Loading Data

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

#Models
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.svm import SVR
```

In [2]:

```
df = pd.read_csv('data.csv')
df
```

Out[2]:

	date	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sq
0	5/2/2014 0:00	3.130000e+05	3	1.50	1340	7912	1.5	0	0	3	1340	
1	5/2/2014 0:00	2.384000e+06	5	2.50	3650	9050	2.0	0	4	5	3370	
2	5/2/2014 0:00	3.420000e+05	3	2.00	1930	11947	1.0	0	0	4	1930	
3	5/2/2014 0:00	4.200000e+05	3	2.25	2000	8030	1.0	0	0	4	1000	
4	5/2/2014 0:00	5.500000e+05	4	2.50	1940	10500	1.0	0	0	4	1140	
...	...	...	...	...	...	...	...	...	...	...	...	
4595	7/9/2014 0:00	3.081667e+05	3	1.75	1510	6360	1.0	0	0	4	1510	
4596	7/9/2014 0:00	5.343333e+05	3	2.50	1460	7573	2.0	0	0	3	1460	
4597	7/9/2014 0:00	4.169042e+05	3	2.50	3010	7014	2.0	0	0	3	3010	
4598	7/10/2014 0:00	2.034000e+05	4	2.00	2090	6630	1.0	0	0	3	1070	
4599	7/10/2014 0:00	2.206000e+05	3	2.50	1490	8102	2.0	0	0	4	1490	

4600 rows × 18 columns

Data Details

In [3]:
```python
df.shape
```

Out[3]:
```
(4600, 18)
```

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4600 entries, 0 to 4599
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   date           4600 non-null   object 
 1   price          4600 non-null   float64
 2   bedrooms       4600 non-null   int64  
 3   bathrooms      4600 non-null   float64
 4   sqft_living    4600 non-null   int64  
 5   sqft_lot       4600 non-null   int64  
 6   floors         4600 non-null   float64
 7   waterfront     4600 non-null   int64  
 8   view           4600 non-null   int64  
 9   condition      4600 non-null   int64  
 10  sqft_above     4600 non-null   int64  
 11  sqft_basement  4600 non-null   int64  
 12  yr_built       4600 non-null   int64  
 13  yr_renovated   4600 non-null   int64  
 14  street         4600 non-null   object 
 15  city           4600 non-null   object 
 16  statezip       4600 non-null   object 
 17  country        4600 non-null   object 
dtypes: float64(3), int64(10), object(5)
memory usage: 647.0+ KB
```

Checking Missing Value

In [5]:
```python
df.isna().sum()
```

Out[5]:
```
date             0
price            0
bedrooms         0
bathrooms        0
sqft_living      0
sqft_lot         0
floors           0
waterfront       0
view             0
condition        0
sqft_above       0
sqft_basement    0
yr_built         0
yr_renovated     0
street           0
city             0
statezip         0
country          0
dtype: int64
```

Data Cleaning and Feature Engineering

In [6]:
```
#Drop the irrelevant columns
df = df.drop(columns=['date', 'street', 'country', 'statezip','yr_renovated'])

#Verify the new structure
print("Irrelevant columns dropped successfully!")
print("Remaining columns:",df.columns.tolist())
```

```
Irrelevant columns dropped successfully!
Remaining columns: ['price', 'bedrooms', 'bathrooms', 'sqft_living', 'sqft_lot', 'floors', 'waterfront', 'view', 'con
dition', 'sqft_above', 'sqft_basement', 'yr_built', 'city']
```

In [7]:
```
df.tail()
```

Out[7]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement
4595	308166.6667	3	1.75	1510	6360	1.0	0	0	4	1510	0
4596	534333.3333	3	2.50	1460	7573	2.0	0	0	3	1460	0
4597	416904.1667	3	2.50	3010	7014	2.0	0	0	3	3010	0
4598	203400.0000	4	2.00	2090	6630	1.0	0	0	3	1070	1020
4599	220600.0000	3	2.50	1490	8102	2.0	0	0	4	1490	0

In [8]:
```
df.head()
```

Out[8]:

	price	bedrooms	bathrooms	sqft_living	sqft_lot	floors	waterfront	view	condition	sqft_above	sqft_basement	yr_bu
0	313000.0	3	1.50	1340	7912	1.5	0	0	3	1340	0	19
1	2384000.0	5	2.50	3650	9050	2.0	0	4	5	3370	280	19
2	342000.0	3	2.00	1930	11947	1.0	0	0	4	1930	0	19
3	420000.0	3	2.25	2000	8030	1.0	0	0	4	1000	1000	19
4	550000.0	4	2.50	1940	10500	1.0	0	0	4	1140	800	19

In [9]:
```
df.describe().transpose()
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
price	4600.0	551962.988473	563834.702547	0.0	322875.00	460943.46155	654962.50	26590000.0
bedrooms	4600.0	3.400870	0.908848	0.0	3.00	3.00000	4.00	9.0
bathrooms	4600.0	2.160815	0.783781	0.0	1.75	2.25000	2.50	8.0
sqft_living	4600.0	2139.346957	963.206916	370.0	1460.00	1980.00000	2620.00	13540.0
sqft_lot	4600.0	14852.516087	35884.436145	638.0	5000.75	7683.00000	11001.25	1074218.0
floors	4600.0	1.512065	0.538288	1.0	1.00	1.50000	2.00	3.5
waterfront	4600.0	0.007174	0.084404	0.0	0.00	0.00000	0.00	1.0
view	4600.0	0.240652	0.778405	0.0	0.00	0.00000	0.00	4.0
condition	4600.0	3.451739	0.677230	1.0	3.00	3.00000	4.00	5.0
sqft_above	4600.0	1827.265435	862.168977	370.0	1190.00	1590.00000	2300.00	9410.0
sqft_basement	4600.0	312.081522	464.137228	0.0	0.00	0.00000	610.00	4820.0
yr_built	4600.0	1970.786304	29.731848	1900.0	1951.00	1976.00000	1997.00	2014.0

In [10]:

```
#Feature Engineering
df['house_age'] = 2025 - df['yr_built']
df['total_rooms'] = df['bathrooms']  + df['bedrooms']
```

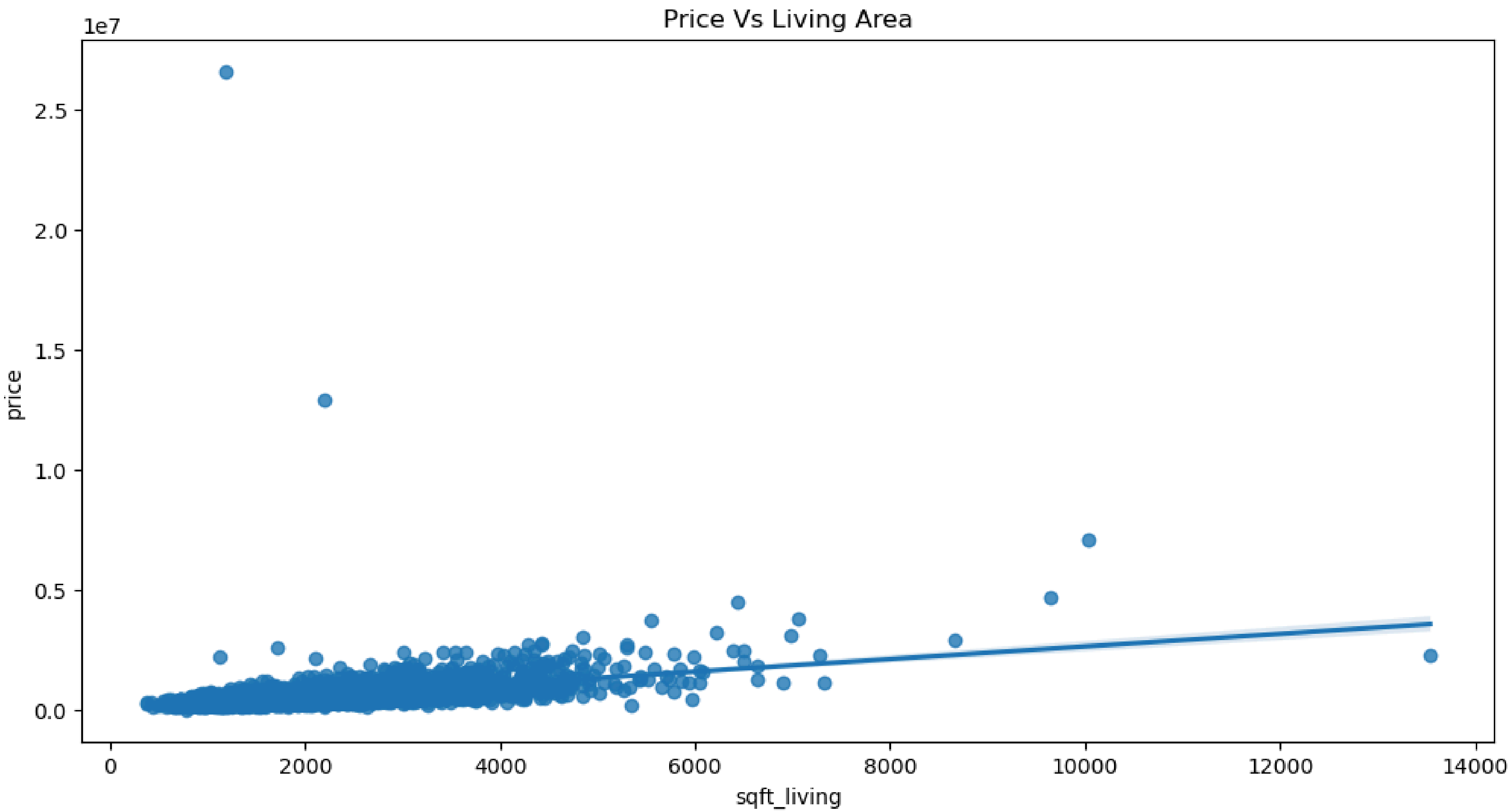
In [11]:

```
# Remove rows with price <= 0
df = df[df['price'] > 0].reset_index(drop=True)
#Apply log transformation
df['log_price'] = np.log1p(df['price'])
print(f"Removed invalid price entries. Remaining records: {len(df)}")
```

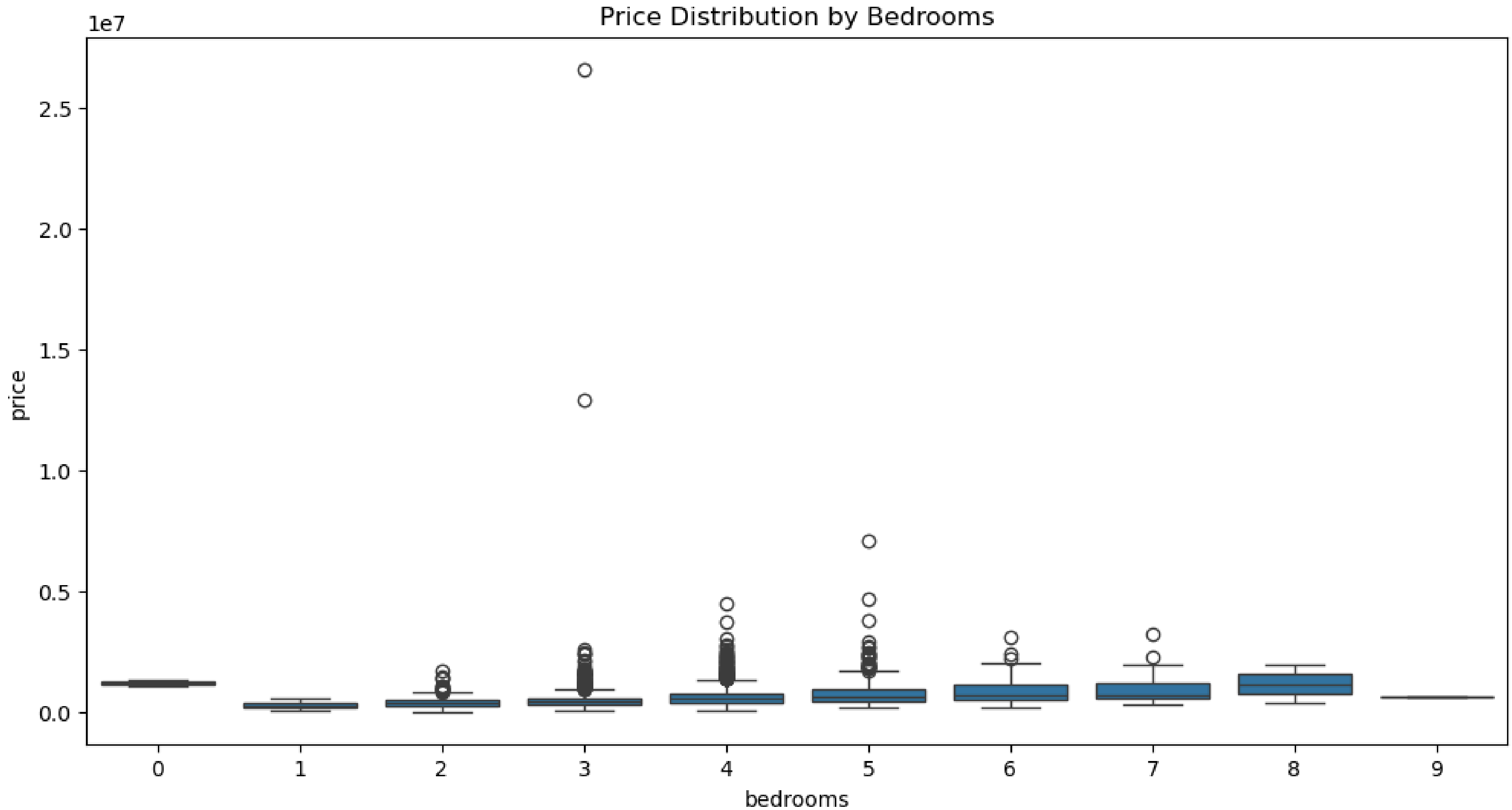
```
Removed invalid price entries. Remaining records: 4551
```

Data Visualization

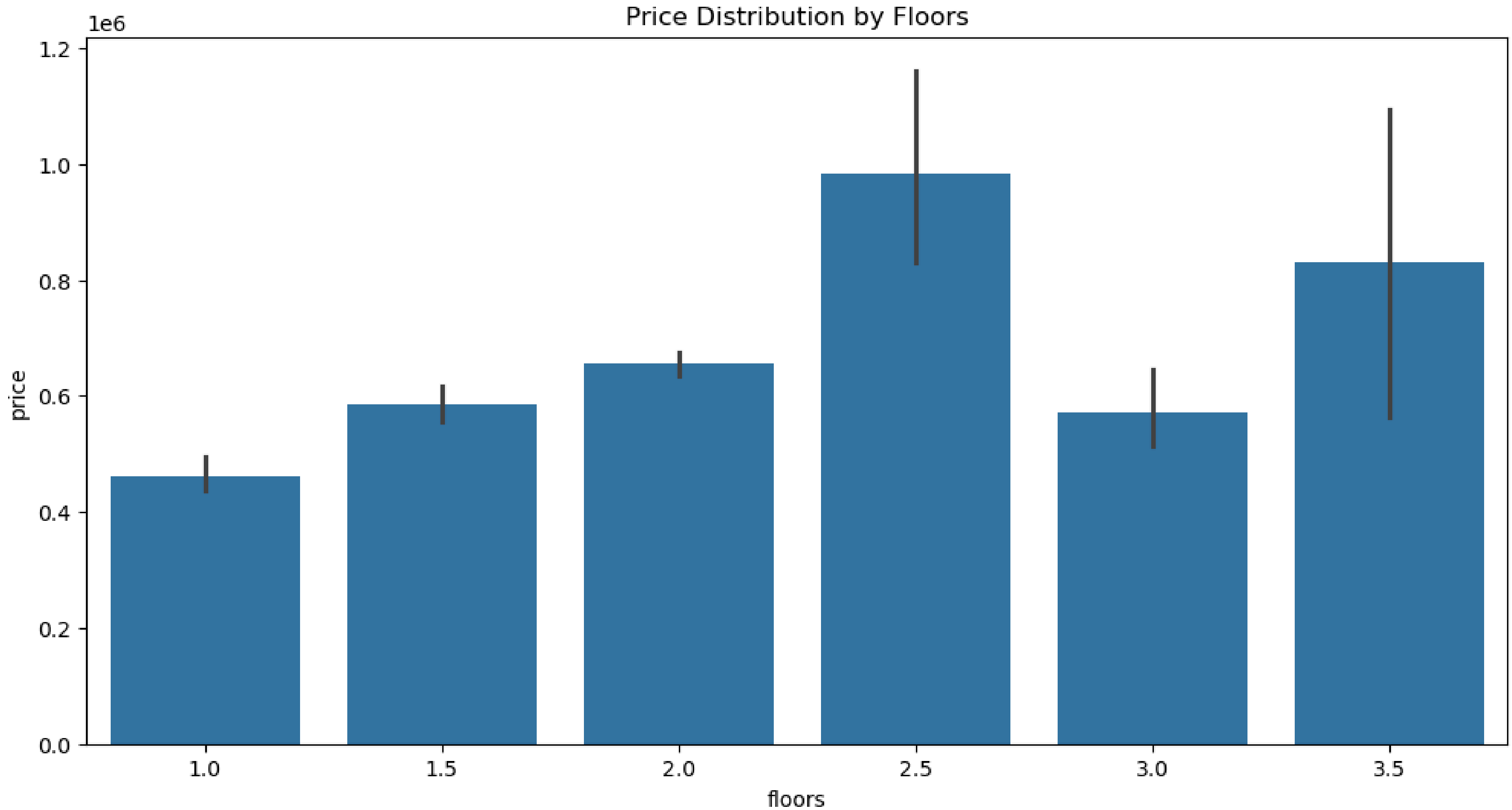
In [12]:
```
plt.figure(figsize=(12,6))
sns.regplot(x='sqft_living', y='price', data=df)
plt.title('Price Vs Living Area')
plt.show()
```



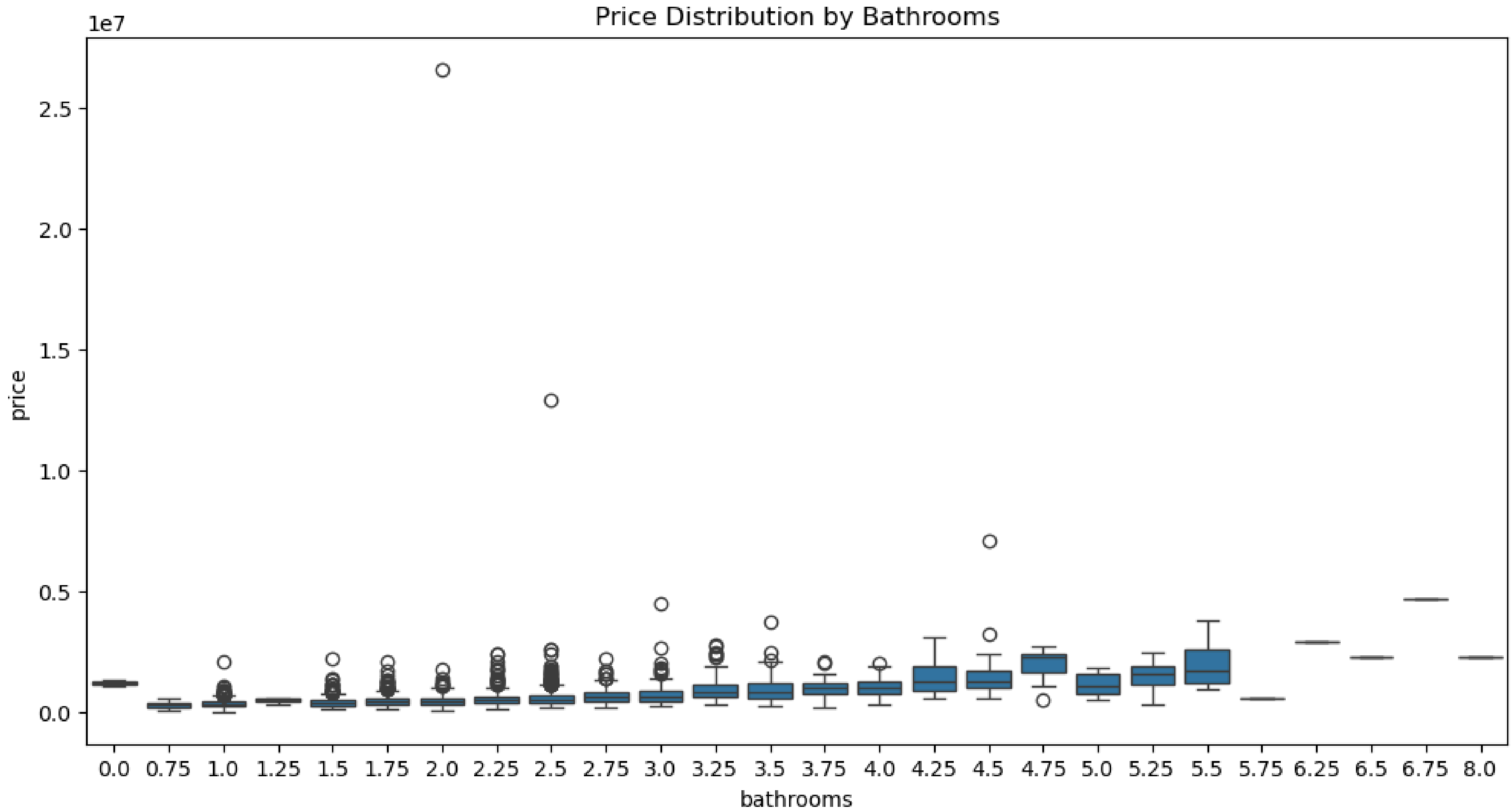
In [13]:
```
plt.figure(figsize=(12,6))
sns.boxplot(x='bedrooms', y='price', data=df)
plt.title('Price Distribution by Bedrooms')
plt.show()
```



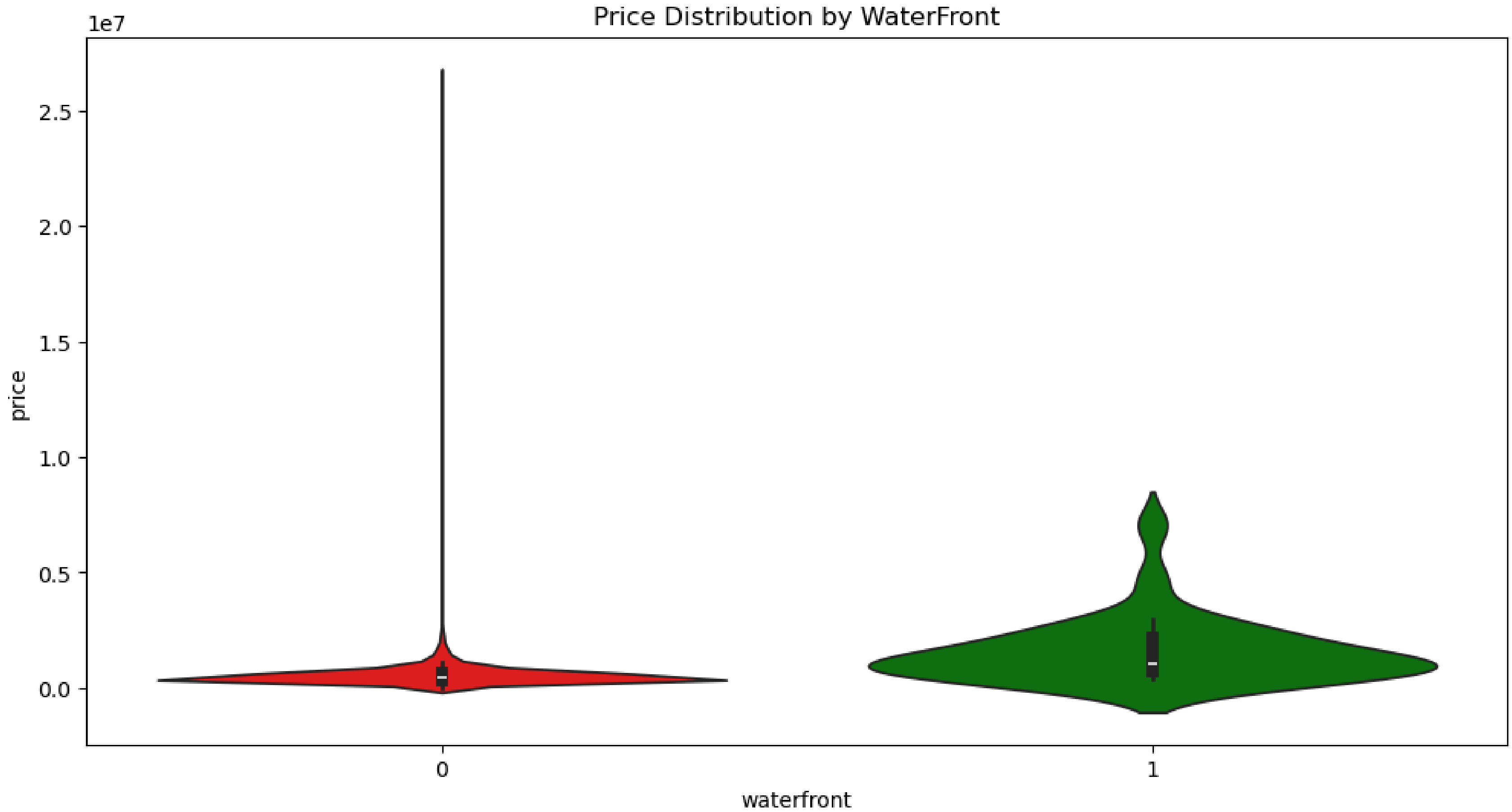
In [14]:
```
