Integrated project

You work for the online store Ice, which sells video games all over the world. User and expert reviews, genres, platforms (e.g. Xbox or PlayStation), and historical data on game sales are available from open sources. You need to identify patterns that determine whether a game succeeds or not. This will allow you to spot potential big winners and plan advertising campaigns.

Step 1. Open the data file and study the general information

In [1]:
```
#load libraries
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn as sns


from functools import reduce
from math import factorial
from scipy import stats as st
from statistics import mean
from IPython.display import display


pd.set_option('display.max_columns', 500)
```

In [2]:
```
#load all data tables
data = pd.read_csv('/datasets/games.csv')
```

In [3]:
```
data.describe()
```

Out[3]:

	Year_of_Release	NA_sales	EU_sales	JP_sales	Other_sales	Critic_Score
count	16446.000000	16715.000000	16715.000000	16715.000000	16715.000000	8137.000000
mean	2006.484616	0.263377	0.145060	0.077617	0.047342	68.967679
std	5.877050	0.813604	0.503339	0.308853	0.186731	13.938165
min	1980.000000	0.000000	0.000000	0.000000	0.000000	13.000000
25%	2003.000000	0.000000	0.000000	0.000000	0.000000	60.000000
50%	2007.000000	0.080000	0.020000	0.000000	0.010000	71.000000
75%	2010.000000	0.240000	0.110000	0.040000	0.030000	79.000000
max	2016.000000	41.360000	28.960000	10.220000	10.570000	98.000000

In [4]:
```
data.describe(include='object')
```

Out[4]:

	Name	Platform	Genre	User_Score	Rating
count	16713	16715	16713	10014	9949
unique	11559	31	12	96	8
top	Need for Speed: Most Wanted	PS2	Action	tbd	E
freq	12	2161	3369	2424	3990

In [5]:
```
data.sample(10)
```

Out[5]:

	Name	Platform	Year_of_Release	Genre	NA_sales	EU_sales	JP_sales	Other_sales	Critic_Score	User_Score	Rating
1487	Petz Wild Animals: Dolphinz	DS	2007.0	Simulation	0.71	0.48	0.0	0.13	NaN	tbd	E
10425	Kamen Rider: Battride War II	PS3	2014.0	Action	0.00	0.00	0.1	0.00	NaN	NaN	NaN
16071	4 Play Collection - Dark Mysteries	PC	2014.0	Misc	0.00	0.01	0.0	0.00	NaN	NaN	NaN
10893	Adventure Time: Finn & Jake Investigations	PS4	2015.0	Action	0.03	0.05	0.0	0.02	NaN	NaN	NaN
2497	Sid Meier's Civilization Revolution	X360	2008.0	Strategy	0.58	0.17	0.0	0.07	84.0	7.8	E10+
12295	Moshi Monsters: Katsuma Unleashed	3DS	2013.0	Action	0.03	0.03	0.0	0.01	NaN	tbd	E
3680	Iron Man	PS2	2008.0	Action	0.36	0.00	0.0	0.19	47.0	5.6	T
5998	FlatOut: Head On	PSP	2008.0	Racing	0.13	0.10	0.0	0.06	74.0	8.2	T
9033	Second Sight	PS2	2004.0	Adventure	0.07	0.05	0.0	0.02	76.0	8	T
803	Sim Theme Park	PC	1998.0	Strategy	2.04	0.04	0.0	0.00	NaN	8.3	E

