Exploratory Data Analysis In this section I simple check variables and their properties. Try to get insight will data enough to train usefull model. You can find descriptions of the data from README.md. **Notebook Structure** Describing Data Correlation The most Correlated 10 Features with SalePrice • Demonstrating Categorical Data Unique Values In [6]: import numpy as np import pandas as pd import matplotlib.pyplot as plt import seaborn as sns from pathlib import Path from src.utils import html_table raw_data_dir = Path('../data/raw/') processed_data_dir = Path('../data/processed/') file_name = 'train.csv' file_path = raw_data_dir / file_name **Describing Data** In [2]: df = pd.read_csv(file_path) df.head() Utilities Id MSSubClass MSZoning LotFrontage LotArea Street Alley LotShape LandContour ... PoolArea PoolQC F Out[2]: **0** 1 RL 65.0 8450 AllPub 0 NaN 60 Pave NaN Lvl Reg 2 20 RL80.0 9600 Pave AllPub 0 1 NaN Reg Lvl NaN 3 RL 11250 2 68.0 Pave NaN IR1 AllPub 0 NaN 60 Lvl 70 RL60.0 9550 Pave NaN IR1 Lvl AllPub 0 NaN IR1 5 60 RL 84.0 14260 AllPub ... 0 Pave NaN Lvl NaN 5 rows × 81 columns In [3]: df.drop(axis=1, columns=['Id'], inplace=True) df.shape Out[3]: (1460, 80) In [4]: df.info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 1460 entries, 0 to 1459 Data columns (total 80 columns): Non-Null Count Dtype # Column ---_____ 1460 non-null int64 0 MSSubClass 1 MSZoning 1460 non-null object 2 LotFrontage 1201 non-null float64 3 LotArea 1460 non-null int64 Street 1460 non-null object 91 non-null 5 Allev obiect object LotShape 1460 non-null LandContour 1460 non-null object 1460 non-null Utilities object LotConfig 1460 non-null object 10 LandSlope 1460 non-null object 11 Neighborhood 1460 non-null object 12 Condition1 1460 non-null object Condition2 1460 non-null object BldgType 1460 non-null object 15 HouseStyle 1460 non-null object OverallQual 1460 non-null int64 17 OverallCond int64 1460 non-null 18 YearBuilt 1460 non-null int64 YearRemodAdd 1460 non-null int64 RoofStyle 1460 non-null object 21 RoofMatl 1460 non-null object 22 Exterior1st 1460 non-null object 23 Exterior2nd 1460 non-null object MasVnrType 1452 non-null object MasVnrArea float64 1452 non-null 26 ExterQual object 1460 non-null 27 ExterCond 1460 non-null object 28 Foundation 1460 non-null object **BsmtQual** 1423 non-null object BsmtCond 1423 non-null object 31 BsmtExposure 1422 non-null object BsmtFinType1 1423 non-null object BsmtFinSF1 1460 non-null 34 BsmtFinType2 1422 non-null object 35 BsmtFinSF2 1460 non-null int64 36 BsmtUnfSF 1460 non-null int64 TotalBsmtSF 1460 non-null int64 Heating 1460 non-null object HeatingQC 1460 non-null object CentralAir 1460 non-null 41 Electrical 1459 