CH5. Fundamentals of Machine Learning

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Fundamentals of Machine Learning

Generalization: The goal of machine learning

Evaluating machine-learning models

Improving model fit

Improving generalization

Generalization: The goal of machine learning

The fundamental issue in machine learning is the tension between optimization and generalization

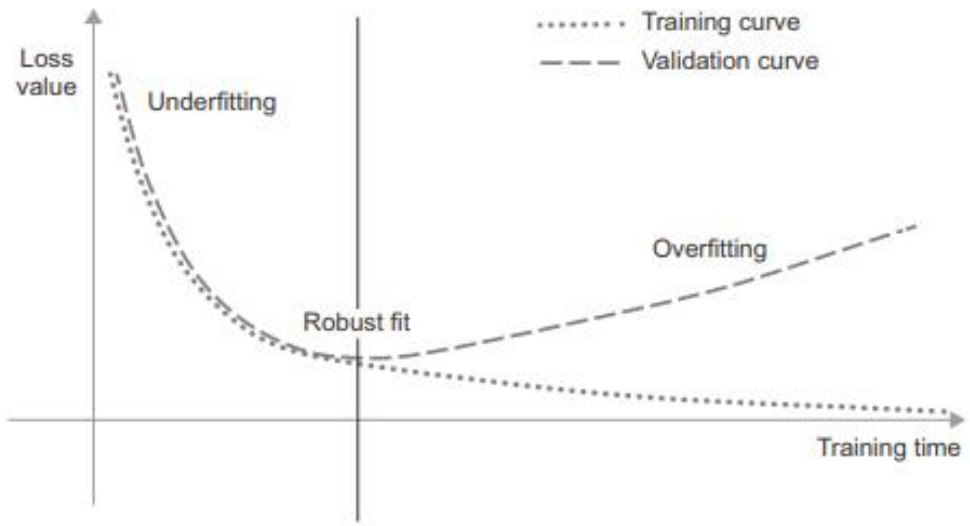


Figure 5.1 Canonical overfitting behavior

training stage; minimizing traing loss

Optimization refers to the process of adjusting a model to get the best performance possible on the training data

Generalization refers to how well the trained model performs on data it has never seen before

The processing of fighting overfitting is called ***regularization***

Underfitting and overfitting

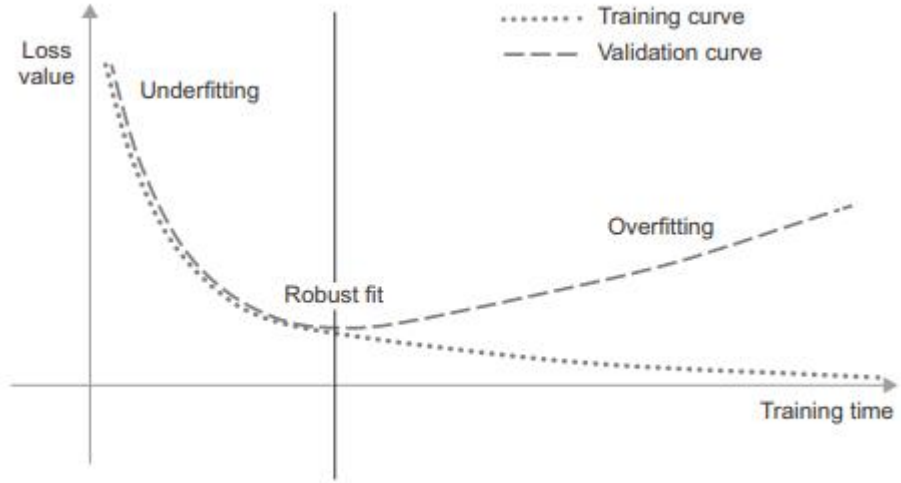
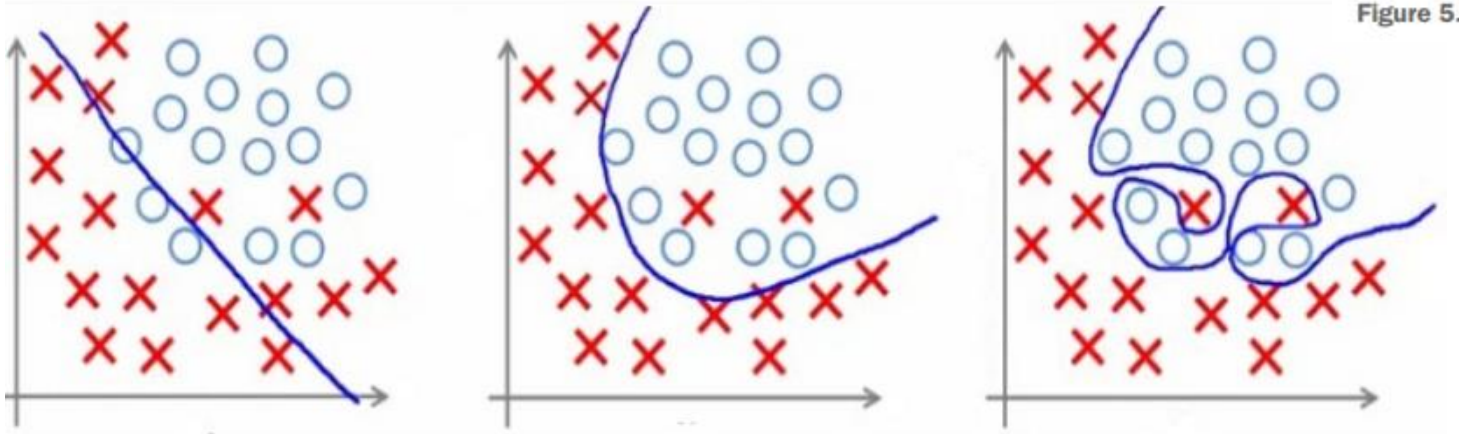


Figure 5.1 Canonical overfitting behavior

low performance on training & test data

good performance

good performance on training set
low performance on valid set



Under-fitting

(too simple to explain the variance)

Appropriate-fitting

Over-fitting

(forcefitting -- too good to be true)

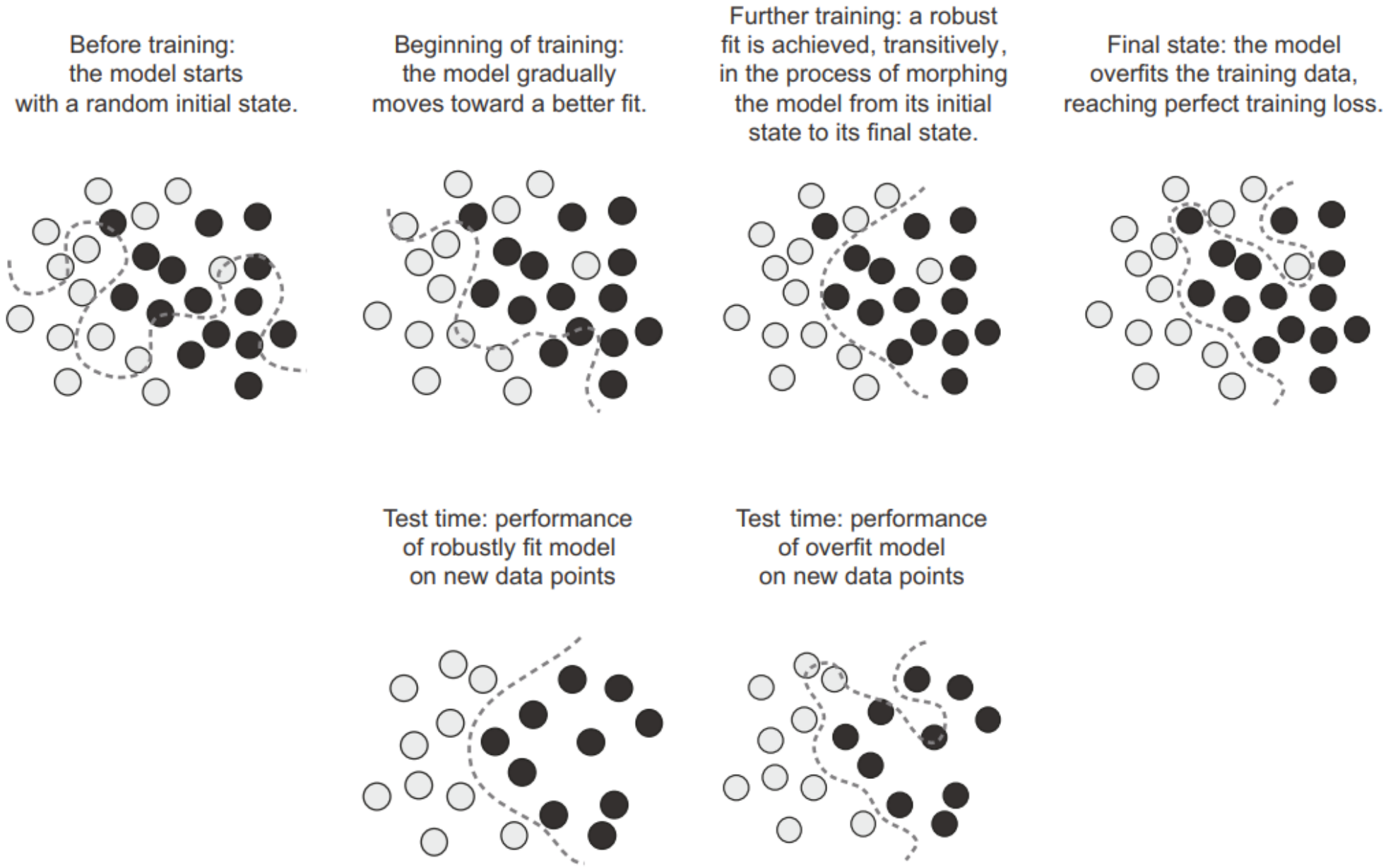


Figure 5.10 Going from a random model to an overfit model, and achieving a robust fit as an intermediate state

Noisy training data

In real-world datasets, it's fairly common for some inputs to be invalid.