In [6]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16715 entries, 0 to 16714
Data columns (total 11 columns):
Name               16713 non-null object
Platform           16715 non-null object
Year_of_Release    16446 non-null float64
Genre              16713 non-null object
NA_sales           16715 non-null float64
EU_sales           16715 non-null float64
JP_sales           16715 non-null float64
Other_sales        16715 non-null float64
Critic_Score       8137 non-null float64
User_Score         10014 non-null object
Rating             9949 non-null object
dtypes: float64(6), object(5)
memory usage: 1.4+ MB
```

I see several flaws in this data:

- lot's of zeros for region sales. Need to check if when only one row has had value, others were filled with zeroes;
- User score is not a float and most popular value there is 'to be determined';
- some missing values in Name, Genre, Critic_Score, User_score and Rating
- column names that are not easy to work with.

Step 2. Prepare the data

In [7]:
```
#rename columns
data.columns = ['name', 'platform', 'release_date', 'genre', 'na_sales', 'eu_sales',
                'jp_sales', 'other_sales', 'critic_score', 'user_score', 'rating']
```

In [8]:
```
#Now let's see what's going on with missing values
data[data.name.isnull()]
```

Out[8]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating
659	NaN	GEN	1993.0	NaN	1.78	0.53	0.00	0.08	NaN	NaN	NaN
14244	NaN	GEN	1993.0	NaN	0.00	0.00	0.03	0.00	NaN	NaN	NaN

Looks like these rows come through some old games that aren't in the database. I'll keep them for now, maybe they will have some effect on further anaysis of sales for this platform.

In [9]:
```
#Now let's check values for release date
data[data.release_date.isnull()]
```

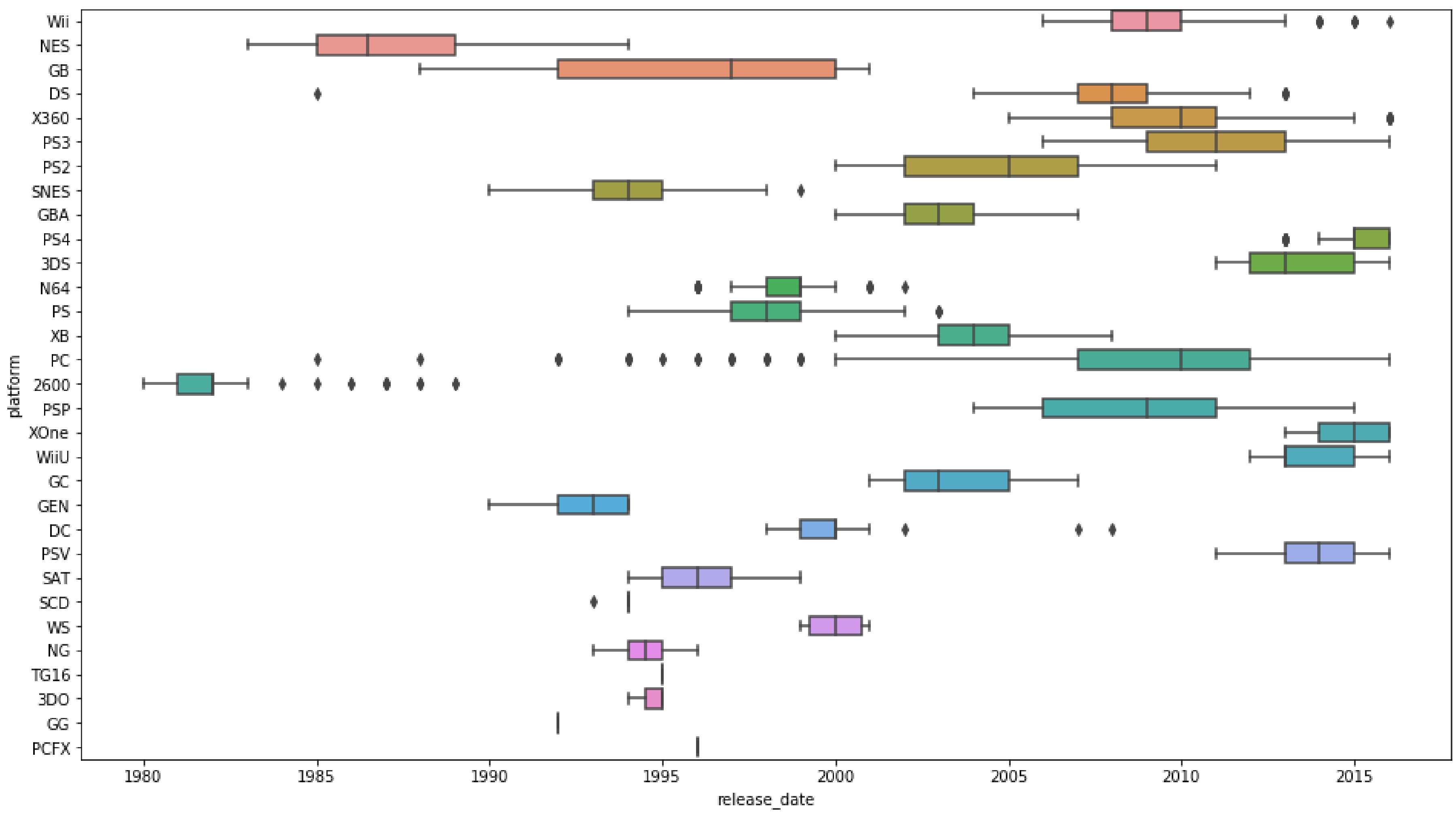
Out[9]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating
183	Madden NFL 2004	PS2	NaN	Sports	4.26	0.26	0.01	0.71	94.0	8.5	E
377	FIFA Soccer 2004	PS2	NaN	Sports	0.59	2.36	0.04	0.51	84.0	6.4	E
456	LEGO Batman: The Videogame	Wii	NaN	Action	1.80	0.97	0.00	0.29	74.0	7.9	E10+
475	wwe Smackdown vs. Raw 2006	PS2	NaN	Fighting	1.57	1.02	0.00	0.41	NaN	NaN	NaN
609	Space Invaders	2600	NaN	Shooter	2.36	0.14	0.00	0.03	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...
16373	PDC World Championship Darts 2008	PSP	NaN	Sports	0.01	0.00	0.00	0.00	43.0	tbd	E10+
16405	Freaky Flyers	GC	NaN	Racing	0.01	0.00	0.00	0.00	69.0	6.5	T
16448	Inversion	PC	NaN	Shooter	0.01	0.00	0.00	0.00	59.0	6.7	M
16458	Hakuouki: Shinsengumi Kitan	PS3	NaN	Adventure	0.01	0.00	0.00	0.00	NaN	NaN	NaN
16522	Virtua Quest	GC	NaN	Role-Playing	0.01	0.00	0.00	0.00	55.0	5.5	T

269 rows × 11 columns

Lot's of rows that don't have release date value, we can't drop them and can't fill them with median. But we all gaming platform usually have limited amount of time that games are released, maybe we can fill missing values with median for each platform. Let's firstly analyse year of release for each platform.

In [10]:
```
ax = plt.subplots(figsize=(16,9))
fig = sns.boxplot(x=data['release_date'], y=data['platform'], data=data)
```



My theory confirmed. Games' year of release is pretty much concentrated within form 5 to 10 years for most of big platforms and is even more narrow for smaller ones. Therefore we can freely change release date for missng columns with mean for that platform.

In [11]:
```
#I'll fill with median using transform method
data['release_date'] = (
    data['release_date']
    .fillna(data.groupby('platform')['release_date'].transform('median'))
    .round(0)
    .astype(int) #change end value to integer
)
```

In [78]:
```
data[data.release_date.isnull()]
```

Out[78]:

name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating

No empty release date left!

In [12]:
```
#check empty values for critic score
data[data.critic_score.isnull()].sample(10)
```

Out[12]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating
3638	Ratchet & Clank: Quest for Booty	PS3	2008	Platform	0.00	0.52	0.00	0.04	NaN	NaN	NaN
12553	Mike Piazza's Strike Zone	N64	1998	Sports	0.05	0.01	0.00	0.00	NaN	NaN	NaN
7747	Shin Megami Tensei IV: Final	3DS	2016	Role-Playing	0.05	0.00	0.14	0.01	NaN	NaN	NaN
3252	Mario's Picross	GB	1995	Puzzle	0.00	0.00	0.62	0.00	NaN	NaN	NaN
8379	NickToons: Racing	PS	2001	Racing	0.09	0.06	0.00	0.01	NaN	NaN	NaN
8455	Chaotic: Shadow Warriors	PS3	2009	Action	0.15	0.00	0.00	0.02	NaN	tbd	E10+
7023	Rock Band Track Pack Volume 2	Wii	2008	Misc	0.20	0.01	0.00	0.02	NaN	NaN	NaN
14680	Nisekoi: Yomeiri!?	PSV	2014	Adventure	0.00	0.00	0.03	0.00	NaN	NaN	NaN
14643	Kung Fu Panda: Showdown of Legendary Legends	3DS	2015	Action	0.00	0.03	0.00	0.00	NaN	tbd	E10+
11947	Crayola: Colorful Journey	Wii	2009	Misc	0.07	0.00	0.00	0.00	NaN	tbd	E

In [13]:
```
data[data.critic_score.isnull()].describe()
```

Out[13]:

	release_date	na_sales	eu_sales	jp_sales	other_sales	critic_score
count	8578.000000	8578.000000	8578.000000	8578.000000	8578.000000	0.0
mean	2005.790044	0.178381	0.085059	0.099045	0.023539	NaN
std	7.091343	0.716068	0.321036	0.343936	0.088740	NaN
min	1980.000000	0.000000	0.000000	0.000000	0.000000	NaN
25%	2001.000000	0.000000	0.000000	0.000000	0.000000	NaN
50%	2008.000000	0.020000	0.000000	0.000000	0.000000	NaN
75%	2011.000000	0.140000	0.050000	0.060000	0.020000	NaN
max	2016.000000	29.080000	10.950000	10.220000	2.740000	NaN

Looks like we have lots of values that are with empty critic score. It may be due to these games didn't get enough critic reviews or maybe they just weren't filled. I don't see a way to fill them, therefore I'll keep these scores as NaN. I will do the same for empty user_score values, because there is nothing I can do about it.

In [14]:
```
#Now let's check what's happening with tbd in user_score value
data.query('user_score =="tbd"')
```

Out[14]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating
119	Zumba Fitness	Wii	2010	Sports	3.45	2.59	0.0	0.66	NaN	tbd	E
301	Namco Museum: 50th Anniversary	PS2	2005	Misc	2.08	1.35	0.0	0.54	61.0	tbd	E10+
520	Zumba Fitness 2	Wii	2011	Sports	1.51	1.03	0.0	0.27	NaN	tbd	T
645	uDraw Studio	Wii	2010	Misc	1.65	0.57	0.0	0.20	71.0	tbd	E
657	Frogger's Adventures: Temple of the Frog	GBA	2003	Adventure	2.15	0.18	0.0	0.07	73.0	tbd	E
...	...	...	...	...	...	...	...	...	...	...	...
16695	Planet Monsters	GBA	2001	Action	0.01	0.00	0.0	0.00	67.0	tbd	E
16697	Bust-A-Move 3000	GC	2003	Puzzle	0.01	0.00	0.0	0.00	53.0	tbd	E
16698	Mega Brain Boost	DS	2008	Puzzle	0.01	0.00	0.0	0.00	48.0	tbd	E
16704	Plushees	DS	2008	Simulation	0.01	0.00	0.0	0.00	NaN	tbd	E
16706	Men in Black II: Alien Escape	GC	2003	Shooter	0.01	0.00	0.0	0.00	NaN	tbd	T

2424 rows × 11 columns

I see that there are lots of rows with this value, but this aren't recent games, so it's highly unlikely that they are going to get user score assigned. Therefore I think it will be better just to change them to NaN, so they won't affect the data, but first I'll check if they are all really old.

In [15]:
```
data.query('user_score =="tbd"').release_date.value_counts()
```

Out[15]:
```
2009    422
2008    338
2010    332
2011    217
2007    192
2002    192
2005    125
2006    124
2004    111
2003    102
2001     82
2000     43
2015     38
2016     34
2012     24
2014     21
2013     17
1999      8
1997      1
1998      1
Name: release_date, dtype: int64
```

In [16]:
```
#There are some new games, but overall it's spred all over, I think it's better to change these values to Nan
data['user_score'] = data['user_score'].replace('tbd', np.nan)
data['user_score'] = data.user_score.astype(float).copy() #change user_score to float
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16715 entries, 0 to 16714
Data columns (total 11 columns):
name               16713 non-null object
platform           16715 non-null object
release_date       16715 non-null int64
genre              16713 non-null object
na_sales           16715 non-null float64
eu_sales           16715 non-null float64
jp_sales           16715 non-null float64
other_sales        16715 non-null float64
critic_score       8137 non-null float64
user_score         7590 non-null float64
rating             9949 non-null object
dtypes: float64(6), int64(1), object(4)
memory usage: 1.4+ MB
```

In [17]:
```
#let's check if all there aren't any rows that have empty values for sales in all regions
data.query('na_sales==0 & eu_sales==0 & jp_sales==0 & other_sales==0')
```

Out[17]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating
16676	G1 Jockey 4 2008	PS3	2008	Sports	0.0	0.0	0.0	0.0	NaN	NaN	NaN
16709	SCORE International Baja 1000: The Official Game	PS2	2008	Racing	0.0	0.0	0.0	0.0	NaN	NaN	NaN

This is a little bit strange. I don't quite understand how did games with 0 in all sales get in this dataset, in real life it would have been better to find out how this dataset was formed to see if we have any mistakes in it. But here I'm just going to drop these rows, because they are no good.

In [18]:
```
data = data.drop([16676, 16709])
```

In [19]:
```
#let's check values for rating
data.rating.value_counts()
```

Out[19]:
```
E       3990
T       2961
M       1563
E10+    1420
EC         8
RP         3
K-A        3
AO         1
Name: rating, dtype: int64
```

In [20]:
```
data[data.rating.isnull()].describe()
```

Out[20]:

	release_date	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score
count	6764.000000	6764.000000	6764.000000	6764.000000	6764.000000	83.000000	86.000000
mean	2004.845949	0.183687	0.090750	0.124477	0.022336	68.614458	6.965116
std	7.546940	0.796317	0.348051	0.383074	0.092142	12.633513	1.432954
min	1980.000000	0.000000	0.000000	0.000000	0.000000	31.000000	3.100000
25%	1999.000000	0.000000	0.000000	0.000000	0.000000	62.000000	6.100000
50%	2007.000000	0.000000	0.000000	0.020000	0.000000	70.000000	7.350000
75%	2011.000000	0.120000	0.050000	0.100000	0.010000	77.500000	8.100000
max	2016.000000	29.080000	10.950000	10.220000	2.740000	93.000000	9.200000

There are 6714 rows with empty rating, that's a lot. Also many of these games have empty critic score and user score. I'will leave these rows empty for now and will drop if I won't need them later.

Now I need to calculate total sales for each game in all the regions.

In [21]:
```
data['total_sales'] = data['na_sales'] + data['eu_sales'] + data['jp_sales'] + data['other_sales']
data.sample(10)
```

Out[21]:

	name	platform	release_date	genre	na_sales	eu_sales	jp_sales	other_sales	critic_score	user_score	rating	total_sales
9775	Ninja Reflex	Wii	2008	Action	0.11	0.00	0.00	0.01	49.0	6.0	E10+	0.12
7522	Midnight Club 3: DUB Edition Remix	XB	2006	Racing	0.15	0.04	0.00	0.01	87.0	5.3	E10+	0.20
2588	Motocross Mania	PS	2001	Racing	0.44	0.30	0.00	0.05	34.0	5.3	E	0.79
9133	Spyro: A Hero's Tail	XB	2004	Platform	0.11	0.03	0.00	0.01	64.0	9.1	E	0.15
544	Yoshi's Island DS	DS	2006	Platform	1.45	0.07	1.10	0.15	81.0	7.4	E	2.77
4368	Watch Dogs	PC	2014	Action	0.15	0.26	0.00	0.03	77.0	4.7	M	0.44
15651	Miyako	PSP	2010	Adventure	0.00	0.00	0.02	0.00	NaN	NaN	NaN	0.02
4144	WipEout	PS	1995	Action	0.26	0.18	0.00	0.03	NaN	NaN	NaN	0.47
6346	Rapala Pro Bass Fishing 2010	PS3	2010	Sports	0.18	0.05	0.00	0.03	NaN	8.5	E	0.26
4671	Tom Clancy's Rainbow Six: Lockdown	XB	2005	Shooter	0.26	0.13	0.00	0.02	74.0	6.6	M	0.41

Conclusion

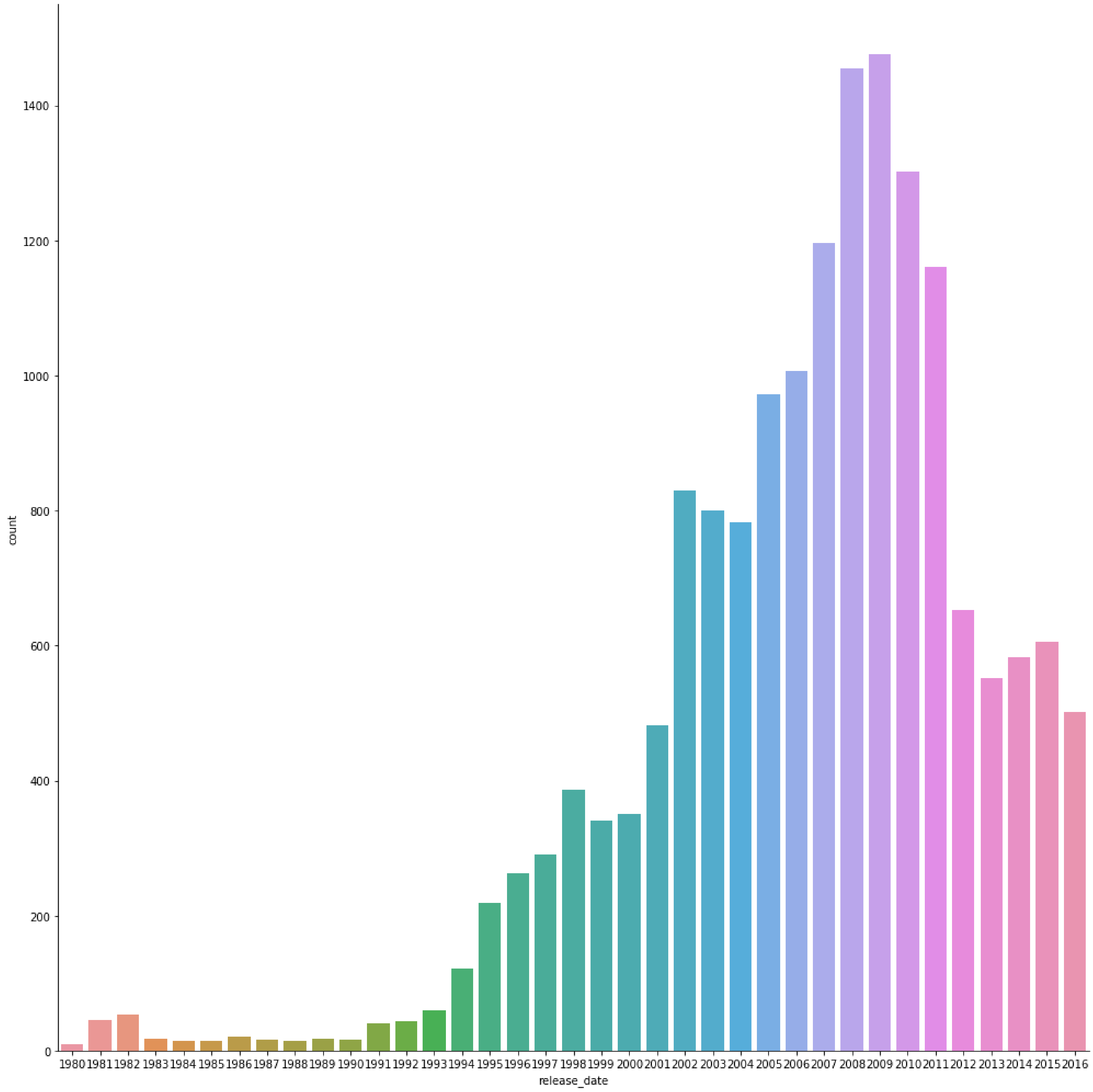
1. I have replased missing release year with mean release year for each platform;
2. I have changed "to be determined" values of user score column to NaN, because they aren't going to be determined;
3. I have left empty values for critic score and for rating to stay empty;
4. I have droped rows that had no sales at all;
5. I have calculated total sales for each game and put them in new column.

Step 3. Analyze the data

Look at how many games were released in different years. Check if the data for every period issignificant?

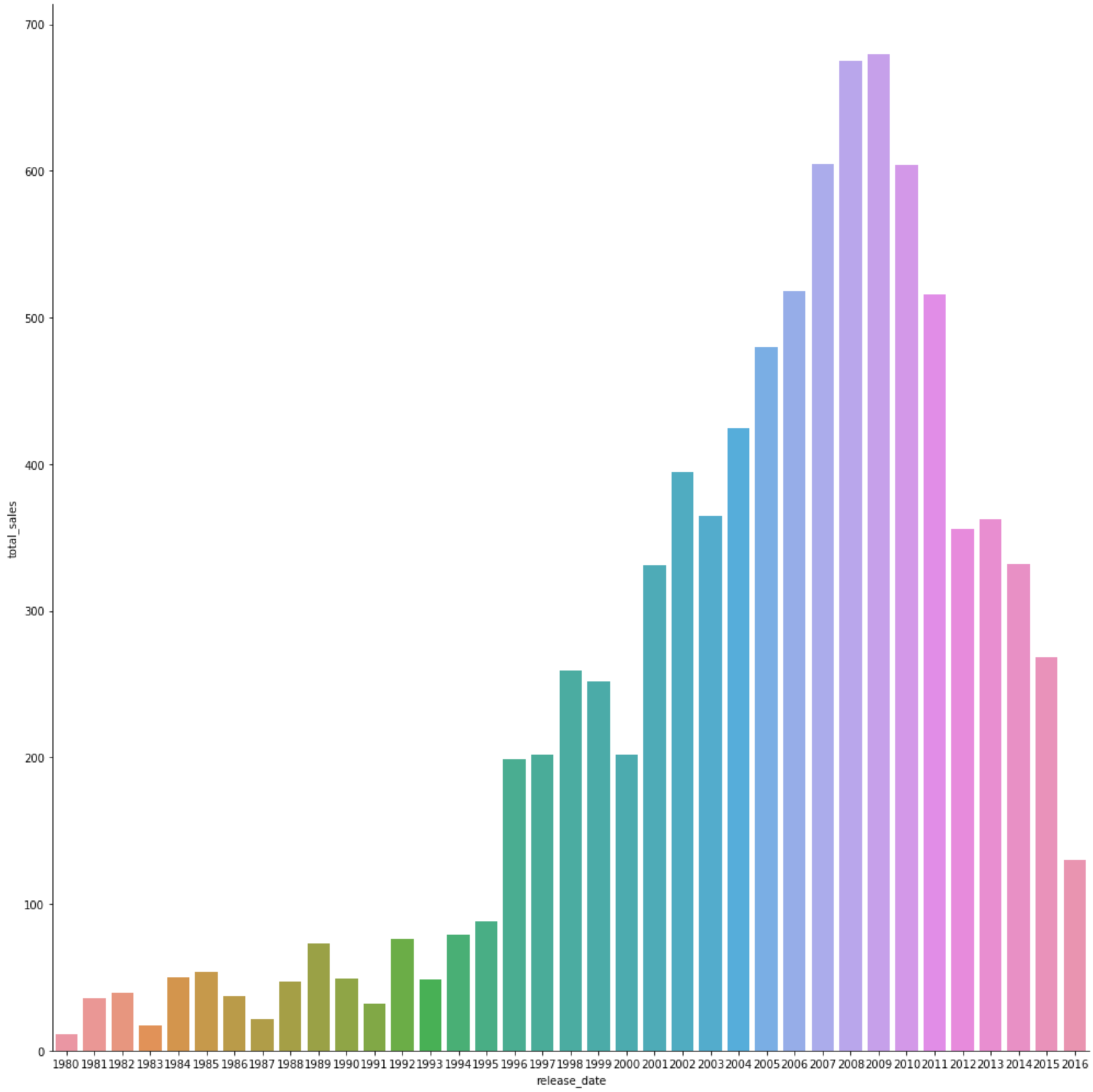
In [22]:
```
#create dataset with years and amount of games released each year
release_year = (data.groupby('release_date')[['name']].count()
            .reset_index()
            .rename(columns={"name": "count"})
           )
#make a catplot for this dataset.
sns.catplot(x="release_date", y="count", kind="bar", data=release_year, height=14)
```

Out[22]: <seaborn.axisgrid.FacetGrid at 0x7eff0b957d90>



In [23]:
```
#Now let's do the same but with sales for each year
year_sales = (data.groupby('release_date')[['total_sales']].sum()
            .reset_index()
          )
sns.catplot(x="release_date", y="total_sales", kind="bar", data=year_sales, height=14)
```

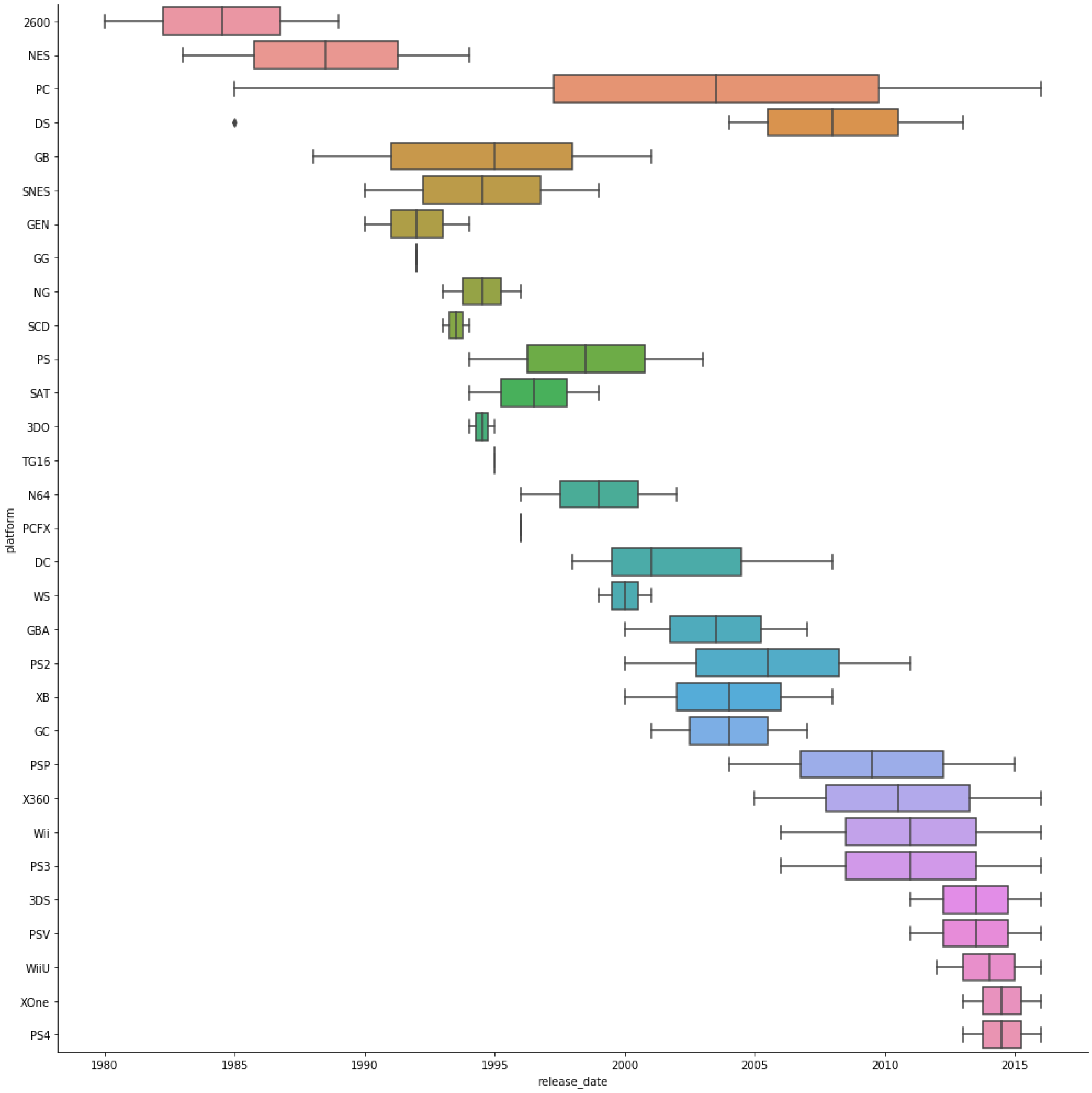
Out[23]: <seaborn.axisgrid.FacetGrid at 0x7eff0aee4b90>



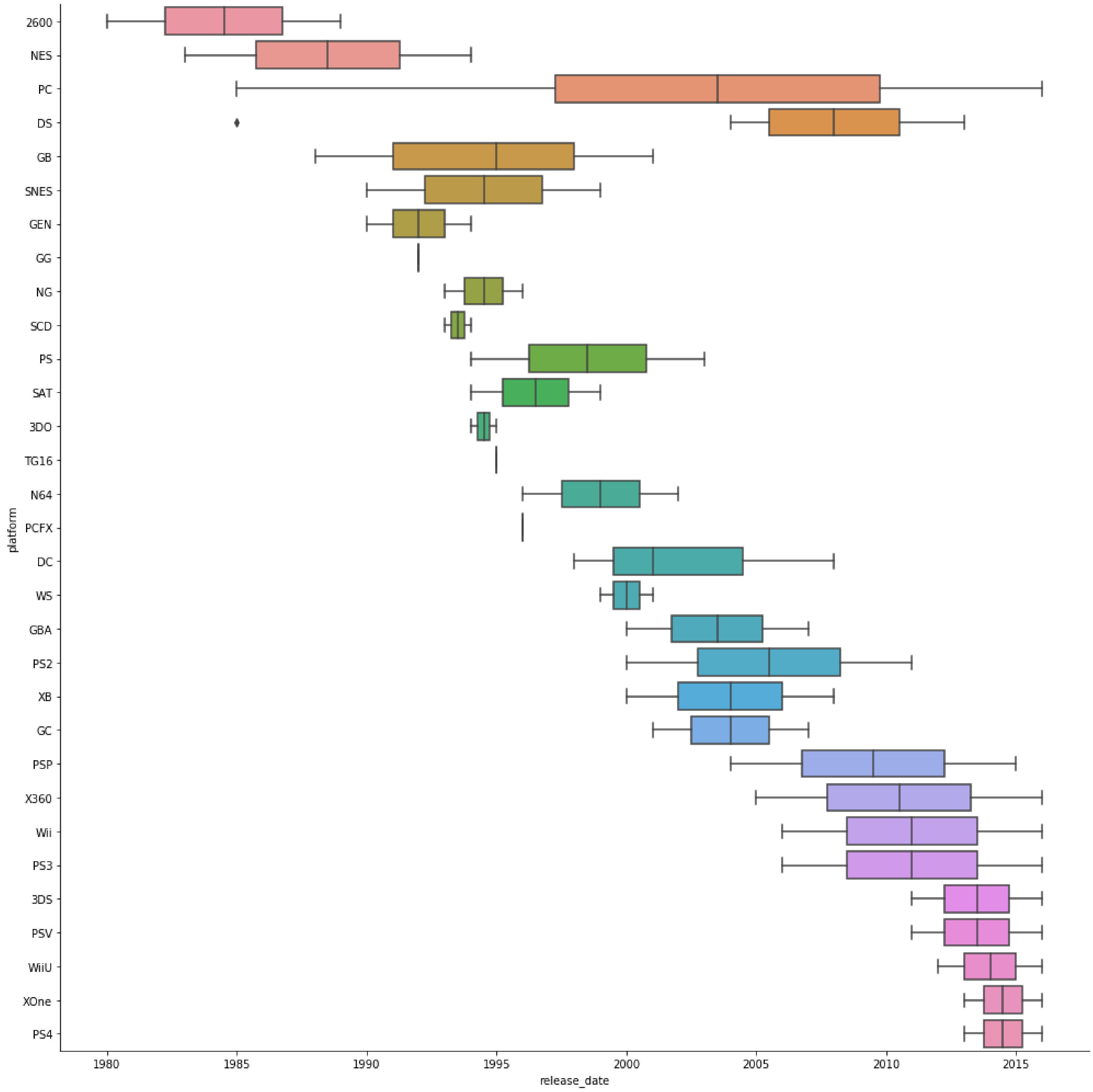
From here I see that before mid 90's game industry had been much smaller than what it became later. So maybe we can ignore data for all data before 1995 as not representive enough. Also It's obvious from this data that industry has picked in 2000's and now is heading towards decline (or maybe stability, we'll see).

Look at how sales varied from platform to platform. Choose the platforms with the greatest total sales and build a distribution based on data for each year. Find platforms that used to be popular but now have zero sales. Find out how long does it generally take for new platforms to appear and old ones to fade.

In [24]:
```
#Let's create table with the data that I'm going to need
df_platform_grouped = (
    data
    .pivot_table(index=['platform', 'release_date'], values='total_sales', aggfunc='sum')
    .reset_index()
    .sort_values('release_date')
)
#look  at lifespan of platforms
sns.catplot(y="platform", x="release_date", kind='box', data=df_platform_grouped, height=14);
```



In [25]:
```
#look at lifespan of platforms
sns.catplot(y="platform", x="release_date", kind='box', data=df_platform_grouped, height=14);
```



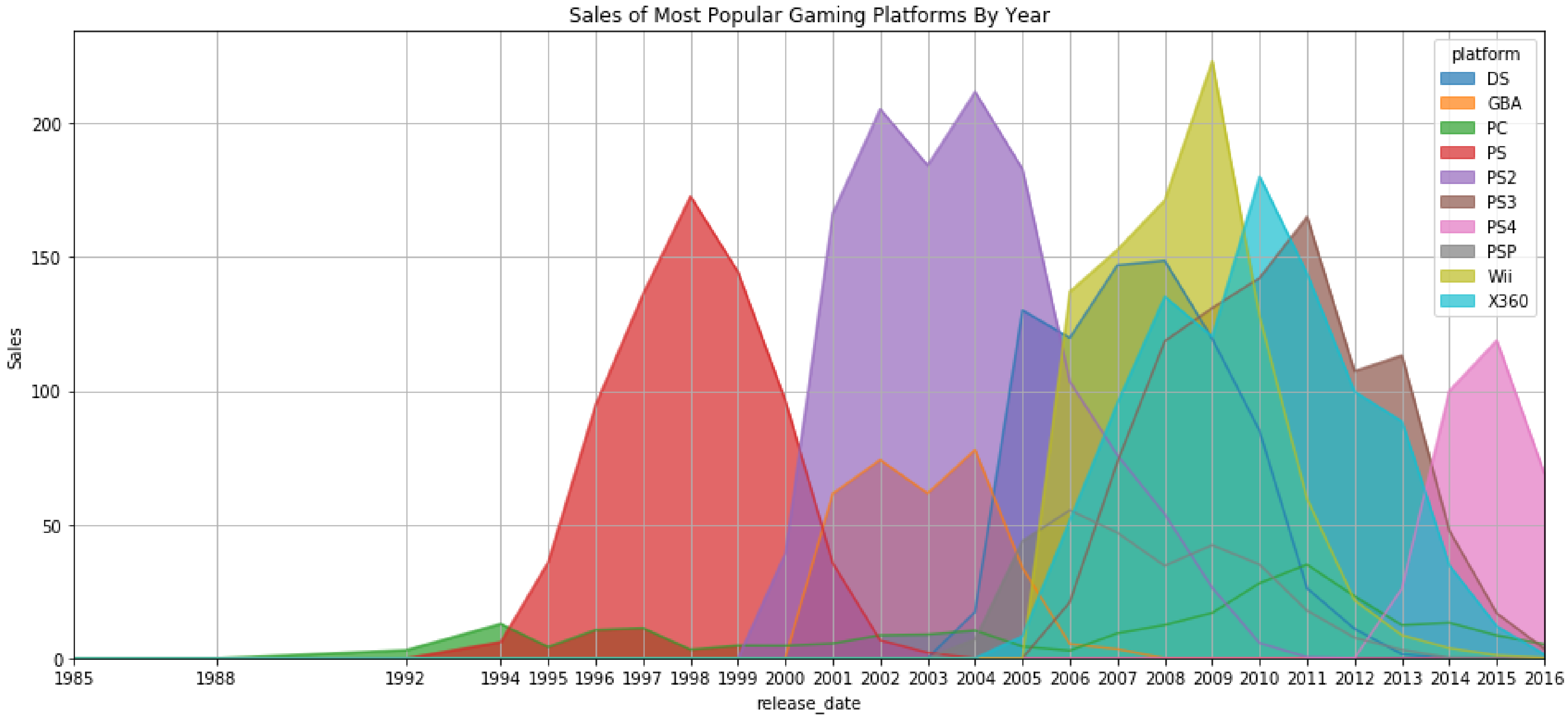
Looks loke lifespan of gaming platfroms is different for different platforms. Some platforms stayed on market for reletively short time, but others stayed on the market for much longer time. Let's select most popular ones based on their total sales.

In [26]:
```
#Create list of topselling platfroms
topsellers = (
    data
    .groupby('platform')["total_sales"].sum()
    .sort_values(ascending=False)
    .head(10) #get top 10
    .index.tolist() #turn it to list
)