non-null object 42 1stFlrSF 1460 non-null int64 43 2ndFlrSF 1460 non-null int64 44 LowQualFinSF 1460 non-null 45 GrLivArea 1460 non-null 46 BsmtFullBath 1460 non-null int64 47 BsmtHalfBath 1460 non-null int64 48 FullBath 1460 non-null 49 HalfBath 1460 non-null BedroomAbvGr 50 1460 non-null int64 51 KitchenAbvGr 1460 non-null int64 52 KitchenQual 1460 non-null object 53 TotRmsAbvGrd 1460 non-null int64 54 Functional 1460 non-null object 55 Fireplaces 1460 non-null int64 object 56 FireplaceQu 770 non-null object GarageType 1379 non-null GarageYrBlt float64 1379 non-null GarageFinish 1379 non-null object 1460 non-null GarageCars GarageArea 1460 non-null 1379 non-null object GarageQual GarageCond 1379 non-null object 63 PavedDrive 1460 non-null object 65 WoodDeckSF 1460 non-null 66 OpenPorchSF 1460 non-null int64 EnclosedPorch 1460 non-null int64 1460 non-null 3SsnPorch ScreenPorch 1460 non-null int64 70 PoolArea 1460 non-null int64 71 PoolQC 7 non-null object 72 Fence 281 non-null MiscFeature 54 non-null object MiscVal 1460 non-null int64 MoSold 1460 non-null 76 YrSold 77 SaleType 1460 non-null object 78 SaleCondition 1460 non-null object 79 SalePrice 1460 non-null int64 dtypes: float64(3), int64(34), object(43) memory usage: 912.6+ KB In [7]: html_table(df.describe().T) **50**% count std min 25% **75**% max mean MSSubClass 1460.0 56.897260 42.300571 20.0 20.00 50.0 70.00 190.0 24.284752 LotFrontage 1201.0 70.049958 21.0 59.00 69.0 80.00 313.0 **LotArea** 1460.0 10516.828082 9981.264932 1300.0 7553.50 9478.5 11601.50 215245.0 1.382997 OverallQual 1460.0 6.099315 5.00 6.0 7.00 10.0 5.575342 OverallCond 1460.0 1.112799 1.0 5.00 5.0 6.00 9.0 YearBuilt 1460.0 1971.267808 30.202904 1872.0 1954.00 1973.0 2000.00 2010.0 1967.00 YearRemodAdd 1460.0 1984.865753 20.645407 1950.0 1994.0 2004.00 2010.0 MasVnrArea 1452.0 103.685262 181.066207 0.00 0.0 166.00 1600.0 **BsmtFinSF1** 1460.0 712.25 443.639726 456.098091 0.0 0.00 383.5 5644.0 **BsmtFinSF2** 1460.0 46.549315 0.00 0.0 0.00 1474.0 161.319273 BsmtUnfSF 1460.0 223.00 567.240411 441.866955 0.0 477.5 808.00 2336.0 TotalBsmtSF 1460.0 0.0 795.75 991.5 1298.25 6110.0 1057.429452 438.705324 **1stFlrSF** 1460.0 1162.626712 386.587738 334.0 882.00 1087.0 1391.25 4692.0 **2ndFlrSF** 1460.0 346.992466 0.00 728.00 2065.0 436.528436 0.0 LowQualFinSF 1460.0 5.844521 48.623081 0.0 0.00 0.0 0.00 572.0 1129.50 5642.0 GrLivArea 1460.0 1515.463699 525.480383 334.0 1464.0 1776.75 BsmtFullBath 1460.0 0.518911 0.425342 0.0 0.00 0.0 1.00 3.0 BsmtHalfBath 1460.0 0.057534 0.238753 0.0 0.00 0.0 0.00 2.0 FullBath 1460.0 1.565068 0.550916 0.0 1.00 2.0 2.00 3.0 HalfBath 1460.0 0.382877 0.502885 0.00 0.0 1.00 2.0 BedroomAbvGr 1460.0 2.866438 0.815778 