# Steam_Dataset

August 8, 2019

[1]:
```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from xgboost import XGBClassifier
import pickle
import time
import wordcloud
import seaborn
%matplotlib inline
```

## 0.1 Goal

The goal of project is to develop a model to predict the number of owners for steam games, which should be useful for new game design.

## 0.2 Outline

This project includes three major parts: 1. EDA: 1) check dataset 2) target feature (owners) 3) consider categorical features (split and frequency) 4) consider numerical features (correlation) 5) generate new features 2. Model development: 1) train model (XGB classification with class weights) 2) performance check 3) error analysis 4) feature importance

## 0.3 1. EDA

[2]:
```
df = pd.read_csv("../data/steam.csv")
print("Dateset includes " + str(df.shape[0]) + " different games")
```

```
Dateset includes 27075 different games
```

### 0.3.1 1) Check Basic Information

[3]:
```
### Check Columns ####
print("There are " + str(len(df.columns)) +  " columns in  data")
```

```python
print("Among them, some features can be got before the game releasing, which can␣
↪be used as our input features")
print("Such as :" + ", ".join(df.columns[1:12]) + ", " +  df.columns[-1])
print("Some of them can only be got after the game releasing, which are the␣
↪targets of our model")
print("Such as :" + ", ".join(df.columns[14:17]))
print("Some of them can be got at both time using pre-release testing, but we␣
↪need to do certain conversion")
print("Such as :" + ", ".join(df.columns[12:14]))
```

```
There are 18 columns in  data
Among them, some features can be got before the game releasing, which can be
used as our input features
Such as :name, release_date, english, developer, publisher, platforms,
required_age, categories, genres, steamspy_tags, achievements, price
Some of them can only be got after the game releasing, which are the targets of
our model
Such as :average_playtime, median_playtime, owners
Some of them can be got at both time using pre-release testing, but we need to
do certain conversion
Such as :positive_ratings, negative_ratings
```

[4]:

```python
#### Check General Information ####
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 27075 entries, 0 to 27074
Data columns (total 18 columns):
appid               27075 non-null int64
name                27075 non-null object
release_date        27075 non-null object
english             27075 non-null int64
developer           27075 non-null object
publisher           27075 non-null object
platforms           27075 non-null object
required_age        27075 non-null int64
categories          27075 non-null object
genres              27075 non-null object
steamspy_tags       27075 non-null object
achievements        27075 non-null int64
positive_ratings    27075 non-null int64
negative_ratings    27075 non-null int64
average_playtime    27075 non-null int64
median_playtime     27075 non-null int64
owners              27075 non-null object
price               27075 non-null float64
```

```
dtypes: float64(1), int64(8), object(9)
memory usage: 3.7+ MB
```

[4]:

```
              appid       english  required_age  achievements  \
count  2.707500e+04  27075.000000  27075.000000  27075.000000
mean   5.962035e+05      0.981127      0.354903     45.248864
std    2.508942e+05      0.136081      2.406044    352.670281
min    1.000000e+01      0.000000      0.000000      0.000000
25%    4.012300e+05      1.000000      0.000000      0.000000
50%    5.990700e+05      1.000000      0.000000      7.000000
75%    7.987600e+05      1.000000      0.000000     23.000000
max    1.069460e+06      1.000000     18.000000   9821.000000

       positive_ratings  negative_ratings  average_playtime  median_playtime  \
count      2.707500e+04      27075.000000      27075.000000      27075.00000
mean       1.000559e+03        211.027147        149.804949        146.05603
std        1.898872e+04       4284.938531       1827.038141       2353.88008
min        0.000000e+00          0.000000          0.000000          0.00000
25%        6.000000e+00          2.000000          0.000000          0.00000
50%        2.400000e+01          9.000000          0.000000          0.00000
75%        1.260000e+02         42.000000          0.000000          0.00000
max        2.644404e+06     487076.000000     190625.000000     190625.00000

              price
count  27075.000000
mean       6.078193
std        7.874922
min        0.000000
25%        1.690000
50%        3.990000
75%        7.190000
max      421.990000
```

[5]:

```
#### Check None ####
df.isnull().sum()
```

[5]:

```
appid               0
name                0
release_date        0
english             0
developer           0
publisher           0
platforms           0
required_age        0
categories          0
genres              0
steamspy_tags       0
achievements        0
```

```
positive_ratings    0
negative_ratings    0
average_playtime    0
median_playtime     0
owners              0
price               0
dtype: int64
```

[6]:
```
#### Check Repeate Game Names ####
name_list = {s:0 for s in set(df["name"])}
for i in df["name"]:
    name_list[i] += 1
name_repeate = []
for key,value in name_list.items():
    if value != 1:
        name_repeate.append(key)

print("There are " + str(len(name_repeate)) + " game names are repetitive")
print("They are: " +  ", ".join(name_repeate))
### One example
df[df["name"] == "New York Bus Simulator"]
```

```
There are 41 game names are repetitive
They are: Rumpus, Mystical, New York Bus Simulator, Surge, Invasion, Santa's
Workshop, RUSH, Bounce, The Tower, Hide and Seek, The Mine, Colony, Alter Ego,
Escape Room, Fireflies, Escape, Space Maze, Dark Matter, Ultimate Arena, Ashes,
Luna, Zombie Apocalypse, Scorch, Cortex, City Builder, Experience, Castles,
Chaos Theory, Dodge, Exodus, The Great Escape, Nightmare Simulator, 2048,
Killing Time, Solitaire, Slice&Dice, Beyond the Wall, Mars 2030, Evolution,
Taxi, Alone
```

[6]:
```
       appid                    name release_date  english  \
2729  283580  New York Bus Simulator   2014-08-06        1
8227  446480  New York Bus Simulator   2016-03-04        1

                   developer                                 publisher platforms  \
2729             TML-Studios                            Aerosoft GmbH   windows
8227  Little Freedom Factory  United Independent Entertainment GmbH   windows

      required_age     categories      genres                    steamspy_tags  \
2729             0  Single-player  Simulation  Simulation;Masterpiece;Driving
8227             0  Single-player  Simulation                      Simulation

      achievements  positive_ratings  negative_ratings  average_playtime  \
2729             0                29                35                 0
8227             0                 7                42                 0

      median_playtime   owners  price
```

```
2729                    0   0-20000    8.99
8227                    0   0-20000    3.99
```

### 0.3.2 2) Target feature: owners

Here, since owners is categorical feature , we tried to use the median(also average here) to replace it.

