2

August 30, 2024

[ ]:
```python
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.feature_selection import mutual_info_regression
from sklearn.model_selection import cross_val_score
from xgboost import XGBRegressor

# Set Matplotlib defaults
plt.style.use("seaborn-v0_8-whitegrid")
plt.rc("figure", autolayout=True)
plt.rc(
    "axes",
    labelweight="bold",
    labelsize="large",
    titleweight="bold",
    titlesize=14,
    titlepad=10,
)


def plot_variance(pca, width=8, dpi=100):
    # Create figure
    fig, axs = plt.subplots(1, 2)
    n = pca.n_components_
    grid = np.arange(1, n + 1)

    # Explained variance
    evr = pca.explained_variance_ratio_  #
    axs[0].bar(grid, evr)  #
    axs[0].set(
        xlabel="Component", title="% Explained Variance", ylim=(0.0, 1.0)
    )

    # Cumulative Variance
    cv = np.cumsum(evr)  #
```

```python
    axs[1].plot(np.r_[0, grid], np.r_[0, cv], "o-")  #
    axs[1].set(
        xlabel="Component", title="% Cumulative Variance", ylim=(0.0, 1.0)
    )

    # Set up figure
    fig.set(figwidth=8, dpi=100)
    return axs



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def make_mi_scores(X, y):
    X = X.copy()
    for colname in X.select_dtypes(["object", "category"]):
        X[colname], _ = X[colname].factorize()
    # All discrete features should now have integer dtypes
    discrete_features = [pd.api.types.is_integer_dtype(t) for t in X.dtypes]
    mi_scores = mutual_info_regression(X, y,␣
 ↪discrete_features=discrete_features, random_state=0)
    mi_scores = pd.Series(mi_scores, name="MI Scores", index=X.columns)
    mi_scores = mi_scores.sort_values(ascending=False)
    return mi_scores


def score_dataset(X, y, model=XGBRegressor()):
```

```python
    # Label encoding for categoricals
    for colname in X.select_dtypes(["category", "object"]):
        X[colname], _ = X[colname].factorize()
    # Metric for Housing competition is RMSLE (Root Mean Squared Log Error)
    score = cross_val_score(
        model, X, y, cv=5, scoring="neg_mean_squared_log_error",
    )
    score = -1 * score.mean()
    score = np.sqrt(score)
    return score

def apply_pca(X, standardize=True):
    # Standardize
    if standardize:
        X = (X - X.mean(axis=0)) / X.std(axis=0)
    # Create principal components
    pca = PCA()
    X_pca = pca.fit_transform(X)
    # Convert to dataframe
    component_names = [f"PC{i+1}" for i in range(X_pca.shape[1])]
    X_pca = pd.DataFrame(X_pca, columns=component_names)
    # Create loadings
    loadings = pd.DataFrame(
        pca.components_.T,  # transpose the matrix of loadings
        columns=component_names,  # so the columns are the principal components
        index=X.columns,  # and the rows are the original features
    )
    return pca, X_pca, loadings
df = pd.read_csv("../input/ames.csv")
```

[ ]:
```python
features = [
    "GarageArea",
    "YearRemodAdd",
    "TotalBsmtSF",
    "GrLivArea",
]

print("Correlation with SalePrice:\n")
print(df[features].corrwith(df.SalePrice))
```

```
Correlation with SalePrice:

GarageArea      0.640138
YearRemodAdd    0.532974
TotalBsmtSF     0.632529
GrLivArea       0.706780
dtype: float64
```

[ ]:
```python

```

[ ]:
```python
X = df.copy()
y = X.pop("SalePrice")
X = X.loc[:, features]

# `apply_pca`, defined above, reproduces the code from the tutorial
pca, X_pca, loadings = apply_pca(X)
print(loadings)
X_pca
```

```
                 PC1       PC2       PC3       PC4
GarageArea    0.541229 -0.102375 -0.038470  0.833733
YearRemodAdd  0.427077  0.886612 -0.049062 -0.170639
TotalBsmtSF   0.510076 -0.360778 -0.666836 -0.406192
GrLivArea     0.514294 -0.270700  0.742592 -0.332837
```

[ ]:

	PC1	PC2	PC3	PC4
0	-0.165346	-1.164936	0.233330	0.283527
1	-0.639050	-0.649561	-0.622155	1.740770
2	-0.794227	-1.175790	-0.580254	-0.551055
3	1.636658	-1.907874	-0.675063	-1.052854
4	0.293648	0.610856	0.342374	-0.047752
…	…	…	…	…
2925	-0.276496	0.239255	-0.676658	0.820547
2926	-0.822084	0.414039	-0.593885	0.620322
2927	-1.730457	0.951137	-0.501221	-1.417521
2928	-0.049130	-0.584898	-0.641779	-0.374198
2929	1.090406	0.106617	0.763916	0.328966