0.0 2.00 3.0 3.00 8.0 KitchenAbvGr 1460.0 1.046575 0.220338 1.0 1.00 3.0 TotRmsAbvGrd 1460.0 6.517808 1.625393 2.0 5.00 6.0 7.00 14.0 Fireplaces 1460.0 0.613014 0.00 1.0 1.00 3.0 0.644666 GarageYrBlt 1379.0 1978.506164 24.689725 1900.0 1961.00 1980.0 2002.00 2010.0 GarageCars 1460.0 1.767123 0.747315 0.0 1.00 2.0 2.00 4.0 GarageArea 1460.0 472.980137 213.804841 0.0 334.50 480.0 576.00 1418.0 WoodDeckSF 1460.0 94.244521 0.00 0.0 168.00 857.0 125.338794 OpenPorchSF 1460.0 46.660274 66.256028 0.0 0.00 25.0 68.00 547.0 EnclosedPorch 1460.0 21.954110 61.119149 0.00 0.0 0.00 552.0 **3SsnPorch** 1460.0 3.409589 29.317331 0.0 0.00 0.0 0.00 508.0 ScreenPorch 1460.0 15.060959 0.0 0.00 0.0 0.00 480.0 55.757415 PoolArea 1460.0 2.758904 40.177307 0.0 0.00 0.0 0.00 738.0 **MiscVal** 1460.0 43.489041 496.123024 0.00 0.0 0.00 15500.0 **MoSold** 1460.0 6.321918 2.703626 1.0 5.00 6.0 8.00 12.0 **YrSold** 1460.0 2007.815753 1.328095 2006.0 2007.00 2009.00 2010.0 SalePrice 1460.0 180921.195890 79442.502883 34900.0 129975.00 163000.0 Correlation I looked for a general correlation between continues variables and after that because of our main goal of predicting SalePrices I focused the correlation on SalePricing I found that there are lots of variables that are highly correlated with SalePrice it seems like we can fit a good model. You can see the results below. corr = df.corr(numeric_only=True).sort_values(by='SalePrice', ascending=False, key=lambda val: abs(val)) html_table(corr) MSSubClass LotFrontage LotArea OverallQual OverallCond YearBuilt YearRemodAdd MasVnrArea BsmtFi **SalePrice** -0.084284 0.351799 0.263843 0.790982 -0.077856 0.522897 0.507101 0.477493 98.0 OverallQual 0.032628 0.251646 0.105806 1.000000 -0.091932 0.572323 0.550684 0.411876 0.23 **GrLivArea** 0.074853 0.402797 0.263116 0.593007 -0.079686 0.199010 0.287389 0.390857 0.20 **GarageCars** -0.040110 0.285691 0.600671 0.537850 0.420622 0.364204 0.22 0.154871 -0.185758 -0.098672 0.344997 0.180403 0.562022 0.478954 0.373066 0.29 GarageArea -0.151521 0.371600 **TotalBsmtSF** -0.238518 0.392075 0.260833 0.537808 -0.171098 0.391452 0.291066 0.363936 0.52 1stFlrSF -0.251758 0.457181 0.299475 0.476224 -0.144203 0.281986 0.240379 0.344501 0.44 **FullBath** 0.131608 0.198769 0.126031 0.550600 -0.194149 0.468271 0.439046 0.276833 0.05 TotRmsAbvGrd 0.040380 0.352096 0.190015 0.427452 -0.057583 0.095589 0.191740 0.280682 0.04 0.123349 0.572323 YearBuilt 0.027850 0.014228 -0.375983 1.000000 0.592855 0.315707 0.24 0.040581 0.013788 YearRemodAdd 0.088866 0.550684 0.073741 0.592855 1.000000 0.179618 0.12 0.070250 0.252691 GarageYrBlt 0.085072 -0.024947 0.547766 0.825667 0.642277 0.15 -0.324297 MasVnrArea 0.022936 0.193458 