#dataframe, that contains data only for topsellers
df_topselling = data.query('platform in @topsellers')
print('Topselling platfroms:', topsellers)
print ('Games for topselling platforms:', df_topselling.shape[0])
print ('Percentage of games for topselling platforms: {:.2%}'.format(df_topselling.shape[0]/len(data)))
```

```
Topselling platfroms: ['PS2', 'X360', 'PS3', 'Wii', 'DS', 'PS', 'GBA', 'PS4', 'PSP', 'PC']
Games for topselling platforms: 12817
Percentage of games for topselling platforms: 76.69%
```

In [27]:
```
fig, ax = plt.subplots()
ax.set_ylabel('Sales')
ax.set_title('Sales of Most Popular Gaming Platforms By Year')
plt.xticks(df_topselling.release_date.unique()) #set ticks for plot
(df_topselling.pivot_table(index='release_date', columns='platform', values='total_sales',
                          aggfunc='sum')
 .plot(kind='area', stacked=False, alpha=0.7, grid=True, figsize=(16,7), ax=ax)
)
```

Out[27]: `<matplotlib.axes._subplots.AxesSubplot at 0x7eff0a2010d0>`



From this plot I see that some of the most popular platforms have no sales nowaday, because they have become outdated. For example PlayStation didn't get much sales since 2005 and PlayStation 2 didn't get much since 2011. We can see from this plot that on average lifespan of a popular platform lasts for around 8-10 years.

There is one exception here - PC, it's lifespan was much longer, because for a long time PC provided the same possibilities as other platforms, it has even become more popular than all the others in late 2000's. But after that it seems like PCs stopped to satisfy gamers' requirements and it has also gone to decline.

Also I see that we are able to disregard all the games that have been released before 2000 as all other data is too old for us to be useful.

In [28]:
```
df_modern = data.query('release_date >=2000')
```

Now I'm going to find out which platform were successful and which weren't. I'll do it by looking at Z score.

In [29]:
```
df = (df_modern[['platform', 'total_sales']].groupby('platform')
      .sum()
      .sort_values(by='total_sales')
      .reset_index())
df
```

Out[29]:

	platform	total_sales
0	WS	0.96
1	DC	7.41
2	GB	29.00
3	N64	37.30
4	PSV	54.07
5	WiiU	82.19
6	PS	140.70
7	XOne	159.32
8	GC	198.93
9	PC	209.48
10	XB	257.74
11	3DS	259.00
12	PSP	294.05
13	PS4	314.14
14	GBA	317.85
15	DS	806.10
16	Wii	907.51
17	PS3	939.65
18	X360	971.42
19	PS2	1255.77

In [30]:
```
df['sales_z']=(df['total_sales'] - df['total_sales'].mean())/df['total_sales'].std()
df.sample(5)
```

Out[30]:

	platform	total_sales	sales_z
10	XB	257.74	-0.271229
0	WS	0.96	-0.938404
9	PC	209.48	-0.396620
7	XOne	159.32	-0.526947
5	WiiU	82.19	-0.727350

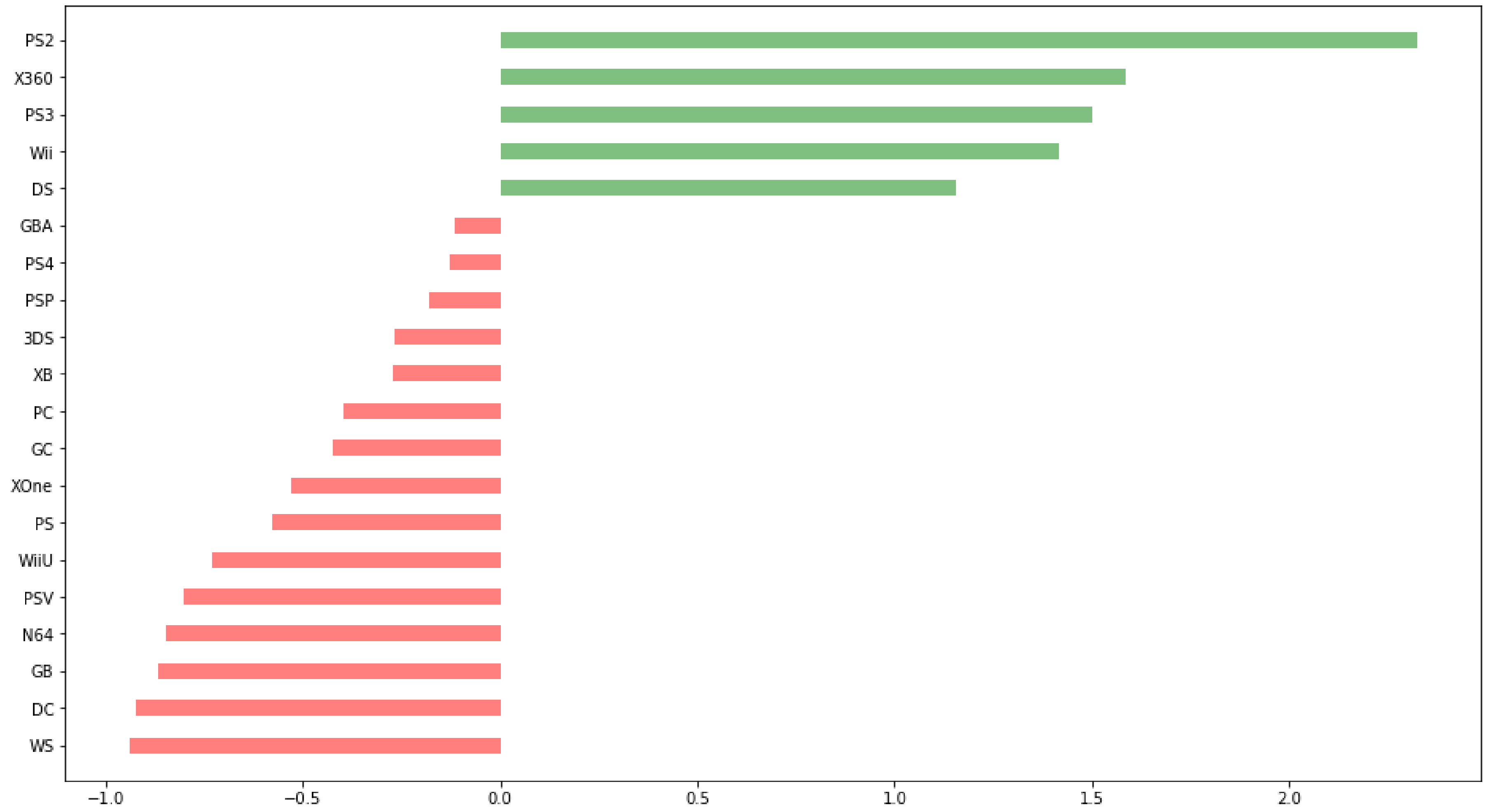
In [31]:
```
df['colors']=['red' if x<0 else 'green' for x in df['sales_z']]
df.sample(5)
```

Out[31]:

	platform	total_sales	sales_z	colors
19	PS2	1255.77	2.321891	green
0	WS	0.96	-0.938404	red
5	WiiU	82.19	-0.727350	red
7	XOne	159.32	-0.526947	red
18	X360	971.42	1.583082	green

In [32]:
```
plt.figure(figsize=(16,9))
plt.hlines(y=df.platform, xmin=0, xmax=df.sales_z, color=df.colors, alpha=0.5, linewidth=10)
```

Out[32]: <matplotlib.collections.LineCollection at 0x7eff08859450>



So we see here that there are some platforms that have been way more successful than others, the alltime leaders are PS2, X360 and PS3. But actually the "losers" aren't so far behind.

Find out which platforms are leading in sales, Which ones are growing or shrinking. Select several potentially profitable platforms.

For this step let's compare sales for each platform for each year with value from previous year and find out which platforms have been rising and which have been shifting for each year.

In [33]:
```
df = df_modern.pivot_table(index='release_date', columns='platform', values='total_sales', aggfunc=sum, fill_value=0)
df.tail()
```

Out[33]:

platform	3DS	DC	DS	GB	GBA	GC	N64	PC	PS	PS2	PS3	PS4	PSP	PSV	WS	Wii	WiiU	X360	XB	XOne
release_date																				
2012	51.36	0.0	11.01	0.0	0.0	0.0	0.0	23.22	0.0	0.0	107.36	0.00	7.69	16.19	0.0	21.71	17.56	99.74	0.0	0.00
2013	57.76	0.0	1.54	0.0	0.0	0.0	0.0	12.38	0.0	0.0	113.25	25.99	3.14	10.59	0.0	8.59	21.65	88.58	0.0	18.96
2014	43.76	0.0	0.00	0.0	0.0	0.0	0.0	13.28	0.0	0.0	47.76	100.00	0.24	12.16	0.0	3.75	22.03	34.74	0.0	54.07
2015	27.78	0.0	0.00	0.0	0.0	0.0	0.0	8.52	0.0	0.0	16.82	118.90	0.12	6.25	0.0	1.14	16.35	11.96	0.0	60.14
2016	15.14	0.0	0.00	0.0	0.0	0.0	0.0	5.25	0.0	0.0	3.60	69.25	0.00	4.25	0.0	0.18	4.60	1.52	0.0	26.15

In [34]:
```
#let's find dynamic using shift method
dynamic = (df - df.shift(+1)).transpose()
dynamic.tail()
```

Out[34]:

release_date	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
platform																	
Wii	NaN	0.00	0.00	0.00	0.00	0.00	137.15	15.62	18.55	51.98	-95.35	-68.30	-37.94	-13.12	-4.84	-2.61	-0.96
WiiU	NaN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.56	4.09	0.38	-5.68	-11.75
X360	NaN	0.00	0.00	0.00	0.00	8.25	43.37	43.79	39.85	-14.97	59.92	-36.37	-44.10	-11.16	-53.84	-22.78	-10.44
XB	NaN	21.27	25.75	7.03	16.55	-22.51	-39.04	-9.49	-0.37	-0.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00
XOne	NaN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	18.96	35.11	6.07	-33.99

In [35]:
```
plt.figure(figsize=(16,9))
sns.heatmap(dynamic, cmap='PRGn')
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7eff08832810>
```

From this heatmap I can see once again see that actually there aren't any rising platforms for 2015-2016 years, but the most popular and worth buying games for are PS4 and XOne, because they are currently beeing used, still have some number of sales (even though they are in decline).

Build a box plot for the global sales of all games, broken down by platform. Are the differences in sales significant? What about average sales on various platforms? Describe your findings.

In [36]:
```
#create a new dataframe for sales for year for every platform
df = df_modern.groupby(['platform', 'release_date'])['total_sales'].sum().reset_index()
#create list of platforms sorted from least profitable to the most profitable
platform_list = data.groupby('platform')['total_sales'].sum().sort_values().reset_index()['platform']
df
```

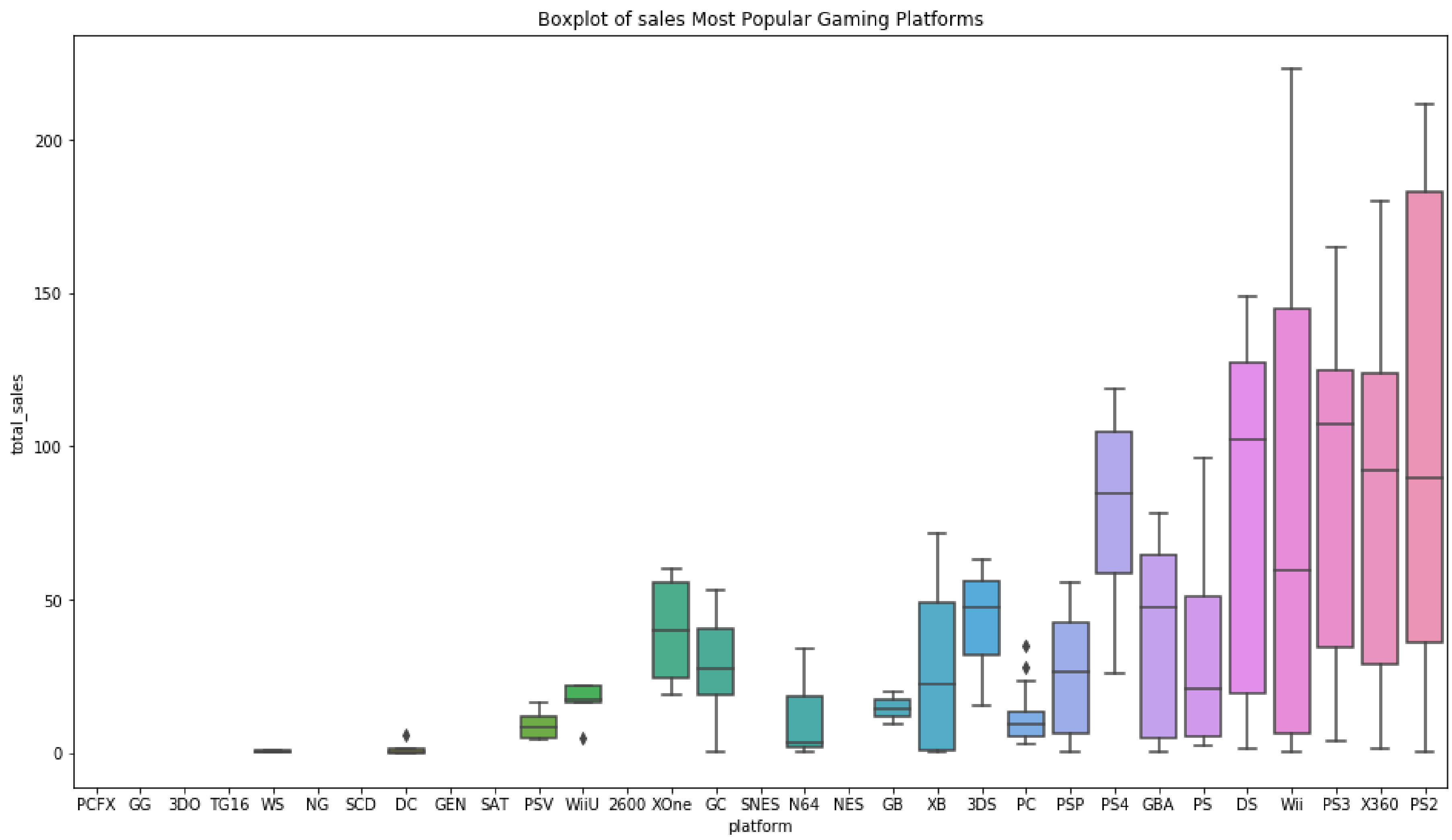
Out[36]:

	platform	release_date	total_sales
0	3DS	2011	63.20
1	3DS	2012	51.36
2	3DS	2013	57.76
3	3DS	2014	43.76
4	3DS	2015	27.78
...	...	...	...
145	XB	2008	0.18
146	XOne	2013	18.96
147	XOne	2014	54.07
148	XOne	2015	60.14
149	XOne	2016	26.15

150 rows × 3 columns

In [37]:
```python
fig, ax = plt.subplots(figsize=(16,9))
ax.set_title('Boxplot of sales Most Popular Gaming Platforms')
sns.boxplot(y="total_sales", x="platform", data=df, order=platform_list, ax=ax)
```

Out[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7eff086dce50>



From this plot I see that even though in absolute values PS2 has been the most profitable platform over time, its average amount of total sales has been less that for X360 or PS3. I also see here that PS4 and Xone that are popular now had never had as few sales as all other platforms have already experienced, so they are definatly expecting some more sales.

Take a look at how user and professional reviews affect sales for one popular platform. Build a scatter plot and calculate the correlation between reviews and sales. Draw conclusions.

For this ananlysis I'm going to check data for popular platform PS3.

In [38]:
```python
df = data.query('platform =="PS3"')[['total_sales', 'critic_score','user_score']]
```

In [39]:
```python
df.shape
```

Out[39]: (1330, 3)

In [40]:
```python
#Now let's check what amount of missing values are here
print ('Percentage of NaN in user_score: {:.2%}'.format(len(df[df.user_score.isna()])/len(df.user_score)))
print ('Percentage of NaN in critic_score: {:.2%}'.format(len(df[df.critic_score.isna()])/len(df.critic_score)))
```