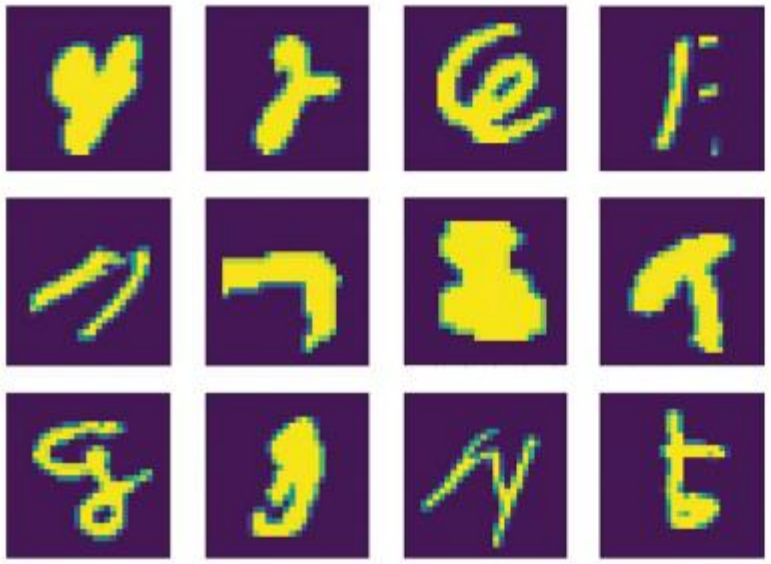


Figure 5.2 Some pretty weird MNIST training samples

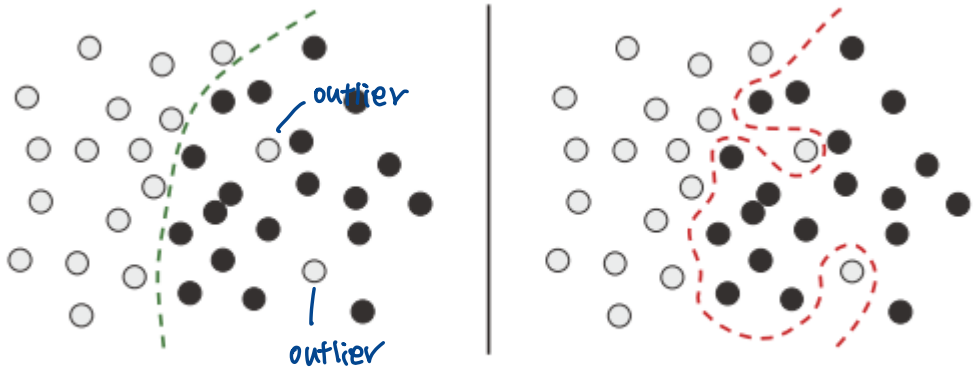


Figure 5.4 Dealing with outliers: robust fit vs. overfitting

need to make robust model

Even worst:

Figure 5.3 Mislabeled MNIST training samples

Wrong label

Rare features and suspicious correlations

Datasets that include rare feature values are highly susceptible to overfitting

they do bad effect on our modeling

Example of suspicious correlations:

Listing 5.1 Adding white noise channels or all-zeros channels to MNIST

```
from tensorflow.keras.datasets import mnist
import numpy as np

(train_images, train_labels), _ = mnist.load_data()
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype("float32") / 255

train_images_with_noise_channels = np.concatenate(
    [train_images, np.random.random((len(train_images), 784))], axis=1)
```

adding random noise channels

```
train_images_with_zeros_channels = np.concatenate(
    [train_images, np.zeros((len(train_images), 784))], axis=1)
```

adding all-zeros channels

Listing 5.2 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)
```

Listing 5.3 Plotting a validation accuracy comparison

```
import matplotlib.pyplot as plt
val_acc_noise = history_noise.history["val_accuracy"]
val_acc_zeros = history_zeros.history["val_accuracy"]
epochs = range(1, 11)
plt.plot(epochs, val_acc_noise, "b-",
         label="Validation accuracy with noise channels")
plt.plot(epochs, val_acc_zeros, "b--",
         label="Validation accuracy with zeros channels")
plt.title("Effect of noise channels on validation accuracy")
plt.xlabel("Epochs")
plt.ylabel("Accuracy")
plt.legend()
```

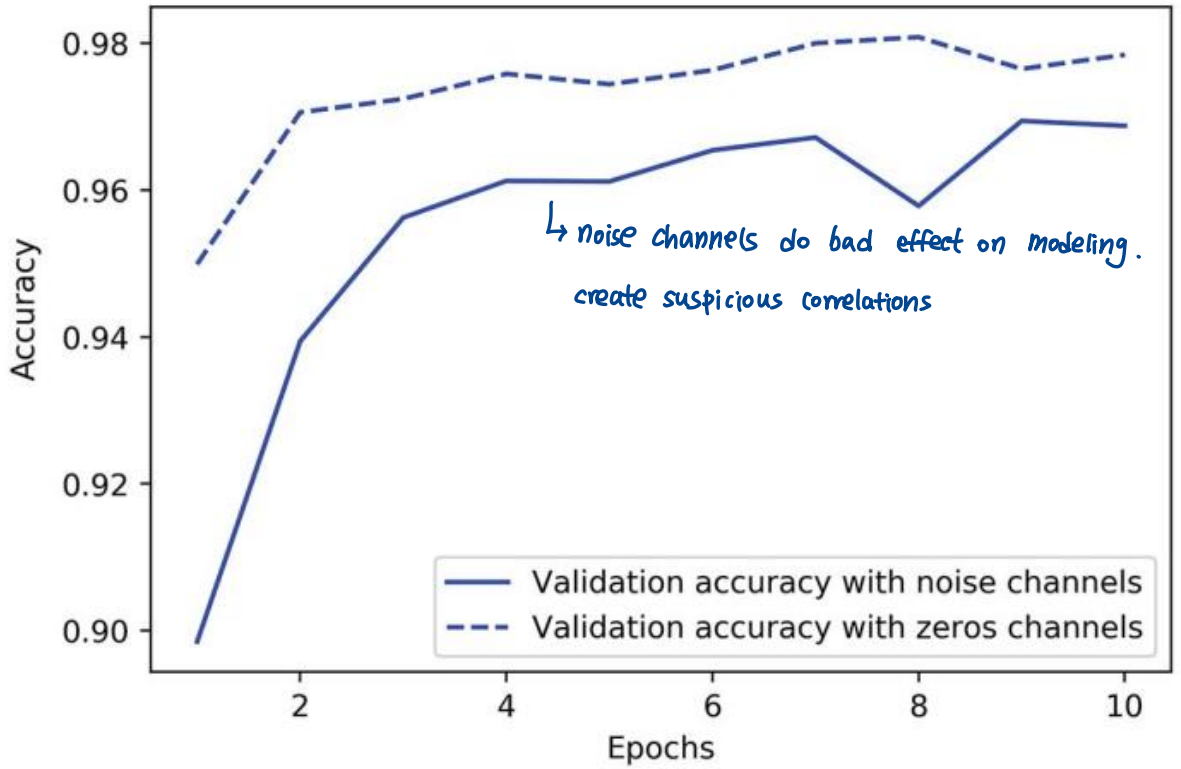


Figure 5.6 Effect of noise channels on validation accuracy

Noisy features inevitably lead to overfitting. As such, in cases where you aren't sure whether the features you have are informative or distracting, it's common to do feature selection before training

colab.research.google.com/github/fchollet/deep-learning-with-python-notebooks/blob/master/chapter05_fundamentals-of-ml.ipynb

업데이트

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2022-03-27

The nature of generalization in deep learning

A remarkable fact about deep learning models is that they can be trained to fit anything, as long as they have enough representational power

As long as they have enough representational power, we can train anything. (we can train to fit anything)

Listing 5.4 Fitting an MNIST model with randomly shuffled labels

