023-price-and-neighborhood

April 29, 2022

Predicting Price with Neighborhood

[191]:
```
import warnings
from glob import glob

import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import wqet_grader
from category_encoders import OneHotEncoder
from IPython.display import VimeoVideo
from sklearn.linear_model import LinearRegression, Ridge  # noqa F401
from sklearn.metrics import mean_absolute_error
from sklearn.pipeline import make_pipeline
from sklearn.utils.validation import check_is_fitted

warnings.simplefilter(action="ignore", category=FutureWarning)
wqet_grader.init("Project 2 Assessment")
```

```
<IPython.core.display.HTML object>
```

In the last lesson, we created a model that used location — represented by latitude and longitude — to predict price. In this lesson, we're going to use a different representation for location: neighborhood.

[192]:
```
VimeoVideo("656790491", h="6325554e55", width=600)
```

[192]:
```
<IPython.lib.display.VimeoVideo at 0x7f0baa86ddc0>
```

1 Prepare Data

1.1 Import

[193]:
```
def wrangle(filepath):
    # Read CSV file
    df = pd.read_csv(filepath)

    # Subset data: Apartments in "Capital Federal", less than 400,000
```

```
    mask_ba = df["place_with_parent_names"].str.contains("Capital Federal")
    mask_apt = df["property_type"] == "apartment"
    mask_price = df["price_aprox_usd"] < 400_000
    df = df[mask_ba & mask_apt & mask_price]

    # Subset data: Remove outliers for "surface_covered_in_m2"
    low, high = df["surface_covered_in_m2"].quantile([0.1, 0.9])
    mask_area = df["surface_covered_in_m2"].between(low, high)
    df = df[mask_area]

    # Split "lat-lon" column
    df[["lat", "lon"]] = df["lat-lon"].str.split(",", expand=True).astype(float)
    df.drop(columns="lat-lon", inplace=True)

    df['neighborhood'] = df['place_with_parent_names'].str.split('|', expand =␣
↪True)[3]
    df.drop(columns = 'place_with_parent_names', inplace = True)


    return df
```

In the last lesson, we used our `wrangle` function to import two CSV files as DataFrames. But what if we had hundreds of CSV files to import? Wrangling them one-by-one wouldn't be an option. So let's start with a technique for reading several CSV files into a single DataFrame.

The first step is to gather the names of all the files we want to import. We can do this using pattern matching.

[194]:
```
VimeoVideo("656790237", h="1502e3765a", width=600)
```

[194]:
```
<IPython.lib.display.VimeoVideo at 0x7f0baa817e20>
```

Task 2.3.1: Use glob to create a list that contains the filenames for all the Buenos Aires real estate CSV files in the `data` directory. Assign this list to the variable name `files`.

- Assemble a list of path names that match a pattern in glob.

[195]:
```
files = sorted( glob('data/buenos-aires-real-estate-*.csv') )
files
```

[195]:
```
['data/buenos-aires-real-estate-1.csv',
 'data/buenos-aires-real-estate-2.csv',
 'data/buenos-aires-real-estate-3.csv',
 'data/buenos-aires-real-estate-4.csv',
 'data/buenos-aires-real-estate-5.csv']
```

[196]:
```
# Check your work
assert len(files) == 5, f"`files` should contain 5 items, not {len(files)}"
```

The next step is to read each of the CSVs in `files` into a DataFrame, and put all of those DataFrames into a list. What's a good way to iterate through `files` so we can do this? A `for` loop!

[197]:
```
VimeoVideo("656789768", h="3b8f3bca0b", width=600)
```

[197]:
```
&lt;IPython.lib.display.VimeoVideo at 0x7f0baa817fa0&gt;
```

Task 2.3.2: Use your `wrangle` function in a `for` loop to create a list named `frames`. The list should the cleaned DataFrames created from the CSV filenames your collected in `files`.

- What's a for loop?
- Write a for loop in Python.

[198]:
```
frames = []
for file in files:
    df = wrangle(file)
    frames.append(df)
```

[199]:
```
# Check your work
assert len(frames) == 5, f"`frames` should contain 5 items, not {len(frames)}"
assert all(
    [isinstance(frame, pd.DataFrame) for frame in frames]
), "The items in `frames` should all be DataFrames."
```

The final step is to use pandas to combine all the DataFrames in `frames`.

[200]:
```
VimeoVideo("656789700", h="57adef4afe", width=600)
```

[200]:
```
&lt;IPython.lib.display.VimeoVideo at 0x7f0c6728a2e0&gt;
```

Task 2.3.3: Use `pd.concat` to concatenate the items in `frames` into a single DataFrame `df`. Make sure you set the `ignore_index` argument to `True`.

- Concatenate two or more DataFrames using pandas.

[201]:
```
df = pd.concat(frames, ignore_index = True)
df.head()
```

[201]:
```
  operation property_type     price currency  price_aprox_local_currency  \
0      sell     apartment  129000.0      USD                   1955949.6
1      sell     apartment   87000.0      USD                   1319128.8
2      sell     apartment  118000.0      USD                   1789163.2
3      sell     apartment   57000.0      USD                    864256.8
4      sell     apartment   90000.0      USD                   1364616.0

   price_aprox_usd  surface_total_in_m2  surface_covered_in_m2  \
0         129000.0                 76.0                   70.0
1          87000.0                 48.0                   42.0
```

```
2         118000.0                   NaN                   54.0
3          57000.0                  42.0                   42.0
4          90000.0                  57.0                   50.0

   price_usd_per_m2  price_per_m2  floor  rooms expenses  \
0       1697.368421   1842.857143    NaN    NaN      NaN
1       1812.500000   2071.428571    NaN    NaN      NaN
2               NaN   2185.185185    NaN    2.0      NaN
3       1357.142857   1357.142857    5.0    2.0      364
4       1578.947368   1800.000000    NaN    3.0      450

                                    properati_url        lat        lon  \
0  http://chacarita.properati.com.ar/10qlv_venta_… -34.584651 -58.454693
1  http://villa-luro.properati.com.ar/12m82_venta… -34.638979 -58.500115
2  http://caballito.properati.com.ar/11wqh_venta_… -34.615847 -58.459957
3  http://constitucion.properati.com.ar/k2f0_vent… -34.625222 -58.382382
4  http://once.properati.com.ar/suwa_venta_depart… -34.610610 -58.412511

   neighborhood
0     Chacarita
1    Villa Luro
2     Caballito
3  Constitución
4          Once
```

[202]:
```
# Check your work
assert len(df) == 6582, f"`df` is the wrong size: {len(df)}."
```

Excellent work! You can now clean and combine as many CSV files as your computer can handle. You're well on your way to working with big data.

1.2 Explore

Looking through the output from the `df.head()` call above, there's a little bit more cleaning we need to do before we can work with the neighborhood information in this dataset. The good news is that, because we're using a `wrangle` function, we only need to change the function to re-clean all of our CSV files. This is why functions are so useful.

[203]:
```
VimeoVideo("656791659", h="581201dc92", width=600)
```

[203]: <IPython.lib.display.VimeoVideo at 0x7f0baa85dfd0>

Task 2.3.4: Modify your `wrangle` function to create a new feature `"neighborhood"`. You can find the neighborhood for each property in the `"place_with_parent_names"` column. For example, a property with the place name `"|Argentina|Capital Federal|Palermo|"` is located in the neighborhood is `"Palermo"`. Also, your function should drop the `"place_with_parent_names"` column.

Be sure to rerun all the cells above before you continue.

- Split the strings in one column to create another using pandas.

[204]:
```python
# Check your work
assert df.shape == (6582, 17), f"`df` is the wrong size: {df.shape}."
assert (
    "place_with_parent_names" not in df
), 'Remember to remove the `"place_with_parent_names"` column.'
```

