3 Machine learning for classification

This chapter covers

- Performing exploratory data analysis for identifying important features
- Encoding categorical variables to use them in machine learning models
- Using logistic regression for classification

In this chapter, we are going to use machine learning to predict churn.

Churn is when customers stop using the services of a company. Thus, churn prediction is about identifying customers who are likely to cancel their contracts soon. If the company can do that, it can offer discounts on these services in an effort to keep the users.

Naturally, we can use machine learning for that: we can use past data about customers who churned and, based on that, create a model for identifying present customers who are about to leave. This is a binary classification problem. The target variable that we want to predict is categorical and has only two possible outcomes: churn or not churn.

In chapter 1, we learned that many supervised machine learning models exist, and we specifically mentioned ones that can be used for binary classification, including logistic regression, decision trees, and neural networks. In this chapter, we start with the simplest one: logistic regression. Even though it's indeed the simplest, it's still powerful and has many advantages over other models: it's fast and easy to understand, and its results are easy to interpret. It's a workhorse of machine learning and the most widely used model in the industry.

3.1 Churn prediction project

The project we prepared for this chapter is churn prediction for a telecom company. We will use logistic regression and Scikit-learn for that.

Imagine that we are working at a telecom company that offers phone and internet services, and we have a problem: some of our customers are churning. They no longer are using our services and are going to a different provider. We would like to prevent that from happening, so we develop a system for identifying these customers and offer them an incentive to stay. We want to target them with promotional messages and give them a discount. We also would like to understand why the model thinks our customers churn, and for that, we need to be able to interpret the model's predictions.

We have collected a dataset where we've recorded some information about our customers: what type of services they used, how much they paid, and how long they stayed with us. We also know who canceled their contracts and stopped using our services (churned). We will use this information as the target variable in the machine learning model and predict it using all other available information.

The plan for the project follows:

1. First, we download the dataset and do some initial preparation: rename columns and change values inside columns to be consistent throughout the entire dataset.
2. Then we split the data into train, validation, and test so we can validate our models.
3. As part of the initial data analysis, we look at feature importance to identify which features are important in our data.
4. We transform categorical variables into numeric variables so we can use them in the model.
5. Finally, we train a logistic regression model.

In the previous chapter, we implemented everything ourselves, using Python and NumPy. In this project, however, we will start using Scikit-learn, a Python library for machine learning. Namely, we will use it for

- Splitting the dataset into train and test
- Encoding categorical variables
- Training logistic regression

3.1.1 Telco churn dataset

As in the previous chapter, we will use Kaggle datasets for data. This time we will use data from **https://www.kaggle.com/blastchar/telco-customer-churn**.

According to the description, this dataset has the following information:

- Services of the customers: phone; multiple lines; internet; tech support and extra services such as online security, backup, device protection, and TV streaming
- Account information: how long they have been clients, type of contract, type of payment method
- Charges: how much the client was charged in the past month and in total
- Demographic information: gender, age, and whether they have dependents or a partner
- Churn: yes/no, whether the customer left the company within the past month

First, we download the dataset. To keep things organized, we first create a folder, chapter-03-churn-prediction. Then we go to that directory and use Kaggle CLI for downloading the data:

```
kaggle datasets download -d blastchar/telco-customer-churn
```

After downloading it, we unzip the archive to get the CSV file from there:

```
unzip telco-customer-churn.zip
```

We are ready to start now.

3.1.2 Initial data preparation

The first step is creating a new notebook in Jupyter. If it's not running, start it:

```
jupyter notebook
```

We name the notebook chapter-03-churn-project (or any other name that we like).

As previously, we begin with adding the usual imports:

```
import pandas as pd
import numpy as np

import seaborn as sns
from matplotlib import pyplot as plt
%matplotlib inline
```

And now we can read the dataset:

```
df = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

We use the `read_csv` function to read the data and then write the results to a dataframe named `df`. To see how many rows it contains, let's use the `len` function:

```
len(df)
```

It prints 7043, so there are 7,043 rows in this dataset. The dataset is not large but should be enough to train a decent model.

Next, let's look at the first couple of rows using `df.head ()` (figure 3.1). By default, it shows the first five rows of the dataframe.

```
df.head()
```

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	Tech
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	

Figure 3.1 The output of the `df.head()` command showing the first five rows of the telco churn dataset

This dataframe has quite a few columns, so they all don't fit on the screen. Instead, we can transpose the dataframe using the `T` function, switching columns and rows so the columns (customerID, gender, and so on) become rows. This way we can see a lot more data (figure 3.2):

```
df.head().T
```

```
df.head().T
```

	0	1	2
customerID	7590-VHVEG	5575-GNVDE	3668-QPYBK
gender	Female	Male	Male
SeniorCitizen	0	0	0
Partner	Yes	No	No
Dependents	No	No	No
tenure	1	34	2
PhoneService	No	Yes	Yes
MultipleLines	No phone service	No	No
InternetService	DSL	DSL	DSL
OnlineSecurity	No	Yes	Yes
OnlineBackup	Yes	No	Yes
DeviceProtection	No	Yes	No
TechSupport	No	No	No
StreamingTV	No	No	No
StreamingMovies	No	No	No
Contract	Month-to-month	One year	Month-to-month
PaperlessBilling	Yes	No	Yes
PaymentMethod	Electronic check	Mailed check	Mailed check
MonthlyCharges	29.85	56.95	53.85
TotalCharges	29.85	1889.5	108.15
Churn	No	No	Yes

Figure 3.2 The output of the `df.head().T` command showing the first three rows of the telco churn dataset. The original rows are shown as columns: this way, it's possible to see more data without having to use the slider.

We see that the dataset has a few columns:

- CustomerID: the ID of the customer
- Gender: male/female
- SeniorCitizen: whether the customer is a senior citizen (0/1)
- Partner: whether they live with a partner (yes/no)

- Dependents: whether they have dependents (yes/no)
- Tenure: number of months since the start of the contract
- PhoneService: whether they have phone service (yes/no)
- MultipleLines: whether they have multiple phone lines (yes/no/no phone service)
- InternetService: the type of internet service (no/fiber/optic)
- OnlineSecurity: if online security is enabled (yes/no/no internet)
- OnlineBackup: if online backup service is enabled (yes/no/no internet)
- DeviceProtection: if the device protection service is enabled (yes/no/no internet)
- TechSupport: if the customer has tech support (yes/no/no internet)
- StreamingTV: if the TV streaming service is enabled (yes/no/no internet)
- StreamingMovies: if the movie streaming service is enabled (yes/no/no internet)
- Contract: the type of contract (monthly/yearly/two years)
- PaperlessBilling: if the billing is paperless (yes/no)
- PaymentMethod: payment method (electronic check, mailed check, bank transfer, credit card)
- MonthlyCharges: the amount charged monthly (numeric)
- TotalCharges: the total amount charged (numeric)
- Churn: if the client has canceled the contract (yes/no)

The most interesting one for us is Churn. As the target variable for our model, this is what we want to learn to predict. It takes two values: yes if the customer churned and no if the customer didn't.

When reading a CSV file, Pandas tries to automatically determine the proper type of each column. However, sometimes it's difficult to do it correctly, and the inferred types aren't what we expect them to be. This is why it's important to check whether the actual types are correct. Let's have a look at them by using `df.dtypes` :

```
df.dtypes
```

We see (figure 3.3) that most of the types are inferred correctly. Recall that object means a string value, which is what we expect for most of the columns. However, we may notice two things. First, SeniorCitizen is detected as int64, so it has a type of integer, not object. The reason for this is that instead of the values yes and no, as we have in other columns, there are 1 and 0 values, so Pandas interprets this as a column with integers. It’s not really a problem for us, so we don’t need to do any additional preprocessing for this column.

```
df.dtypes
```

```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

SeniorCitizen is of type "integer"

TotalCharges is not correctly identified as a numeric type (float or int).

Figure 3.3 Automatically inferred types for all the columns of the dataframe. Object means a string. TotalCharges is incorrectly identified as “object,” but it should be “float.”

The other thing to note is the type for TotalCharges. We would expect this column to be numeric: it contains the total amount of money the client was charged, so it should be a number, not a string. Yet Pandas infers the type as “object.” The reason is that in some cases this column contains a space (“ ”) to represent a missing value. When coming across nonnumeric characters, Pandas has no other option but to declare the column “object.”

IMPORTANT Watch out for cases when you expect a column to be numeric, but Pandas says it’s not: most likely the column contains special encoding for missing values that require additional preprocessing.

We can force this column to be numeric by converting it to numbers using a special function in Pandas: `to_numeric`. By default, this function raises an exception when it sees nonnumeric data (such as spaces), but we can make it skip these cases by specifying the `errors='coerce'` option. This way Pandas will replace all nonnumeric values with a `NaN` (not a number):

```
total_charges = pd.to_numeric(df.TotalCharges, errors='coerce')
```

To confirm that data indeed contains nonnumeric characters, we can now use the `isnull()` function of `total_charges` to refer to all the rows where Pandas couldn’t parse the original string:

```
df[total_charges.isnull()][['customerID', 'TotalCharges']]
```

We see that indeed there are spaces in the TotalCharges column (figure 3.4).

```
total_charges = pd.to_numeric(df.TotalCharges, errors='coerce')
df[total_charges.isnull()][['customerID', 'TotalCharges']]
```

	customerID	TotalCharges
488	4472-LVYGI	
753	3115-CZMZD	
936	5709-LVOEQ	
1082	4367-NUYAO	
1340	1371-DWPAZ	
3331	7644-OMVMY	
3826	3213-VVOLG	
4380	2520-SGTTA	
5218	2923-ARZLG	
6670	4075-WKNIU	
6754	2775-SEFEE	

Figure 3.4 We can spot nonnumeric data in a column by parsing the content as numeric and see at which rows the parsing fails.

Now it's up to us to decide what to do with these missing values. Although we could do many things with them, we are going to do the same thing we did in the previous chapter—set the missing values to zero:

```
df.TotalCharges = pd.to_numeric(df.TotalCharges, errors='coerce')
df.TotalCharges = df.TotalCharges.fillna(0)
```

In addition, we notice that the column names don't follow the same naming convention. Some of them start with a lower letter, whereas others start with a capital letter, and there are also spaces in the values.

Let's make it uniform by lowercasing everything and replacing spaces with underscores. This way we remove all the inconsistencies in the data. We use the exact same code we used in the previous chapter:

```
df.columns = df.columns.str.lower().str.replace(' ', '_')

string_columns = list(df.dtypes[df.dtypes == 'object'].index)

for col in string_columns:
    df[col] = df[col].str.lower().str.replace(' ', '_')
```

Next, let's look at our target variable: `churn`. Currently, it's categorical, with two values, "yes" and "no" (figure 3.5A). For binary classification, all models typically expect a number: 0 for "no" and 1 for "yes." Let's convert it to numbers:

```
df.churn = (df.churn == 'yes').astype(int)
```

When we use `df.churn == 'yes'`, we create a Pandas series of type boolean. A position in the series is equal to `True` if it's "yes" in the original series and `False` otherwise. Because the only other value it can take is "no," this converts "yes" to `True` and "no" to `False` (figure 3.5B). When we perform casting by using the `astype(int)` function, we convert `True` to 1 and `False` to 0 (figure. 3.5C). This is exactly the same idea that we used in the previous chapter when we implemented category encoding.

```
df.churn.head()
```

```
0     no
1     no
2    yes
3     no
4    yes
Name: churn, dtype: object
```

(A) The original Churn column: it's a Pandas series that contains only "yes" and "no" values.

```
(df.churn == 'yes').head()
```

```
0    False
1    False
2     True
3    False
4     True
Name: churn, dtype: bool
```

(B) The result of the == operator: it's a Boolean series with `True` when the elements of the original series are "yes" and `False` otherwise.

```
(df.churn == 'yes').astype(int).head()
```

```
0    0
1    0
2    1
3    0
4    1
Name: churn, dtype: int64
```

(C) The result of converting the Boolean series to integer: `True` is converted to 1 and `False` is converted to 0.

