This notebook is an exercise in the <u>Intermediate Machine Learning</u> course. You can reference the tutorial at <u>this link</u>.

Now it's your turn to test your new knowledge of **missing values** handling. You'll probably find it makes a big difference.

### Setup

The questions will give you feedback on your work. Run the following cell to set up the feedback system.

```
In []: # Set up code checking
    import os
    if not os.path.exists("../input/train.csv"):
        os.symlink("../input/home-data-for-ml-course/train.csv", "../input/train.csv")
        os.symlink("../input/home-data-for-ml-course/test.csv", "../input/test.csv")
    from learntools.core import binder
    binder.bind(globals())
    from learntools.ml_intermediate.ex2 import *
    print("Setup Complete")
```

In this exercise, you will work with data from the <u>Housing Prices Competition for Kaggle Learn Users</u>.



Run the next code cell without changes to load the training and validation sets in X\_train, X\_valid, y\_train, and y\_valid. The test set is loaded in X\_test.

```
In []: import pandas as pd
        from sklearn.model selection import train test split
        # Read the data
        X full = pd.read_csv('../input/train.csv', index_col='Id')
        X test full = pd.read csv('.../input/test.csv', index col='Id')
        # Remove rows with missing target, separate target from predictors
        X full.dropna(axis=0, subset=['SalePrice'], inplace=True)
        y = X full.SalePrice
        X full.drop(['SalePrice'], axis=1, inplace=True)
        # To keep things simple, we'll use only numerical predictors
        X = X full.select dtypes(exclude=['object'])
        X test = X test full.select dtypes(exclude=['object'])
        # Break off validation set from training data
        X train, X valid, y train, y valid = train test split(X, y, train size=
        0.8, test size=0.2,
                                                               random state=0)
```

Use the next code cell to print the first five rows of the data.

```
In [ ]: X_train.head()
```

You can already see a few missing values in the first several rows. In the next step, you'll obtain a more comprehensive understanding of the missing values in the dataset.

# **Step 1: Preliminary investigation**

Run the code cell below without changes.

```
In []: # Shape of training data (num_rows, num_columns)
    print(X_train.shape)

# Number of missing values in each column of training data
    missing_val_count_by_column = (X_train.isnull().sum())
    print(missing_val_count_by_column[missing_val_count_by_column > 0])
```

### Part A

Use the above output to answer the questions below.

```
In [ ]: # Fill in the line below: How many rows are in the training data?
    num_rows = 1168

# Fill in the line below: How many columns in the training data
# have missing values?
    num_cols_with_missing = 3

# Fill in the line below: How many missing entries are contained in
# all of the training data?
    tot_missing = 276

# Check your answers
step_1.a.check()
In [ ]: # Lines below will give you a hint or solution code
#step_1.a.hint()
#step_1.a.solution()
```

### Part B

Considering your answers above, what do you think is likely the best approach to dealing with the missing values?

```
In [ ]: # Check your answer (Run this code cell to receive credit!)
step_1.b.check()
```

```
In [ ]: #step_1.b.hint()
```

To compare different approaches to dealing with missing values, you'll use the same score\_dataset() function from the tutorial. This function reports the mean absolute error (MAE) from a random forest model.

```
In []: from sklearn.ensemble import RandomForestRegressor
    from sklearn.metrics import mean_absolute_error

# Function for comparing different approaches
    def score_dataset(X_train, X_valid, y_train, y_valid):
        model = RandomForestRegressor(n_estimators=100, random_state=0)
        model.fit(X_train, y_train)
        preds = model.predict(X_valid)
        return mean_absolute_error(y_valid, preds)
```

# **Step 2: Drop columns with missing values**

In this step, you'll preprocess the data in X\_train and X\_valid to remove columns with missing values. Set the preprocessed DataFrames to reduced\_X\_train and reduced\_X\_valid, respectively.

```
reduced_X_train = X_train.drop(col_with_missing_values,axis=1)
reduced_X_valid = X_valid.drop(col_with_missing_values,axis=1)
# Check your answers
step_2.check()
```

Run the next code cell without changes to obtain the MAE for this approach.

```
In [ ]: print("MAE (Drop columns with missing values):")
    print(score_dataset(reduced_X_train, reduced_X_valid, y_train, y_valid
    ))
```

## **Step 3: Imputation**

#### Part A

Use the next code cell to impute missing values with the mean value along each column. Set the preprocessed DataFrames to imputed\_X\_train and imputed\_X\_valid. Make sure that the column names match those in X\_train and X\_valid.

```
In []: from sklearn.impute import SimpleImputer

# Fill in the lines below: imputation
my_imputer= SimpleImputer(strategy="mean") # Your code here
imputed_X_train = pd.DataFrame(my_imputer.fit_transform(X_train))
imputed_X_valid = pd.DataFrame(my_imputer.transform(X_valid))

# Fill in the lines below: imputation removed column names; put them ba
ck
imputed_X_train.columns = X_train.columns
```

```
imputed_X_valid.columns = X_valid.columns

# Check your answers
step_3.a.check()
```

