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## House Prices dataset: Feature Selection

In the following cells, we will select a group of variables, the most predictive ones, to build our machine learning model.

## Why do we select variables?

- For production: Fewer variables mean smaller client input requirements (e.g. customers filling out a form on a website or mobile app), and hence less code for error handling. This reduces the chances of introducing bugs.
- For model performance: Fewer variables mean simpler, more interpretable, better generalizing models

We will select variables using the Lasso regression: Lasso has the property of setting the coefficient of non-informative variables to zero. This way we can identify those variables and remove them from our final model.

```
import pandas as pd
In [1]:
          import numpy as np
          import matplotlib.pyplot as plt
          from sklearn.linear model import Lasso
          from sklearn.feature selection import SelectFromModel
          pd.pandas.set_option('display.max_columns', None)
          X train = pd.read csv('xtrain.csv')
In [2]:
          X test = pd.read csv('xtest.csv')
          X_train.head()
Out[2]:
              Id MSSubClass MSZoning LotFrontage
                                                    LotArea Street Alley LotShape LandContour Utilities
                                                                            0.333333
         0
             931
                     0.000000
                                   0.75
                                                                                         1.000000
                                            0.461171 0.377048
                                                                 1.0
                                                                       1.0
                                                                                                       1.0
             657
                    0.000000
                                   0.75
                                            0.456066 0.399443
                                                                            0.333333
         1
                                                                 1.0
                                                                       1.0
                                                                                         0.333333
                                                                                                       1.0
         2
              46
                    0.588235
                                   0.75
                                            0.394699 0.347082
                                                                 1.0
                                                                       1.0
                                                                            0.000000
                                                                                         0.333333
                                                                                                       1.0
                                            0.388581 0.493677
         3
            1349
                    0.000000
                                   0.75
                                                                 1.0
                                                                       1.0
                                                                            0.666667
                                                                                         0.666667
                                                                                                       1.0
                    0.000000
                                   0.75
              56
                                            0.577658 0.402702
                                                                 1.0
                                                                       1.0
                                                                            0.333333
                                                                                         0.333333
                                                                                                       1.0
          # capture the target (remember that the target is log transformed)
In [4]:
          y train = X train['SalePrice']
          y_test = X_test['SalePrice']
          # drop unnecessary variables from our training and testing sets
          X_train.drop(['Id', 'SalePrice'], axis=1, inplace=True)
          X_test.drop(['Id', 'SalePrice'], axis=1, inplace=True)
```

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```
# We will do the model fitting and feature selection
In [5]:
         # altogether in a few lines of code
         # first, we specify the Lasso Regression model, and we
         # select a suitable alpha (equivalent of penalty).
         # The bigger the alpha the less features that will be selected.
         # Then we use the selectFromModel object from sklearn, which
         # will select automatically the features which coefficients are non-zero
         # remember to set the seed, the random state in this function
         selection = SelectFromModel(Lasso(alpha=0.005, random state=0))
         # train Lasso model and select features
         selection.fit(X_train, y_train)
Out[5]: SelectFromModel(estimator=Lasso(alpha=0.005, copy X=True, fit intercept=True,
                                         max iter=1000, normalize=False, positive=False,
                                         precompute=False, random_state=0,
                                         selection='cyclic', tol=0.0001,
                                         warm start=False),
                         max features=None, norm order=1, prefit=False, threshold=None)
         selection.get support()
In [6]:
Out[6]: array([ True, True, False, False, False, False, False, False,
                False, False, True, False, False, False, False, True, True, False, True, False, False, True, False, False,
                False, False, True, False, True, False, False, False,
                False, False, True, True, False, True, False, False,
                 True, True, False, False, False, False, True, False,
                False, True, True, False, True, False, False,
                False, True, False, False, False, False, False, False,
                False, False, False, False, False, False, False, False,
                Falsel)
         # print the number of total and selected features
In [7]:
         # this is how we can make a list of the selected features
         selected feats = X train.columns[(selection.get support())]
         # let's print some stats
         print('total features: {}'.format((X_train.shape[1])))
         print('selected features: {}'.format(len(selected_feats)))
         print('features with coefficients shrank to zero: {}'.format(
             np.sum(selection.estimator .coef == 0)))
        total features: 82
         selected features: 22
        features with coefficients shrank to zero: 60
         selected feats
In [8]:
Out[8]: Index(['MSSubClass', 'MSZoning', 'Neighborhood', 'OverallQual', 'OverallCond', 'YearRemodAdd', 'RoofStyle', 'MasVnrType', 'BsmtQual', 'BsmtExposure',
                'HeatingQC', 'CentralAir', '1stFlrSF', 'GrLivArea', 'BsmtFullBath',
                'KitchenQual', 'Fireplaces', 'FireplaceQu', 'GarageType',
                'GarageFinish', 'GarageCars', 'PavedDrive'],
               dtype='object')
         pd.Series(selected_feats).to_csv('selected_features.csv', index=False)
In [9]:
```

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e:\users\user.desktop-3hhgvth\anaconda3\envs\mytfenv\lib\site-packages\ipykernel\_launche r.py:1: FutureWarning: The signature of `Series.to\_csv` was aligned to that of `DataFram e.to\_csv`, and argument 'header' will change its default value from False to True: pleas e pass an explicit value to suppress this warning.

"""Entry point for launching an IPython kernel.

In [ ]: