In [1]: import pandas as pd from sklearn.model_selection import train_test_split from sklearn.linear_model import LinearRegression import joblib In [2]: train = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techniques/train.csv') test = pd.read_csv('/kaggle/input/house-prices-advanced-regression-techniques/test.csv') In [3]: train.columns Out[3]: Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual', 'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition', 'SalePrice'], dtype='object') In [4]: test.columns Out[4]: Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAdd', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'MasVnrArea', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinSF1', 'BsmtFinType2', 'BsmtFinSF2', 'BsmtUnfSF', 'TotalBsmtSF', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', '1stFlrSF', '2ndFlrSF', 'LowQualFinSF', 'GrLivArea', 'BsmtFullBath', 'BsmtHalfBath', 'FullBath', 'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageType', 'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQual', 'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF', 'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC', 'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType', 'SaleCondition'], dtype='object') In [5]: train Out[5]: Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour Utilities ... PoolArea PoolQC Fence MiscFeature MiscVal M 0 60 RL65.0 8450 Pave NaN Reg AllPub ... 0 NaN NaN NaN 2 20 RL 80.0 9600 Pave NaN AllPub ... 0 NaN NaN NaN Reg 2 AllPub ... 3 60 RL68.0 11250 Pave NaN IR1 0 NaN NaN NaN 70 RL60.0 9550 Pave NaN IR1 AllPub 0 NaN NaN NaN Lvl RL5 60 84.0 14260 Pave NaN IR1 Lvl AllPub ... 0 NaN NaN NaN **1455** 1456 60 RL62.0 7917 Pave NaN AllPub ... NaN NaN NaN 0 Reg **1456** 1457 20 RL13175 Pave 85.0 NaN Reg Lvl AllPub ... 0 NaN MnPrv NaN 0 70 **1457** 1458 RL66.0 9042 Pave NaN Reg AllPub ... 0 NaN GdPrv Shed 2500 **1458** 1459 20 RL 68.0 9717 Pave NaN AllPub ... 0 NaN NaN 0 Reg Lvl NaN 0 **1459** 1460 20 RL75.0 9937 Pave NaN Reg AllPub ... 0 NaN NaN NaN 1460 rows × 81 columns In [6]: train.isna().sum() Out[6]: Id 0 MSSubClass 0 MSZoning 0 LotFrontage 259 LotArea 0 MoSold 0 YrSold 0 SaleType 0 SaleCondition 0 SalePrice 0 Length: 81, dtype: int64 In [7]: train.describe() Out[7]: Id MSSubClass LotFrontage LotArea OverallQual OverallCond YearBuilt YearRemodAdd Mas**V**nrArea BsmtFinSF1 ... WoodDe count 1460.000000 1460.000000 1201.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1452.000000 1460.000000 ... 1460.00 730.500000 10516.828082 5.575342 1971.267808 56.897260 70.049958 6.099315 1984.865753 103.685262 443.639726 ... 94.24 mean std 421.610009 42.300571 24.284752 9981.264932 1.382997 1.112799 30.202904 20.645407 181.066207 456.098091 ... 125.33 1.000000 20.000000 1300.000000 min 21.000000 1.000000 1.000000 1872.000000 1950.000000 0.000000 0.000000 ... 0.00 25% 365.750000 20.000000 59.000000 7553.500000 5.000000 5.000000 1954.000000 1967.000000 0.000000 0.000000 ... 0.00 730.500000 69.000000 9478.500000 5.000000 1973.000000 1994.000000 0.000000 50% 50.000000 6.000000 383.500000 ... 0.00 1095.250000 70.000000 80.000000 11601.500000 7.000000 6.000000 2000.000000 2004.000000 166.000000 712.250000 ... 168.00 max 1460.000000 190.000000 313.000000 215245.000000 10.000000 9.000000 2010.000000 2010.000000 1600.000000 5644.000000 ... 