In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import statsmodels.formula.api as smf
import seaborn as sns

from scipy.stats import ttest_ind
from scipy.stats import f_oneway
from sklearn.model_selection import train_test_split, KFold, cross_val_s
core
from sklearn.preprocessing import StandardScaler
from sklearn import linear_model
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from scipy.cluster.hierarchy import linkage, fcluster
from sklearn.cluster import KMeans, DBSCAN
from sklearn import metrics
```

In [2]:
```
# Load dataset from vgsales.csv and display first five rows
sales_data = pd.read_csv('vgsales.csv')
sales_data.head()
```

Out[2]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Oth
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	

In [3]:
```python
# Explore the dataset
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16598 entries, 0 to 16597
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Rank          16598 non-null  int64  
 1   Name          16598 non-null  object 
 2   Platform      16598 non-null  object 
 3   Year          16327 non-null  float64
 4   Genre         16598 non-null  object 
 5   Publisher     16540 non-null  object 
 6   NA_Sales      16598 non-null  float64
 7   EU_Sales      16598 non-null  float64
 8   JP_Sales      16598 non-null  float64
 9   Other_Sales   16598 non-null  float64
 10  Global_Sales  16598 non-null  float64
dtypes: float64(6), int64(1), object(4)
memory usage: 1.4+ MB
```

In [4]:
```python
# Explore the dataset (continued)
sales_data.describe(include="all")
```

Out[4]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_S
count	16598.000000	16598	16598	16327.000000	16598	16540	16598.000000	16598.00
unique	NaN	11493	31	NaN	12	578	NaN	
top	NaN	Need for Speed: Most Wanted	DS	NaN	Action	Electronic Arts	NaN	
freq	NaN	12	2163	NaN	3316	1351	NaN	
mean	8300.605254	NaN	NaN	2006.406443	NaN	NaN	0.264667	0.14
std	4791.853933	NaN	NaN	5.828981	NaN	NaN	0.816683	0.50
min	1.000000	NaN	NaN	1980.000000	NaN	NaN	0.000000	0.00
25%	4151.250000	NaN	NaN	2003.000000	NaN	NaN	0.000000	0.00
50%	8300.500000	NaN	NaN	2007.000000	NaN	NaN	0.080000	0.02
75%	12449.750000	NaN	NaN	2010.000000	NaN	NaN	0.240000	0.11
max	16600.000000	NaN	NaN	2020.000000	NaN	NaN	41.490000	29.02

In [5]:
```
# Load dataset from vgratings.csv and display first five rows
ratings_data = pd.read_csv('vgratings.csv')
ratings_data.head()
```

Out[5]:

	Number	Name	Platform	Release_Date	Metascore	Userscore
0	1.0	The Legend of Zelda: Ocarina of Time	Nintendo 64	November 23, 1998	99	9.1
1	2.0	Tony Hawk's Pro Skater 2	PlayStation	September 20, 2000	98	7.4
2	3.0	Grand Theft Auto IV	PlayStation 3	April 29, 2008	98	7.6
3	4.0	SoulCalibur	Dreamcast	September 8, 1999	98	8.5
4	5.0	Grand Theft Auto IV	Xbox 360	April 29, 2008	98	7.9

In [6]:
```
# Explore the dataset
ratings_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 18009 entries, 0 to 18008
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Number        18009 non-null  float64
 1   Name          18009 non-null  object 
 2   Platform      18009 non-null  object 
 3   Release_Date  18009 non-null  object 
 4   Metascore     18009 non-null  int64  
 5   Userscore     18009 non-null  object 
dtypes: float64(1), int64(1), object(4)
memory usage: 844.3+ KB
```

In [7]:
```
# Explore the dataset (continued)
ratings_data.describe(include="all")
```

Out[7]:

	Number	Name	Platform	Release_Date	Metascore	Userscore
count	18009.000000	18009	18009	18009	18009.000000	18009
unique	NaN	11820	22	4366	NaN	95
top	NaN	Cars	PC	November 14, 2006	NaN	tbd
freq	NaN	9	4605	48	NaN	1277
mean	9005.000000	NaN	NaN	NaN	70.405408	NaN
std	5198.894834	NaN	NaN	NaN	12.396993	NaN
min	1.000000	NaN	NaN	NaN	11.000000	NaN
25%	4503.000000	NaN	NaN	NaN	63.000000	NaN
50%	9005.000000	NaN	NaN	NaN	72.000000	NaN
75%	13507.000000	NaN	NaN	NaN	79.000000	NaN
max	18009.000000	NaN	NaN	NaN	99.000000	NaN

In [8]:
```
# Display all distinct platforms for each dataset
print('Distinct platforms in sales_data: ', sales_data['Platform'].uniqu
e())
print('Distinct platforms in ratings_data: ', ratings_data['Platform'].u
nique())
```

```
Distinct platforms in sales_data:  ['Wii' 'NES' 'GB' 'DS' 'X360' 'PS3'
'PS2' 'SNES' 'GBA' '3DS' 'PS4' 'N64'
 'PS' 'XB' 'PC' '2600' 'PSP' 'XOne' 'GC' 'WiiU' 'GEN' 'DC' 'PSV' 'SAT'
 'SCD' 'WS' 'NG' 'TG16' '3DO' 'GG' 'PCFX']
Distinct platforms in ratings_data:  ['Nintendo 64' 'PlayStation' 'Play
Station 3' 'Dreamcast' 'Xbox 360' 'Wii'
 'Xbox One' 'Switch' 'PlayStation 2' 'PlayStation 4' 'GameCube' 'Xbox'
 'PC' 'Wii U' 'Game Boy Advance' '3DS' 'DS' 'PlayStation Vita'
 'PlayStation 5' 'PSP' 'Xbox Series X' 'Stadia']
```

In [9]:
```
# Display number of unique games and platforms for each dataset
print('# of unique games in sales_data: ', sales_data['Name'].unique().s
ize)
print('# of unique games in ratings_data: ', ratings_data['Name'].unique
().size)
print('# of unique platforms in sales_data: ', sales_data['Platform'].un
ique().size)
print('# of unique platforms in ratings_data: ', ratings_data['Platform'
].unique().size)
```

```
# of unique games in sales_data:  11493
# of unique games in ratings_data:  11820
# of unique platforms in sales_data:  31
# of unique platforms in ratings_data:  22
```

In [10]:
```
# Replace the abbreviated 'Platform' data in sales_data w/ its full abbr
eviation
abbreviated_platforms = {
    "Wii": "Wii",
    "NES": "Nintendo Entertainment System",
    "GB": "Game Boy",
    "DS": "DS",
    "X360": "Xbox 360",
    "PS3": "PlayStation 3",
    "PS2": "PlayStation 2",
    "SNES": "Super Nintendo Entertainment System",
    "GBA": "Game Boy Advance",
    "3DS": "3DS",
    "PS4": "PlayStation 4",
    "N64": "Nintendo 64",
    "PS": "PlayStation",
    "XB": "Xbox",
    "PC": "PC",
    "2600": "Atari 2600",
    "PSP": "PSP",
    "XOne": "Xbox One",
    "GC": "GameCube",
    "WiiU": "Wii U",
    "GEN": "Sega Genesis",
    "DC": "Dreamcast",
    "PSV": "PlayStation Vita",
    "SAT": "Sega Saturn",
    "SCD": "SCD",
    "WS": "WonderSwan",
    "NG": "NG",
    "TG16": "TurboGrafx-16",
    "3DO": "3DO Interactive Multiplayer",
    "GG": "Game Gear",
    "PCFX": "PC-FX",
}
sales_data['Platform'] = sales_data['Platform'].map(abbreviated_platform
s)
print('Distinct platforms in sales_data: ', sales_data['Platform'].uniqu
e())
print('Distinct platforms in ratings_data: ', ratings_data['Platform'].u
nique())
```

```
Distinct platforms in sales_data:  ['Wii' 'Nintendo Entertainment Syste
m' 'Game Boy' 'DS' 'Xbox 360'
 'PlayStation 3' 'PlayStation 2' 'Super Nintendo Entertainment System'
 'Game Boy Advance' '3DS' 'PlayStation 4' 'Nintendo 64' 'PlayStation'
 'Xbox' 'PC' 'Atari 2600' 'PSP' 'Xbox One' 'GameCube' 'Wii U'
 'Sega Genesis' 'Dreamcast' 'PlayStation Vita' 'Sega Saturn' 'SCD'
 'WonderSwan' 'NG' 'TurboGrafx-16' '3DO Interactive Multiplayer'
 'Game Gear' 'PC-FX']
Distinct platforms in ratings_data:  ['Nintendo 64' 'PlayStation' 'Play
Station 3' 'Dreamcast' 'Xbox 360' 'Wii'
 'Xbox One' 'Switch' 'PlayStation 2' 'PlayStation 4' 'GameCube' 'Xbox'
 'PC' 'Wii U' 'Game Boy Advance' '3DS' 'DS' 'PlayStation Vita'
 'PlayStation 5' 'PSP' 'Xbox Series X' 'Stadia']
```

In [11]:
```
# Drop 'Rank' in sales_data
sales_data = sales_data.drop(columns=['Rank'])
sales_data.shape
```

Out[11]:
```
(16598, 10)
```

In [12]:
```
# Replace 'Publisher' missing values in sales_data (e.g., with 'Unknow
n')
sales_data['Publisher'] = sales_data['Publisher'].fillna('Unknown')
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16598 entries, 0 to 16597
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Name          16598 non-null  object 
 1   Platform      16598 non-null  object 
 2   Year          16327 non-null  float64
 3   Genre         16598 non-null  object 
 4   Publisher     16598 non-null  object 
 5   NA_Sales      16598 non-null  float64
 6   EU_Sales      16598 non-null  float64
 7   JP_Sales      16598 non-null  float64
 8   Other_Sales   16598 non-null  float64
 9   Global_Sales  16598 non-null  float64
dtypes: float64(6), object(4)
memory usage: 1.3+ MB
```

In [13]:
```
# Drop missing values from variable 'Year' in sales_data
sales_data = sales_data.dropna()
sales_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16327 entries, 0 to 16597
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Name          16327 non-null  object 
 1   Platform      16327 non-null  object 
 2   Year          16327 non-null  float64
 3   Genre         16327 non-null  object 
 4   Publisher     16327 non-null  object 
 5   NA_Sales      16327 non-null  float64
 6   EU_Sales      16327 non-null  float64
 7   JP_Sales      16327 non-null  float64
 8   Other_Sales   16327 non-null  float64
 9   Global_Sales  16327 non-null  float64
dtypes: float64(6), object(4)
memory usage: 1.4+ MB
```

In [14]:
```
# Convert the variable 'Year' in sales_data from type float64 to type in
t64
sales_data['Year'] = sales_data['Year'].map(lambda x: int(x))
print('Year type:', type(sales_data['Year'][0]))
```

```
Year type: <class 'numpy.int64'>
```

In [15]:
```
# Drop 'Number' in sales_data
ratings_data = ratings_data.drop(columns=['Number'])
ratings_data.shape
```

Out[15]:
```
(18009, 5)
```

In [16]:
```
# Replace 'tbd' values in ratings_data with np.nan and convert 'Userscor
e' variable to type float64
ratings_data['Userscore'] = ratings_data['Userscore'].replace('tbd', np.
nan).astype(float)
print('Userscore type:', type(ratings_data['Userscore'][0]))
ratings_data[ratings_data.isna().any(axis=1)]
```

```
Userscore type: <class 'numpy.float64'>
```

Out[16]:

	Name	Platform	Release_Date	Metascore	Userscore
497	Madden NFL 2005	GameCube	August 9, 2004	90	NaN
924	Tiger Woods PGA Tour 2005	GameCube	September 20, 2004	88	NaN
1220	NASCAR 2005: Chase for the Cup	Xbox	August 31, 2004	86	NaN
1410	Moto Racer Advance	Game Boy Advance	December 5, 2002	86	NaN
2109	Pinball FX 2: Marvel Pinball - Vengeance and V...	Xbox 360	December 13, 2011	84	NaN
...	...	...	...	...	...
17817	Jackass the Game	DS	January 8, 2008	35	NaN
17840	King of Clubs	Wii	August 4, 2008	35	NaN
17900	Jenga World Tour	DS	November 13, 2007	32	NaN
17915	Dream Chronicles	PlayStation 3	November 23, 2010	31	NaN
17917	Smash 'N' Survive	PlayStation 3	February 22, 2012	31	NaN

1277 rows × 5 columns

In [17]:
```
# Create a new variable named 'Year' in the ratings_data from the 'Relea
se_Date' variable
ratings_data['Year'] = ratings_data['Release_Date'].map(lambda str: int(
str.split()[2]))
ratings_data.head()
```

Out[17]:

	Name	Platform	Release_Date	Metascore	Userscore	Year
0	The Legend of Zelda: Ocarina of Time	Nintendo 64	November 23, 1998	99	9.1	1998
1	Tony Hawk's Pro Skater 2	PlayStation	September 20, 2000	98	7.4	2000
2	Grand Theft Auto IV	PlayStation 3	April 29, 2008	98	7.6	2008
3	SoulCalibur	Dreamcast	September 8, 1999	98	8.5	1999
4	Grand Theft Auto IV	Xbox 360	April 29, 2008	98	7.9	2008

In [18]:
```
# Drop missing values from variable 'Userscore' in ratings_data
ratings_data = ratings_data.dropna()
ratings_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 16732 entries, 0 to 18008
Data columns (total 6 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Name          16732 non-null  object 
 1   Platform      16732 non-null  object 
 2   Release_Date  16732 non-null  object 
 3   Metascore     16732 non-null  int64  
 4   Userscore     16732 non-null  float64
 5   Year          16732 non-null  int64  
dtypes: float64(1), int64(2), object(3)
memory usage: 915.0+ KB
```

In [19]:
```
# Lowercase variable 'Name' on both datasets
sales_data['Name'] = sales_data['Name'].str.lower()
ratings_data['Name'] = ratings_data['Name'].str.lower()
```

In [20]:

```
# Merge both datasets into one using 'Name', 'Platform' and 'Year' and d
rop 'Year'
data = pd.merge(sales_data, ratings_data, how="inner", on=['Name', 'Plat
form', 'Year'])
data = data.drop(columns=['Year'])
data['Name'] = data['Name'].map(lambda str: str.title()) # For ecstatic
data.head()
```

Out[20]:

	Name	Platform	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sale
0	Wii Sports	Wii	Sports	Nintendo	41.49	29.02	3.77	8.46	82.7
1	Mario Kart Wii	Wii	Racing	Nintendo	15.85	12.88	3.79	3.31	35.8
2	Wii Sports Resort	Wii	Sports	Nintendo	15.75	11.01	3.28	2.96	33.0
3	New Super Mario Bros.	DS	Platform	Nintendo	11.38	9.23	6.50	2.90	30.0
4	New Super Mario Bros. Wii	Wii	Platform	Nintendo	14.59	7.06	4.70	2.26	28.6

In [21]:
```
# Create two new variables named 'Season' and 'Season_Number' in the mer
ged dataset
def get_season(str):
    if (str == 'March' or str == 'April' or str == 'May'):
        return 'Spring'
    elif (str == 'June' or str == 'July' or str == 'August'):
        return 'Summer'
    elif (str == 'September' or str == 'October' or str == 'November'):
        return 'Autumn'
    elif (str == 'December' or str == 'January' or str == 'February'):
        return 'Winter'
    else:
        return 'Other'

data['Season'] = data['Release_Date'].map(lambda x: get_season(x.split()
[0]))
print('Unique seasons:', data['Season'].unique()) # Verify we didn't get
'Other'

seasons_key = {
    "Spring": 0,
    "Summer": 1,
    "Autumn": 2,
    "Winter": 3,
}

data['Season_Number'] = data['Season'].map(seasons_key)
print('Unique season numbers:', data['Season_Number'].unique()) # Verify
we only got 0-3
```