0.104160 0.411876 -0.128101 0.315707 0.179618 1.000000 0.26 0.266639 **Fireplaces** -0.045569 0.271364 0.396765 -0.023820 0.147716 0.249070 0.26 0.112581 0.214103 -0.046231 BsmtFinSF1 -0.069836 0.233633 0.239666 0.249503 0.128451 0.264736 1.00 LotFrontage -0.386347 1.000000 0.426095 0.251646 -0.059213 0.123349 0.088866 0.193458 0.23 0.238923 WoodDeckSF -0.012579 0.088521 -0.003334 0.224880 0.205726 0.159718 0.20 0.171698 2ndFlrSF 0.307886 0.080177 0.050986 0.295493 0.028942 0.010308 0.140024 0.174561 -0.13 OpenPorchSF -0.006100 0.151972 0.084774 0.308819 -0.032589 0.188686 0.226298 0.125703 0.11 -0.060769 0.242656 0.201444 **HalfBath** 0.177354 0.053532 0.014259 0.273458 0.00 0.183331 0.105806 LotArea -0.139781 0.426095 1.000000 -0.005636 0.014228 0.013788 0.104160 0.21 0.100949 0.111098 0.119470 **BsmtFullBath** 0.003491 0.158155 -0.054942 0.187599 0.085310 0.64 **BsmtUnfSF** -0.140759 0.132644 -0.002618 0.308159 -0.136841 0.149040 0.114442 -0.49 0.181133 BedroomAbvGr -0.040581 -0.023438 0.263170 0.101676 0.012980 -0.070651 0.102821 -0.10 0.119690 KitchenAbvGr 0.281721 -0.006069 -0.017784 -0.183882 -0.087001 -0.174800 -0.149598 -0.037610 -0.08 **EnclosedPorch** -0.012037 0.010700 -0.018340 -0.113937 0.070356 -0.387268 -0.193919 -0.110204 -0.10 -0.038740 ScreenPorch -0.026030 0.041383 0.043160 0.064886 0.054811 -0.050364 0.061466 0.06 **PoolArea** 0.008283 0.206167 0.077672 -0.001985 0.004950 0.005829 0.011723 0.065166 0.14 0.027850 **MSSubClass** 1.000000 -0.386347 -0.139781 0.032628 -0.059316 0.040581 0.022936 -0.06 1.000000 OverallCond -0.059316 -0.059213 -0.005636 -0.091932 -0.375983 0.073741 -0.128101 -0.04 MoSold -0.013585 0.011200 0.001205 0.070815 -0.003511 0.012398 0.021490 -0.005965 -0.01 0.070029 0.025504 3SsnPorch -0.043825 0.020423 0.030371 0.031355 0.045286 0.018796 0.02 YrSold -0.021407 0.007450 -0.014261 -0.027347 0.043950 -0.013618 0.035743 -0.008201 0.01 -0.183784 LowQualFinSF 0.046474 0.038469 0.004779 -0.030429 0.025494 -0.062419 -0.069071 -0.06 0.068777 -0.034383 MiscVal -0.007683 0.003368 0.038068 -0.031406 -0.010286 -0.029815 0.00 -0.007234 -0.012337 **BsmtHalfBath** -0.002333 0.048046 -0.040150 0.117821 -0.038162 0.026673 0.06 0.040229 -0.049107 -0.067759 -0.072319 BsmtFinSF2 -0.065649 0.049900 0.111170 -0.059119 -0.05 The most Correlated 10 Features with SalePrice hc_columns = corr.index[:10] In [10]: sns.heatmap(df[hc_columns].corr()) Out[10]: <AxesSubplot: > 1.0 SalePrice OverallQual 0.8 GrLivArea GarageCars 0.6 GarageArea TotalBsmtSF 1stFlrSF - 0.4 FullBath TotRmsAbvGrd 0.2 YearBuilt GrLivArea OverallQual 1stFIrSF **TotRmsAbvGrd** FullBath YearBuilt GarageCars GarageArea TotalBsmtSF In [11]: df[hc_columns].info() <class 