```
(train_images, train_labels), _ = mnist.load_data()
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype("float32") / 255

random_train_labels = train_labels[:]
np.random.shuffle(random_train_labels)
model = keras.Sequential([
    layers.Dense(512, activation="relu"),
    layers.Dense(10, activation="softmax")
])
model.compile(optimizer="rmsprop",
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, random_train_labels,
          epochs=100,
          batch_size=128,
          validation_split=0.2)
```

↳ fitting MNIST model with randomly shuffled labels

Even though there is no relationship whatsoever between the inputs and the shuffled labels, the training loss goes down just fine

Naturally, the validation loss does not improve at all over time

"Deep Learning model since we have very good representational power, the nature fact of this deep learning model is trying to fit anything" we should train the data correctly.

Fundamentals of machine learning
Generalization: The goal of machine learning
Underfitting and overfitting
Noisy training data
Ambiguous features
Rare features and spurious correlations
The nature of generalization in deep learning
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

The nature of generalization in deep learning

Fitting a MNIST model with randomly shuffled labels

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[ ] (train_images, train_labels), _ = mnist.load_data()
    train_images = train_images.reshape((60000, 28 * 28))
    train_images = train_images.astype("float32") / 255

    random_train_labels = train_labels[:]
    np.random.shuffle(random_train_labels)

    model = keras.Sequential([
        layers.Dense(512, activation="relu"),
        layers.Dense(10, activation="softmax")
    ])
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                  loss="sparse_categorical_crossentropy",
                  metrics=["accuracy"])
    model.fit(train_images, random_train_labels,
              epochs=100,
              batch_size=128,
              validation_split=0.2)
```

The manifold hypothesis

Interpolation as a source of generalization

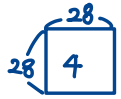
The maniford hypothesis

ch.12

; what the deep learning try to fit

Actual handwritten digits only occupy a tiny subspace of the parent space of all possible 28 × 28 uint8 arrays

space where this mnist data set encoded



All samples in the valid subspace are connected by smooth paths that run through the subspace.

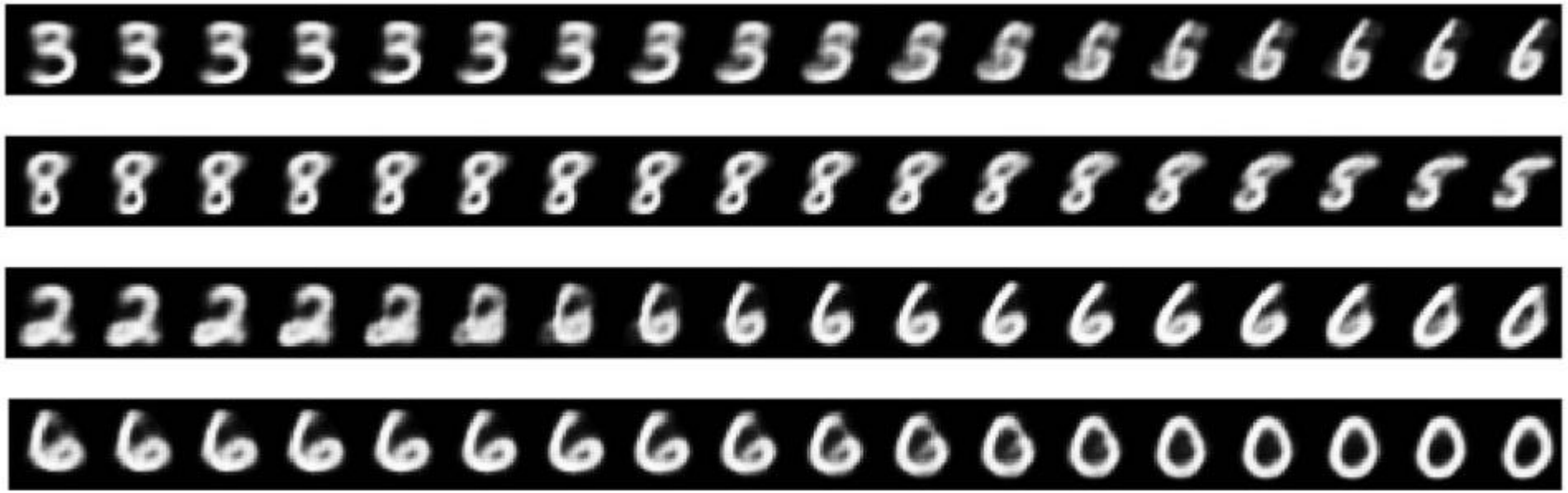


Figure 5.7 Different MNIST digits gradually morphing into one another, showing that the space of handwritten digits forms a "manifold." This image was generated using code from chapter 12.

The maniford hypothesis

"Manifold Hypothesis"
· 고차원 데이터라 할지라도, 실질적으로 해당 데이터를 나타내주는 저차원 공간인 manifold가 존재한다는 것을 의미
· sparse한 고차원데이터를 간추려서 봤 저차원 공간으로 나타낼 수 있다는 의미

Manifold hypothesis posits that all natural data lies on a low-dimensional manifold within the high-dimensional space where it is encoded

Machine learning models only have to fit relatively simple, low-dimensional, highly structured subspaces within their potential input space (latent manifolds).

eg) 데이터 단위에서 보면, 실존하는 데이터들의 결과를 해당 좌표 위에 올려놨을 때 어느 축으로 가면 강아지, 어느 축으로 가면 고양이 ⇒ 이런 식으로 분류

Within one of these manifolds, it's always possible to interpolate between two inputs, that is to say, morph one into another via a continuous path along which all points fall on the manifold.

*딥러닝에서, 특히나 머신러닝 학습에서는 이러한 적절한 manifold를 찾는것이 매우 중요!

요약!
manifold란, 다차원 데이터에서 실질적 의미를 가지는 특징을 모아둔 고유한 특성공간을 뜻하며, 실제 데이터를 통해 스스로 학습하는 딥러닝 머신러닝 학습이 이러한 manifold를 스스로 찾아냅니다.

From the deep learning models, the tiny subspace (manifold) → the interpolation is possible
보간법 ↳ good source of generalization.

Interpolation as a source of generalization

Deep learning achieves generalization via interpolation on a learned approximation of the data manifold

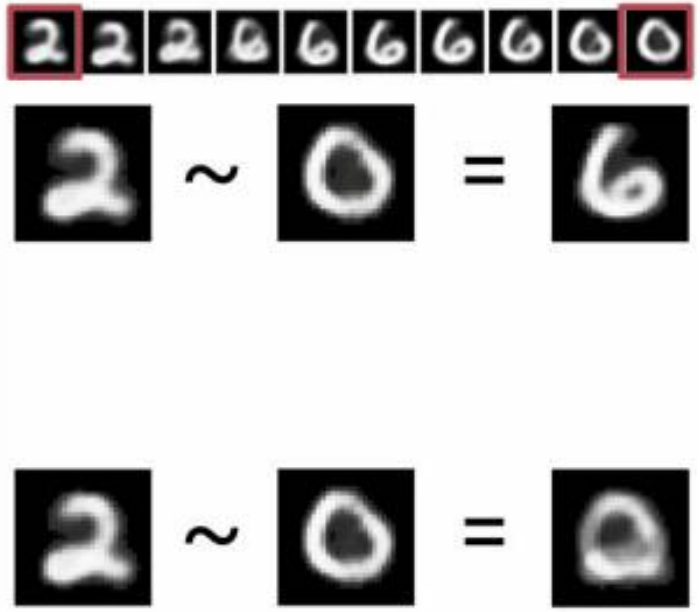


Figure 5.8 Difference between linear interpolation and interpolation on the latent manifold. Every point on the latent manifold of digits is a valid digit, but the average of two digits usually isn't.

Why deep learning works?

