Final Project - Real Estate Sale Price

For my final project, I chose to use unsupervised learning to predict the sale price of a house given a variety of inputs. The use case would be to provide interested sellers and their real estate agents with an estimate of their listing price.

Setup

In [29]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import math
import seaborn as sns
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
```

In [30]:
```
train_data = pd.read_csv('train.csv')
train_data.head()
```

Out[30]:

	Id	MSSubClass	MSZoning	LotFrontage	LotArea	Street	Alley	LotShape	LandContour	Utilities	...
0	1	60	RL	65.0	8450	Pave	NaN	Reg	Lvl	AllPub	...
1	2	20	RL	80.0	9600	Pave	NaN	Reg	Lvl	AllPub	...
2	3	60	RL	68.0	11250	Pave	NaN	IR1	Lvl	AllPub	...
3	4	70	RL	60.0	9550	Pave	NaN	IR1	Lvl	AllPub	...
4	5	60	RL	84.0	14260	Pave	NaN	IR1	Lvl	AllPub	...

5 rows × 81 columns

Data Cleaning

In [31]:
```
train_data.columns
```

Out[31]:
```
Index(['Id', 'MSSubClass', 'MSZoning', 'LotFrontage', 'LotArea', 'Street',
       'Alley', 'LotShape', 'LandContour', 'Utilities', 'LotConfig',
       'LandSlope', 'Neighborhood', 'Condition1', 'Condition2', 'BldgType',
       'HouseStyle', 'OverallQual', 'OverallCond', 'YearBuilt', 'YearRemodAd
d',
       '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', 'FullBat
h',
       'HalfBath', 'BedroomAbvGr', 'KitchenAbvGr', 'KitchenQual',
       'TotRmsAbvGrd', 'Functional', 'Fireplaces', 'FireplaceQu', 'GarageTyp
e',
       'GarageYrBlt', 'GarageFinish', 'GarageCars', 'GarageArea', 'GarageQua
l',
       'GarageCond', 'PavedDrive', 'WoodDeckSF', 'OpenPorchSF',
       'EnclosedPorch', '3SsnPorch', 'ScreenPorch', 'PoolArea', 'PoolQC',
       'Fence', 'MiscFeature', 'MiscVal', 'MoSold', 'YrSold', 'SaleType',
       'SaleCondition', 'SalePrice'],
      dtype='object')
```

In [32]:
```
def clean(df):
    percentages = [i/len(df) for i in df.isnull().sum()]
    CCA = pd.DataFrame({'features': df.columns, 'percentage_missing': percentag
    impute = []
    throw = []
    for i in np.arange(len(CCA)):
        if CCA['percentage_missing'][i] > 0.1:
            throw.append(CCA['features'][i])
        elif CCA['percentage_missing'][i] > 0 and CCA['percentage_missing'][i]
            impute.append(CCA['features'][i])
        else:
            continue

    features_to_impute = impute
    features_to_throw = throw
    temp_df = df.drop(features_to_throw, 1)
    impute_dict = {}
    for i in features_to_impute:
        if temp_df[i].dtype == float:
            impute_dict[i] = temp_df[i].median()
        else:
            impute_dict[i] = temp_df[i].mode().iloc[0]
    temp_df = temp_df.fillna(value=impute_dict)
    return temp_df
```

In [33]:
```
def numeric(df):
    new_df = pd.DataFrame()
    for col in df.columns:
        if type(df[col][0]) != str:
            new_df[col] = df[col]
        else:
            continue
    return new_df
```

In [34]:
```
train_data = clean(train_data)
train_data.head()
```

```
/var/folders/5c/fd850vrj48v7jb6xpw9dy4v00000gn/T/ipykernel_69764/3916390727.p
y:16: FutureWarning: In a future version of pandas all arguments of DataFram
e.drop except for the argument 'labels' will be keyword-only.
