This is a companion notebook for the book <u>Deep Learning with Python, Second Edition</u>. For readability, it only contains runnable code blocks and section titles, and omits everything else in the book: text paragraphs, figures, and pseudocode.

If you want to be able to follow what's going on, I recommend reading the notebook side by side with your copy of the book.

This notebook was generated for TensorFlow 2.6.

- Fundamentals of machine learning
- Generalization: The goal of machine learning
- Underfitting and overfitting

Noisy training data

Ambiguous features

▼ Rare features and spurious correlations

Adding white-noise channels or all-zeros channels to MNIST

Training the same model on MNIST data with noise channels or all-zero channels

```
from tensorflow import keras
from tensorflow.keras import layers
def get_model():
   model = keras.Sequential([
        layers.Dense(512, activation="relu"),
        layers.Dense(10, activation="softmax")
    ])
   model.compile(optimizer="rmsprop",
                  loss="sparse_categorical_crossentropy",
                  metrics=["accuracy"])
    return model
model = get_model()
history_noise = model.fit(
   train_images_with_noise_channels, train_labels,
   epochs=10,
   batch_size=128,
   validation_split=0.2)
model = get_model()
history_zeros = model.fit(
   train_images_with_zeros_channels, train_labels,
   epochs=10,
   batch_size=128,
   validation_split=0.2)
```

Plotting a validation accuracy comparison

▼ The nature of generalization in deep learning

Fitting a MNIST model with randomly shuffled labels

```
(train_images, train_labels), _ = mnist.load_data()
train_images = train_images.reshape((60000, 28 * 28))
```

The manifold hypothesis

Interpolation as a source of generalization

Why deep learning works

Training data is paramount

- ▼ Evaluating machine-learning models
- Training, validation, and test sets

Simple hold-out validation

K-fold validation

Iterated K-fold validation with shuffling

Beating a common-sense baseline

Things to keep in mind about model evaluation

- ▼ Improving model fit
- ▼ Tuning key gradient descent parameters

Training a MNIST model with an incorrectly high learning rate

The same model with a more appropriate learning rate

Leveraging better architecture priors

▼ Increasing model capacity

A simple logistic regression on MNIST

```
model = keras.Sequential([layers.Dense(10, activation="softmax")])
```

```
model.compile(optimizer="rmsprop",
              loss="sparse categorical crossentropy",
              metrics=["accuracy"])
history_small_model = model.fit(
    train_images, train_labels,
    epochs=20,
    batch_size=128,
    validation_split=0.2)
import matplotlib.pyplot as plt
val_loss = history_small_model.history["val_loss"]
epochs = range(1, 21)
plt.plot(epochs, val_loss, "b--",
         label="Validation loss")
plt.title("Effect of insufficient model capacity on validation loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()
model = keras.Sequential([
    layers.Dense(96, activation="relu"),
    layers.Dense(96, activation="relu"),
    layers.Dense(10, activation="softmax"),
1)
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
history_large_model = model.fit(
    train_images, train_labels,
    epochs=20,
    batch_size=128,
    validation_split=0.2)
```

Improving generalization

Dataset curation

Feature engineering

Using early stopping

Regularizing your model

▼ Reducing the network's size

Original model

```
from tensorflow.keras.datasets import imdb
(train_data, train_labels), _ = imdb.load_data(num_words=10000)
def vectorize_sequences(sequences, dimension=10000):
    results = np.zeros((len(sequences), dimension))
    for i, sequence in enumerate(sequences):
        results[i, sequence] = 1.
    return results
train_data = vectorize_sequences(train_data)
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation="relu"),
   layers.Dense(1, activation="sigmoid")
])
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
history_original = model.fit(train_data, train_labels,
                             epochs=20, batch_size=512, validation_split=0.4)
```

Version of the model with lower capacity

Version of the model with higher capacity

```
train_data, train_labels,
epochs=20, batch_size=512, validation_split=0.4)
```

Adding weight regularization

Adding L2 weight regularization to the model

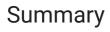
```
from tensorflow.keras import regularizers
model = keras.Sequential([
    layers.Dense(16,
                 kernel_regularizer=regularizers.12(0.002),
                 activation="relu"),
    layers.Dense(16,
                 kernel_regularizer=regularizers.12(0.002),
                 activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
model.compile(optimizer="rmsprop",
              loss="binary_crossentropy",
              metrics=["accuracy"])
history_12_reg = model.fit(
    train_data, train_labels,
    epochs=20, batch_size=512, validation_split=0.4)
```

Different weight regularizers available in Keras

```
from tensorflow.keras import regularizers regularizers.l1(0.001) regularizers.l1_l2(l1=0.001, l2=0.001)
```

Adding dropout

Adding dropout to the IMDB model



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