HousePriceChallenge.pdf

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1 House Price Challenge

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2 Preparation

2.1 Libraries

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from scipy.stats import skew
        from sklearn import linear_model
        from sklearn.preprocessing import StandardScaler
        from sklearn.model_selection import cross_val_score
        from IPython.display import display
```

2.2 Load input data

```
In [2]: train = pd.read_csv("input/train.csv")
        test = pd.read_csv("input/test.csv")
```

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2.3 Check data dimensions

```
In [3]: print("Number of features in training set: {}".format(train.shape[1]))
        print("Number of training data entries: {}".format(train.shape[0]))
        print("Number of test data entries: {}".format(test.shape[0]))
```

```
Number of features in training set: 81
Number of training data entries: 1460
Number of test data entries: 1459
```

2.4 Where is the ID / the training prices?

```
In [4]: print("First column in both sets is: {}".format(train.columns[0]))
        print("Last column in training set is: {}".format(train.columns[-1]))
```

```
First column in both sets is: Id
Last column in training set is: SalePrice
```

2.5 What do the features look like?

```
In [5]: train.iloc[:,:10].head(5)
```

```
Out[5]:    Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
        0   1          60       RL         65.0     8450   Pave   NaN      Reg
        1   2          20       RL         80.0     9600   Pave   NaN      Reg
        2   3          60       RL         68.0    11250   Pave   NaN      IR1
        3   4          70       RL         60.0     9550   Pave   NaN      IR1
        4   5          60       RL         84.0    14260   Pave   NaN      IR1

          LandContour Utilities
        0         Lvl    AllPub
        1         Lvl    AllPub
        2         Lvl    AllPub
        3         Lvl    AllPub
        4         Lvl    AllPub
```

```
In [6]: fig, axs = plt.subplots(1,2,figsize=(17,7))

        train['LotArea'].plot.density(ax=axs[0])
        train['LotArea'].plot.density(ax=axs[1])

        print("Max. lot area: {} ftš".format(train['LotArea'].max()))
        print("Mean lot area: {:.2f} ftš".format(train['LotArea'].mean()))
```

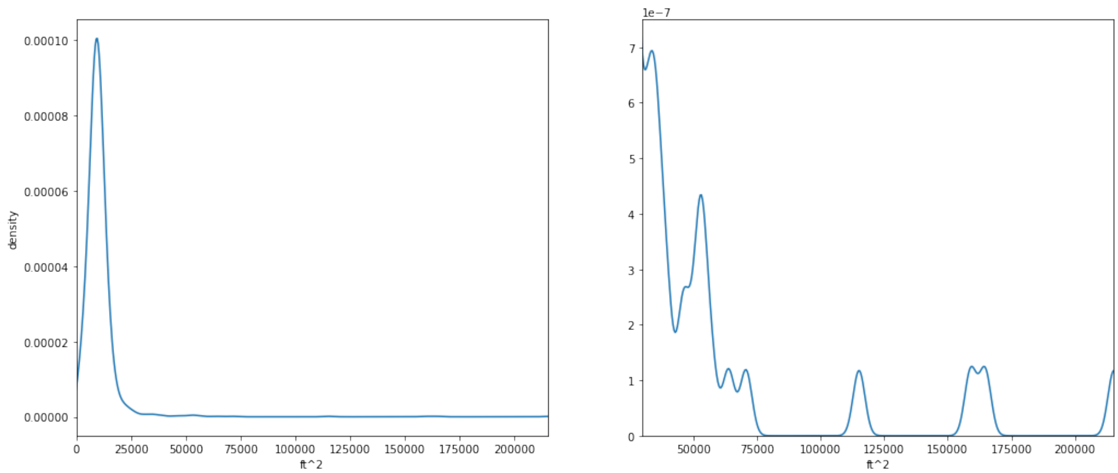
```
Max. lot area: 215245 ftš
Mean lot area: 10516.83 ftš
```