  temp_df = df.drop(features_to_throw, 1)
```

Out[34]:

	Id	MSSubClass	MSZoning	LotArea	Street	LotShape	LandContour	Utilities	LotConfig	LandSlope
0	1	60	RL	8450	Pave	Reg	Lvl	AllPub	Inside	Gtl
1	2	20	RL	9600	Pave	Reg	Lvl	AllPub	FR2	Gtl
2	3	60	RL	11250	Pave	IR1	Lvl	AllPub	Inside	Gtl
3	4	70	RL	9550	Pave	IR1	Lvl	AllPub	Corner	Gtl
4	5	60	RL	14260	Pave	IR1	Lvl	AllPub	FR2	Gtl

5 rows × 75 columns

In [35]:
```
numeric_train_data = numeric(train_data)
numeric_train_data.head()
```

Out[35]:

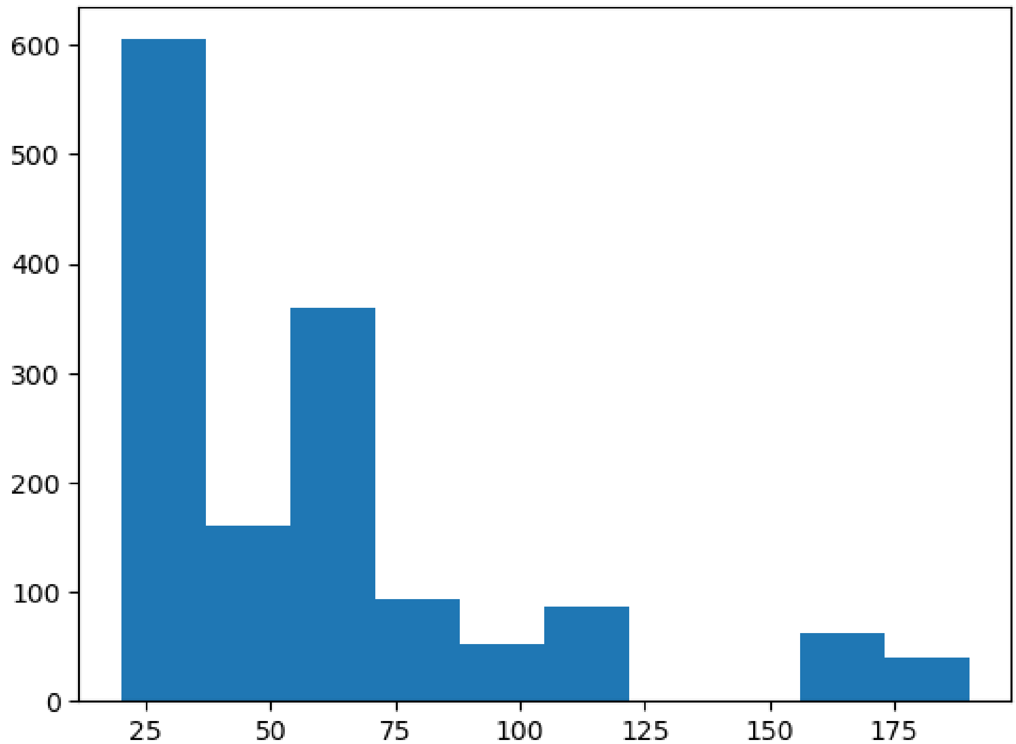
	Id	MSSubClass	LotArea	OverallQual	OverallCond	YearBuilt	YearRemodAdd	MasVnrArea	BsmtFinSI
0	1	60	8450	7	5	2003	2003	196.0	7
1	2	20	9600	6	8	1976	1976	0.0	9
2	3	60	11250	7	5	2001	2002	162.0	4
3	4	70	9550	7	5	1915	1970	0.0	2
4	5	60	14260	8	5	2000	2000	350.0	6

5 rows × 37 columns

Exploratory Data Analysis