[205]:
```python
df.head()
```

[205]:
```
  operation property_type     price currency  price_aprox_local_currency  \
0      sell     apartment  129000.0      USD                   1955949.6
1      sell     apartment   87000.0      USD                   1319128.8
2      sell     apartment  118000.0      USD                   1789163.2
3      sell     apartment   57000.0      USD                    864256.8
4      sell     apartment   90000.0      USD                   1364616.0

   price_aprox_usd  surface_total_in_m2  surface_covered_in_m2  \
0         129000.0                 76.0                   70.0
1          87000.0                 48.0                   42.0
2         118000.0                  NaN                   54.0
3          57000.0                 42.0                   42.0
4          90000.0                 57.0                   50.0

   price_usd_per_m2  price_per_m2  floor  rooms expenses  \
0       1697.368421   1842.857143    NaN    NaN      NaN
1       1812.500000   2071.428571    NaN    NaN      NaN
2               NaN   2185.185185    NaN    2.0      NaN
3       1357.142857   1357.142857    5.0    2.0      364
4       1578.947368   1800.000000    NaN    3.0      450

                                     properati_url        lat        lon  \
0  http://chacarita.properati.com.ar/10qlv_venta_… -34.584651 -58.454693
1  http://villa-luro.properati.com.ar/12m82_venta… -34.638979 -58.500115
2  http://caballito.properati.com.ar/11wqh_venta_… -34.615847 -58.459957
3  http://constitucion.properati.com.ar/k2f0_vent… -34.625222 -58.382382
4  http://once.properati.com.ar/suwa_venta_depart… -34.610610 -58.412511

   neighborhood
0     Chacarita
1    Villa Luro
2     Caballito
3  Constitución
4          Once
```

1.3 Split

At this point, you should feel more comfortable with the splitting data, so we're going to condense the whole process down to one task.

[206]:
```
VimeoVideo("656791577", h="0ceb5341f8", width=600)
```

[206]: <IPython.lib.display.VimeoVideo at 0x7f0c5ffaec10>

Task 2.3.5: Create your feature matrix `X_train` and target vector `y_train`. `X_train` should contain one feature: `"neighborhood"`. Your target is `"price_aprox_usd"`.

- What's a feature matrix?
- What's a target vector?
- Subset a DataFrame by selecting one or more columns in pandas.
- Select a Series from a DataFrame in pandas.

[207]:
```
target = "price_aprox_usd"
features = ["neighborhood"]
y_train = df[target]
X_train = df[features]
```

[208]:
```
# Check your work
assert X_train.shape == (6582, 1), f"`X_train` is the wrong size: {X_train.
↪shape}."
assert y_train.shape == (6582,), f"`y_train` is the wrong size: {y_train.shape}.
↪"
```

2 Build Model

2.1 Baseline

Let's also condense the code we use to establish our baseline.

[209]:
```
VimeoVideo("656791443", h="120a740cc3", width=600)
```

[209]: <IPython.lib.display.VimeoVideo at 0x7f0c5ff892b0>

Task 2.3.6: Calculate the baseline mean absolute error for your model.

- What's a performance metric?
- What's mean absolute error?
- Calculate summary statistics for a DataFrame or Series in pandas.
- Calculate the mean absolute error for a list of predictions in scikit-learn.

[210]:
```
y_mean = y_train.mean()
y_pred_baseline = [y_mean] * len(y_train)
print("Mean apt price:", y_mean)

print("Baseline MAE:", mean_absolute_error(y_train, y_pred_baseline))
```

```
Mean apt price: 132383.83701458527
Baseline MAE: 44860.10834274134
```

The mean apartment price and baseline MAE should be similar but not identical to last lesson. The numbers will change since we're working with more data.

2.2 Iterate

If you try to fit a `LinearRegression` predictor to your training data at this point, you'll get an error that looks like this:

```
ValueError: could not convert string to float
```

What does this mean? When you fit a linear regression model, you're asking scikit-learn to perform a mathematical operation. The problem is that our training set contains neighborhood information in non-numerical form. In order to create our model we need to **encode** that information so that it's represented numerically. The good news is that there are lots of transformers that can do this. Here, we'll use the one from the Category Encoders library, called a `OneHotEncoder`.

Before we build include this transformer in our pipeline, let's explore how it works.