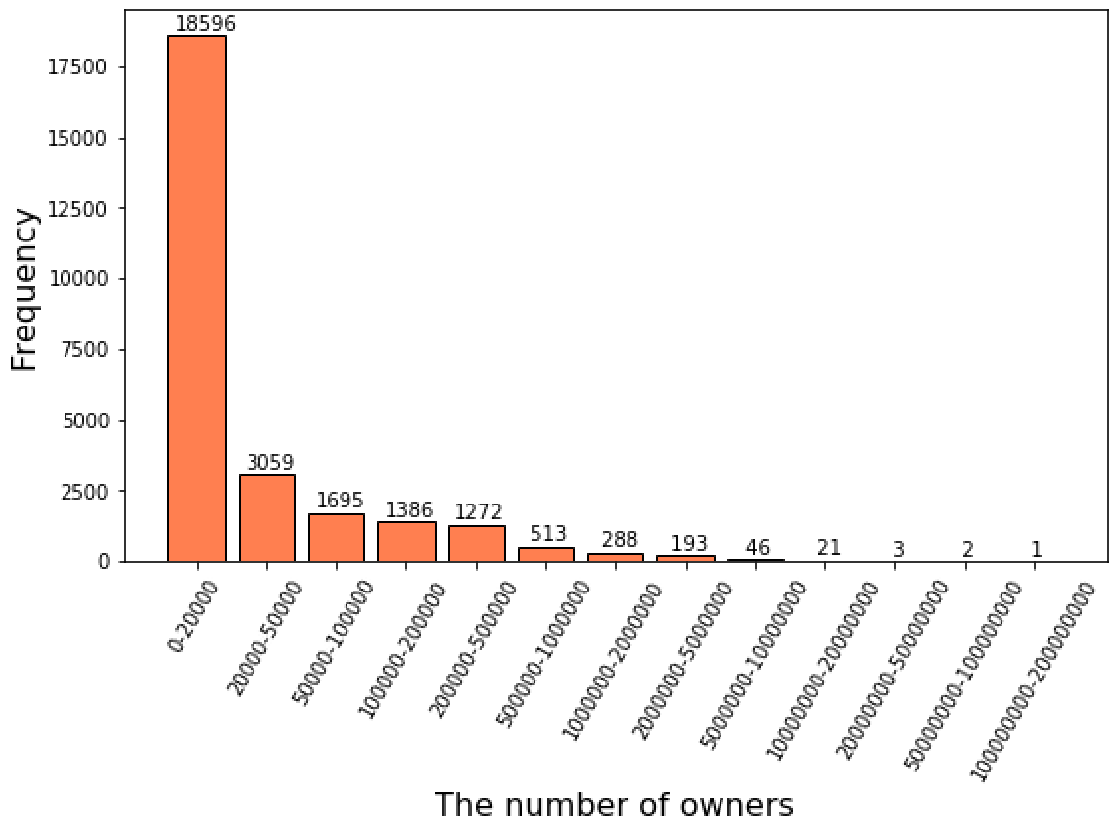
[7]:
```python
def getMedian(x):
    x_list = [ float(x) for x in x.split("-")]
    x_median = np.median(x_list)
    return x_median
```

[8]:
```python
df_prepare = df.copy()
df_prepare["owners_median"] = df["owners"].apply(lambda x: getMedian(x))
```

Check the distribution of owners

[9]:
```python
df_owner_infor = { df_tmp[0]: len(df_tmp[1]) for df_tmp in df_prepare.
 ↪groupby("owners")}
df_owner_infor = { x:y for x,y in sorted(df_owner_infor.items(), key = lambda x:␣
 ↪getMedian(x[0]))}
```

[10]:
```python
fig = plt.figure(figsize=[8,6])
ax = plt.gca()
plt.bar(df_owner_infor.keys(), df_owner_infor.values(), edgecolor="black",␣
 ↪color="coral")
for idx, key in enumerate(df_owner_infor.keys()):
    ax.annotate("{:>4s}".format(str(df_owner_infor[key])), (idx-0.3,␣
 ↪df_owner_infor[key] + 200), fontsize=10)
plt.xticks(rotation="60", fontsize=10)
plt.tight_layout(pad=2)
plt.xlabel("The number of owners", size=16)
plt.ylabel("Frequency", size=16);
#plt.savefig("Owners_distribution.jpg", dpi=300);
```




It is clearly that the owners of most games are in 0-20000 range, and some games have very high number owners, which are larger than 50 million. This results indicates that our dataset is unbalanced and should be processed carefully in the model development. Since there are only 27 games have owners larger than 10 million, we combine these games together and form the "lager than 10 million" class

[11]:
```
### Games with high onwers
df_prepare[df_prepare["owners"] == "100000000-200000000"]
```

[11]:
```
    appid    name release_date  english developer publisher  \
22    570  Dota 2   2013-07-09        1     Valve     Valve

            platforms  required_age  \
22  windows;mac;linux             0

                                           categories  \
22  Multi-player;Co-op;Steam Trading Cards;Steam W...

                           genres              steamspy_tags  achievements  \
22  Action;Free to Play;Strategy  Free to Play;MOBA;Strategy             0

    positive_ratings  negative_ratings  average_playtime  median_playtime  \
22            863507            142079             23944              801
```

```
                 owners  price  owners_median
22  100000000-200000000    0.0    150000000.0
```

### 0.3.3 3) Categorical features

There are many categorical features. Let's check if there is any significant trend in categorical features for successful games

[12]:
```
def getTopN(infile, variable, sort_value="owners_median", TopN=5):
    '''
    Get data grouped by certain features and return the TopN results ranking by␣
 ↪owners_median

    '''
    infile_tmp = infile.groupby(variable).agg({"owners_median":np.mean,␣
 ↪"positive_ratings":np.mean,"average_playtime": np.mean, "median_playtime": np.
 ↪mean})

    return infile_tmp.sort_values(sort_value, ascending = False)[0:TopN]
```

[13]:
```
def getDict(infile, variable):
    '''
    Get data grouped by certain features and return the dictionary

    '''
    infile_tmp = infile.groupby(variable).agg({"owners_median":np.mean,␣
 ↪"positive_ratings":np.mean,"average_playtime": np.mean, "median_playtime": np.
 ↪mean})

    return infile_tmp.to_dict()
```

[14]:
```
def drawWordCloud(freq_dict):
    '''
    Draw wordcloud for freq_dict
    '''
    wc = wordcloud.WordCloud(background_color="white", max_font_size=100,␣
 ↪max_words=100, random_state=0).generate_from_frequencies(freq_dict)
    plt.figure(figsize=[8,6])
    plt.imshow(wc,interpolation="bilinear")
    plt.axis("off");
```

**a. Developer**

[15]:
```
#### Show Top 10 developer companies ####
getTopN(df_prepare,"developer")
```

[15]:
```
                                          owners_median  positive_ratings  \
developer
```

```
PUBG Corporation                    7.500000e+07      4.961840e+05
Valve;Hidden Path Entertainment     7.500000e+07      2.644404e+06
Smartly Dressed Games               3.500000e+07      2.925740e+05
Valve                               1.560577e+07      8.667212e+04
Blue Mammoth Games                  1.500000e+07      7.326800e+04

                                   average_playtime  median_playtime
developer
PUBG Corporation                       22938.000000     12434.000000
Valve;Hidden Path Entertainment        22494.000000      6502.000000
Smartly Dressed Games                   3248.000000       413.000000
Valve                                   2663.538462       282.230769
Blue Mammoth Games                       724.000000       146.000000
```

[16]:
```
#### Draw Wordcloud for them ####
developer_dict = getDict(df_prepare,"developer")
drawWordCloud(developer_dict["owners_median"])
```


PUBG Corporation is the developer with highest average owners, since its the developer of PlayerUnknown's Battlegrounds

**b. Publisher**

[17]:
```
#### Show Top10 publisher ####
getTopN(df_prepare,"publisher")
```

[17]:
```
                        owners_median  positive_ratings  average_playtime  \
publisher
PUBG Corporation           75000000.0     496184.000000           22938.0
Digital Extremes           35000000.0     226541.000000            5845.0
```

```
Smartly Dressed Games      35000000.0     292574.000000            3248.0
Valve                      17025000.0     175689.066667            3505.1
Grinding Gear Games        15000000.0      71593.000000            5263.0

                      median_playtime
publisher
PUBG Corporation              12434.0
Digital Extremes                394.0
Smartly Dressed Games           413.0
Valve                           544.5
Grinding Gear Games             492.0
```