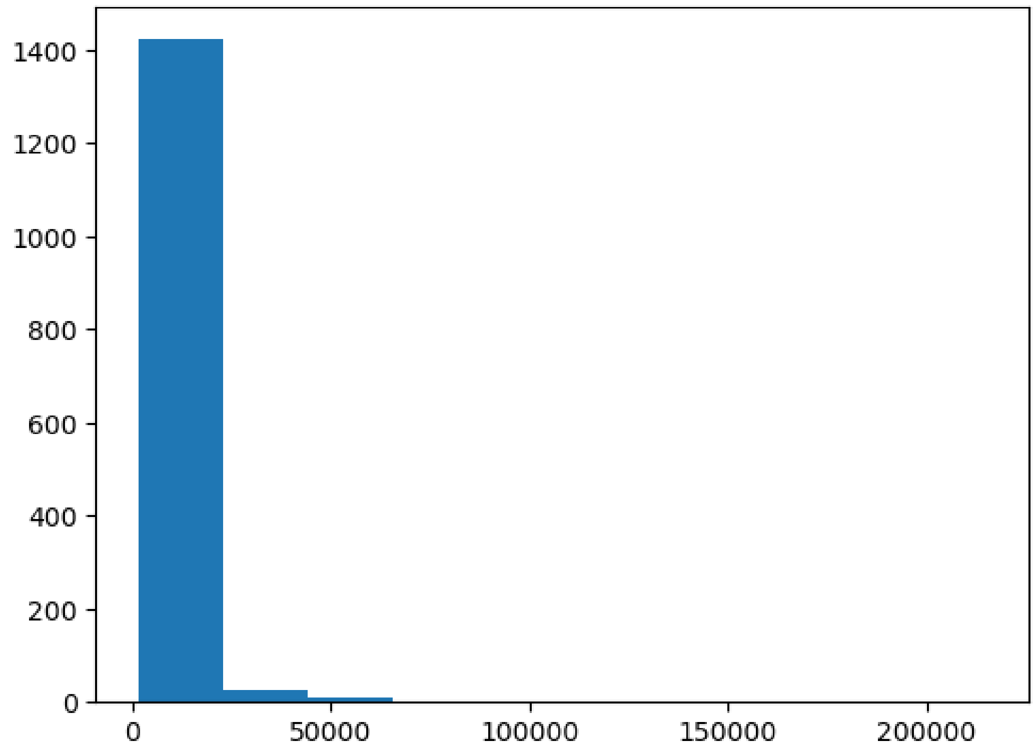
In [36]:
```
plt.hist(train_data['MSSubClass'])
```

Out[36]:
```
(array([605., 160., 359.,  94.,  52.,  87.,   0.,   0.,  63.,  40.]),
 array([ 20.,  37.,  54.,  71.,  88., 105., 122., 139., 156., 173., 190.]),
 <BarContainer object of 10 artists>)
```



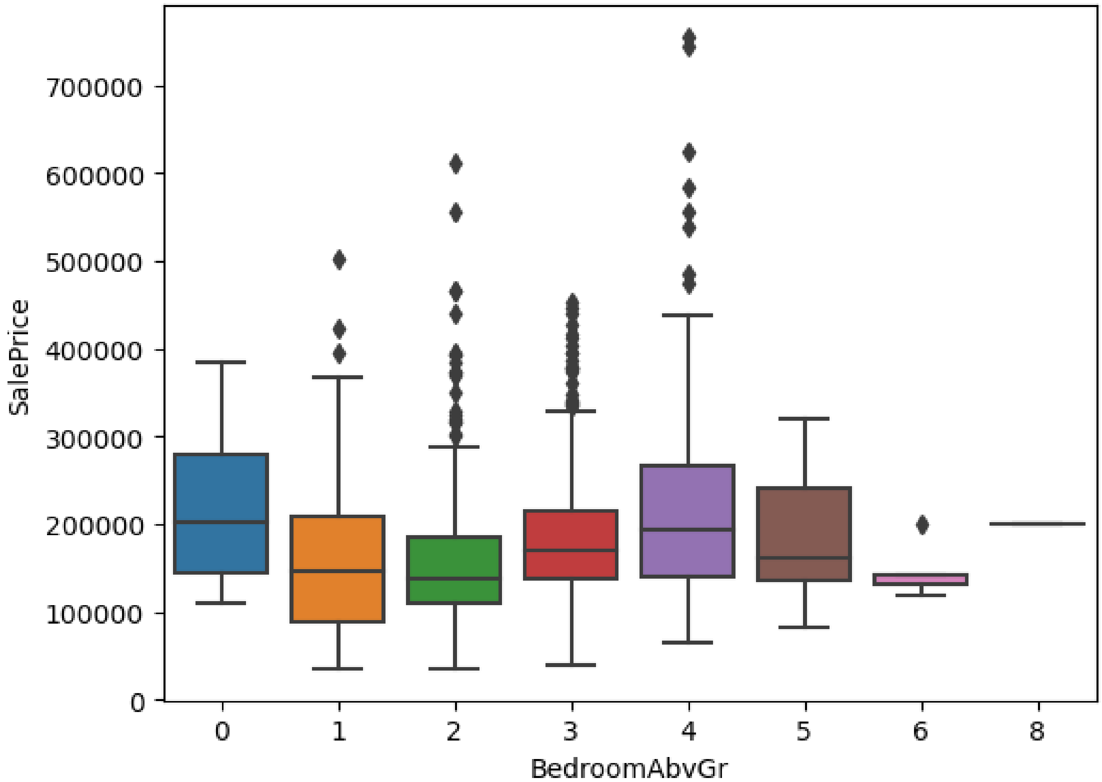
In [37]:
```
plt.hist(train_data['LotArea'])
```

Out[37]:
```
(array([1.423e+03, 2.400e+01, 8.000e+00, 1.000e+00, 0.000e+00, 1.000e+00,
        0.000e+00, 2.000e+00, 0.000e+00, 1.000e+00]),
 array([  1300. ,  22694.5,  44089. ,  65483.5,  86878. , 108272.5,
        129667. , 151061.5, 172456. , 193850.5, 215245. ]),
 <BarContainer object of 10 artists>)
```



In [38]:
```
sns.boxplot(y='SalePrice',x='BedroomAbvGr',data=train_data)
```

Out[38]: <Axes: xlabel='BedroomAbvGr', ylabel='SalePrice'>