A sheet of paper represents a 2D manifold within 3D space. A deep learning model is a tool for uncrumpling paper balls, that is, for disentangling latent manifolds.

learning low dimensional manifold

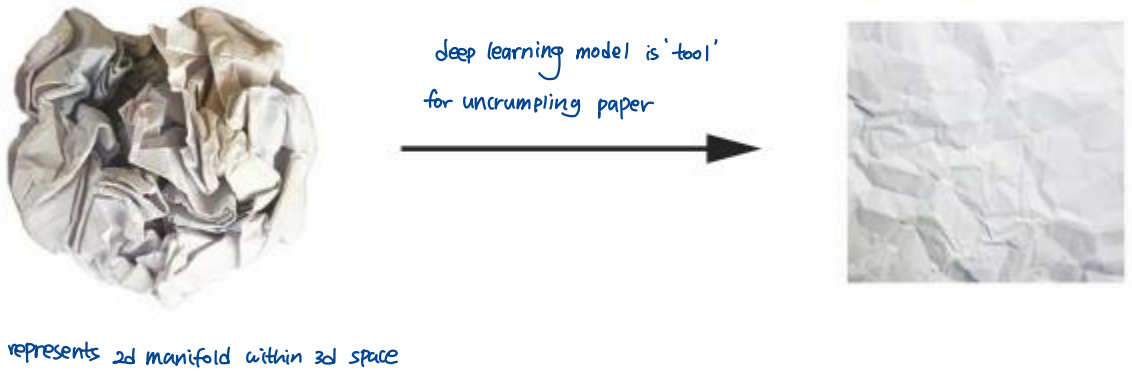


Figure 5.9 Uncrumpling a complicated manifold of data

Training data is paramount

가장 중요한

Deep learning is curve fitting, for a model to perform well it needs to be trained on a dense sampling of its input space

deep learning is trying to fit the low dimensional manifold to model perform well.

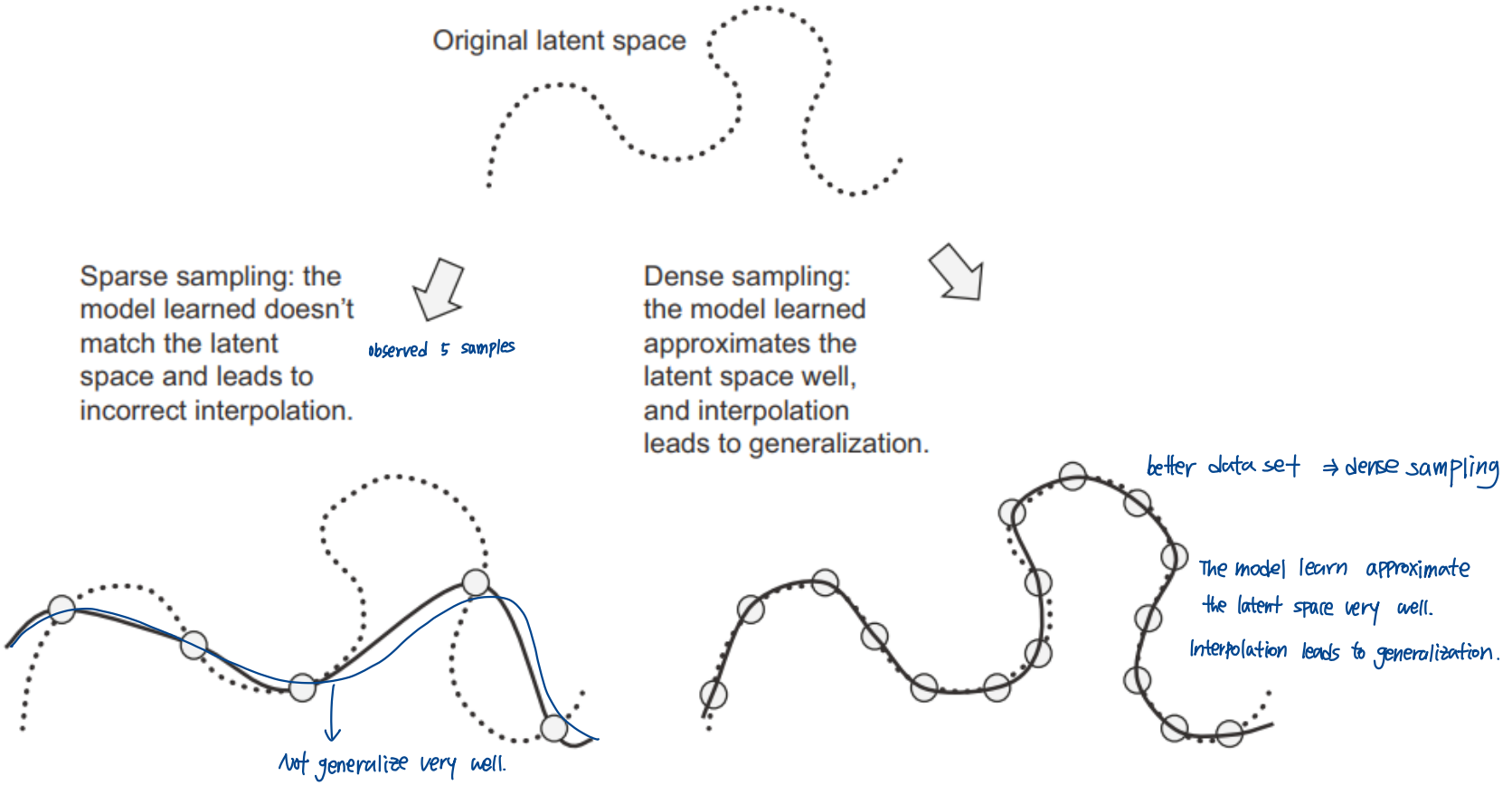


Figure 5.11 A dense sampling of the input space is necessary in order to learn a model capable of accurate generalization.

Evaluating machine-learning models

Goal is to achieve models that generalize well

It's essential to be able to reliably measure the generalization power of your model

Training, validation, and test sets

Tuning *parameters* and *hyperparameters* is a form of *learning*

Tuning is based on its performance on validation set

Tuning a lot would cause *information leak*

Thus, you need never-before-seen test dataset

Simple hold-out validation

Figure 5.12 Simple holdout validation split

Listing 5.5 Holdout validation (note that labels are omitted for simplicity)

```
num_validation_samples = 10000
np.random.shuffle(data)
validation_data = data[:num_validation_samples]
training_data = data[num_validation_samples:]
model = get_model()
model.fit(training_data, ...)
validation_score = model.evaluate(validation_data, ...)

...

model = get_model()
model.fit(np.concatenate([training_data,
                          validation_data]), ...)
test_score = model.evaluate(test_data, ...)
```

Shuffling the data is usually appropriate.

Defines the validation set

Defines the training set

Trains a model on the training data, and evaluates it on the validation data

At this point you can tune your model, retrain it, evaluate it, tune it again.

Once you've tuned your hyperparameters, it's common to train your final model from scratch on all non-test data available.