[18]:
```
publisher_dict = getDict(df_prepare,"publisher")
drawWordCloud(publisher_dict["owners_median"])
```


**c. Developer & Publisher**

[19]:
```
#### Show Top 10 developer & publisher combinations ####
getTopN(df_prepare,["developer","publisher"])
```

[19]:
```
                                                             owners_median  \
developer                      publisher
PUBG Corporation               PUBG Corporation               7.500000e+07
Valve;Hidden Path Entertainment Valve                         7.500000e+07
Smartly Dressed Games          Smartly Dressed Games          3.500000e+07
Digital Extremes               Digital Extremes               3.500000e+07
Valve                          Valve                          1.560577e+07

                                                             positive_ratings  \
```

```
developer                      publisher
PUBG Corporation               PUBG Corporation         4.961840e+05
Valve;Hidden Path Entertainment Valve                   2.644404e+06
Smartly Dressed Games          Smartly Dressed Games    2.925740e+05
Digital Extremes               Digital Extremes         2.265410e+05
Valve                          Valve                    8.667212e+04

                                                     average_playtime  \
developer                      publisher
PUBG Corporation               PUBG Corporation         22938.000000
Valve;Hidden Path Entertainment Valve                   22494.000000
Smartly Dressed Games          Smartly Dressed Games     3248.000000
Digital Extremes               Digital Extremes          5845.000000
Valve                          Valve                     2663.538462

                                                     median_playtime
developer                      publisher
PUBG Corporation               PUBG Corporation        12434.000000
Valve;Hidden Path Entertainment Valve                   6502.000000
Smartly Dressed Games          Smartly Dressed Games     413.000000
Digital Extremes               Digital Extremes          394.000000
Valve                          Valve                     282.230769
```

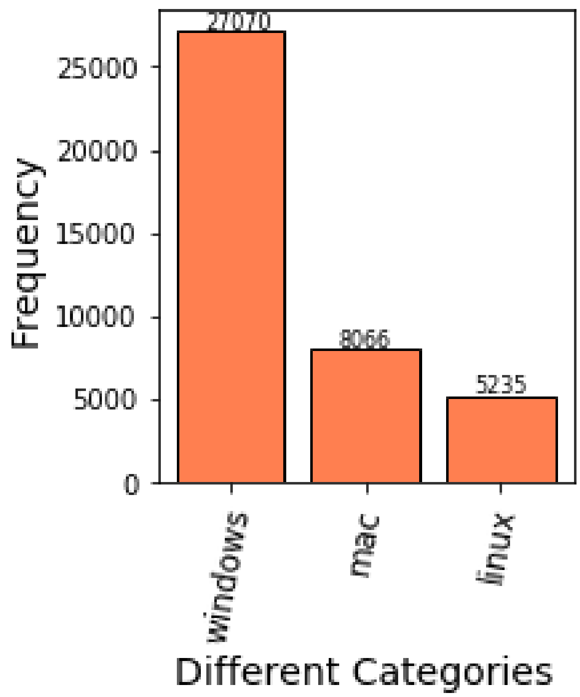
**d. categories features with subclass** For platform, categories, genres, steamspy_tags, each game has multiple types. To make the analysis easier, I first split them and get the vocabulary of them, then changed them into one-hot features, which can be used in future model development.

[20]:
```
def getVocab(data, variable):
    '''
    Get vocabulary for certain feature(variable)
    '''
    vocab = {}
    for line in data[variable].tolist():
        if ";" in line:
            line = line.split(";")
        else:
            line = [line]
        for v in line:
            if v not in vocab:
                vocab[v] = 1
            else:
                vocab[v] += 1

    vocab = {x:y for x, y in sorted(vocab.items(), key = lambda x: x[1], reverse␣
 ↪= True)}

    return vocab
```

[21]:
```python
def splitCateg(data, variable, vocab):
    '''
    Split feature with its vocabulary and change it into onehot, and added split␣
 ↪feature columns into initial data
    data: initial data
    variable: feature name
    vocab: its vocabulary
    '''
    v_split = {key:[] for key in vocab.keys()}
    for v in data[variable]:
        if ";" in v:
            v = v.split(";")
        else:
            v = [v]
        for key in v_split.keys():
            if key in v:
                v_split[key].append(1)
            else:
                v_split[key].append(0)

    v_data = pd.DataFrame(v_split)

    data_add = pd.merge(data, v_data , on = data.index)
    data_add.drop("key_0", axis = 1, inplace = True)

    return data_add
```

**Platform**

[22]:
```python
platform_vocab = getVocab(df_prepare, "platforms")
fig = plt.figure(figsize=[3,3])
ax = plt.gca()
plt.bar(platform_vocab.keys(),platform_vocab.values(), edgecolor="black",␣
 ↪color="coral")
for idx, key in enumerate(platform_vocab.keys()):
    ax.annotate("{:>4s}".format(str(platform_vocab[key])), (idx-0.2,␣
 ↪platform_vocab[key] + 100), fontsize=8)
plt.tight_layout()
plt.xticks(rotation="80", fontsize=12)
plt.xlabel("Different Categories", size=14)
plt.ylabel("Frequency", size=14);
```




[23]:
```
#### Add split onehot fetaures ####
df_prepare = splitCateg(df_prepare, "platforms", platform_vocab)
df_prepare.shape
```

[23]: (27075, 22)

**categories**

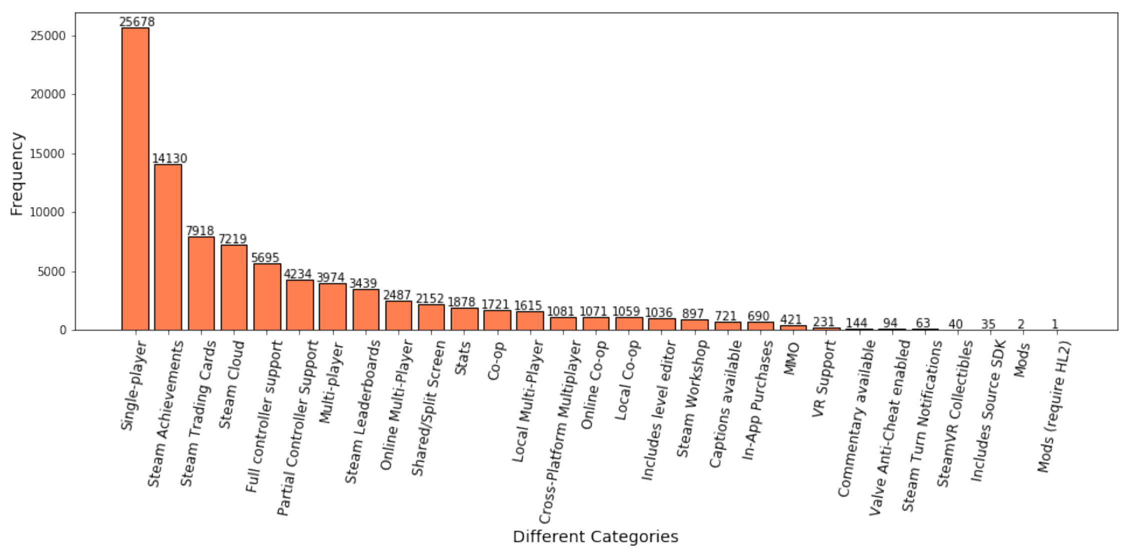
[24]:
```
### initial data, show the top 10 categories
getTopN(df_prepare,["categories"])
```