plt.figure(figsize=(12,6))
sns.barplot(x='floors', y='price', data=df)
plt.title('Price Distribution by Floors')
plt.show()
```



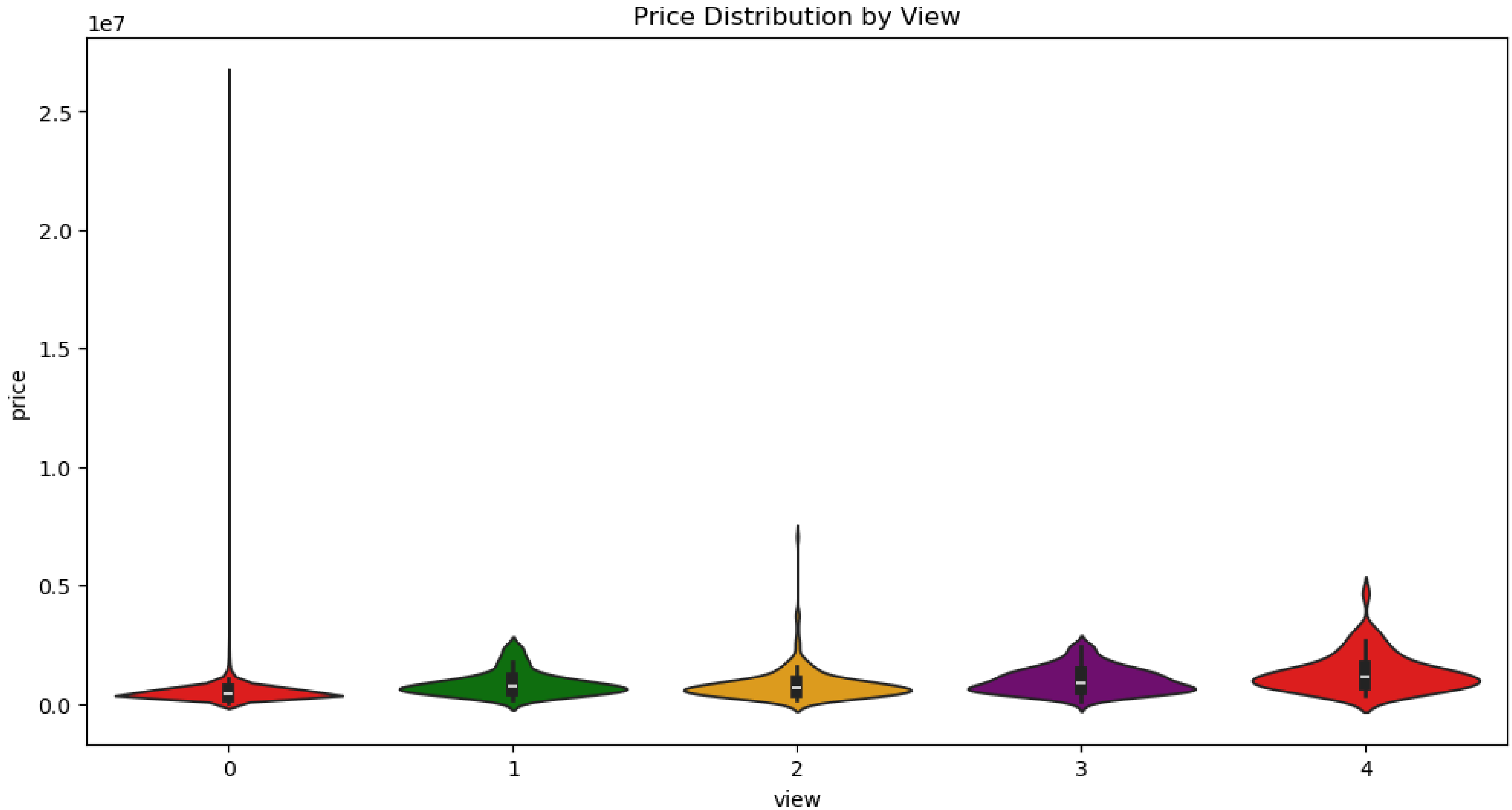
In [15]:
```
plt.figure(figsize=(12,6))
sns.boxplot(x='bathrooms', y='price', data=df)
plt.title('Price Distribution by Bathrooms')
plt.show()
```



In [16]:
```
plt.figure(figsize=(12,6))
sns.violinplot(x='waterfront', y='price', data=df, palette=['red','green'])
plt.title('Price Distribution by WaterFront')
plt.show()
```

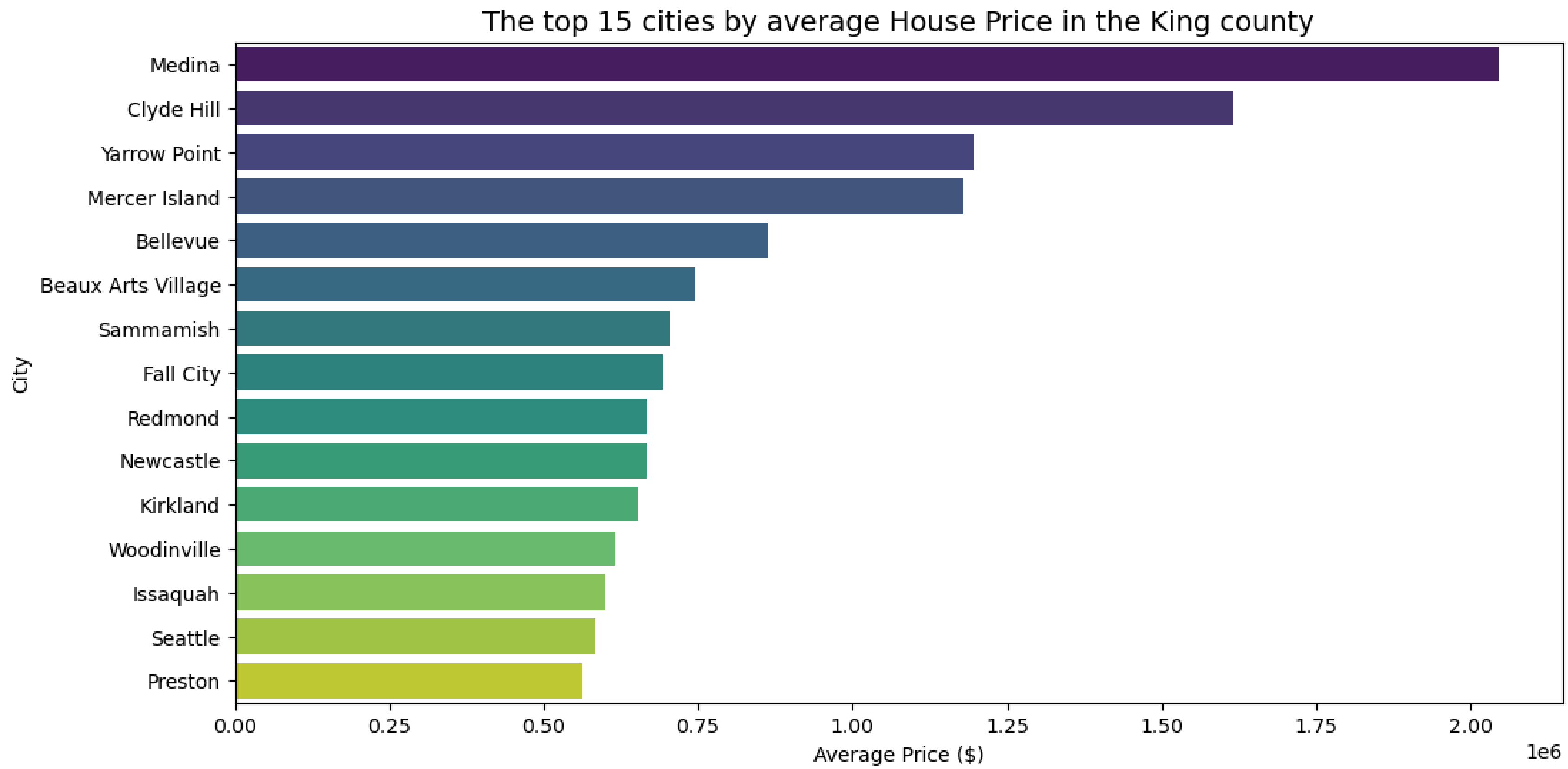


In [17]:
```
plt.figure(figsize=(12,6))
sns.violinplot(x='view', y='price', data=df, palette=['red','green', 'orange', 'purple'])
plt.title('Price Distribution by View')
plt.show()
```

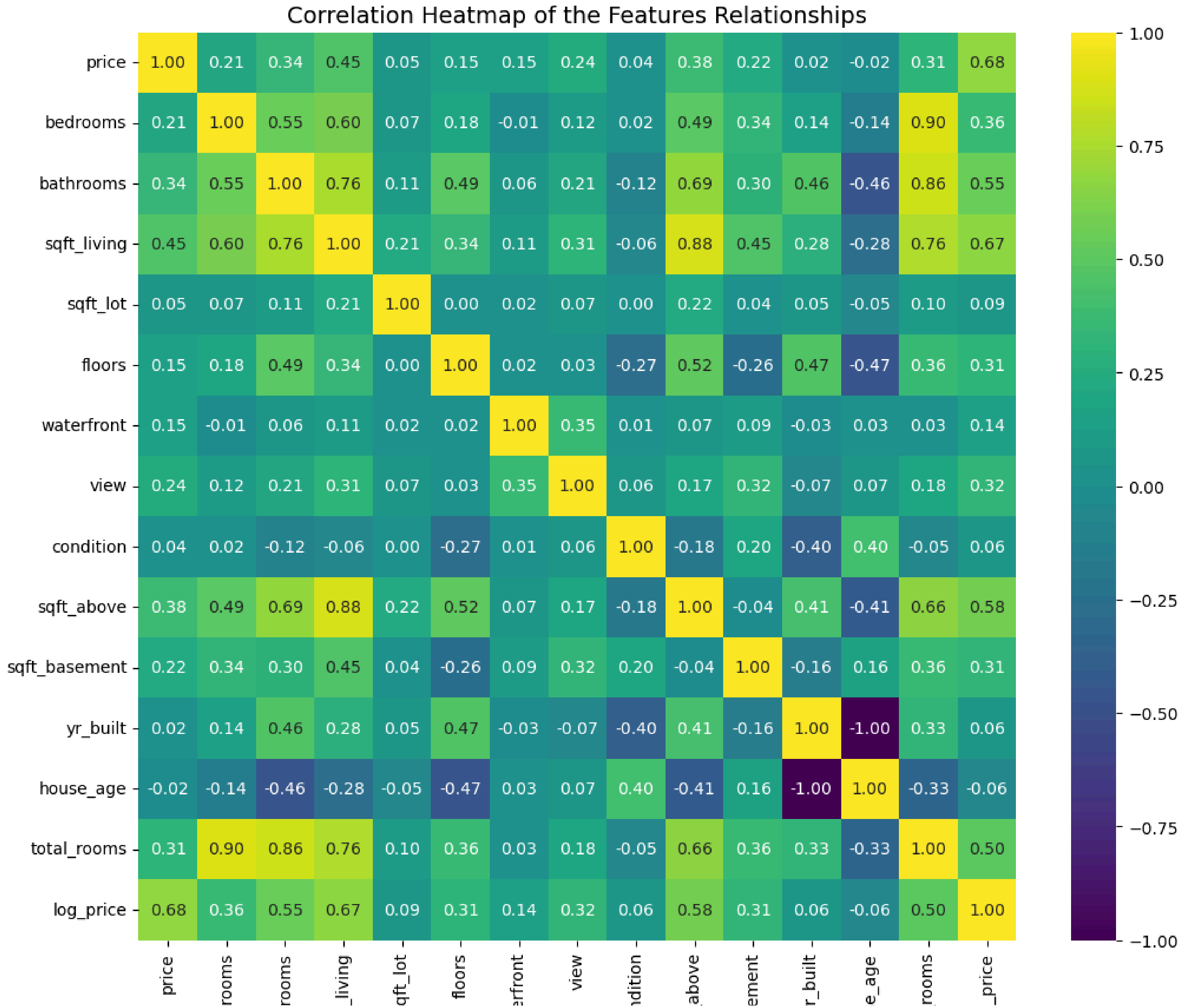


In [18]:

```
plt.figure(figsize=(12,6))
city_avg = df.groupby('city')['price'].mean().sort_values(ascending=False).head(15)
sns.barplot(x=city_avg.values, y=city_avg.index, palette='viridis')
plt.title('The top 15 cities by average House Price in the King county', fontsize=14)
plt.xlabel('Average Price ($)')
plt.ylabel('City')
plt.show()
```



In [19]:
```
#  Correlation Heatmap
plt.figure(figsize=(12,10))
corr = df.corr(numeric_only=True)
sns.heatmap(corr, annot=True, fmt=".2f", cmap="viridis", center=0)
plt.title("Correlation Heatmap of the Features Relationships", fontsize=14)
plt.show()
 # correlation with log_price
corr_Matrix = corr['log_price'].sort_values(ascending=False)
print("correlations with log_price:\n")
print(corr_Matrix)
```


Correlation Heatmap of the Features Relationships
price
bedrooms
bathrooms
sqft_living
sqft_lot
floors
waterfront
view
condition
sqft_above
sqft_basement
yr_built
house_age
total_rooms
log_price
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00


```
correlations with log_price:

log_price        1.000000
price            0.677508
sqft_living      0.671307
sqft_above       0.582012
bathrooms        0.548583
total_rooms      0.504984
bedrooms         0.355346
view             0.324040
sqft_basement    0.312636
floors           0.305319
waterfront       0.141863
sqft_lot         0.085856
condition        0.059256
yr_built         0.059101
house_age       -0.059101
Name: log_price, dtype: float64
```

Model Pipeline Code

In [20]:

```python
# Drop target leakage columns
X = df.drop(columns=['price', 'log_price'], axis=1)
y = df['log_price']
 # Identify categorical & numerical columns
cat_cols = X.select_dtypes(include=['object']).columns.tolist()
num_cols = X.select_dtypes(exclude=['object']).columns.tolist()
 #  Preprocessing Pipeline
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), num_cols),
        ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'), cat_cols)
    ])
 # Split data
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
```

```
 )
 # : Define Models and Param Grids
models = {
    'Linear Regression': (LinearRegression(), {}),
    'Ridge Regression': (Ridge(), {'model__alpha': np.logspace(-3, 3, 10)}),
    'Lasso Regression': (Lasso(), {'model__alpha': np.logspace(-3, 3, 10)}),
    'ElasticNet': (ElasticNet(), {'model__alpha': np.logspace(-3, 3, 10), 'model__l1_ratio': np.linspace(0.1, 1, 10)
    }),
    'Decision Tree': (DecisionTreeRegressor(random_state=42), {
        'model__max_depth': [3, 5, 10, 20, None],
        'model__min_samples_split': [2, 5, 10],
        'model__min_samples_leaf': [1, 2, 5]
    }),
    'Random Forest': (RandomForestRegressor(random_state=42), {
        'model__n_estimators': [100, 200, 300],
        'model__max_depth': [5, 10, 20, None],
        'model__min_samples_split': [2, 5, 10],
        'model__min_samples_leaf': [1, 2, 5]
    }),
    'Gradient Boosting': (GradientBoostingRegressor(random_state=42), {
        'model__n_estimators': [100, 200, 300],
        'model__learning_rate': [0.01, 0.05, 0.1],
        'model__max_depth': [3, 5, 8]
    }),
    'KNN': (KNeighborsRegressor(), {
        'model__n_neighbors': [3, 5, 7, 9, 11],
        'model__weights': ['uniform', 'distance']
    }),
    'SVR': (SVR(), {
        'model__C': [0.1, 1, 10],
        'model__kernel': ['linear', 'rbf', 'poly'],
        'model__gamma': ['scale', 'auto']
    })
 }
 #  Train + Tune Each Model
results = []
for name, (model, params) in models.items():
    print(f"\n Training {name} ...")

    pipe = Pipeline(steps=[
        ('preprocessor', preprocessor),
        ('model', model)
```

```
    ])

    if params:  # Perform tuning
        search = RandomizedSearchCV(
            pipe,
            param_distributions=params,
            n_iter=10,
            scoring='r2',
            n_jobs=-1,
            cv=5,
            verbose=1,
            random_state=42
        )
        search.fit(X_train, y_train)
        best_model = search.best_estimator_
        print(f" Best params for {name}: {search.best_params_}")
    else:
        pipe.fit(X_train, y_train)
        best_model = pipe

    # Predictions
    y_pred = best_model.predict(X_test)

    # Metrics
    mae = mean_absolute_error(y_test, y_pred)
    mse = mean_squared_error(y_test, y_pred)
    rmse = np.sqrt(mse)
    r2 = r2_score(y_test, y_pred)

    results.append({
        'Model': name,
        'MAE': mae * 100,
        'MSE': mse * 100,
        'RMSE': rmse * 100,
        'R2 Score': r2 * 100
    })
#  Summarize Results
results_df = pd.DataFrame(results).sort_values(by='R2 Score', ascending=False)
print("\n Model Performance Summary (in %):")
print(results_df)
```

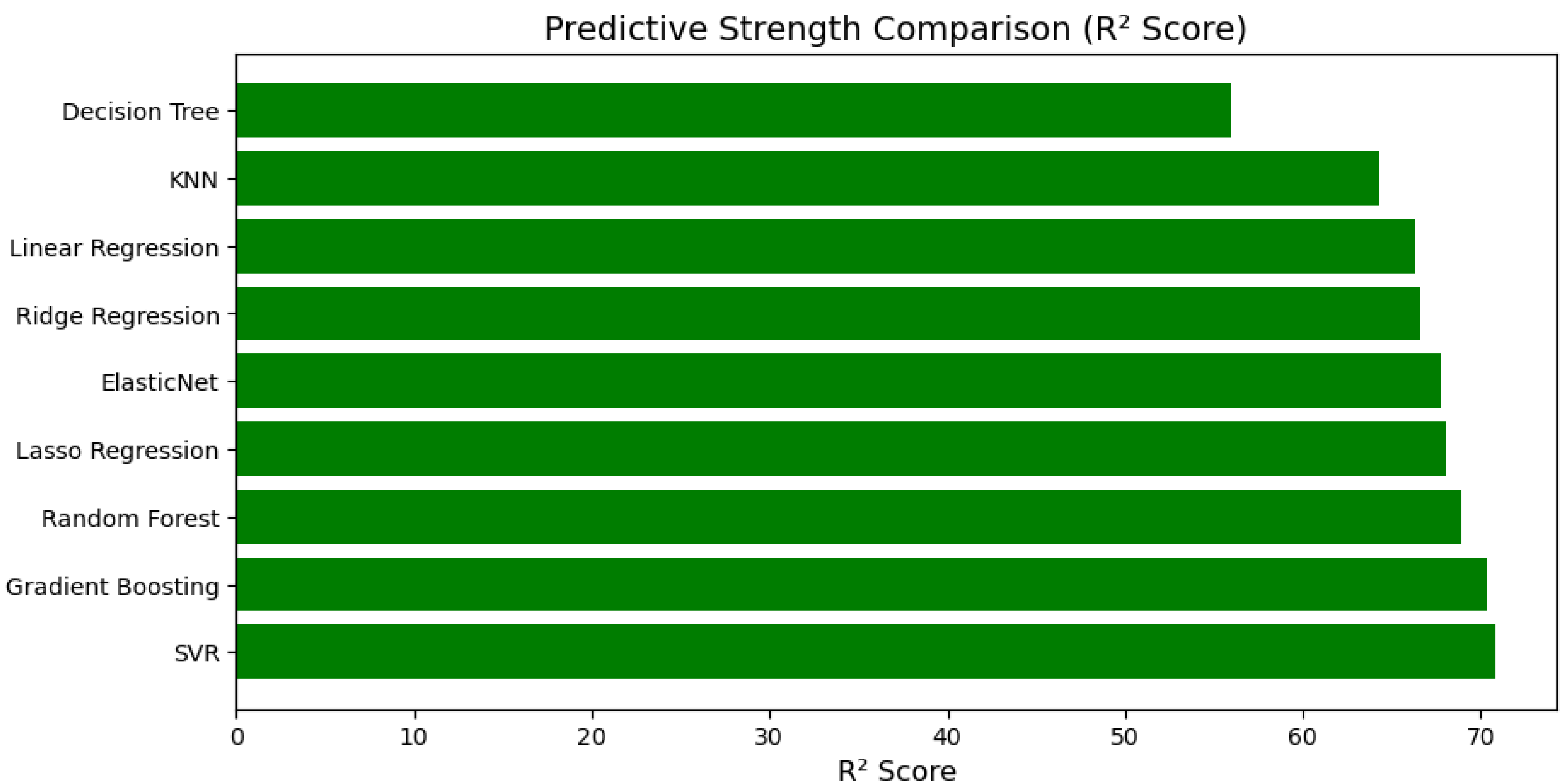
```
 Training Linear Regression ...