K fold validation

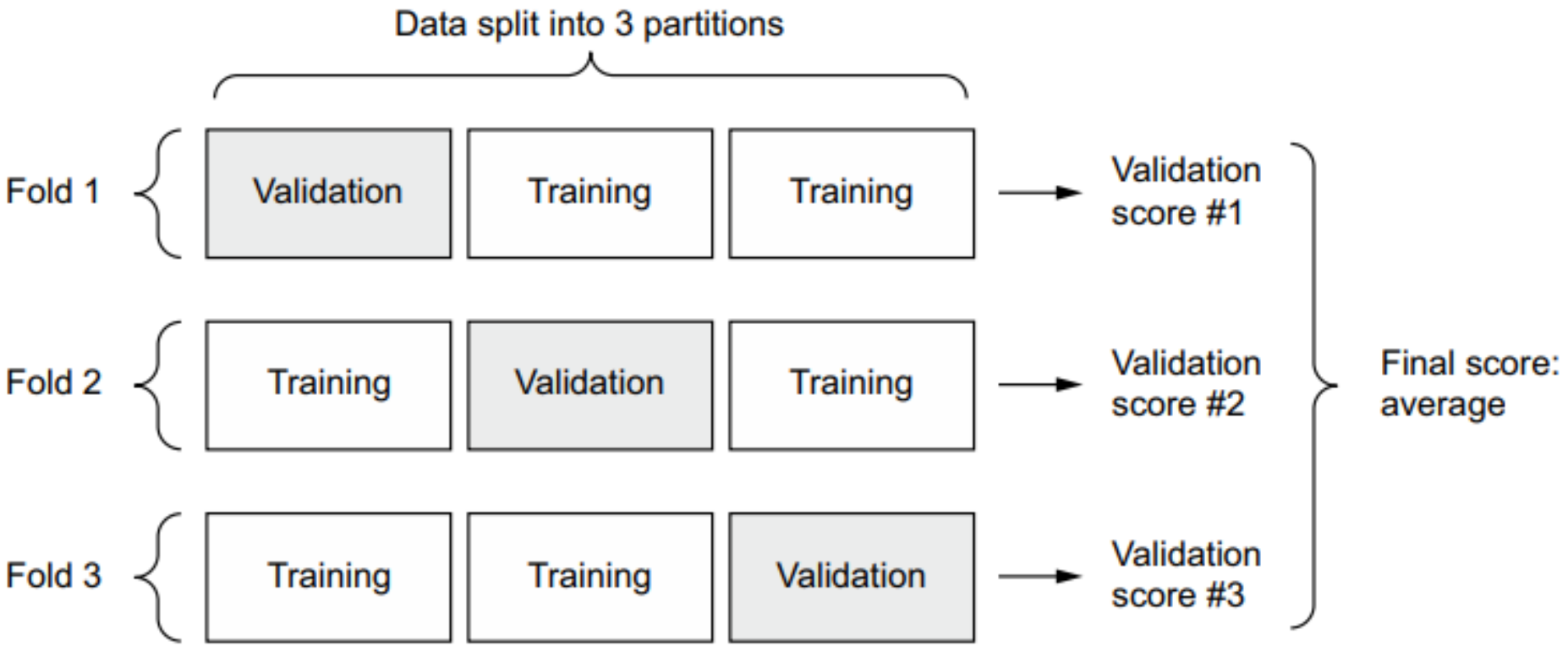


Figure 5.13 K-fold cross-validation with K=3

K fold validation

Listing 5.6 K-fold cross-validation (note that labels are omitted for simplicity)

```
k = 3
num_validation_samples = len(data) // k
np.random.shuffle(data)
validation_scores = []
for fold in range(k):
    validation_data = data[num_validation_samples * fold:
                           num_validation_samples * (fold + 1)]
    training_data = np.concatenate(
        data[:num_validation_samples * fold],
        data[num_validation_samples * (fold + 1):])
    model = get_model()
    model.fit(training_data, ...)
    validation_score = model.evaluate(validation_data, ...)
    validation_scores.append(validation_score)
validation_score = np.average(validation_scores)
model = get_model()
model.fit(data, ...)
test_score = model.evaluate(test_data, ...)
```

Selects the validation-data partition

Creates a brand-new instance of the model (untrained)

Validation score: average of the validation scores of the k folds

Trains the final model on all non-test data available

Uses the remainder of the data as training data. Note that the + operator represents list concatenation, not summation.

Iterated K fold validation with shuffling

This one is for situations in which you have relatively little data available and you need to evaluate your model as precisely as possible

Applying K-fold validation multiple times, shuffling the data every time before splitting it K ways

Things to keep in mind

Data representativeness

- Randomly shuffle data before splitting it

The arrow of time

eg) Time-Series Dataset

- If you are predicting future event, don't shuffle. Use future data as test set

Redundancy in your data

- Remove redundant data before the start

Improving model fit

To achieve the perfect fit, you must first overfit. Since you don't know in advance where the boundary lies, you must cross it to find it. I must find overfit.

Once you have such a model, you'll focus on refining generalization by fighting overfitting.

Three common problems: 1) training loss doesn't go down, 2) model doesn't meaningfully generalize, 3) training and validation loss both go down but model still underfitting.

valid acc doesn't improve.

For the first problem, 1) training loss doesn't go down.

Tuning key gradient descent parameters

Sometimes training doesn't get started

When this happens, it's always a problem with the configuration of the gradient descent process

→ should check optimizer / gradient descent parameters

example of training doesn't get started

Listing 5.7 Training an MNIST model with an incorrectly high learning rate

```
(train_images, train_labels), _ = mnist.load_data()
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype("float32") / 255

model = keras.Sequential([
    layers.Dense(512, activation="relu"),
    layers.Dense(10, activation="softmax")
])
model.compile(optimizer=keras.optimizers.RMSprop(1.),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=10,
          batch_size=128,
          validation_split=0.2)
```

too large number of learning rate.

example of training doesn't get started

Listing 5.8 The same model with a more appropriate learning rate

```
model = keras.Sequential([
    layers.Dense(512, activation="relu"),
    layers.Dense(10, activation="softmax")
])
model.compile(optimizer=keras.optimizers.RMSprop(1e-2),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=10,
          batch_size=128,
          validation_split=0.2)
```

may define too low learning rate.

Problem 2) model doesn't generalize very well.

Leveraging better architecture priors

Model trains but doesn't generalize. What's going on?

The kind of model you're using is not suited for the problem

In the following chapters, you'll learn about the best architectures to use for a variety of data modalities—images, text, timeseries, and so on.

Problem 3) train & valid loss go down but still under-fitting

Increasing model capacity

If you manage to get to a model that fits, you need to get your model to start overfitting.

by increasing model capacity.

Listing 5.9 A simple logistic regression on MNIST

simple

define 1 simple dense layer (w/ softmax activation) → logistic regression model)

```
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)
```

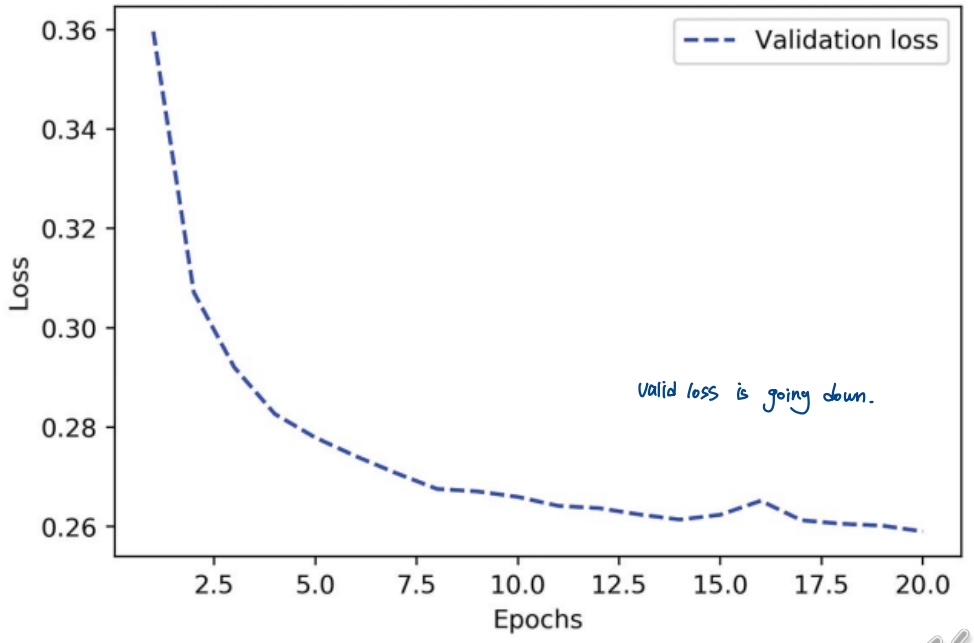


Figure 5.14 Effect of insufficient model capacity on loss curves

it's likely a problem with the representational power of your model

* probably our model is too simple.

Use bigger model

```
model = keras.Sequential([
    layers.Dense(96, activation="relu"),
    layers.Dense(96, activation="relu"),
    layers.Dense(10, activation="softmax"),
])
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)
```