Figure 3.5 The expression `(df.churn == 'yes').astype(int)` broken down by individual steps

We've done a bit of preprocessing already, so let's put aside some data for testing. In the previous chapter, we implemented the code for doing it ourselves. This is great for understanding how it works, but typically we don't write such things from scratch every time we need them. Instead, we use existing implementations from libraries. In this chapter we use Scikit-learn, and it has a module called `model_selection` that can handle data splitting. Let's use it.

The function we need to import from `model_selection` is called `train_test_split`:

```
from sklearn.model_selection import train_test_split
```

After importing, it's ready to be used:

```
df_train_full, df_test = train_test_split(df, test_size=0.2, random_state=1)
```

The function `train_test_split` takes a dataframe `df` and creates two new dataframes: `df_train_full` and `df_test`. It does this by shuffling the original dataset and then splitting it in such a way that the test set contains 20% of the data and the train set contains the remaining 80% (figure 3.6). Internally, it's implemented similarly to what we did ourselves in the previous chapter.

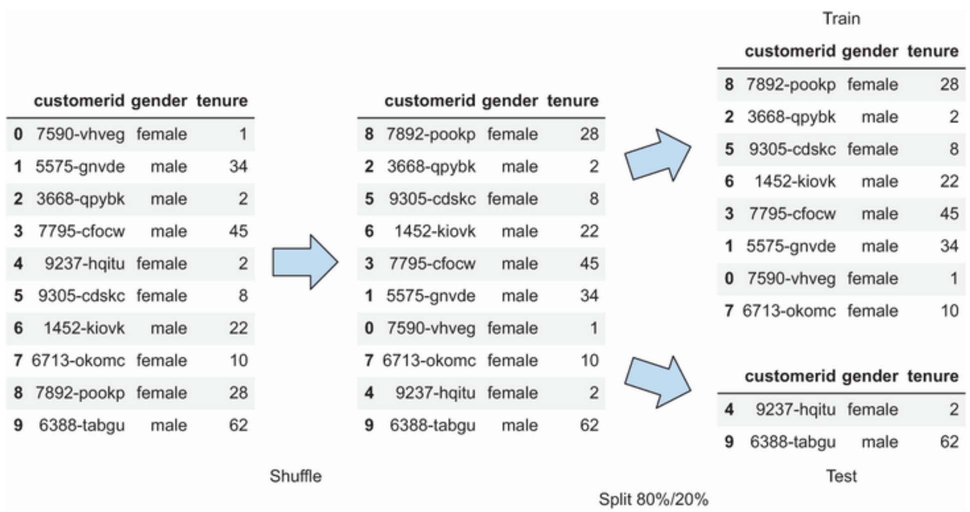


Figure 3.6 When using `train_test_split`, the original dataset is shuffled and then split such that 80% of the data goes to the train set and the remaining 20% goes to the test set.

This function contains a few parameters:

1. The first parameter that we pass is the dataframe that we want to split: `df`.
2. The second parameter is `test_size`, which specifies the size of the dataset we want to set aside for testing—20% for our case.

3. The third parameter we pass is `random_state`. It's needed for ensuring that every time we run this code, the dataframe is split in the exact same way.

Shuffling of data is done using a random-number generator; it's important to fix the random seed to ensure that every time we shuffle the data, the final arrangement of rows will be the same.

We do see a side effect from shuffling: if we look at the dataframes after splitting by using the `head()` method, for example, we notice that the indices appear to be randomly ordered (figure 3.7).

```
df_train_full.head()
```

	customerid	gender	seniorcitizen	partner	dependents	tenure	phoneservice
1814	5442-pptjy	male	0	yes	yes	12	yes
5946	6261-rcvns	female	0	no	no	42	yes
3881	2176-osjuv	male	0	yes	no	71	yes
2389	6161-erdgd	male	0	yes	yes	71	yes
3676	2364-ufrom	male	0	no	no	30	yes

Figure 3.7 The side effect of `train_test_split`: the indices (the first column) are shuffled in the new dataframes, so instead of consecutive numbers like 0, 1, 2, ..., they look random.

In the previous chapter, we split the data into three parts: train, validation, and test. However, the `train_test_split` function splits the data into only two parts: train and test. In spite of that, we can still split the original dataset into three parts; we just take one part and split it again (figure 3.8).

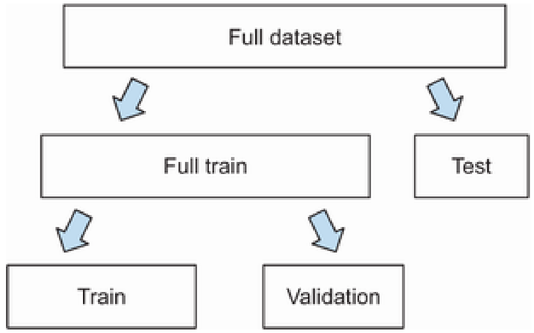


Figure 3.8 Because `train_test_split` splits a dataset into only two parts, we perform the split two times because we need three parts. First, we split the entire dataset into full train and test, and then we split full train into train and validation.

Let’s take the `df_train_full` dataframe and split it one more time into train and validation:

```
df_train, df_val = train_test_split(df_train_full, test_size=0.33, random_state=11)

y_train = df_train.churn.values     ❷
y_val = df_val.churn.values         ❷

del df_train['churn']               ❸
del df_val['churn']                 ❸
```

❶ Sets the random seed when doing the split to make sure that every time we run the code, the result is the same

❷ Takes the column with the target variable, churn, and saves it outside the dataframe

❸ Deletes the churn columns from both dataframes to make sure we don’t accidentally use the churn variable as a feature during training

Now the dataframes are prepared, and we are ready to use the training dataset for performing initial exploratory data analysis.

3.1.3 Exploratory data analysis

Looking at the data before training a model is important. The more we know about the data and the problems inside, the better the model we can build afterward.

We should always check for any missing values in the dataset because many machine learning models cannot easily deal with missing data. We have already found a problem with the TotalCharges column and replaced the missing values with zeros. Now let's see if we need to perform any additional null handling:

```
df_train_full.isnull().sum()
```

It prints all zeros (figure 3.9), so we have no missing values in the dataset and don't need to do anything extra.

```
df_train_full.isnull().sum()
```

```
customerid          0
gender              0
seniorcitizen       0
partner             0
dependents          0
tenure              0
phoneservice        0
multiplelines       0
internetservice     0
onlinesecurity      0
onlinebackup        0
deviceprotection    0
techsupport         0
streamingtv         0
streamingmovies     0
contract            0
paperlessbilling    0
paymentmethod       0
monthlycharges      0
totalcharges        0
churn               0
dtype: int64
```

Figure 3.9 We don't have to handle missing values in the dataset: all the values in all the columns are present.

Another thing we should do is check the distribution of values in the target variable. Let's take a look at it using the `value_counts()` method:

```
df_train_full.churn.value_counts()
```

It prints

```
0    4113
1    1521
```

The first column is the value of the target variable, and the second is the count. As we see, the majority of the customers didn't churn.

We know the absolute numbers, but let's also check the proportion of churned users among all customers. For that, we need to divide the number of customers who churned by the total number of customers. We know that 1,521 of 5,634 churned, so the proportion is

1521 / 5634 = 0.27

This gives us the proportion of churned users, or the probability that a customer will churn. As we see in the training dataset, approximately 27% of the customers stopped using our services, and the rest remained as customers.

The proportion of churned users, or the probability of churning, has a special name: churn rate.

There's another way to calculate the churn rate: the `mean()` method. It's more convenient to use than manually calculating the rate:

```
global_mean = df_train_full.churn.mean()
```

Using this method, we also get 0.27 (figure 3.10).

```
global_mean = df_train_full.churn.mean()
round(global_mean, 3)
```

```
0.27
```

Figure 3.10 Calculating the global churn rate in the training dataset

The reason it produces the same result is the way we calculate the mean value. If you don't remember, the formula for that is

$$\frac{1}{n}\sum_{i=1}^{n} y_i$$

where n is the number of items in the dataset.

Because y_i can take only zeros and ones, when we sum all of them, we get the number of ones, or the number of people who churned. Then we divide it by the total number of customers, which is exactly the same as the formula we used for calculating the churn rate previously.

Our churn dataset is an example of a so-called *imbalanced* dataset. There were three times as many people who didn't churn in our dataset as those who did churn, and we say that the nonchurn class dominates the churn class. We can clearly see that: the churn rate in our data is 0.27, which is a strong indicator of class imbalance. The opposite of *imbalanced* is the *balanced* case, when positive and negative classes are equally distributed among all observations.

Exercise 3.1

The mean of a Boolean array is

a) The percentage of `False` elements in the array: the number of `False` elements divided by the length of the array

b) The percentage of `True` elements in the array: the number of `True` elements divided by the length of the array

c) The length of an array

Both the categorical and numerical variables in our dataset are important, but they are also different and need different treatment. For that, we want to look at them separately.

We will create two lists:

- `categorical` , which will contain the names of categorical variables
- `numerical` , which, likewise, will have the names of numerical variables

Let's create them:

```
categorical = ['gender', 'seniorcitizen', 'partner', 'dependents',
               'phoneservice', 'multiplelines', 'internetservice',
               'onlinesecurity', 'onlinebackup', 'deviceprotection',
               'techsupport', 'streamingtv', 'streamingmovies',
               'contract', 'paperlessbilling', 'paymentmethod']
numerical = ['tenure', 'monthlycharges', 'totalcharges']
```

First, we can see how many unique values each variable has. We already know we should have just a few for each column, but let's verify it:

```
df_train_full[categorical].nunique()
```

Indeed, we see that most of the columns have two or three values and one (paymentmethod) has four (figure 3.11). This is good. We don't need to spend extra time preparing and cleaning the data; everything is already good to go.

```
df_train_full[categorical].nunique()
```

```
gender              2
seniorcitizen       2
partner             2
dependents          2
phoneservice        2
multiplelines       3
internetservice     3
onlinesecurity      3
onlinebackup        3
deviceprotection    3
techsupport         3
streamingtv         3
streamingmovies     3
contract            3
paperlessbilling    2
paymentmethod       4
dtype: int64
```

Figure 3.11 The number of distinct values for each categorical variable. We see that all the variables have very few unique values.

Now we come to another important part of exploratory data analysis: understanding which features may be important for our model.

3.1.4 Feature importance

Knowing how other variables affect the target variable, churn, is the key to understanding the data and building a good model. This process is called *feature importance analysis*, and it's often done as a part of exploratory data analysis to figure out which variables will be useful for the model. It also gives us additional insights about the dataset and helps answer questions like "What makes customers churn?" and "What are the characteristics of people who churn?"

We have two different kinds of features: categorical and numerical. Each kind has different ways of measuring feature importance, so we will look at each separately.

CHURN RATE

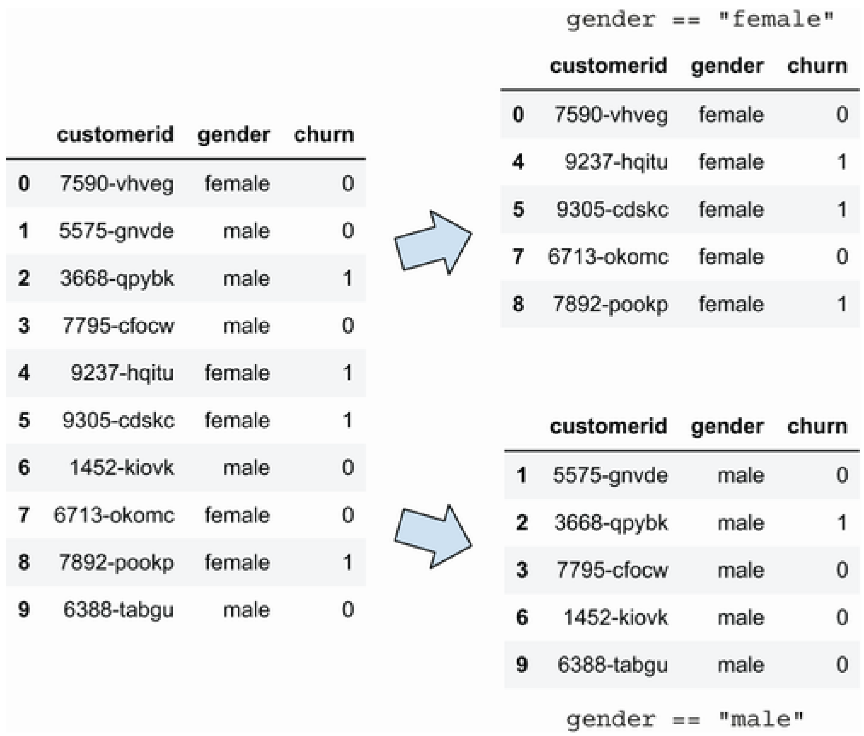
Let's start by looking at categorical variables. The first thing we can do is look at the churn rate for each variable. We know that a categorical variable has a set of values it can take, and each value defines a group inside the dataset.