[24]:
```
                                                   owners_median  \
categories
Multi-player;Co-op;Steam Trading Cards;Steam Wo...    150000000.0
Multi-player;Steam Achievements;Full controller...     75000000.0
Multi-player;Online Multi-Player;Stats                 37575000.0
Single-player;Online Multi-Player;Online Co-op;...     35000000.0
Multi-player;Cross-Platform Multiplayer;Steam A...     35000000.0

                                                   positive_ratings  \
categories
Multi-player;Co-op;Steam Trading Cards;Steam Wo...          863507.0
Multi-player;Steam Achievements;Full controller...         2644404.0
Multi-player;Online Multi-Player;Stats                      248303.5
Single-player;Online Multi-Player;Online Co-op;...          292574.0
Multi-player;Cross-Platform Multiplayer;Steam A...          515879.0
```

```
                                                    average_playtime  \
categories
Multi-player;Co-op;Steam Trading Cards;Steam Wo...           23944.0
Multi-player;Steam Achievements;Full controller...           22494.0
Multi-player;Online Multi-Player;Stats                       11502.5
Single-player;Online Multi-Player;Online Co-op;...            3248.0
Multi-player;Cross-Platform Multiplayer;Steam A...            8495.0

                                                    median_playtime
categories
Multi-player;Co-op;Steam Trading Cards;Steam Wo...            801.0
Multi-player;Steam Achievements;Full controller...           6502.0
Multi-player;Online Multi-Player;Stats                       6250.5
Single-player;Online Multi-Player;Online Co-op;...            413.0
Multi-player;Cross-Platform Multiplayer;Steam A...            623.0
```

[25]:
```
#### Get categories vocabulary ####
cat_vocab = getVocab(df_prepare, "categories")
print("There are " + str(len(cat_vocab)) + " categories")
fig = plt.figure(figsize=[16,5])
ax = plt.gca()
plt.bar(cat_vocab.keys(),cat_vocab.values(), edgecolor="black", color="coral")
for idx, key in enumerate(cat_vocab.keys()):
    ax.annotate("{:>4s}".format(str(cat_vocab[key])), (idx-0.5, cat_vocab[key] +
 ↪100), fontsize=10)
plt.xticks(rotation="80", fontsize=12)
plt.xlabel("Different Categories", size=14)
plt.ylabel("Frequency", size=14);
```

```
There are 29 categories
```



[26]:
```
#### Add split categories features ####
df_prepare = splitCateg(df_prepare, "categories", cat_vocab)
```

**Genres**

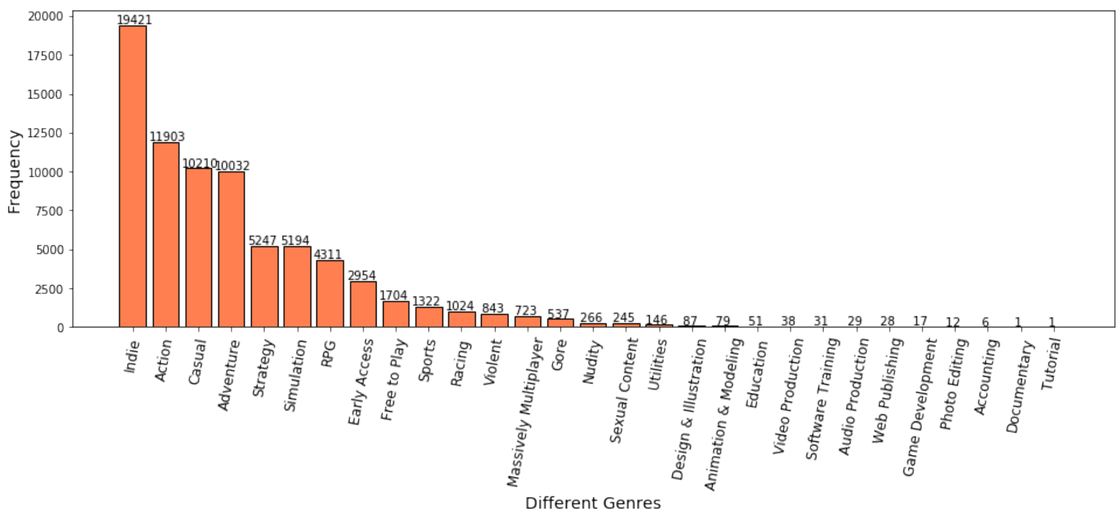
[27]:
```
#### Initial genres ####
getTopN(df_prepare,["genres"])
```

[27]:
```
                                                    owners_median  \
genres
Action;Free to Play;Strategy                          1.905688e+07
Action;Free to Play;Indie;Massively Multiplayer...    1.500000e+07
Action;Adventure;Massively Multiplayer                1.311167e+07
Action;Adventure;Free to Play;Massively Multipl...    7.675000e+06
Action;Adventure;Free to Play;Simulation;Sports       7.500000e+06

                                                    positive_ratings  \
genres
Action;Free to Play;Strategy                           108938.000000
Action;Free to Play;Indie;Massively Multiplayer...      80360.000000
Action;Adventure;Massively Multiplayer                 102626.833333
Action;Adventure;Free to Play;Massively Multipl...      55847.500000
Action;Adventure;Free to Play;Simulation;Sports         11440.000000

                                                    average_playtime  \
genres
Action;Free to Play;Strategy                                3156.875
Action;Free to Play;Indie;Massively Multiplayer...          1369.000
Action;Adventure;Massively Multiplayer                      5141.000
Action;Adventure;Free to Play;Massively Multipl...          1589.000
Action;Adventure;Free to Play;Simulation;Sports              163.000

                                                    median_playtime
genres
Action;Free to Play;Strategy                                 325.25
Action;Free to Play;Indie;Massively Multiplayer...           211.00
Action;Adventure;Massively Multiplayer                      2654.00
Action;Adventure;Free to Play;Massively Multipl...            99.50
Action;Adventure;Free to Play;Simulation;Sports               29.00
```

[28]:
```
#### Get genres vocabulary ####
genres_vocab = getVocab(df_prepare, "genres")
print("There are " + str(len(genres_vocab)) + " genres")
fig = plt.figure(figsize=[16,5])
ax = plt.gca()
```

```
plt.bar(genres_vocab.keys(),genres_vocab.values(), edgecolor="black",␣
 ↪color="coral")
for idx, key in enumerate(genres_vocab.keys()):
    ax.annotate("{:>4s}".format(str(genres_vocab[key])), (idx-0.5,␣
 ↪genres_vocab[key] + 100), fontsize=10)
plt.xticks(rotation="80", fontsize=12)
plt.xlabel("Different Genres", size=14)
plt.ylabel("Frequency", size=14);
```

```
There are 29 genres
```




[29]:
```
#### Add split genres features ####
df_prepare = splitCateg(df_prepare, "genres", genres_vocab)
```

**Steam tags**

[30]:
```
#### Initial top 10 steamspy_tags ####
getTopN(df_prepare,"steamspy_tags")
```