'pandas.core.frame.DataFrame'> RangeIndex: 1460 entries, 0 to 1459 Data columns (total 10 columns): Non-Null Count Dtype Column SalePrice 1460 non-null int64 OverallQual 1460 non-null 1 int64 1460 non-null 2 GrLivArea int64 1460 non-null GarageCars 3 int64 1460 non-null GarageArea int64 5 TotalBsmtSF 1460 non-null int64 6 1stFlrSF 1460 non-null int64 7 FullBath 1460 non-null int64 TotRmsAbvGrd 1460 non-null int64 YearBuilt 1460 non-null int64 dtypes: int64(10) memory usage: 114.2 KB In [16]: rows = 5 cols = 2fig, axs = plt.subplots(rows, cols, figsize=[9, 18], dpi=150) fig.tight_layout(pad=4.0) for c in range(2): for r in range(5): sns.scatterplot(x=df[corr.index[rows * c + r + 1]], y=df['SalePrice'], 700000 700000 600000 600000 500000 500000 SalePrice SalePrice 400000 300000 300000 200000 200000 100000 100000 0 10 3000 6 1000 2000 4000 OverallQual 1stFlrSF 700000 700000 600000 600000 500000 500000 SalePrice SalePrice 400000 400000 300000 300000 200000 200000 100000 100000 0 0 3000 3.0 2000 4000 5000 0.0 0.5 1.0 1.5 2.0 2.5 GrLivArea FullBath 700000 700000 600000 600000 500000 500000 SalePrice 400000 400000 300000 300000 200000 200000 100000 100000 0 0 2 3 4 2 8 10 12 14 0 1 4 GarageCars TotRmsAbvGrd 700000 700000 600000 600000 500000 500000 SalePrice SalePrice 400000 400000 300000 300000 200000 200000 100000 100000 1000 1900 250 750 1250 1875 1950 1975 2000 500 YearBuilt GarageArea 700000 700000 600000 600000 500000 500000 SalePrice SalePrice 400000 400000 300000 300000 200000 200000 100000 100000 0 0 2000 3000 4000 5000 6000 1950 1960 1980 1990 2000 **TotalBsmtSF** YearRemodAdd **Demonstrating Categorical Data Unique Values** In [17]: isCategorical = (df.dtypes == object) cat_cols = isCategorical[isCategorical > 0].index In [18]: unique_count = df[cat_cols].nunique().sort_values(ascending=False) unique_count Out[18]: Neighborhood 25 16 Exterior2nd Exterior1st 15 SaleType 9 9 Condition1 Condition2 8 HouseStyle RoofMat1 7 Functional BsmtFinType2 6 Heating RoofStyle 6 SaleCondition BsmtFinType1 GarageType Foundation 6 5 Electrical FireplaceQu 5 HeatingQC 5 5 GarageQual GarageCond 5 5 MSZoning 5 LotConfig ExterCond BldgType 4 BsmtExposure MiscFeature 4 Fence LotShape LandContour BsmtCond KitchenQual MasVnrType 4 ExterQual 4 BsmtQual 4 LandSlope 3 GarageFinish 3 PavedDrive 3 PoolQC Utilities CentralAir 2 Street Alley 2 dtype: int64 In [20]: # Demonstrate all categories max_cat = unique_count[0] categories = pd.DataFrame(columns=range(max_cat)) for col_name in list(cat_cols): unqs = df[col_name].unique() if len(unqs) == max_cat: categories.loc[col_name] = unqs continue categories.loc[col_name] = np.concatenate((unqs, np.array([np.nan,] * (max_cat - len(unqs))))) html_table(categories) 