We can look at all the distinct values of a variable. Then, for each variable, there's a group of customers: all the customers who have this value. For each such group, we can compute the churn rate, which is the group churn rate. When we have it, we can compare it with the global churn rate—the churn rate calculated for all the observations at once.

If the difference between the rates is small, the value is not important when predicting churn because this group of customers is not really different from the rest of the customers. On the other hand, if the difference is not small, something inside that group sets it apart from the rest. A machine learning algorithm should be able to pick this up and use it when making predictions.

Let’s check first for the `gender` variable. This `gender` variable can take two values, female and male. There are two groups of customers: ones that have `gender == 'female'` and ones that have `gender == 'male'` (figure 3.12). To compute the churn rate for all female customers, we first select only rows that correspond to `gender == 'female'` and then compute the churn rate for them:

```
female_mean = df_train_full[df_train_full.gender == 'female'].churn.mean()
```



	customerid	gender	churn
0	7590-vhveg	female	0
1	5575-gnvde	male	0
2	3668-qpybk	male	1
3	7795-cfocw	male	0
4	9237-hqitu	female	1
5	9305-cdskc	female	1
6	1452-kiovk	male	0
7	6713-okomc	female	0
8	7892-pookp	female	1
9	6388-tabgu	male	0

gender == "female"

	customerid	gender	churn
0	7590-vhveg	female	0
4	9237-hqitu	female	1
5	9305-cdskc	female	1
7	6713-okomc	female	0
8	7892-pookp	female	1

	customerid	gender	churn
1	5575-gnvde	male	0
2	3668-qpybk	male	1
3	7795-cfocw	male	0
6	1452-kiovk	male	0
9	6388-tabgu	male	0

gender == "male"

Figure 3.12 The dataframe is split by the values of the `gender` variable into two groups: a group with `gender == "female"` and a group with `gender == "male"`.

We then do the same for all male customers:

```
male_mean = df_train_full[df_train_full.gender == 'male'].churn.mean()
```

When we execute this code and check the results, we see that the churn rate of female customers is 27.7% and that of male customers is 26.3%, whereas the global churn rate is 27% (figure 3.13). The difference between the group rates for both females and males is quite small, which indicates that knowing the gender of the customer doesn't help us identify whether they will churn.

```
global_mean = df_train_full.churn.mean()
round(global_mean, 3)
```

```
0.27
```

```
female_mean = df_train_full[df_train_full.gender == 'female'].churn.mean()
print('gender == female:', round(female_mean, 3))

male_mean = df_train_full[df_train_full.gender == 'male'].churn.mean()
print('gender == male:  ', round(male_mean, 3))
```

```
gender == female: 0.277
gender == male:   0.263
```

Figure 3.13 The global churn rate compared with churn rates among males and females. The numbers are quite close, which means that `gender` is not a useful variable when predicting churn.

Now let's take a look at another variable: `partner`. It takes values of yes and no, so there are two groups of customers: the ones for which `partner == 'yes'` and the ones for which `partner == 'no'`.

We can check the group churn rates using the same code as we used previously. All we need to change is the filter conditions:

```
partner_yes = df_train_full[df_train_full.partner == 'yes'].churn.mean()
partner_no = df_train_full[df_train_full.partner == 'no'].churn.mean()
```

As we see, the rates for those who have a partner are quite different from rates for those who don't: 20% and 33%, respectively. It means that clients with no partner are more likely to churn than the ones with a partner (figure 3.14).

```
partner_yes = df_train_full[df_train_full.partner == 'yes'].churn.mean()
print('partner == yes:', round(partner_yes, 3))

partner_no = df_train_full[df_train_full.partner == 'no'].churn.mean()
print('partner == no :', round(partner_no, 3))
```

```
partner == yes: 0.205
partner == no : 0.33
```

Figure 3.14 The churn rate for people with a partner is significantly less than the rate for the ones without a partner—20.5% versus 33%—which indicates that the `partner` variable is useful for predicting churn.

RISK RATIO

In addition to looking at the difference between the group rate and the global rate, it's interesting to look at the ratio between them. In statistics, the ratio between probabilities in different groups is called the *risk ratio*, where *risk* refers to the risk of having the effect. In our case, the effect is churn, so it's the risk of churning:

risk = group rate / global rate

For `gender == female`, for example, the risk of churning is 1.02:

risk = 27.7% / 27% = 1.02

Risk is a number between zero and infinity. It has a nice interpretation that tells you how likely the elements of the group are to have the effect (churn) compared with the entire population.

If the difference between the group rate and the global rate is small, the risk is close to 1: this group has the same level of risk as the rest of the population. Customers in the group are as likely to churn as anyone else. In other words, a group with a risk close to 1 is not risky at all (figure 3.15, group A).

If the risk is lower than 1, the group has lower risks: the churn rate in this group is smaller than the global churn. For example, the value 0.5 means that the clients in this group are two times less likely to churn than clients in general (figure 3.15, group B).

On the other hand, if the value is higher than 1, the group is risky: there's more churn in the group than in the population. So a risk of 2 means that customers from the group are two times more likely to churn (figure 3.15, group C).

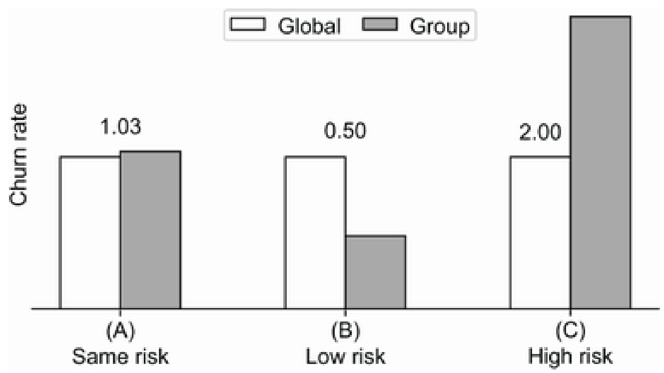


Figure 3.15 Churn rate of different groups compared with the global churn rate. In group (A), the rates are approximately the same, so the risk of churn is around 1. In group (B), the group churn rate is smaller than the global rate, so the risk is around 0.5. Finally, in group (C), the group churn rate is higher than the global rate, so the risk is close to 2.

The term *risk* originally comes from controlled trials, in which one group of patients is given a treatment (a medicine) and the other group isn't (only a placebo). Then we compare how effective the medicine is by calculating the rate of negative outcomes in each group and then calculating the ratio between the rates:

risk = negative outcome rate in group 1 / negative outcome rate in group 2

If medicine turns out to be effective, it's said to reduce the risk of having the negative outcome, and the value of the risk is less than 1.

Let's calculate the risks for `gender` and `partner`. For the `gender` variable, the risks for both males and females is around 1 because the rates in both groups aren't significantly different from the global rate. Not surprisingly, it's different for the `partner` variable; having no partner is more risky (table 3.1).

Table 3.1 Churn rates and risks for the `gender` and `partner` variables. The churn rates for females and males are not significantly different from the global churn rates, so the risks for them to churn are low: both have risks values around 1. On the other hand, the churn rate for people with no partner is significantly higher than average, making them risky, with the risk value of 1.22. People with partners tend to churn less, so for them, the risk is only 0.75.

Variable	Value	Churn rate	Risk
gender	Female	27.7%	1.02
	Male	26.3%	0.97
partner	Yes	20.5%	0.75
	No	33%	1.22

We did this from only two variables. Let's now do this for all the categorical variables. To do that, we need a piece of code that checks all the values a variable has and computes churn rate for each of these values.

If we used SQL, that would be straightforward to do. For gender, we'd need to do something like this:

```
SELECT
    gender, AVG(churn),
    AVG(churn) - global_churn,
    AVG(churn) / global_churn
FROM
    data
GROUP BY
    gender
```

This is a rough translation to Pandas:

```
global_mean = df_train_full.churn.mean()

df_group = df_train_full.groupby(by='gender').churn.agg(['mean'])    ❶
df_group['diff'] = df_group['mean'] - global_mean                    ❷
df_group['risk'] = df_group['mean'] / global_mean                    ❸

df_group
```

❶ Computes the AVG(churn)

❷ Calculates the difference between group churn rate and global rate

❸ Calculates the risk of churning

In ❶ we calculate the `AVG(churn )` part. For that, we use the `agg` function to indicate that we need to aggregate data into one value per group: the mean value. In ❷ we create another column, diff, where we will keep the difference between the group mean and the global mean. Likewise, in ❸ we create the column risk, where we calculate the fraction between the group mean and the global mean.

We can see the results in figure 3.16.

	mean	diff	risk
gender			
female	0.276824	0.006856	1.025396
male	0.263214	-0.006755	0.974980

Figure 3.16 The churn rate for the `gender` variable. We see that for both values, the difference between the group churn rate and the global churn rate is not very large.

Let's now do that for all categorical variables. We can iterate through them and apply the same code for each:

```
from IPython.display import display

for col in categorical:                                                ❶
    df_group = df_train_full.groupby(by=col).churn.agg(['mean'])       ❷
    df_group['diff'] = df_group['mean'] - global_mean
    df_group['rate'] = df_group['mean'] / global_mean
    display(df_group)                                                  ❸
```

❶ Loops over all categorical variables

❷ Performs groupby for each categorical variable

❸ Displays the resulting dataframe

Two things are different in this code. First, instead of manually specifying the column name, we iterate over all categorical variables.

The second difference is more subtle: we need to call the `display` function to render a dataframe inside the loop. The way we typically display a dataframe is to leave it as the last line in a Jupyter Notebook cell and then execute the cell. If we do it that way, the dataframe is displayed as the cell output. This is exactly how we managed to see the content of the dataframe at the beginning of the chapter (figure 3.1). However, we cannot do this inside a loop. To still be able to see the content of the dataframe, we call the `display` function explicitly.

From the results (figure 3.17) we learn that

- For gender, there is not much difference between females and males. Both means are approximately the same, and for both groups the risks are close to 1.
- Senior citizens tend to churn more than nonseniors: the risk of churning is 1.53 for seniors and 0.89 for nonseniors.
- People with a partner churn less than people with no partner. The risks are 0.75 and 1.22, respectively.
- People who use phone service are not at risk of churning: the risk is close to 1, and there's almost no difference with the global churn rate. People who don't use phone service are even less likely to churn: the risk is below 1, and the difference with the global churn rate is negative.

	mean	diff	risk
gender			
female	0.276824	0.006856	1.025396
male	0.263214	-0.006755	0.974980

(A) Churn ratio and risk: `gender`

	mean	diff	risk
seniorcitizen			
0	0.242270	-0.027698	0.897403
1	0.413377	0.143409	1.531208

(B) Churn ratio and risk: `seniorcitizen`

partner	mean	diff	risk
no	0.329809	0.059841	1.221659
yes	0.205033	-0.064935	0.759472

(C) Churn ratio and risk: `partner`

phoneservice	mean	diff	risk
no	0.241316	-0.028652	0.893870
yes	0.273049	0.003081	1.011412

(D) Churn ratio and risk: `phoneservice`

Figure 3.17 Churn rate difference and risk for four categorical variables: `gender`, `seniorcitizen`, `partner`, and `phoneservice`

Some of the variables have quite significant differences (figure 3.18):

- Clients with no tech support tend to churn more than those who do.
- People with monthly contracts cancel the contract a lot more often than others, and people with two-year contacts churn very rarely.

techsupport	mean	diff	risk
no	0.418914	0.148946	1.551717
no_internet_service	0.077805	-0.192163	0.288201
yes	0.159926	-0.110042	0.592390

(A) Churn ratio and risk: `techsupport`

contract	mean	diff	risk
month-to-month	0.431701	0.161733	1.599082
one_year	0.120573	-0.149395	0.446621
two_year	0.028274	-0.241694	0.104730

(B) Churn ratio and risk: `contract`

Figure 3.18 Difference between the group churn rate and the global churn rate for `techsupport` and `contract`. People with no tech support and month-to-month contracts tend to churn a lot more than clients from other groups, whereas people with tech support and two-year contracts are very low-risk clients.