[30]:
```
                               owners_median  positive_ratings  \
steamspy_tags
Free to Play;MOBA;Strategy        75375000.0          432730.5
Survival;Shooter;Multiplayer      75000000.0          496184.0
FPS;Multiplayer;Shooter           75000000.0         2644404.0
Free to Play;Survival;Zombies     35000000.0          292574.0
Free to Play;Action;Co-op         35000000.0          226541.0

                               average_playtime  median_playtime
steamspy_tags
Free to Play;MOBA;Strategy                11986.0            417.0
```

```
Survival;Shooter;Multiplayer             22938.0          12434.0
FPS;Multiplayer;Shooter                  22494.0           6502.0
Free to Play;Survival;Zombies             3248.0            413.0
Free to Play;Action;Co-op                 5845.0            394.0
```

[31]:
```python
#### Get genres vocabulary ####
steamspy_vocab = getVocab(df_prepare, "steamspy_tags")
print("There are " + str(len(steamspy_vocab)) + " steamspy_tags")
```

```
There are 339 steamspy_tags
```

[32]:
```python
#### Add split genres features ####
df_prepare = splitCateg(df_prepare, "steamspy_tags", steamspy_vocab)
df_prepare.shape
```

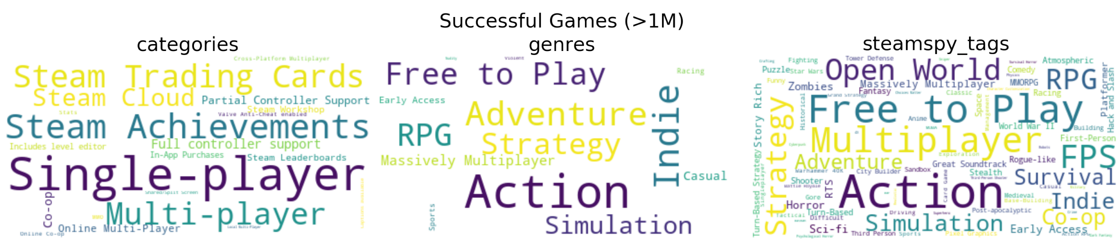
[32]: (27075, 419)

### Check Game Type Effect on Successful Games

[33]:
```python
#### For total games ####
fig = plt.figure(figsize=[40,10])
fig.suptitle("Total Games", fontsize=50)
list_vcab = [cat_vocab, genres_vocab, steamspy_vocab]
titles = ["categories", "genres", "steamspy_tags"]
for i in range(1,4):
    ax = fig.add_subplot(1,3,i)
    wc = wordcloud.WordCloud(background_color="white", max_font_size=50,␣
 ↪random_state=0).generate_from_frequencies(list_vcab[i-1])
    plt.imshow(wc,interpolation="bilinear")
    plt.axis("off")
    ax.set_title(titles[i-1], size=50)
plt.tight_layout()
plt.show();
```


[34]:
```python
#### For successful games (owners > 1M ) ####
df_prepare_success = df_prepare[df_prepare["owners_median"] >= 1500000]
success_cat_vocab = {key:sum(df_prepare_success[key + "_x"]) if key in␣
 ↪steamspy_vocab.keys() else sum(df_prepare_success[key]) for key in cat_vocab}
```

```
success_genres_vocab = {key:sum(df_prepare_success[key + "_x"]) if key in␣
↪steamspy_vocab.keys() else sum(df_prepare_success[key]) for key in␣
↪genres_vocab}
success_steamspy_vocab = {key:sum(df_prepare_success[key + "_y"]) if (key in␣
↪cat_vocab.keys()) or (key in genres_vocab.keys()) else␣
↪sum(df_prepare_success[key]) for key in steamspy_vocab}
fig = plt.figure(figsize=[40,10])
fig.suptitle("Successful Games (>1M)", fontsize=50)
list_vcab = [success_cat_vocab, success_genres_vocab, success_steamspy_vocab]
titles = ["categories", "genres", "steamspy_tags"]
for i in range(1,4):
    ax = fig.add_subplot(1,3,i)
    wc = wordcloud.WordCloud(background_color="white", max_font_size=50,␣
↪random_state=0).generate_from_frequencies(list_vcab[i-1])
    plt.imshow(wc,interpolation="bilinear")
    plt.axis("off")
    ax.set_title(titles[i-1], size=50)
plt.tight_layout()
plt.show();
```




### 0.3.4 4) Numerical features: correlation

Check the correlation between numerical features and owners number. Here, we converted ratings number to percentage. In addition, we also split release date features into year, month, and day.

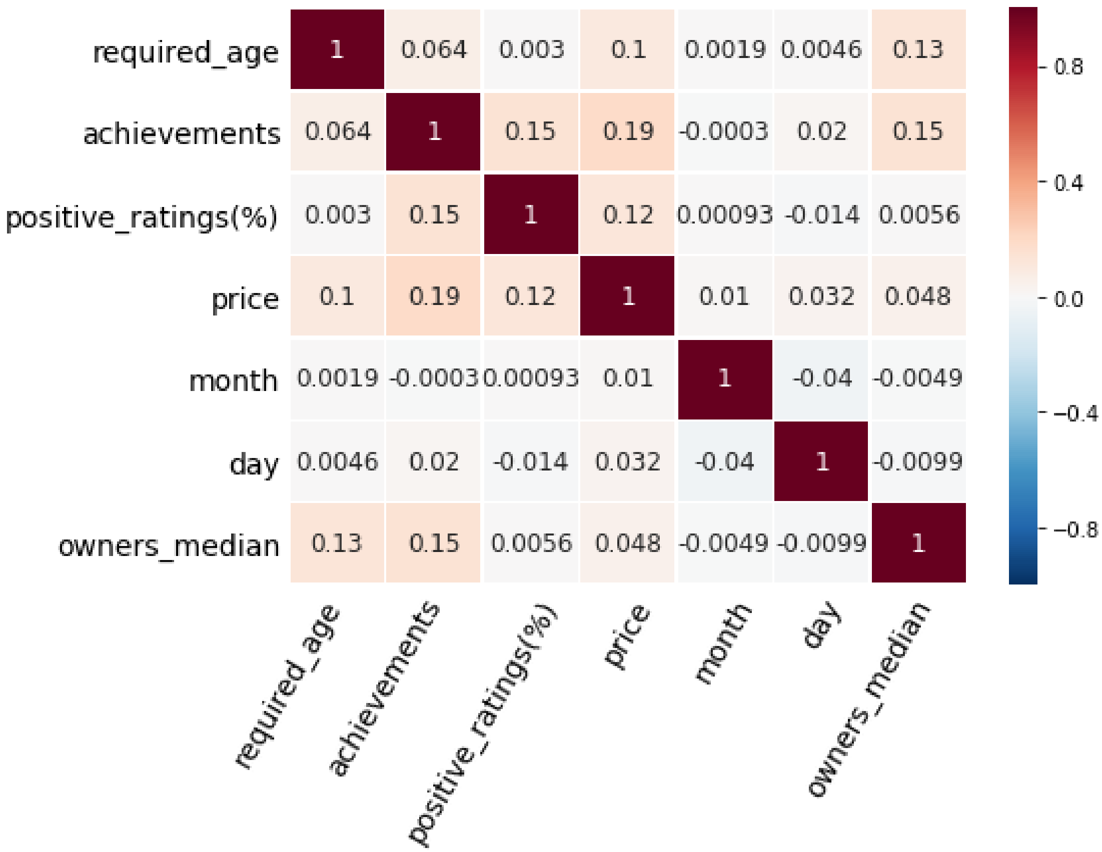
[35]:
```
df_prepare["positive_ratings_percentage"] = df_prepare["positive_ratings"]/(␣
↪df_prepare["positive_ratings"]+ df_prepare["negative_ratings"])
df_prepare["negative_ratings_percentage"] = df_prepare["negative_ratings"]/(␣
↪df_prepare["positive_ratings"]+ df_prepare["negative_ratings"])
```