```
Unique seasons: ['Autumn' 'Spring' 'Summer' 'Winter']
Unique season numbers: [2 0 1 3]
```

In [22]:
```
# Explore the merged dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5733 entries, 0 to 5732
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Name            5733 non-null   object 
 1   Platform        5733 non-null   object 
 2   Genre           5733 non-null   object 
 3   Publisher       5733 non-null   object 
 4   NA_Sales        5733 non-null   float64
 5   EU_Sales        5733 non-null   float64
 6   JP_Sales        5733 non-null   float64
 7   Other_Sales     5733 non-null   float64
 8   Global_Sales    5733 non-null   float64
 9   Release_Date    5733 non-null   object 
 10  Metascore       5733 non-null   int64  
 11  Userscore       5733 non-null   float64
 12  Season          5733 non-null   object 
 13  Season_Number   5733 non-null   int64  
dtypes: float64(6), int64(2), object(6)
memory usage: 671.8+ KB
```

In [23]:
```
# Explore the merged dataset (continued)
data.describe(include="all")
```

Out[23]:

	Name	Platform	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sal
count	5733	5733	5733	5733	5733.000000	5733.000000	5733.000000	5733.0000
unique	3614	18	12	215	NaN	NaN	NaN	Na
top	Harry Potter And The Order Of The Phoenix	PlayStation 2	Action	Electronic Arts	NaN	NaN	NaN	Na
freq	7	931	1387	837	NaN	NaN	NaN	Na
mean	NaN	NaN	NaN	NaN	0.431366	0.255125	0.051877	0.0869
std	NaN	NaN	NaN	NaN	1.028085	0.709980	0.250638	0.2670
min	NaN	NaN	NaN	NaN	0.000000	0.000000	0.000000	0.0000
25%	NaN	NaN	NaN	NaN	0.070000	0.020000	0.000000	0.0100
50%	NaN	NaN	NaN	NaN	0.170000	0.070000	0.000000	0.0200
75%	NaN	NaN	NaN	NaN	0.430000	0.230000	0.010000	0.0800
max	NaN	NaN	NaN	NaN	41.490000	29.020000	6.500000	10.5700

In [24]:
```
#4 Compute the mean for sales in the spring season

#Spring NA sales
na_spring = data.loc[data['Season_Number'].isin(["0"]), 'NA_Sales'].mean
()
print("Spring mean of NA_Sales (in millions):",na_spring)

#Spring EU sales
eu_spring = data.loc[data['Season_Number'].isin(["0"]), 'EU_Sales'].mean
()
print("Spring mean of EU_Sales (in millions):",eu_spring)

#Spring JP sales
jp_spring = data.loc[data['Season_Number'].isin(["0"]), 'JP_Sales'].mean
()
print("Spring mean of JP_Sales (in millions):",jp_spring)

#Spring Other sales
oth_spring = data.loc[data['Season_Number'].isin(["0"]), 'Other_Sales'].
mean()
print("Spring mean of Other_Sales (in millions):",oth_spring)

#Spring Global sales
glo_spring = data.loc[data['Season_Number'].isin(["0"]), 'Global_Sales']
.mean()
print("Spring mean of Global_Sales (in millions):",glo_spring)

na_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'NA_Sales']
eu_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'EU_Sales']
jp_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'JP_Sales']
oth_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Other_Sales']
glo_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Global_Sales'
]

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
spring_stat, p_spring = f_oneway(na_spring2 , eu_spring2 , jp_spring2, o
th_spring2 , glo_spring2)
print('Spring Statistics =%.3f, Spring p value =%.10f' % (spring_stat, p
_spring))

a = 0.05
if p_spring > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Spring mean of NA_Sales (in millions): 0.34773471145564
Spring mean of EU_Sales (in millions): 0.21390180878552978
Spring mean of JP_Sales (in millions): 0.050378983634797626
Spring mean of Other_Sales (in millions): 0.07100775193798539
Spring mean of Global_Sales (in millions): 0.6834366925064586
Spring Statistics =96.749, Spring p value =0.0000000000
Different distributions (reject null)
```

In [25]:
```
#4 Compute the mean for sales in the summer season

# Compute summer NA sales
na_summer = data.loc[data['Season_Number'].isin(["1"]), 'NA_Sales'].mean
()
print("Summer mean of NA_Sales (in millions):",na_summer)

#Computer summer EU sales
eu_summer = data.loc[data['Season_Number'].isin(["1"]), 'EU_Sales'].mean
()
print("Summer mean of EU_Sales (in millions):",eu_summer)

#Compute summer JP sales
jp_summer = data.loc[data['Season_Number'].isin(["1"]), 'JP_Sales'].mean
()
print("Summer mean of JP_Sales (in millions):",jp_summer)

#Compute summer Other sales
oth_summer = data.loc[data['Season_Number'].isin(["1"]), 'Other_Sales'].
mean()
print("Summer mean of Other_Sales (in millions):",oth_summer)


#Compute summer Global sales
glo_summer = data.loc[data['Season_Number'].isin(["1"]), 'Global_Sales']
.mean()
print("Summer mean of Global_Sales (in millions):",glo_summer)

na_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'NA_Sales']
eu_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'EU_Sales']
jp_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'JP_Sales']
oth_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Other_Sales']
glo_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Global_Sales'
]

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
summer_stat, p_summer = f_oneway(na_summer2 , eu_summer2 , jp_summer2, o
th_summer2 , glo_summer2)
print('Summer Statistics =%.3f, Summer p value =%.10f' % (summer_stat, p
_summer))

a = 0.05
if p_summer > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Summer mean of NA_Sales (in millions): 0.379971126082771
Summer mean of EU_Sales (in millions): 0.1739557266602502
Summer mean of JP_Sales (in millions): 0.03943214629451397
Summer mean of Other_Sales (in millions): 0.06118383060635219
Summer mean of Global_Sales (in millions): 0.6546775745909503
Summer Statistics =112.122, Summer p value =0.0000000000
Different distributions (reject null)
```

In [26]:
```
#4 Compute the mean for sales in the autumn season

# Compute autumn NA sales
na_autumn = data.loc[data['Season_Number'].isin(["2"]), 'NA_Sales'].mean
()
print("Autumn mean of NA_Sales (in millions):",na_autumn)

#Compute autumn EU sales
eu_autumn = data.loc[data['Season_Number'].isin(["2"]), 'EU_Sales'].mean
()
print("Autumn mean of EU_Sales (in millions):",eu_autumn)

#Compute autumn JP sales
jp_autumn = data.loc[data['Season_Number'].isin(["2"]), 'JP_Sales'].mean
()
print("Autumn mean of JP_Sales (in millions):",jp_autumn)

#Compute autumn Other sales
oth_autumn = data.loc[data['Season_Number'].isin(["2"]), 'Other_Sales'].
mean()
print("Autumn mean of Other_Sales (in millions):",oth_autumn)


#Compute autumn Global sales
glo_autumn = data.loc[data['Season_Number'].isin(["2"]), 'Global_Sales']
.mean()
print("Autumn mean of Global_Sales (in millions):",glo_autumn)

na_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'NA_Sales']
eu_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'EU_Sales']
jp_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'JP_Sales']
oth_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Other_Sales']
glo_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Global_Sales'
]

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
autumn_stat, p_autumn = f_oneway(na_autumn2 , eu_autumn2 , jp_autumn2, o
th_autumn2 , glo_autumn2)
print('Autumn Statistics =%.3f, Autumn p value =%.10f' % (autumn_stat, p
_autumn))

a = 0.05
if p_autumn > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Autumn mean of NA_Sales (in millions): 0.5144139387539517
Autumn mean of EU_Sales (in millions): 0.3199999999999944
Autumn mean of JP_Sales (in millions): 0.05778247096092911
Autumn mean of Other_Sales (in millions): 0.10954593453009044
Autumn mean of Global_Sales (in millions): 1.00194649771208
Autumn Statistics =241.236, Autumn p value =0.0000000000
Different distributions (reject null)
```

In [27]:
```
#4 Compute the mean for sales in the winter season