```
Percentage of NaN in user_score: 34.06%
Percentage of NaN in critic_score: 38.35%
```

So we really have a lot of missing values here, and there is no way for me to fill this values. Therefore our analysis of this data will not be representive enough, in real life situation I would have to get this data from the client of some other place for my analysis to be more percise. Here I'm going to drop these values for each score.

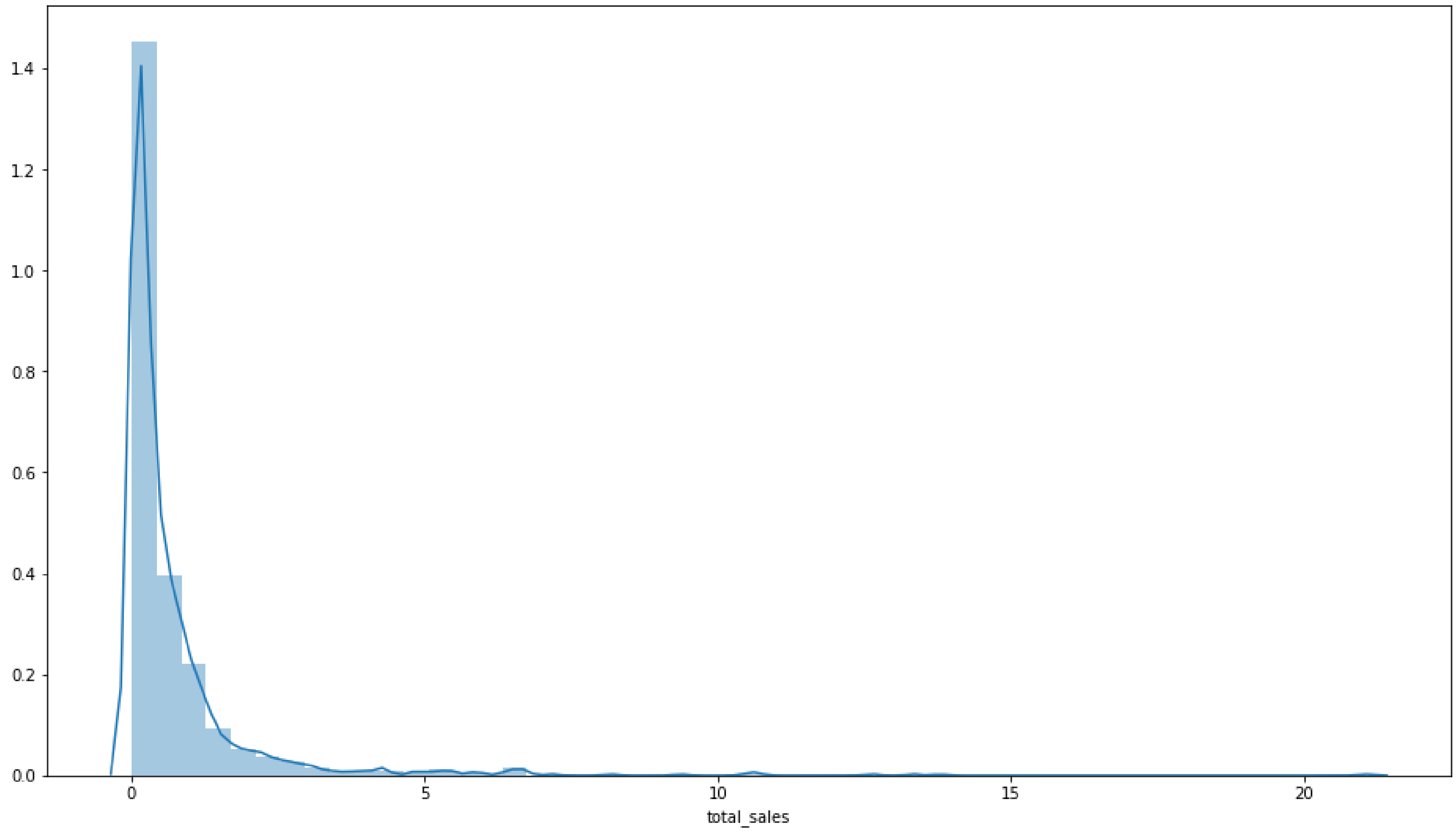
In [41]:
```
df.describe()
```

Out[41]:

	total_sales	critic_score	user_score
count	1330.000000	820.000000	877.000000
mean	0.706504	70.382927	6.726568
std	1.392138	14.043094	1.461223
min	0.010000	13.000000	0.200000
25%	0.110000	61.000000	6.000000
50%	0.270000	73.000000	7.100000
75%	0.750000	81.000000	7.800000
max	21.050000	98.000000	9.100000

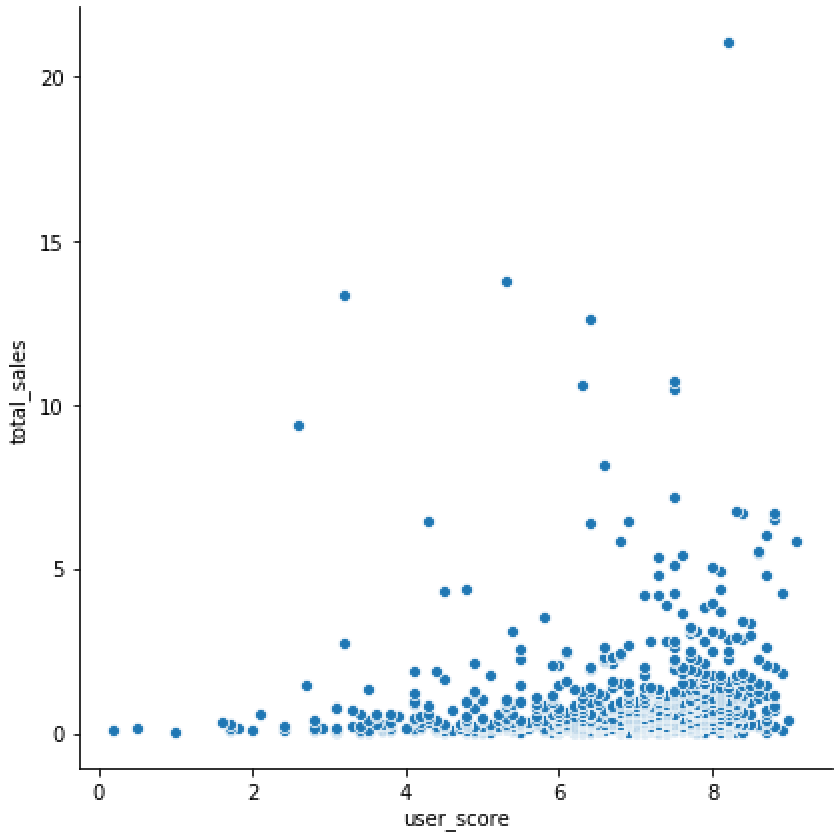
Looks like we have some definite outliers with very high amount of sales for game, they will affect our analysis. Let's look at them.

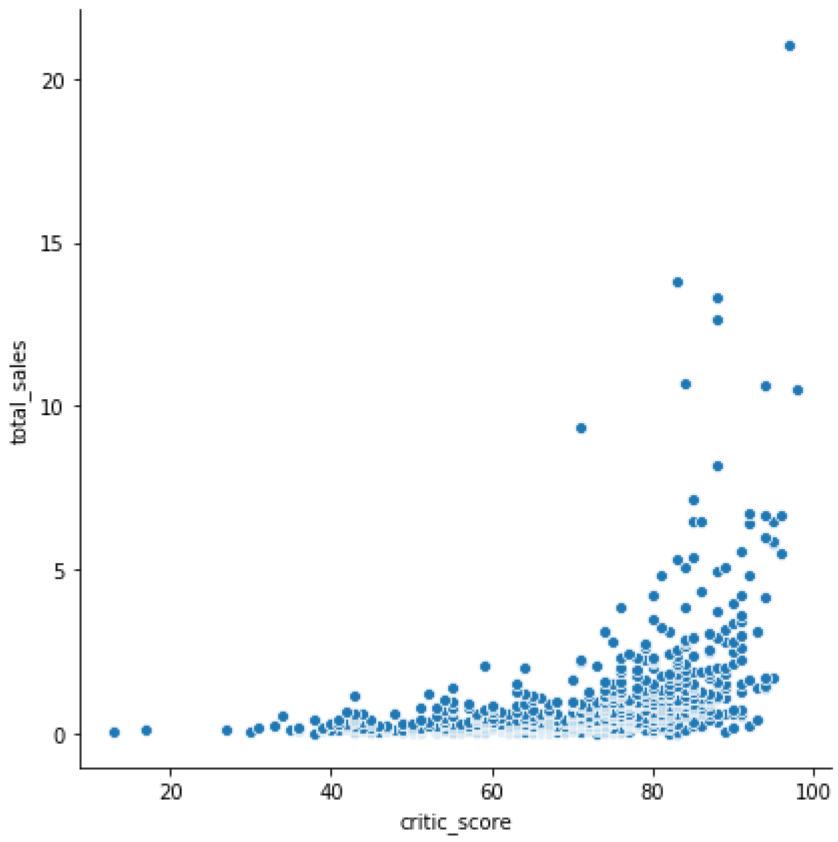
In [42]:
```
fig, ax = plt.subplots(figsize=(16,9))
sns.distplot(df['total_sales'], ax=ax);
```



Most of the games didn't even have 0.5 million dollars in sales, but some have gone way to far from there.

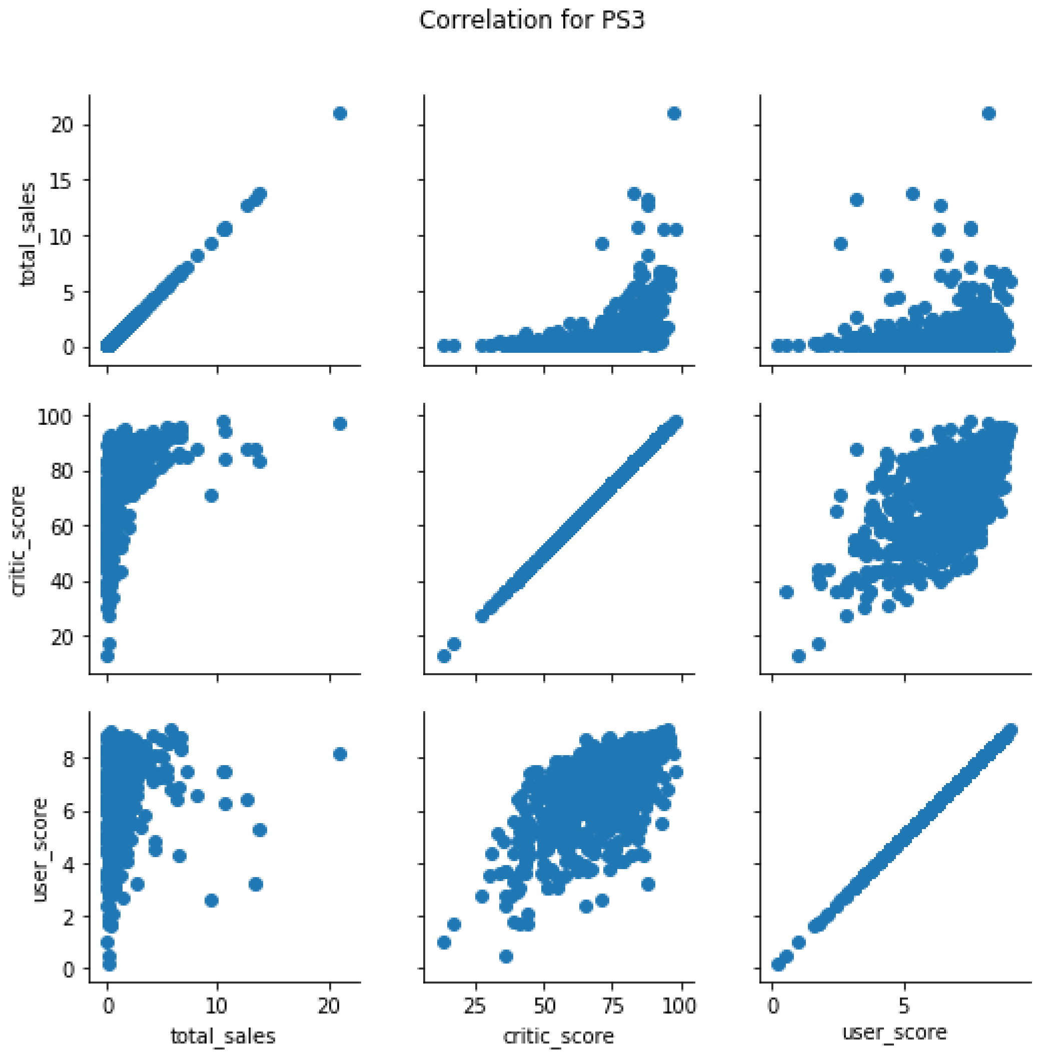
In [43]:
```
for col in ['user_score', 'critic_score']:
    df_notna = df[df[col].notnull()]
    sns.relplot(y="total_sales", x=col, data=df_notna.sort_values('total_sales'), height=6);
```





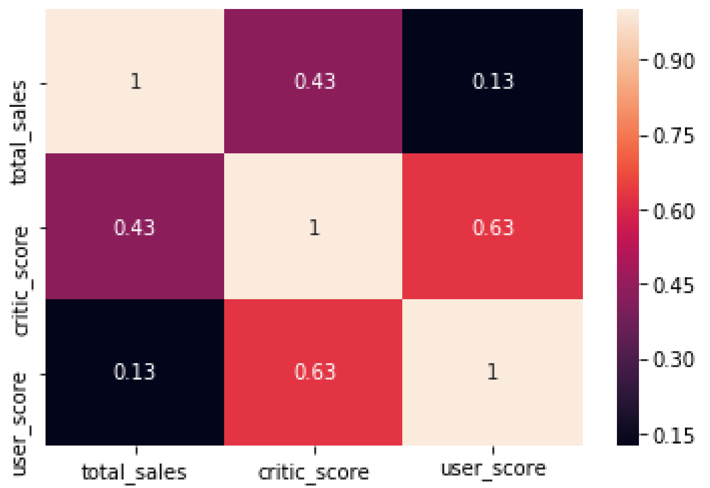
I can see that critics' rating is showing much more correlation to amount of total sales of the most profitable games than users' rating.