three layers

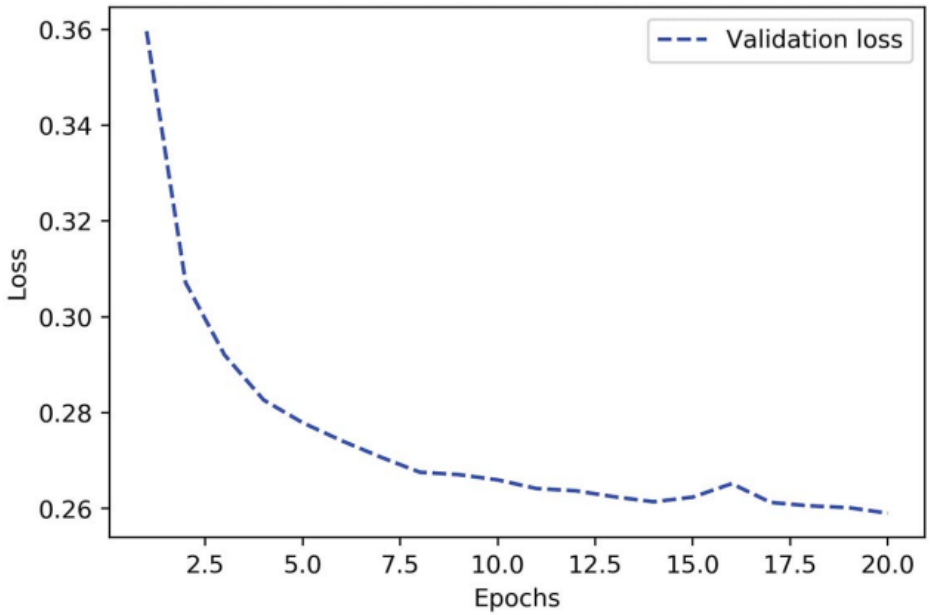


Figure 5.14 Effect of insufficient model capacity on loss curves

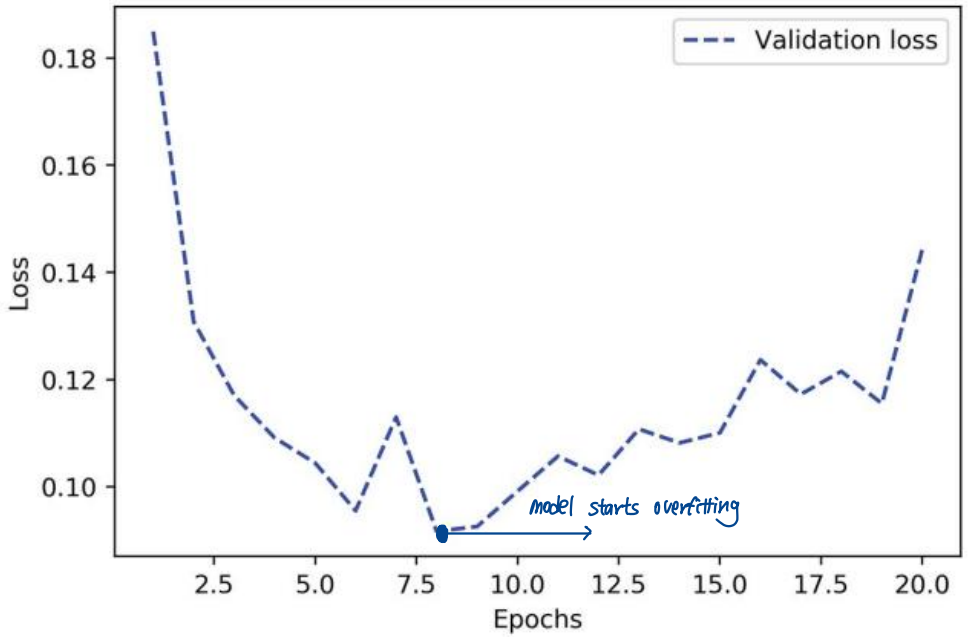


Figure 5.15 Validation loss for a model with appropriate capacity

Improving generalization

Once your model has shown itself to have some generalization power and to be able to overfit, it's time to switch your focus to maximizing generalization.

Dataset curation: Make sure you have enough data, Minimize labeling errors, Clean your data and deal with missing values, Feature selection, etc

Feature engineering

Feature engineering is the process of using your own knowledge about the data to make the algorithm work better by applying hardcoded (non-learned) transformations to the data

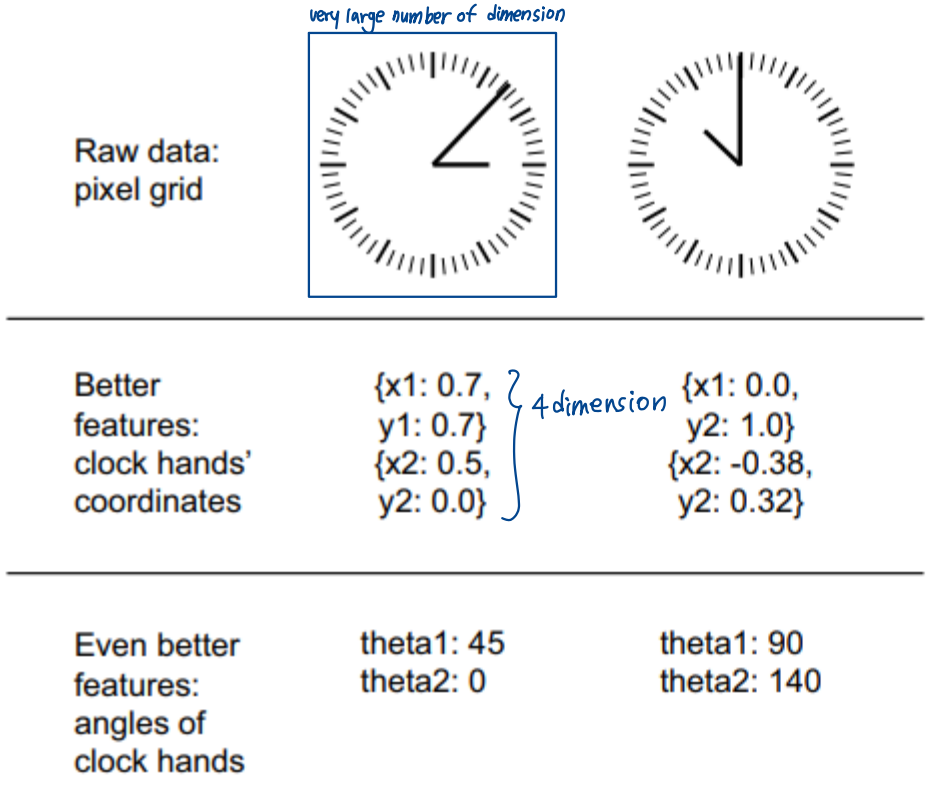


Figure 5.16 Feature engineering for reading the time on a clock

Good features allow you to solve problems using fewer resources

Good features let you solve a problem with far less data

Using early stopping

In deep learning, we always use models that are vastly overparameterized. Interrupt training long before you've reached the minimum possible training loss.

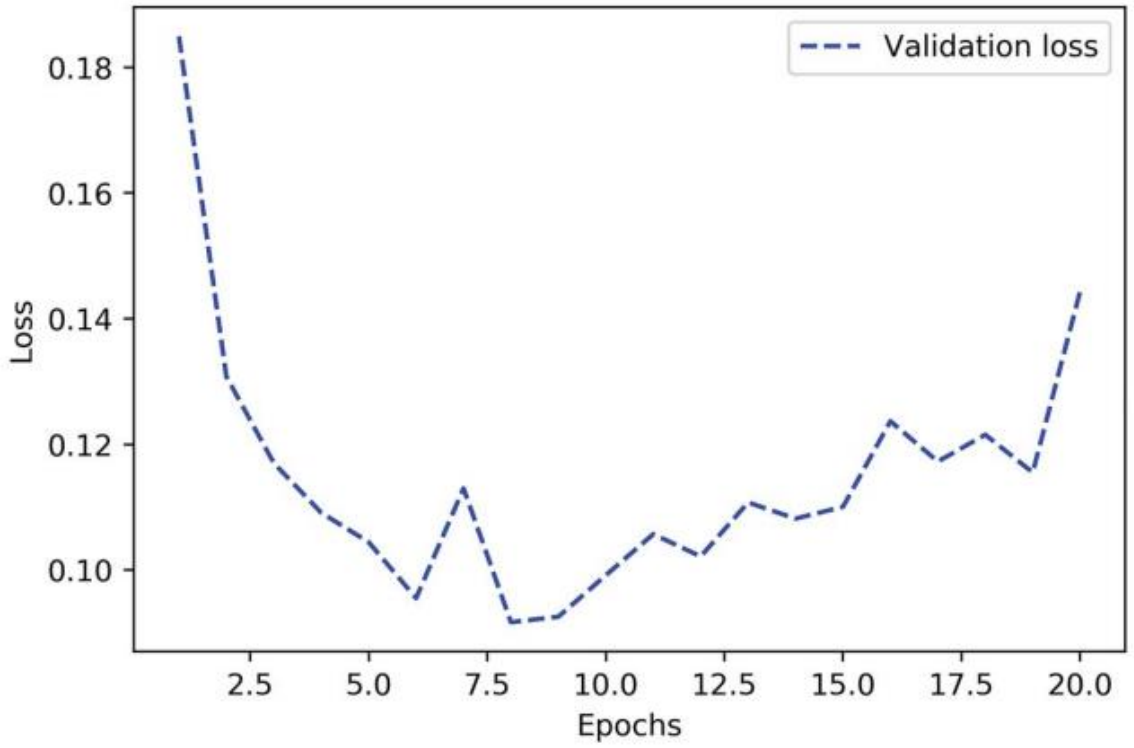


Figure 5.15 Validation loss for a model with appropriate capacity

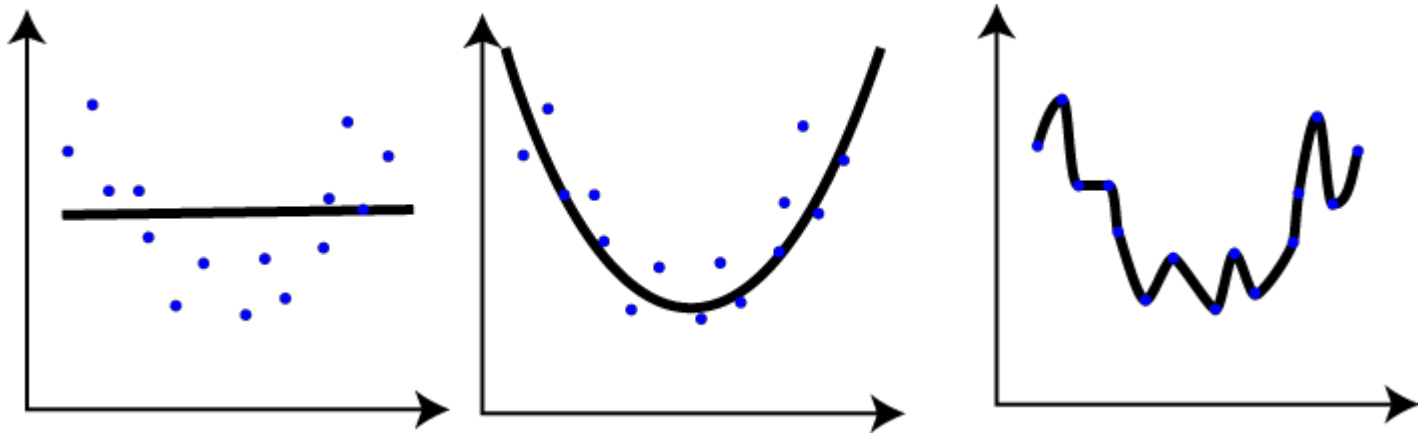
In Keras, it's typical to do this with an EarlyStopping callback

Regularizing your model

Regularization techniques are a set of best practices that actively impede the model's ability to fit perfectly to the training data, with the goal of making the model perform better during validation.