2 5 7 8 9 10 1 3 4 6 **MSZoning** RL RM C (all) FV RHNaN NaN NaN NaN NaN NaN NaN NaN Street Pave Grvl NaN NaN NaN NaN NaN NaN NaN Alley NaN NaN NaN NaN NaN NaN NaN NaN NaN Grvl Pave IR1 IR2 IR3 NaN NaN NaN NaN LotShape Reg NaN NaN NaN LandContour Bnk HLS NaN NaN NaN NaN Lvl Low NaN NaN NaN **Utilities** AllPub NoSeWa NaN NaN NaN NaN NaN NaN NaN CulDSac Inside FR2 Corner FR3 NaN NaN NaN NaN NaN NaN LotConfig NaN NaN LandSlope Gtl Mod Sev NaN NaN NaN NaN NaN NaN Neighborhood Crawfor NridgHt CollgCr NoRidge Somerst NWAmes OldTown BrkSide Sawyer Veenker Mitchel Condition1 RRAe RRNn RRAn RRNe NaN Norm Feedr PosN Artery PosA NaN Condition2 Norm Artery RRNn Feedr PosN PosA RRAn RRAe NaN NaN NaN **BldgType** 2fmCon TwnhsE NaN NaN 1Fam Duplex Twnhs NaN NaN NaN NaN HouseStyle 1.5Fin 1.5Unf **SFoyer** SLvl 2.5Unf 2.5Fin NaN 2Story 1Story NaN NaN RoofStyle Gable Gambrel Shed NaN Hip Mansard Flat NaN NaN NaN RoofMatl CompShg WdShngl WdShake Membran Tar&Grv ClyTile NaN NaN NaN Metal Roll Wd Exterior1st VinylSd HdBoard WdShing CemntBd Plywood BrkComm MetalSd BrkFace AsbShng Stucco Sdng Wd Wd Exterior2nd VinylSd BrkFace MetalSd HdBoard CmentBd Stucco AsbShng Brk Cmn Plywood Shng Sdng MasVnrType BrkFace BrkCmn NaN NaN NaN NaN None Stone NaN NaN NaN **ExterQual** Gd TΑ Fa NaN NaN NaN NaN NaN NaN NaN Ex **ExterCond** TΑ Ро NaN NaN NaN Gd Fa Ex NaN NaN NaN **Foundation PConc CBlock** BrkTil Wood NaN NaN NaN Slab Stone NaN NaN **BsmtQual** Gd TΑ Ex NaN Fa NaN NaN NaN NaN NaN **BsmtCond** Gd NaN Ро NaN NaN NaN NaN NaN NaN Fa **BsmtExposure** NaN NaN No Gd Mn Αv NaN NaN NaN NaN NaN BsmtFinType1 **GLQ ALQ** Unf **BLQ** NaN NaN NaN NaN Rec LwQ NaN BsmtFinType2 Unf BLQ NaN NaN NaN **ALQ** Rec LwQ **GLQ** NaN NaN Heating GasA GasW Grav Wall OthW Floor NaN NaN NaN NaN NaN **HeatingQC** Gd TΑ NaN NaN NaN NaN NaN NaN CentralAir Υ Ν NaN NaN NaN NaN NaN NaN NaN NaN NaN SBrkr **Electrical** FuseF FuseA FuseP Mix NaN NaN NaN NaN NaN NaN KitchenQual NaN Gd TΑ Ex Fa NaN NaN NaN NaN NaN NaN **Functional** Тур Min1 Maj1 Min2 Mod Maj2 Sev NaN NaN NaN NaN FireplaceQu NaN TΑ Gd Fa Ex Ро NaN NaN NaN NaN NaN GarageType Attchd Detchd BuiltIn CarPort NaN Basment 2Types NaN NaN NaN GarageFinish RFn Unf Fin NaN NaN NaN NaN NaN NaN NaN NaN GarageQual TΑ Fa Gd NaN Ex Ро NaN NaN NaN NaN NaN GarageCond TΑ Fa NaN Gd Ро Ex NaN NaN NaN NaN NaN Р **PavedDrive** Ν NaN NaN NaN NaN NaN NaN NaN NaN **PoolQC** NaN Ex Fa Gd NaN NaN NaN NaN NaN NaN NaN **Fence** NaN MnPrv GdWo GdPrv MnWw NaN NaN NaN NaN NaN NaN MiscFeature NaN Shed Gar2 Othr TenC NaN NaN NaN NaN NaN NaN COD CWD SaleType WD New ConLD ConLI ConLw Con Oth NaN NaN Abnorml AdjLand SaleCondition Normal **Partial** Alloca Family NaN NaN NaN NaN NaN