This way, just by looking at the differences and the risks, we can identify the most discriminative features: the features that are helpful for detecting churn. Thus, we expect that these features will be useful for our future models.

MUTUAL INFORMATION

The kinds of differences we just explored are useful for our analysis and important for understanding the data, but it's hard to use them to say what the most important feature is and whether tech support is more useful than the type of contract.

Luckily, the metrics of importance can help us: we can measure the degree of dependency between a categorical variable and the target variable. If two variables are dependent, knowing the value of one variable gives us some information about another. On the other hand, if a variable is completely independent of the target variable, it's not useful and can be safely removed from the dataset.

In our case, knowing that the customer has a month-to-month contract may indicate that this customer is more likely to churn than not.

IMPORTANT Customers with month-to-month contracts tend to churn a lot more than customers with other kinds of contracts. This is exactly the kind of relationship we want to find in our data. Without such relationships in data, machine learning models will not work—they will not be able to make predictions. The higher the degree of dependency, the more useful a feature is.

For categorical variables, one such metric is mutual information, which tells how much information we learn about one variable if we learn the value of the other variable. It’s a concept from information theory, and in machine learning, we often use it to measure the mutual dependency between two variables.

Higher values of mutual information mean a higher degree of dependence: if the mutual information between a categorical variable and the target is high, this categorical variable will be quite useful for predicting the target. On the other hand, if the mutual information is low, the categorical variable and the target are independent, and thus the variable will not be useful for predicting the target.

Mutual information is already implemented in Scikit-learn in the `mutual_info_ score` function from the `metrics` package, so we can just use it:

```
from sklearn.metrics import mutual_info_score

def calculate_mi(series):                                          ❶
    return mutual_info_score(series, df_train_full.churn)          ❷

df_mi = df_train_full[categorical].apply(calculate_mi)             ❸
```

```
df_mi = df_mi.sort_values(ascending=False).to_frame(name='MI') ❹
df_mi
```

❶ Creates a stand-alone function for calculating mutual information

❷ Uses the mutual _info_score function from Scikit-learn

❸ Applies the function from ❶ to each categorical column of the dataset

❹ Sorts the values of the result

In ❸, we use the `apply` method to apply the `calculate_mi` function we defined in ❶ to each column of the `df_train_full` dataframe. Because we include an additional step of selecting only categorical variables, it's applied only to them. The function we define in ❶ takes only one parameter: `series`. This is a column from the dataframe on which we invoked the `apply()` method. In ❷, we compute the mutual information score between the series and the target variable `churn`. The output is a single number, so the output of the `apply()` method is a Pandas series. Finally, we sort the elements of the series by the mutual information score and convert the series to a dataframe. This way, the result is rendered nicely in Jupyter.

As we see, `contract`, `onlinesecurity`, and `techsupport` are among the most important features (figure 3.19). Indeed, we've already noted that `contract` and `techsupport` are quite informative. It's also not surprising that `gender` is among the least important features, so we shouldn't expect it to be useful for the model.

	MI
contract	0.098320
onlinesecurity	0.063085
techsupport	0.061032
internetservice	0.055868
onlinebackup	0.046923

(A) The most useful features according to the mutual information score.

	MI
partner	0.009968
seniorcitizen	0.009410
multiplelines	0.000857
phoneservice	0.000229
gender	0.000117

(B) The least useful features according to the mutual information score.

Figure 3.19 Mutual information between categorical variables and the target variable. Higher values are better. According to it, `contract` is the most useful variable, whereas `gender` is the least useful.

CORRELATION COEFFICIENT

Mutual information is a way to quantify the degree of dependency between two categorical variables, but it doesn't work when one of the features is numerical, so we cannot apply it to the three numerical variables that we have.

We can, however, measure the dependency between a binary target variable and a numerical variable. We can pretend that the binary variable is numerical (containing only the numbers zero and one) and then use the classical methods from statistics to check for any dependency between these variables.

One such method is the *correlation* coefficient (sometimes referred as *Pearson's correlation coefficient*). It is a value from –1 to 1:

- Positive correlation means that when one variable goes up, the other variable tends to go up as well. In the case of a binary target, when the values of the variable are high, we see ones more often than zeros. But when the values of the variable are low, zeros become more frequent than ones.
- Zero correlation means no relationship between two variables: they are completely independent.
- Negative correlation occurs when one variable goes up and the other goes down. In the binary case, if the values are high, we see more zeros than ones in the target variable. When the values are low, we see more ones.

It's very easy to calculate the correlation coefficient in Pandas:

```
df_train_full[numerical].corrwith(df_train_full.churn)
```

We see the results in figure 3.20:

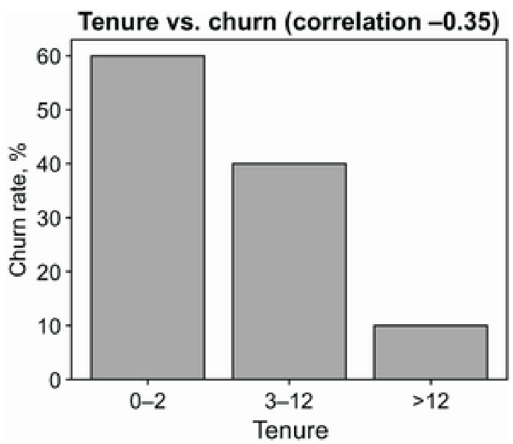
- The correlation between `tenure` and churn is –0.35: it has a negative sign, so the longer customers stay, the less often they tend to churn. For customers staying with the company for two months or less, the churn rate is 60%; for customers with tenure between 3 and 12 months, the churn rate is 40%; and for customers staying longer than a year, the churn rate is 17%. So the higher the value of tenure, the smaller the churn rate (figure 3.21A).
- `monthlycharges` has a positive coefficient of 0.19, which means that customers who pay more tend to leave more often. Only 8% of those who pay less than $20 monthly churned; customers paying between $21 and $50 churn more frequently with a churn rate of 18%; and 32% of people paying more than $50 churned (figure 3.21B).

- `totalcharges` has a negative correlation, which makes sense: the longer people stay with the company, the more they have paid in total, so it's less likely that they will leave. In this case, we expect a pattern similar to `tenure`. For small values, the churn rate is high; for larger values, it's lower.

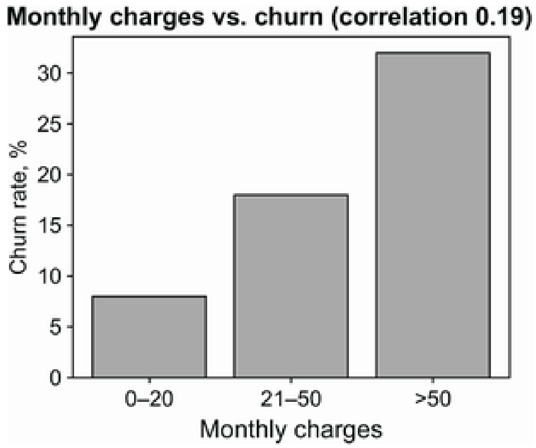
	correlation
tenure	-0.351885
monthlycharges	0.196805
totalcharges	-0.196353

Figure 3.20 Correlation between numerical variables and churn. `tenure` has a high negative correlation: as tenure grows, churn rate goes down. `monthlycharges` has positive correlation: the more customers pay, the more likely they are to churn.

After doing initial exploratory data analysis, identifying important features, and getting some insights into the problem, we are ready to do the next step: feature engineering and model training.



(A) Churn rate for different values of `tenure`. The correlation coefficient is negative, so the trend is downward: for higher values of `tenure`, the churn rate is smaller.



(B) Churn rate for different values of `monthlycharges`. The correlation coefficient is positive, so the trend is upward: for higher values of `monthlycharges`, the churn rate is higher.

Figure 3.21 Churn rate for `tenure` (negative correlation of –0.35) and `monthlycharges` (positive correlation of 0.19)

3.2 Feature engineering

We had an initial look at the data and identified what could be useful for the model. After doing that, we have a clear understanding how other variables affect churn—our target.

Before we proceed to training, however, we need to perform the feature engineering step: transforming all categorical variables to numeric features. We'll do that in the next section, and after that, we'll be ready to train the logistic regression model.

3.2.1 One-hot encoding for categorical variables

As we already know from the first chapter, we cannot just take a categorical variable and put it into a machine learning model. The models can deal only with numbers in matrices. So, we need to convert our categorical data into a matrix form, or encode.

One such encoding technique is *one-hot encoding*. We already saw this encoding technique in the previous chapter, when creating features for the make of a car and other categorical variables. There, we mentioned it only briefly and used it in a very simple way. In this chapter, we will spend more time understanding and using it.

If a variable `contract` has possible values (monthly, yearly, and two-year), we can represent a customer with the yearly contract as (0, 1, 0). In this case, the yearly value is active, or *hot*, so it gets 1, whereas the remaining values are not active, or *cold*, so they are 0.

To understand this better, let's consider a case with two categorical variables and see how we create a matrix from them. These variables are

- `gender` , with values female and male
- `contract` , with values monthly, yearly, and two-year

Because the `gender` variable has only two possible values, we create two columns in the resulting matrix. The `contract` variable has three columns, and in total, our new matrix will have five columns:

- gender=female
- gender=male
- contract=monthly
- contract=yearly
- contract=two-year

Let's consider two customers (figure 3.22):

- A female customer with a yearly contract
- A male customer with a monthly contract

For the first customer, the `gender` variable is encoded by putting 1 in the gender =female column and 0 in the gender=male column. Likewise, contract=yearly gets 1, whereas the remaining contract columns, contract=monthly and contract=two-year, get 0.

As for the second customer, gender=male and contract=monthly get ones, and the rest of the columns get zeros (figure 3.22).

gender	contract
male	monthly
female	yearly

gender		contract		
female	male	monthly	yearly	two-year
0	**1**	**1**	0	0
1	0	0	**1**	0

Figure 3.22 The original dataset with categorical variables is on the left and the one-hot encoded representation on the right. For the first customer, gender=male and contract=monthly are the hot columns, so they get 1. For the second customer, the hot columns are gender=female and contract=yearly.

The way we implemented it previously was simple but quite limited. We first looked at the top five values of the variable and then looped over each value and manually created a column in the dataframe. When the number of features grows, however, this process becomes tedious.

Luckily, we don't need to implement this by hand: we can use Scikit-learn. We can perform one-hot encoding in multiple ways in Scikit-learn, but we will use `DictVectorizer`.

As the name suggests, `DictVectorizer` takes in a dictionary and *vectorizes* it—that is, it creates vectors from it. Then the vectors are put together as rows of one matrix. This matrix is used as input to a machine learning algorithm (figure 3.23).