[2930 rows x 4 columns]

[ ]:
```python
X
```

[ ]:

	GarageArea	YearRemodAdd	TotalBsmtSF	GrLivArea
0	528.0	1960	1080.0	1656.0
1	730.0	1961	882.0	896.0
2	312.0	1958	1329.0	1329.0
3	522.0	1968	2110.0	2110.0
4	482.0	1998	928.0	1629.0
…	…	…	…	…
2925	588.0	1984	1003.0	1003.0
2926	484.0	1983	864.0	902.0
2927	0.0	1992	912.0	970.0
2928	418.0	1975	1389.0	1389.0
2929	650.0	1994	996.0	2000.0

[2930 rows x 4 columns]

[ ]:
```
pca.components_
```

[ ]:
```
array([[ 0.54122942,  0.42707725,  0.5100756 ,  0.51429428],
       [-0.10237467,  0.88661165, -0.36077798, -0.27069995],
       [-0.03846963, -0.04906151, -0.66683607,  0.74259189],
       [ 0.83373271, -0.17063932, -0.4061918 , -0.33283662]])
```

[ ]:
```
X = df.copy()
y = X.pop("SalePrice")

X = X.join(X_pca)
score = score_dataset(X, y)
print(f"Your score: {score:.5f} RMSLE")
```

