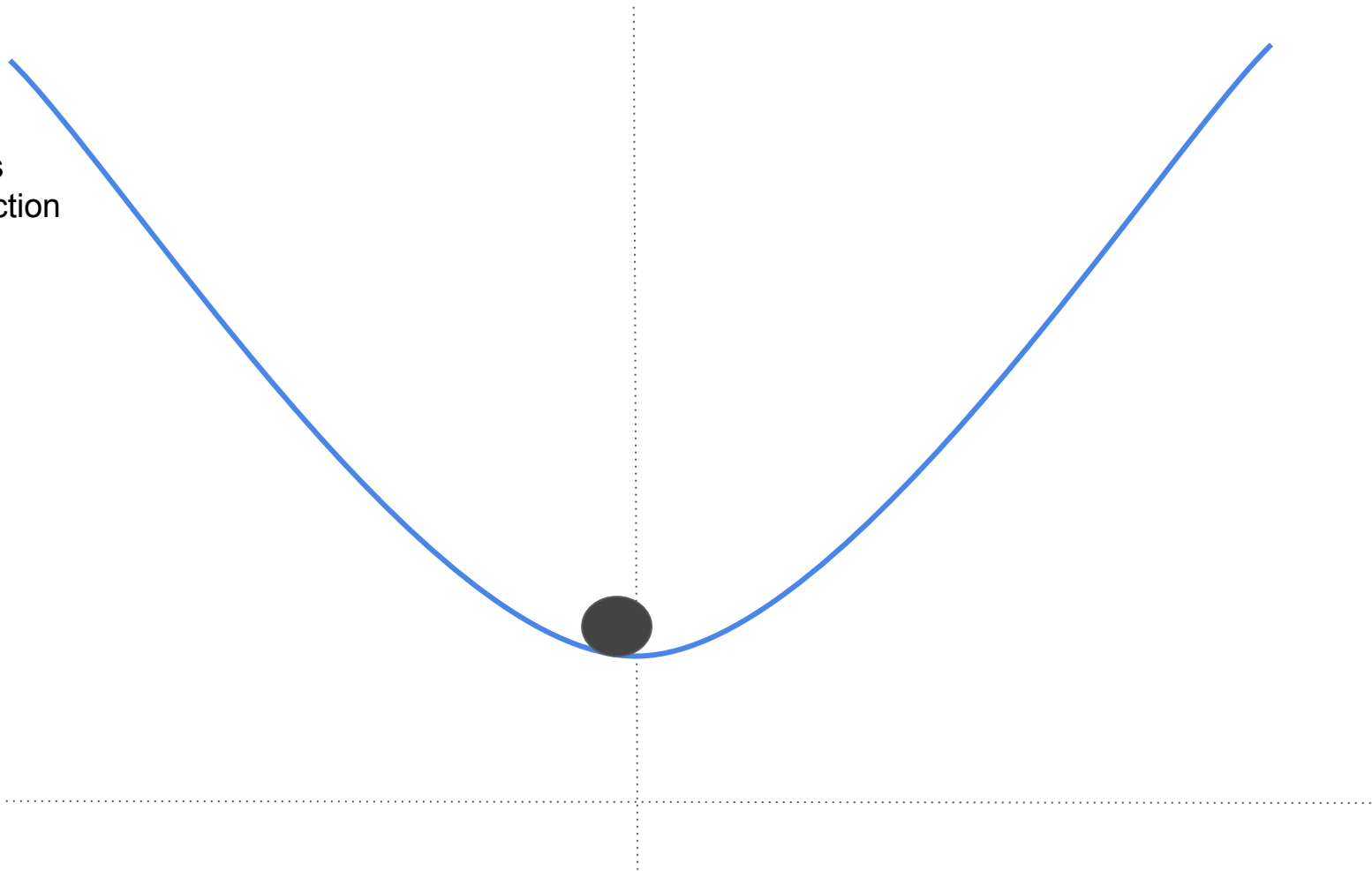
Loss  
Function



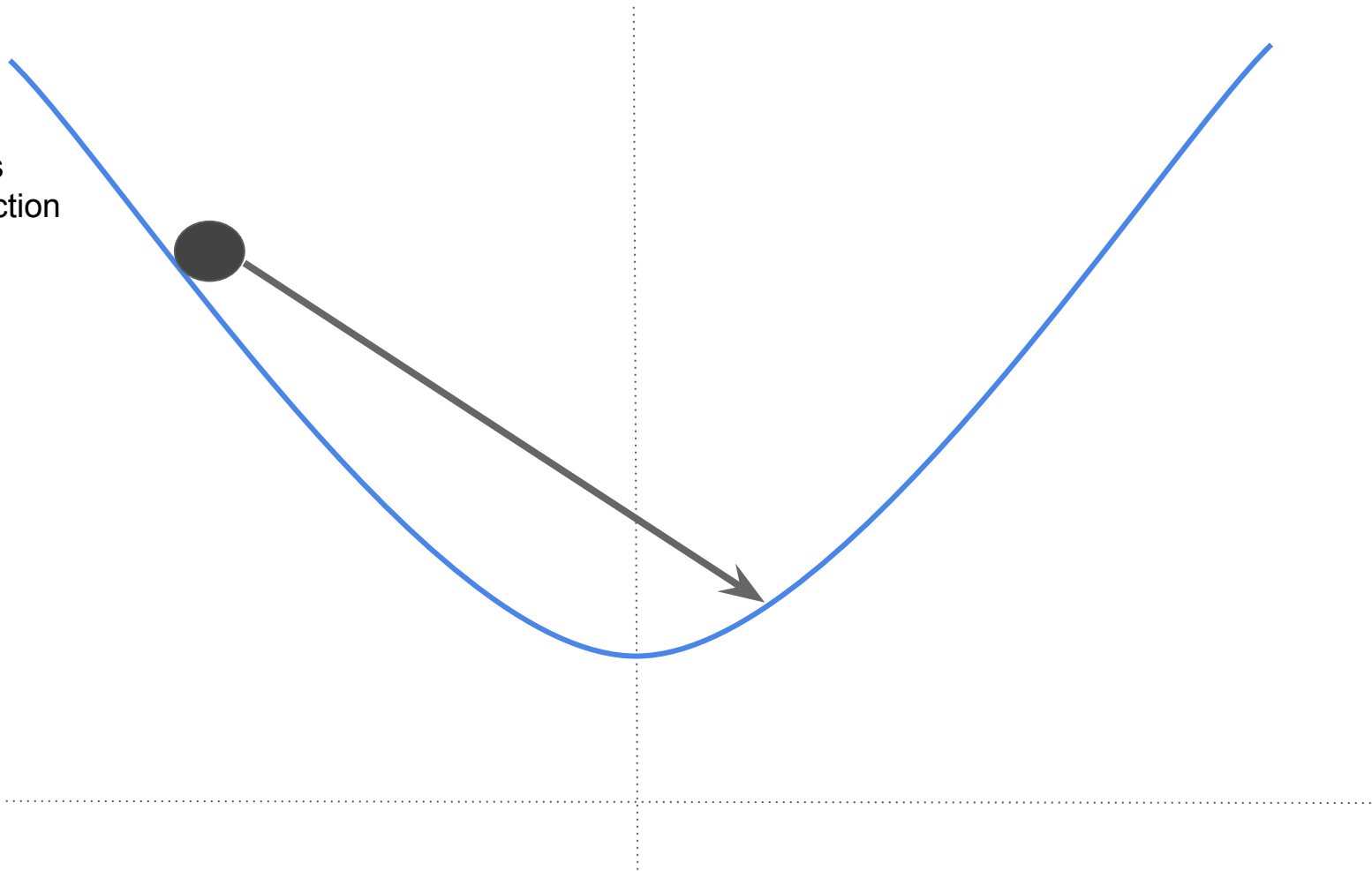
Loss  
Function



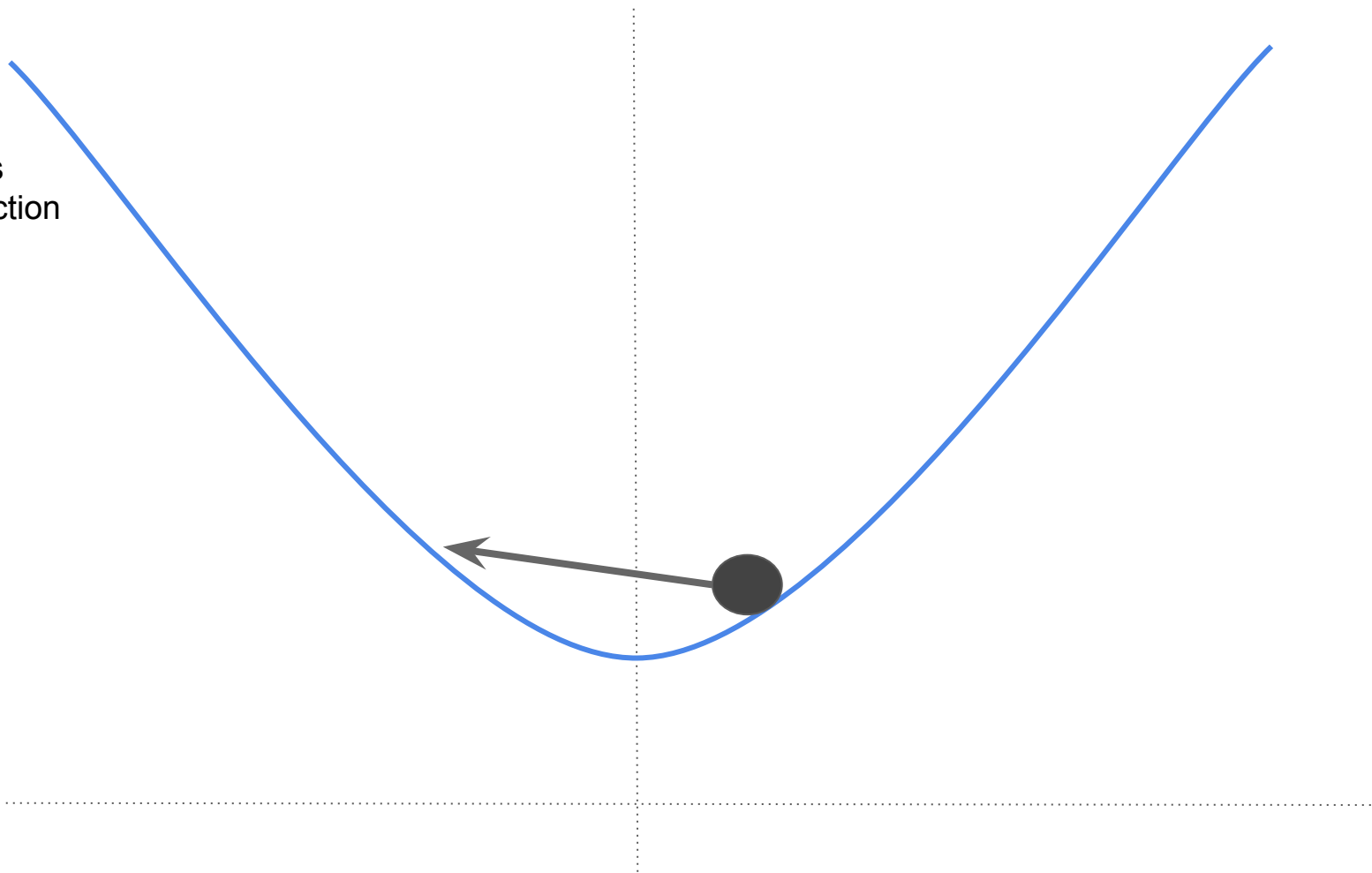
Loss  
Function



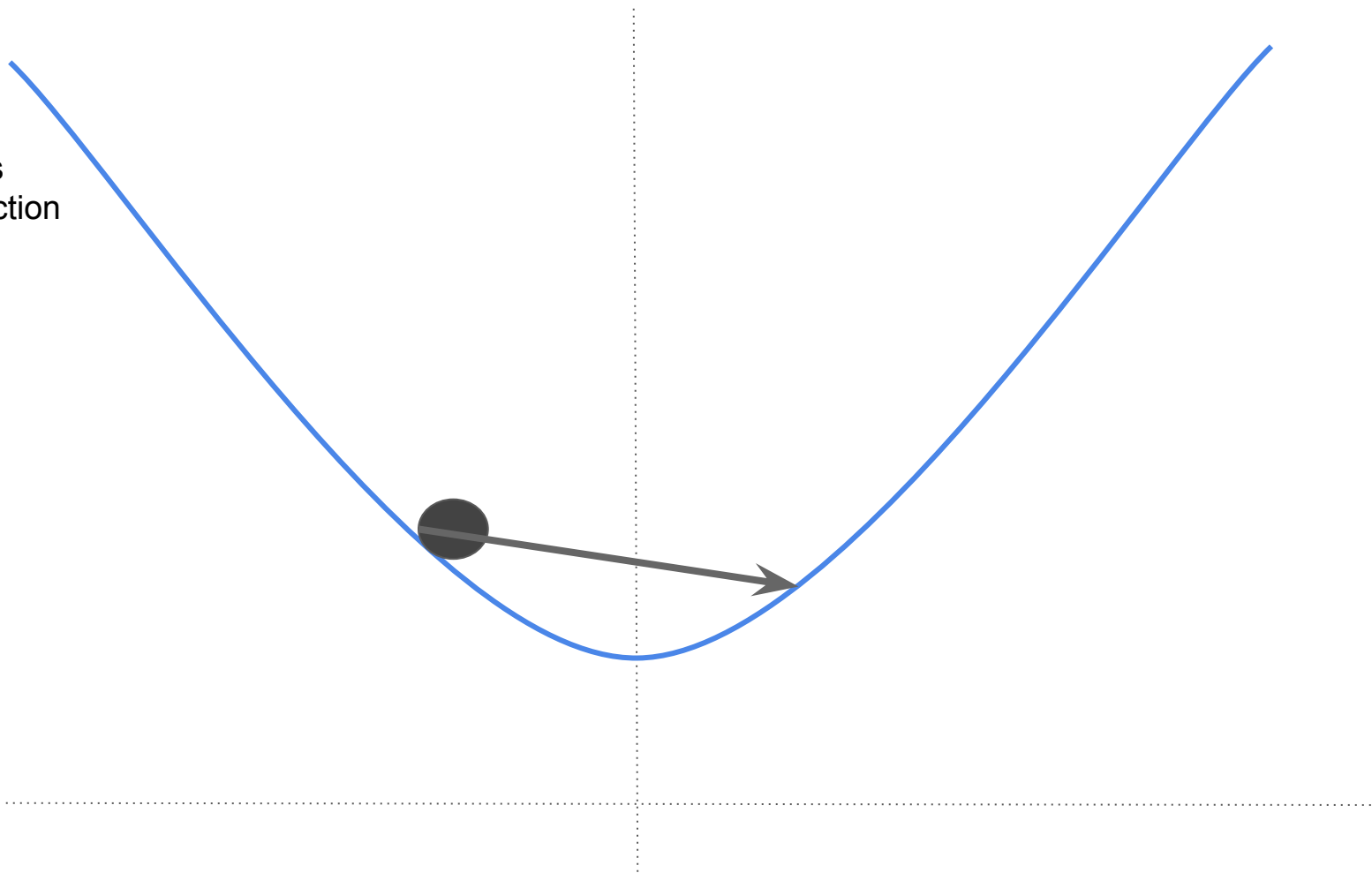
Loss  
Function



Loss  
Function



Loss  
Function



Loss  
Function

Move in Direction of Gradient





Loss  
Function

Move in Direction of Gradient



Loss  
Function

Move in Direction of Gradient



Loss  
Function

Move in Direction of Gradient



Loss  
Function

Move in Direction of Gradient

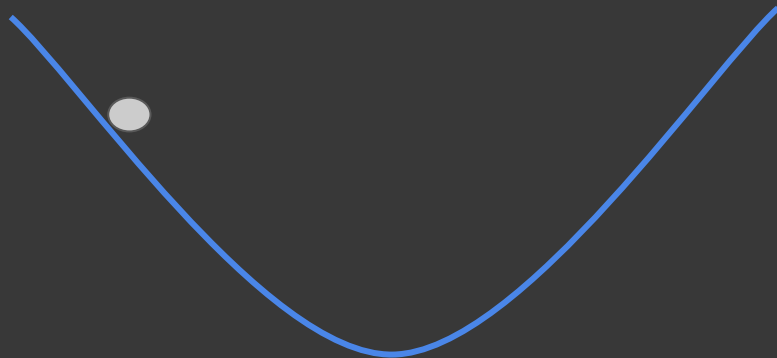


# Calculate Partial Derivative of Loss

```
def train(model, inputs, outputs, learning_rate):  
    with tf.GradientTape() as tape:  
        current_loss = loss(outputs, model(inputs))  
        dw, db = tape.gradient(current_loss, [model.w, model.b])  
  
        model.w.assign_sub(learning_rate * dw)  
        model.b.assign_sub(learning_rate * db)
```

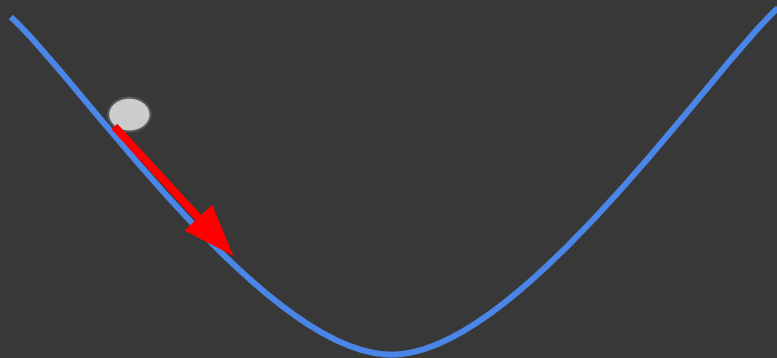
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```



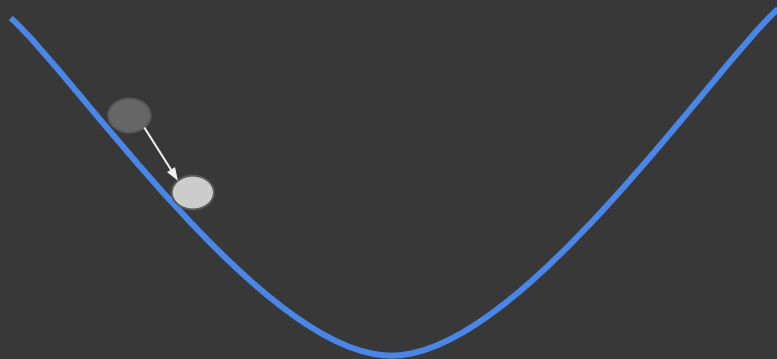
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    with tf.GradientTape() as tape:  
        current_loss = loss(outputs, model(inputs))  
    dw, db = tape.gradient(current_loss, [model.w, model.b])
```

```
model.w.assign_sub(learning_rate * dw)  
model.b.assign_sub(learning_rate * db)
```

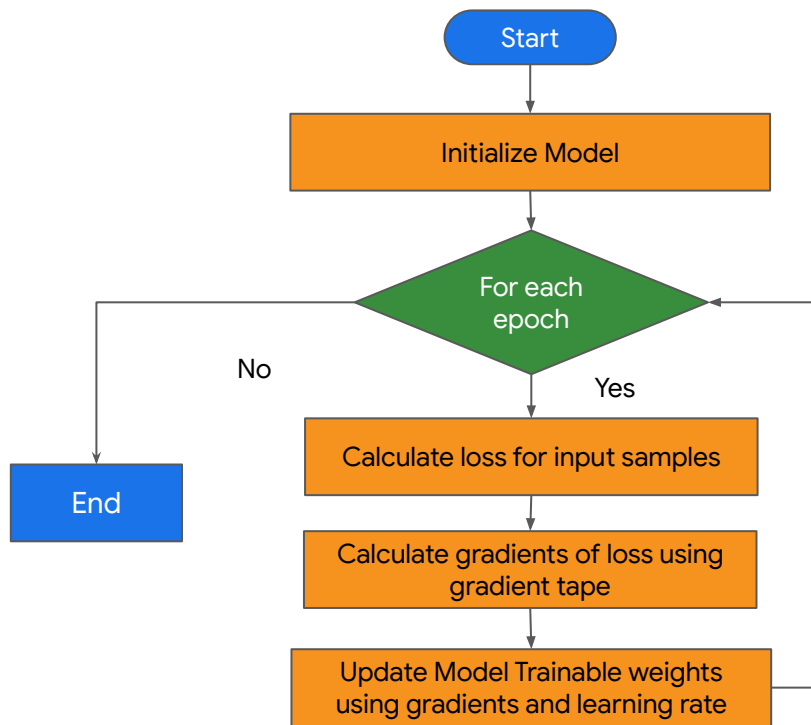
$$w = w - \alpha \times \frac{dL}{dw}$$

$$b = b - \alpha \times \frac{dL}{db}$$

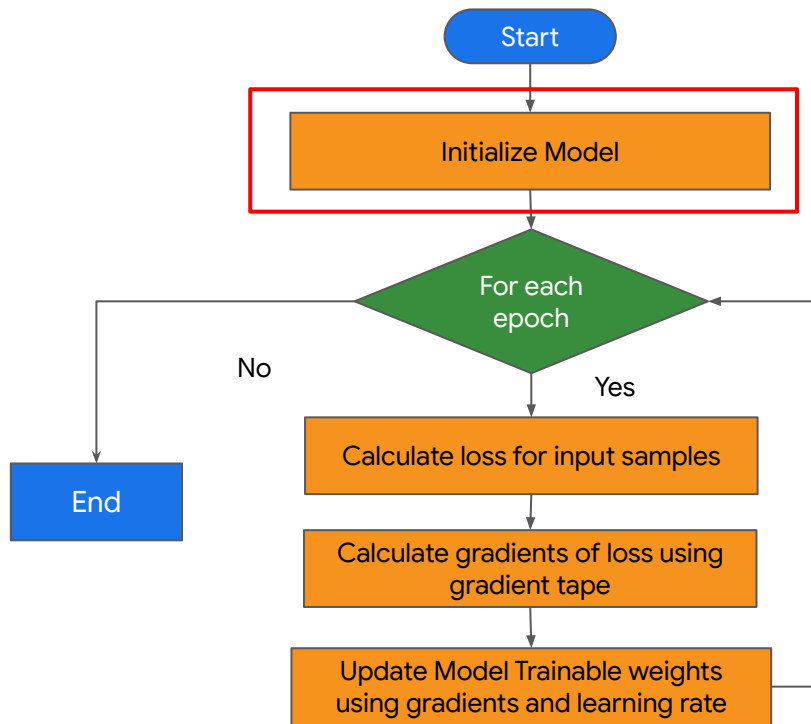




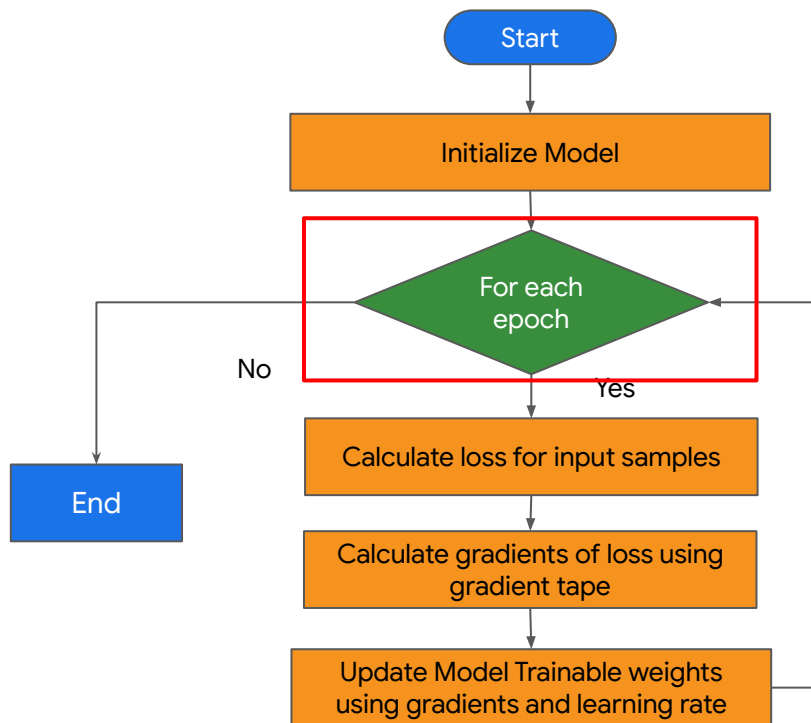
# 4. Training Loop



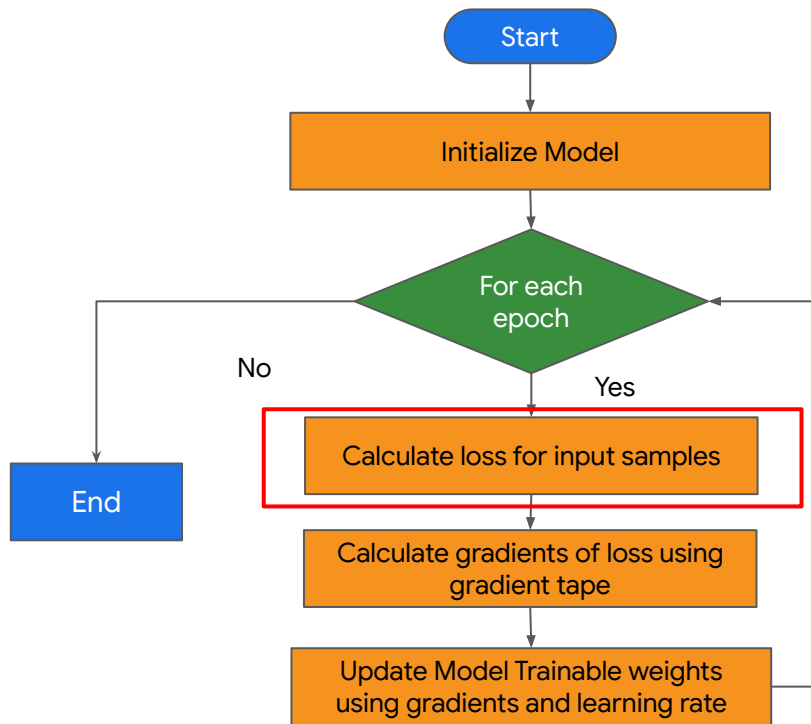