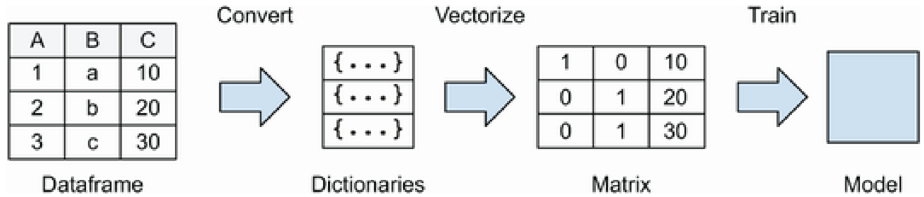


Figure 3.23 The process of creating a model. First, we convert a dataframe to a list of dictionaries, then we vectorize the list to a matrix, and finally, we use the matrix to train a model.

To use this method, we need to convert our dataframe to a list of dictionaries, which is simple to do in Pandas using the `to_dict` method with the `orient="records"` parameter:

```
train_dict = df_train[categorical + numerical].to_dict(orient='records')
```

If we take a look at the first element of this new list, we see

```
{'gender': 'male',
 'seniorcitizen': 0,
 'partner': 'yes',
 'dependents': 'yes',
 'phoneservice': 'yes',
 'multiplelines': 'no',
 'internetservice': 'no',
 'onlinesecurity': 'no_internet_service',
 'onlinebackup': 'no_internet_service',
 'deviceprotection': 'no_internet_service',
 'techsupport': 'no_internet_service',
 'streamingtv': 'no_internet_service',
 'streamingmovies': 'no_internet_service',
 'contract': 'two_year',
 'paperlessbilling': 'no',
 'paymentmethod': 'mailed_check',
 'tenure': 12,
```

```
 'monthlycharges': 19.7,
 'totalcharges': 258.35}
```

Each column from the dataframe is the key in this dictionary, with values coming from the actual dataframe row values.

Now we can use `DictVectorizer`. We create it and then fit it to the list of dictionaries we created previously:

```
from sklearn.feature_extraction import DictVectorizer

dv = DictVectorizer(sparse=False)
dv.fit(train_dict)
```

In this code we create a `DictVectorizer` instance, which we call `dv`, and “train” it by invoking the `fit` method. The `fit` method looks at the content of these dictionaries and figures out the possible values for each variable and how to map them to the columns in the output matrix. If a feature is categorical, it applies the one-hot encoding scheme, but if a feature is numerical, it’s left intact.

The `DictVectorizer` class can take in a set of parameters. We specify one of them: `sparse=False`. This parameter means that the created matrix will not be sparse and instead will create a simple NumPy array. If you don’t know about sparse matrices, don’t worry: we don’t need them in this chapter.

After we fit the vectorizer, we can use it for converting the dictionaries to a matrix by using the `transform` method:

```
X_train = dv.transform(train_dict)
```

This operation creates a matrix with 45 columns. Let's have a look at the first row, which corresponds to the customer we looked at previously:

```
X_train[0]
```

When we put this code into a Jupyter Notebook cell and execute it, we get the following output:

```
array([   0. ,    0. ,    1. ,    1. ,    0. ,    0. ,    0. ,    1. ,
          0. ,    1. ,    1. ,    0. ,    0. ,   86.1,    1. ,    0. ,
          0. ,    0. ,    0. ,    1. ,    0. ,    0. ,    1. ,    0. ,
          1. ,    0. ,    1. ,    1. ,    0. ,    0. ,    0. ,    0. ,
          1. ,    0. ,    0. ,    0. ,    1. ,    0. ,    0. ,    1. ,
          0. ,    0. ,    1. ,   71. , 6045.9])
```

As we see, most of the elements are ones and zeros—they're one-hot encoded categorical variables. Not all of them are ones and zeros, however. We see that three of them are other numbers. These are our numeric variables: `monthlycharges`, `tenure`, and `totalcharges`.

We can learn the names of all these columns by using the `get_feature_names` method:

```
dv.get_feature_names()
```

It prints

```
['contract=month-to-month',
 'contract=one_year',
 'contract=two_year',
 'dependents=no',
 'dependents=yes',
 # some rows omitted
```

```
 'tenure',
 'totalcharges']
```

As we see, for each categorical feature it creates multiple columns for each of its distinct values. For `contract`, we have `contract=month-to-month`, `contract=one_year`, and `contract=two_year`, and for `dependents`, we have `dependents=no` and `dependents =yes`. Features such as `tenure` and `totalcharges` keep the original names because they are numerical; therefore, `DictVectorizer` doesn't change them.

Now our features are encoded as a matrix, so we can move to the next step: using a model to predict churn.

Exercise 3.2

How would `DictVectorizer` encode the following list of dictionaries?

```
records = [
    {'total_charges': 10, 'paperless_billing': 'yes'},
    {'total_charges': 30, 'paperless_billing': 'no'},
    {'total_charges': 20, 'paperless_billing': 'no'}
]
```

a) Columns: `['total_charges', 'paperless_billing=yes', 'paperless_ billing=no']`

Values: `[10, 1, 0], [30, 0, 1], [20, 0, 1]`

b) Columns: `['total_charges=10', 'total_charges=20', 'total_charges= 30', 'paperless_billing=yes', 'paperless_billing=no']`

Values: `[1, 0, 0, 1, 0], [0, 0, 1, 0, 1], [0, 1, 0, 0, 1]`

3.3 Machine learning for classification

We have learned how to use Scikit-learn to perform one-hot encoding for categorical variables, and now we can transform them into a set of numerical features and put everything together into a matrix.

When we have a matrix, we are ready to do the model training part. In this section we learn how to train the logistic regression model and interpret its results.

3.3.1 Logistic regression

In this chapter, we use logistic regression as a classification model, and now we train it to distinguish churned and not-churned users.

Logistic regression has a lot in common with linear regression, the model we learned in the previous chapter. If you remember, the linear regression model is a regression model that can predict a number. It has the form

$$g(x_i) = w_0 + x_i^T w$$

where

- x_i is the feature vector corresponding to the i th observation.
- w_0 is the bias term.
- w is a vector with the weights of the model.

We apply this model and get $g(x_i)$—the prediction of what we think the value for x_i should be. Linear regression is trained to predict the target variable y_i—the actual value of the observation i. In the previous chapter, this was the price of a car.

Linear regression is a linear model. It's called *linear* because it combines the weights of the model with the feature vector *linearly*, using the dot product. Linear models are simple to implement, train, and use. Because of their simplicity, they are also fast.

Logistic regression is also a linear model, but unlike linear regression, it's a classification model, not regression, even though the name might suggest that. It's a binary classification model, so the target variable y_i is binary; the only values it can have are zero and one. Observations with $y_i = 1$ are typically called *positive examples*: examples in which the effect we want to predict is present. Likewise, examples with $y_i = 0$ are called *negative examples*: the effect we want to predict is absent. For our project, $y_i = 1$ means that the customer churned, and $y_i = 0$ means the opposite: the customer stayed with us.

The output of logistic regression is probability—the probability that the observation x_i is positive, or, in other words, the probability that $y_i = 1$. For our case, it's the probability that the customer i will churn.

To be able to treat the output as a probability, we need to make sure that the predictions of the model always stay between zero and one. We use a special mathematical function for this purpose called *sigmoid*, and the full formula for the logistic regression model is

$$g(x_i) = \text{sigmoid}(w_0 + x_i^T w)$$

If we compare it with the linear regression formula, the only difference is this sigmoid function: in case of linear regression, we have only $w_0 + x_i^T w$. This is why both of these models are linear; they are both based on the dot product operation.

The sigmoid function maps any value to a number between zero and one (figure 3.24). It's defined this way:

$$\text{sigmoid}(x) = \frac{1}{1+\exp(-x)}$$

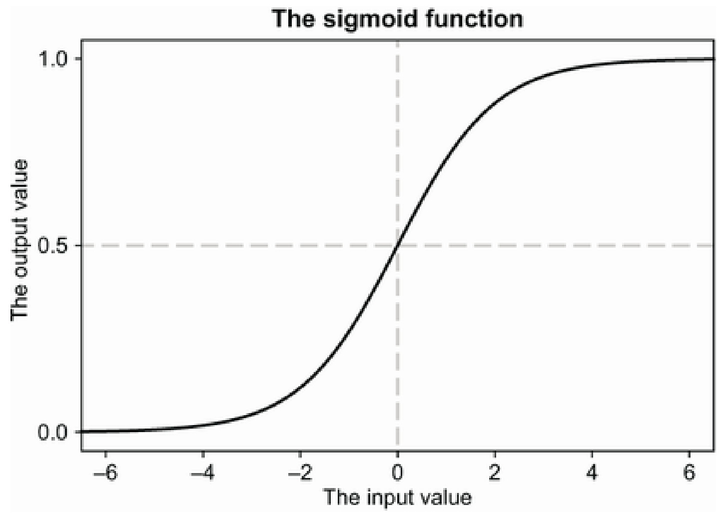


Figure 3.24 The sigmoid function outputs values that are always between 0 and 1. When the input is 0, the result of sigmoid is 0.5; for negative values, the results are below 0.5 and start approaching 0 for input values less than –6. When the input is positive, the result of sigmoid is above 0.5 and approaches 1 for input values starting from 6.

We know from chapter 2 that if the feature vector x_i is n-dimensional, the dot product $x_i^T w$ can be unwrapped as a sum, and we can write $g(x_i)$ as

$$g(x_i) = \text{sigmoid}(w_0 + x_{i1}w_1 + x_{i2}w_2 + \ldots + x_{in}w_n)$$

Or, using sum notation, as

$$g(x_i) = \text{sigmoid}(w_0 + \sum_{j=1}^{n} x_{ij}w_j)$$

Previously, we translated the formulas to Python for illustration. Let's do the same here.

The linear regression model has the following formula:

$$g(x_i) = w_0 + \sum_{j=1}^{n} x_{ij} w_j$$

If you remember from the previous chapter, this formula translates to the following Python code:

```
def linear_regression(xi):
    result = bias
    for j in range(n):
        result = result + xi[j] * w[j]
    return result
```

The translation of the logistic regression formula to Python is almost identical to the linear regression case, except that at the end, we apply the sigmoid function:

```
def logistic_regression(xi):
    score = bias
    for j in range(n):
        score = score + xi[j] * w[j]
    prob = sigmoid(score)
    return prob
```

Of course, we also need to define the sigmoid function:

```
import math

def sigmoid(score):
    return 1 / (1 + math.exp(-score))
```

We use *score* to mean the intermediate result before applying the sigmoid function. The score can take any real value. The *probability* is the result of applying the sigmoid function to the score; this is the final output, and it can take only the values between zero and one.

The parameters of the logistic regression model are the same as for linear regression:

- w_0 is the bias term.
- $w = (w_1, w_2, ..., w_n)$ is the weights vector.

To learn the weights, we need to train the model, which we will do now using Scikit-learn.

Exercise 3.3

Why do we need sigmoid for logistic regression?

a) Sigmoid converts the output to values between –6 and 6, which is easier to deal with.

b) Sigmoid makes sure the output is between zero and one, which can be interpreted as probability.

3.3.2 Training logistic regression

To get started, we first import the model:

```
from sklearn.linear_model import LogisticRegression
```

Then we train it by calling the `fit` method:

```
model = LogisticRegression(solver='liblinear', random_state=1)
model.fit(X_train, y_train)
```

The class `LogisticRegression` from Scikit-learn encapsulates the training logic behind this model. It's configurable, and we can change quite a few parameters. In fact, we already specify two of them: `solver` and `random_state`. Both are needed for reproducibility:

- `random_state`. The seed number for the random-number generator. It shuffles the data when training the model; to make sure the shuffle is the same every time, we fix the seed.
- `solver`. The underlying optimization library. In the current version (at the moment of writing, v0.20.3), the default value for this parameter is `liblinear`, but according to the documentation (**[https://scikit-learn.org/stable/modules/ generated/sklearn.linear_model.LogisticRegression.html](https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html)**), it will change to a different one in version v0.22. To make sure our results are reproducible in the later versions, we also set this parameter.

Other useful parameters for the model include `C`, which controls the regularization level. We talk about it in the next chapter when we cover parameter tuning. Specifying `C` is optional; by default, it gets the value 1.0.