[211]:
```
VimeoVideo("656792790", h="4097efb40d", width=600)
```

[211]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff89a00>
```

Task 2.3.7: First, instantiate a `OneHotEncoder` named `ohe`. Make sure to set the `use_cat_names` argument to `True`. Next, fit your transformer to the feature matrix `X_train`. Finally, use your encoder to transform the feature matrix `X_train`, and assign the transformed data to the variable `XT_train`.

- What's one-hot encoding?
- Instantiate a transformer in scikit-learn.
- Fit a transformer to training data in scikit-learn.
- Transform data using a transformer in scikit-learn.

[212]:
```
ohe = OneHotEncoder(use_cat_names = True)
ohe.fit(X_train)

XT_train = ohe.transform(X_train)
print(XT_train.shape)
XT_train.head()
```

```
(6582, 57)
```

[212]:
```
   neighborhood_Chacarita  neighborhood_Villa Luro  neighborhood_Caballito  \
0                       1                        0                       0
1                       0                        1                       0
2                       0                        0                       1
3                       0                        0                       0
4                       0                        0                       0
```

```
   neighborhood_Constitución  neighborhood_Once  neighborhood_Almagro  \
0                          0                  0                     0
1                          0                  0                     0
2                          0                  0                     0
3                          1                  0                     0
4                          0                  1                     0

   neighborhood_Palermo  neighborhood_Flores  neighborhood_Belgrano  \
0                     0                    0                      0
1                     0                    0                      0
2                     0                    0                      0
3                     0                    0                      0
4                     0                    0                      0

   neighborhood_Liniers  …  neighborhood_Puerto Madero  \
0                     0  …                           0
1                     0  …                           0
2                     0  …                           0
3                     0  …                           0
4                     0  …                           0

   neighborhood_Agronomía  neighborhood_Monte Castro  neighborhood_Tribunales  \
0                       0                          0                        0
1                       0                          0                        0
2                       0                          0                        0
3                       0                          0                        0
4                       0                          0                        0

   neighborhood_Villa Santa Rita  neighborhood_Velez Sarsfield  \
0                              0                             0
1                              0                             0
2                              0                             0
3                              0                             0
4                              0                             0

   neighborhood_Villa Soldati  neighborhood_Villa Real  neighborhood_Pompeya  \
0                           0                        0                     0
1                           0                        0                     0
2                           0                        0                     0
3                           0                        0                     0
4                           0                        0                     0

   neighborhood_Catalinas
0                       0
1                       0
2                       0
3                       0
```

```
4                        0

[5 rows x 57 columns]
```

[213]:
```
# Check your work
assert XT_train.shape == (6582, 57), f"`XT_train` is the wrong shape: {XT_train.
 ↪shape}"
```

Now that we have an idea for how the `OneHotEncoder` works, let's bring it into our pipeline.

[214]:
```
VimeoVideo("656792622", h="0b9d189e8f", width=600)
```

[214]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff89910>
```

Task 2.3.8: Create a pipeline named `model` that contains a `OneHotEncoder` transformer and a `LinearRegression` predictor. Then fit your model to the training data.

- What's a pipeline?
- Create a pipeline in scikit-learn.

[215]:
```
model = make_pipeline(
    OneHotEncoder(use_cat_names =True),
    Ridge()
)
model.fit(X_train, y_train)
```

[215]:
```
Pipeline(steps=[('onehotencoder',
                 OneHotEncoder(cols=['neighborhood'], use_cat_names=True)),
                ('ridge', Ridge())])
```

[216]:
```
# Check your work
check_is_fitted(model[-1])
```

Wow, you just built a model with two transformers and a predictor! When you started this course, did you think you'd be able to do something like that?

2.3 Evaluate

Regardless of how you build your model, the evaluation step stays the same. Let's see how our model performs with the training set.

[217]:
```
VimeoVideo("656792525", h="09edc1c3d6", width=600)
```

[217]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff8c4f0>
```

Task 2.3.9: First, create a list of predictions for the observations in your feature matrix `X_train`. Name this list `y_pred_training`. Then calculate the training mean absolute error for your predictions in `y_pred_training` as compared to the true targets in `y_train`.

- Generate predictions using a trained model in scikit-learn.

- Calculate the mean absolute error for a list of predictions in scikit-learn.

[218]:
```python
y_pred_training = model.predict(X_train)
mae_training = mean_absolute_error(y_train, y_pred_training)
print("Training MAE:", round(mae_training, 2))
```

