Notebook for Data Science Final Project: Trying to make a model to predict the rating of a video game in the steam dataset

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In [ ]:
```
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.svm import SVR
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn import metrics
```

Load Dataset / Adjust Features

In [ ]:
```
# sometimes steam.csv works, other times it is /steam.csv
df = pd.read_csv("steam.csv")
```

In [ ]:
```
# Creating a release_month column taking the month value from the release_date column.
df['release_month'] = pd.DatetimeIndex(df['release_date']).month
```

In [ ]:
```
# this would be our output/ response variable
df["rating"] = df["positive_ratings"] / (df["positive_ratings"] + df["negative_ratings"]) * 100
```

For the sake of this analysis, we will be removing some features that we don't want to use for our analysis. We also need to change the datatypes for some of the features.

In [ ]:
```
# For developer and publisher, there are too many unique values to make it a u
sable categorical variable ~15k each
# I think we would have to categorize each game developer as small/medium/larg
e or something but that would take a lot of work
df = df.drop('appid', 1)
df = df.drop('release_date', 1)
df = df.drop('developer', 1)
df = df.drop('publisher', 1)
df = df[df.owners != '0-20000']
df.reset_index(inplace=True,drop=True)
```

In [ ]:
```
# converting relevant columns to categorical variables
df["owners"] = df["owners"].astype('category')
df["required_age"] = df["required_age"].astype('category')
df["categories"] = df["categories"].astype('category')
df["genres"] = df["genres"].astype('category')
df["steamspy_tags"] = df["steamspy_tags"].astype('category') # there does seem
to be overlap between this column and genres
df["platforms"] = df["platforms"].astype('category')
df["release_month"] = df["release_month"].astype('category')
df["english"] = df["english"].astype('category')
```

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8479 entries, 0 to 8478
Data columns (total 16 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   name              8479 non-null   object
 1   english           8479 non-null   category
 2   platforms         8479 non-null   category
 3   required_age      8479 non-null   category
 4   categories        8479 non-null   category
 5   genres            8479 non-null   category
 6   steamspy_tags     8479 non-null   category
 7   achievements      8479 non-null   int64
 8   positive_ratings  8479 non-null   int64
 9   negative_ratings  8479 non-null   int64
 10  average_playtime  8479 non-null   int64
 11  median_playtime   8479 non-null   int64
 12  owners            8479 non-null   category
 13  price             8479 non-null   float64
 14  release_month     8479 non-null   category
 15  rating            8479 non-null   float64
dtypes: category(8), float64(2), int64(5), object(1)
memory usage: 955.2+ KB
```

using p-value of 0.01

Linear Regression Tests

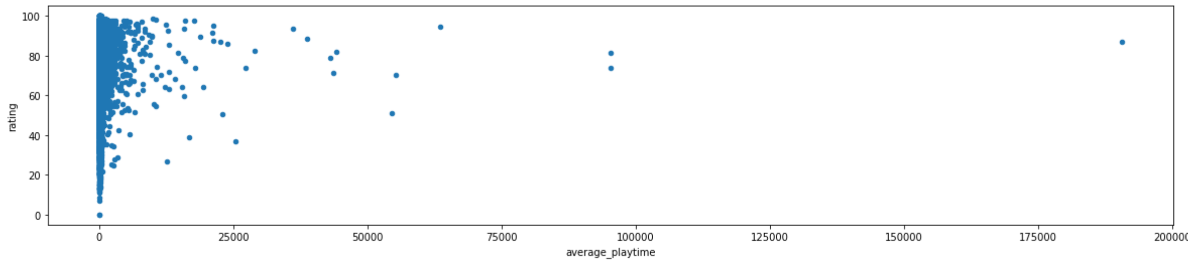
Variable Name	p-value	pearson	statistically significant
average_playtime	0.00073	0.036	yes
median_playtime	0.04	0.022	no
price	1.45e-45	0.15	yes
achievements	0.018	-0.026	yes

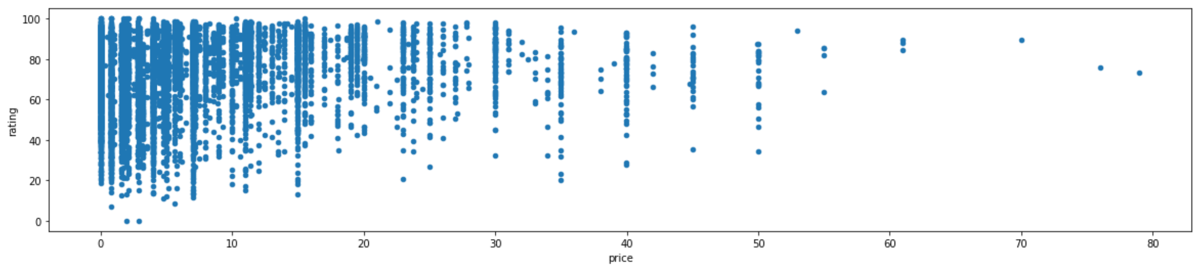
In [ ]:

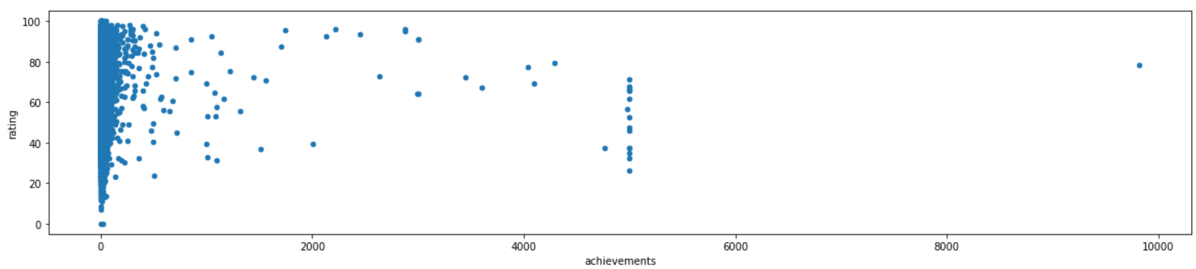
```
headers = ["average_playtime", "median_playtime", "price", "achievements"]

for name in headers:
    _, _, _, p, _ = stats.linregress(df["rating"], df[name])
    r, _ = stats.pearsonr(df["rating"], df[name])
    print(name, "versus rating: p-value =", p, "\npearson correlation coeffici
ent =", r, "\n")
```

```
average_playtime versus rating: p-value = 0.0007377162599912958
pearson correlation coefficient = 0.03664719505209066

median_playtime versus rating: p-value = 0.039691263231792596
pearson correlation coefficient = 0.02233884729939114

price versus rating: p-value = 1.5625976957597286e-45
pearson correlation coefficient = 0.15292149182807477

achievements versus rating: p-value = 0.01817846203729662
pearson correlation coefficient = -0.025650352052030274
```

In [ ]:
```python
# Plotting scatter plots of the predictive numerical variables
df.plot.scatter(x='average_playtime', y='rating', figsize=(20,4))
df.plot.scatter(x='price', y='rating', figsize=(20,4));
df.plot.scatter(x='achievements', y='rating', figsize=(20,4));
```







using p-value of 0.01

Kruskal-Wallis Tests

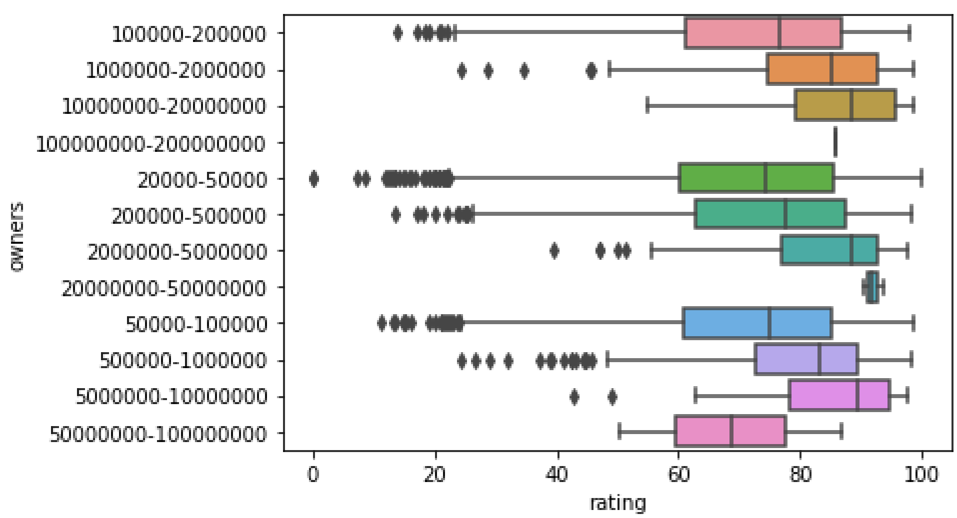
Variable Name	p-value	statistically significant
required age	.006	yes
owners	1.44e-62	yes
platforms	3.43e-81	yes
release_month	0.036	yes
english	.29	no

In [ ]:
```
headers = ["required_age", "owners", "platforms", "release_month", "english"]