```
In [44]: g = sns.PairGrid(df)
         g.fig.suptitle('Correlation for PS3')
         plt.subplots_adjust(top=0.9)
         g.map(plt.scatter);
```




```
In [45]: fig, ax = plt.subplots(figsize=(6,4))
         corrMatrix = df.corr()
         sns.heatmap(corrMatrix, annot=True, ax=ax)
```

```
Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7eff0b9b9c10>
```



From this analysis I can make a conclusion that critics' score has some correlation to total sales of each game, but user_score doesn't show anything valuable. So I would suppose for the gamestore to take in slight consideration critic score for the games he'll be purchasing, but to completelly ignore user score (haters gonna hate).

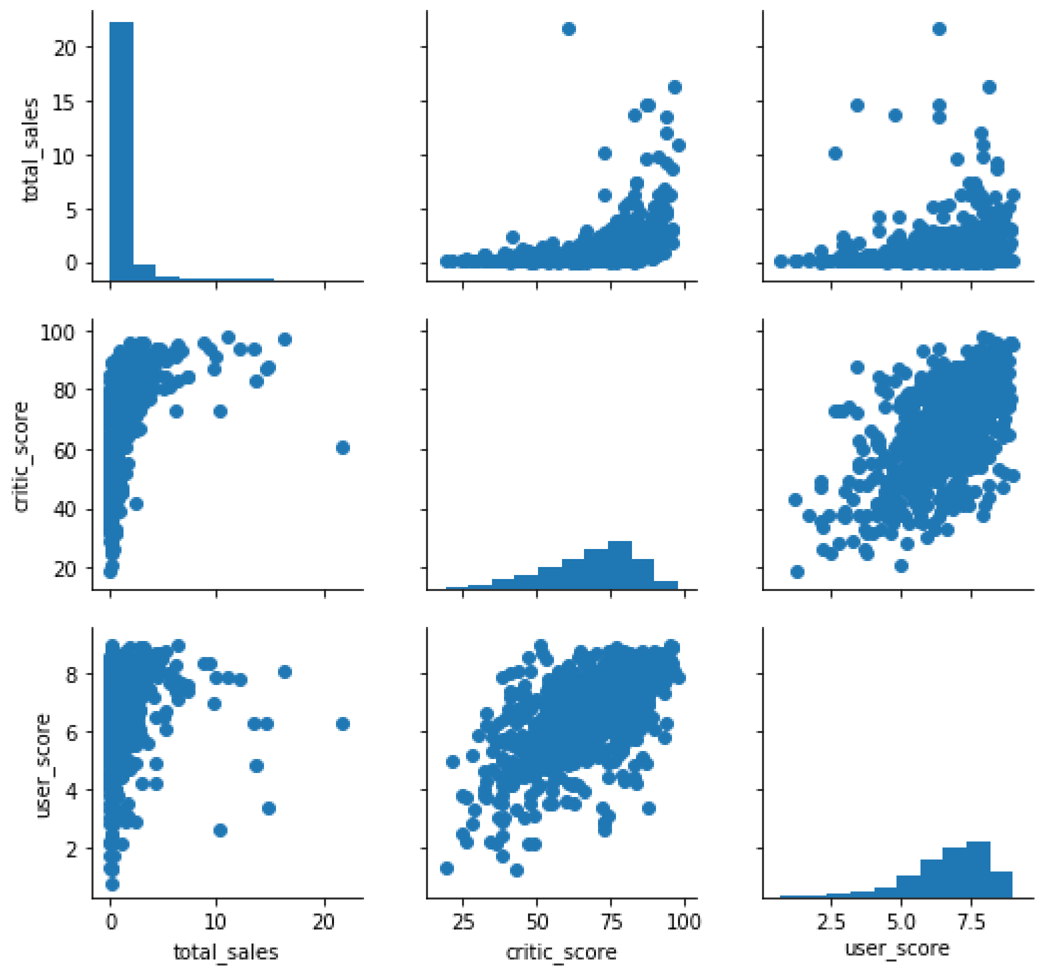
Keeping your conclusions in mind, compare the sales of the same games on other platforms.

Okay so to check my conclusions I will take other gaming platforms that were popular at the same era as PS3 and calculate this correlations for them. I'll take X360, PC, Wii and PS2.

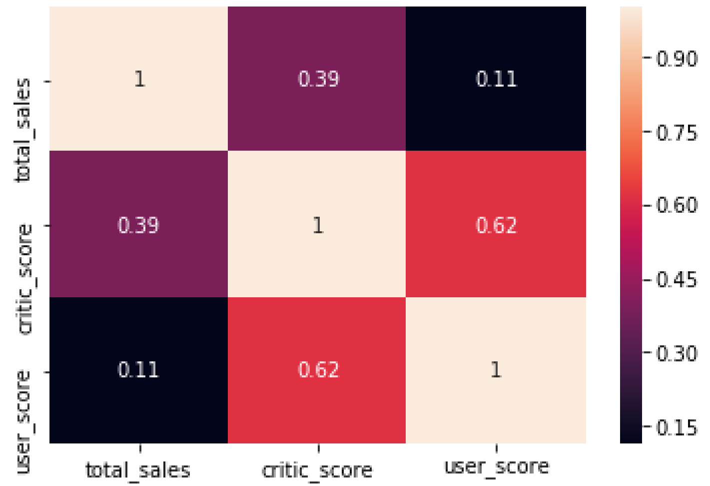
In [46]:
```
def platform_sales_score(data, platform):
    #platform for getting paired grid and correlation matrix for each platform

    df = data.query('platform ==@platform')[['total_sales', 'critic_score','user_score']] #create slice of df
#     print ('Platform: ', platform)
    #create pairgrid
    g = sns.PairGrid(df)
    g.fig.suptitle('Correlation for {}'.format(platform))
    plt.subplots_adjust(top=0.9)
    g.map_diag(plt.hist)
    g.map_offdiag(plt.scatter);

    #create corrmatrix
    fig, ax = plt.subplots(figsize=(6,4))
    ax.set_title('Correlation matrix for {}'.format(platform))

    corrMatrix = df.corr()
    sns.heatmap(corrMatrix, annot=True)
```

In [47]:
```
for platform in ['X360', 'PC', 'Wii', 'PS2']:
    platform_sales_score(data, platform)
```

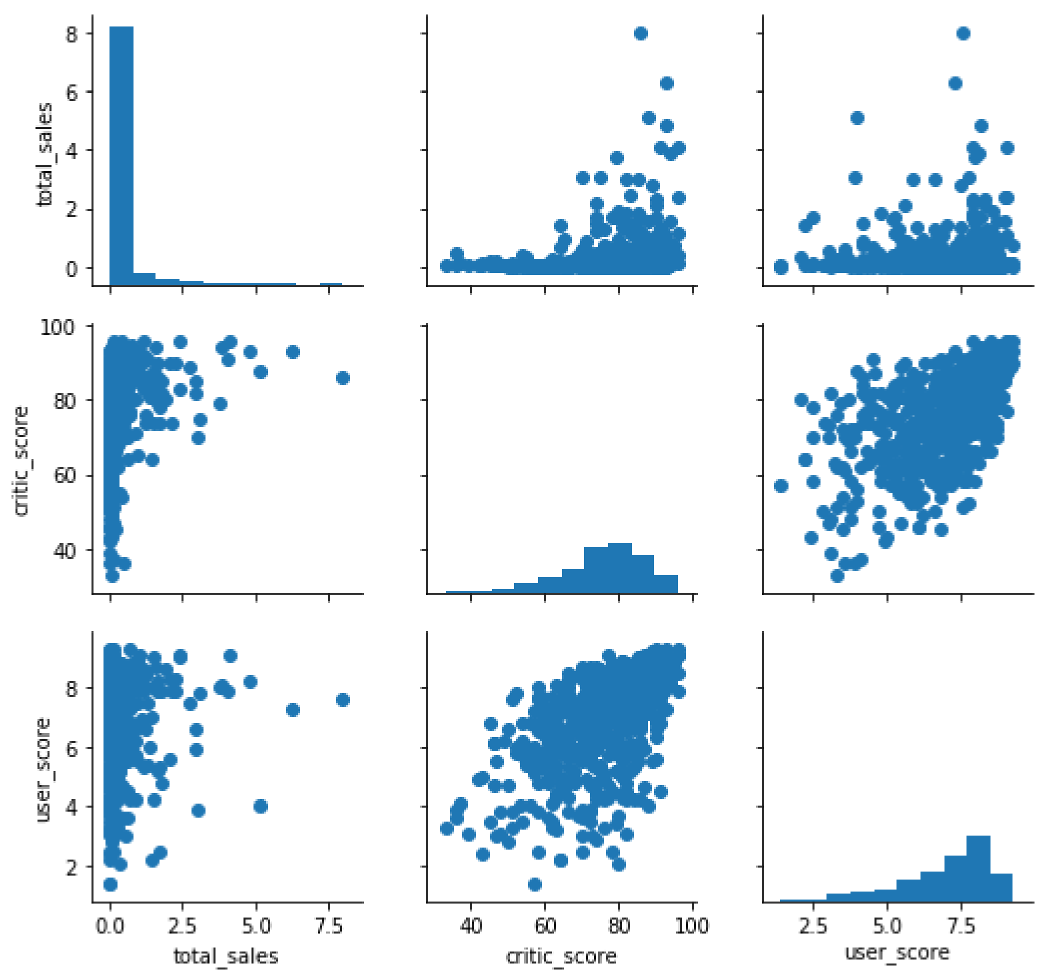
Correlation for X360

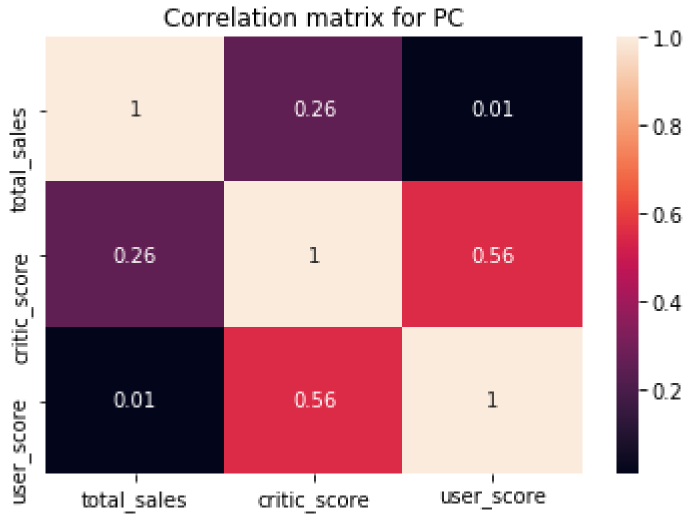


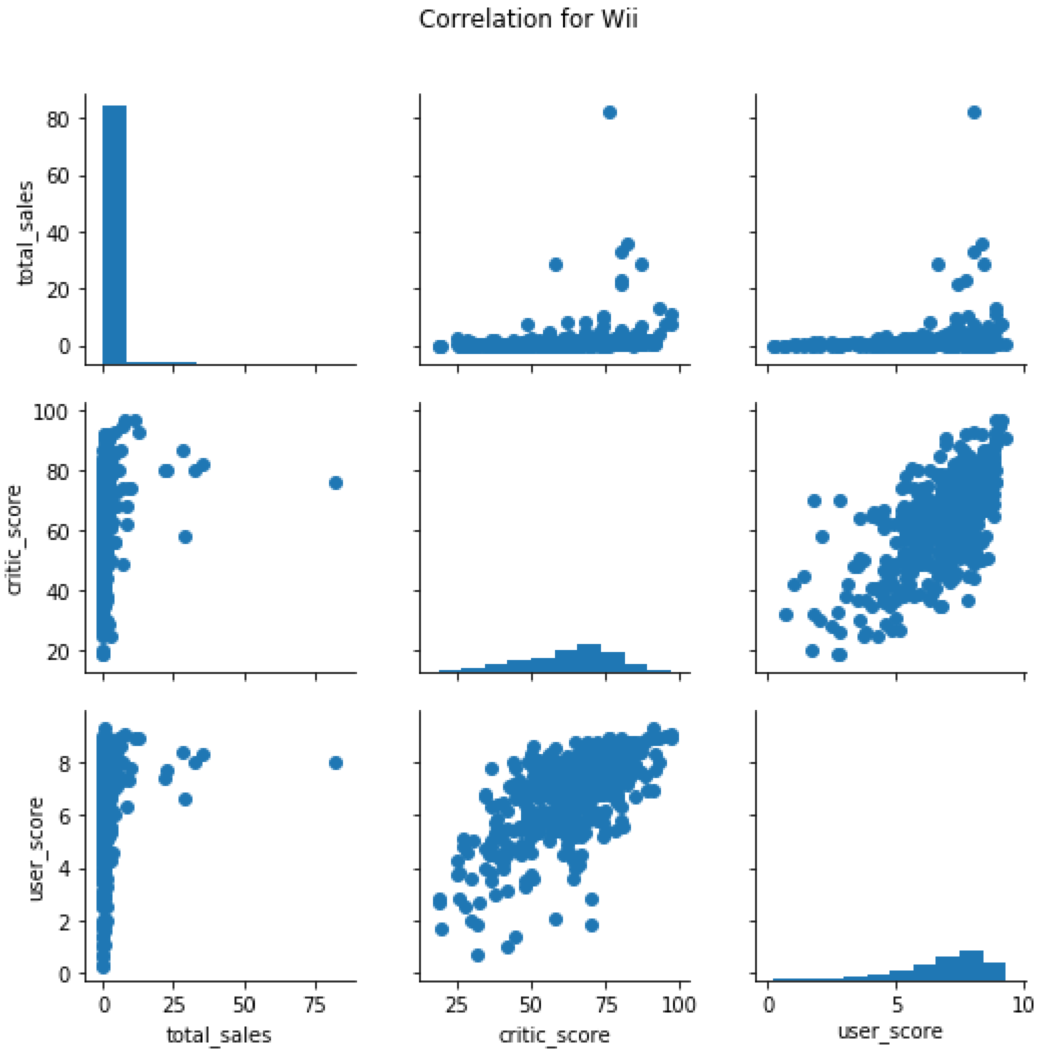
Correlation matrix for X360

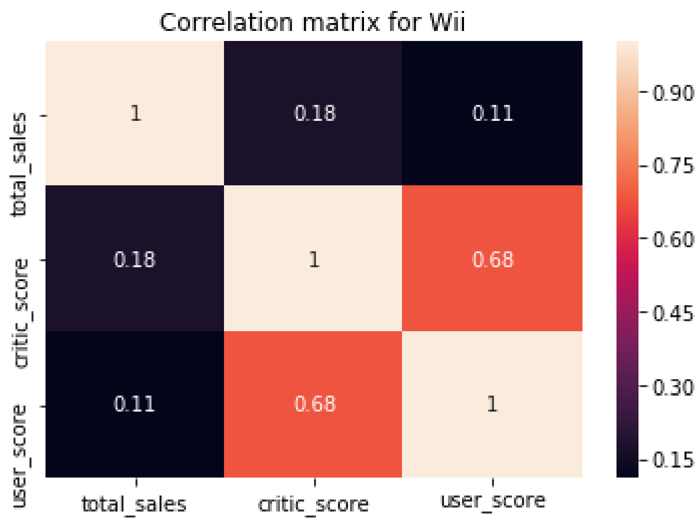


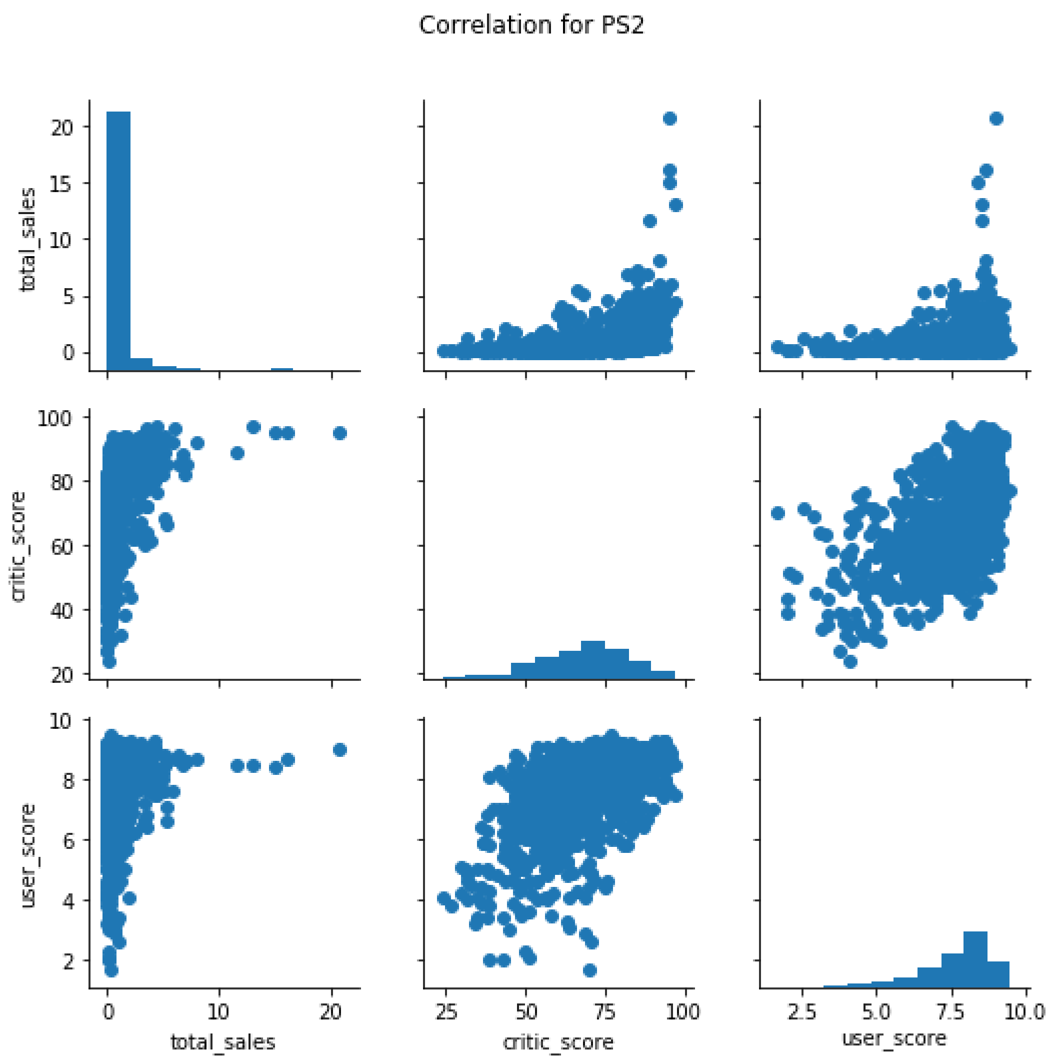
Correlation for PC

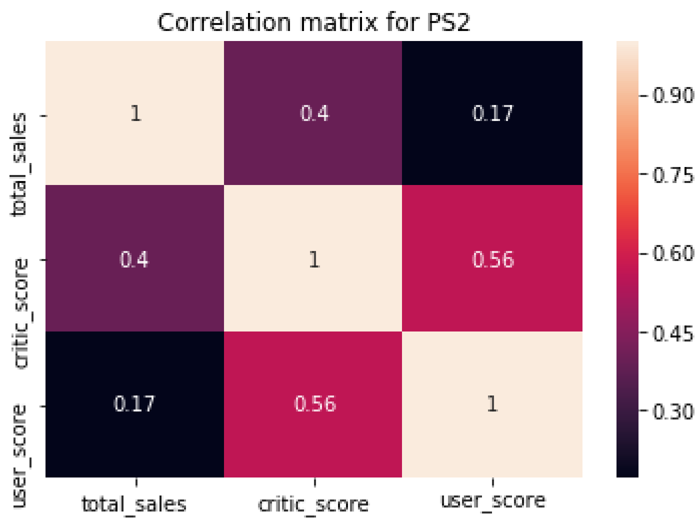



Correlation matrix for PC
total_sales
critic_score
user_score
1
0.26
0.01
0.56
1.0
0.8
0.6
0.4
0.2


Correlation for Wii
total_sales
critic_score
user_score


Correlation matrix for Wii
total_sales
critic_score
user_score
1
0.18
0.11
0.68
0.90
0.75
0.60
0.45
0.30
0.15



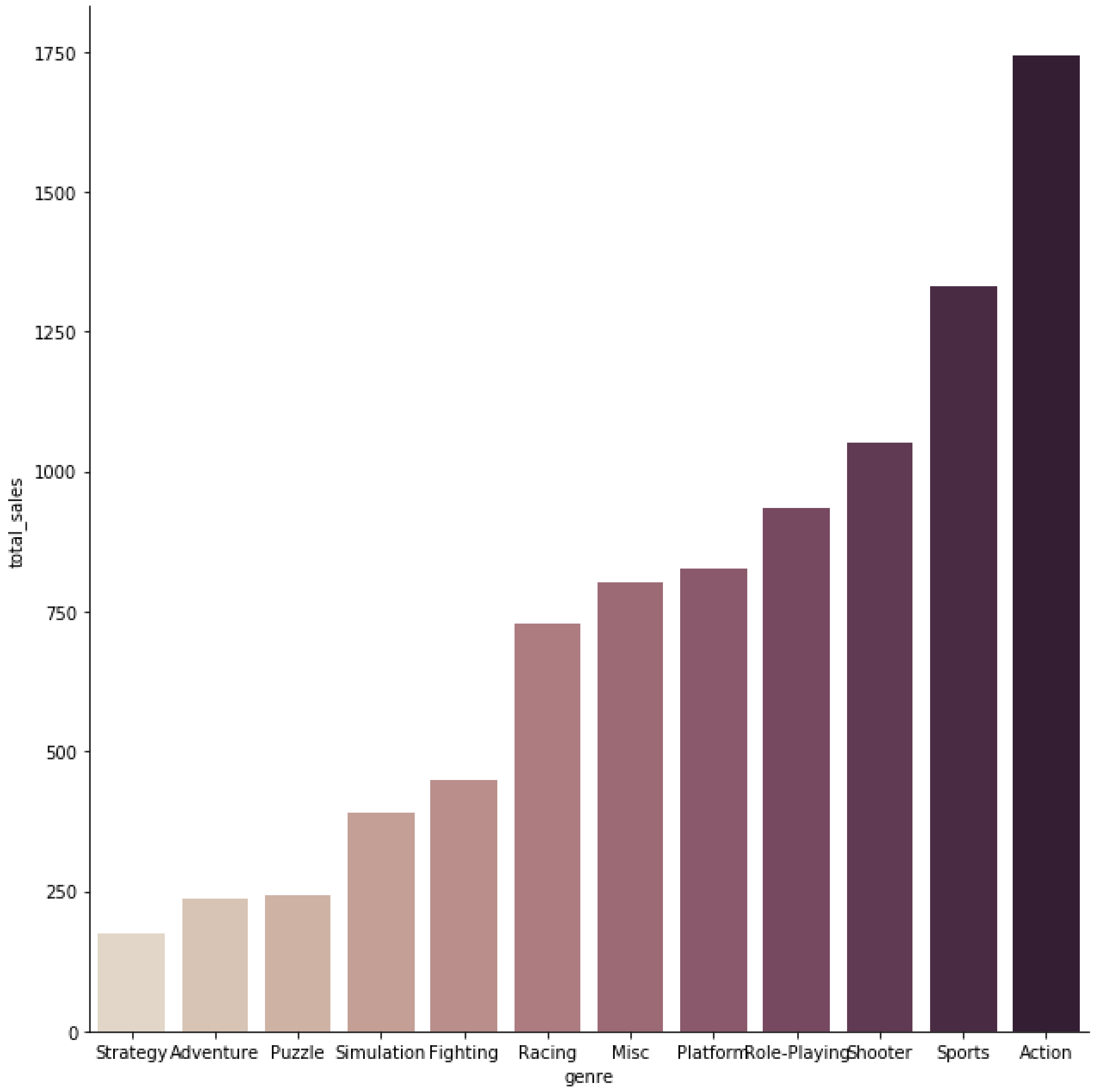


From here I see that this correlation has been simillar for all the popular platforms in 2000s. All this platforms have around 0.5 correlation between critic score and total sales, and almost no correlation between user score and total sales. So my recomendation stays the same: ignore user score and pay some attention to critic score, games with higher critic score are more likely to have higher sales.

Take a look at the general distribution of games by genre. What can we say about the most profitable genres? Can you generalize about genres with high and low sales

In [48]:
```python
df = data.groupby('genre')[['total_sales']].sum().sort_values(by='total_sales').reset_index()