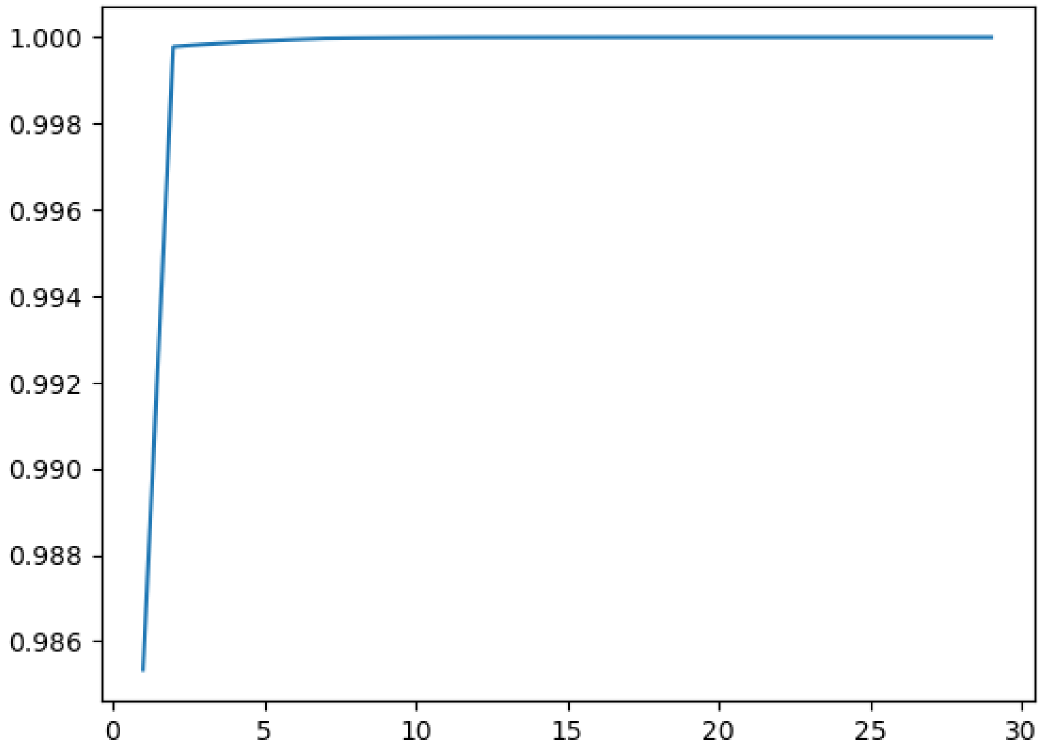
PCA Preprocessing

In [39]:
```
to_drop = []
for col in numeric_train_data.columns:
    if np.any(np.isnan(numeric_train_data[col])) == True:
        to_drop.append(col)
numeric_train_data = numeric_train_data.drop(to_drop, 1)
```

```
/var/folders/5c/fd850vrj48v7jb6xpw9dy4v00000gn/T/ipykernel_69764/3182981199.p
y:5: FutureWarning: In a future version of pandas all arguments of DataFrame.
drop except for the argument 'labels' will be keyword-only.
  numeric_train_data = numeric_train_data.drop(to_drop, 1)
```

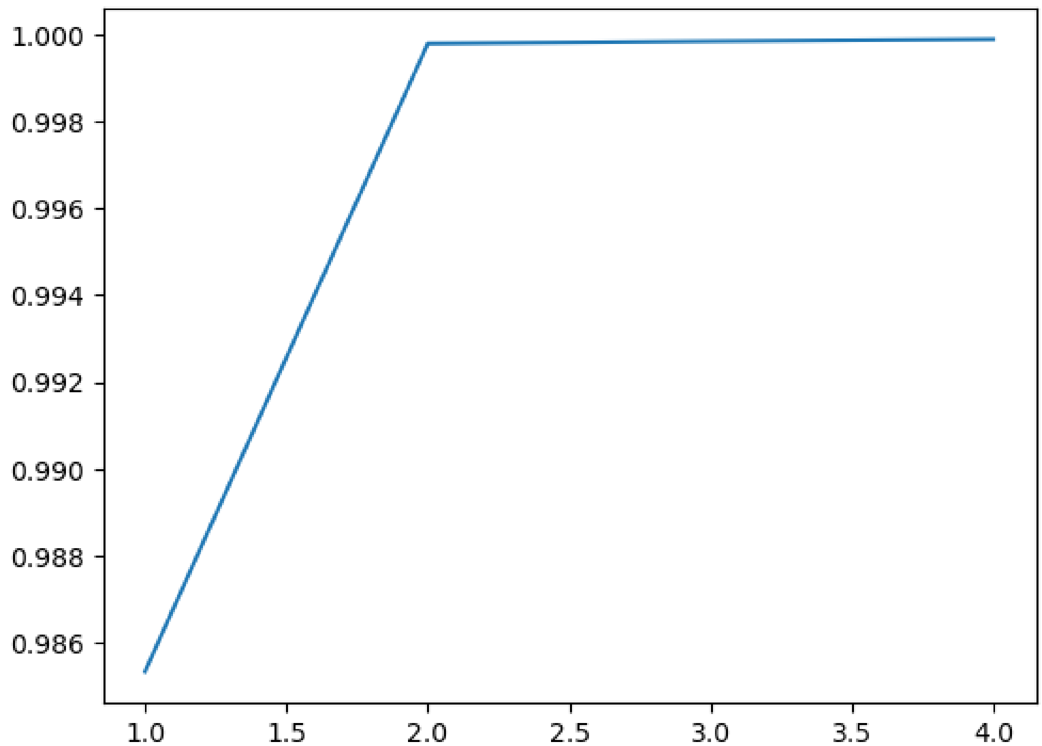
In [40]:
```
components = list(range(1, 30))
variance_ratio = []
for i in components:
    pca = PCA(n_components=i).fit(numeric_train_data)
    x_reduced = PCA(n_components=i).fit_transform(numeric_train_data)