for name in headers:
    samples_by_group = []
    for value in set(df[name]):
        mask = df[name] == value
        samples_by_group.append(df["rating"][mask])
    stat, p = stats.kruskal(*samples_by_group)
    print(name, "versus rating: p-value =", p)
```

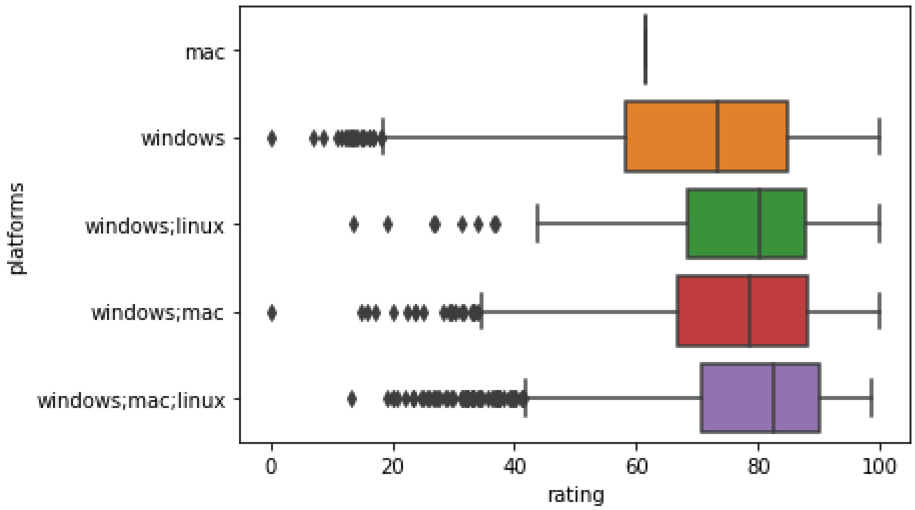
```
required_age versus rating: p-value = 0.006196189364389729
owners versus rating: p-value = 1.4453473612126944e-62
platforms versus rating: p-value = 3.423304406077233e-81
release_month versus rating: p-value = 0.03622843060491119
english versus rating: p-value = 0.2926425829733527
```

Graphical Testing

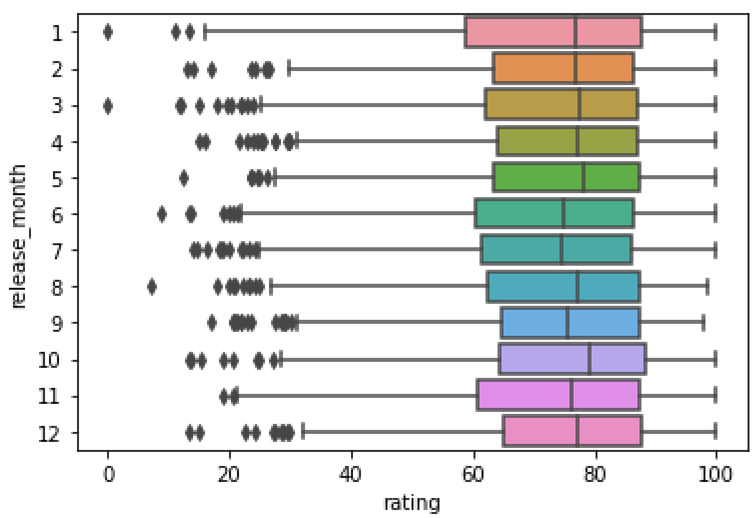
In [ ]:
```
# Plotting boxplots of the predictive categorical variables
sns.boxplot(x='rating', y='owners', data=df);
```



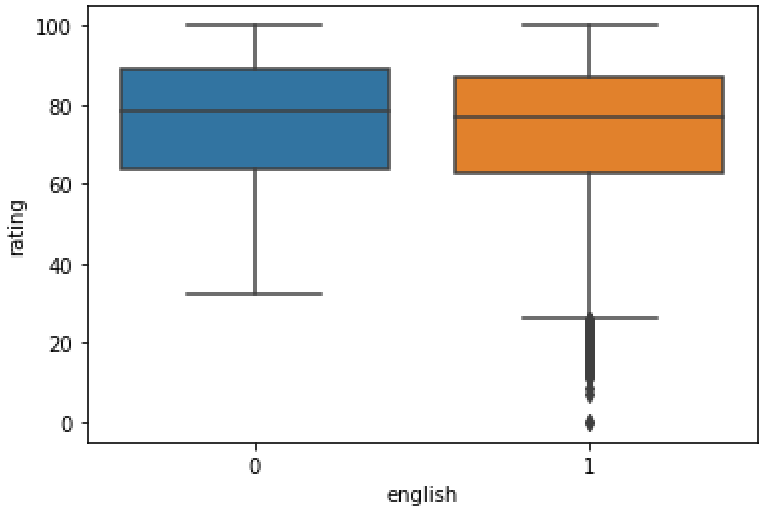
In [ ]:
```
sns.boxplot(x='rating', y='platforms', data=df);
```



In [ ]:
```
# Based off the boxplot, I would say month really isn't that predictive even t
ho it had a stat. sig. p-value
sns.boxplot(x='rating', y='release_month', data=df);
```



In [ ]:
```
sns.boxplot(x='english', y='rating', data=df);
```



One Hot Encode Features

Attempt to deal with the categorical variables with a one hot encoded matrix is below.

In [ ]:
```
def oneHotEncodedDfFromNumberSeries(name, prefix):
  return pd.get_dummies(df[name], prefix=prefix)

# takes series with values like Action;Adventure;Horror and makes a one hot en
coded df with columns Action, Adventure, and Horror
def oneHotEncodedDfFromStringSeries(name, prefix):
  # split on ; and get dummies from resulting matrix
  new_df = pd.get_dummies(df[name].str.split(';', expand=True), prefix=prefix)
  # above results in duplicated column names create set of expected column nam
es
  column_names = list(set(new_df.columns))
  # group by expected columns names
  new_df = new_df.groupby(column_names, level=0, axis=1).max()
  return new_df
```

In [ ]:

```python
# Takes the feature name, iterates through column and extracts unique values
def oneHotEncodingSplit(name):
    # Create set to avoid having duplicate values
    features = set([])

    # Iterate through feature
    for x in range(len(df[name])):
        # Add the values found from spliting the string to features
        features.update(df[name][x].split(';'))
    return list(features)

# Will one hot encode a feature
def oneHotEncodingAggegate(name):
    # Get unique list of features from the feature column
    features = oneHotEncodingSplit(name)
    # Create empty 2d array to hold our one hot encoding
    features_values = np.zeros((len(df[name]), len(features)), dtype=int)

    # Iterate through full feature and update rows in features_values
    for x in range(len(df[name])):
        # Split values from feature
        vals = df[name][x].split(';')

        # Add values to features_values
        for v in range(len(vals)):
            col = features.index(vals[v])
            features_values[x][col] = 1

    # Adjust name and add to features
    name += ":"
    features = [name + feature for feature in features]

    # Add data and columns to dataframe
    new_df = pd.DataFrame(data=features_values, columns=features)
    return new_df
```

In [ ]:
```
genre_df = oneHotEncodingAggegate("genres")
cat_df = oneHotEncodingAggegate("categories")
owner_df = oneHotEncodedDfFromStringSeries("owners", "owner")
age_df = oneHotEncodedDfFromNumberSeries("required_age", "age")
tag_df = oneHotEncodingAggegate("steamspy_tags")
platform_df = oneHotEncodingAggegate("platforms")

# will want to add positive/neg ratings, price, etc.
new_df = pd.concat([genre_df, cat_df, owner_df, age_df, tag_df], axis=1)
new_df
```

Out[ ]:

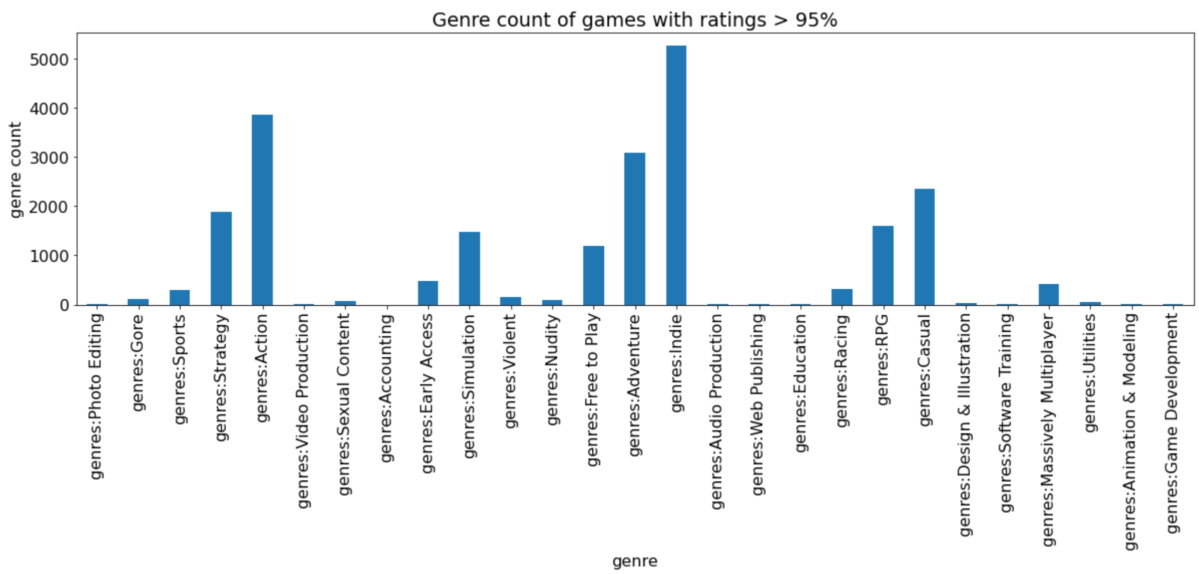
	genres:Photo Editing	genres:Gore	genres:Sports	genres:Strategy	genres:Action	genres:Video Production	g
0	0	0	0	0	1	0	
1	0	0	0	0	1	0	
2	0	0	0	0	1	0	
3	0	0	0	0	1	0	
4	0	0	0	0	1	0	
...	...	...	...	...	...	...	
8474	0	0	0	0	1	0	
8475	0	0	0	1	1	0	
8476	0	0	0	0	0	0	
8477	0	0	0	0	1	0	
8478	0	0	0	1	0	0	

8479 rows × 380 columns

Visualization to help understand dataset and highly rated games

In [ ]:
```python
# print out most popular genres for games with rating > 95%
mask = df['rating'] > .95
popular_genre_count = genre_df[mask].sum()
plt.rcParams.update({'font.size': 16})
plt.figure(figsize=(20,5))
plt.xlabel('genre')
plt.ylabel('genre count')
plt.title('Genre count of games with ratings > 95%')
popular_genre_count.plot(kind='bar')
```

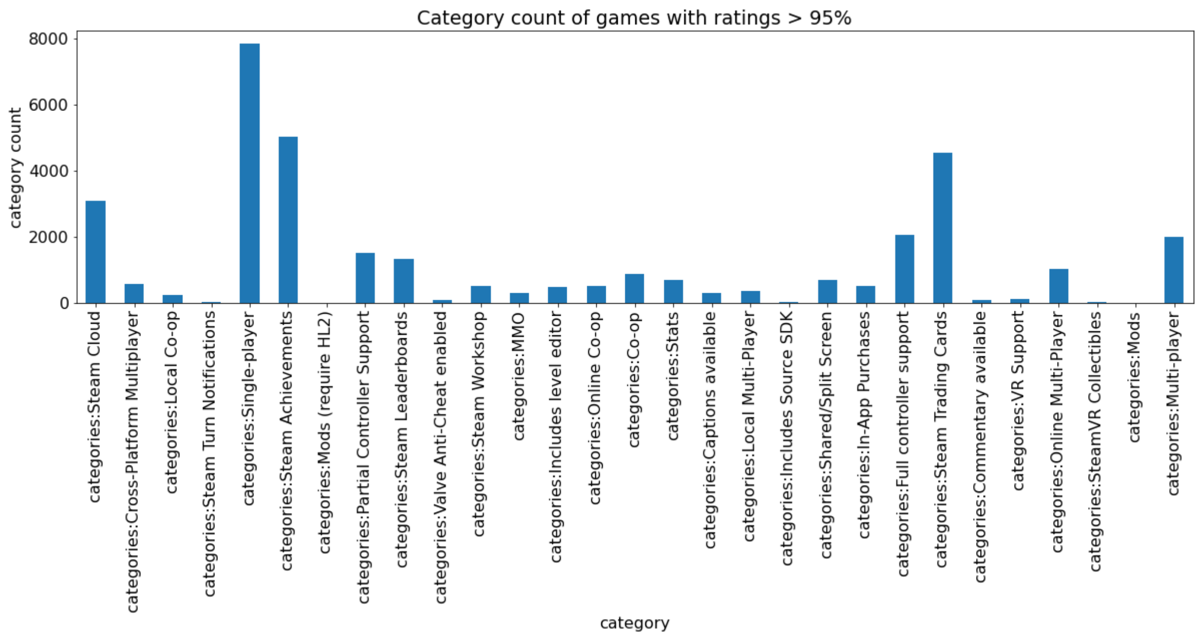
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc10297b4a8>



Statistic