```
In [7]: axs[0].set_xlim([0,train['LotArea'].max()])
        axs[0].set_xlabel("ft^2")
        axs[0].set_ylabel("density")

        axs[1].set_xlim([30000,train['LotArea'].max()]);
        axs[1].set_ylim([0.,0.00000075])
        axs[1].set_xlabel("ft^2"); axs[1].set_ylabel("")
```

```
Out[7]: <matplotlib.text.Text at 0xb9a5550>
```

```
In [8]: plt.show()
```



2.6 Make index column the actual data frame index

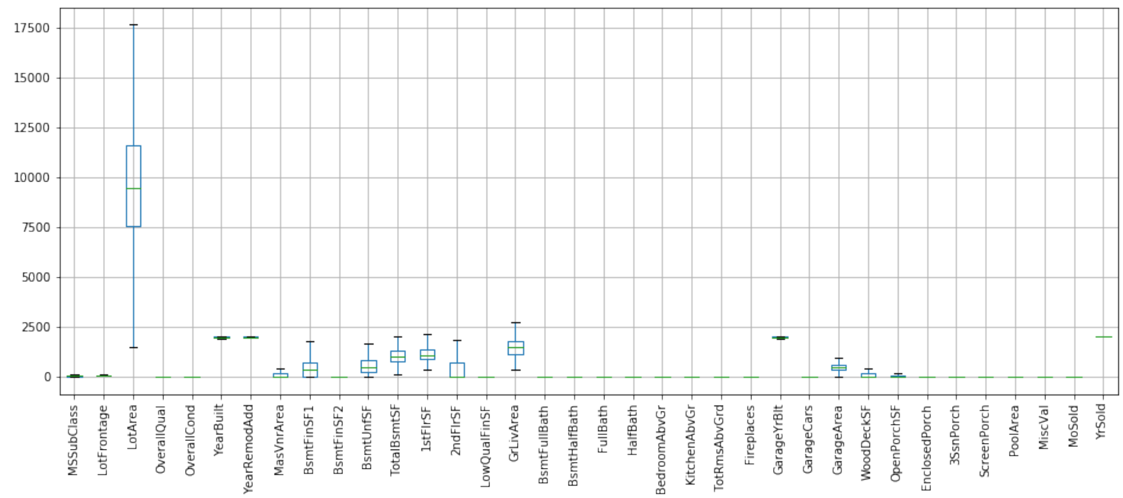
```
In [9]: train.set_index('Id', inplace=True)
        test.set_index('Id', inplace=True)
```

2.7 Split off the price column from the training data

```
In [10]: train_price = train["SalePrice"]
         train.drop("SalePrice", axis=1, inplace=True)
```

2.8 Check value ranges of (numerical) features

```
In [11]: plt.rcParams['figure.figsize'] = (16, 6)
         train.boxplot(showfliers=False, rot=90)
         plt.show()
```



2.9 Deal with numerical features first

```
In [12]: # extract locations of numerical features
         num_feat = (train.dtypes != "object").as_matrix()
         print("Number of numerical features: {}".format(np.sum(num_feat)))

         train_num = train.iloc[:, num_feat]
         test_num = test.iloc[:, num_feat]
```