The training takes a few seconds, and when it's done, the model is ready to make predictions. Let's see how well the model performs. We can apply it to our validation data to obtain the probability of churn for each customer in the validation dataset.

To do that, we need to apply the one-hot encoding scheme to all the categorical variables. First, we convert the dataframe to a list of dictionaries and then feed it to the `DictVectorizer` we fit previously:

```
val_dict = df_val[categorical + numerical].to_dict(orient='records')   ❶
X_val = dv.transform(val_dict)                                          ❷
```

❶ We perform one-hot encoding in exactly the same way as during training.

❷ Instead of fit and then transform, we use transform, which we fit previously.

As a result, we get `X_val`, a matrix with features from the validation dataset. Now we are ready to put this matrix to the model. To get the probabilities, we use the `predict_ proba` method of the model:

```
y_pred = model.predict_proba(X_val)
```

The result of `predict_proba` is a two-dimensional NumPy array, or a two-column matrix. The first column of the array contains the probability that the target is negative (no churn), and the second column contains the probability that the target is positive (churn) (figure 3.25).

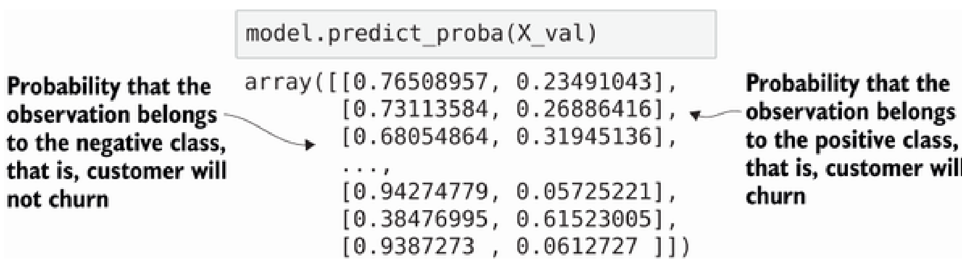


Figure 3.25 The predictions of the model: a two-column matrix. The first column contains the probability that the target is zero (the client won't churn). The second column contains the opposite probability (the target is one, and the client will churn).

These columns convey the same information. We know the probability of churn—it's *p*—and the probability of not churning is always 1 – *p*, so we don't need both columns.

Thus, it's enough to take only the second column of the prediction. To select only one column from a two-dimensional array in NumPy, we can use the slicing operation `[:, 1]`:

```
y_pred = model.predict_proba(X_val)[:, 1]
```

This syntax might be confusing, so let's break it down. Two positions are inside the brackets, the first one for rows and the second one for columns.

When we use `[:, 1]`, NumPy interprets it this way:

- `:` means select all the rows.
- `1` means select only the column at index 1, and because the indexing starts at 0, it's the second column.

As a result, we get a one-dimensional NumPy array that contains the values from the second column only.

This output (probabilities) is often called *soft* predictions. These tell us the probability of churning as a number between zero and one. It's up to us to decide how to interpret this number and how to use it.

Remember how we wanted to use this model: we wanted to retain customers by identifying those who are about to cancel their contract with the company and send them promotional messages, offering discounts and other benefits. We do this in the hope that after receiving the benefit, they will stay with the company. On the other hand, we don't want to give promotions to all our customers, because it will hurt us financially: we will make less profit, if any.

To make the actual decision about whether to send a promotional letter to our customers, using the probability alone is not enough. We need *hard* predictions—binary values of `True` (churn, so send the mail) or `False` (not churn, so don't send the mail).

To get the binary predictions, we take the probabilities and cut them above a certain threshold. If the probability for a customer is higher than this threshold, we predict churn, otherwise, not churn. If we select 0.5 to be this threshold, making the binary predictions is easy. We just use the " >= " operator:

```
y_pred >= 0.5
```

The comparison operators in NumPy are applied element-wise, and the result is a new array that contains only Boolean values: `True` and `False`. Under the hood, it performs the comparison for each element of the `y_pred` array. If the element is greater than 0.5 or equal to 0.5, the corresponding element in the output array is `True`, and otherwise, it's `False` (figure 3.26).

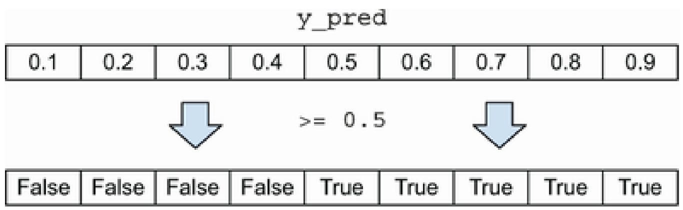


Figure 3.26 The `>=` operator is applied element-wise in NumPy. For every element, it performs the comparison, and the result is another array with `True` or `False` values, depending on the result of the comparison.

Let's write the results to the `churn` array:

```
churn = y_pred >= 0.5
```

When we have these hard predictions made by our model, we would like to understand how good they are, so we are ready to move to the next step: evaluating the quality of these predictions. In the next chapter, we will spend a lot more time learning about different evaluation techniques for binary classification, but for now, let's do a simple check to make sure our model learned something useful.

The simplest thing to check is to take each prediction and compare it with the actual value. If we predict churn and the actual value is churn, or we predict non-churn and the actual value is non-churn, our model made the correct prediction. If the predictions don't match, they aren't good. If we calculate the number of times our predictions match the actual value, we can use it for measuring the quality of our model.

This quality measure is called *accuracy*. It's very easy to calculate accuracy with NumPy:

```
(y_val == churn).mean()
```

Even though it's easy to calculate, it might be difficult to understand what this expression does when you see it for the first time. Let's try to break it down into individual steps.

First, we apply the `==` operator to compare two NumPy arrays: `y_val` and `churn`. If you remember, the first array, `y_val`, contains only numbers: zeros and ones. This is our target variable: one if the customer churned and zero otherwise. The second array contains Boolean predictions: `True` and `False` values. In this case `True` means we predict the customer will churn, and `False` means the customer will not churn (figure 3.27).

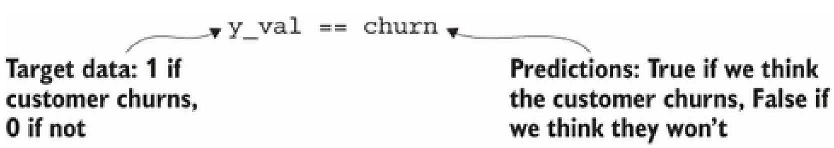


Figure 3.27 Applying the `==` operator to compare the target data with our predictions

Even though these two arrays have different types inside (integer and Boolean), it's still possible to compare them. The Boolean array is cast to integer such that `True` values are turned to "1" and `False` values are turned to "0." Then it's possible for NumPy to perform the actual comparison (figure 3.28).

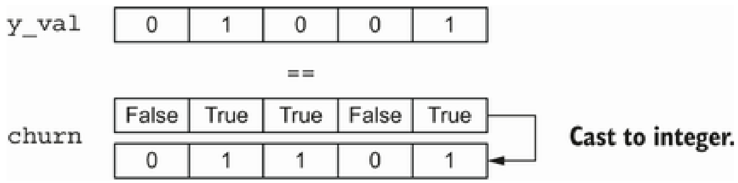


Figure 3.28 To compare the prediction with the target data, the array with predictions is cast to integer.

Like the `>=` operator, the `==` operator is applied element-wise. In this case, however, we have two arrays to compare, and here, we compare each element of one array with the respective element of the other array. The result is again a Boolean array with `True` or `False` values, depending on the outcome of the comparison (figure 3.29).

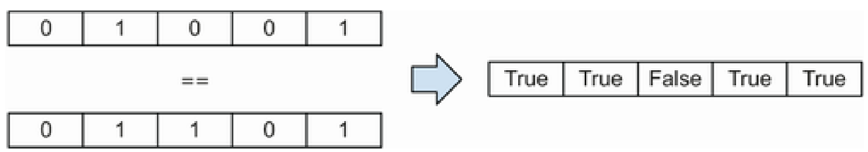


Figure 3.29 The `==` operator from NumPy is applied element-wise for two NumPy arrays.

In our case, if the true value in `y_pred` matches our prediction in churn, the label is `True`, and if it doesn't, the label is `False`. In other words, we have `True` if our prediction is correct and `False` if it's not.

Finally, we take the results of comparison—the Boolean array—and compute its mean using the `mean()` method. This method, however, is applied to numbers, not Boolean values, so before calculating the mean, the values are cast to integers: `True` values to “1” and `False` values to “0” (figure 3.30).

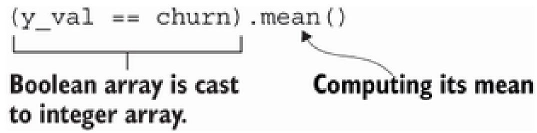


Figure 3.30 When computing the mean of a Boolean array, NumPy first casts it to integers and then computes the mean.

Finally, as we already know, if we compute the mean of an array that contains only ones and zeros, the result is the fraction of ones in that array, which we already used for calculating the churn rate. Because “1” (`True`) in this case is a correct prediction and “0” (`False`) is an incorrect prediction, the resulting number tells us the percentage of correct predictions.

After executing this line of code, we see 0.8 in output. This means that the model predictions matched the actual value 80% of the time, or the model makes correct predictions in 80% of cases. This is what we call the accuracy of the model.

Now we know how to train a model and evaluate its accuracy, but it’s still useful to understand how it makes the predictions. In the next section, we try to look inside the models and see how we can interpret the coefficients it learned.

3.3.3 Model interpretation

We know that the logistic regression model has two parameters that it learns from data:

- w_0 is the bias term.
- $w = (w_1, w_2, ..., w_n)$ is the weights vector.

We can get the bias term from `model.intercept_[0]`. When we train our model on all features, the bias term is –0.12.

The rest of the weights are stored in `model.coef_[0]`. If we look inside, it's just an array of numbers, which is hard to understand on its own.

To see which feature is associated with each weight, let's use the `get_feature_ names` method of the `DictVectorizer`. We can zip the feature names together with the coefficients before looking at them:

```
dict(zip(dv.get_feature_names(), model.coef_[0].round(3)))
```

This prints

```
{'contract=month-to-month': 0.563,
 'contract=one_year': -0.086,
 'contract=two_year': -0.599,
 'dependents=no': -0.03,
 'dependents=yes': -0.092,
 ... # the rest of the weights is omitted
 'tenure': -0.069,
 'totalcharges': 0.0}
```

To understand how the model works, let's consider what happens when we apply this model. To build the intuition, let's train a simpler and smaller model that uses only three variables: `contract`, `tenure`, and `totalcharges`.

The variables `tenure` and `totalcharges` are numeric so we don't need to do any additional preprocessing; we can take them as is. On the other hand, `contract` is a categorical variable, so to be able to use it, we need to apply one-hot encoding.

Let's redo the same steps we did for training, this time using a smaller set of features:

```
small_subset = ['contract', 'tenure', 'totalcharges']
train_dict_small = df_train[small_subset].to_dict(orient='records')
dv_small = DictVectorizer(sparse=False)
dv_small.fit(train_dict_small)

X_small_train = dv_small.transform(train_dict_small)
```

So as not to confuse it with the previous model, we add `small` to all the names. This way, it's clear that we use a smaller model, and it saves us from accidentally overwriting the results we already have. Additionally, we will use it to compare the quality of the small model with the full one.

Let's see which features the small model will use. For that, as previously, we use the `get_feature_names` method from `DictVectorizer`:

```
dv_small.get_feature_names()
```

It outputs the feature names:

```
['contract=month-to-month',
 'contract=one_year',
 'contract=two_year',
 'tenure',
 'totalcharges']
```

There are five features. As expected, we have `tenure` and `totalcharges`, and because they are numeric, their names are not changed.

As for the `contract` variable, it's categorical, so `DictVectorizer` applies the one-hot encoding scheme to convert it to numbers. `contract` has three distinct values: month-to-month, one year, and two years. Thus, one-hot encoding scheme creates three new features: `contract=month-to-month`, `contract=one_year`, and `contract= two_years`.