    variance_ratio.append(sum(pca.explained_variance_ratio_))
plt.plot(components, variance_ratio)
```

Out[40]:
```
[<matplotlib.lines.Line2D at 0x127c138d0>]
```



In [41]:
```
num_components = list(range(1, 5))
variance_ratio = []
for i in num_components:
    pca = PCA(n_components=i).fit(numeric_train_data)
    x_reduced = PCA(n_components=i).fit_transform(numeric_train_data)
    variance_ratio.append(sum(pca.explained_variance_ratio_))
plt.plot(num_components, variance_ratio)
```

Out[41]:
```
[<matplotlib.lines.Line2D at 0x127cb4710>]
```



As seen in the graph above, 2 components captures the vast majority of the variance in this dataset. Given that information, I created a new dataframe containing the PCA values. Ultimately, I will feed this into the k-means clustering algorithm to break out the data into clusters.

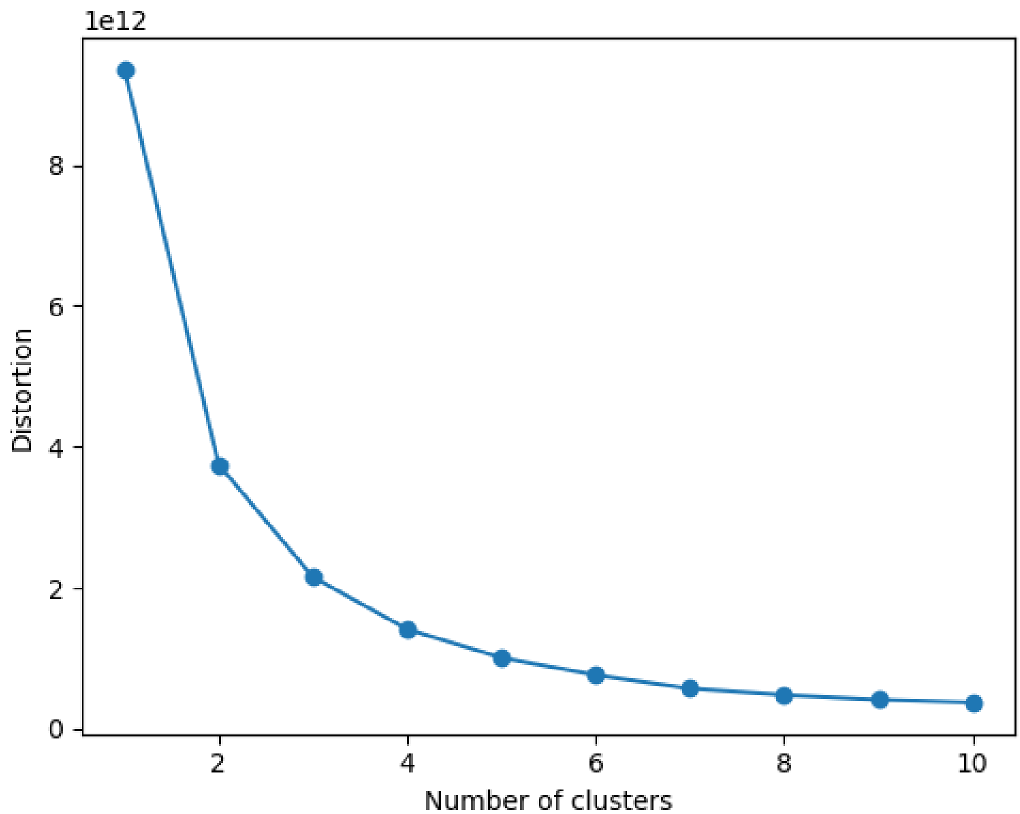
