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model.predict(X_valid)\n    return mean_absolute_error(y_valid, preds)","execution_count":null,"outputs":[{}],{"metadata":
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`X_train` and `X_valid` to remove columns with missing values. Set the preprocessed DataFrames to `reduced_X_train` and
`reduced_X_valid`, respectively. "},{ "metadata":{"trusted":false},"cell_type":"code","source":"# Fill in the line below: get names
of columns with missing values\ncol_with_missing_values=[col for col in X_train.columns\n                        if
X_train[col].isnull().any()] # Your code here\n\n# Fill in the lines below: drop columns in training and validation
data\nreduced_X_train = X_train.drop(col_with_missing_values,axis=1)\nreduced_X_valid =
X_valid.drop(col_with_missing_values,axis=1)\n\n# Check your answers\nstep_2.check()","execution_count":null,"outputs":[{}],
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the next code cell without changes to obtain the MAE for this approach."},{ "metadata":
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values):\")\nprint(score_dataset(reduced_X_train, reduced_X_valid, y_train, y_valid))","execution_count":null,"outputs":[{}],
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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`. "},{ "metadata":
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imputation\nmy_imputer= SimpleImputer(strategy=\"mean\") # Your code here\n\nimputed_X_train =
pd.DataFrame(my_imputer.fit_transform(X_train))\nimputed_X_valid = pd.DataFrame(my_imputer.transform(X_valid))\n\n# Fill in the
lines below: imputation removed column names; put them back\nimputed_X_train.columns = X_train.columns\nimputed_X_valid.columns =
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y_train, y_valid))","execution_count":null,"outputs":[{}],{"metadata":{"trusted":false},"cell_type":"markdown","source":"### Part B\n\nCompare the
MAE from each approach. Does anything surprise you about the results? Why do you think one approach performed better than the
other?"},{ "metadata":{"trusted":false},"cell_type":"code","source":"# Check your answer (Run this code cell to receive
credit!)\nstep_3.b.check()","execution_count":null,"outputs":[{}],{"metadata":
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{},"cell_type":"markdown","source":"# Step 4: Generate test predictions\n\nIn 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!\n\n### Part A\n\nUse 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:\n- the preprocessed DataFrames have the same number of columns,\n- the preprocessed
DataFrames have no missing values, \n- `final_X_train` and `y_train` have the same number of rows, and\n- `final_X_valid` and
`y_valid` have the same number of rows."},{ "metadata":{"trusted":false},"cell_type":"code","source":"# Preprocessed training and
validation features\nfinal_imputer = SimpleImputer(strategy='median')\nfinal_X_train =
pd.DataFrame(final_imputer.fit_transform(X_train))\nfinal_X_valid = pd.DataFrame(final_imputer.transform(X_valid))\n\n# Restoring
column names\nfinal_X_train.columns = X_train.columns\nfinal_X_valid.columns = X_valid.columns\n\n\n# Check your
answers\nstep_4.a.check()","execution_count":null,"outputs":[{}],{"metadata":{"trusted":false},"cell_type":"code","source":"# Lines
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don't use the `score_dataset()` function above, because we will soon use the trained model to generate test predictions!*)"},

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{"metadata":{"trusted":false},"cell_type":"code","source":"# Define and fit model\nmodel = RandomForestRegressor(n_estimators=100,\nrandom_state=0)\nmodel.fit(final_X_train, y_train)\n\n# Get validation predictions and MAE\npreds_valid =\nmodel.predict(final_X_valid)\nprint(\"MAE (Your approach):\")\nprint(mean_absolute_error(y_valid,\npreds_valid))","execution_count":null,"outputs":[],"metadata":{"trusted":false},"cell_type":"markdown","source":"### Part B\n\nUse 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`. \n\nThen, use the preprocessed test features and the trained model to generate test predictions in `preds_test`. \n\nIn order for this step to be marked correct, you need only ensure:\n- the preprocessed test DataFrame has no missing values, and\n- `final_X_test` has the same number of rows as `X_test`."}, {"metadata":{"trusted":false},"cell_type":"code","source":"# Fill in the line below: preprocess test data\nfinal_X_test =\npd.DataFrame(my_imputer.transform(X_test))\n\n# Fill in the line below: get test predictions\npreds_test =\nmodel.predict(final_X_test)\n\nstep_4.b.check()","execution_count":null,"outputs":[],"metadata":{"trusted":false},"cell_type":"code","source":"# Lines below will give you a hint or solution\ncode\n#step_4.b.hint()\n#step_4.b.solution()","execution_count":null,"outputs":[],"metadata":{"trusted":false},"cell_type":"markdown","source":"Run the next code cell without changes to save your results to a CSV file that can be submitted directly to the competition."}, {"metadata":{"trusted":false},"cell_type":"code","source":"# Save test predictions to file\noutput =\npd.DataFrame({'Id': X_test.index,\n              'SalePrice': preds_test})\noutput.to_csv('submission.csv',\nindex=False)","execution_count":null,"outputs":[],"metadata":{"trusted":false},"cell_type":"markdown","source":"# Submit your results\n\nOnce 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.) \n\nFirst, you'll need to join the competition if you haven't already. So open a new window by clicking on [this link](https://www.kaggle.com/c/home-data-for-ml-course). Then click on the Join Competition button.\n\n[Save Version button in the top right corner of the window. This will generate a pop-up window. \n2. Ensure that the Save and Run All option is selected, and then click on the blue Save button. \n3. 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. \n4. 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. \n\nYou have now successfully submitted to the competition!\n\nIf 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. \n\n# Keep going\n\nMove on to learn what [categorical variables](https://www.kaggle.com/alexisbcook/categorical-variables) 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!"}, {"metadata":{"trusted":false},"cell_type":"markdown","source":"---\n\nHave questions or comments? Visit the [Learn Discussion forum](https://www.kaggle.com/learn-forum/161289) to chat with other Learners.*"}], {"metadata":{"language":"python","display_name":"Python 3","name":"python3"},"language_info":{"pygments_lexer":"ipython3","nbconvert_exporter":"python","version":"3.6.4","file_extension":".py","codemirror_mode":{"name":"ipython","version":3},"name":"python","mimetype":"text/x-python"},"nbformat":4,"nbformat_minor":4}

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