Let's train the small model on this set of features:

```
model_small = LogisticRegression(solver='liblinear', random_state=1)
model_small.fit(X_small_train, y_train)
```

The model is ready after a few seconds, and we can look inside the weights it learned. Let's first check the bias term:

```
model_small.intercept_[0]
```

It outputs –0.638. Then we can check the other weights, using the same code as previously:

```
dict(zip(dv_small.get_feature_names(), model_small.coef_[0].round(3)))
```

This line of code shows the weight for each feature:

```
{'contract=month-to-month': 0.91,
 'contract=one_year': -0.144,
 'contract=two_year': -1.404,
 'tenure': -0.097,
 'totalcharges': 0.000}
```

Let's put all these weights together in one table and call them w_1, w_2, w_3, w_4, and w_5 (table 3.2).

Table 3.2 The weights of a logistic regression model

Bias	contract			tenure	charges
	month	year	2-year		
w_0	w_1	w_2	w_3	w_4	w_5
—0.639	0.91	—0.144	—1.404	—0.097	0.0

Now let's take a look at these weights and try to understand what they mean and how we can interpret them.

First, let's think about the bias term and what it means. Recall that in the case of linear regression, it's the baseline prediction: the prediction we would make without knowing anything else about the observation. In the car price prediction project, it would be the price of a car on average. This is not the final prediction; later, this baseline is corrected with other weights.

In the case of logistic regression, it's similar: it's the baseline prediction—or the score we would make on average. Likewise, we later correct this score with the other weights. However, for logistic regression, interpretation is a bit trickier because we also need to apply the sigmoid function before we get the final output. Let's consider an example to help us understand that.

In our case, the bias term has the value of –0.639. This value is negative. If we look at the sigmoid function, we can see that for negative values, the output is lower than 0.5 (figure 3.31). For –0.639, the resulting probability of churning is 34%. This means that on average, a customer is more likely to stay with us than churn.

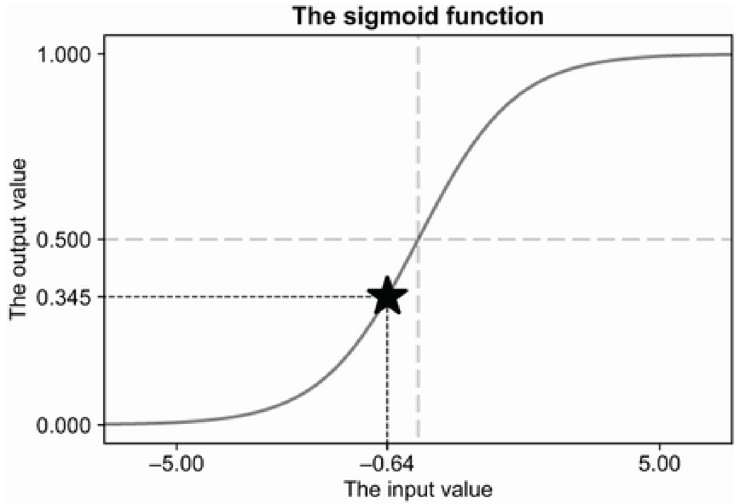


Figure 3.31 The bias term –0.639 on the sigmoid curve. The resulting probability is less than 0.5, so the average customer is more likely to not churn.

The reason why the sign before the bias term is negative is the class imbalance. There are a lot fewer churned users in the training data than non-churned ones, meaning the probability of churn on average is low, so this value for the bias term makes sense.

The next three weights are the weights for the contract variable. Because we use one-hot encoding, we have three `contract` features and three weights, one for each feature:

```
'contract=month-to-month': 0.91,
'contract=one_year': -0.144,
'contract=two_year': -1.404.
```

To build our intuition on how one-hot encoded weights can be understood and interpreted, let's think of a client with a month-to-month contract. The `contract` variable has the following one-hot encoding representation: the first position corresponds to the month-to-month value and is hot, so it’s set to “1.” The remaining positions correspond to one_year and two_years, so they are cold and set to “0” (figure 3.32).

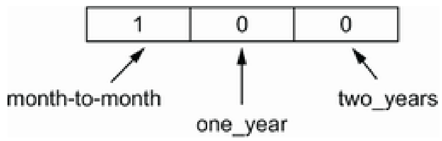


Figure 3.32 The one-hot encoding representation for a customer with a month-to-month contract

We also know the weights w_1, w_2, and w_3 that correspond to `contract=month-to-month`, `contract=one_year`, and `contract=two_years` (figure 3.33).

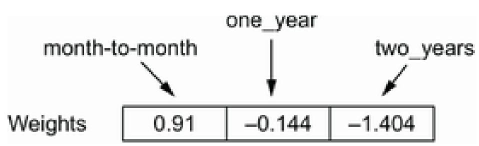


Figure 3.33 The weights of the contract=month-to-month, contract=one_year, and contract=two_years features

To make a prediction, we perform the dot product between the feature vector and the weights, which is multiplication of the values in each position and then summation. The result of the multiplication is 0.91, which turns out to be the same as the weight of the `contract=month-to-month` feature (figure 3.34).

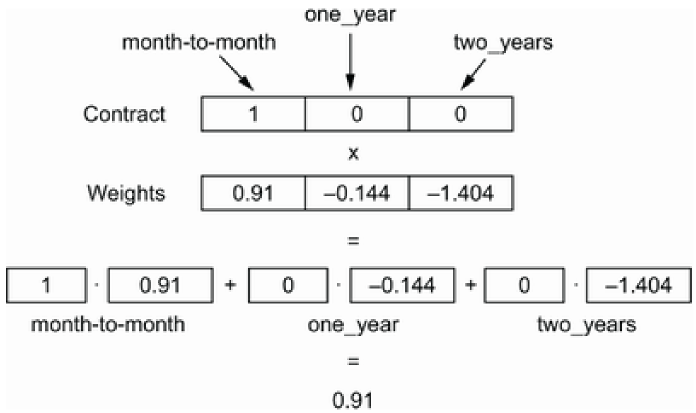


Figure 3.34 The dot product between the one-hot encoding representation of the contract variable and the corresponding weights. The result is 0.91, which is the weight of the hot feature.

Let's consider another example: a client with a two-year contract. In this case, the `contract=two_year` feature is hot and has a value of "1," and the rest are cold. When we multiply the vector with the one-hot encoding representation of the variable by the weight vector, we get –1.404 (figure 3.35).

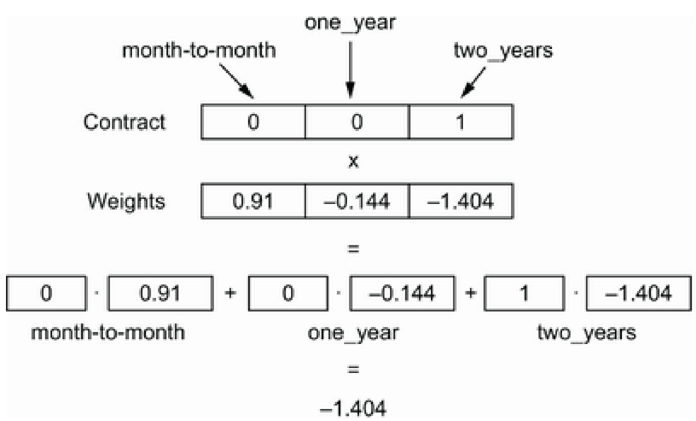


Figure 3.35 For a customer with a two-year contract, the result of the dot product is –1.404.

As we see, during the prediction, only the weight of the hot feature is taken into account, and the rest of the weights are not considered in calculating the score. This makes sense: the cold features have values of zero, and when we multiply by zero, we get zero again (figure 3.36).

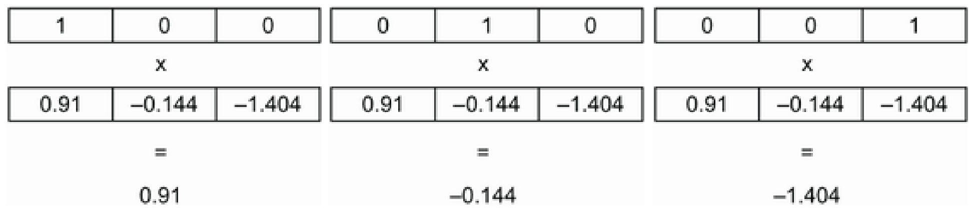


Figure 3.36 When we multiply the one-hot encoding representation of a variable by the weight vector from the model, the result is the weight corresponding to the hot feature.

The interpretation of the signs of the weights for one-hot encoded features follows the same intuition as the bias term. If a weight is positive, the respective feature is an indicator of churn, and vice versa. If it's negative, it's more likely to belong to a non-churning customer.

Let's look again at the weights of the `contract` variable. The first weight for `contract=month-to-month` is positive, so customers with this type of contract are more likely to churn than not. The other two features, `contract=one_year` and `contract=two_years`, have negative signs, so such clients are more likely to remain loyal to the company (figure 3.37).

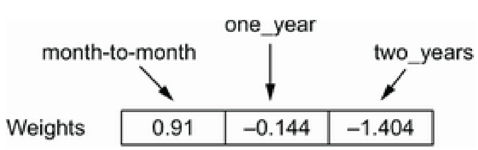


Figure 3.37 The sign of the weight matters. If it's positive, it's a good indicator of churn; if it's negative, it indicates a loyal customer.

The magnitude of the weights also matters. For `two_year`, the weight is –1.404, which is greater in magnitude than –0.144—the weight for `one_year`. So, a two-year contract is a stronger indicator of not churning than a one-year one. It confirms the feature importance analysis we did previously. The risk ratios (the risk of churning) for this set of features are 1.55 for monthly, 0.44 for one-year, and 0.10 for two-year (figure 3.38).

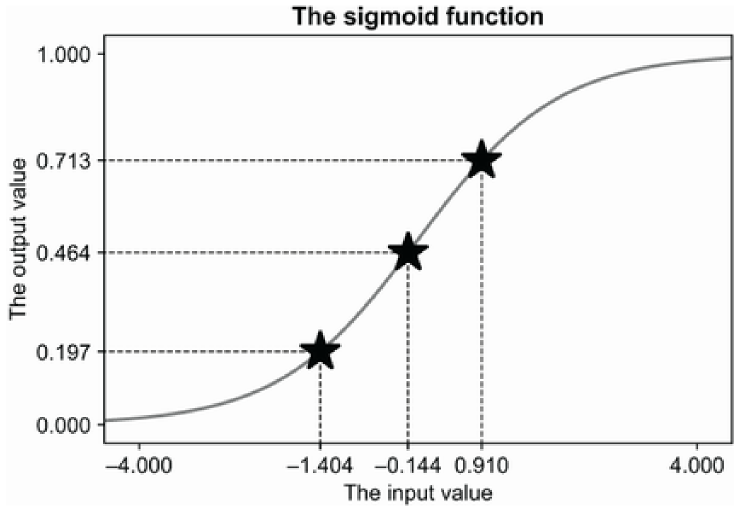


Figure 3.38 The weights for the contract features and their translation to probabilities. For `contract=two_year`, the weight is –1.404, which translates to very low probability of churn. For `contract=one_year`, the weight is –0.144, so the probability is moderate. And for `contract=month-to-month`, the weight is 0.910, and the probability is quite high.

Now let's have a look at the numerical features. We have two of them: `tenure` and `totalcharges`. The weight of the `tenure` feature is –0.097, which has a negative sign. This means the same thing: the feature is an indicator of no churn. We already know from the feature importance analysis that the longer clients stay with us, the less likely they are to churn. The correlation between `tenure` and churn is –0.35, which is also a negative number. The weight of this feature confirms it: for every month that the client spends with us, the total score gets lower by 0.097.

The other numerical feature, `totalchanges`, has weight of zero. Because it's zero, no matter what the value of this feature is, the model will never consider it, so this feature is not really important for making the predictions.