sns.catplot(x="genre", y='total_sales', kind="bar", palette="ch:.25", data=df, height=9)
```

Out[48]: <seaborn.axisgrid.FacetGrid at 0x7eff03aded50>



So I see that the most overall popular genre is action. Sport is also pretty close. Let's look at how it changed throughout the years. I'll have the data normalized, because amount of sales has changed drasticly over the years.

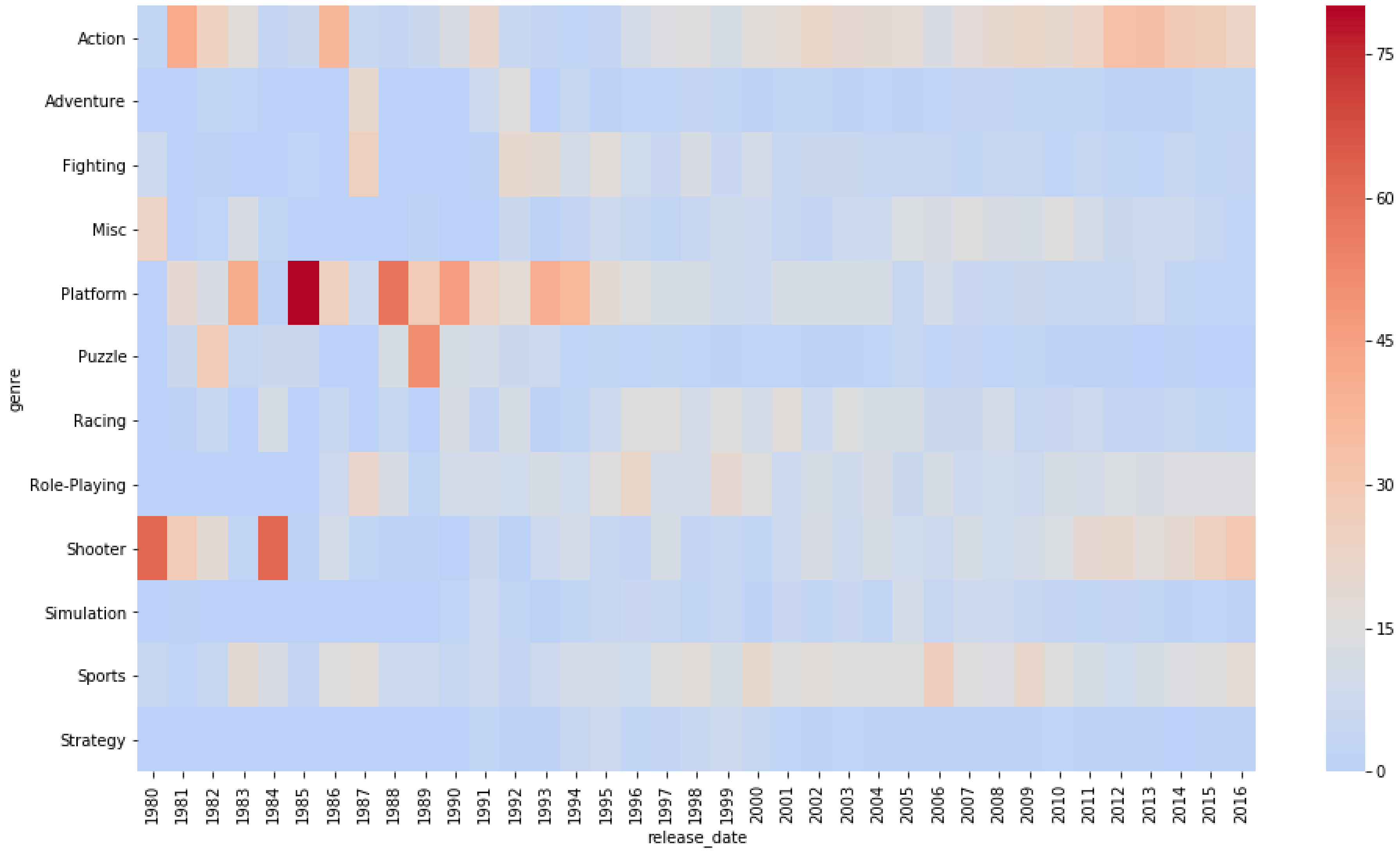
In [49]:
```python
genre_year_df = (data.pivot_table(index='genre',
                                  values='total_sales', columns='release_date',
                                       aggfunc='sum')
                      .fillna(0) #fill empty values
                      .apply(lambda x:100 * x / float(x.sum())).round(2)
                      #get % of total for each year instead of abcolute value
)
genre_year_df
```

Out[49]:

release_date	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998
genre																			
Action	2.99	41.45	23.97	17.02	3.67	6.52	37.06	5.12	3.69	6.33	12.94	20.97	5.04	3.94	1.96	4.06	10.34	13.65	15.69
Adventure	0.00	0.00	3.30	2.38	0.00	0.00	0.00	20.18	0.00	0.00	0.00	6.95	16.08	0.15	4.72	0.81	2.10	2.46	3.56
Fighting	6.77	0.00	1.19	0.00	0.00	1.95	0.00	24.98	0.00	0.00	0.00	1.21	20.00	19.03	10.70	16.84	9.06	5.84	12.20
Misc	23.73	0.00	2.21	12.74	2.88	0.00	0.00	0.00	0.00	1.74	0.00	0.25	6.49	0.65	3.61	7.26	5.35	2.81	4.58
Platform	0.00	19.39	12.77	41.25	1.37	80.02	25.32	8.02	58.74	28.13	46.55	23.67	17.61	40.62	36.30	18.94	14.18	11.33	11.49
Puzzle	0.00	6.31	28.09	4.64	6.24	5.95	0.00	0.00	11.82	51.40	12.13	10.05	6.36	6.89	1.93	3.05	1.97	2.90	2.45
Racing	0.00	1.35	5.49	0.00	11.82	0.00	5.29	0.00	4.53	0.00	12.66	3.54	11.88	0.78	2.75	6.91	14.20	15.79	10.86
Role-Playing	0.00	0.00	0.00	0.00	0.00	0.00	6.80	21.43	12.45	3.00	9.16	10.11	9.01	12.15	9.00	16.19	22.09	10.80	10.82
Shooter	62.13	28.08	18.59	2.92	61.77	1.85	10.49	3.18	1.08	1.62	0.00	6.17	0.37	6.70	10.48	4.71	3.46	10.96	3.78
Simulation	0.00	1.23	0.00	0.00	0.00	0.07	0.00	0.00	0.06	0.00	2.29	6.67	2.81	0.41	3.43	4.73	5.69	4.77	2.74
Sports	4.39	2.19	4.39	19.05	12.25	3.63	15.05	17.10	7.63	7.79	4.27	7.48	3.87	6.91	10.61	9.07	8.75	14.86	16.65
Strategy	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.92	0.49	1.76	4.51	7.42	2.82	3.82	5.19

In [50]:
```
plt.figure(figsize=(16,9))
sns.heatmap(genre_year_df, cmap='coolwarm', center=15)
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x7eff0374ac50>



From this I see that several things:

- There are some genres that used to be popular be very popular before (like platform or puzzle. But have completely lost their popularity over the years;
- Platform games have been ppopular through 80's and 90's but now nobody really plays them;
- Action games have been very popular since the begining of gaming industry;
- Shooter games have been popular in the 80's, then lost their popularity, but now they seem to be getting it back on the market. There are more sales every year (so I recomend to buy more of these in folowing years);
- Sport games maintain their popularity through the years. There always are some people willing to play them;
- Nobody has ever liked strategy games :(

Step 4. Create a user profile for each region

In [51]:
```
data
df = data.groupby('rating').sum().sort_values('eu_sales', ascending = False)[['eu_sales']].reset_index().head()
# sns.catplot(y='top_platforms',x=df.rating, height=6, palette='muted', data=df)
df
```

Out[51]:

	rating	eu_sales
0	E	710.25
1	M	483.97
2	T	427.03
3	E10+	188.52
4	AO	0.61

In [52]:
```
def region_user_profile (data, region_sales):

    df = data[['name', 'platform', 'release_date','genre', region_sales, 'rating']]
    #get a Series for most popular platforms
    top_platforms = (data.groupby('platform')
                     .sum().sort_values(region_sales, ascending = False)[region_sales]
                     .head())
    top_genres = data.groupby('genre').sum().sort_values(region_sales, ascending = False)[[region_sales]].head()
    top_ratings = data.groupby('rating').sum().sort_values(region_sales, ascending = False)[[region_sales]].head()

    region_sale = pd.DataFrame({'top_platforms': list(top_platforms.index), 'top_genres': list(top_genres.index),
                                'top_ratings': list(top_ratings.index)})
#     sns.catplot(y='top_platforms',)
    return region_sale
```

In [53]:
```
for region in ['eu_sales', 'na_sales', 'jp_sales', 'other_sales']:
    print (region)
    region_sales = region_user_profile(data, region)
#     g = sns.catplot(x="class", y="survived", hue="sex", data=titanic,
#                 height=6, kind="bar", palette="muted")
    display(region_sales)
```

eu_sales

	top_platforms	top_genres	top_ratings
0	PS2	Action	E
1	PS3	Sports	M
2	X360	Shooter	T
3	Wii	Racing	E10+
4	PS	Misc	AO

na_sales

	top_platforms	top_genres	top_ratings
0	X360	Action	E
1	PS2	Sports	T
2	Wii	Shooter	M
3	PS3	Platform	E10+
4	DS	Misc	K-A

jp_sales

	top_platforms	top_genres	top_ratings
0	DS	Role-Playing	E
1	PS	Action	T
2	PS2	Sports	M
3	SNES	Platform	E10+
4	3DS	Misc	K-A

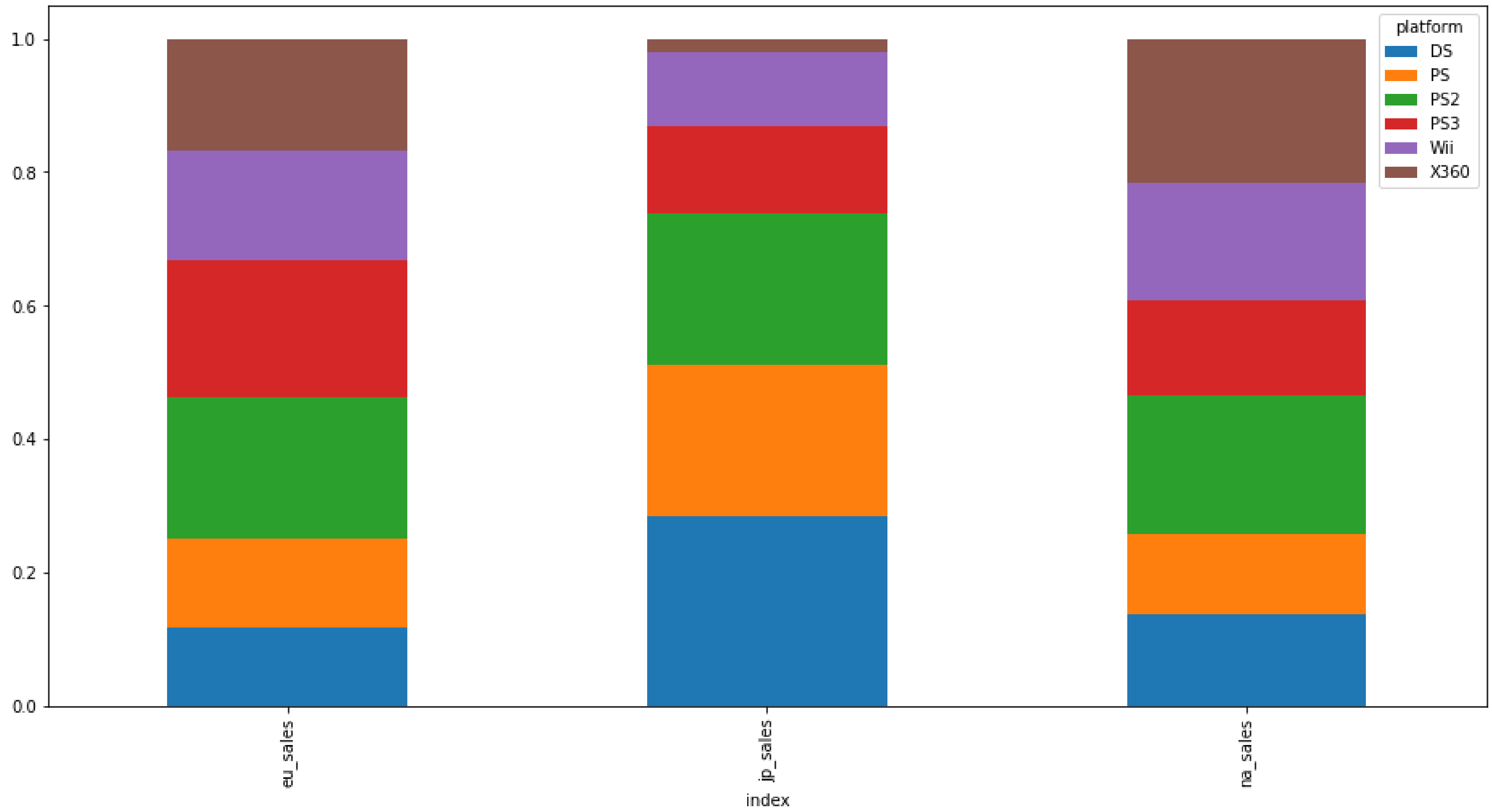
other_sales

	top_platforms	top_genres	top_ratings
0	PS2	Action	E
1	PS3	Sports	M
2	X360	Shooter	T
3	Wii	Racing	E10+
4	DS	Misc	EC

From this I see that in different regions different games were popular and different genres have been popular throughout the time. But most of top platforms are the same, so let's look at the combined data and create charts for it.