```
Training MAE: 39350.22
```

[219]:
```python
y_train
```

[219]:
```
0       129000.0
1        87000.0
2       118000.0
3        57000.0
4        90000.0
          …
6577    290000.0
6578    150000.0
6579     65000.0
6580     91440.0
6581     89000.0
Name: price_aprox_usd, Length: 6582, dtype: float64
```

Now let's check our test performance.

Task 2.3.10: Run the code below to import your test data `buenos-aires-test-features.csv` into a DataFrame and generate a Series of predictions using your model. Then run the following cell to submit your predictions to the grader.

- What's generalizability?
- Generate predictions using a trained model in scikit-learn.
- Calculate the mean absolute error for a list of predictions in scikit-learn.

[220]:
```python
X_test = pd.read_csv("data/buenos-aires-test-features.csv")[features]
y_pred_test = pd.Series(model.predict(X_test))
y_pred_test.head()
```

[220]:
```
0    246624.694624
1    161355.968734
2     98232.051308
3    110846.030377
4    127777.538197
dtype: float64
```

[221]:
```python
wqet_grader.grade("Project 2 Assessment", "Task 2.3.10", y_pred_test)
```

```
<IPython.core.display.HTML object>
```

3 Communicate Results

If we write out the equation for our model, it'll be too big to fit on the screen. That's because, when we used the `OneHotEncoder` to encode the neighborhood data, we created a much wider DataFrame, and each column/feature has it's own coefficient in our model's equation.

This is important to keep in mind for two reasons. First, it means that this is a **high-dimensional** model. Instead of a 2D or 3D plot, we'd need a 58-dimensional plot to represent it, which is impossible! Second, it means that we'll need to extract and represent the information for our equation a little differently than before. Let's start by getting our intercept and coefficient.

[222]:
```
VimeoVideo("656793909", h="fca67856b4", width=600)
```

[222]:
```
<IPython.lib.display.VimeoVideo at 0x7f0baa8179d0>
```

Task 2.3.11: Extract the intercept and coefficients for your model.

- What's an intercept in a linear model?
- What's a coefficient in a linear model?
- Access an object in a pipeline in scikit-learn.

[223]:
```
intercept = model.named_steps['ridge'].intercept_
coefficients = model.named_steps['ridge'].coef_
print("coefficients len:", len(coefficients))
print(coefficients[:5])  # First five coefficients
```

```
coefficients len: 57
[-2.89895934e+03 -6.29555347e+00  9.25289088e+03 -4.17487330e+04
 -3.23037446e+03]
```

[224]:
```
# Check your work
assert isinstance(
    intercept, float
), f"`intercept` should be a `float`, not {type(intercept)}."
assert isinstance(
    coefficients, np.ndarray
), f"`coefficients` should be a `float`, not {type(coefficients)}."
assert coefficients.shape == (
    57,
), f"`coefficients` is wrong shape: {coefficients.shape}."
```

We have the values of our coefficients, but how do we know which features they belong to? We'll need to get that information by going into the part of our pipeline that did the encoding.

[225]:
```
VimeoVideo("656793812", h="810161b84e", width=600)
```

[225]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff8cd90>
```

Task 2.3.12: Extract the feature names of your encoded data from the `OneHotEncoder` in your model.

- Access an object in a pipeline in scikit-learn.

[226]:
```
feature_names = model.named_steps['onehotencoder'].get_feature_names()
print("features len:", len(feature_names))
print(feature_names[:5])  # First five feature names
```

```
features len: 57
['neighborhood_Chacarita', 'neighborhood_Villa Luro', 'neighborhood_Caballito',
'neighborhood_Constitución', 'neighborhood_Once']
```

[227]:
```
# Check your work
assert isinstance(
    feature_names, list
), f"`features` should be a `list`, not {type(features)}."
assert len(feature_names) == len(
    coefficients
), "You should have the same number of features and coefficients."
```

We have coefficients and feature names, and now we need to put them together. For that, we'll use a Series.