# Compute winter NA sales
na_winter = data.loc[data['Season_Number'].isin(["3"]), 'NA_Sales'].mean
()
print("Winter mean of NA_Sales (in millions):",na_winter)

#Compute winter EU sales
eu_winter = data.loc[data['Season_Number'].isin(["3"]), 'EU_Sales'].mean
()
print("Winter mean of EU_Sales (in millions):",eu_winter)

#Compute winter JP sales
jp_winter = data.loc[data['Season_Number'].isin(["3"]), 'JP_Sales'].mean
()
print("Winter mean of JP_Sales (in millions):",jp_winter)

#Compute winter Other sales
oth_winter = data.loc[data['Season_Number'].isin(["3"]), 'Other_Sales'].
mean()
print("Winter mean of Other_Sales (in millions):",oth_winter)


#Computer winter Global sales
glo_winter = data.loc[data['Season_Number'].isin(["3"]), 'Global_Sales']
.mean()
print("Winter mean of Global_Sales (in millions):",glo_winter)

na_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'NA_Sales']
eu_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'EU_Sales']
jp_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'JP_Sales']
oth_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Other_Sales']
glo_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Global_Sales'
]

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
winter_stat, p_winter = f_oneway(na_winter2 , eu_winter2 , jp_winter2, o
th_winter2 , glo_winter2)
print('Winter Statistics =%.3f, Winter p value =%.10f' % (winter_stat, p
_winter))

a = 0.05
if p_winter > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Winter mean of NA_Sales (in millions): 0.30789017341040487
Winter mean of EU_Sales (in millions): 0.17981213872832416
Winter mean of JP_Sales (in millions): 0.04882947976878619 6
Winter mean of Other_Sales (in millions): 0.05989884393063566
Winter mean of Global_Sales (in millions): 0.5965462427745645
Winter Statistics =116.492, Winter p value =0.0000000000
Different distributions (reject null)
```

In [28]:
```
#4 Compute the mean for metascore in all of the seasons

#Spring metascore
spring_meta = data.loc[data['Season_Number'].isin(["0"]), 'Metascore'].m
ean()
print("Spring mean of metascore (out of 100):",spring_meta)

#Summer metascore
summer_meta = data.loc[data['Season_Number'].isin(["1"]), 'Metascore'].m
ean()
print("Summer mean of metascore (out of 100):",summer_meta)

#Autumn metascore
autumn_meta = data.loc[data['Season_Number'].isin(["2"]), 'Metascore'].m
ean()
print("Autumn mean of metascore (out of 100):",autumn_meta)

#Winter metascore
winter_meta = data.loc[data['Season_Number'].isin(["3"]), 'Metascore'].m
ean()
print("Winter mean of metascore (out of 100):",winter_meta)

spring_meta2 = data.loc[data['Season_Number'].isin(["0"]), 'Metascore']
summer_meta2 = data.loc[data['Season_Number'].isin(["1"]), 'Metascore']
autumn_meta2 = data.loc[data['Season_Number'].isin(["2"]), 'Metascore']
winter_meta2 = data.loc[data['Season_Number'].isin(["3"]), 'Metascore']

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
meta_stat, p_meta = f_oneway(spring_meta2 , summer_meta2 , autumn_meta2
, winter_meta2)
print('Metascore Statistics =%.3f, Metascore p value =%.10f' % (meta_sta
t, p_meta))

a = 0.05
if p_meta > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Spring mean of metascore (out of 100): 70.64599483204134
Summer mean of metascore (out of 100): 70.2752646775746
Autumn mean of metascore (out of 100): 71.79584653291094
Winter mean of metascore (out of 100): 70.35549132947978
Metascore Statistics =4.940, Metascore p value =0.0019951256
Different distributions (reject null)
```

In [29]:
```
#4 Compute the mean for userscore in all of the seasons

#Spring userscore
spring_user = data.loc[data['Season_Number'].isin(["0"]), 'Userscore'].m
ean()
print("Spring mean of userscore (out of 10):",spring_user)

#Summer userscore
summer_user = data.loc[data['Season_Number'].isin(["1"]), 'Userscore'].m
ean()
print("Summer mean of userscore (out of 10):",summer_user)

#Autumn userscore
autumn_user = data.loc[data['Season_Number'].isin(["2"]), 'Userscore'].m
ean()
print("Autumn mean of userscore (out of 10):",autumn_user)

#Winter userscore
winter_user = data.loc[data['Season_Number'].isin(["3"]), 'Userscore'].m
ean()
print("Winter mean of userscore (out of 10):",winter_user)

spring_user2 = data.loc[data['Season_Number'].isin(["0"]), 'Userscore']
summer_user2 = data.loc[data['Season_Number'].isin(["1"]), 'Userscore']
autumn_user2 = data.loc[data['Season_Number'].isin(["2"]), 'Userscore']
winter_user2 = data.loc[data['Season_Number'].isin(["3"]), 'Userscore']

#Perform a hypothesis test to determine whether this difference is stati
stically significant at the α = 0.05 significance level.
user_stat, p_user = f_oneway(spring_user2 , summer_user2 , autumn_user2
, winter_user2)
print('Userscore Statistics =%.3f, Userscore p value =%.10f' % (user_sta
t, p_user))

a = 0.05
if p_user > a:
    print('Same distributions (fail to reject null)')
else:
    print('Different distributions (reject null)')
```

```
Spring mean of userscore (out of 10): 7.157105943152471
Summer mean of userscore (out of 10): 7.112897016361882
Autumn mean of userscore (out of 10): 7.213586765223489
Winter mean of userscore (out of 10): 7.223410404624274
Userscore Statistics =1.804, Userscore p value =0.1440623382
Same distributions (fail to reject null)
```

In [30]:
```
#4 Compare the spring sales, metascore, and user score

# Compute descriptive statistics
na_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'NA_Sales'].des
cribe()
eu_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'EU_Sales'].des
cribe()
jp_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'JP_Sales'].des
cribe()
oth_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Other_Sales']
.describe()
glo_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Global_Sales'
].describe()
spring_user2 = data.loc[data['Season_Number'].isin(["0"]), 'Userscore'].
describe()
spring_meta2 = data.loc[data['Season_Number'].isin(["0"]), 'Metascore'].
describe()

# Print descriptive statistics
print("Spring summary for NA_Sales")
print(na_spring2)
print("\n")
print("Spring summary for EU_Sales")
print(eu_spring2)
print("\n")
print("Spring summary for JP_Sales")
print(jp_spring2)
print("\n")
print("Spring summary for Other_Sales")
print(oth_spring2)
print("\n")
print("Spring summary for Global_Sales")
print(glo_spring2)
print("\n")
print("Spring summary for Userscore")
print(spring_user2)
print("\n")
print("Spring summary for Metascore")
print(spring_meta2)
```

```
Spring summary for NA_Sales
count    1161.000000
mean        0.347735
std         0.788533
min         0.000000
25%         0.060000
50%         0.150000
75%         0.360000
max        15.850000
Name: NA_Sales, dtype: float64


Spring summary for EU_Sales
count    1161.000000
mean        0.213902
std         0.572546
min         0.000000
25%         0.020000
50%         0.070000
75%         0.210000
max        12.880000
Name: EU_Sales, dtype: float64


Spring summary for JP_Sales
count    1161.000000
mean        0.050379
std         0.279975
min         0.000000
25%         0.000000
50%         0.000000
75%         0.010000
max         6.500000
Name: JP_Sales, dtype: float64