Reducing the network's size

The simplest way to prevent overfitting is to reduce the size of the model



Reducing the network's size

Listing 5.10 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")
])
```

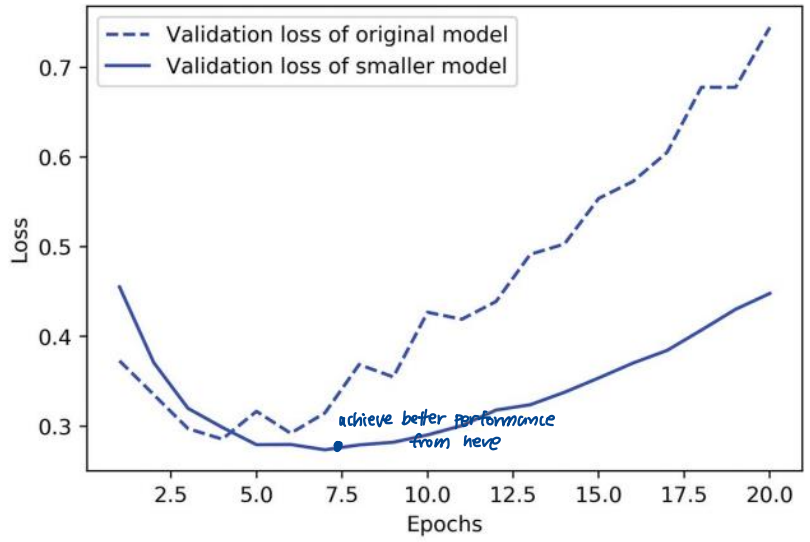


Figure 5.17 Original model vs. smaller model on IMDB review classification

Listing 5.11 Version of the model with lower capacity

```
model = keras.Sequential([
    layers.Dense(4, activation="relu"),
    layers.Dense(4, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

Listing 5.12 Version of the model with higher capacity

```
model = keras.Sequential([
    layers.Dense(512, activation="relu"),
    layers.Dense(512, activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

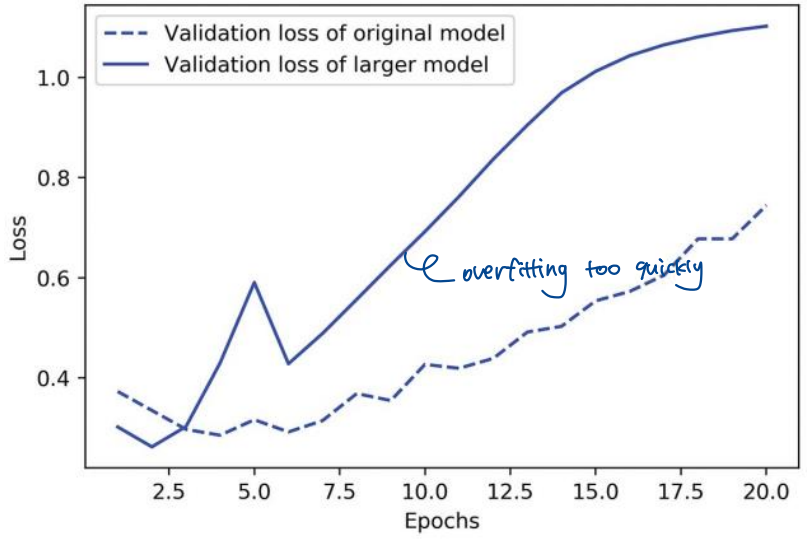


Figure 5.18 Original model vs. much larger model on IMDB review classification

Adding weight regularization

Simpler models are less likely to overfit than complex ones

Simple model is a model where the parameter values has less entropy

↳ we would like to control the entropy using L_1 or L_2 regularization penalty.

L1 regularization:

Lasso penalty

$$C(\mathbf{w}, b) = \sum_{i=1}^{m} L(\hat{y}_i, y_i) + \frac{\lambda}{2m}\|\mathbf{w}\| \qquad \|\mathbf{w}\| = \sum_{j=1}^{n_x} |w_j|$$

$\hat{f}_w(x)$

↳ trainable parameters of our deep learning model.

restrict trainable parameters to have less entropies.

L2 regularization:

Ridge penalty

$$C(\mathbf{w}, b) = \sum_{i=1}^{m} L(\hat{y}_i, y_i) + \frac{\lambda}{2m}\|\mathbf{w}\|^2 \qquad \|\mathbf{w}\|^2 = \sum_{j=1}^{n_x} w_j^2$$

Adding weight regularization

Listing 5.13 Adding L2 weight regularization to the model

```
from tensorflow.keras import regularizers
model = keras.Sequential([
    layers.Dense(16,
                 kernel_regularizer=regularizers.l2(0.002),
                 activation="relu"),
    layers.Dense(16,
                 kernel_regularizer=regularizers.l2(0.002),
                 activation="relu"),
    layers.Dense(1, activation="sigmoid")
])
```

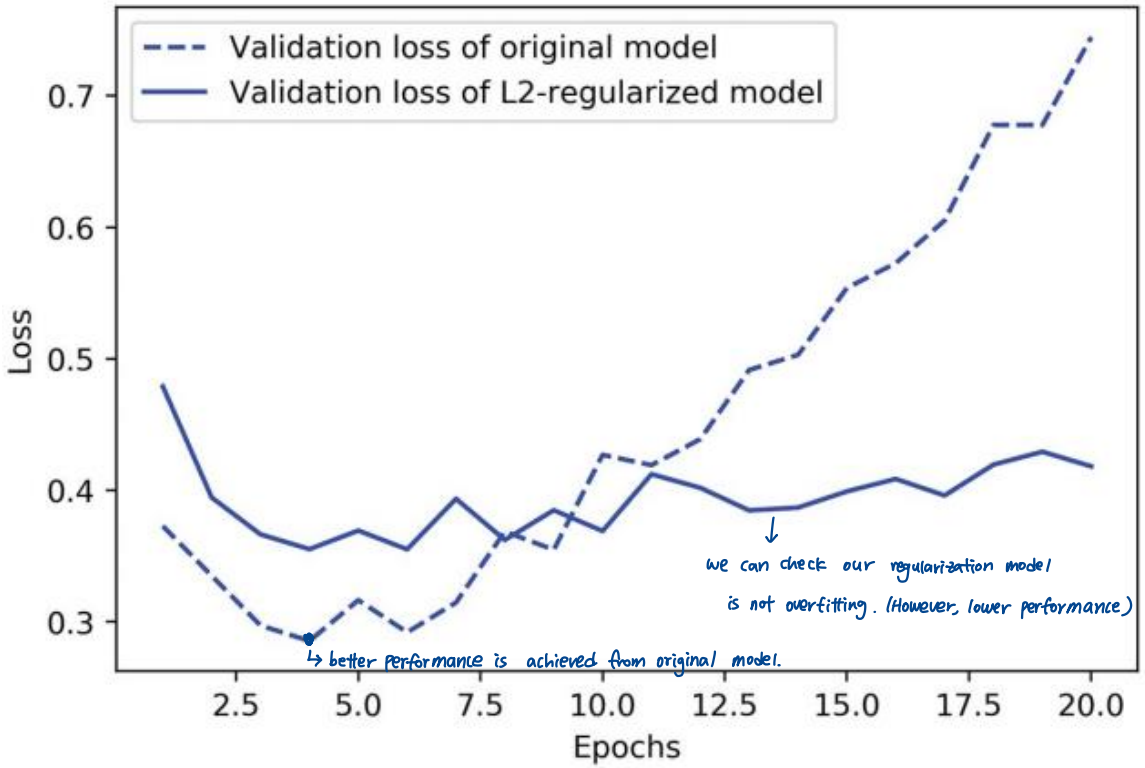


Figure 5.19 Effect of L2 weight regularization on validation loss

Listing 5.14 Different weight regularizers available in Keras

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

L1 regularization

Simultaneous L1 and L2 regularization

*교수님 의견

→ 딥러닝에선 L1 or L2 규제보다 dropout 규제가 더 나은 것 같다.

Adding dropout

Randomly *dropping out* (setting to zero) a number of output features of the layer during training

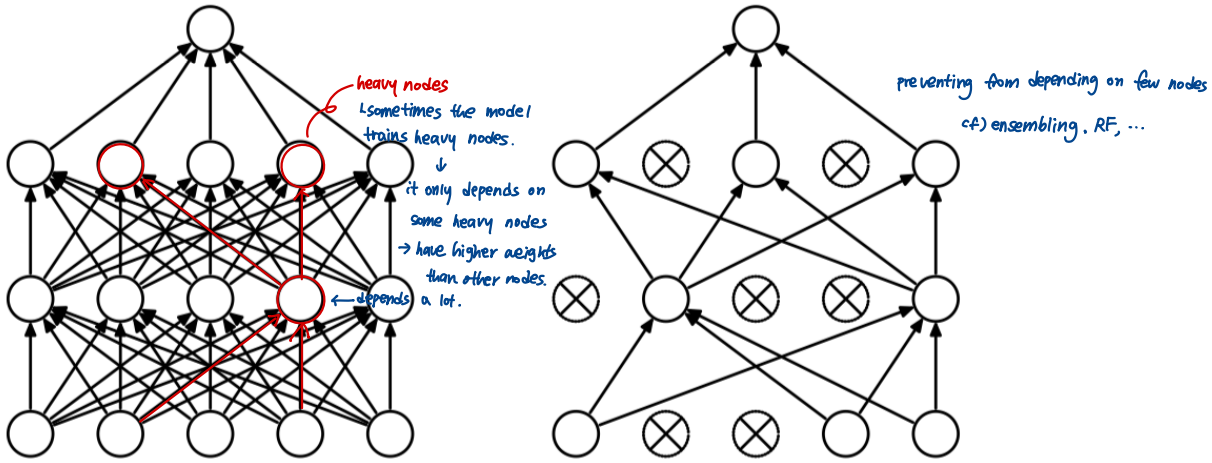
0.3	0.2	1.5	0.0
0.6	0.1	0.0	0.3
0.2	1.9	0.3	1.2
0.7	0.5	1.0	0.0

50% dropout →

0.0	0.2	1.5	0.0
0.6	0.1	0.0	0.3
0.0	1.9	0.3	0.0
0.7	0.0	0.0	0.0

* 2

Figure 5.20 Dropout applied to an activation matrix at training time, with rescaling happening during training. At test time the activation matrix is unchanged.



(a) Standard Neural Net (b) After applying dropout.

Adding dropout

Listing 5.15 Adding dropout to the IMDB model

