Dealing with Categorical Variables

Introduction

So far, we have assumed that our predictors (independent variables) are numeric. How can we incorporate categorical data into our regression models as well? This lesson demonstrates how to use an approach called one-hot encoding to do just this.

Objectives

You will be able to:

- Determine whether variables are categorical or numeric
- Describe why dummy variables are necessary
- Use one-hot encoding to create dummy variables

Variable Types: Numeric and Categorical

Let's look at the Auto MPG dataset:

In [1]:
```
import pandas as pd
data = pd.read_csv("auto-mpg.csv")
data
```

Out[1]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino
...	...	...	...	...	...	...	...	...	...
387	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl
388	44.0	4	97.0	52	2130	24.6	82	2	vw pickup
389	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage
390	28.0	4	120.0	79	2625	18.6	82	1	ford ranger
391	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10

392 rows × 9 columns

We'll also engineer a new feature, `make`, using the `car name` feature:

In [2]:
```
data["make"] = data["car name"].str.split().apply(lambda x: x[0])
data
```

Out[2]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name	make
0	18.0	8	307.0	130	3504	12.0	70	1	chevrolet chevelle malibu	chevrolet
1	15.0	8	350.0	165	3693	11.5	70	1	buick skylark 320	buick
2	18.0	8	318.0	150	3436	11.0	70	1	plymouth satellite	plymouth
3	16.0	8	304.0	150	3433	12.0	70	1	amc rebel sst	amc
4	17.0	8	302.0	140	3449	10.5	70	1	ford torino	ford
...	...	...	...	...	...	...	...	...	...	...
387	27.0	4	140.0	86	2790	15.6	82	1	ford mustang gl	ford
388	44.0	4	97.0	52	2130	24.6	82	2	vw pickup	vw
389	32.0	4	135.0	84	2295	11.6	82	1	dodge rampage	dodge
390	28.0	4	120.0	79	2625	18.6	82	1	ford ranger	ford
391	31.0	4	119.0	82	2720	19.4	82	1	chevy s-10	chevy

392 rows × 10 columns

We can look at the `pandas` data types for this dataset using `.info()` :

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 392 entries, 0 to 391
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   mpg           392 non-null    float64
 1   cylinders     392 non-null    int64  
 2   displacement  392 non-null    float64
 3   horsepower    392 non-null    int64  
 4   weight        392 non-null    int64  
 5   acceleration  392 non-null    float64
 6   model year    392 non-null    int64  
 7   origin        392 non-null    int64  
 8   car name      392 non-null    object 
 9   make          392 non-null    object 
dtypes: float64(3), int64(5), object(2)
memory usage: 30.8+ KB
```

Without digging any further into the *meaning* of these columns, this print-out tells us that we *can* use all columns except for `car name` and `make` in a multiple linear regression, without the model crashing.

However a better modeling process would attempt to make a distinction between which of the variables are genuinely representing numbers, and which are actually representing categories.

Numeric Variables

Numeric variables can be either continuous or discrete.

Continuous variables correspond to "real numbers" in mathematics, and floating point numbers in code. Essentially these variables can have any value on the number line, and usually have a decimal place in their code representation.

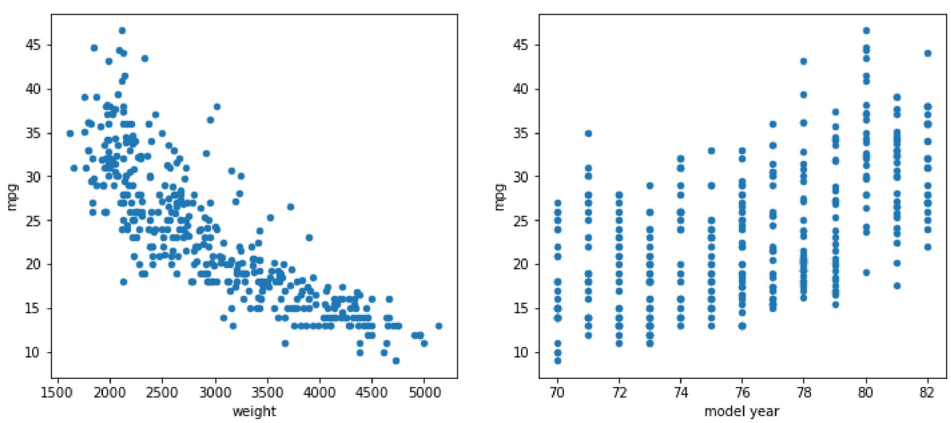
Discrete numeric variables typically correspond to "whole numbers" in mathematics, and integers in code. These variables have gaps between their values.

Below we plot `weight` , an example of a continuous variable, and `model year` , an example of a discrete variable, vs. the target, `mpg` .

In [4]:
```
import matplotlib.pyplot as plt

fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12,5))

data.plot.scatter(x="weight", y="mpg", ax=ax1)
data.plot.scatter(x="model year", y="mpg", ax=ax2);
```



You can tell that `model year` is discrete because of the gaps between the vertical lines of values, whereas `weight` is continuous because it's more filled in, like a "cloud", and doesn't have those gaps.

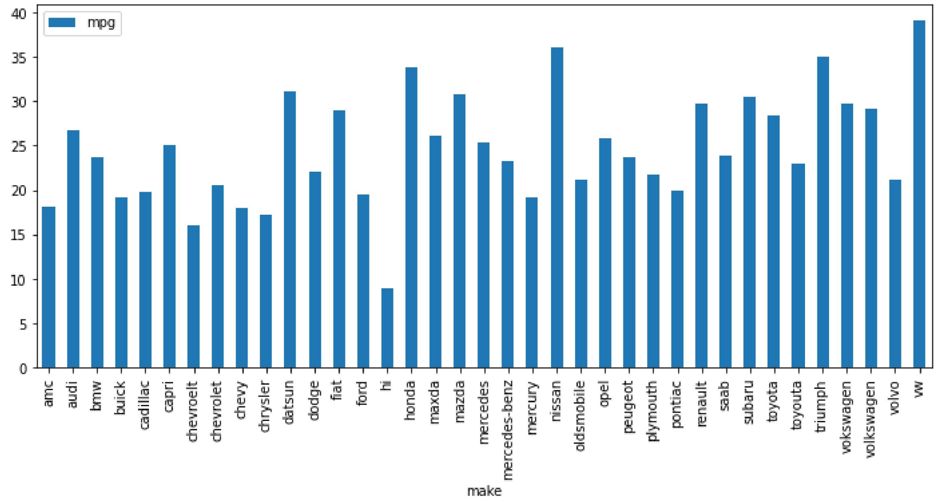
Categorical Variables

Categorical variables can actually be strings *or* numbers.

String categorical variables will be fairly obvious due to their data type (`object` in `pandas`). For example, `make` is a categorical variable. It cannot be used in a scatter plot, and it will cause an error if you try to use it in a multiple regression model without additional transformations.

However it can be represented by a bar plot. For example, we can plot the mean `mpg` , grouped by `make` .

In [5]:
```
fig, ax = plt.subplots(figsize=(12,5))
data.groupby("make").mean().plot.bar(y="mpg", ax=ax);
```



Discrete number categorical variables can be more difficult to spot. For example, `origin` is actually a categorical variable in this dataset, even though it is encoded as a number.

In [6]:
```
data["origin"].value_counts()
```

Out[6]:
```
1    245
3     79
2     68
Name: origin, dtype: int64
```

An `origin` of 1 means the car maker is from the United States, 2 means the car maker is from Europe, and 3 means the car maker is from Asia.

In [7]:
```
data[["make", "origin"]].groupby("make").first().sort_values("origin")
```

Out[7]:

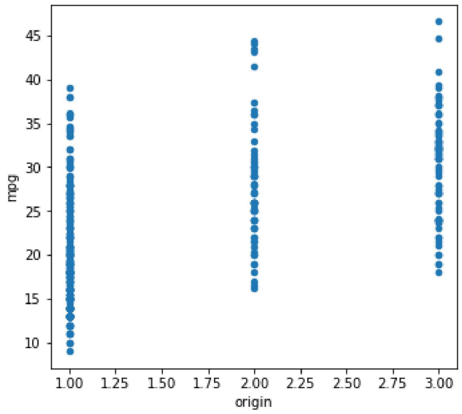
make	origin
amc	1
plymouth	1
pontiac	1
hi	1
ford	1
dodge	1
mercury	1
chrysler	1
oldsmobile	1
chevrolet	1
chevroelt	1
capri	1
cadillac	1
buick	1
chevy	1
saab	2
renault	2
vokswagen	2
volkswagen	2
peugeot	2
opel	2
triumph	2
mercedes	2
mercedes-benz	2
volvo	2
fiat	2
bmw	2
audi	2
vw	2
mazda	3
maxda	3
honda	3
subaru	3
toyota	3
toyouta	3
datsun	3
nissan	3

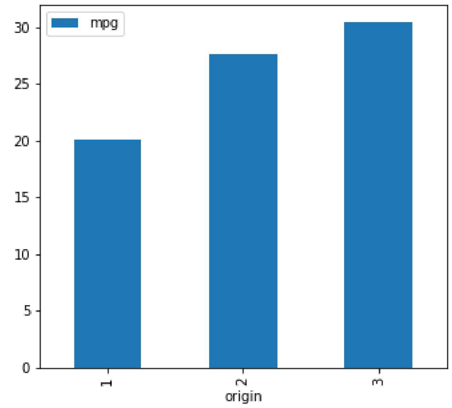
(Looking at the list above, you might notice some typos in the `make` column. We'll address those later!)

Discrete categorical variables like `origin` can be represented with either a scatter plot or a bar plot.

In [8]:
```
fig, (ax1, ax2) = plt.subplots(ncols=2, figsize=(12,5))