# 4. Training Loop



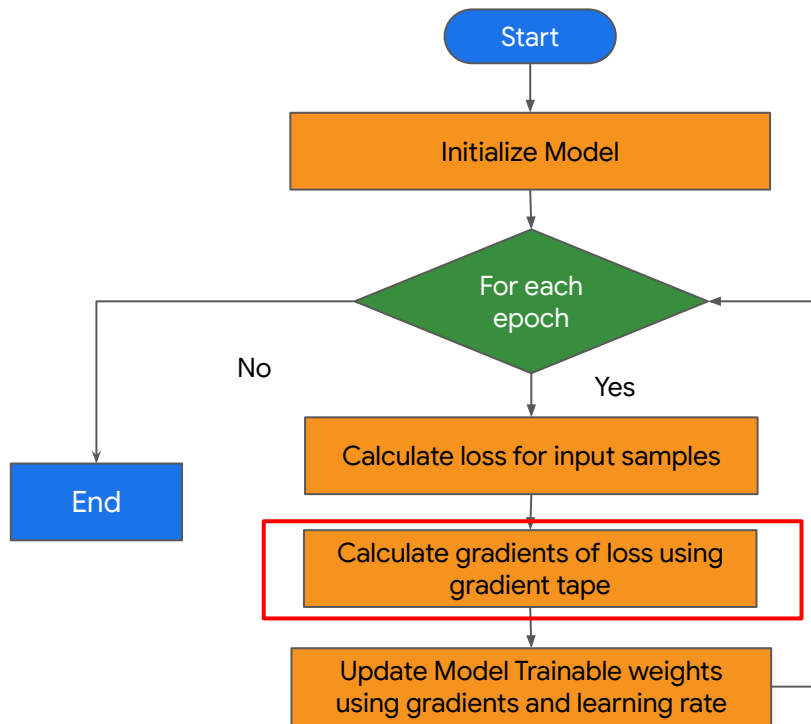
# 4. Training Loop



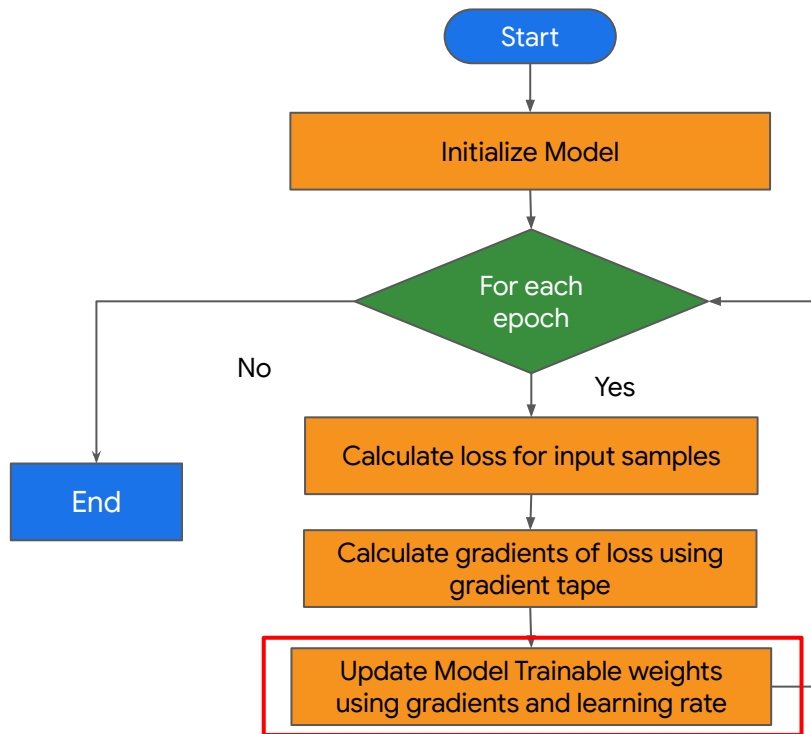
# 4. Training Loop



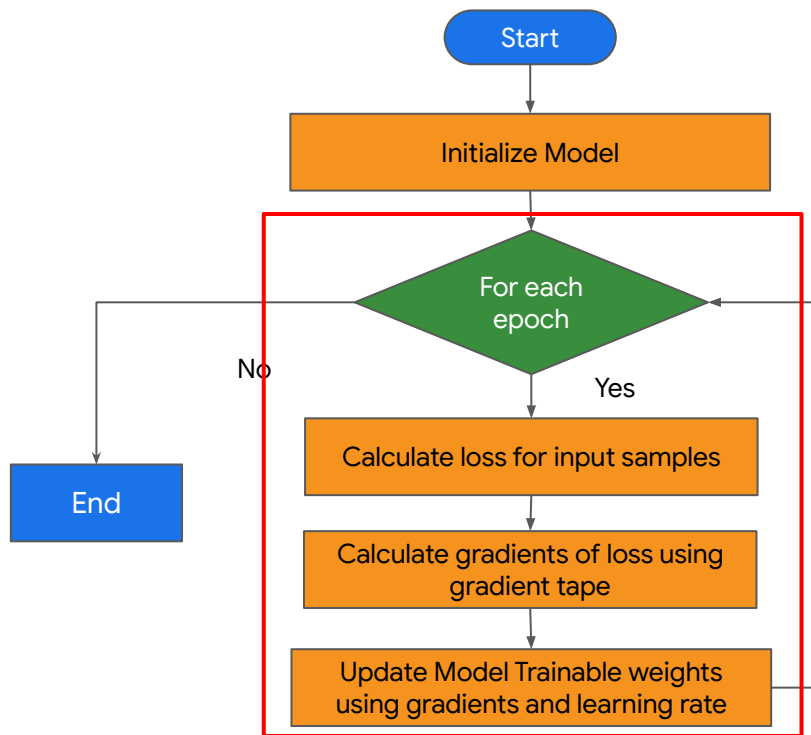
# 4. Training Loop



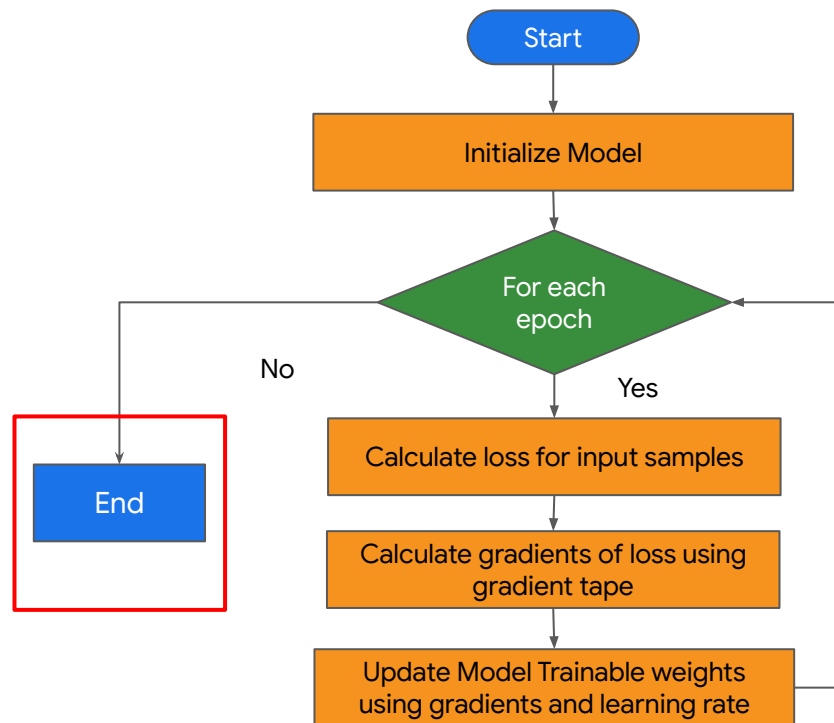
# 4. Training Loop



# 4. Training Loop



# 4. Training Loop