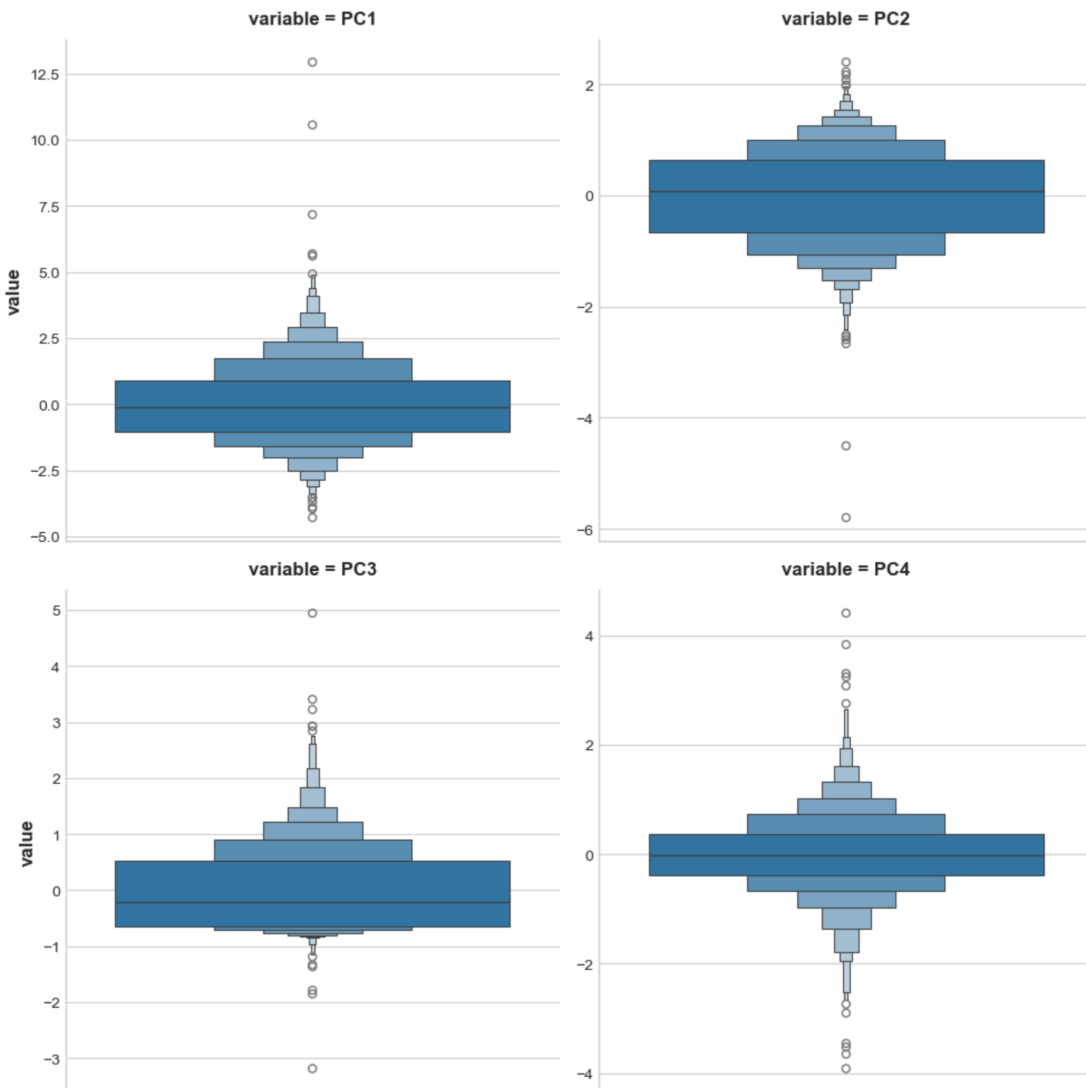
```
Your score: 0.13957 RMSLE
```

[ ]:
```
X
```

[ ]:
```
      MSSubClass  MSZoning  LotFrontage  LotArea  Street  Alley  LotShape  \
0              0         0        141.0  31770.0       0      0         0
1              0         1         80.0  11622.0       0      0         1
2              0         0         81.0  14267.0       0      0         0
3              0         0         93.0  11160.0       0      0         1
4              1         0         74.0  13830.0       0      0         0
…            …        …          …      …      …      …
2925           6         0         37.0   7937.0       0      0         0
2926           0         0          0.0   8885.0       0      0         0
2927           4         0         62.0  10441.0       0      0         1
2928           0         0         77.0  10010.0       0      0         1
2929           1         0         74.0   9627.0       0      0         1

      LandContour  Utilities  LotConfig  …  MiscFeature  MiscVal  MoSold  \
0               0          0          0  …           -1      0.0       5
1               0          0          1  …           -1      0.0       6
2               0          0          0  …            0  12500.0       6
3               0          0          0  …           -1      0.0       4
4               0          0          1  …           -1      0.0       3
…             …        …          …  …          …      …      …
2925            0          0          2  …           -1      0.0       3
2926            3          0          1  …           -1      0.0       6
2927            0          0          1  …            1    700.0       7
2928            0          0          1  …           -1      0.0       4
2929            0          0          1  …           -1      0.0      11

      YearSold  SaleType  SaleCondition       PC1       PC2       PC3  \
0         2010         0              0 -0.165346 -1.164936  0.233330
1         2010         0              0 -0.639050 -0.649561 -0.622155
2         2010         0              0 -0.794227 -1.175790 -0.580254
```

```
3          2010         0             0  1.636658 -1.907874 -0.675063
4          2010         0             0  0.293648  0.610856  0.342374
…          …       …            …        …        …        …
2925       2006         0             0 -0.276496  0.239255 -0.676658
2926       2006         0             0 -0.822084  0.414039 -0.593885
2927       2006         0             0 -1.730457  0.951137 -0.501221
2928       2006         0             0 -0.049130 -0.584898 -0.641779
2929       2006         0             0  1.090406  0.106617  0.763916

           PC4
0     0.283527
1     1.740770
2    -0.551055
3    -1.052854
4    -0.047752
…          …
2925  0.820547
2926  0.620322
2927 -1.417521
2928 -0.374198
2929  0.328966

[2930 rows x 82 columns]
```

[ ]:
```python
sns.catplot(
    y="value",
    col="variable",
    data=X_pca.melt(),
    kind='boxen',
    sharey=False,
    col_wrap=2,
);
```



[ ]:
```python
# You can change PC1 to PC2, PC3, or PC4
component = "PC1"

idx = X_pca[component].sort_values(ascending=False).index
df.loc[idx, ["SalePrice", "Neighborhood", "SaleCondition"] + features]
```

[ ]:
```
      SalePrice        Neighborhood SaleCondition  GarageArea  \
1498    160000              Edwards       Partial      1418.0
2180    183850              Edwards       Partial      1154.0
2181    184750              Edwards       Partial       884.0
1760    745000           Northridge       Abnorml       813.0
1767    755000           Northridge        Normal       832.0
…          …                   …            …            …
```

```
662       59000               Old_Town       Normal          0.0
2679      80500              Brookside       Normal          0.0
2879      51689  Iowa_DOT_and_Rail_Road      Abnorml          0.0
780       63900                 Sawyer       Normal          0.0
1901      39300              Brookside       Normal          0.0

      YearRemodAdd  TotalBsmtSF  GrLivArea
1498          2008       6110.0     5642.0
2180          2009       5095.0     5095.0
2181          2008       3138.0     4676.0
1760          1996       2396.0     4476.0
1767          1995       2444.0     4316.0
…              …           …         …
662           1950        416.0      599.0
2679          1950          0.0      912.0
2879          1950          0.0      729.0
780           1950          0.0      660.0
1901          1950          0.0      334.0

[2930 rows x 7 columns]
```