[36]:
```
def splitTime(ref_date):
    '''
    Split release date into year, month, and day
    '''
    ref_year, ref_month, ref_day = time.strptime(ref_date,'%Y-%m-%d').tm_year,␣
↪time.strptime(ref_date,'%Y-%m-%d').tm_mon, time.strptime(ref_date,'%Y-%m-%d').
↪tm_mday
```

```
    return ref_year, ref_month, ref_day
```

[37]:
```
year = []
month = []
day = []
for i in range(df_prepare.shape[0]):
    y,m,d = splitTime(df_prepare.loc[i,"release_date"])
    year.append(y)
    month.append(m)
    day.append(d)
df_prepare["year"] = year
df_prepare["month"] = month
df_prepare["day"] = day
```

[38]:
```
### Final correlation graph, should use data after adding release date␣
 ↪information
figure = plt.figure(figsize=[8,6])
ax = plt.gca()
seaborn.heatmap(df_prepare[["required_age", "achievements",␣
 ↪"positive_ratings_percentage", "price", "month", "day", "owners_median"]].
 ↪corr(method="spearman"), cmap="RdBu_r", annot=True, annot_kws={"size": 12},␣
 ↪vmin=-1, linewidths=0.5)
plt.xticks([0,1,2,3.5,4.5,5.5,6],["required_age", "achievements",␣
 ↪"positive_ratings(%)", "price", "month", "day", "owners_median"], size=14,␣
 ↪rotation="60")
plt.yticks([0.5,1.5,2.5,3.5,4.5,5.5,6.5],["required_age", "achievements",␣
 ↪"positive_ratings(%)", "price", "month", "day", "owners_median"], size=14)
ax.tick_params(axis='both', which='both', length=0)
plt.tight_layout();
#plt.savefig("correlation.png", dpi=300);
```




Currently, it seems no feature shows good correlation with owners_median, which indicates the challenge of this project.

#### 0.3.5 5) New features: Developer_famous & Publisher_famous

**Developer & Publisher** For the developer and publisher, since there are two many different categorials, we converted them into two new features: famous and non-famous, based on previous owners. These two features indicate the developer/publisher reputation effect on game success If a developer has average owners higher than 75% of developers before the target game release date, we assume it's a famous developer. If a publisher has average owners higher than 75% of publishers before the target game release date, we assume it's a famous publisher.

[39]:
```
def time_filter(data, ref_date):
    '''
    Remove games released after ref_date
    '''
    ref_year, ref_month, ref_day = time.strptime(ref_date,'%Y-%m-%d').tm_year,␣
↪time.strptime(ref_date,'%Y-%m-%d').tm_mon, time.strptime(ref_date,'%Y-%m-%d').
↪tm_mday
    data.release_date = data["release_date"].astype("datetime64")
    df_tmp = data[(data["release_date"].dt.year < ref_year) |
```

```
                  ((data["release_date"].dt.year == ref_year) &␣
↪(data["release_date"].dt.month < ref_month)) |
                  ((data["release_date"].dt.year == ref_year) &␣
↪(data["release_date"].dt.month == ref_month) & (data["release_date"].dt.day <␣
↪ref_day))
                 ]
    return df_tmp
```

[40]:
```
def checkFamous(data, variable, ref_idx):
    '''
    Check the publisher/developer of certain game is famous or not (based on␣
↪ref_idx) before game release.
    The assumption here, is the owners of certain games always increase␣
↪significantly in a short time after game relaese.
    Based on this assumption, we can determine whether a company is famous or␣
↪not using this simple function.
    However, this assumption might be not True.
    We can also use other information, such as metacritic score to determine␣
↪whether a company is famous or not
    '''
    df_tmp = data[data.index != ref_idx]
    ref_date = data.iloc[ref_idx]["release_date"]
    ref_variable = data.iloc[ref_idx][variable]
    df_tmp = time_filter(df_tmp,ref_date)
    df_tmp_group = df_tmp.groupby(variable).agg({"owners_median": np.mean})
    df_tmp_group.reset_index(inplace=True)
    value = df_tmp.describe().loc["75%"].values[0]
    if df_tmp_group[df_tmp_group[variable] == ref_variable]["owners_median"].
↪values >= value:
        return True
    else:
        return False
```

[41]:
```
def addFamous(data, variable):
    '''
    Get famous data and add them into initial data
    '''
    out = open("../data/famous_" + variable + ".csv", "w")
    famous_list = []
    for i in range(data.shape[0]):
        famous = checkFamous(data, variable, i)
        if famous:
            famous_list.append(1)
        else:
            famous_list.append(0)
        print(str(i) + "," + str(famous))
        out.write(str(famous) + "\n")
```

```
    out.close()
    #data[variable + "_famous"] = famous_list

    famous_percentage = len([i for i in famous_list if i == 1]) /␣
↪len(famous_list)
    print("Famous percentage is " + str(famous_percentage))
    return data
```

[ ]:
```
pd.options.mode.chained_assignment = None
df_prepare = addFamous(df_prepare, "developer")
```

[ ]:
```
df_prepare = addFamous(df_prepare, "publisher")
```

[43]:
```
df_famous_developer = pd.read_csv("../data/famous_developer.csv", header=None)
developer_famous = [1 if i == True else 0 for i in df_famous_developer[0].
↪tolist()]
df_famous_publisher = pd.read_csv("../data/famous_publisher.csv", header=None)
publisher_famous = [1 if i == True else 0 for i in df_famous_publisher[0].
↪tolist()]
```

[44]:
```
df_prepare["developer_famous"] = developer_famous
df_prepare["publisher_famous"] = publisher_famous
```

## 0.4 3. Build Model

Since there are too less games with owners larger than 10 million, we combined the games with owners lager than 10 million and use the average number to replace the initial owners_media.

[45]:
```
df_use = df_prepare.copy()
```

[46]:
```
for idx in df_use.loc[df_use["owners"].isin(["100000000-200000000",␣
↪"50000000-100000000", "20000000-50000000", "10000000-20000000"])].index:
    df_use.iloc[idx, 18] = 26666667
```

26666667 is the average of owners_median of these games

[47]:
```
#### Change number into classes ####
Y = df_use[["owners_median"]]
ec = LabelEncoder()
df_use["target"] = ec.fit_transform(Y)
```

```
/Users/jianinglu1/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/label.py:235: DataConversionWarning: A column-
vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

[48]:
```
#### Split dataset using 8:1:1 ####
train_idx, test_idx = train_test_split(df_use["appid"].values,  test_size=0.10,␣
↪stratify=df_use["target"], random_state=0)
```