In [42]:
```
pca = PCA(n_components=2)
pca_features = pca.fit_transform(numeric_train_data)
pca_df_train = pd.DataFrame(
    data=pca_features,
    columns=['PC1', 'PC2'],
    dtype=float)
new_pc1 = [float(i) for i in pca_df_train['PC1']]
new_pc2 = [float(i) for i in pca_df_train['PC2']]
pca_df_train.head()
```

Out[42]:

	PC1	PC2
0	27493.523736	-2993.914641
1	547.725922	-929.997186
2	42579.460424	-701.918117
3	-40929.738935	409.263624
4	69169.762247	1418.332744

K-Means Clustering (without PCA)

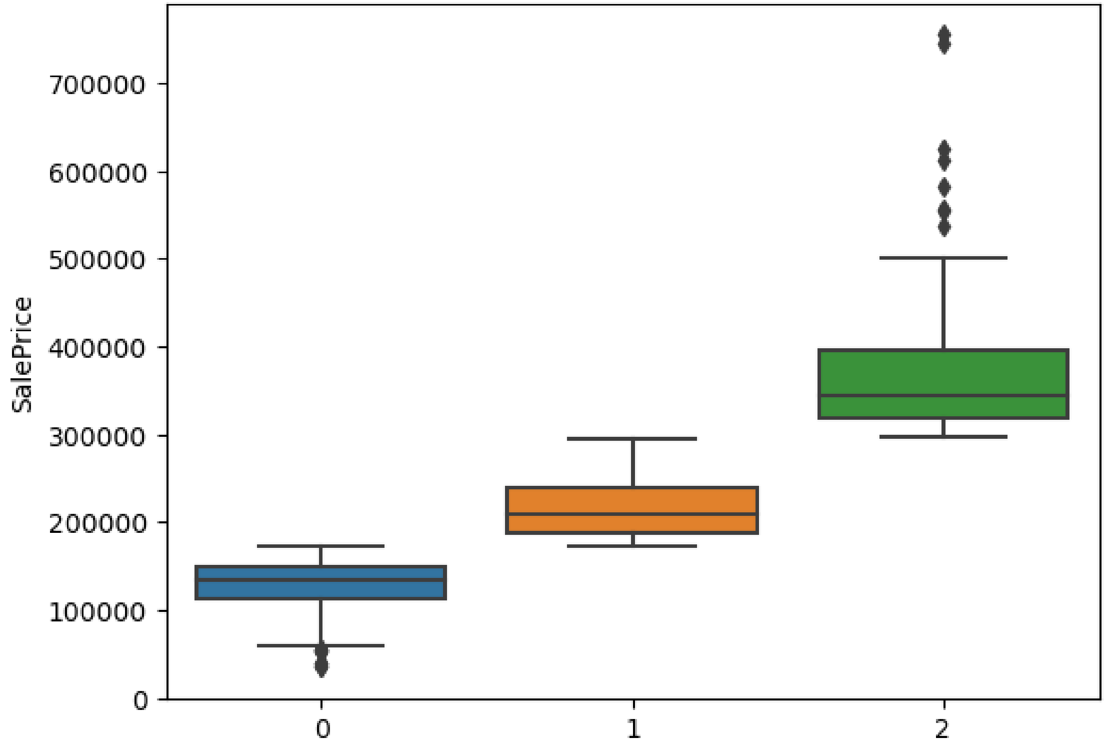
In [43]:
```
distortions = []
for i in range(1, 11):
    km = KMeans(
        n_clusters=i, init='random',
        n_init=10, max_iter=300,
        tol=1e-04, random_state=0
    )
    km.fit(numeric_train_data)
    distortions.append(km.inertia_)