```
In [ ]: # print out most popular genres for games with rating > 95%
mask = df['rating'] > .95
popular_cat_count = cat_df[mask].sum()
plt.rcParams.update({'font.size': 16})
plt.figure(figsize=(20,5))
plt.xlabel('category')
plt.ylabel('category count')
plt.title('Category count of games with ratings > 95%')
popular_cat_count.plot(kind='bar')
```

```
Out[ ]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc1015857b8>
```



using p-value of 0.01

Kruskal-Wallis Tests for platforms

Variable Name	p-value	pearson	statistically significant
platforms:mac	4.02e-73	0.195	yes
platforms:linux	1.74e-67	0.18	yes
platforms:windows	.362	-0.007	no

In [ ]:

```
stat_df = pd.concat([df, platform_df], axis=1)
headers = ["platforms:mac", "platforms:linux", "platforms:windows"]

for name in headers:
    samples_by_group = []
    for value in set(stat_df[name]):
        mask = stat_df[name] == value
        samples_by_group.append(df["rating"][mask])
    stat, p = stats.kruskal(*samples_by_group)
    r, _ = stats.pearsonr(df["rating"], platform_df[name])
    print(name, "versus rating: p-value =", p, "\npearson: ", r)
```

```
platforms:mac versus rating: p-value = 4.0209896511727516e-73
pearson:  0.19578234276346462
platforms:linux versus rating: p-value = 1.7442968945923128e-67
pearson:  0.1807311188054108
platforms:windows versus rating: p-value = 0.3618290561071478
pearson:  0.007114600318711102
```

using p-value of 0.01

Genres Kruskal-Wallis Tests - Only putting in statistically sig genre features

Variable Name	p-value	pearson	statistically significant
genres:Violent	.00079	-0.033	yes
genres:Simulation	9.9e-.08	-0.06	yes
genres:Strategy	2.06e-.07	-0.04	yes
genres:Racing	8.51e-05	-0.041	yes
genres:Gore	0.001	-0.37	yes
genres:Indie	.0002	0.037	yes
genres:Sports	.003	-0.03	yes
genres:Massively Multiplayer	7.04e-43	-0.125	yes
genres:Free to Play	5.95e-14	-0.66	yes

In [ ]:

```
stat_df = pd.concat([df, genre_df], axis=1)
headers = genre_df.columns

for name in headers:
    samples_by_group = []
    for value in set(stat_df[name]):
        mask = stat_df[name] == value
        samples_by_group.append(df["rating"][mask])
    stat, p = stats.kruskal(*samples_by_group)
    r, _ = stats.pearsonr(df["rating"], genre_df[name])
    print(name, "versus rating: p-value =", p, "\npearson: ", r)
```

```
genres:Photo Editing versus rating: p-value = 0.1344361752449218
pearson:  -0.012219759617410661
genres:Gore versus rating: p-value = 0.001168953820943914
pearson:  -0.03790714674885067
genres:Sports versus rating: p-value = 0.0030753163621015755
pearson:  -0.02633962370111069
genres:Strategy versus rating: p-value = 2.061917867187756e-07
pearson:  -0.03998742939091457
genres:Action versus rating: p-value = 0.003051268195935146
pearson:  -0.034115112363700434
genres:Video Production versus rating: p-value = 0.2409848362422249
pearson:  0.014166267842428013
genres:Sexual Content versus rating: p-value = 0.0031057333570609297
pearson:  0.035336389761007926
genres:Accounting versus rating: p-value = 0.8357447037613519
pearson:  0.0004955369109837277
genres:Early Access versus rating: p-value = 2.487096539888663e-05
pearson:  -0.0402936161073502
genres:Simulation versus rating: p-value = 9.900199114359023e-08
pearson:  -0.05727312536584341
genres:Violent versus rating: p-value = 0.0007945820879161177
pearson:  -0.03374049883740143
genres:Nudity versus rating: p-value = 0.0713768246519459
pearson:  0.01965366007852036
genres:Free to Play versus rating: p-value = 5.950699991841683e-14
pearson:  -0.06566483372423017
genres:Adventure versus rating: p-value = 0.03423207424106657
pearson:  0.025360323105106324
genres:Indie versus rating: p-value = 0.00022356967888899254
pearson:  0.037046801279844756
genres:Audio Production versus rating: p-value = 0.3951334841023586
pearson:  0.010165976970030511
genres:Web Publishing versus rating: p-value = 0.07096651149886643
pearson:  0.018425349634873488
genres:Education versus rating: p-value = 0.8185415268460773
pearson:  0.00637146344222202
genres:Racing versus rating: p-value = 8.514545922632313e-05
pearson:  -0.04100936018813073
genres:RPG versus rating: p-value = 0.454853507265622
pearson:  0.005864231961952609
genres:Casual versus rating: p-value = 0.06274975231610422
pearson:  -0.027597624760392455
genres:Design & Illustration versus rating: p-value = 0.10674996783998172
pearson:  0.019880452711208335
genres:Software Training versus rating: p-value = 0.6428848950010861
pearson:  0.009584601283881633
genres:Massively Multiplayer versus rating: p-value = 7.045082399025699e-43
pearson:  -0.1258310258456193
genres:Utilities versus rating: p-value = 0.5093510396064032
pearson:  0.01142538965940595
genres:Animation & Modeling versus rating: p-value = 0.10014043652283929
pearson:  0.019619321184117515
genres:Game Development versus rating: p-value = 0.33568441831061885
pearson:  -0.008196857869839376
```

using p-value of 0.01

Category Kruskal-Wallis Tests - Only putting in statistically sig category features

Variable Name	p-value	pearson	statistically significant
categories:In-App Purchases	3.68e-39	-.117	yes
categories:SteamVR Collectibles	4.04e-06	.045	yes
categories:Single-player	7.00e-30	.108	yes
categories:Steam Workshop	1.64e-22	.104	yes
categories:Includes level editor	6.35e-15	.081	yes
categories:Full controller support	4.32e-55	.168	yes
categories:Multi-player	9.37e-10	-.043	yes
categories:Captions available	2.26e-08	.058	yes
categories:Shared/Split Screen	3.65e-08	.058	yes
categories:Steam Leaderboards	6.37e-22	.114	yes
categories:Local Multi-Player	1.22e-05	.044	yes
categories:Steam Cloud	8.70e-108	.236	yes
categories:Local Co-op	8.96e-12	.069	yes
categories:Steam Achievements	2.03e-55	.181	yes
categories:MMO	6.83e-35	-.111	yes
categories:Online Multi-Player	8.54e-12	-.048	yes

In [ ]:

```
stat_df = pd.concat([df, cat_df], axis=1)
headers = cat_df.columns

for name in headers:
    samples_by_group = []
    for value in set(stat_df[name]):
        mask = stat_df[name] == value
        samples_by_group.append(df["rating"][mask])
    stat, p = stats.kruskal(*samples_by_group)
    r, _ = stats.pearsonr(df["rating"], cat_df[name])
    print(name, "versus rating: p-value =", p, "\npearson: ", r)
```