```
train_idx, val_idx = train_test_split(train_idx,  test_size=0.11,␣
↪stratify=df_use[df_use["appid"].isin(train_idx)]["target"], random_state=0)
```

[49]:
```
train_idx.shape
test_idx.shape
val_idx.shape
```

[49]: (21686,)

[49]: (2708,)

[49]: (2681,)

We first trained a baseline model with all features(no time features) and simple XGB classifer, and found there are some features with 0 feature importance. To accelerate the model training process, we retrained the model without features, and includes time features(month and day). We also added class weight for each class.

[50]:
```
#### Remove non-important features ####
features = ['english','required_age','achievements', 'price',
            'positive_ratings_percentage', 'windows', 'mac', 'linux',␣
↪'developer_famous', 'publisher_famous'] + \
            list([key if key not in steamspy_vocab.keys() else key + "_x" for␣
↪key in cat_vocab.keys()]) + \
            list([key if key not in steamspy_vocab.keys() else key + "_x" for␣
↪key in genres_vocab.keys()]) + \
            list([key + "_y" if (key in cat_vocab.keys()) or (key in␣
↪genres_vocab.keys()) else key for key in steamspy_vocab.keys()])

features_imp = pd.read_csv("../models/Base_line/feature_imp.csv", header = None,␣
↪index_col=0)
features_imp.columns = features
mean_features_imp = features_imp.describe()[1:2].transpose()
mean_features_imp.sort_values("mean", inplace = True)
features_remove = [i for i in features if i not in␣
↪mean_features_imp[mean_features_imp["mean"] == 0].index.tolist()]
features_remove = features_remove + ["month", "day"]
print(str(len(features_remove)) + " features")
```

```
217 features
```

[51]:
```
X_train = df_use[df_use["appid"].isin(train_idx)][features_remove].values
Y_train = df_use[df_use["appid"].isin(train_idx)]["target"].values
#### sample weight is based on its target class
Y_train_weight = (Y_train + 1)/np.max(Y_train + 1)
X_val = df_use[df_use["appid"].isin(val_idx)][features_remove].values
Y_val = df_use[df_use["appid"].isin(val_idx)]["target"].values
Y_val_weight = (Y_val + 1)/np.max(Y_val + 1)
X_test = df_use[df_use["appid"].isin(test_idx)][features_remove].values
Y_test = df_use[df_use["appid"].isin(test_idx)]["target"].values
```

We use hold out validation set, which is split based on target classes. We also applied ensemble model to do the prediction.

### 0.4.1 1) Train Model

[53]:
```
trnp_df = pd.DataFrame({"index":[i for i in range(X_train.shape[0])]})
tesp_df = pd.DataFrame({"index":[i for i in range(X_test.shape[0])]})
valp_df = pd.DataFrame({"index":[i for i in range(X_val.shape[0])]})
out = open("../models/Final/feature_imp.csv", "w")
for i in range(10):
    if "pima.pickle_" + str(i) + ".dat" in os.listdir("../models/Final/"):
        xgb = pickle.load(open("../models/Final/pima.pickle_" + str(i) + ".dat",␣
 ↪"rb"))
    else:
        xgb = XGBClassifier(n_estimators=1000, random_state=(i-1) * 10,␣
 ↪colsample_bytree=0.8, learning_rate=0.2, objective="multi:softmax",␣
 ↪num_class=10)
        xgb.fit(X_train, Y_train, sample_weight=Y_train_weight,␣
 ↪eval_set=[(X_val, Y_val)], eval_metric="mlogloss", early_stopping_rounds=50,␣
 ↪sample_weight_eval_set=[Y_val_weight])
    pickle.dump(xgb, open("../models/Final/pima.pickle_" + str(i) + ".dat",␣
 ↪"wb"))
    f_importance = xgb.feature_importances_
    out.write(str(i) + "," + ",".join([str(f) for f in f_importance]) + '\n')
    trnp = xgb.predict(X_train)
    tesp = xgb.predict(X_test)
    valp = xgb.predict(X_val)
    if i == 1:
        trnp_df = pd.DataFrame({"data" + str(i):trnp})
        tesp_df = pd.DataFrame({"data" + str(i):tesp})
        valp_df = pd.DataFrame({"data" + str(i):valp})
    else:
        trnp_df["data" + str(i)] = trnp
        tesp_df["data" + str(i)] = tesp
        valp_df["data" + str(i)] = valp
out.close()
```

[53]: 2632

[53]: 2655

[53]: 2655

[53]: 2601

[53]: 2601

[53]: 2663

[53]: 2652

[53]: 2655

[53]: 2637

[53]: 2664

[54]:
```
trnp_df_final = trnp_df.mode(axis = 1)[0]
tesp_df_final = tesp_df.mode(axis = 1)[0]
valp_df_final = valp_df.mode(axis = 1)[0]
```

### 0.4.2 2) Check Performance

[55]:
```
def getAccuracy(Y_true, Y_pred):
    '''
    Get prediction accuracy
    '''
    acc = (Y_pred == Y_true).sum().astype(float) / len(Y_true)*100
    return str(round(acc,2)) + "%"

def calTPR(predict, target, threshold):
    '''
    Calculate true positive rate
    '''
    tesFP_class = (lambda x: [1 if i >= threshold else 0 for i in x])(predict)
    tesFY_class = (lambda x: [1 if i >= threshold else 0 for i in x])(target)
    TP = [ idx for idx, i in enumerate(tesFY_class) if (i == 1) and␣
 ↪(tesFP_class[idx] == 1) ]
    TotalP = [ idx for idx, i in enumerate(tesFY_class) if i == 1]
    TPR = len(TP) / len(TotalP)
    return TPR

def calFPR(predict, target, threshold):
    '''
    Calculate false positive rate
    '''
    tesFP_class = (lambda x: [1 if i >= threshold else 0 for i in x])(predict)
    tesFY_class = (lambda x: [1 if i >= threshold else 0 for i in x])(target)
    FP = [ idx for idx, i in enumerate(tesFY_class) if (i == 0) and␣
 ↪(tesFP_class[idx] == 1) ]
    TotalN = [ idx for idx, i in enumerate(tesFY_class) if i == 0]
    FPR = len(FP) / len(TotalN)
    return FPR
```

[56]:
```
acc_train = getAccuracy(Y_train, trnp_df_final)
acc_val = getAccuracy(Y_val, valp_df_final)
acc_test = getAccuracy(Y_test, tesp_df_final)
print("Prediction accuracy:\n" + "Train:" + acc_train + "," + "Validation:" +␣
 ↪acc_val + "," + "Test:" + acc_test )
```

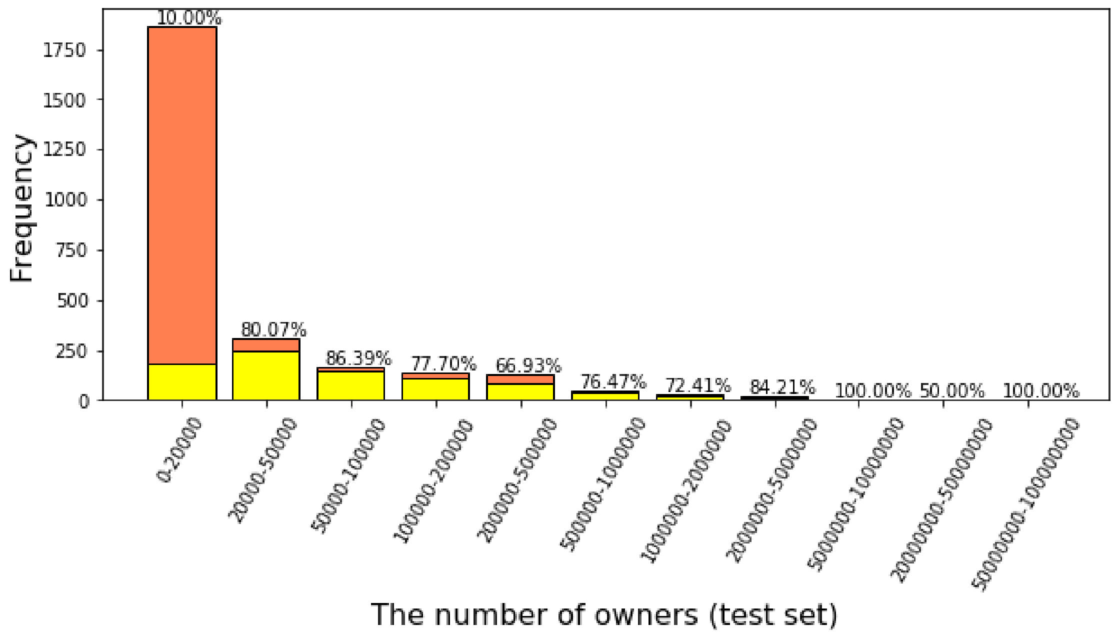
```
Prediction accuracy:
Train:80.51%,Validation:69.56%,Test:68.5%
```

[57]:
```
results_train = calTPR(trnp_df_final, Y_train, 1), calFPR(trnp_df_final,␣
 ↪Y_train, 1)
results_val = calTPR(valp_df_final, Y_val, 1), calFPR(valp_df_final, Y_val, 1)
results_test = calTPR(tesp_df_final, Y_test, 1), calFPR(tesp_df_final, Y_test, 1)
print("TPR:\n" + "Train:" + str(results_train[0]) + ",Validation:" +␣
 ↪str(results_val[0]) + ",Test:" + str(results_test[0]))
print("FPR:\n" + "Train:" + str(results_train[1]) + ",Validation:" +␣
 ↪str(results_val[1]) + ",Test:" + str(results_test[1]))
```