857.00 8 rows × 38 columns In [8]: train = train.ffill() test = test.ffill() In [9]: train Out[9]: Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour Utilities ... PoolArea PoolQC Fence MiscFeature MiscVal M 0 1 60 RL65.0 8450 Pave NaN AllPub ... 0 NaN NaN NaN 0 Reg Lvl 2 20 RL80.0 9600 Pave NaN AllPub 0 NaN 0 Reg Lvl NaN NaN 2 3 60 0 RL68.0 11250 Pave NaN IR1 Lvl AllPub ... 0 NaN NaN NaN AllPub ... 3 4 70 RL 60.0 9550 Pave NaN IR1 0 NaN 0 Lvl NaN NaN 5 0 4 60 RL84.0 14260 Pave NaN IR1 AllPub ... 0 NaN NaN NaN **1455** 1456 RL62.0 7917 Pave Pave AllPub GdWo TenC 0 Reg 20 RL TenC 0 **1456** 1457 85.0 13175 AllPub 0 Gd MnPrv Pave Pave Reg **1457** 1458 70 RL66.0 9042 Pave Pave AllPub ... 0 Gd GdPrv Shed 2500 Reg Pave **1458** 1459 20 RL68.0 9717 Pave Reg Lvl AllPub 0 Gd GdPrv Shed 0 Pave Pave 0 0 **1459** 1460 20 RL75.0 9937 Reg AllPub ... Gd GdPrv Shed 1460 rows × 81 columns In [10]: train.describe() Out[10]: MasVnrArea Id MSSubClass LotFrontage LotArea OverallQual OverallCond YearBuilt YearRemodAdd BsmtFinSF1 ... WoodDe count 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 1460.000000 ... 1460.00 mean 730.500000 56.897260 70.104795 10516.828082 6.099315 5.575342 1971.267808 1984.865753 103.492466 443.639726 ... 94.24 456.098091 ... std 421.610009 42.300571 23.846996 9981.264932 1.382997 1.112799 30.202904 20.645407 180.795612 125.33 1.000000 1300.000000 1.000000 1872.000000 0.000000 ... min 20.000000 21.000000 1.000000 1950.000000 0.000000 0.00 365.750000 20.000000 0.000000 ... 25% 59.000000 7553.500000 5.000000 5.000000 1954.000000 1967.000000 0.000000 0.00 730.500000 50.000000 70.000000 6.000000 5.000000 1973.000000 50% 9478.500000 1994.000000 0.000000 383.500000 ... 0.00 1095.250000 70.000000 80.000000 11601.500000 7.000000 6.000000 2000.000000 2004.000000 165.250000 712.250000 ... 168.00 75% 10.000000 9.000000 2010.000000 max 1460.000000 190.000000 313.000000 215245.000000 2010.000000 1600.000000 5644.000000 ... 857.00 8 rows × 38 columns In [11]: train.isna().sum() Out[11]: Id 0 MSSubClass 0 MSZoning 0 LotFrontage 0 LotArea 0 MoSold 0 YrSold SaleType 0 ${\tt SaleCondition}$ 0 SalePrice Length: 81, dtype: int64 In [12]: train = train.drop("Id", axis=1) In [13]: # train = pd.get_dummies(train) # test = pd.get_dummies(test) In [14]: | train Out[14]: MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour Utilities LotConfig ... PoolArea PoolQC Fence MiscFeature MiscVa 0 60 RL65.0 8450 Pave NaN Reg Lvl AllPub Inside NaN NaN NaN 20 RL 80.0 Pave AllPub 1 9600 NaN Reg Lvl FR2 ... 0 NaN NaN NaN 2 60 RL68.0 11250 Pave NaN IR1 **AllPub** Inside ... NaN NaN NaN Lvl AllPub 3 70 RL 60.0 9550 IR1 NaN NaN Pave NaN 0 NaN Lvl Corner ... 60 RL14260 IR1 AllPub FR2 ... 84.0 Pave NaN Lvl NaN NaN NaN 7917 AllPub GdWo 1455 60 RL62.0 Pave Pave Reg Lvl Inside ... 0 Gd TenC (1456 20 RL 85.0 13175 (Pave Pave Lvl AllPub Gd MnPrv TenC Reg Inside ... 1457 70 RL 66.0 9042 Pave Pave Reg AllPub Inside ... 0 Gd GdPrv Shed 2500 Lvl Pave Pave Gd GdPrv Shed 1458 20 RL 68.0 9717 Lvl AllPub Reg Inside ... 0 (1459 20 RL 75.0 9937 Pave Pave Reg AllPub Inside ... 