data.plot.scatter(x="origin", y="mpg", ax=ax1)
data.groupby("origin").mean().plot.bar(y="mpg", ax=ax2);
```





Identifying Numeric vs. Categorical Variables

In some cases, the data type clearly indicates what kind of variable it should be. A **continuous** variable is essentially always **numeric**, and a **string** variable is essentially always **categorical**.

For **discrete** variables, you need to investigate the values as well as any provided documentation. Then ask yourself:

> Is an increase of 2 in this variable twice as much as an increase of 1?

If 2 is "twice as much" as 1, that means it is reasonable to treat the variable as a numeric discrete variable. If not, the variable should be treated as categorical.

Going back to our examples above:

- `model year` : Is an increase of 2 years twice as much as an increase of 1 year?
  - This seems like a reasonable way to think about the data, so we'll treat it as numeric
- `origin` : Is an increase of 2 (US to Asia) twice as much as an increase of 1 (US to Europe, or Europe to Asia)?
  - It's hard to make sense of this. Treating `origin` as categorical makes a lot more sense

Transforming Categorical Variables with One-Hot Encoding

In order to use a categorical variable in a model, we'll create multiple ***dummy variables***, one for each category of the categorical variable.

First we'll walk through how this could be done step-by-step, then show you the `get_dummies` method that can achieve this more quickly and efficiently.

Creating Dummy Variables from Scratch

Let's create a copy of our data that only includes the `origin` column.

In [9]:
```
origin_df = data[["origin"]].copy()
origin_df.sample(10, random_state=1)
```

Out[9]:

	origin
81	3
165	3
351	3
119	2
379	3
236	1
78	2
92	1
80	3
333	3

The intuition here is, *what if we create a column that just says whether* `origin` *is equal to 1?*

We might do something like this:

In [10]:
```
origin_df["origin_us"] = origin_df["origin"] == 1
origin_df.sample(10, random_state=1)
```

Out[10]:

	origin	origin_us
81	3	False
165	3	False
351	3	False
119	2	False
379	3	False
236	1	True
78	2	False
92	1	True
80	3	False
333	3	False

Except, our StatsModels model is expecting *integers*, not *booleans*, so we convert `True` to 1 and `False` to 0:

In [11]:
```
origin_df["origin_us"] = (origin_df["origin"] == 1).apply(int)
origin_df.sample(10, random_state=1)
```

Out[11]:

	origin	origin_us
81	3	0
165	3	0
351	3	0
119	2	0
379	3	0
236	1	1
78	2	0
92	1	1
80	3	0
333	3	0

Then we could repeat the process for European origin and Asian origin:

In [12]:
```
origin_df["origin_eu"] = (origin_df["origin"] == 2).apply(int)
origin_df["origin_as"] = (origin_df["origin"] == 3).apply(int)
origin_df.sample(10, random_state=1)
```

Out[12]:

	origin	origin_us	origin_eu	origin_as
81	3	0	0	1
165	3	0	0	1
351	3	0	0	1
119	2	0	1	0
379	3	0	0	1
236	1	1	0	0
78	2	0	1	0
92	1	1	0	0
80	3	0	0	1
333	3	0	0	1

Each of these newly-created variables, `origin_us` , `origin_eu` , and `origin_as` , are *dummy* variables. They are called this because the "real" variable is `origin` , and these are just stand-ins.

The overall process of creating a dummy variable for each value of `origin` is called ***one-hot encoding***. The name "one-hot" comes from digital circuitry, and it means that when you look across all of the dummy variables from one original variable, only one of them should have a value of 1, and the rest should be 0.

One-Hot Encoding with `pandas`

Instead of creating a new line of code for each value of a column, you can use the `get_dummies` function from `pandas` ([documentation here (https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html)](https://pandas.pydata.org/docs/reference/api/pandas.get_dummies.html)).

In [13]:
```
origin_df = data[["origin"]].copy()
origin_df.sample(10, random_state=1)
```

Out[13]:

	origin
81	3
165	3
351	3
119	2
379	3
236	1
78	2
92	1
80	3
333	3

In [14]:
```
origin_df = pd.get_dummies(origin_df, columns=["origin"])
origin_df
```

Out[14]:

	origin_1	origin_2	origin_3
0	1	0	0
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
...	...	...	...
387	1	0	0
388	0	1	0
389	1	0	0
390	1	0	0
391	1	0	0

392 rows × 3 columns

Some things to note about this version of one-hot encoding:

- The original column (`origin`) has been removed
- The names of the new columns come from the original column name `"origin" + _` + the value (1, 2, or 3)
  - If you want these to be more descriptive, consider changing their values *before* one-hot encoding. For example, you could replace 1, 2, and 3 with "us", "eu", and "as" to be more similar to the example above. This choice is up to you, since these are the names that will appear in the regression results

We can also do one-hot encoding on the entire DataFrame at once, just specifying the columns we consider to be categorical:

In [15]:
```
pd.get_dummies(data, columns=["origin", "make"])
```