# Calculate Partial Derivative of Loss

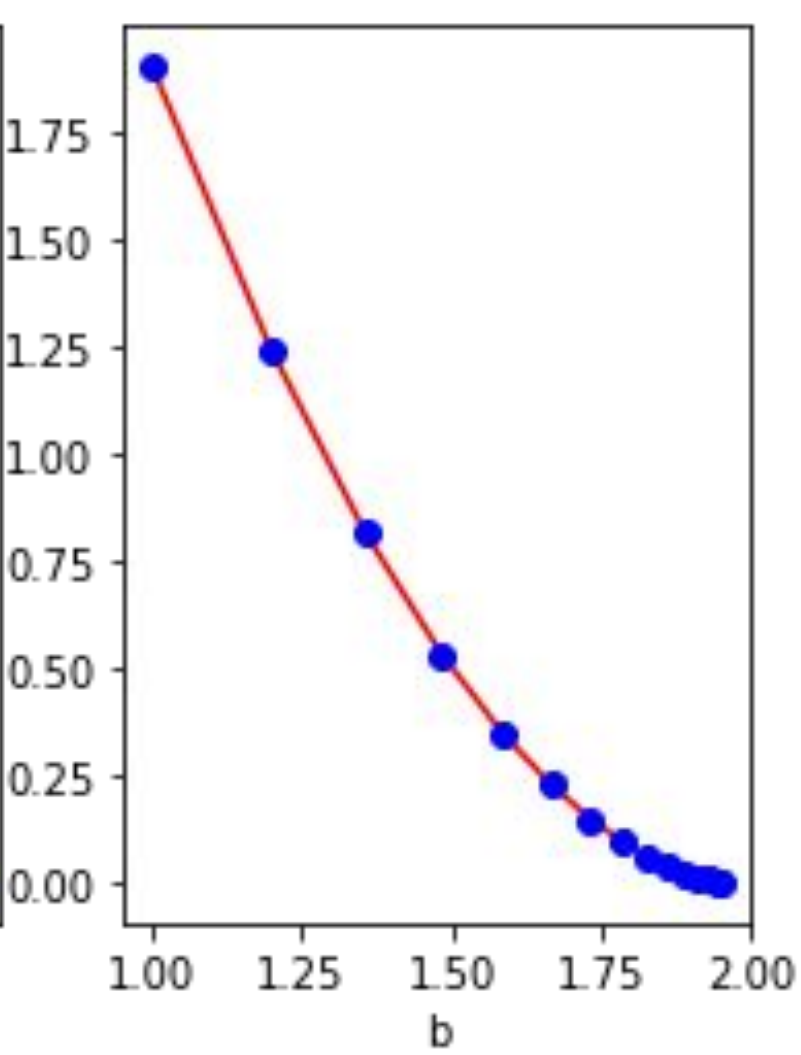
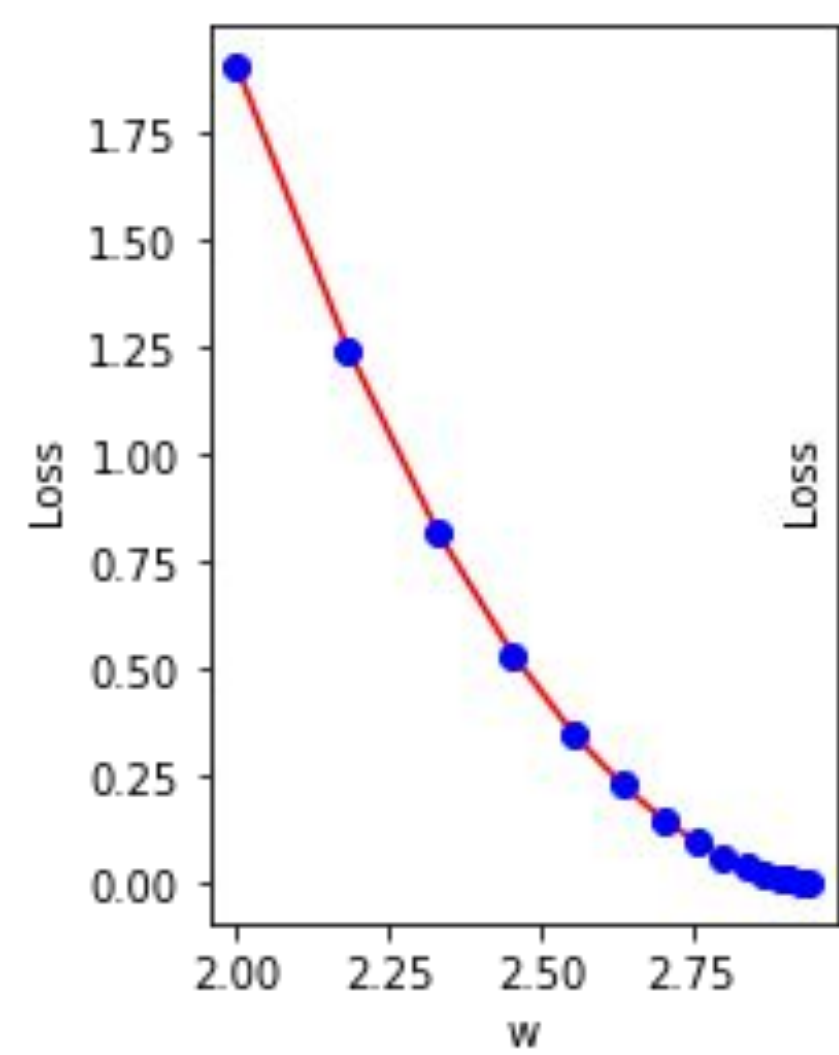
```
def train(model, inputs, outputs, learning_rate):  
    with tf.GradientTape() as tape:  
        current_loss = loss(outputs, model(inputs))  
        da, db = tape.gradient(current_loss, [model.a, model.b])  
  