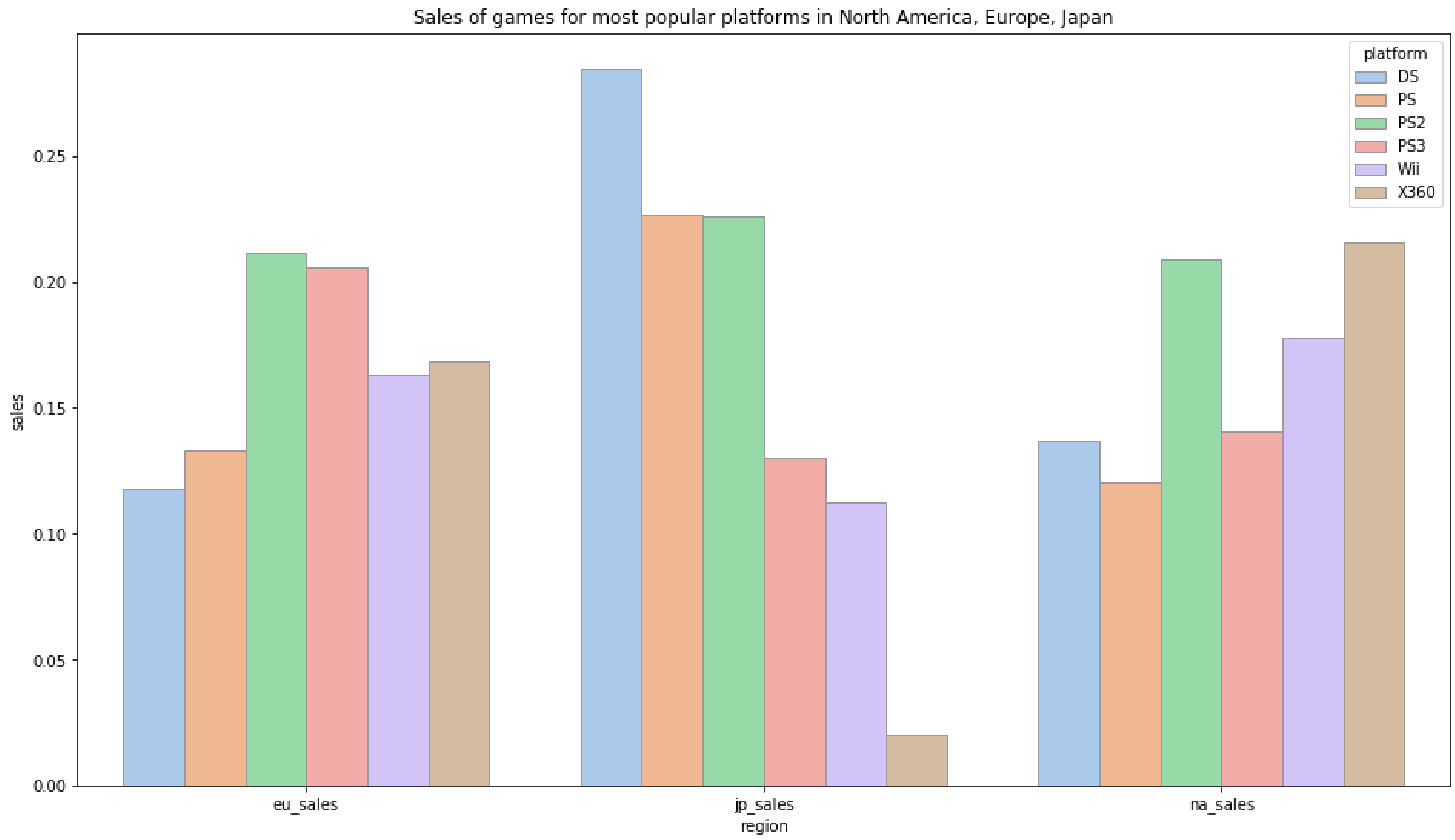
In [54]:
```
top_platforms = ['X360', 'PS2', 'Wii', 'PS3', 'DS', 'PS', 'PS3']
df = data.query('platform in @top_platforms')
df = df.pivot_table(index=['platform'], values=['eu_sales','jp_sales','na_sales'], aggfunc='sum')
df = df.apply(lambda x: x / float(x.sum())).transpose().reset_index() #change absolute values to percentages

fig, ax = plt.subplots(figsize=(16,8))
df.plot(kind='bar', x='index', stacked=True, ax=ax)
```

Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7eff03673190>



In [55]:
```
df = data.query('platform in @top_platforms')
df = (df.pivot_table(index=['platform'], values=['eu_sales','jp_sales','na_sales'], aggfunc='sum')
      .apply(lambda x: x / float(x.sum()))
      .reset_index()
      .melt(id_vars='platform')
     )
df.columns = ['platform', 'region', 'sales']
fig, ax = plt.subplots(figsize=(16, 9))
ax.set_title('Sales of games for most popular platforms in North America, Europe, Japan')

sns.barplot(x='region', y='sales', hue='platform', data=df, palette="pastel", edgecolor=".6", ax=ax)

# # sns.set()
# # df.set_index('region').T.plot(kind='bar', stacked=True)
# # ig, ax = plt.subplots(figsize=(16,8))
# # df.plot(kind='bar', x='region', y='sales', hue='platform', stacked=True, ax=ax)

# from matplotlib.colors import ListedColormap

# df.set_index('platform')\
#   .reindex(df.set_index('platform').sum().sort_values().index, axis=1)\
#   .T.plot(kind='bar', stacked=True,
#           colormap=ListedColormap(sns.color_palette("GnBu", 10)),
#           figsize=(12,6))
```

Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x7eff03587210>



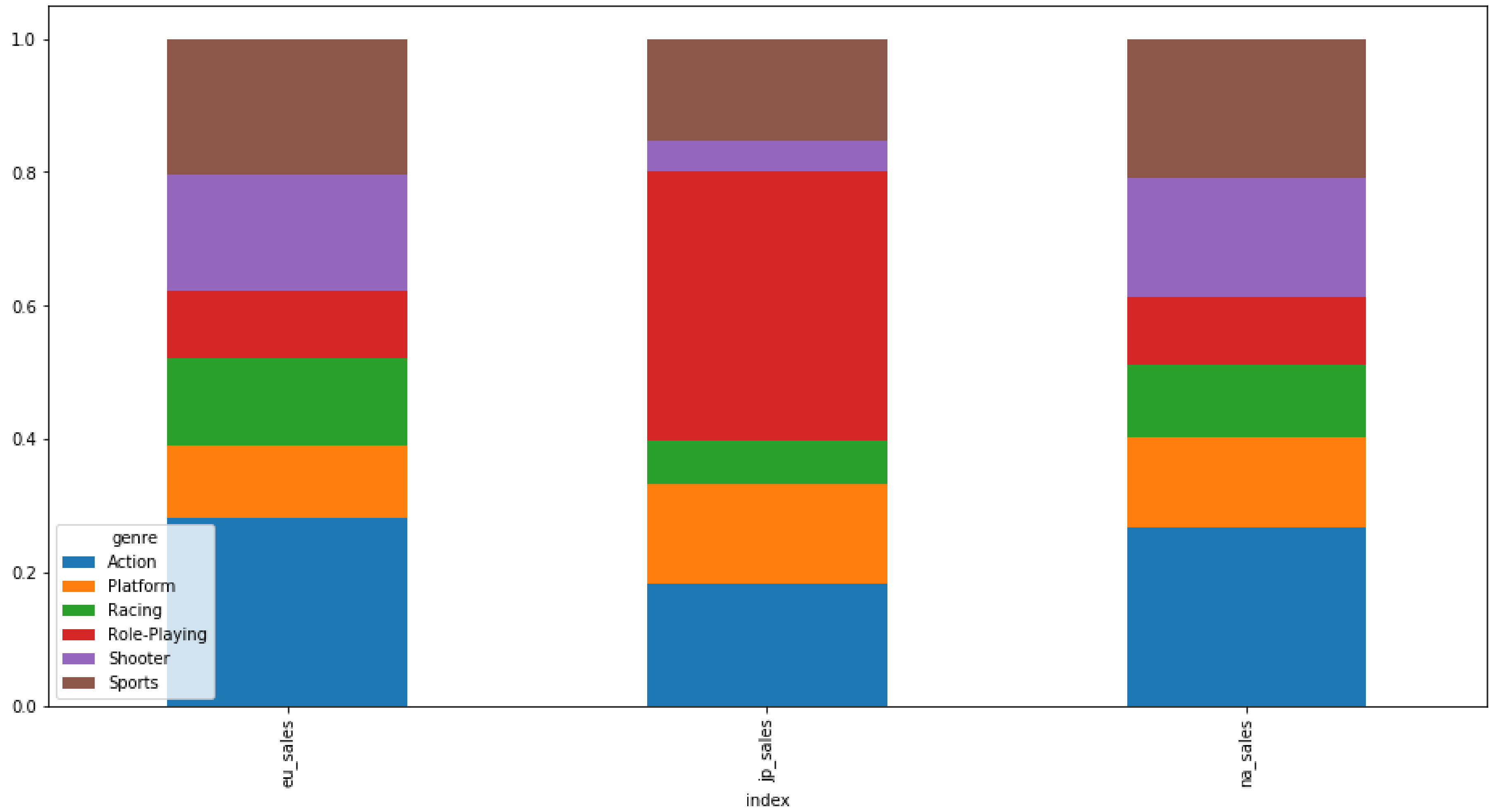
So here I see that some gaming platforms hthat are popular in one region, aren't popular in others at all. For example very few people have played X360 in Japan, while it has been the biggest platform in North America.

The top five genres. Explain the difference.

For analysing genre I'll do the same visualisation.

In [56]:
```
top_genres = ['Action', 'Sports', 'Shooter', 'Platform', 'Role-Playing', 'Racing', 'Platform']
df = data.query('genre in @top_genres')
df = df.pivot_table(index=['genre'], values=['eu_sales','jp_sales','na_sales'], aggfunc='sum')
df = df.apply(lambda x: x / float(x.sum())).transpose().reset_index() #change absolute values to percentages

fig, ax = plt.subplots(figsize=(16,8))
df.plot(kind='bar', x='index', stacked=True, ax=ax)
```

Out[56]: `<matplotlib.axes._subplots.AxesSubplot at 0x7eff034e3ad0>`



We see simillar differences in genres. There is a definite deifference between "western" world and Japan. Japan always stands aside with different gaming priorities than EU and NA. For example role-playing is the most popular genre in Japan, While in NA it has far smaller percentage. On the other hand NA an EU play much more shooters than japaneese consumers. Soo the store should really pay attention to that fact.

Do ESRB ratings affect sales in individual regions?

For this analysis I'll firstly need to create a dataframe where I will fill empty values of rating with "other".

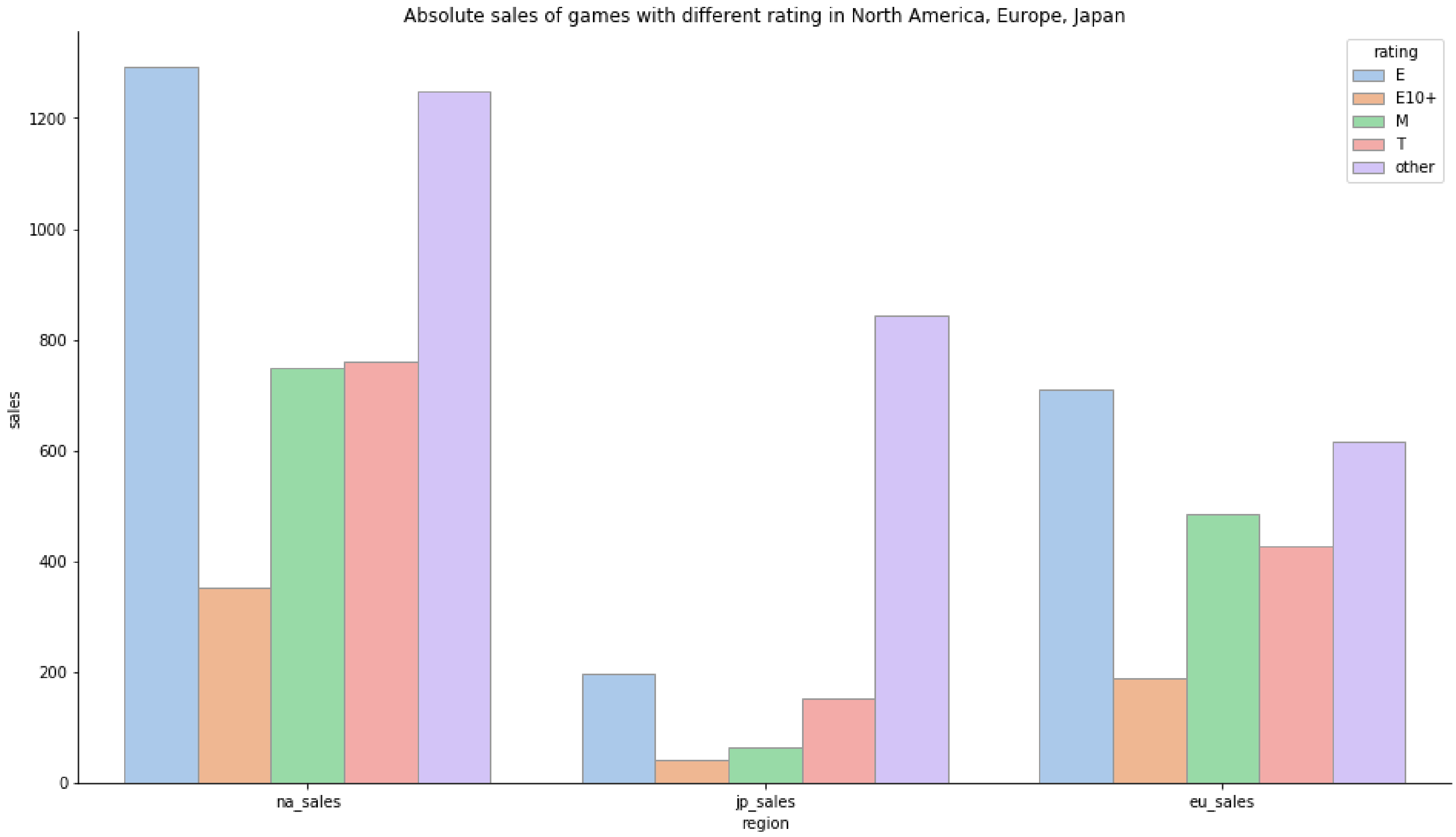
In [57]:
```
df = data
df['rating'] = data['rating'].fillna('other')
data.rating.value_counts()
```

Out[57]:
```
other    6764
E        3990
T        2961
M        1563
E10+     1420
EC          8
RP          3
K-A         3
AO          1
Name: rating, dtype: int64
```

I see that there are some rating values that have been extremelly rare. For my analysis I'll also replase them with "other".