Spring summary for Other_Sales
count    1161.000000
mean        0.071008
std         0.181341
min         0.000000
25%         0.010000
50%         0.020000
75%         0.070000
max         3.310000
Name: Other_Sales, dtype: float64


Spring summary for Global_Sales
count    1161.000000
mean        0.683437
std         1.719771
min         0.010000
25%         0.110000
50%         0.290000
75%         0.680000
max        35.820000
```

```
Name: Global_Sales, dtype: float64


Spring summary for Userscore
count    1161.000000
mean        7.157106
std         1.307691
min         1.300000
25%         6.500000
50%         7.400000
75%         8.100000
max         9.400000
Name: Userscore, dtype: float64


Spring summary for Metascore
count    1161.000000
mean       70.645995
std        13.774899
min        17.000000
25%        62.000000
50%        73.000000
75%        81.000000
max        98.000000
Name: Metascore, dtype: float64
```

In [31]:
```
#4 Compare the summer sales, metascore, and user score

# Compute descriptive statistics
na_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'NA_Sales'].des
cribe()
eu_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'EU_Sales'].des
cribe()
jp_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'JP_Sales'].des
cribe()
oth_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Other_Sales']
.describe()
glo_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Global_Sales'
].describe()
summer_user2 = data.loc[data['Season_Number'].isin(["1"]), 'Userscore'].
describe()
summer_meta2 = data.loc[data['Season_Number'].isin(["1"]), 'Metascore'].
describe()
# Print descriptive statistics
print("Summer summary for NA_Sales")
print(na_summer2)
print("\n")
print("Summer summary for EU_Sales")
print(eu_summer2)
print("\n")
print("Summer summary for JP_Sales")
print(jp_summer2)
print("\n")
print("Summer summary for Other_Sales")
print(oth_summer2)
print("\n")
print("Summer summary for Global_Sales")
print(glo_summer2)
print("\n")
print("Summer summary for Userscore")
print(summer_user2)
print("\n")
print("Summer summary for Metascore")
print(summer_meta2)
```

```
Summer summary for NA_Sales
count    1039.000000
mean        0.379971
std         0.789904
min         0.000000
25%         0.050000
50%         0.140000
75%         0.375000
max        15.750000
Name: NA_Sales, dtype: float64


Summer summary for EU_Sales
count    1039.000000
mean        0.173956
std         0.503039
min         0.000000
25%         0.020000
50%         0.060000
75%         0.170000
max        11.010000
Name: EU_Sales, dtype: float64


Summer summary for JP_Sales
count    1039.000000
mean        0.039432
std         0.190785
min         0.000000
25%         0.000000
50%         0.000000
75%         0.000000
max         3.280000
Name: JP_Sales, dtype: float64


Summer summary for Other_Sales
count    1039.000000
mean        0.061184
std         0.140068
min         0.000000
25%         0.010000
50%         0.020000
75%         0.060000
max         2.960000
Name: Other_Sales, dtype: float64


Summer summary for Global_Sales
count    1039.000000
mean        0.654678
std         1.464588
min         0.010000
25%         0.100000
50%         0.270000
75%         0.710000
max        33.000000
```

```
Name: Global_Sales, dtype: float64


Summer summary for Userscore
count    1039.000000
mean        7.112897
std         1.352272
min         1.500000
25%         6.400000
50%         7.400000
75%         8.100000
max         9.800000
Name: Userscore, dtype: float64


Summer summary for Metascore
count    1039.000000
mean       70.275265
std        13.883609
min        20.000000
25%        62.000000
50%        72.000000
75%        80.500000
max        96.000000
Name: Metascore, dtype: float64
```

In [32]:
```
#4 Compare the autumn sales, metascore, and user score

# Compute descriptive statistics
na_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'NA_Sales'].des
cribe()
eu_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'EU_Sales'].des
cribe()
jp_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'JP_Sales'].des
cribe()
oth_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Other_Sales']
.describe()
glo_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Global_Sales'
].describe()
autumn_user2 = data.loc[data['Season_Number'].isin(["1"]), 'Userscore'].
describe()
autumn_meta2 = data.loc[data['Season_Number'].isin(["1"]), 'Metascore'].
describe()
# Print descriptive statistics
print("Autumn summary for NA_Sales")
print(na_autumn2)
print("\n")
print("Autumn summary for EU_Sales")
print(eu_autumn2)
print("\n")
print("Autumn summary for JP_Sales")
print(jp_autumn2)
print("\n")
print("Autumn summary for Other_Sales")
print(oth_autumn2)
print("\n")
print("Autumn summary for Global_Sales")
print(glo_autumn2)
print("\n")
print("Autumn summary for Userscore")
print(autumn_user2)
print("\n")
print("Autumn summary for Metascore")
print(autumn_meta2)
```

```
Autumn summary for NA_Sales
count    2841.000000
mean        0.514414
std         1.258246
min         0.000000
25%         0.080000
50%         0.200000
75%         0.500000
max        41.490000
Name: NA_Sales, dtype: float64


Autumn summary for EU_Sales
count    2841.000000
mean        0.320000
std         0.867835
min         0.000000
25%         0.020000
50%         0.080000
75%         0.290000
max        29.020000
Name: EU_Sales, dtype: float64


Autumn summary for JP_Sales
count    2841.000000
mean        0.057782
std         0.249768
min         0.000000
25%         0.000000
50%         0.000000
75%         0.010000
max         4.700000
Name: JP_Sales, dtype: float64


Autumn summary for Other_Sales
count    2841.000000
mean        0.109546
std         0.345211
min         0.000000
25%         0.010000
50%         0.030000
75%         0.090000
max        10.570000
Name: Other_Sales, dtype: float64


Autumn summary for Global_Sales
count    2841.000000
mean        1.001946
std         2.463533
min         0.010000
25%         0.140000
50%         0.380000
75%         0.970000
max        82.740000
```

```
Name: Global_Sales, dtype: float64


Autumn summary for Userscore
count    1039.000000
mean        7.112897
std         1.352272
min         1.500000
25%         6.400000
50%         7.400000
75%         8.100000
max         9.800000
Name: Userscore, dtype: float64


Autumn summary for Metascore
count    1039.000000
mean       70.275265
std        13.883609
min        20.000000
25%        62.000000
50%        72.000000
75%        80.500000
max        96.000000
Name: Metascore, dtype: float64
```

In [33]:
```
#4 Compare the winter sales, metascore, and user score

# Compute descriptive statistics
na_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'NA_Sales'].des
cribe()
eu_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'EU_Sales'].des
cribe()
jp_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'JP_Sales'].des
cribe()
oth_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Other_Sales']
.describe()
glo_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Global_Sales'
].describe()
winter_user2 = data.loc[data['Season_Number'].isin(["1"]), 'Userscore'].
describe()
winter_meta2 = data.loc[data['Season_Number'].isin(["1"]), 'Metascore'].
describe()

# Print descriptive statistics
print("Winter summary for NA_Sales")
print(na_winter2)
print("\n")
print("Winter summary for EU_Sales")
print(eu_winter2)
print("\n")
print("Winter summary for JP_Sales")
print(jp_winter2)
print("\n")
print("Winter summary for Other_Sales")
print(oth_winter2)
print("\n")
print("Winter summary for Global_Sales")
print(glo_winter2)
print("\n")
print("Winter summary for Userscore")
print(winter_user2)
print("\n")
print("Winter summary for Metascore")
print(winter_meta2)
```

```
Winter summary for NA_Sales
count    692.000000
mean       0.307890
std        0.469482
min        0.000000
25%        0.060000
50%        0.140000
75%        0.350000
max        4.740000
Name: NA_Sales, dtype: float64


Winter summary for EU_Sales
count    692.000000
mean       0.179812
std        0.346168
min        0.000000
25%        0.020000
50%        0.060000
75%        0.200000
max        3.910000
Name: EU_Sales, dtype: float64


Winter summary for JP_Sales
count    692.000000
mean       0.048829
std        0.279374
min        0.000000
25%        0.000000
50%        0.000000
75%        0.000000
max        5.330000
Name: JP_Sales, dtype: float64