[228]:
```
VimeoVideo("656793718", h="1e2a1e1de8", width=600)
```

[228]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff8cfa0>
```

Task 2.3.13: Create a pandas Series named `feat_imp` where the index is your `features` and the values are your `coefficients`.

- Create a Series in pandas.

[229]:
```
feat_imp = pd.Series(coefficients, index = feature_names)
feat_imp.head()
```

[229]:
```
neighborhood_Chacarita       -2898.959335
neighborhood_Villa Luro         -6.295553
neighborhood_Caballito        9252.890876
neighborhood_Constitución   -41748.733031
neighborhood_Once            -3230.374461
dtype: float64
```

[230]:
```
# Check your work
assert isinstance(
    feat_imp, pd.Series
), f"`feat_imp` should be a `float`, not {type(feat_imp)}."
assert feat_imp.shape == (57,), f"`feat_imp` is wrong shape: {feat_imp.shape}."
assert all(
    a == b for a, b in zip(sorted(feature_names), sorted(feat_imp.index))
), "The index of `feat_imp` should be identical to `features`."
```

To be clear, it's definitely not a good idea to show this long equation to an audience, but let's print it out just to check our work. Since there are so many terms to print, we'll use a `for` loop.

[231]:
```
VimeoVideo("656797021", h="dc90e6dac3", width=600)
```

[231]: <IPython.lib.display.VimeoVideo at 0x7f0c5ff90a00>

Task 2.3.14: Run the cell below to print the equation that your model has determined for predicting apartment price based on longitude and latitude.

- What's an f-string?

[232]:
```
print(f"price = {intercept.round(2)}")
for f, c in feat_imp.items():
    print(f"+ ({round(c, 2)} * {f})")
```

```
price = 118524.65
+ (-2898.96 * neighborhood_Chacarita)
+ (-6.3 * neighborhood_Villa Luro)
+ (9252.89 * neighborhood_Caballito)
+ (-41748.73 * neighborhood_Constitución)
+ (-3230.37 * neighborhood_Once)
+ (2903.34 * neighborhood_Almagro)
+ (45934.41 * neighborhood_Palermo)
+ (-8662.28 * neighborhood_Flores)
+ (46954.21 * neighborhood_Belgrano)
+ (-13729.1 * neighborhood_Liniers)
+ (6277.05 * neighborhood_Villa Crespo)
+ (-10678.63 * neighborhood_San Cristobal)
+ (-7974.66 * neighborhood_Congreso)
+ (14701.16 * neighborhood_Saavedra)
+ (-11172.55 * neighborhood_Balvanera)
+ (-29585.61 * neighborhood_Parque Avellaneda)
+ (72740.78 * neighborhood_Recoleta)
+ (5638.47 * neighborhood_San Telmo)
+ (42831.32 * neighborhood_Nuñez)
+ (55590.93 * neighborhood_Barrio Norte)
+ (-6323.68 * neighborhood_Parque Centenario)
+ (4330.55 * neighborhood_Abasto)
+ (-7905.29 * neighborhood_Centro / Microcentro)
+ (-19370.74 * neighborhood_)
+ (-7108.23 * neighborhood_Paternal)
+ (-21078.78 * neighborhood_Mataderos)
+ (-48669.35 * neighborhood_Villa Lugano)
+ (12223.11 * neighborhood_Coghlan)
+ (72270.21 * neighborhood_Las Cañitas)
+ (12671.71 * neighborhood_Villa Urquiza)
+ (-20292.6 * neighborhood_Monserrat)
+ (-8093.45 * neighborhood_Villa Pueyrredón)
```

```
+ (-15807.01 * neighborhood_Parque Patricios)
+ (-10734.35 * neighborhood_San Nicolás)
+ (-12595.5 * neighborhood_Villa del Parque)
+ (-6837.4 * neighborhood_Boedo)
+ (-7678.62 * neighborhood_Parque Chacabuco)
+ (-4618.66 * neighborhood_Barracas)
+ (-32439.87 * neighborhood_Parque Chas)
+ (38436.33 * neighborhood_Colegiales)
+ (7714.62 * neighborhood_Villa General Mitre)
+ (-11208.9 * neighborhood_Villa Ortuzar)
+ (3860.58 * neighborhood_Villa Devoto)
+ (-14088.02 * neighborhood_Floresta)
+ (27042.61 * neighborhood_Retiro)
+ (-4937.21 * neighborhood_Versalles)
+ (-28353.36 * neighborhood_Boca)
+ (128100.05 * neighborhood_Puerto Madero)
+ (-772.7 * neighborhood_Agronomía)
+ (-3427.44 * neighborhood_Monte Castro)
+ (-7818.09 * neighborhood_Tribunales)
+ (-19843.92 * neighborhood_Villa Santa Rita)
+ (-27219.72 * neighborhood_Velez Sarsfield)
+ (-59248.81 * neighborhood_Villa Soldati)
+ (-7393.49 * neighborhood_Villa Real)
+ (-43909.59 * neighborhood_Pompeya)
+ (-22012.32 * neighborhood_Catalinas)
```

Warning: In the first lesson for this project, we said that you shouldn't make any changes to your model after you see your test metrics. That's still true. However, we're breaking that rule here so that we can discuss overfitting. In future lessons, you'll learn how to protect against overfitting without checking your test set.

[233]:
```
VimeoVideo("656799309", h="a7130deb64", width=600)
```

[233]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff90e80>
```