```
model = keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.5),
    layers.Dense(1, activation="sigmoid")
])
```

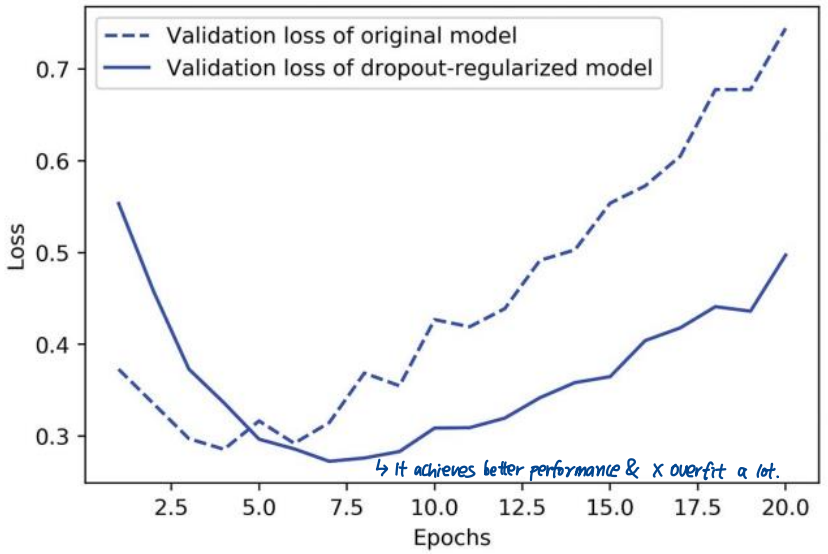


Figure 5.21 Effect of dropout on validation loss

```
layer_output *= np.random.randint(0, high=2, size=layer_output.shape)
```

16 dimensional vector

At training time, drops out 50% of the units in the output

At testing time

```
layer_output *= 0.5
```

← At test time

Or, at training time

```
layer_output *= np.random.randint(0, high=2, size=layer_output.shape)
layer_output /= 0.5
```

← Note that we're scaling up rather scaling down in this case.

At training time

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

```
(train_images, train_labels), _ = mnist.load_data()
train_images = train_images.reshape((60000, 28 * 28))
train_images = train_images.astype("float32") / 255

model = keras.Sequential([
    layers.Dense(512, activation="relu"),
    layers.Dense(10, activation="softmax")
])
model.compile(optimizer=keras.optimizers.RMSprop(1.),
              loss="sparse_categorical_crossentropy",
              metrics=["accuracy"])
model.fit(train_images, train_labels,
          epochs=10,
          batch_size=128,
          validation_split=0.2)
```

8s

```
Epoch 1/10
```

7s completed at 9:37 PM

Thank you!

CH6. The universal workflow of machine learning

Il-Youp Kwak

Chung-Ang University

The universal workflow of machine learning

Define the task

Develop a model

Deploy the model

Define the task

1. Frame the problem:

   What will the input data? What we want to predict?

   What type of machine learning task are you facing?

   What do existing solutions look like?

   Are there particular constraints you will need to deal with?

Why Voice Liveness Detection?

HOME › ADVERTISING

Burger King's Google Home Whopper stunt just won a big advertising award

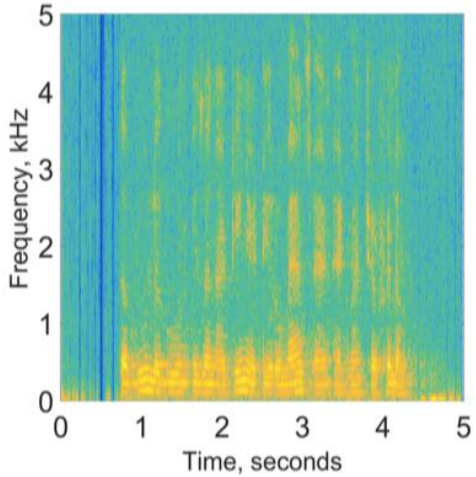
Tanya Dua Jun 21, 2017, 6:11 AM

After sneaking into people's homes, Burger King has managed to sneak out with an award at the Cannes Lions, advertising's biggest annual gathering.

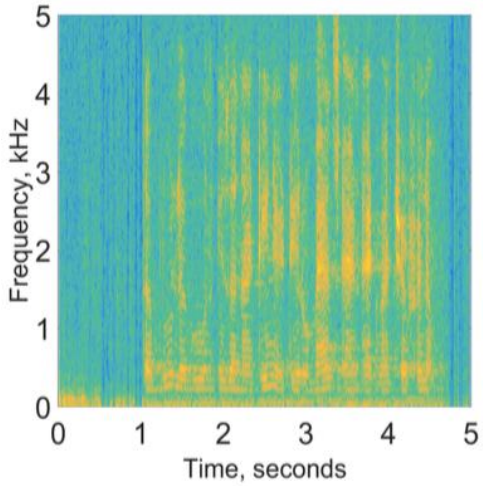
Back in April, the fast food

Voice Liveness Detection

Genuine

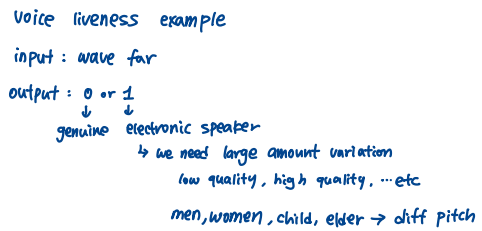


Replayed



2. Collect a dataset:

Inputs and targets are decided, Time for data collection—the most arduous, time-consuming part of most machine learning projects.



Beaware of non-representative data

it’s critical that the data used for training should be representative of the production data

3. **Understand your data** EDA

   Before you start training models, you should explore and visualize your data to gain insights about what makes it predictive

4. **Choose a measure of success**

   Define what you mean by success. Define the evaluation metric and business requirement for the solution

Develop a model

Prepare the data

Choose an evaluation protocol

Beat a baseline

Scale up: Develop a model that overfits

Regularize and tune your model

Deploy the model

Explain your work to stakeholders and set expectations

Ship an inference model

Monitor your model in the wild

Maintain your model

Thank you!