 Training Ridge Regression ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for Ridge Regression: {'model__alpha': 0.1}

 Training Lasso Regression ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for Lasso Regression: {'model__alpha': 0.001}

 Training ElasticNet ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for ElasticNet: {'model__l1_ratio': 0.1, 'model__alpha': 0.001}

 Training Decision Tree ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for Decision Tree: {'model__min_samples_split': 5, 'model__min_samples_leaf': 5, 'model__max_depth': 10}

 Training Random Forest ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for Random Forest: {'model__n_estimators': 300, 'model__min_samples_split': 10, 'model__min_samples_lea
f': 1, 'model__max_depth': 20}

 Training Gradient Boosting ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for Gradient Boosting: {'model__n_estimators': 200, 'model__max_depth': 5, 'model__learning_rate': 0.05}

 Training KNN ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for KNN: {'model__weights': 'distance', 'model__n_neighbors': 9}

 Training SVR ...
Fitting 5 folds for each of 10 candidates, totalling 50 fits
 Best params for SVR: {'model__kernel': 'rbf', 'model__gamma': 'auto', 'model__C': 10}

 Model Performance Summary (in %):
              Model        MAE        MSE       RMSE   R2 Score
8               SVR  18.425482   8.559043  29.255842  70.780656
6  Gradient Boosting  19.371914   8.689276  29.477577  70.336059
5      Random Forest  20.270355   9.113961  30.189337  68.886245
2   Lasso Regression  20.014257   9.368372  30.607797  68.017721
3         ElasticNet  19.761295   9.431787  30.711215  67.801231
```