Task 2.3.15: Scroll up, change the predictor in your model to `Ridge`, and retrain it. Then evaluate the model's training and test performance. Do you still have an overfitting problem? If not, extract the intercept and coefficients again (you'll need to change your code a little bit) and regenerate the model's equation. Does it look different than before?

- What's overfitting?
- What's regularization?
- What's ridge regression?

[190]:
```
# Check your work
assert isinstance(
    model[-1], Ridge
), "Did you retrain your model using a `Ridge` predictor?"
```

We're back on track with our model, so let's create a visualization that will help a non-technical audience understand what the most important features for our model in predicting apartment price.

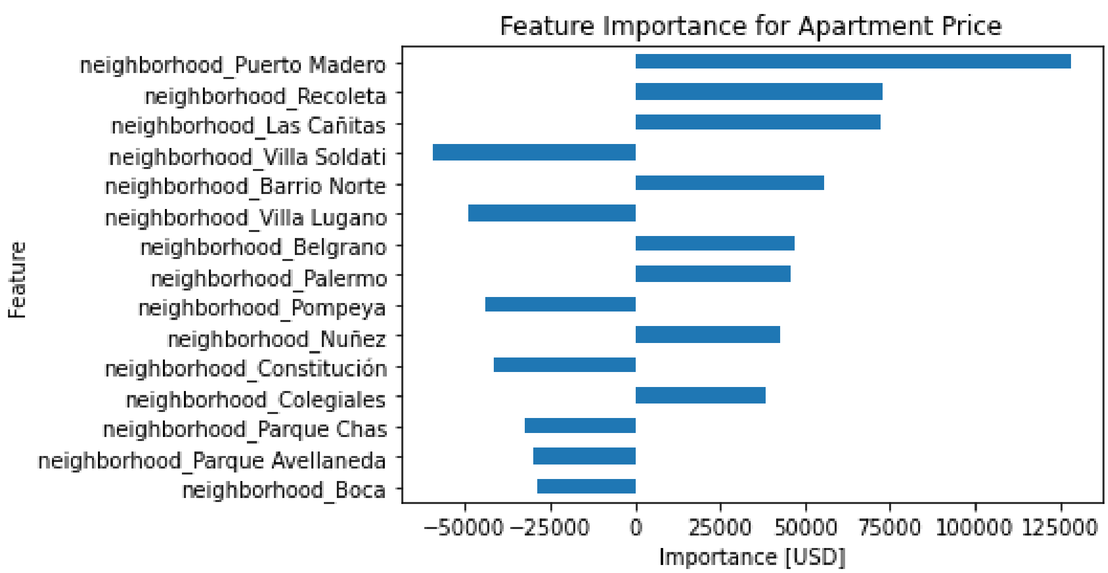
[234]:
```
VimeoVideo("656798530", h="9a9350eff1", width=600)
```

[234]:
```
<IPython.lib.display.VimeoVideo at 0x7f0c5ff89ac0>
```

Task 2.3.16: Create a horizontal bar chart that shows the top 15 coefficients for your model, based on their absolute value.

- What's a bar chart?
- Create a bar chart using pandas.

[238]:
```
feat_imp.sort_values(key = abs).tail(15).plot(kind = 'barh')
plt.xlabel('Importance [USD]')
plt.ylabel('Feature')
plt.title('Feature Importance for Apartment Price');
```



Looking at this bar chart, we can see that the poshest neighborhoods in Buenos Aires like Puerto Madero and Recoleta increase the predicted price of an apartment, while more working-class neighborhoods like Villa Soldati and Villa Lugano decrease the predicted price.

Just for fun, check out this song by Kevin Johansen about Puerto Madero.