        model.a.assign_sub(learning_rate * da)  
        model.b.assign_sub(learning_rate * db)
```

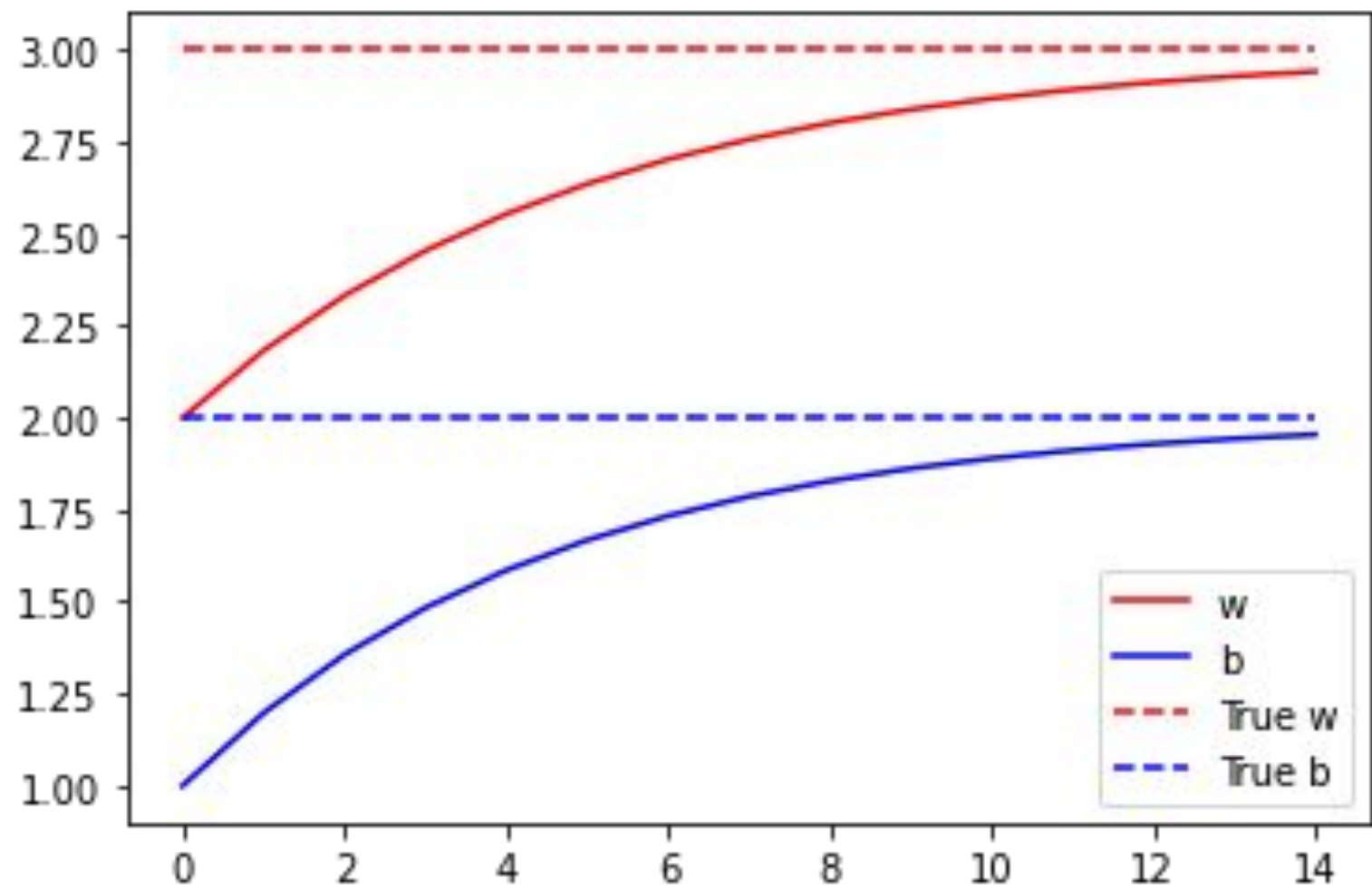
# Define Training Loop