```
categories:Steam Cloud versus rating: p-value = 8.69811656379754e-108
pearson:  0.23593000346471402
categories:Cross-Platform Multiplayer versus rating: p-value = 0.061548581537
68373
pearson:  -0.0028724723950129746
categories:Local Co-op versus rating: p-value = 8.961094687725238e-12
pearson:  0.06917960025977163
categories:Steam Turn Notifications versus rating: p-value = 0.94031747317660
56
pearson:  0.007238240079729603
categories:Single-player versus rating: p-value = 6.999625025669635e-30
pearson:  0.10812286660950102
categories:Steam Achievements versus rating: p-value = 2.0324323370268004e-55
pearson:  0.18067096429853804
categories:Mods (require HL2) versus rating: p-value = 0.4865778832419174
pearson:  0.007444645023252949
categories:Partial Controller Support versus rating: p-value = 0.377922489346
026
pearson:  0.00041110186826776626
categories:Steam Leaderboards versus rating: p-value = 6.374488132303549e-22
pearson:  0.11415335050295485
categories:Valve Anti-Cheat enabled versus rating: p-value = 0.00175736905512
44143
pearson:  0.03653941321254239
categories:Steam Workshop versus rating: p-value = 1.638123447201571e-22
pearson:  0.10355232715151418
categories:MMO versus rating: p-value = 6.826798487903196e-35
pearson:  -0.11151980954783823
categories:Includes level editor versus rating: p-value = 6.353928181021331e-
15
pearson:  0.08080829030489915
categories:Online Co-op versus rating: p-value = 0.010909238232710184
pearson:  -0.011879852263008887
categories:Co-op versus rating: p-value = 0.7166189607449914
pearson:  0.009014804420847051
categories:Stats versus rating: p-value = 0.0042826420331625046
pearson:  0.03929231693710654
categories:Captions available versus rating: p-value = 2.2550632304321805e-08
pearson:  0.058276187238491546
categories:Local Multi-Player versus rating: p-value = 1.2186379407169724e-05
pearson:  0.044287522711502866
categories:Includes Source SDK versus rating: p-value = 0.0007919539219208952
pearson:  0.031382228827039345
categories:Shared/Split Screen versus rating: p-value = 3.6462659598028615e-0
8
pearson:  0.05813542271057235
categories:In-App Purchases versus rating: p-value = 3.6841765258722303e-39
pearson:  -0.11665496931636997
categories:Full controller support versus rating: p-value = 4.315190130816179
5e-51
pearson:  0.16774271283934342
categories:Steam Trading Cards versus rating: p-value = 0.025135897239139504
pearson:  0.036914571679709989
categories:Commentary available versus rating: p-value = 0.027741548093113615
pearson:  0.02041999647669771
categories:VR Support versus rating: p-value = 0.005222124877072341
pearson:  0.03338204730342055
```

```
categories:Online Multi-Player versus rating: p-value = 8.535304604827194e-12
pearson:  -0.0483267489134999
categories:SteamVR Collectibles versus rating: p-value = 4.037988612986182e-0
6
pearson:  0.04516409588988091
categories:Mods versus rating: p-value = 0.27901661224146596
pearson:  0.011234671126443089
categories:Multi-player versus rating: p-value = 9.367568979960334e-10
pearson:  -0.04308861455000433
```

Tags statistical testing (too many tags for a table)

In [ ]:
```
stat_df = pd.concat([df, tag_df], axis=1)
headers = tag_df.columns

for name in headers:
    samples_by_group = []
    for value in set(stat_df[name]):
        mask = stat_df[name] == value
        samples_by_group.append(df["rating"][mask])
    stat, p = stats.kruskal(*samples_by_group)
    r, _ = stats.pearsonr(df["rating"], tag_df[name])
    if p < 0.01:
      print(name, "versus rating: p-value =", p, "\npearson: ", r) # Printed o
ut only the ones with stat sig values below
```

```
steamspy_tags:Action versus rating: p-value = 3.01021737476843e-19
pearson:  -0.0967626972714711
steamspy_tags:Adventure versus rating: p-value = 0.0002237883867324203
pearson:  -0.03702907855082436
steamspy_tags:Story Rich versus rating: p-value = 3.9918394160324927e-19
pearson:  0.08563967380613872
steamspy_tags:Survival Horror versus rating: p-value = 0.0004246261940407429
pearson:  0.036767431944494014
steamspy_tags:Post-apocalyptic versus rating: p-value = 0.009598144678803303
pearson:  0.03012905722936082
steamspy_tags:MMORPG versus rating: p-value = 2.74384271766446e-05
pearson:  -0.04126677706473756
steamspy_tags:Co-op versus rating: p-value = 5.87895962828063e-07
pearson:  0.051342964749699044
steamspy_tags:Nudity versus rating: p-value = 1.74682438499845e-08
pearson:  0.056855784780179885
steamspy_tags:Difficult versus rating: p-value = 1.256623475815541e-08
pearson:  0.05460763034228783
steamspy_tags:1990's versus rating: p-value = 0.009696754180735952
pearson:  0.0226357290930128
steamspy_tags:Massively Multiplayer versus rating: p-value = 9.55317795288528
4e-30
pearson:  -0.112887566661916
steamspy_tags:Female Protagonist versus rating: p-value = 0.00138902547498718
84
pearson:  0.03684527461747291
steamspy_tags:Mature versus rating: p-value = 0.0018530890704517384
pearson:  0.029044838809718917
steamspy_tags:Comedy versus rating: p-value = 1.0381449645977591e-07
pearson:  0.049901908759630895
steamspy_tags:Choices Matter versus rating: p-value = 8.346015755671815e-06
pearson:  0.04274540158125618
steamspy_tags:Great Soundtrack versus rating: p-value = 2.7417229695417043e-1
9
pearson:  0.0821849496408339
steamspy_tags:Strategy versus rating: p-value = 8.544525770279422e-12
pearson:  -0.06021437800384908
steamspy_tags:Visual Novel versus rating: p-value = 2.192112376177077e-21
pearson:  0.09086787425211174
steamspy_tags:VR versus rating: p-value = 1.8939477726547595e-09
pearson:  0.0616154522301969
steamspy_tags:Simulation versus rating: p-value = 1.1231448093859661e-15
pearson:  -0.08480330343594553
steamspy_tags:Free to Play versus rating: p-value = 8.609864371229191e-11
pearson:  -0.05696057982543953
steamspy_tags:Indie versus rating: p-value = 4.538488208765161e-05
pearson:  -0.04793744501637714
steamspy_tags:Family Friendly versus rating: p-value = 0.0048583664971073885
pearson:  0.02725875030940781
steamspy_tags:Music versus rating: p-value = 0.0030530593816791886
pearson:  0.029708798581317898
steamspy_tags:Metroidvania versus rating: p-value = 9.982955817743577e-07
pearson:  0.047345545435955705
steamspy_tags:Puzzle versus rating: p-value = 1.224078963165509e-21
pearson:  0.09690881559007455
steamspy_tags:Anime versus rating: p-value = 7.10705017427464e-27
pearson:  0.10859270397676533
```

```
steamspy_tags:Naval versus rating: p-value = 0.005156128736626449
pearson:  -0.033703359392001996
steamspy_tags:Classic versus rating: p-value = 1.1548555171831486e-19
pearson:  0.089219541623527
steamspy_tags:Platformer versus rating: p-value = 3.6119653361141596e-08
pearson:  0.05525109834243486
steamspy_tags:Cute versus rating: p-value = 3.57292525555288e-07
pearson:  0.04730454524725297
steamspy_tags:Sexual Content versus rating: p-value = 1.800324474823319e-10
pearson:  0.06410148889801397
steamspy_tags:JRPG versus rating: p-value = 3.180168381615249e-05
pearson:  0.046055115083566814
steamspy_tags:Rogue-like versus rating: p-value = 0.0003036882911080384
pearson:  0.03440874114058343
steamspy_tags:Dating Sim versus rating: p-value = 1.058071162190582e-07
pearson:  0.04870307879802576
steamspy_tags:Local Co-Op versus rating: p-value = 0.007709155818639999
pearson:  0.02882616787492183
steamspy_tags:Racing versus rating: p-value = 8.431003217381011e-05
pearson:  -0.042454153996008374
steamspy_tags:Programming versus rating: p-value = 9.250556618500587e-05
pearson:  0.0353199150876965
steamspy_tags:Local Multiplayer versus rating: p-value = 1.0718000372725032e-
05
pearson:  0.04339369999884422
steamspy_tags:Minimalist versus rating: p-value = 0.0007268723422909912
pearson:  0.03036029874287719
steamspy_tags:Choose Your Own Adventure versus rating: p-value = 0.0063935676
57012509
pearson:  0.02726342042727639
steamspy_tags:Parkour versus rating: p-value = 0.003479706975924743
pearson:  0.030480582561938398
steamspy_tags:Trains versus rating: p-value = 0.009692500313091865
pearson:  -0.02252469227255903
steamspy_tags:Survival versus rating: p-value = 0.0086082989255685
pearson:  -0.021145074448116957
steamspy_tags:FMV versus rating: p-value = 0.003593525986456252
pearson:  0.028188077591988322
steamspy_tags:Point & Click versus rating: p-value = 2.2850136230362148e-07
pearson:  0.052734336579677854
steamspy_tags:First-Person versus rating: p-value = 0.0008625915724920402
pearson:  0.030161418809798873
steamspy_tags:Sports versus rating: p-value = 0.0009191788976703013
pearson:  -0.028818914346424734
steamspy_tags:Basketball versus rating: p-value = 0.003509326989372594
pearson:  -0.04201045407610871
steamspy_tags:Stealth versus rating: p-value = 0.005823493441872338
pearson:  0.030570339280724293
steamspy_tags:Pixel Graphics versus rating: p-value = 3.239408138183344e-11
pearson:  0.0656515595480245
steamspy_tags:Early Access versus rating: p-value = 2.487096539888663e-05
pearson:  -0.0402936161073502
steamspy_tags:Funny versus rating: p-value = 0.00020300548286633193
pearson:  0.03651133385951396
steamspy_tags:Atmospheric versus rating: p-value = 2.219611106130198e-10
pearson:  0.061946653568464904
steamspy_tags:3D Platformer versus rating: p-value = 0.000904468611547676
```