0 Gd GdPrv Shed (Lvl 1460 rows × 80 columns In [15]: columns_to_encode = ['MSZoning', 'Street', 'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig', 'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType', 'HouseStyle', 'RoofStyle', 'RoofMatl', 'Exterior1st', 'Exterior2nd', 'MasVnrType', 'ExterQual', 'ExterCond', 'Foundation', 'BsmtQual', 'BsmtCond', 'BsmtExposure', 'BsmtFinType1', 'BsmtFinType2', 'Heating', 'HeatingQC', 'CentralAir', 'Electrical', 'KitchenQual', 'Functional', 'FireplaceQu', 'GarageType', 'GarageFinish', 'GarageQual', 'GarageCond', 'PavedDrive', 'PoolQC', 'Fence', 'MiscFeature', 'SaleType', 'SaleCondition'] # for column in columns_to_encode: label_encoder = LabelEncoder() train[column] = label_encoder.fit_transform(train[column]) train = train.drop(columns=columns_to_encode) test = test.drop(columns=columns_to_encode) In [16]: train Out[16]: MSSubClass LotFrontage LotArea OverallQual OverallCond YearBuilt YearRemodAdd MasVnrArea BsmtFinSF1 BsmtFinSF2 ... WoodDeckSF OpenPorch 0 ... 0 60 65.0 8450 5 2003 2003 196.0 706 0 20 80.0 9600 8 1976 1976 0.0 978 0 ... 298 2 11250 7 2002 60 68.0 5 2001 162.0 486 0 ... 0 60.0 9550 1970 216 3 70 5 1915 0.0 0 0 ... 0 ... 4 60 84.0 14260 8 5 2000 2000 350.0 655 192 ... 1455 60 62.0 7917 6 5 1999 2000 0.0 0 0 ... 0 790 349 1456 20 85.0 13175 6 6 1978 1988 119.0 163 ... 7 0 ... 1457 70 66.0 9042 9 1941 2006 0.0 275 0 9717 1458 20 68.0 6 1950 1996 0.0 1029 ... 366 49 5 6 1965 1965 736 1459 20 75.0 9937 0.0 830 290 ... 1460 rows × 37 columns In [17]: X=train.drop(columns='SalePrice') y=train['SalePrice'] In [18]: X Out[18] LotFrontage Yearkemodadd Masynrarea Bsmtfin5f1 Bsmtfin5f2 GarageArea 0 60 65.0 8450 5 2003 2003 196.0 706 0 ... 548 20 9600 1976 0 ... 29 0.08 8 1976 0.0 978 460 7 2 60 11250 2002 162.0 0 ... 68.0 5 2001 486 608 3 70 9550 1915 1970 0.0 216 60.0 5 0 ... 642 8 2000 4 60 84.0 14260 5 2000 350.0 655 836 19 0 ... 60 62.0 7917 6 5 1999 2000 0 460 1455 0.0 0 ... 163 ... 20 13175 6 1988 119.0 790 1456 85.0 6 1978 500 34 70 7 0 ... 1457 66.0 9042 9 2006 0.0 275 252 1941 36 1458 20 68.0 9717 5 6 1950 1996 0.0 49 1029 ... 240 5 1459 20 75.0 9937 6 1965 1965 0.0 830 290 ... 276 73 1460 rows × 36 columns In [19]: y Out[19]: 0 208500 181500 1 2 223500 3 140000 4 250000 . . . 1455 175000 1456 210000 1457 266500 142125 1458 1459 147500 Name: SalePrice, Length: 1460, dtype: int64 In [20]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42) In [21]: model = LinearRegression() model.fit(X_train,y_train) Out[21]: ▼ LinearRegression LinearRegression() y_pred=model.predict(X_train) In [22]: In [23]: model.score(X_train,y_train) Out[23]: 0.8015281494106271 In [24]: model.score(X_test,y_test) Out[24]: 0.8218984206447474 In [25]: model.intercept_ -815908.849522751 Out[25]: In [26]: model.coef_ Out[26]: array([-2.28758022e+02, -1.30274291e+02, 4.41475081e-01, 1.84916371e+04, 3.17649210e+03, 2.69678017e+02, 1.81435648e+02, 2.11078675e+01, 8.16044018e+00, -3.21945401e+00, -1.68887757e+00, 3.25210859e+00, 1.06037439e+01, 1.19683935e+01, 9.75414631e+00, 3.23262838e+01, 1.20663858e+04, -5.51389369e+02, 4.11521605e+03, -1.91986453e+03, -9.32378685e+03, -7.97990985e+03, 5.35009480e+03, 5.17524789e+03, 8.99565969e+01, 1.53206678e+04, -9.25095806e+00, 1.90169178e+01, -1.94315073e+01, 2.43639078e+00, 4.41582379e+01, 7.16368010e+01, -1.19194250e+01, -2.38295259e+00, 3.22607017e+01, -1.49040988e+02]) In [27]: SalePrice = model.predict(test.drop(columns='Id')) In [28]: submission_df = pd.DataFrame({"Id": test['Id'], "SalePrice": SalePrice}) submission_df.to_csv("LinearRegression.csv", index=False) data = pd.read_csv("LinearRegression.csv") data.head() Out[30]: Id SalePrice **0** 1461 115699.581663 1 1462 123576.160107 **2** 1463 173714.288809 **3** 1464 199306.794830 **4** 1465 197913.200367

In [31]: joblib.dump(model, 'House_price_linear_regression_model.pkl')

Out[31]: ['House_price_linear_regression_model.pkl']