```
epochs = range(20)
for epoch in epochs:
    train(model, inputs, outputs, learning_rate=0.1)
```

## 6. Validate the Model

1. Draw plots of loss for  $w$  and  $b$  over time
2. Draw plots of trainable weights over time.
3. Calculate loss





Epoch 0: w=2.00 b=1.00, loss=1.90155  
Epoch 1: w=2.18 b=1.20, loss=1.24631  
Epoch 2: w=2.33 b=1.36, loss=0.81714  
Epoch 3: w=2.45 b=1.48, loss=0.53595  
Epoch 4: w=2.55 b=1.59, loss=0.35164  
Epoch 5: w=2.64 b=1.67, loss=0.23080  
Epoch 6: w=2.70 b=1.73, loss=0.15153  
Epoch 7: w=2.76 b=1.79, loss=0.09953  
Epoch 8: w=2.80 b=1.83, loss=0.06539  
Epoch 9: w=2.84 b=1.86, loss=0.04297  
Epoch 10: w=2.87 b=1.89, loss=0.02825  
Epoch 11: w=2.89 b=1.91, loss=0.01858  
Epoch 12: w=2.91 b=1.93, loss=0.01222  
Epoch 13: w=2.93 b=1.94, loss=0.00804  
Epoch 14: w=2.94 b=1.95, loss=0.00529

# What we'll cover

1. Define custom training loop that takes input pipeline from Tensorflow Datasets.
2. Use pre-built loss function and optimizer within training loop
3. Use and track performance with test set
4. Handling training metrics.

# Steps to training this network

1. **Define** the network
2. **Prepare** the training data pipeline
3. **Specify** Loss and Optimizer
4. **Train** the model to minimize loss using optimizer.
5. **Test** the model.



# 1. Define Network

```
def base_model():  
    inputs = tf.keras.Input(shape=(784,), name='clothing')  
    x = tf.keras.layers.Dense(64, activation='relu', name='dense_1')(inputs)  
    x = tf.keras.layers.Dense(64, activation='relu', name='dense_2')(x)  
    outputs = tf.keras.layers.Dense(10, activation='softmax', name='predictions')(x)  
    model = tf.keras.Model(inputs=inputs, outputs=outputs)  
    return model
```

## 2. Prepare Training Data Pipeline

1. Load Fashion MNIST using TensorFlow Datasets
2. We *normalize* the inputs pixels to restrict them between 0 and 1.
3. Split dataset into training and test sets.

```
train_data = tfds.load("fashion_mnist", split = "train")
test_data = tfds.load("fashion_mnist", split = "test")

def format_image(data):
    image = data["image"]
    image = tf.reshape(image, [-1])
    image = tf.cast(image, 'float32')
    image = image / 255.0
    return image, data["label"]

train_data = train_data.map(format_image)
test_data = test_data.map(format_image)

batch_size = 64

train = train_data.shuffle(buffer_size=1024).batch(batch_size)
test = test_data.batch(batch_size=batch_size)
```

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### 3. Define Loss and Optimizer

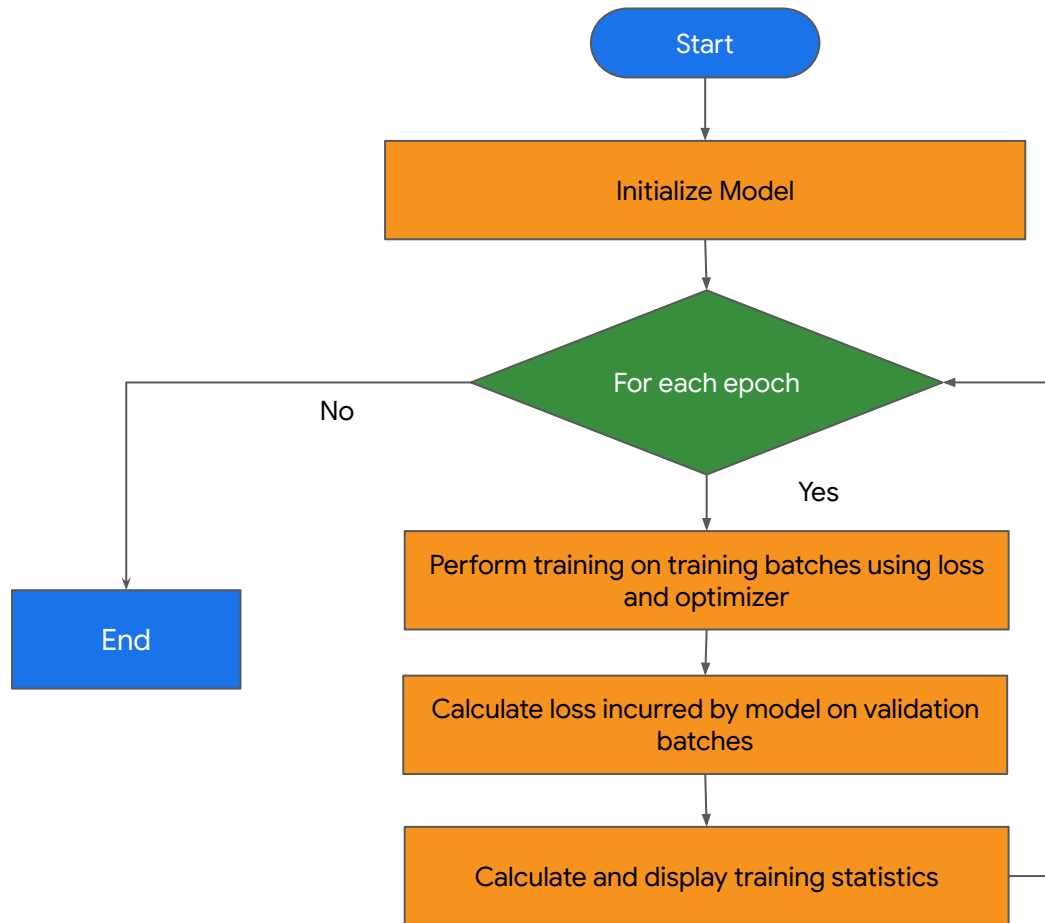
```
loss_object = tf.keras.losses.SparseCategoricalCrossentropy()
```

```
optimizer = tf.keras.optimizers.Adam()
```



## 4. Define Custom Training Loop

1. For each epoch, loop through the training batches and calculate gradients
2. These gradients are used according to the optimization algorithm chosen, to update the trainable weights of the model.
3. Loop through validation batches and calculate validation loss.



# Training Loop - Architecture

Repeat for each epoch

Repeat for each training batch

Calculate logits, loss

Calculate gradients of  
loss with respect to  
model trainable weights

Apply gradients on  
model using optimizer

Accumulate accuracy  
metric

Repeat for each test batch

Calculate loss

Accumulate accuracy  
metric

1. Reset states of metrics
2. Calculate training and test loss for epoch.
3. Display epoch statistics

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# Training Loop - Architecture

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Apply gradients on  
model using optimizer

Accumulate accuracy  
metric

Repeat for each validation batch

Calculate loss

Accumulate accuracy  
metric

1. Reset states of metrics
2. Calculate training and test loss for epoch.
3. Display epoch statistics

# Define Custom Training Loop

```
model = base_model()
epochs = 20
for epoch in range(epochs):
    #Run through training batch
    losses_train = train_data_for_one_epoch()

    #Calculate validation losses and metrics.
    losses_val = perform_validation()

    losses_train_mean = np.mean(losses_train)
    losses_val_mean = np.mean(losses_val)
```

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    losses_val = perform_validation()

    losses_train_mean = np.mean(losses_train)
    losses_val_mean = np.mean(losses_val)
```

# Define Custom Training Loop

```
def train_data_for_one_epoch():  
    losses = []  
    for step, (x_batch_train, y_batch_train) in enumerate(train_datset):  
        logits, loss_value = apply_gradient(optimizer, model, x_batch_train, y_batch_train)  
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# Define Custom Training Loop

```
def train_data_for_one_epoch():  
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```

# Calculate and Apply Gradients

```
def apply_gradient(optimizer, model, x, y):  
    with tf.GradientTape() as tape:  
        logits = model(x)  
        loss_value = loss_object(y_true=y, y_pred=logits)  
  
        gradients = tape.gradient(loss_value, model.trainable_weights)  
        optimizer.apply_gradients(zip(gradients, model.trainable_weights))  
  
    return logits, loss_value
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# Calculate Validation Loss

```
def perform_validation():  
    losses = []  
    #Run through the validation batches  
    for x_val, y_val in test:  
        val_logits = model(x_val)  
        val_loss = loss_object(y_true=y_val, y_pred=val_logits)  
        losses.append(val_loss)  
    return losses
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```

# Metrics in Keras

- **Metrics** can be modelled as **function** or **class**.
- Defined in *tf.keras.metrics*
  - **mean\_squared\_error(...)**      **class MeanSquaredError**
  - **mean\_absolute\_error(...)**      **class MeanAbsoluteError**

[https://www.tensorflow.org/api\\_docs/python/tf/keras/metrics](https://www.tensorflow.org/api_docs/python/tf/keras/metrics)

# Low Level Handling of Metrics

1. Call ***metric.update\_state()*** to accumulate metric statistics after each batch.
2. Call ***metric.result*** to get current value of metric for display.
3. Call ***metric.reset\_state()*** to reset metric value typically at end of epoch.

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# Low Level Handling of Metrics in Practice

```
train_acc_metric = tf.keras.metrics.SparseCategoricalAccuracy()  
val_acc_metric = tf.keras.metrics.SparseCategoricalAccuracy()
```



# Low Level Handling of Metrics - Training

```
def train_data_for_one_epoch():  
    losses = []  
    for step, (x_batch_train, y_batch_train) in enumerate(train_datset):  
        ...  
        #Accumulate metrics  
        train_acc_metric.update_state(y_batch_train, logits)  
  
    return losses
```

# Low Level Handling of Metrics - Training

```
for epoch in range(epochs):  
    #Run through training batch  
    losses_train = train_data_for_one_epoch()  
  
    ...  
    train_acc = train_acc_metric.result()  
    train_acc_metric.reset_states()  
  
    ...
```

# Low Level Handling of Metrics - Validation

```
def perform_validation():  
    losses = []  
    for x_val, y_val in test_dataset:  
        logits = model(x_val)  
        ...  
        #Accumulate metrics  
        val_acc_metric.update_state(y_val, logits)  
  
    return losses
```

# Low Level Handling of Metrics - Validation

```
for epoch in range(epochs):  
    #Run through training batch  
    losses_val = perform_validation()  
  
    ...  
    val_acc = val_acc_metric.result()  
    val_acc_metric.reset_states()  
  
    ...
```

## 6. Validate the Model

1. Show training progress and calculate loss and accuracy for each epoch.
2. Draw plots for loss function.
3. Visualize performance on test data.