```
pearson:  0.031888115955143785
steamspy_tags:Relaxing versus rating: p-value = 0.007115452046279349
pearson:  0.02680479220608213
steamspy_tags:Base-Building versus rating: p-value = 0.005525151629527739
pearson:  0.029416374321825776
steamspy_tags:Bullet Hell versus rating: p-value = 2.8602673640834353e-05
pearson:  0.039491436296976344
steamspy_tags:Casual versus rating: p-value = 2.809030138780043e-08
pearson:  -0.06694404136198463
steamspy_tags:Rhythm versus rating: p-value = 0.0026666852854044477
pearson:  0.028332497454495245
steamspy_tags:Time Management versus rating: p-value = 0.008187966363699083
pearson:  0.025982102314552044
steamspy_tags:2D Fighter versus rating: p-value = 0.002474828073496017
pearson:  0.030224316555099405
```

Applying Models

Experiment 1 (combined significant categorical and numeric variables)

Result: Combined performed the best of all our experiments but the difference was negligible.

In [ ]:

```
# Combining the one-hot encoding matrix and the other predictive features into one df
# Predictive features: english, achievements, average_playtime, price, platforms(mac & linux), age, owner, genre(some), category(some), steamspy_tag(some)

pred_df = pd.concat([df[['name', 'english', 'achievements', 'average_playtime', 'price']], platform_df[['platforms:linux', 'platforms:mac']], age_df, owner_df,
                     genre_df[['genres:Violent', 'genres:Simulation', 'genres:Strategy', 'genres:Racing', 'genres:Gore', 'genres:Indie', 'genres:Sports',
                               'genres:Massively Multiplayer', 'genres:Free to Play']],
                     cat_df[['categories:In-App Purchases', 'categories:SteamVR Collectibles', 'categories:Single-player', 'categories:Steam Workshop',
                             'categories:Includes level editor', 'categories:Full controller support', 'categories:Multi-player',
                             'categories:Captions available', 'categories:Shared/Split Screen', 'categories:Steam Leaderboards', 'categories:Local Multi-Player',
                             'categories:Steam Cloud', 'categories:Local Co-op', 'categories:Steam Achievements', 'categories:MMO',
                             'categories:Online Multi-Player']],
                     tag_df[['steamspy_tags:Hidden Object', 'steamspy_tags:Racing', 'steamspy_tags:Classic', 'steamspy_tags:Sports', 'steamspy_tags:Survival',
                             'steamspy_tags:Story Rich', 'steamspy_tags:Atmospheric', 'steamspy_tags:Difficult', 'steamspy_tags:Indie', 'steamspy_tags:Cute',
                             'steamspy_tags:Violent', 'steamspy_tags:Platformer', 'steamspy_tags:Pixel Graphics', 'steamspy_tags:Comedy', 'steamspy_tags:Visual Novel',
                             'steamspy_tags:Strategy', 'steamspy_tags:Simulation', 'steamspy_tags:Great Soundtrack', 'steamspy_tags:Massively Multiplayer',
                             'steamspy_tags:Point & Click', 'steamspy_tags:Action', 'steamspy_tags:Free to Play', 'steamspy_tags:Anime', 'steamspy_tags:Co-op',
                             'steamspy_tags:Choices Matter', 'steamspy_tags:Twin Stick Shooter', 'steamspy_tags:Local Multiplayer', 'steamspy_tags:Puzzle',
                             'steamspy_tags:Bullet Hell', 'steamspy_tags:Shoot\'Em Up']], df['rating']], axis=1);
```

In [ ]:
```
pred_df.head()
```

Out[ ]:

	name	english	achievements	average_playtime	price	platforms:linux	platforms:mac	a
0	Counter-Strike	1	0	17612	7.19	1	1	
1	Team Fortress Classic	1	0	277	3.99	1	1	
2	Day of Defeat	1	0	187	3.99	1	1	
3	Deathmatch Classic	1	0	258	3.99	1	1	
4	Half-Life: Opposing Force	1	0	624	3.99	1	1	

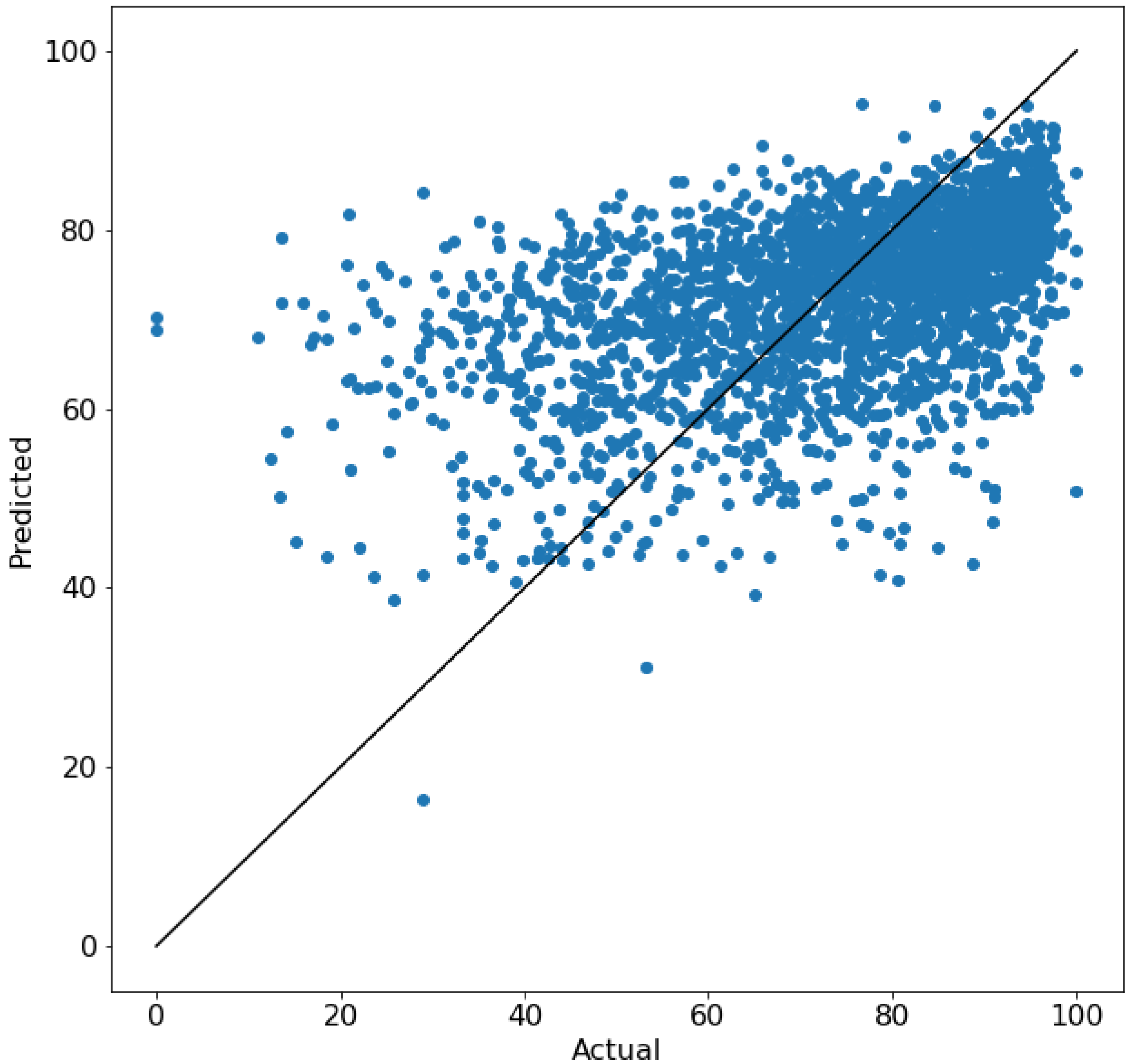
5 rows × 81 columns

In [ ]:
```
# Scaling and train/test splitting
X = pred_df.drop(['name', 'rating'], axis=1).to_numpy()
Y = pred_df['rating'].to_numpy()
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, Y, test_size=0.3
0)

# Linear Regression
regr = LinearRegression()
regr.fit(X_train, y_train)
pred = regr.predict(X_test)
print("Linear Regression")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred))
+ "\n")

# Support Vector Machine - Takes significantly longer than the other 2 models
 ~ 1min
svm = SVR()
svm.fit(X_train, y_train)
pred = svm.predict(X_test)
print("SVM")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred))
+ "\n")

# Random Forest
rf = RandomForestRegressor(n_estimators=100, bootstrap = True, max_features =
'sqrt')
rf.fit(X_train, y_train)
pred = rf.predict(X_test)
print("Random Forest")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred
)))
```

```
Linear Regression
Mean Squared Error: 3.240753223855792e+28
Mean Absolute Error: 3569146934813.7153

SVM
Mean Squared Error: 268.9283221306796
Mean Absolute Error: 12.455787963120661

Random Forest
Mean Squared Error: 246.6030884218192
Mean Absolute Error: 12.275283247729556
```

In [ ]:

```
fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred) # Only plotting 1/4 of points because it gets dense
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');
```



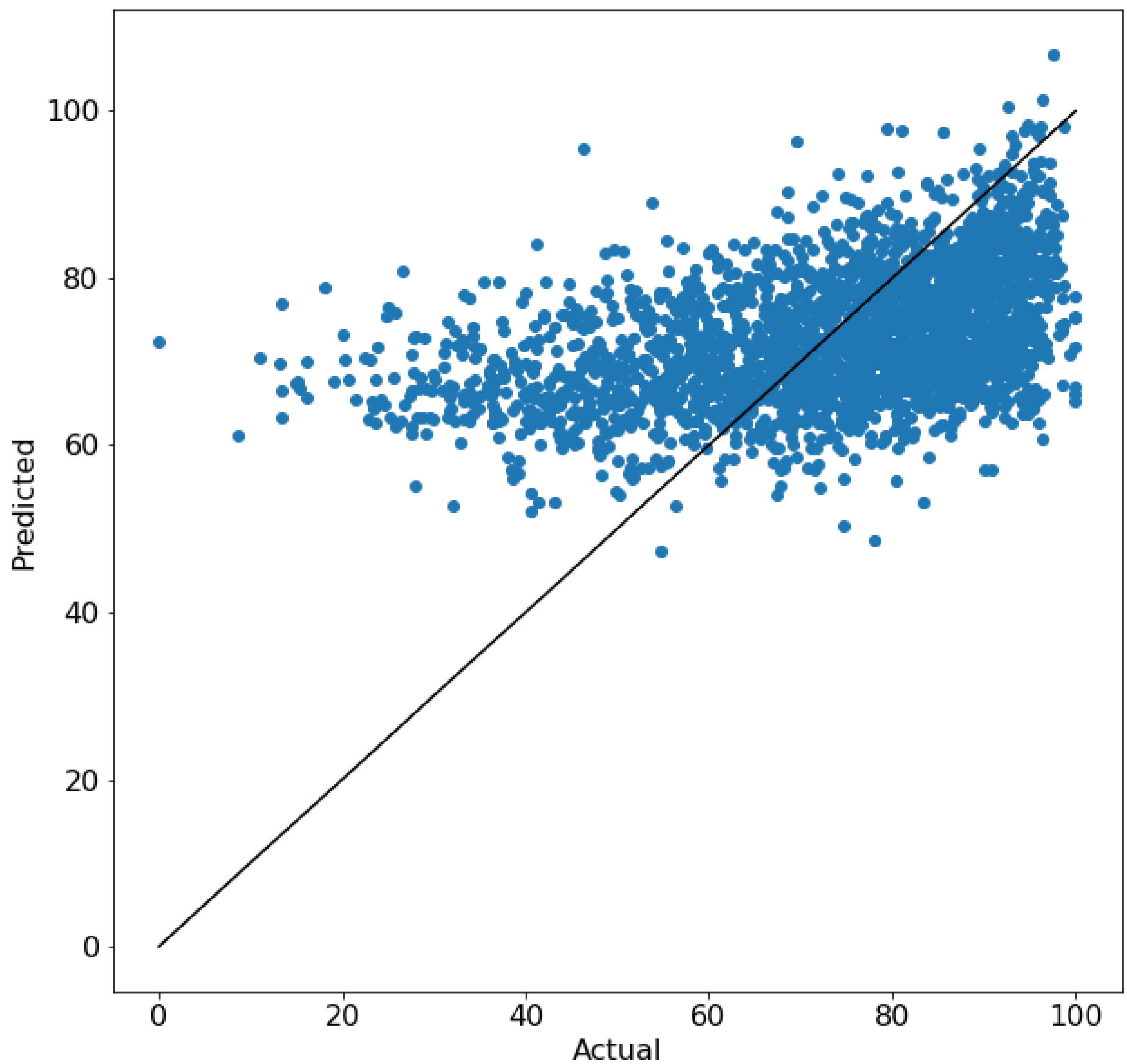
Experiment 2 - All predictive features that would be known at publishing time of a game. This would allow us to predict the rating of a game before anyone downloads it.

```
In [ ]: # not including average_playtime, achievements, owner features (would not be k
nown before a game is published. All other features are included.)
pred_df = pd.concat([df[['english', 'achievements', 'price']], platform_df[['p
latforms:linux', 'platforms:mac']], age_df,
                     genre_df[['genres:Violent', 'genres:Simulation', 'genres:
Strategy', 'genres:Racing', 'genres:Gore', 'genres:Indie', 'genres:Sports',
                               'genres:Massively Multiplayer', 'genres:Free to
Play']],
                     cat_df[['categories:In-App Purchases', 'categories:SteamV
R Collectibles', 'categories:Single-player', 'categories:Steam Workshop',
                             'categories:Includes level editor', 'categories:F
ull controller support', 'categories:Multi-player',
                             'categories:Captions available', 'categories:Shar
ed/Split Screen', 'categories:Steam Leaderboards', 'categories:Local Multi-Pla
yer',
                             'categories:Steam Cloud', 'categories:Local Co-o
p', 'categories:Steam Achievements', 'categories:MMO',
                             'categories:Online Multi-Player']],
                     tag_df[['steamspy_tags:Hidden Object', 'steamspy_tags:Rac
ing', 'steamspy_tags:Classic', 'steamspy_tags:Sports', 'steamspy_tags:Surviva
l',
                             'steamspy_tags:Story Rich', 'steamspy_tags:Atmosp
heric', 'steamspy_tags:Difficult', 'steamspy_tags:Indie', 'steamspy_tags:Cute'
,
                             'steamspy_tags:Violent', 'steamspy_tags:Platforme
r', 'steamspy_tags:Pixel Graphics', 'steamspy_tags:Comedy', 'steamspy_tags:Vis
ual Novel',
                             'steamspy_tags:Strategy', 'steamspy_tags:Simulati
on', 'steamspy_tags:Great Soundtrack', 'steamspy_tags:Massively Multiplayer',
                             'steamspy_tags:Point & Click', 'steamspy_tags:Act
ion', 'steamspy_tags:Free to Play', 'steamspy_tags:Anime', 'steamspy_tags:Co-o
p',
                             'steamspy_tags:Choices Matter', 'steamspy_tags:Tw
in Stick Shooter', 'steamspy_tags:Local Multiplayer', 'steamspy_tags:Puzzle',
                             'steamspy_tags:Bullet Hell', 'steamspy_tags:Shoot
\'Em Up']]], axis=1);
X = pred_df.to_numpy()
Y = df["rating"]
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, Y, test_size=0.3
0)
```

In [ ]:

```
# Linear Regression
regr = LinearRegression()
regr.fit(X_train, y_train)
pred = regr.predict(X_test)
print("Linear Regression")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred
)))