```
1   Ridge Regression  19.861531   9.796747  31.299755  66.555312
0  Linear Regression  19.871851   9.862520  31.404649  66.330771
7                KNN  22.608534  10.456293  32.336191  64.303716
4      Decision Tree  25.671627  12.896608  35.911847  55.972831
```

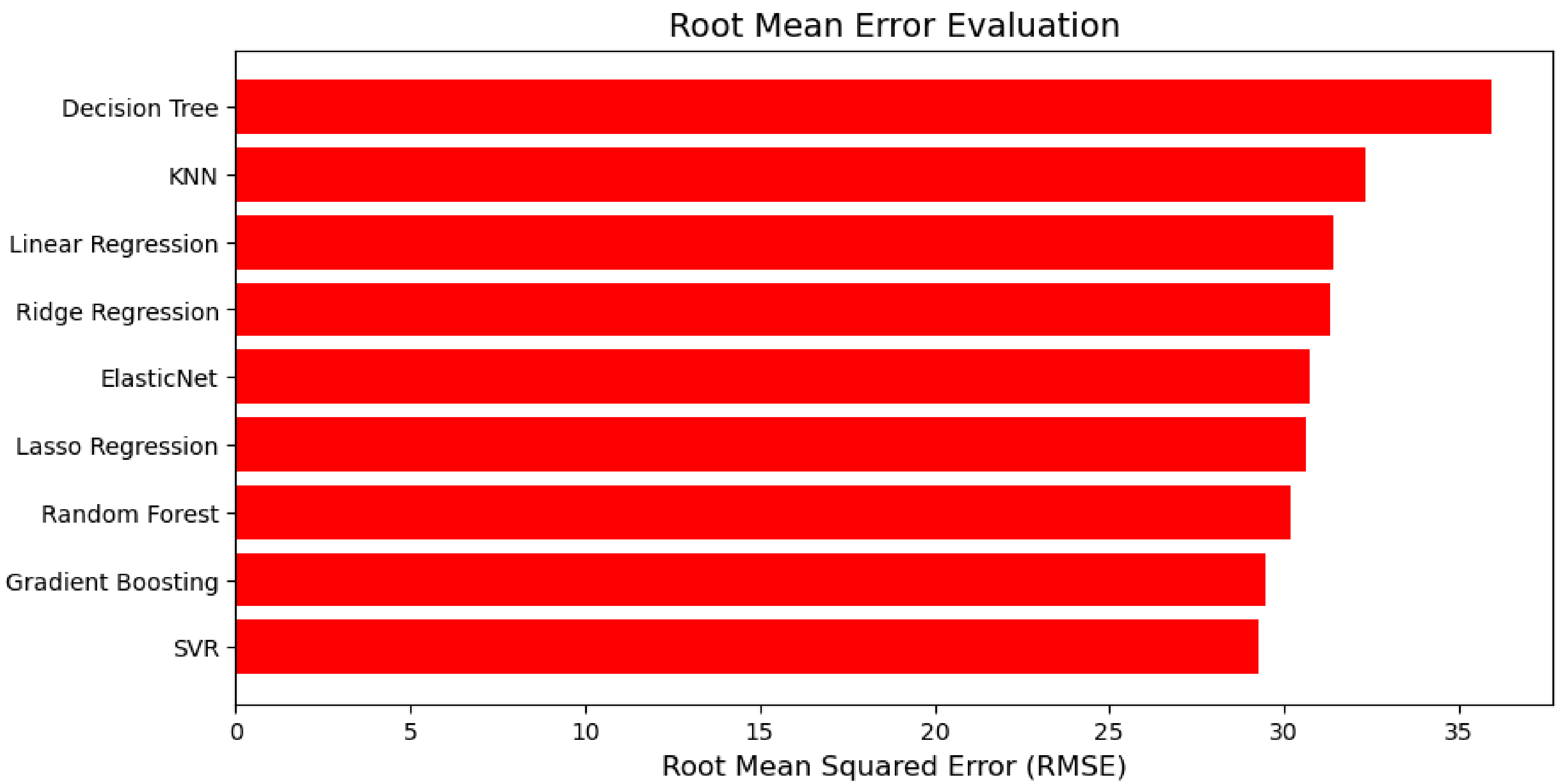
Visualizing Model Comparison

In [21]:

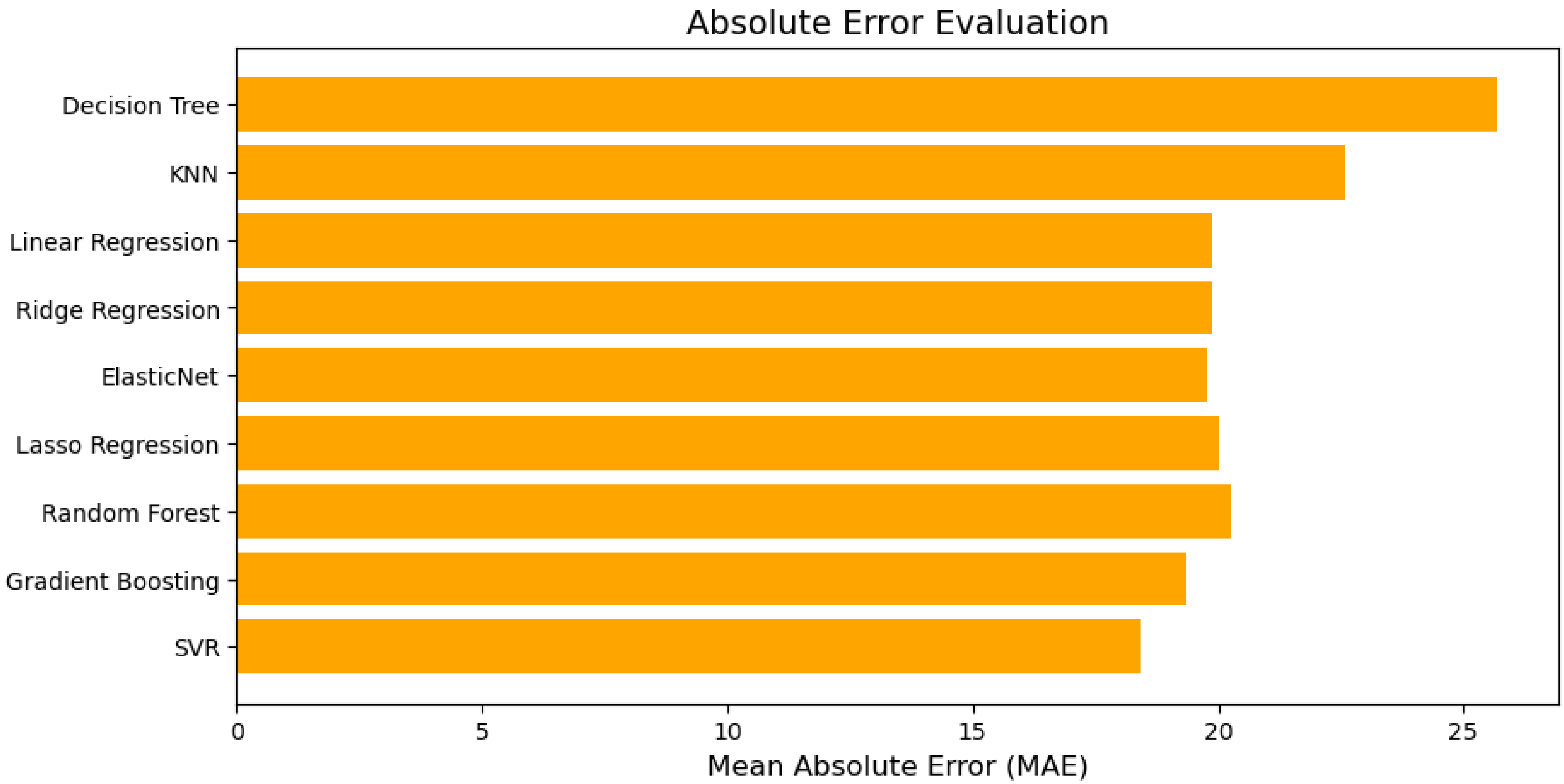
```
plt.figure(figsize=(10, 5))
plt.barh(results_df['Model'], results_df['R2 Score'], color='green')
plt.xlabel('R² Score', fontsize=12)
plt.title('Predictive Strength Comparison (R² Score)', fontsize=14)
plt.show()
```



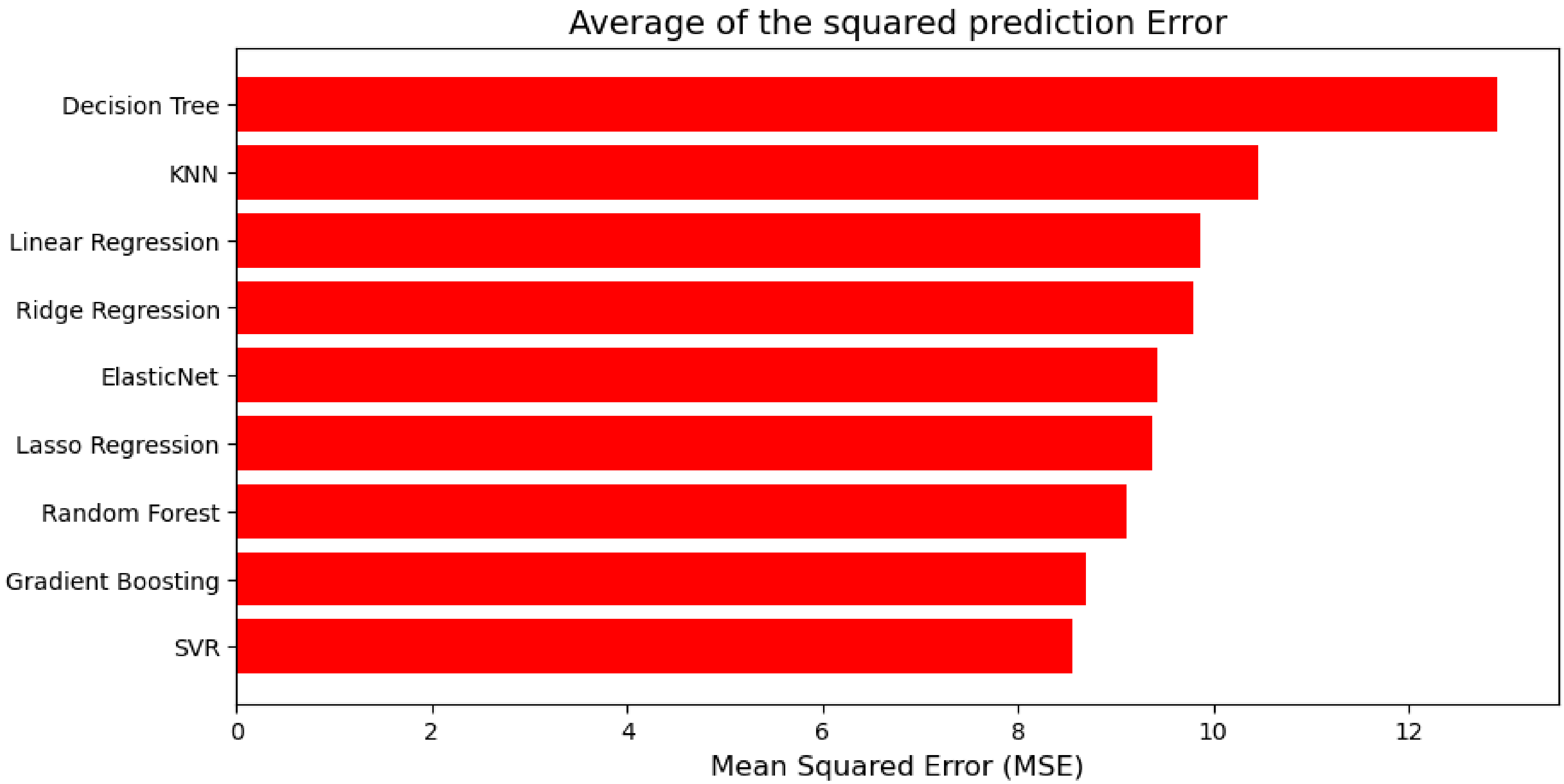
In [22]:
```
plt.figure(figsize=(10, 5))
plt.barh(results_df['Model'], results_df['RMSE'], color='red')
plt.xlabel('Root Mean Squared Error (RMSE)', fontsize=12)
plt.title('Root Mean Error Evaluation', fontsize=14)
plt.show()
```



In [23]:
```
plt.figure(figsize=(10, 5))
plt.barh(results_df['Model'], results_df['MAE'], color='orange')
plt.xlabel('Mean Absolute Error (MAE)', fontsize=12)
plt.title('Absolute Error Evaluation', fontsize=14)
plt.show()
```



In [24]:
```
plt.figure(figsize=(10, 5))
plt.barh(results_df['Model'], results_df['MSE'], color='red')
plt.xlabel('Mean Squared Error (MSE)', fontsize=12)
plt.title('Average of the squared prediction Error', fontsize=14)
plt.show()
```


Average of the squared prediction Error
Decision Tree
KNN
Linear Regression
Ridge Regression
ElasticNet
Lasso Regression
Random Forest
Gradient Boosting
SVR
0
2
4
6
8
10
12
Mean Squared Error (MSE)