Winter summary for Other_Sales
count    692.000000
mean       0.059899
std        0.112471
min        0.000000
25%        0.010000
50%        0.020000
75%        0.070000
max        1.090000
Name: Other_Sales, dtype: float64


Winter summary for Global_Sales
count    692.000000
mean       0.596546
std        1.042251
min        0.010000
25%        0.100000
50%        0.270000
75%        0.672500
max       12.270000
```

```
Name: Global_Sales, dtype: float64


Winter summary for Userscore
count    1039.000000
mean        7.112897
std         1.352272
min         1.500000
25%         6.400000
50%         7.400000
75%         8.100000
max         9.800000
Name: Userscore, dtype: float64


Winter summary for Metascore
count    1039.000000
mean       70.275265
std        13.883609
min        20.000000
25%        62.000000
50%        72.000000
75%        80.500000
max        96.000000
Name: Metascore, dtype: float64
```

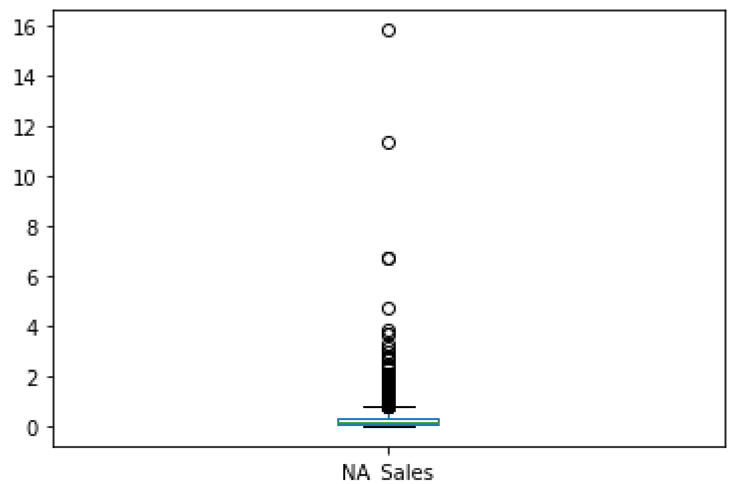
In [34]:

```
#4 Create plots to visualize the results
# Spring NA_Sales
print("Visualizing Spring NA_Sales")
na_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'NA_Sales']
na_spring2.plot(kind="box")
```

```
Visualizing Spring NA_Sales
```

Out[34]:

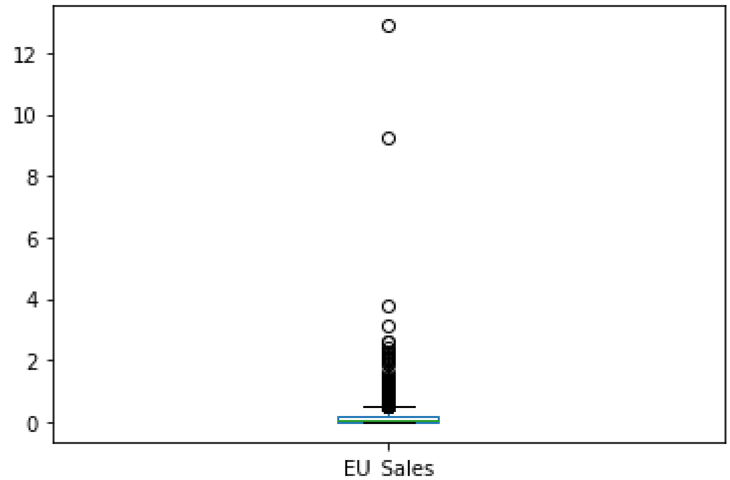
```
<matplotlib.axes._subplots.AxesSubplot at 0x11af5c040>
```



In [35]:
```
#4 Create plots to visualize the results
# Spring EU_Sales
print("Visualizing Spring EU_Sales")
eu_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'EU_Sales']
eu_spring2.plot(kind="box")
```

```
Visualizing Spring EU_Sales
```

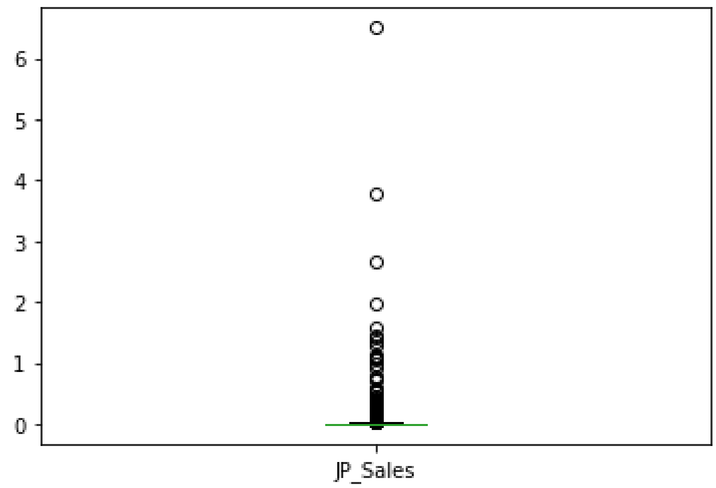
Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b0b2ca0>
```



In [36]:
```
#4 Create plots to visualize the results
# Spring JP_Sales
print("Visualizing Spring JP_Sales")
jp_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'JP_Sales']
jp_spring2.plot(kind="box")
```

```
Visualizing Spring JP_Sales
```

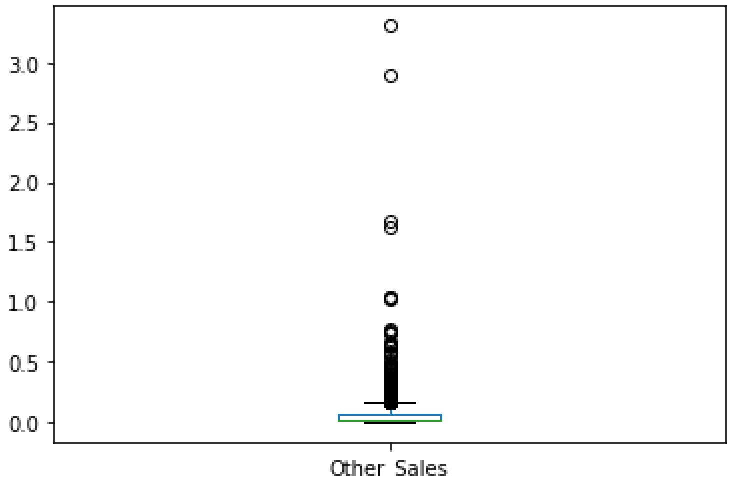
Out[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b245b50>
```



In [37]:
```
#4 Create plots to visualize the results
# Spring Other_Sales
print("Visualizing Spring Other_Sales")
oth_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Other_Sales']
oth_spring2.plot(kind="box")
```

```
Visualizing Spring Other_Sales
```

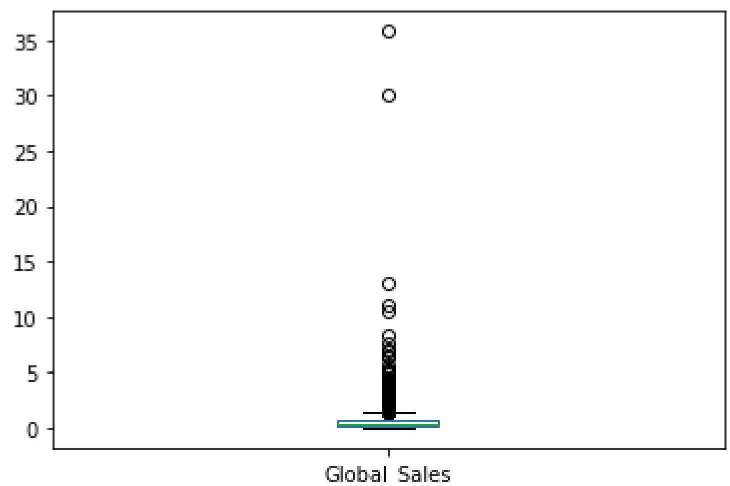
Out[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b332e80>
```