```
Number of numerical features: 36
```

2.9.1 Check positivity and fill missing values with column means

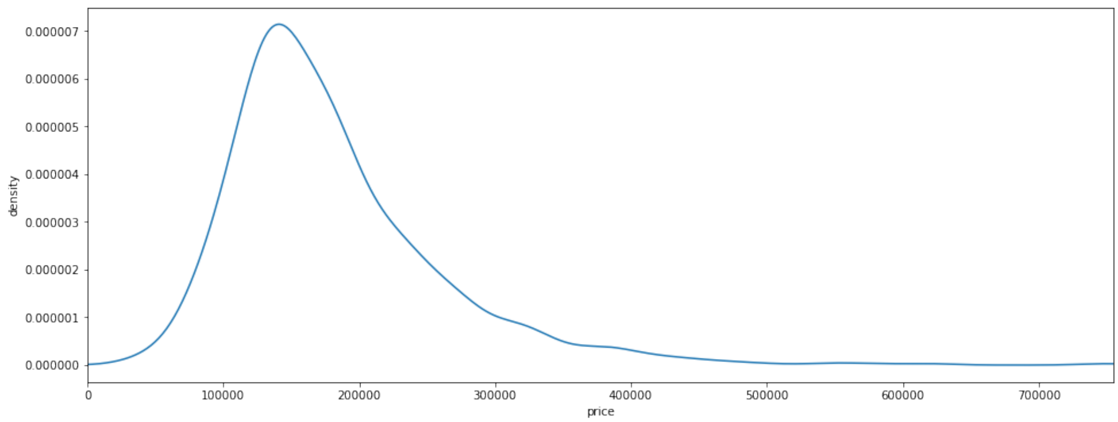
```
In [13]: print("All numerical values in training set positive? {}"
               .format(not (train_num < 0).any().any()))
         # fill missing values in training set with column means
         train_num = train_num.fillna(train_num.mean())
         train.iloc[:, num_feat] = train_num

         print("All numerical values in test set positive? {}"
               .format(not (test_num < 0).any().any()))
         # fill missing values in test set with TRAINING column means
         test_num = test_num.fillna(train_num.mean())
         test.iloc[:, num_feat] = test_num
```

```
All numerical values in training set positive? True
All numerical values in test set positive? True
```

2.10 Check skewness (third central moment)

```
In [14]: ax = train_price.plot.density()
         ax.set_xlim([0,train_price.max()])
         ax.set_xlabel("price")
         ax.set_ylabel("density")
         plt.show()
```




```
In [15]: print("Numerical feature columns:")
         display(train.columns[num_feat])
         print("Skeweness of numerical training features:")
         display(skew(train_num))
```

```
Numerical feature columns:


Index([u'MSSubClass', u'LotFrontage', u'LotArea', u'OverallQual',
       u'OverallCond', u'YearBuilt', u'YearRemodAdd', u'MasVnrArea',
       u'BsmtFinSF1', u'BsmtFinSF2', u'BsmtUnfSF', u'TotalBsmtSF', u'1stFlrSF',
       u'2ndFlrSF', u'LowQualFinSF', u'GrLivArea', u'BsmtFullBath',
       u'BsmtHalfBath', u'FullBath', u'HalfBath', u'BedroomAbvGr',
       u'KitchenAbvGr', u'TotRmsAbvGrd', u'Fireplaces', u'GarageYrBlt',
       u'GarageCars', u'GarageArea', u'WoodDeckSF', u'OpenPorchSF',
       u'EnclosedPorch', u'3SsnPorch', u'ScreenPorch', u'PoolArea', u'MiscVal',
       u'MoSold', u'YrSold'],
      dtype='object')


Skeweness of numerical training features:


array([  1.40621011,   2.38249918,  12.19514213,   0.21672098,
         0.69235521,  -0.61283072,  -0.5030445 ,   2.67366126,
```

```
          1.6837709 ,   4.25088802,   0.9193227 ,   1.52268809,
          1.37534174,   0.81219427,   9.00208042,   1.36515595,
          0.59545404,   4.09918567,   0.03652398,   0.67520283,
          0.21157244,   4.48378409,   0.67564577,   0.64889763,
         -0.66748815,  -0.3421969 ,   0.17979594,   1.5397917 ,
          2.36191193,   3.08669647,  10.29375236,   4.11797738,
         14.81313466,  24.45163962,   0.21183506,   0.09616958])
```

2.11 Log(1+p) transform of skewed features

In [16]:
```
skewed = (np.absolute(skew(train_num)) > 1)
train_num.iloc[:, skewed] = np.log1p(train_num.iloc[:, skewed])
test_num.iloc[:, skewed] = np.log1p(test_num.iloc[:, skewed])
train_price = np.log1p(train_price)

print("Skeweness of numerical training features after transformation:")
display(skew(train_num))
```