To understand it better, let's consider a couple of examples. For the first example, let's imagine we have a user with a month-to-month contract, who spent a year with us and paid $1,000 (figure 3.39).

$$\underbrace{-0.639}_{\text{Bias}} + \underbrace{0.91}_{\text{Monthly contract}} - \underbrace{12 \cdot 0.097}_{\text{12 months of tenure}} + \underbrace{0 \cdot 1000}_{\text{Total charges don't matter.}} = \underbrace{-0.893}_{\text{Negative, so low likelihood of churn}}$$

Figure 3.39 The score the model calculates for a customer with a month-to-month contract and 12 months of tenure

This is the prediction we make for this customer:

- We start with the baseline score. It's the bias term with the value of –0.639.
- Because it's a month-to-month contract, we add 0.91 to this value and get 0.271. Now the score becomes positive, so it may mean that the client is going to churn. We know that a monthly contract is a strong indicator of churning.
- Next, we consider the `tenure` variable. For each month that the customer stayed with us, we subtract 0.097 from the score so far. Thus, we get $0.271 - 12 \cdot 0.097 = -0.893$. Now the score is negative again, so the likelihood of churn decreases.
- Now we add the amount of money the customer paid us (`totalcharges`) multiplied by the weight of this feature, but because it's zero, we don't do anything. The result stays –0.893.
- The final score is a negative number, so we believe that the customer is not very likely to churn soon.
- To see the actual probability of churn, we compute the sigmoid of the score, and it's approximately 0.29. We can treat this as the probability that this customer will churn.

If we have another client with a yearly contract who stayed 24 months with us and spent $2,000, the score is –2.823 (figure 3.40).

$$\underbrace{-0.639}_{\text{Bias}} + \underbrace{0.144}_{\text{Yearly contract}} - \underbrace{24 \cdot 0.097}_{\text{24 months of tenure}} + \underbrace{0 \cdot 2000}_{\text{Total charges don't matter.}} = \underbrace{-2.823}_{\text{Negative, very low likelihood of churn}}$$

Figure 3.40 The score that the model calculates for a customer with a yearly contract and 24 months of tenure

After taking sigmoid, the score of –2.823 becomes 0.056, so the probability of churn for this customer is even lower (figure 3.41).

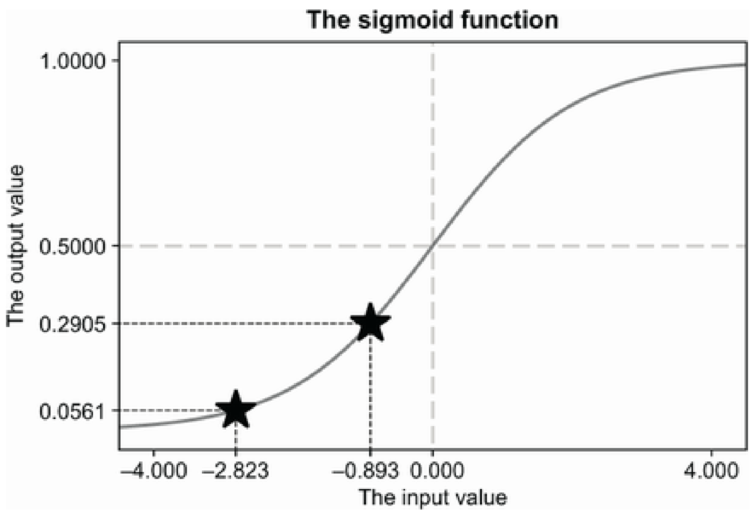


Figure 3.41 The scores of –2.823 and –0.893 translated to probability: 0.05 and 0.29, respectively

3.3.4 Using the model

Now we know a lot better how logistic regression, and we can also interpret what our model learned and understand how it makes the predictions.

Additionally, we applied the model to the validation set, computed the probabilities of churning for every customer there, and concluded that the model is 80% accurate. In the next chapter we will evaluate whether this number is satisfactory, but for now, let's try to use the model we trained. Now we can apply the model to customers for scoring them. It's quite easy.

First, we take a customer we want to score and put all the variable values in a dictionary:

```
customer = {
    'customerid': '8879-zkjof',
    'gender': 'female',
    'seniorcitizen': 0,
    'partner': 'no',
    'dependents': 'no',
    'tenure': 41,
    'phoneservice': 'yes',
    'multiplelines': 'no',
    'internetservice': 'dsl',
    'onlinesecurity': 'yes',
    'onlinebackup': 'no',
    'deviceprotection': 'yes',
    'techsupport': 'yes',
    'streamingtv': 'yes',
    'streamingmovies': 'yes',
    'contract': 'one_year',
    'paperlessbilling': 'yes',
    'paymentmethod': 'bank_transfer_(automatic)',
    'monthlycharges': 79.85,
    'totalcharges': 3320.75,
}
```

NOTE When we prepare items for prediction, they should undergo the same preprocessing steps we did for training the model. If we don't do it in exactly the same way, the model might not get things it expects to see, and, in this case, the predictions could get really off. This is why in the previous example, in the `customer` dictionary, the field names and string values are lowercased and spaces are replaced with underscores.

Now we can use our model to see whether this customer is going to churn. Let's do it.

First, we convert this dictionary to a matrix by using the `DictVectorizer`:

```
X_test = dv.transform([customer])
```

The input to the vectorizer is a list with one item: we want to score only one customer. The output is a matrix with features, and this matrix contains only one row—the features for this one customer:

```
[[    0.   ,     1.   ,     0.   ,     1.   ,     0.   ,     0.   ,     0.   ,
      1.   ,     1.   ,     0.   ,     1.   ,     0.   ,     0.   ,   79.85,
      1.   ,     0.   ,     0.   ,     1.   ,     0.   ,     0.   ,     0.   ,
      0.   ,     1.   ,     0.   ,     1.   ,     1.   ,     0.   ,     1.   ,
      0.   ,     0.   ,     0.   ,     0.   ,     1.   ,     0.   ,     0.   ,
      0.   ,     1.   ,     0.   ,     0.   ,     1.   ,     0.   ,     0.   ,
      1.   ,    41.   , 3320.75]]
```

We see a bunch of one-hot encoding features (ones and zeros) as well as some numeric ones (`monthlycharges`, `tenure`, and `totalcharges`).

Now we take this matrix and put it into the trained model:

```
model.predict_proba(X_test)
```

The output is a matrix with predictions. For each customer, it outputs two numbers, which are the probability of staying with the company and the probability of churn. Because there's only one customer, we get a tiny NumPy array with one row and two columns:

```
[[0.93, 0.07]]
```

All we need from the matrix is the number at the first row and second column: the probability of churning for this customer. To select this number from the array, we use the brackets operator:

```
model.predict_proba(X_test)[0, 1]
```

We used this operator to select the second column from the array. However, this time there's only one row, so we can explicitly ask NumPy to return the value from that row. Because indexes start from 0 in NumPy, `[0, 1]` means first row, second column.

When we execute this line, we see that the output is 0.073, so that the probability that this customer will churn is only 7%. It's less than 50%, so we will not send this customer a promotional mail.

We can try to score another client:

```
customer = {
    'gender': 'female',
    'seniorcitizen': 1,
    'partner': 'no',
    'dependents': 'no',
    'phoneservice': 'yes',
    'multiplelines': 'yes',
    'internetservice': 'fiber_optic',
    'onlinesecurity': 'no',
    'onlinebackup': 'no',
    'deviceprotection': 'no',
    'techsupport': 'no',
```

```
        'streamingtv': 'yes',
        'streamingmovies': 'no',
        'contract': 'month-to-month',
        'paperlessbilling': 'yes',
        'paymentmethod': 'electronic_check',
        'tenure': 1,
        'monthlycharges': 85.7,
        'totalcharges': 85.7
    }
```

Let's make a prediction:

```
X_test = dv.transform([customer])
model.predict_proba(X_test)[0, 1]
```

The output of the model is 83% likelihood of churn, so we should send this client a promotional mail in the hope of retaining them.

So far, we've built intuition on how logistic regression works, how to train it with Scikit-learn, and how to apply it to new data. We haven't covered the evaluation of the results yet; this is what we will do in the next chapter.

3.4 Next steps

3.4.1 Exercises

You can try a couple of things to learn the topic better:

- In the previous chapter, we implemented many things ourselves, including linear regression and dataset splitting. In this chapter we learned how to use Scikit-learn for that. Try to redo the project from the previous chapter using Scikit-learn. To use linear regression, you need `LinearRegression` from the `sklearn.linear_model` package. To use regularized regression, you need to import `Ridge` from the same package `sklearn.linear_model`.
- We looked at feature importance metrics to get some insights into the dataset but did not really use this information for other purposes. One way to use this information could be removing features that aren't useful from the dataset to make the model simpler, faster, and potentially better. Try to exclude the two least useful features (`gender` and `phoneservices`) from the training data matrix, and see what happens to validation accuracy. What if we remove the most useful feature (`contract`)?

3.4.2 Other projects

We can use classification in numerous ways to solve real-life problems, and now, after learning the materials of this chapter, you should have enough knowledge to apply logistic regression to solve similar problems. In particular, we suggest these:

- Classification models are often used for marketing purposes, and one of the problems it solves is *lead scoring*. A *lead* is a potential customer who may convert (become an actual customer) or not. In this case, the conversion is the target we want to predict. You can take a dataset from **https://www.kaggle.com/ashydv/ leads-dataset** and build a model for that. You may notice that the lead-scoring problem is similar to churn prediction, but in one case, we want to get a new client to sign a contract with us, and in another case, we want a client not to cancel the contract.

- Another popular application of classification is default prediction, which is estimating the risk of a customer's not paying back a loan. In this case, the variable we want to predict is default, and it also has two outcomes: whether the customer managed to pay back the loan in time (good customer) or not (default). You can find many datasets online for training a model, such as **https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients** (or the same one available via Kaggle: **https://www.kaggle.com/pratjain/credit-card-default**).

Summary

- The *risk* of a categorical feature tells us if a group that has the feature will have the condition we model. For churn, values lower than 1.0 indicate low risk of churning, whereas values higher than 1.0 indicate high risk of churning. It tells us which features are important for predicting the target variable and helps us better understand the problem we're solving.
- Mutual information measures the degree of (in)dependence between a categorical variable and the target. It's a good way of determining important features: the higher the mutual information is, the more important the feature.
- Correlation measures the dependence between two numerical variables, and it can be used for determining if a numerical feature is useful for predicting the target variable.
- One-hot encoding gives us a way to represent categorical variables as numbers. Without it, it wouldn't be possible to easily use these variables in a model. Machine learning models typically expect all input variables to be numeric, so having an encoding scheme is crucial if we want to use categorical features in modeling.

- We can implement one-hot encoding by using `DictVectorizer` from Scikit-learn. It automatically detects categorical variables and applies the one-hot encoding scheme to them while leaving numerical variables intact. It's very convenient to use and doesn't require a lot of coding on our side.
- Logistic regression is a linear model, just like linear regression. The difference is that logistic regression has an extra step at the end: it applies the sigmoid function to convert the scores to probabilities (a number between zero and one). That allows us to use it for classification. The output is the probability of belonging to a positive class (churn, in our case).
- When the data is prepared, training logistic regression is very simple: we use the `LogisticRegression` class from Scikit-learn and invoke the `fit` function.
- The model outputs probabilities, not hard predictions. To binarize the output, we cut the predictions at a certain threshold. If the probability is greater than or equal to 0.5, we predict `True` (churn), and `False` (no churn) otherwise. This allows us to use the model for solving our problem: predicting customers who churn.
- The weights of the logistic regression model are easy to interpret and explain, especially when it comes to the categorical variables encoded using the one-hot encoding scheme. It helps us understand the behavior of the model better and explain to others what it's doing and how it's working.

In the next chapter we will continue with this project on churn prediction. We will look at ways of evaluating binary classifiers and then use this information for tuning the model's performance.

Answers to exercises

- Exercise 3.1 B) The percentage of `True` elements

- Exercise 3.2 A) It will keep a numeric variable as is and encode only the categorical variable.
- Exercise 3.3 B) Sigmoid converts the output to a value between zero and one.