In [38]:
```
#4 Create plots to visualize the results
# Spring Global_Sales
print("Visualizing Spring Global_Sales")
glo_spring2 = data.loc[data['Season_Number'].isin(["0"]), 'Global_Sales'
]
glo_spring2.plot(kind="box")
```

```
Visualizing Spring Global_Sales
```

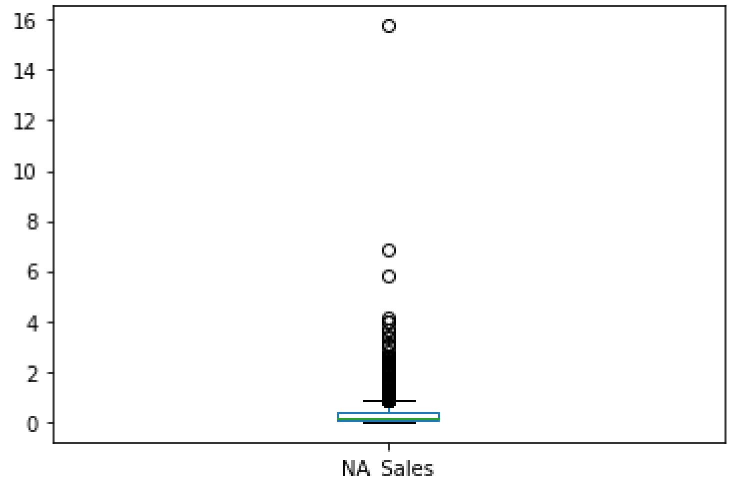
Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b4b1fd0>
```



In [39]:
```
#4 Create plots to visualize the results
# Summer NA_Sales
print("Visualizing Summer NA_Sales")
na_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'NA_Sales']
na_summer2.plot(kind="box")
```

```
Visualizing Summer NA_Sales
```

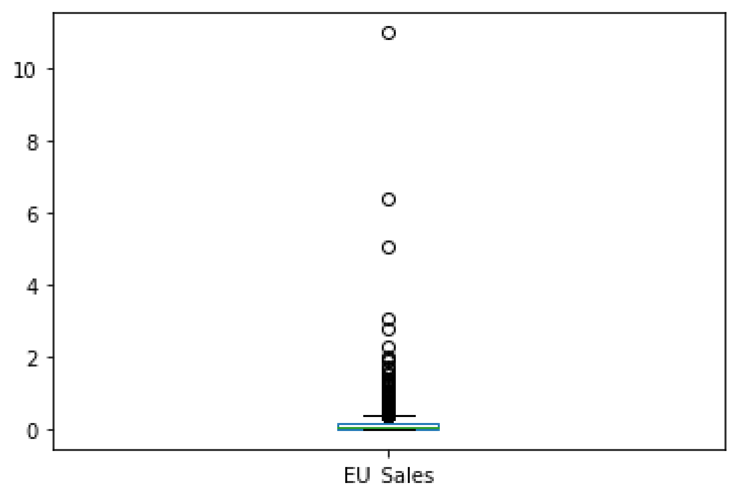
Out[39]: <matplotlib.axes._subplots.AxesSubplot at 0x11b6de910>



In [40]:
```
#4 Create plots to visualize the results
# Summer EU_Sales
print("Visualizing Summer EU_Sales")
eu_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'EU_Sales']
eu_summer2.plot(kind="box")
```

```
Visualizing Summer EU_Sales
```

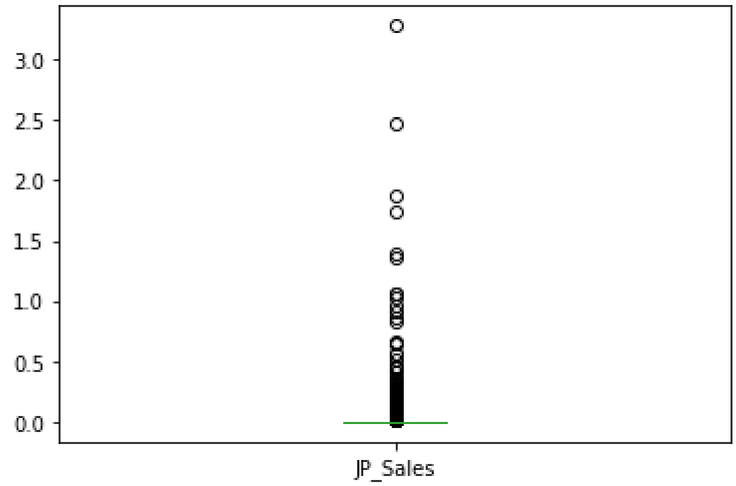
Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x11b9e7c10>



In [41]:
```
#4 Create plots to visualize the results
# Summer JP_Sales
print("Visualizing Summer JP_Sales")
jp_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'JP_Sales']
jp_summer2.plot(kind="box")
```

```
Visualizing Summer JP_Sales
```

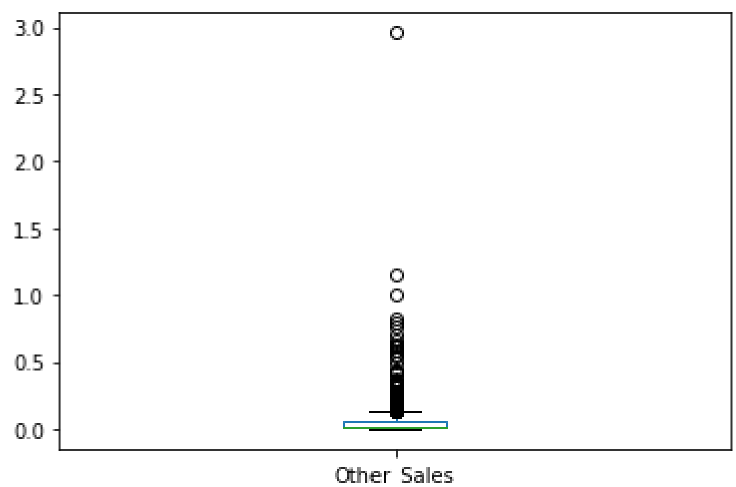
Out[41]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11b24ddf0>
```



In [42]:
```
# Create plots to visualize the results
# Summer Other_Sales
print("Visualizing Summer Other_Sales")
oth_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Other_Sales']
oth_summer2.plot(kind="box")
```

```
Visualizing Summer Other_Sales
```

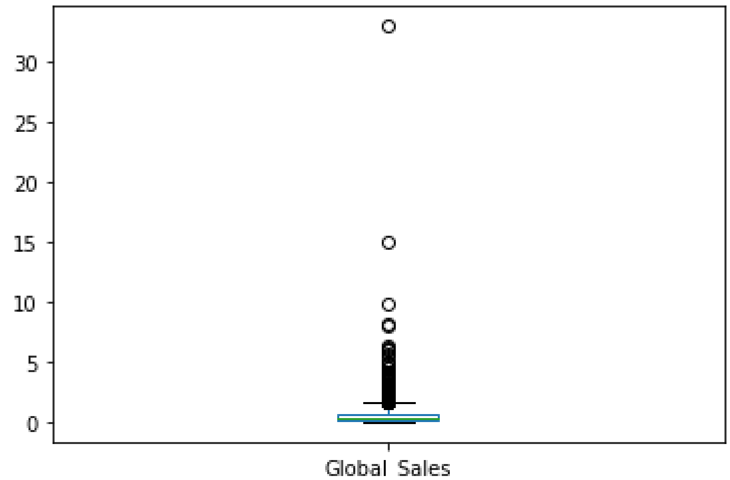
Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11ba96190>
```



In [43]:
```
#4 Create plots to visualize the results
# Summer Global_Sales
print("Visualizing Summer Global_Sales")
glo_summer2 = data.loc[data['Season_Number'].isin(["1"]), 'Global_Sales'
]
glo_summer2.plot(kind="box")
```