plt.plot(range(1, 11), distortions, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Distortion')
plt.show()
```



In [44]:
```
km = KMeans(
    n_clusters=3, init='random',
    n_init=10, max_iter=300,
    tol=1e-04, random_state=0
)
y_km = km.fit_predict(numeric_train_data)
```

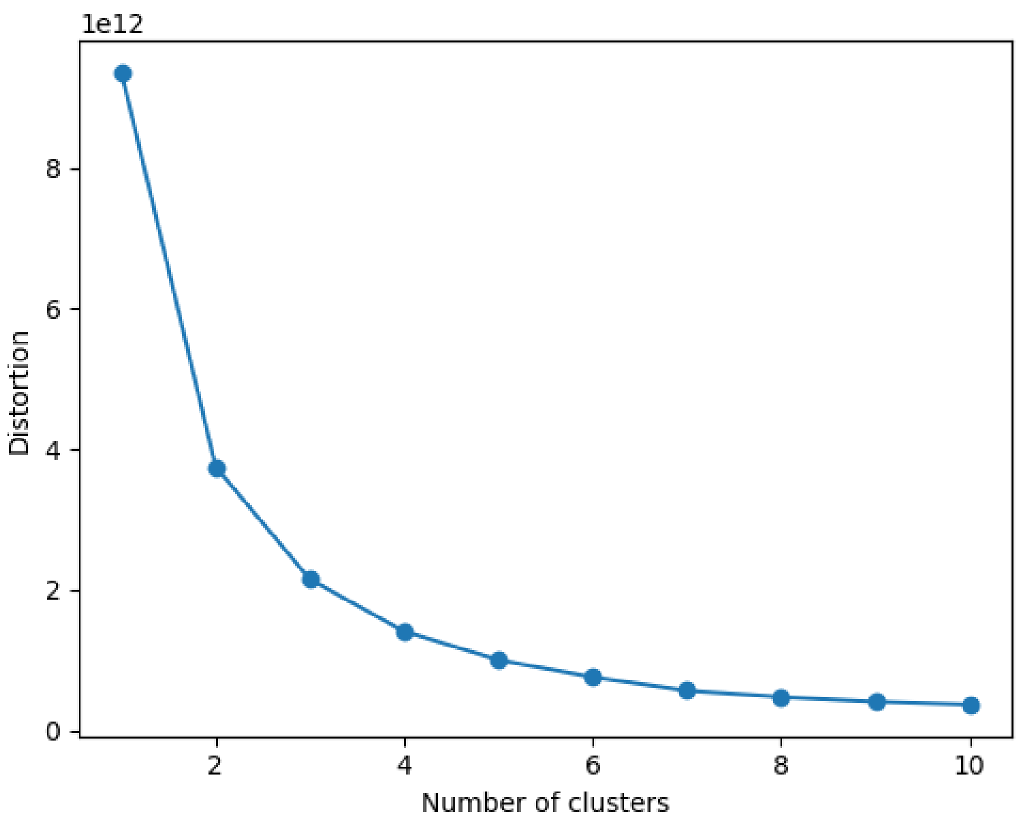
In [45]:
```
sns.boxplot(x = km.labels_, y = numeric_train_data['SalePrice'])
```

Out[45]:
```
<Axes: ylabel='SalePrice'>
```



K-Means Clustering (with PCA)

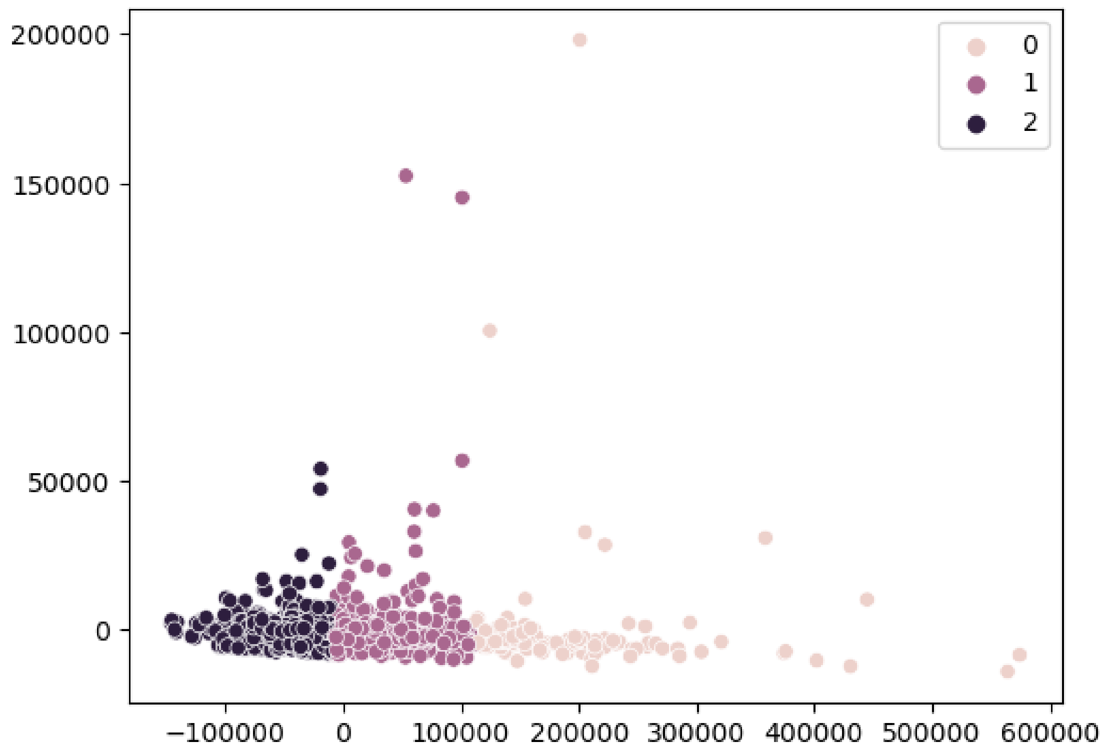
In [46]:
```
distortions = []
for i in range(1, 11):
    km = KMeans(
        n_clusters=i, init='random',
        n_init=10, max_iter=300,
        tol=1e-04, random_state=0
    )
    km.fit(pca_df_train)
    distortions.append(km.inertia_)

plt.plot(range(1, 11), distortions, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Distortion')