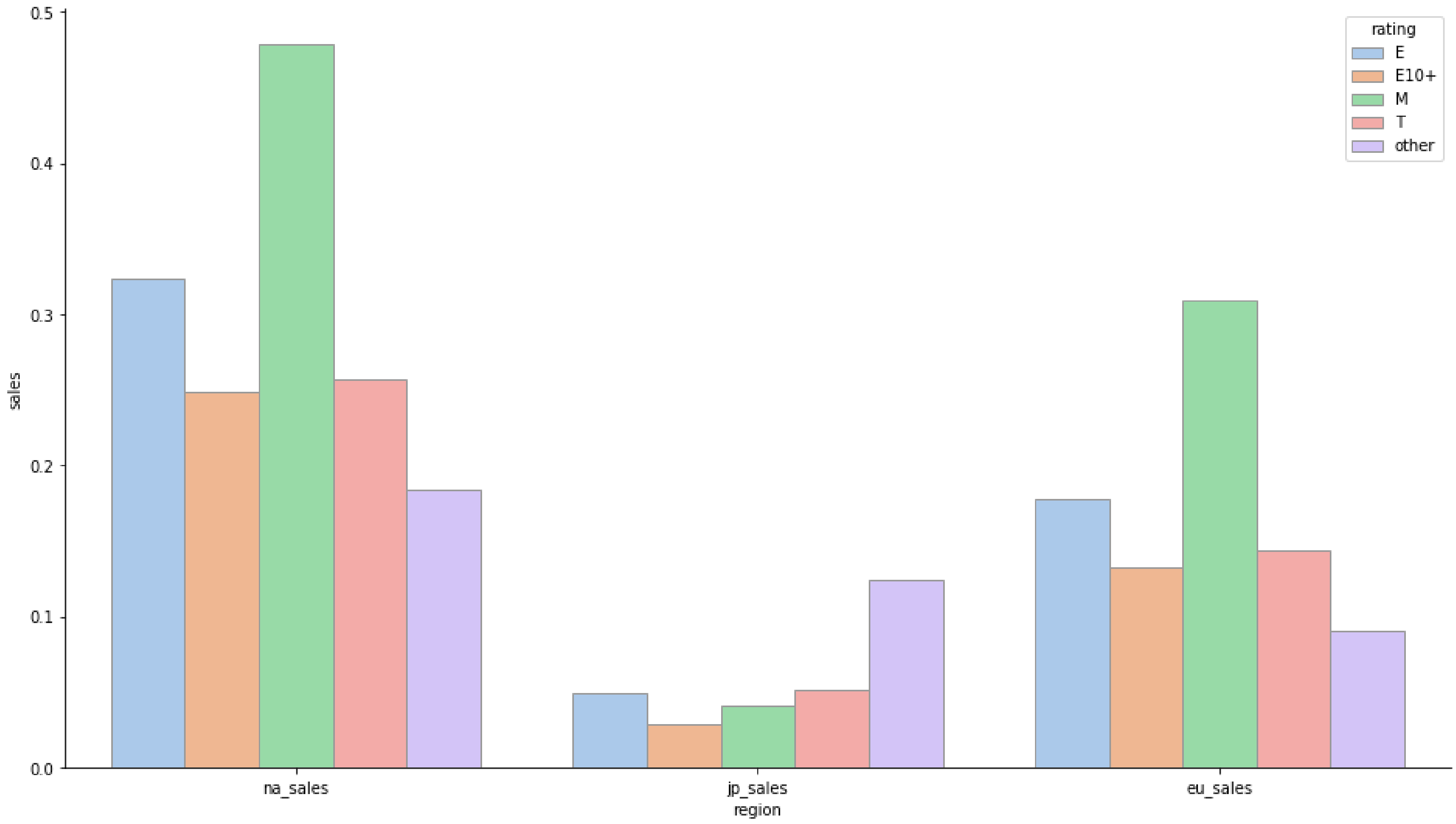
In [58]:
```
not_popular = df.rating.value_counts().tail(4).index.tolist()
df['rating'] = df["rating"].replace(not_popular, 'other')
```

In [59]:
```
#top_ratings = ['E', 'T', 'M', 'E10+', 'other']

df_total = (df.groupby('rating')[['na_sales','jp_sales','eu_sales']].sum() #group to have sum for each rating
            .reset_index()
            .melt(id_vars='rating') #melt for it to be easily plotted
           )
df_total.columns = ['rating', 'region', 'sales']
fig, ax = plt.subplots(figsize=(16, 9))
ax.set_title('Absolute sales of games with different rating in North America, Europe, Japan')

sns.barplot(x='region', y='sales', hue='rating', data=df_total, palette="pastel", edgecolor=".6", ax=ax)
sns.despine(fig)
```



To be percise I'll make another comparacement, but now I won't take sum of sales for each region, I'll take average sale of each game for every rating.

In [60]:
```
df_mean = (df.groupby('rating')[['na_sales','jp_sales','eu_sales']].mean() #group to have sum for each rating
            .reset_index()
            .melt(id_vars='rating') #melt for it to be easily plotted
           )
df_mean.columns = ['rating', 'region', 'sales']
ax.set_title('Average sales per game for games different rating in North America, Europe, Japan')
fig, ax = plt.subplots(figsize=(16, 9))
sns.barplot(x='region', y='sales', hue='rating', data=df_mean, palette="pastel", edgecolor=".6", ax=ax)
sns.despine(fig)
```



Conclusions:

- There is different importance of game ratings in different regions. Most of the games sold in Japan don't have assigned ESRP rating, but in US and in EU this rating seems to be more important. Maybe Japan uses its own game rating cryteria, that differs from international.
- Alltogether games with "E" rating make more money than games with other ratings (in NA and EU), but each game with M rating seems to have on average higher profit than games with any other genre. This diefference may be due to the fact that there are actually more games reliesed with lower ratings (like E or E10+), but there games wwith M seem to show more quality due to limits of age groups that they are designed for).
- Therefore I will recomend for the store owner to sell huge variety of games with "E" rating, but have high quantity of popular "M" games in stock (especially in NA and EU).

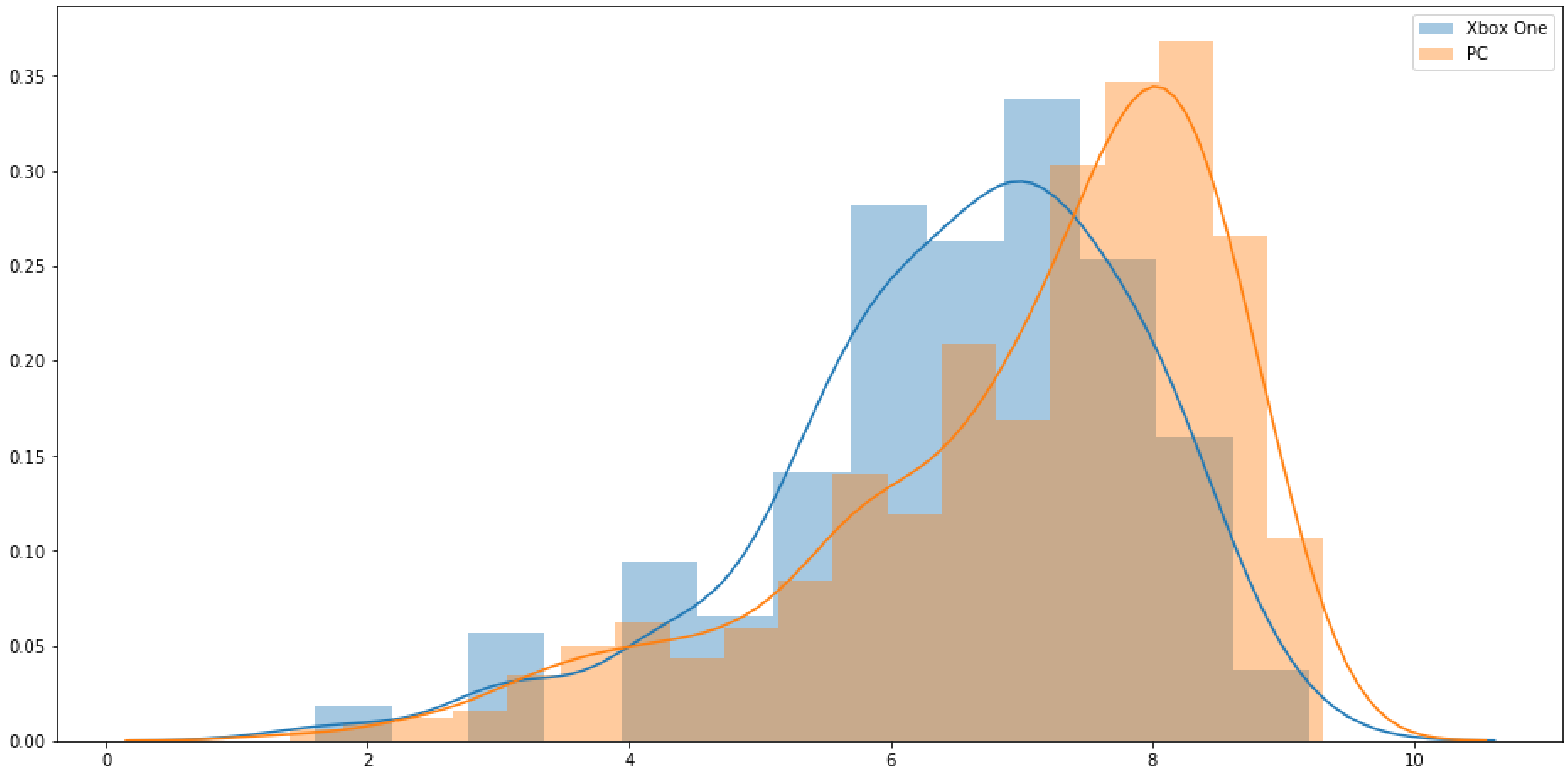
Step 5. Test hypotheses

Average user ratings of the Xbox One and PC platforms are the same.

Null hypothesys always needs to be a positive one for this test to be correct. Therefore our hypothesis is **Average user ratings of the Xbox One and PC platforms are the same.**

In [61]:
```
xbox_ratings = data.query('platform =="XOne"')['user_score'].dropna().tolist()
pc_ratings = data.query('platform == "PC"')['user_score'].dropna().tolist()


#check how does the data look
fig, ax = plt.subplots(figsize=(16,8))
sns.distplot(xbox_ratings, label='Xbox One');
sns.distplot(pc_ratings, label='PC');
plt.legend()
print ("Amount of values for Xbox One:", len(xbox_ratings))
print ("Amount of values for PC:", len(pc_ratings))

print ('Variance of user score for XOne: {:.2f}'.format(np.var(xbox_ratings)))
print ('Variance of user score for PC: {:.2f}'.format(np.var(pc_ratings)))
print ('Average user score for XOne: {:.2f}'.format(mean(xbox_ratings)))
print ('Average user score for Pn: {:.2f}'.format(mean(pc_ratings)))
```

```
Amount of values for Xbox One: 182
Amount of values for PC: 770
Variance of user score for XOne: 1.90
Variance of user score for PC: 2.34
Average user score for XOne: 6.52
Average user score for Pn: 7.06
```



I see that the distribution of data isn't normal, both datasets are negatively skewed, so it would be better to use Mann–Whitney U test, but because we haven't learned it yet, I will use A-B test. I'm going to use alpha value of 5% because it's industry standart and I don't see any reason to use more o less conservative alpha. They have simillar valiances, and they have been taken from populations with similar parameters, therefore we can consider their variances equal.

In [62]:
```
alpha = .05 # critical statistical significance level
                        # if the p-value is less than alpha, we reject the hypothesis




results = st.ttest_ind(
    xbox_ratings,
    pc_ratings)

print('p-value: {:.6f}'.format(results.pvalue))

if (results.pvalue < alpha):
        print("We reject the null hypothesis")
else:
        print("We can't reject the null hypothesis")
```

```
p-value: 0.000014
We reject the null hypothesis
```

Conclusion

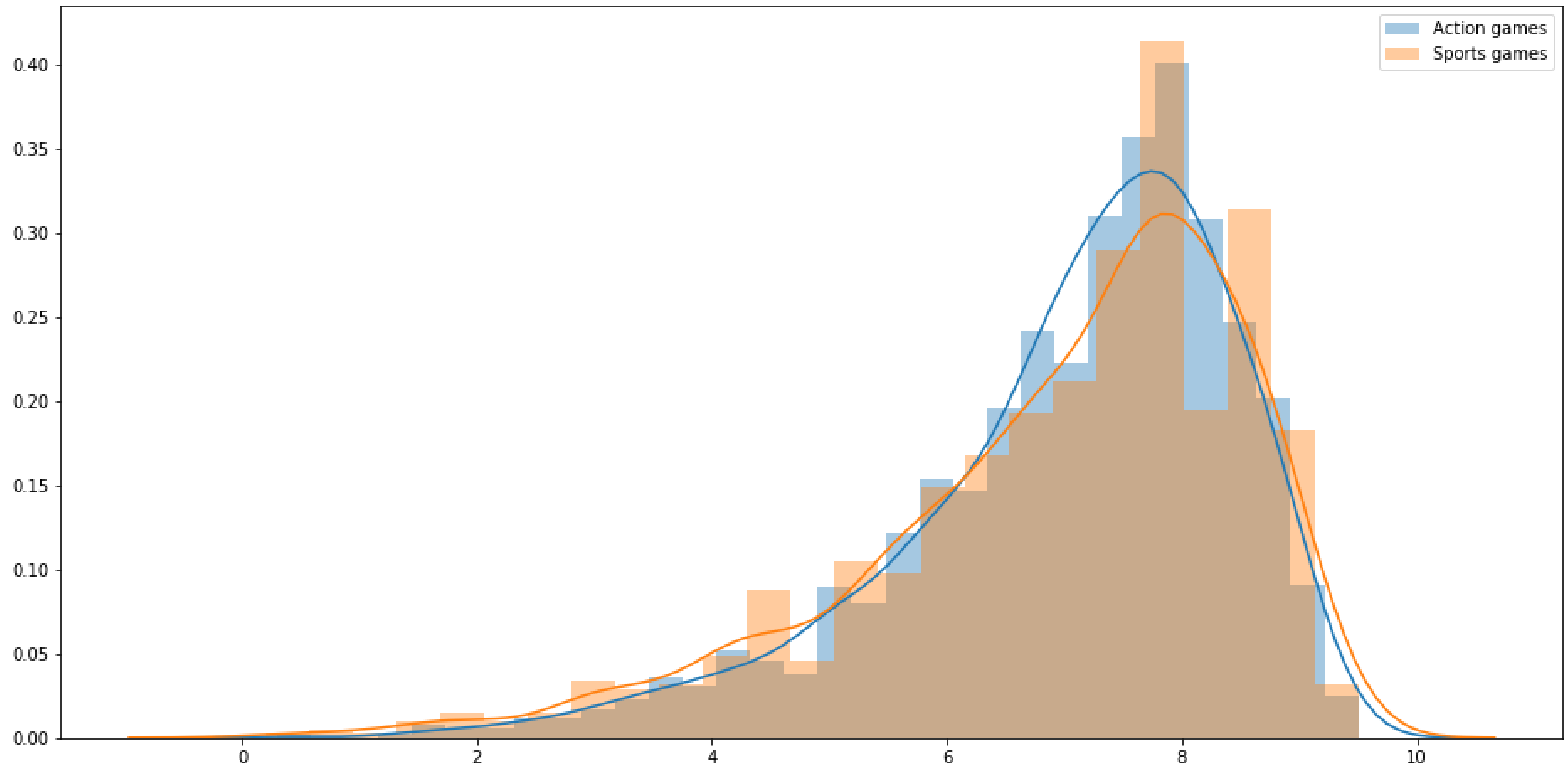
Average user ratings for Xbox One and for PC are not the same.

Average user ratings for the Action and Sports genres are different.

Right null hypothesys here is: **Average user ratings for the Action and Sports genres are the same.**

In [63]:
```
action_ratings = data.query('genre =="Action"')['user_score'].dropna().tolist()
sports_ratings = data.query('genre == "Sports"')['user_score'].dropna().tolist()


#check how does the data look
fig, ax = plt.subplots(figsize=(16,8))
sns.distplot(action_ratings, label='Action games');
sns.distplot(sports_ratings, label='Sports games');
plt.legend();

print ("Amount of values for action games:", len(action_ratings))
print ("Amount of values for sports games:", len(sports_ratings))

print ('Variance of user score for action games: {:.2f}'.format(np.var(action_ratings)))
print ('Variance of user score for sports game: {:.2f}'.format(np.var(sports_ratings)))
print ('Average user score for action games: {:.2f}'.format(mean(action_ratings)))
print ('Average user score for sports game: {:.2f}'.format(mean(sports_ratings)))
```

```
Amount of values for action games: 1830
Amount of values for sports games: 1103
Variance of user score for action games: 2.03
Variance of user score for sports game: 2.59
Average user score for action games: 7.05
Average user score for sports game: 6.96
```



The distribution of data isn't normal, both datasets are negatively skewed, so it would be better to use Mann–Whitney U test, but I will use A-B test. I'm going to use alpha value of 5% because it's industry standart and I don't see any reason to use more o less conservative alpha. They have simillar valiances, and they have been taken from populations with similar parameters, therefore we can consider their variances equal.

In [64]:
```
alpha = .05 # critical statistical significance level
                        # if the p-value is less than alpha, we reject the hypothesis


results = st.ttest_ind(
    action_ratings,
    sports_ratings)

print('p-value: {:.6f}'.format(results.pvalue))

if (results.pvalue < alpha):
        print("We reject the null hypothesis")
else:
        print("We can't reject the null hypothesis")
```

```
p-value: 0.104070
We can't reject the null hypothesis
```

Conclusion

We can't make definite conclusion if user scores for sport games and for action games are the same or different.

General conclusion

My conclusions will mostly be recomendations for online-store based on the analysis that I have made.

- First and faremost important conclusion is that the industry is now in stable/declining state. There aren't any platforms that show any rise and worldwide sales are going down;
- On average one platform has a lifespan of 8-10 years;
- There is no need to invest money in selling games for old platforms;
- The most popular platfroms now are PS4 and XOne, they still have some time to live left, but there may be some new platforms coming out next year or two (due to decline of current ones);
- There are game genres that tend to stay popular throughout the years, like action and sports, shooters seem to be gaining popularity for last years. Some genres are never popular, like Strategy;
- Japan market is very different from NA and EU market: different platforms are popular in Japan (nobody plays Xbox, and everybody play PS), different genres are popular (role-playing is a huge thing there) and ESRP ratings don't affect the price of games;
- I will recomend for the store owner to try to sell huge variety of games with "E" rating, but have high quantity of popular "M" games in stock (this only applies to NA and EU);
- Games that have good crotic score seem to have higher sales, but that's not always the point, some of the highest selling games have had very low critic score. So a good recomendation here is to pay attention to it, but not to have it as a valuable point of making decision;
- Users tend to love and to hate all the games: with high critic score, with low, with high and low sales. So user rating should never be a deciding point of promoting/selling/stocking games.