Out[15]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	origin_1	origin_2	...	make_renault	make_saab	make_subaru	make_to
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu	1	0	...	0	0	0	
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320	1	0	...	0	0	0	
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite	1	0	...	0	0	0	
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst	1	0	...	0	0	0	
4	17.0	8	302.0	140	3449	10.5	70	ford torino	1	0	...	0	0	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
387	27.0	4	140.0	86	2790	15.6	82	ford mustang gl	1	0	...	0	0	0	
388	44.0	4	97.0	52	2130	24.6	82	vw pickup	0	1	...	0	0	0	
389	32.0	4	135.0	84	2295	11.6	82	dodge rampage	1	0	...	0	0	0	
390	28.0	4	120.0	79	2625	18.6	82	ford ranger	1	0	...	0	0	0	
391	31.0	4	119.0	82	2720	19.4	82	chevy s-10	1	0	...	0	0	0	

392 rows × 48 columns

Note that you can skip specifying a `columns` argument and `get_dummies` will automatically create dummy variables for all columns with a data type of `object` or `category` . This is a convenient shortcut if your dataset is set up appropriately, but in this case we specified the `columns` because:

1. `car name` is type `object` but we don't actually want to one-hot encode it. We'll drop it before feeding it into the final model, but for now it's there for informational purposes.
2. `origin` is type `int` but we want to treat it as a category and one-hot encode it. If we wanted to change the data type so that `get_dummies` would automatically encode `origin` , we could run `data["origin"] = data["origin"].astype("category")`

The Dummy Variable Trap

Due to the nature of how dummy variables are created, one variable can be predicted from all of the others. For example, if you know that `origin_1` is 0 and `origin_2` is 0, then you already know that `origin_3` must be 1.

We demonstrate this in code below.

In [16]:
```
origin_df["origin_1_prediction"] = 1 - origin_df["origin_2"] - origin_df["origin_3"]
origin_df
```

Out[16]:

	origin_1	origin_2	origin_3	origin_1_prediction
0	1	0	0	1
1	1	0	0	1
2	1	0	0	1
3	1	0	0	1
4	1	0	0	1
...	...	...	...	...
387	1	0	0	1
388	0	1	0	0
389	1	0	0	1
390	1	0	0	1
391	1	0	0	1

392 rows × 4 columns

Our `origin_1_prediction` matches our `origin_1` value 100% of the time:

In [17]:
```
(origin_df["origin_1_prediction"] == origin_df["origin_1"]).value_counts(normalize=True)
```

Out[17]:
```
True    1.0
dtype: float64
```

This is known as perfect ***multicollinearity*** and it can be a problem for regression. Multicollinearity will be covered in depth later but the basic idea behind perfect multicollinearity is that you can *perfectly* predict what one variable will be using some combination of the other variables.

When features in a linear regression have perfect multicollinearity due to the algorithm for creating dummy variables, this is known as the ***dummy variable trap***.

Fortunately, the dummy variable trap can be avoided by simply dropping one of the dummy variables. You can do this by subsetting the dataframe manually or, more conveniently, by passing `drop_first=True` into `get_dummies()` :

In [18]:
```
pd.get_dummies(data, columns=["origin"], drop_first=True)
```

Out[18]:

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	car name	make	origin_2	origin_3
0	18.0	8	307.0	130	3504	12.0	70	chevrolet chevelle malibu	chevrolet	0	0
1	15.0	8	350.0	165	3693	11.5	70	buick skylark 320	buick	0	0
2	18.0	8	318.0	150	3436	11.0	70	plymouth satellite	plymouth	0	0
3	16.0	8	304.0	150	3433	12.0	70	amc rebel sst	amc	0	0
4	17.0	8	302.0	140	3449	10.5	70	ford torino	ford	0	0
...	...	...	...	...	...	...	...	...	...	...	...
387	27.0	4	140.0	86	2790	15.6	82	ford mustang gl	ford	0	0
388	44.0	4	97.0	52	2130	24.6	82	vw pickup	vw	1	0
389	32.0	4	135.0	84	2295	11.6	82	dodge rampage	dodge	0	0
390	28.0	4	120.0	79	2625	18.6	82	ford ranger	ford	0	0
391	31.0	4	119.0	82	2720	19.4	82	chevy s-10	chevy	0	0

392 rows × 11 columns

Because this dataframe no longer includes `origin_1` , there is no longer enough information to perfectly predict `origin_2` or `origin_3` . The perfect multicollinearity has been eliminated!

Multiple Regression with One-Hot Encoded Variables

Let's go ahead and create a linear regression model with `weight` , `model year` , and `origin` .

In [19]:
```
y = data["mpg"]
X = data[["weight", "model year", "origin"]]
X
```

Out[19]:

	weight	model year	origin
0	3504	70	1
1	3693	70	1
2	3436	70	1
3	3433	70	1
4	3449	70	1
...	...	...	...
387	2790	82	1
388	2130	82	2
389	2295	82	1
390	2625	82	1
391	2720	82	1

392 rows × 3 columns

In [20]:
```
X = pd.get_dummies(X, columns=["origin"], drop_first=True)
X
```

Out[20]:

	weight	model year	origin_2	origin_3
0	3504	70	0	0
1	3693	70	0	0
2	3436	70	0	0
3	3433	70	0	0
4	3449	70	0	0
...	...	...	...	...
387	2790	82	0	0
388	2130	82	1	0
389	2295	82	0	0
390	2625	82	0	0
391	2720	82	0	0

392 rows × 4 columns

In [21]:
```
import statsmodels.api as sm

model = sm.OLS(y, sm.add_constant(X))
results = model.fit()

print(results.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                    mpg   R-squared:                       0.819
Model:                            OLS   Adj. R-squared:                  0.817
Method:                 Least Squares   F-statistic:                     437.9
Date:                Wed, 01 Jun 2022   Prob (F-statistic):          3.53e-142
Time:                        15:44:58   Log-Likelihood:                -1026.1
No. Observations:                 392   AIC:                             2062.
Df Residuals:                     387   BIC:                             2082.
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -18.3069      4.017     -4.557      0.000     -26.205     -10.409
weight        -0.0059      0.000    -22.647      0.000      -0.006      -0.005
model year     0.7698      0.049     15.818      0.000       0.674       0.866
origin_2       1.9763      0.518      3.815      0.000       0.958       2.995
origin_3       2.2145      0.519      4.268      0.000       1.194       3.235
==============================================================================
Omnibus:                       32.293   Durbin-Watson:                   1.251
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               58.234
Skew:                           0.507   Prob(JB):                     2.26e-13
Kurtosis:                       4.593   Cond. No.                     7.39e+04
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 7.39e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Interpreting Model Results

Now, how do we interpret these results?

Just like any other multiple regression model, we can look at the F-statistic p-value to see if it's statistically significant (it is!) and at the adjusted R-Squared to see the proportion of variance explained (around 82%).

The `weight` , and `model year` interpretations are also very similar to previous models we've created. For each increase of 1 lb in weight, we see an associated drop of about 0.006 MPG. For each increase of 1 in model year, we see an associated increase of about 0.77 MPG.