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');
```

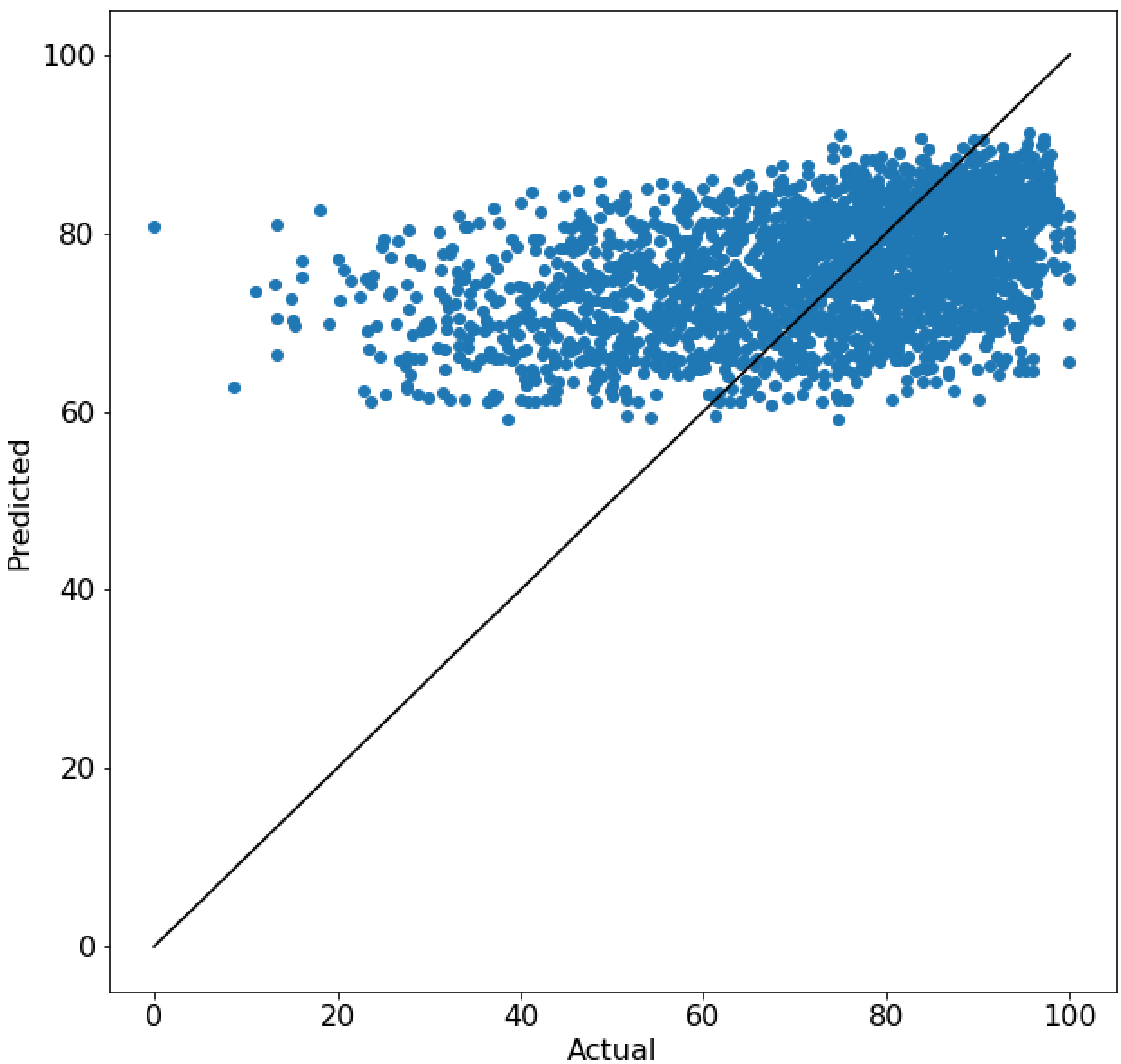
```
Linear Regression
Mean Squared Error: 257.8493683463039
Mean Absolute Error: 12.699013368374466
```



In [ ]:

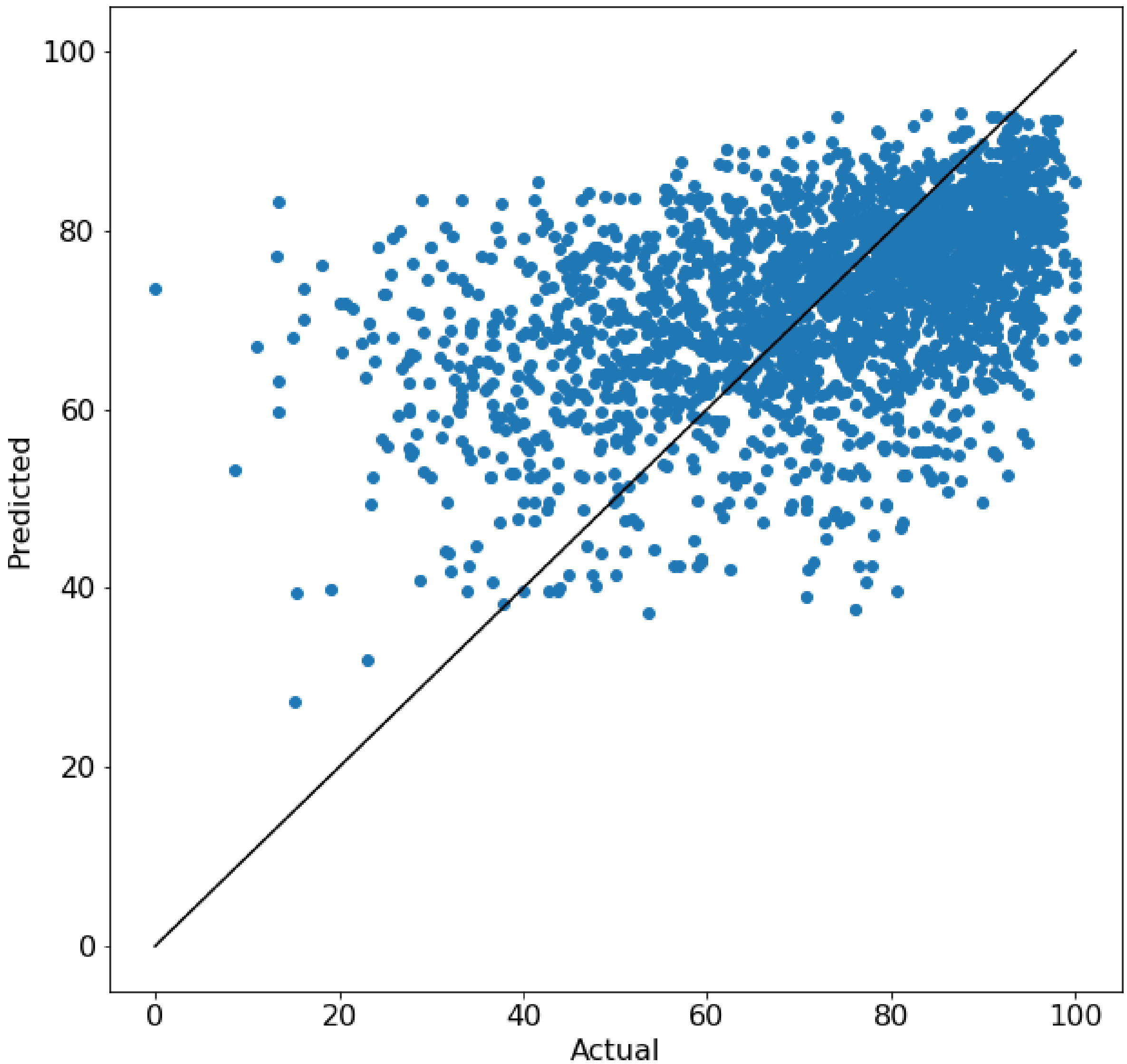
```
# Support Vector Machine
svm = SVR()
svm.fit(X_train, y_train)
pred = svm.predict(X_test)
print("SVM")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred
)))

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');
```

```
SVM
Mean Squared Error: 267.6251941961098
Mean Absolute Error: 12.528353170525158
```



In [ ]:
```
# Random Forest
rf = RandomForestRegressor(n_estimators=100, bootstrap = True, max_features =
'sqrt')
rf.fit(X_train, y_train)
pred = rf.predict(X_test)
print("Random Forest")
print("Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pred)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred
)))
print("Predictions: " + str(pred.mean()) + " ± " + str(pred.std()))
print("Actual: " + str(df['rating'].mean()) + " ± " + str(df['rating'].std()))

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');
```

```
Random Forest
Mean Squared Error: 252.17516654384184
Mean Absolute Error: 12.355474191133636
Predictions: 72.76709276826121 ± 9.976017577772108
Actual: 73.10726798117321 ± 17.661067601607705
```



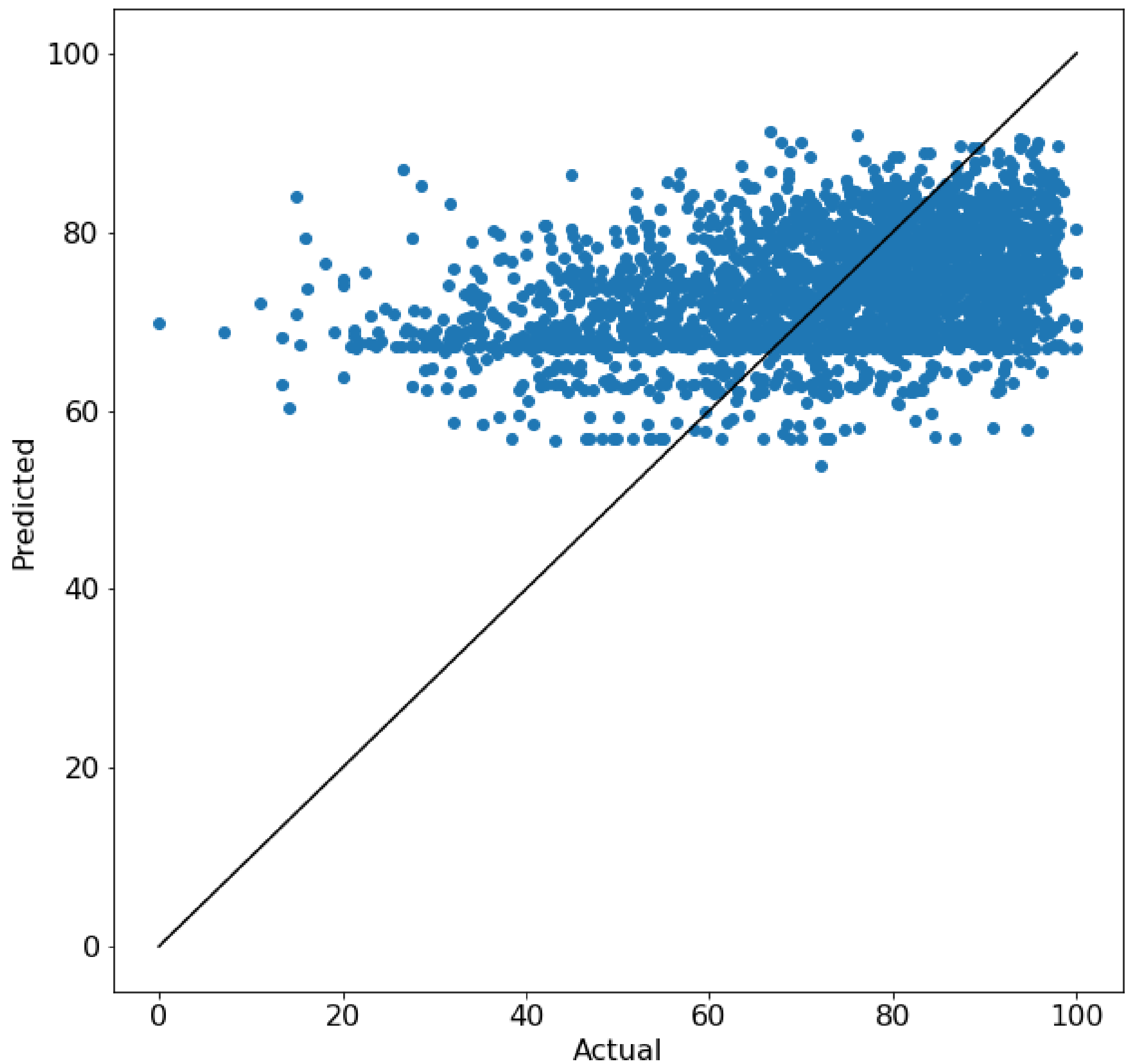
Experiment 3 - Only the best features known at publishing time

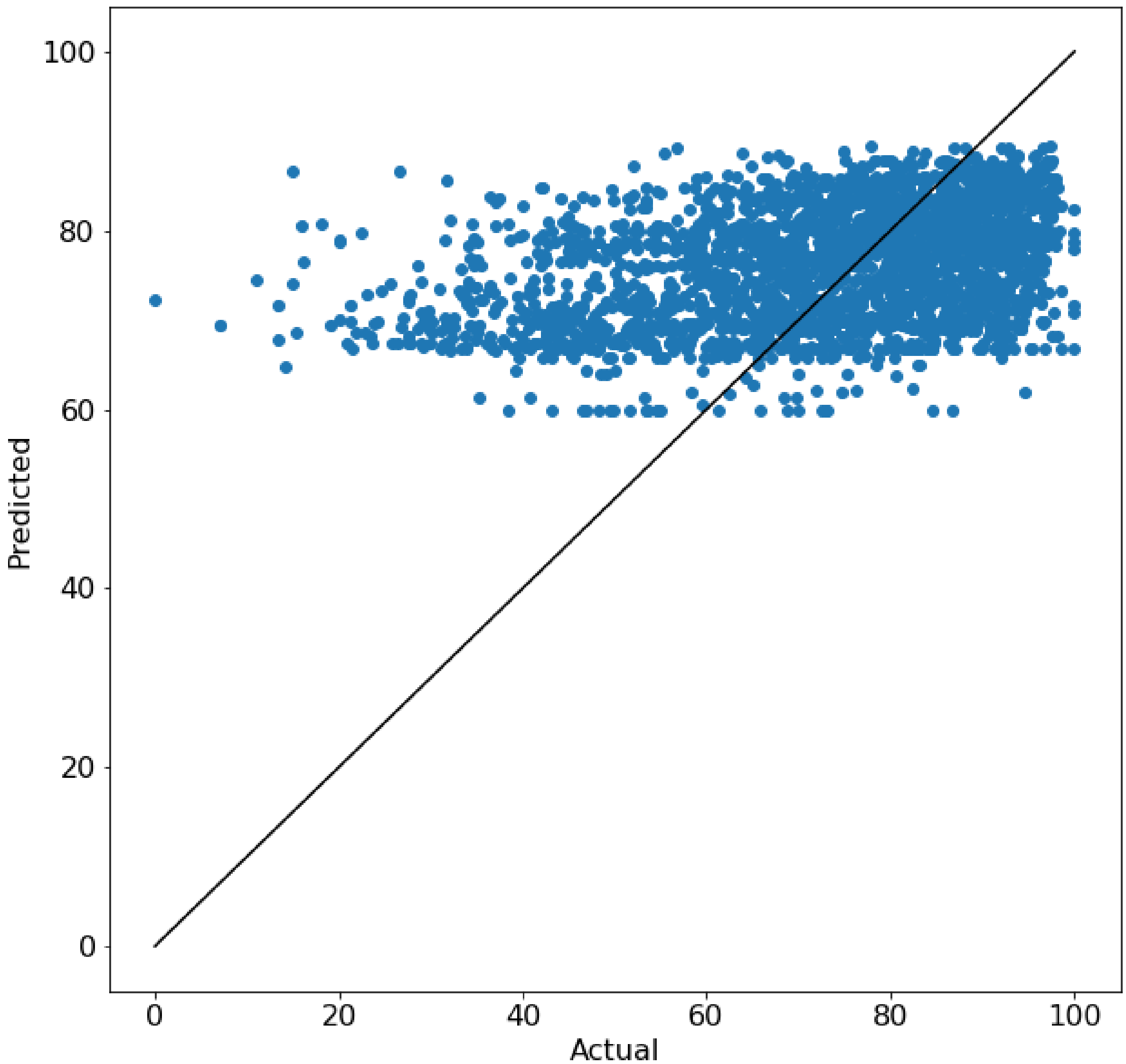
In [ ]:

```
# will be only categorical variables
pred_df = pd.concat([df[['english', 'achievements', 'price']], platform_df[['p
latforms:linux', 'platforms:mac']],
                     genre_df[['genres:Simulation', 'genres:Massively Multipla
yer']],
                     cat_df[['categories:Full controller support', 'categorie
s:Steam Cloud', 'categories:Steam Achievements']],
                     tag_df[['steamspy_tags:Simulation', 'steamspy_tags:Massiv
ely Multiplayer','steamspy_tags:Local Multiplayer', 'steamspy_tags:Puzzle']]],
axis=1);

X = pred_df.to_numpy()
Y = df["rating"]
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, Y, test_size=0.3
0)

# Linear Regression
regr = LinearRegression()
regr.fit(X_train, y_train)
pred = regr.predict(X_test)
print("Linear Regression")
print("Root Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pre
d, squared=False)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred))
+ "\n")

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');

# Support Vector Machine
svm = SVR()
svm.fit(X_train, y_train)
pred = svm.predict(X_test)
print("SVM")
print("Root Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pre
d, squared=False)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred))
+ "\n")

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');

# Random Forest
rf = RandomForestRegressor(n_estimators=100, bootstrap = True, max_features =
'sqrt')
rf.fit(X_train, y_train)
pred = rf.predict(X_test)
```

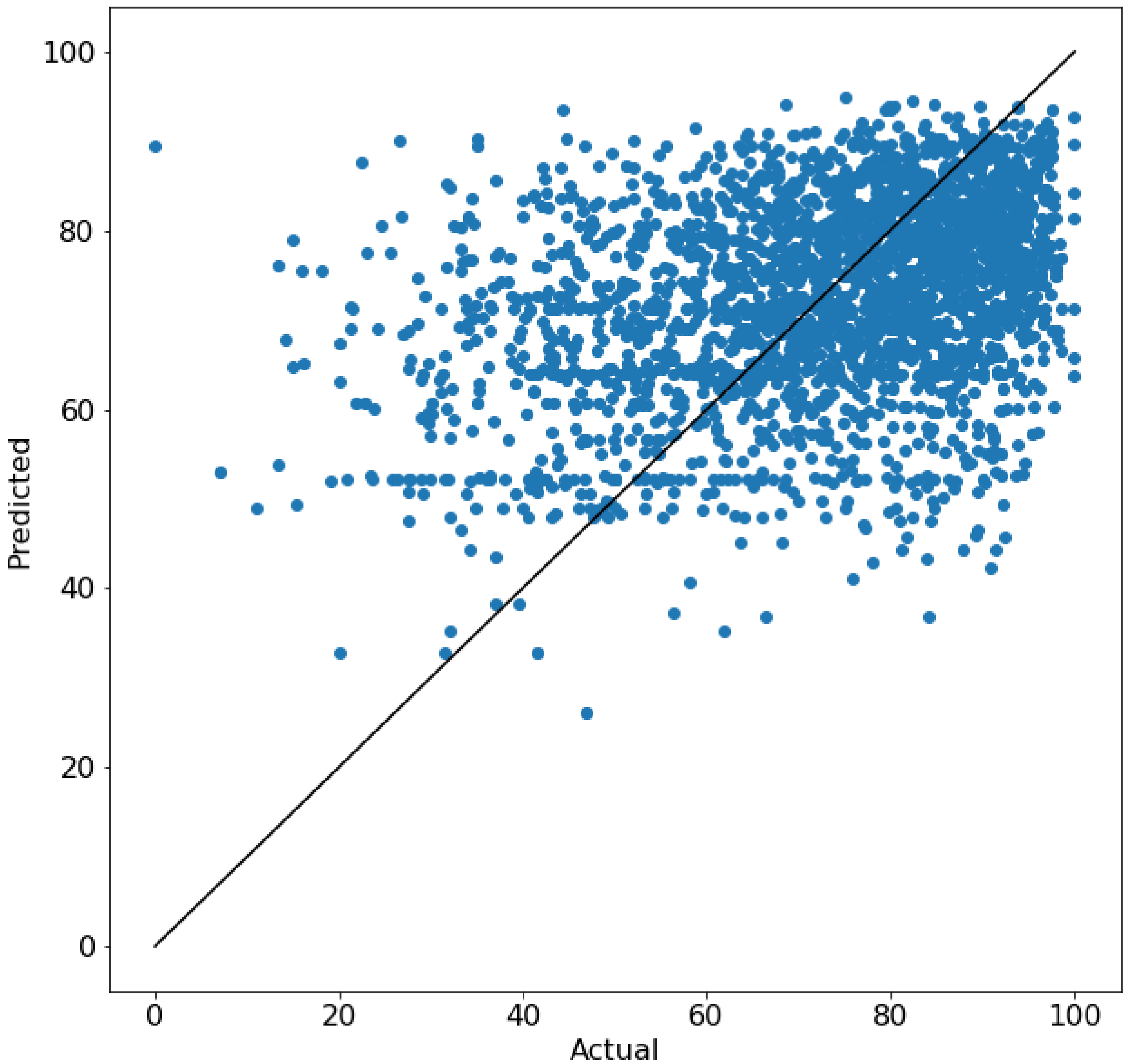
```
print("Random Forest")
print("Root Mean Squared Error: " + str(metrics.mean_squared_error(y_test, pre
d, squared=False)))
print("Mean Absolute Error: " + str(metrics.mean_absolute_error(y_test, pred
)))

fig, axes = plt.subplots(figsize=(10,10))
axes.scatter(y_test, pred)
axes.set_xlabel('Actual')
axes.set_ylabel('Predicted')
axes.plot([0, 100], [0,100], c='k');
```

```
Linear Regression
Root Mean Squared Error: 16.66453986391377
Mean Absolute Error: 13.2196022918167

SVM
Root Mean Squared Error: 16.86177925383966
Mean Absolute Error: 13.01704665012471

Random Forest
Root Mean Squared Error: 17.419714557751238
Mean Absolute Error: 13.589424221730566
```





100
80
60
40
20
0
Predicted
0
20
40
60
80
100
Actual


Predicted
Actual
0
20
40
60
80
100