```
Skeweness of numerical training features after transformation:
```

```
array([ 2.48741218e-01, -8.91060059e-01, -1.37263272e-01,
        2.16720977e-01,  6.92355214e-01, -6.12830724e-01,
       -5.03044497e-01,  4.80625684e-01, -6.17774284e-01,
        2.52110019e+00,  9.19322702e-01, -5.14937258e+00,
        8.00317572e-02,  8.12194273e-01,  7.45264962e+00,
       -6.13394321e-03,  5.95454038e-01,  3.92902155e+00,
        3.65239844e-02,  6.75202835e-01,  2.11572442e-01,
        3.86543714e+00,  6.75645767e-01,  6.48897631e-01,
       -6.67488146e-01, -3.42196895e-01,  1.79795942e-01,
        1.53378802e-01, -2.33732497e-02,  2.11010418e+00,
        7.72702571e+00,  3.14717122e+00,  1.43483416e+01,
        5.16538998e+00,  2.11835060e-01,  9.61695796e-02])
```

2.12 Normalize numerical features

In [17]:
```
scaler = StandardScaler().fit(train_num)
train_num = scaler.transform(train_num)
test_num = scaler.transform(test_num)
```

2.12.1 Apply the transformed values to the orginial sets

In [18]:
```
train.iloc[:, num_feat] = train_num
test.iloc[:, num_feat] = test_num
```

2.13 Transform categorical to numerical features

```
In [19]: train_test = pd.concat([train, test])
         train_test = pd.get_dummies(train_test)
         train_test.iloc[:,40:50].head(4)
```

Out[19]:

Id	MSZoning_RM	Street_Grvl	Street_Pave	Alley_Grvl	Alley_Pave
1	0	0	1	0	0
2	0	0	1	0	0
3	0	0	1	0	0
4	0	0	1	0	0

Id	LotShape_IR1	LotShape_IR2	LotShape_IR3	LotShape_Reg	LandContour_Bnk
1	0	0	0	1	0
2	0	0	0	1	0
3	1	0	0	0	0
4	1	0	0	0	0

2.14 Split sets again

```
In [20]: train = train_test.iloc[:train.shape[0], :]
         test = train_test.iloc[train.shape[0]:, :]
```

3 Finally we can start with machine learning

3.1 First try: Linear Regression

```
In [21]: lin_reg = linear_model.LinearRegression()
         scores = cross_val_score(lin_reg, train, train_price,
                                  cv=5, scoring='neg_mean_squared_error')
         print("Mean of 5 CV sqrt MSE: {:.4f}".format(np.sqrt(-scores.mean())))
```

```
Mean of 5 CV sqrt MSE: 1392066367.1519
```

3.2 Second try: Ridge Regression

```
In [22]: ridge = linear_model.Ridge(alpha=10.)
         scores = cross_val_score(ridge, train, train_price,
                                  cv=5, scoring='neg_mean_squared_error')
         print("Mean of 5 CV sqrt MSE: {:.4f}".format(np.sqrt(-scores.mean())))
```

```
Mean of 5 CV sqrt MSE: 0.1279
```

Ridge Regression seems to work better!

3.3 Fit estimator to training data

```
In [23]: ridge.fit(train, train_price)
```

```
Out[23]: Ridge(alpha=10.0, copy_X=True, fit_intercept=True, max_iter=None,
            normalize=False, random_state=None, solver='auto', tol=0.001)
```

3.3.1 Apply estimator to test set and retransform predicted prices

```
In [24]: preds = ridge.predict(test)
```

```
In [25]: preds_price = np.expm1(preds)
```

3.3.2 Prepare format for submission and save as CSV

```
In [26]: test_results = pd.DataFrame({'SalePrice': preds_price,
                                      'Id': test.index})
         test_results.set_index('Id', inplace=True)

         test_results.to_csv("output/test_results.csv")
```