Run the next code cell without changes to obtain the MAE for this approach.

```
In [ ]: print("MAE (Imputation):")
    print(score_dataset(imputed_X_train, imputed_X_valid, y_train, y_valid
    ))
```

### Part B

Compare the MAE from each approach. Does anything surprise you about the results? Why do you think one approach performed better than the other?

```
In [ ]: # Check your answer (Run this code cell to receive credit!)
step_3.b.check()
In [ ]: #step 3.b.hint()
```

## **Step 4: Generate test predictions**

In this final step, you'll use any approach of your choosing to deal with missing values. Once you've preprocessed the training and validation features, you'll train and evaluate a random forest model. Then, you'll preprocess the test data before generating predictions that can be submitted to the competition!

#### Part A

Use the next code cell to preprocess the training and validation data. Set the preprocessed DataFrames to final\_X\_train and final\_X\_valid. You can use any approach of your choosing here! in order for this step to be marked as correct, you need only ensure:

- the preprocessed DataFrames have the same number of columns,
- the preprocessed DataFrames have no missing values,
- final X train and y train have the same number of rows, and
- final\_X\_valid and y\_valid have the same number of rows.

```
In []: # Preprocessed training and validation features
    final_imputer = SimpleImputer(strategy='median')
    final_X_train = pd.DataFrame(final_imputer.fit_transform(X_train))
    final_X_valid = pd.DataFrame(final_imputer.transform(X_valid))

# Restoring column names
    final_X_train.columns = X_train.columns
    final_X_valid.columns = X_valid.columns

# Check your answers
    step_4.a.check()
```

Run the next code cell to train and evaluate a random forest model. (*Note that we don't use the score\_dataset()* function above, because we will soon use the trained model to generate test predictions!)

```
In [ ]: # Define and fit model
    model = RandomForestRegressor(n_estimators=100, random_state=0)
    model.fit(final_X_train, y_train)
```

```
# Get validation predictions and MAE
preds_valid = model.predict(final_X_valid)
print("MAE (Your approach):")
print(mean_absolute_error(y_valid, preds_valid))
```

#### Part B

Use the next code cell to preprocess your test data. Make sure that you use a method that agrees with how you preprocessed the training and validation data, and set the preprocessed test features to final\_X\_test.

Then, use the preprocessed test features and the trained model to generate test predictions in preds\_test.

In order for this step to be marked correct, you need only ensure:

- · the preprocessed test DataFrame has no missing values, and
- final\_X\_test has the same number of rows as X\_test.

```
In [ ]: # Fill in the line below: preprocess test data
    final_X_test = pd.DataFrame(my_imputer.transform(X_test))

# Fill in the line below: get test predictions
    preds_test = model.predict(final_X_test)

step_4.b.check()

In [ ]: # Lines below will give you a hint or solution code
    #step_4.b.hint()
    #step_4.b.solution()
```

Run the next code cell without changes to save your results to a CSV file that can be submitted

directly to the competition.

## **Submit your results**

Once you have successfully completed Step 4, you're ready to submit your results to the leaderboard! (You also learned how to do this in the previous exercise. If you need a reminder of how to do this, please use the instructions below.)

First, you'll need to join the competition if you haven't already. So open a new window by clicking on this link. Then click on the **Join Competition** button.



Next, follow the instructions below:

- 1. Begin by clicking on the blue **Save Version** button in the top right corner of the window. This will generate a pop-up window.
- 2. Ensure that the **Save and Run All** option is selected, and then click on the blue **Save** button.
- 3. This generates a window in the bottom left corner of the notebook. After it has finished running, click on the number to the right of the **Save Version** button. This pulls up a list of versions on the right of the screen. Click on the ellipsis (...) to the right of the most recent

- version, and select **Open in Viewer**. This brings you into view mode of the same page. You will need to scroll down to get back to these instructions.
- 4. Click on the **Output** tab on the right of the screen. Then, click on the file you would like to submit, and click on the blue **Submit** button to submit your results to the leaderboard.

You have now successfully submitted to the competition!

If you want to keep working to improve your performance, select the blue **Edit** button in the top right of the screen. Then you can change your code and repeat the process. There's a lot of room to improve, and you will climb up the leaderboard as you work.

# Keep going

Move on to learn what <u>categorical variables</u> are, along with how to incorporate them into your machine learning models. Categorical variables are very common in real-world data, but you'll get an error if you try to plug them into your models without processing them first!

Have questions or comments? Visit the <u>Learn Discussion forum</u> to chat with other Learners.