```
TPR:
Train:0.748377581120944,Validation:0.7027027027027027,Test:0.6851415094339622
FPR:
Train:0.0779551858312089,Validation:0.08469945355191257,Test:0.1
```

### 0.4.3 3) Error Analysis

[61]:
```
df_test = df_use[df_use["appid"].isin(test_idx)]
### Initial target class distribution ###
df_test_owner_infor = { df_tmp[0]: len(df_tmp[1]) for df_tmp in df_test.
 ↪groupby("owners")}
df_test_owner_infor = { x:y for x,y in sorted(df_test_owner_infor.items(), key =␣
 ↪lambda x: getMedian(x[0]))}
df_test_owner_infor
df_test["predict"] = tesp_df_final.values
df_test_error = df_test[df_test["predict"] != df_test["target"]]
df_test_error_owner_infor = { df_tmp[0]: len(df_tmp[1]) for df_tmp in␣
 ↪df_test_error.groupby("owners")}
df_test_error_owner_infor = { x:y for x,y in sorted(df_test_error_owner_infor.
 ↪items(), key = lambda x: getMedian(x[0]))}
fig = plt.figure(figsize=[10,4])
ax = plt.gca()
plt.bar(df_test_owner_infor.keys(), df_test_owner_infor.values(),␣
 ↪edgecolor="black", color="coral")
plt.bar(df_test_error_owner_infor.keys(), df_test_error_owner_infor.values(),␣
 ↪edgecolor="black", color="yellow")

for idx, key in enumerate(df_test_owner_infor.keys()):
    ax.annotate("{:.2f}%".format(float(df_test_error_owner_infor[key]/
 ↪df_test_owner_infor[key] * 100)), (idx-0.3, df_test_owner_infor[key] + 10),␣
 ↪fontsize=10)
plt.xticks(rotation="60", fontsize=10)
plt.xlabel("The number of owners (test set)", size=16)
plt.ylabel("Frequency", size=16);
```



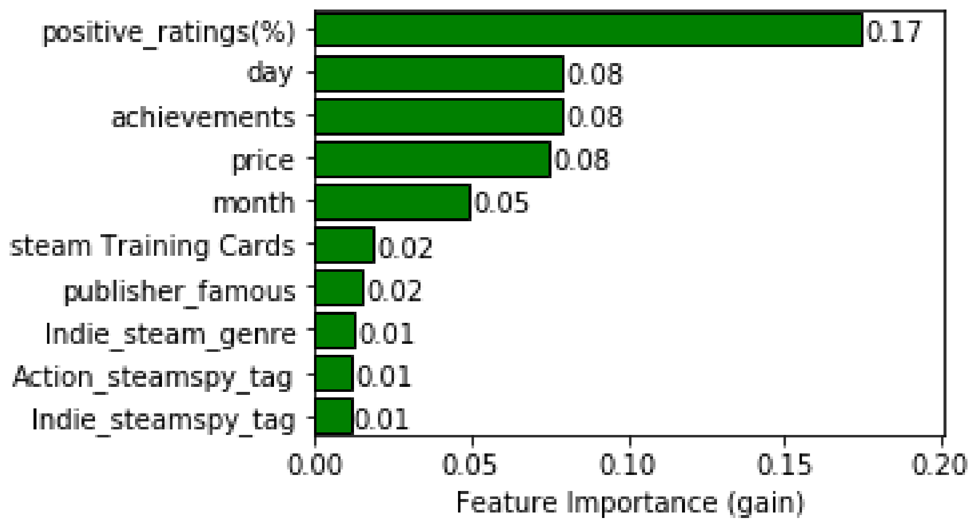

### 0.4.4 4) Feature Importance

[62]:
```
features_imp = pd.read_csv("../models/Final/feature_imp.csv", header = None,␣
↪index_col=0)
features_imp.columns = features_remove
mean_features_imp = features_imp.describe()[1:2].transpose()
mean_features_imp.sort_values("mean", inplace = True)
mean_features_imp[mean_features_imp["mean"] == 0].index
```

[62]:
```
Index(['Rogue-lite', 'Wargame', 'Short', 'Chess', 'Cats', 'Underwater',
       'Turn-Based Tactics', 'Offroad', 'Cold War', 'Procedural Generation',
       'Video Production_y', 'Photo Editing_y', 'Cult Classic',
       'Real-Time with Pause', 'Magic', 'Photo Editing_x'],
      dtype='object')
```

[63]:
```
fig = plt.figure(figsize=[6,3])
ax = plt.gca()
plt.barh(mean_features_imp.index[-10:], mean_features_imp["mean"][-10:],␣
↪color="green", edgecolor="black")
for idx, x in enumerate(mean_features_imp["mean"][-10:]):
    ax.annotate("{:.2f}".format(x), (x + 0.001, idx-0.3))
plt.tight_layout(pad=2.0)
plt.yticks([9,8,7,6,5,4,3,2,1,0], ["positive_ratings(%)", "day", "achievements",␣
↪"price", "month", "steam Training Cards", "publisher_famous",␣
↪"Indie_steam_genre", "Action_steamspy_tag", "Indie_steamspy_tag"])
plt.margins(x=0.15, y = 0.005)
```

```
plt.xlabel("Feature Importance (gain)");
#plt.savefig("Feature_importance.png", dpi=300);
```




From the feature importance results, we found that the Top1 important features is positive_rating_percentage, which can be got from a pre-releasing game test.