plt.show()
```



In [47]:
```
km = KMeans(
    n_clusters=3, init='random',
    n_init=10, max_iter=300,
    tol=1e-04, random_state=0
)
y_km = km.fit_predict(pca_df_train)
```

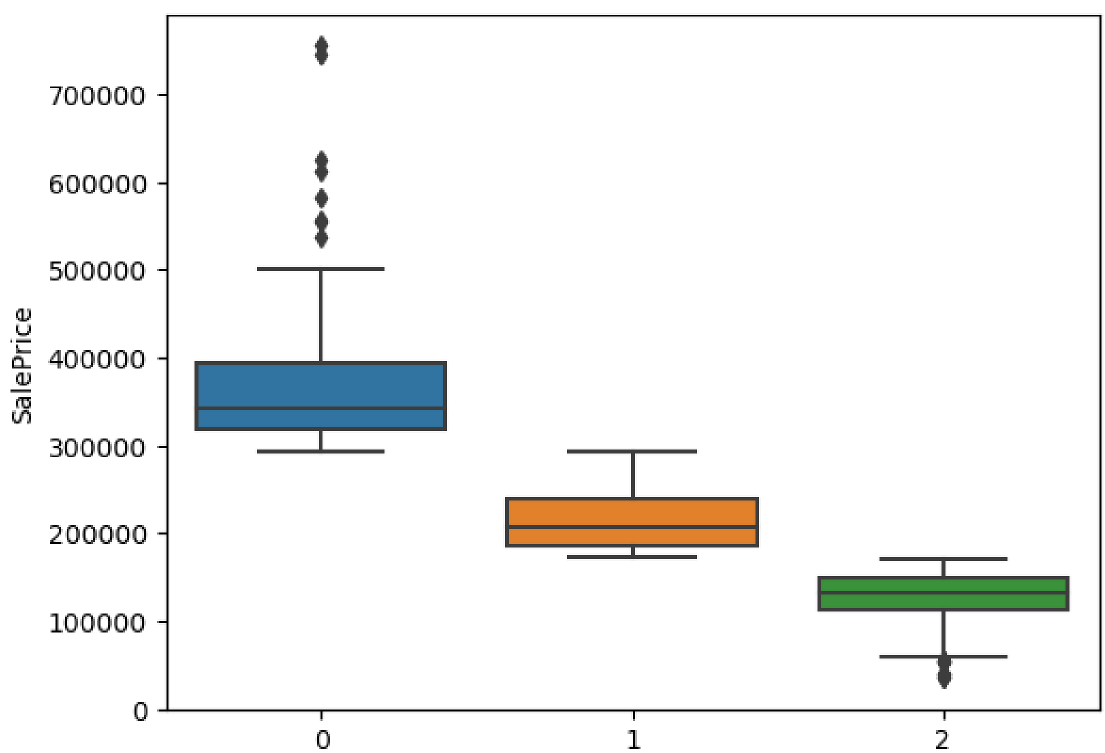
In [48]:
```
sns.scatterplot(x = new_pc1, y = new_pc2, hue = km.labels_)
```

Out[48]: <Axes: >



In [49]:
```
sns.boxplot(x = km.labels_, y = numeric_train_data['SalePrice'])
```

Out[49]: <Axes: ylabel='SalePrice'>



Discussion and Conclusion

In conclusion, this model uses kmeans clustering to provide accurate estimates of house price based on a variety of features. As shown above (disregardng the opposite labeling in the two kmeans methods), the models using principal component analysis and not both came to very similar conclusions regarding the sales price clusters found in the data.

In [ ]:

```

```