Dropping the first variable affects the interpretation of the other regression coefficients. The dropped category becomes what is known as the ***reference category***. The regression coefficients that result from fitting the remaining variables represent the change *relative* to the reference.

In this regression, an `origin` of 1 (i.e. US origin) is the reference category. This has implications for the interpretation of `const` as well as the other `origin` features.

First, `const` means that all other variables are 0. This means `weight` is 0, `model year` is 0, and `origin` is category 1 (i.e. US origin).

`origin_2` means the difference associated with a car being from a European car maker vs. a US car maker. In other words, compared to US car makers, we see an associated increase of about 2 MPG for European car makers.

`origin_3` is also comparing to US car makers. We see an associated increase of about 2.2 MPG for Asian car makers compared to US car makers.

Level Up: One-Hot Encoding with Scikit-Learn

The machine learning library scikit-learn also has functionality for one-hot encoding ([documentation here (https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html)](https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html)). It is essential to use this approach to one-hot encoding in a predictive machine learning context, and optional to use it in an inferential context like we are currently using.

In [22]:
```
from sklearn.preprocessing import OneHotEncoder

ohe = OneHotEncoder(drop="first", sparse=False)
```

`drop="first"` is equivalent to `drop_first=True` in `pd.get_dummies` . `sparse=False` specifies that we want the result to be a NumPy array rather than a [sparse matrix (https://docs.scipy.org/doc/scipy/reference/sparse.html)](https://docs.scipy.org/doc/scipy/reference/sparse.html). Sparse matrices are more efficient in their use of memory space but can't be converted to dataframes as easily.

This approach does not allow you to specify certain columns and pass the entire dataframe in. Instead, you need to create a dataframe with only the column(s) that require one-hot encoding.

For this example we'll select just `origin` .

In [23]:
```
data_cat = data[["origin"]].copy()
data_cat
```

Out[23]:

	origin
0	1
1	1
2	1
3	1
4	1
...	...
387	1
388	2
389	1
390	1
391	1

392 rows × 1 columns

The result from the scikit-learn one-hot encoder is also not a dataframe.

In [24]:
```
ohe.fit(data_cat)

ohe.transform(data_cat)
```

Out[24]:
```
array([[0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 1.],
       [0., 0.],
       [0., 0.],
       [0., 0.],
       [0., 1.],
```

We will need to create a new dataframe ourselves.

In [25]:
```
data_cat_ohe = pd.DataFrame(
    data=ohe.transform(data_cat),
    columns=[f"origin_{cat}" for cat in ohe.categories_[0][1:]]
)
data_cat_ohe
```

Out[25]:

	origin_2	origin_3
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0
...	...	...
387	0.0	0.0
388	1.0	0.0
389	0.0	0.0
390	0.0	0.0
391	0.0	0.0

392 rows × 2 columns

Then we can append the one-hot encoded data back with the numeric data to create an overall X dataframe:

In [26]:
```
X_sklearn = pd.concat([data[["weight", "model year"]], data_cat_ohe], axis=1)
X_sklearn
```

Out[26]:

	weight	model year	origin_2	origin_3
0	3504	70	0.0	0.0
1	3693	70	0.0	0.0
2	3436	70	0.0	0.0
3	3433	70	0.0	0.0
4	3449	70	0.0	0.0
...	...	...	...	...
387	2790	82	0.0	0.0
388	2130	82	1.0	0.0
389	2295	82	0.0	0.0
390	2625	82	0.0	0.0
391	2720	82	0.0	0.0

392 rows × 4 columns

Then we can plug that dataframe into the model, with the same results as `pd.get_dummies` :

In [27]:
```
model_2 = sm.OLS(y, sm.add_constant(X_sklearn))
results_2 = model_2.fit()

print(results.params)
print(results_2.params)
```

```
const        -18.306944
weight        -0.005887
model year     0.769849
origin_2       1.976306
origin_3       2.214534
dtype: float64
const        -18.306944
weight        -0.005887
model year     0.769849
origin_2       1.976306
origin_3       2.214534
dtype: float64
```

This may seem like a lot of extra work, but the key difference is that the scikit-learn `ohe` object "remembers" the categories that it created, and can apply the same transformation to a future dataset. This is necessary in a machine learning context, but you can consider it optional for now.

Summary

Great! In this lesson, you learned about categorical variables and how they are different from numeric variables. You also learned how to include them in your multiple linear regression model using dummy variables. You also learned about the dummy variable trap and how it can be avoided.