```
Visualizing Summer Global_Sales
```

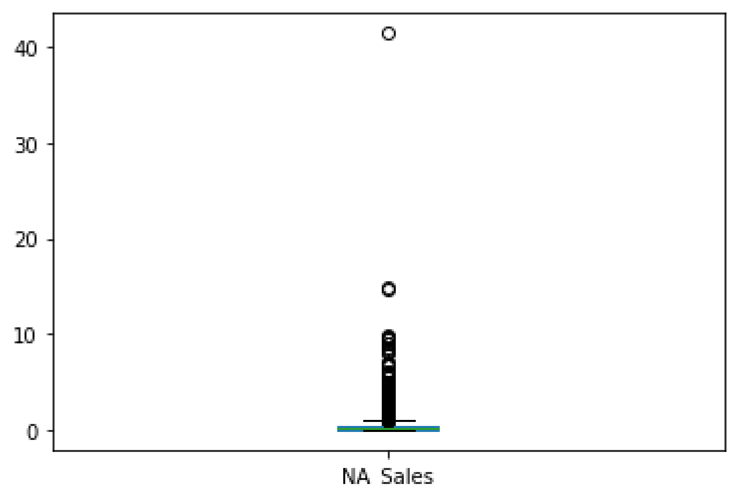
Out[43]: <matplotlib.axes._subplots.AxesSubplot at 0x11bca0670>



In [44]:
```
#4 Create plots to visualize the results
# Autumn NA_Sales
print("Visualizing Autumn NA_Sales")
na_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'NA_Sales']
na_autumn2.plot(kind="box")
```

```
Visualizing Autumn NA_Sales
```

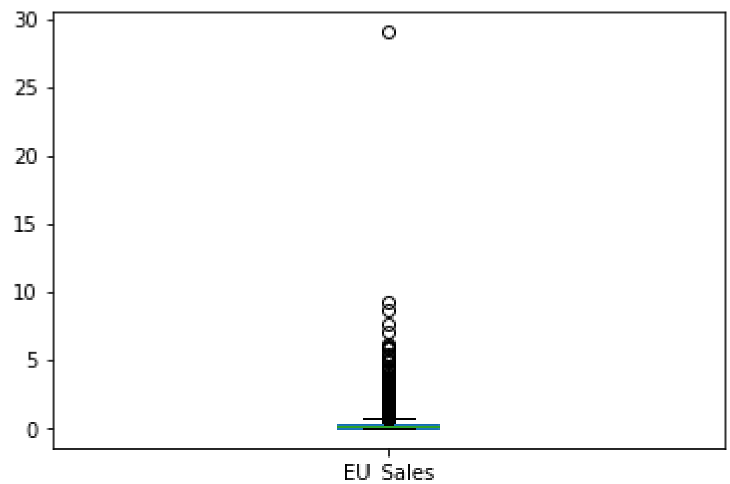
Out[44]: <matplotlib.axes._subplots.AxesSubplot at 0x11bc428b0>



In [45]:
```
#4 Create plots to visualize the results
# Autumn EU_Sales
print("Visualizing Autumn EU_Sales")
eu_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'EU_Sales']
eu_autumn2.plot(kind="box")
```

```
Visualizing Autumn EU_Sales
```

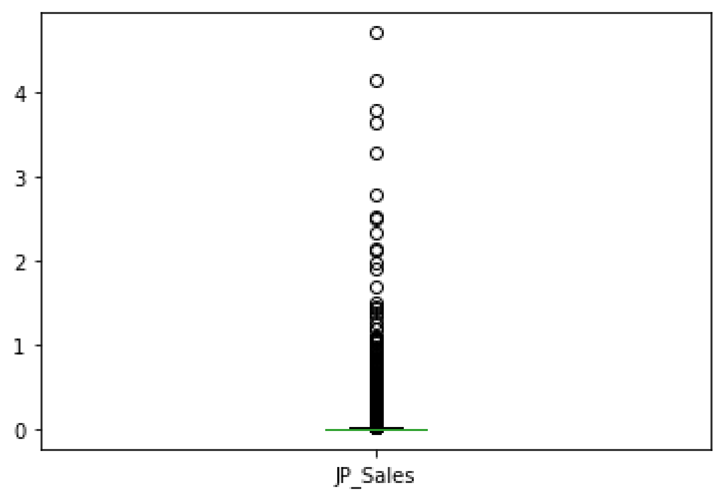
Out[45]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11bd5d6d0>
```



In [46]:
```
#4 Create plots to visualize the results
# Autumn JP_Sales
print("Visualizing Autumn JP_Sales")
jp_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'JP_Sales']
jp_autumn2.plot(kind="box")
```

```
Visualizing Autumn JP_Sales
```

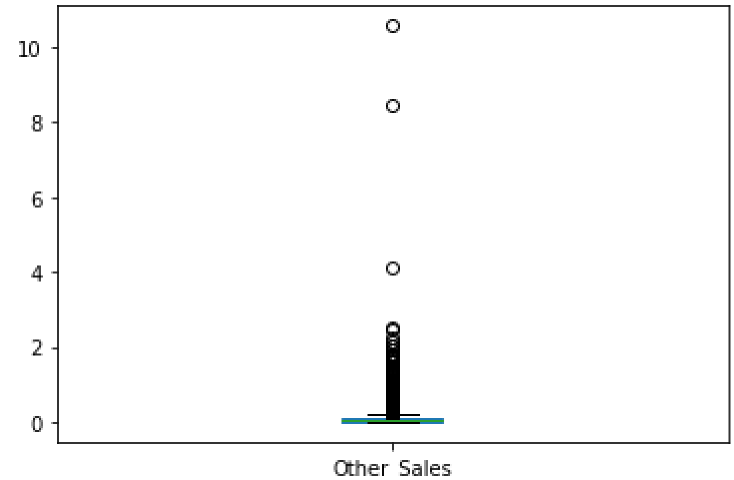
Out[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11be1fd00>
```



In [47]:
```
#4 Create plots to visualize the results
# Autumn Other_Sales
print("Visualizing Autumn Other_Sales")
oth_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Other_Sales']
oth_autumn2.plot(kind="box")
```

```
Visualizing Autumn Other_Sales
```

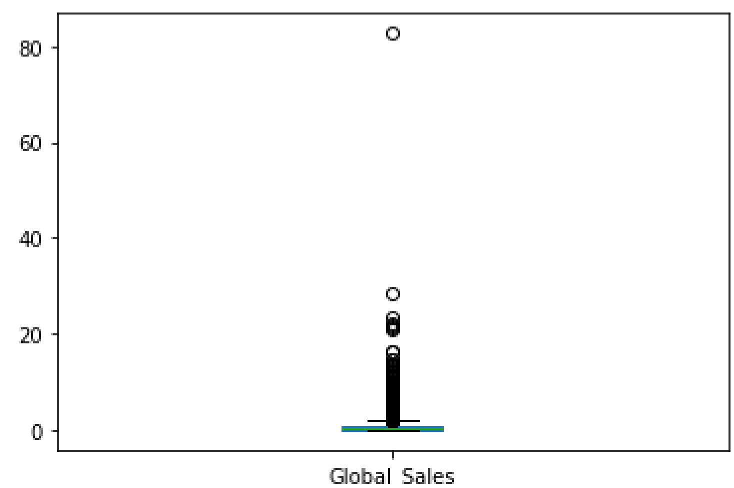
Out[47]: <matplotlib.axes._subplots.AxesSubplot at 0x11bf598e0>



In [48]:
```
#4 Create plots to visualize the results
# Autumn Global_Sales
print("Visualizing Autumn Global_Sales")
glo_autumn2 = data.loc[data['Season_Number'].isin(["2"]), 'Global_Sales'
]
glo_autumn2.plot(kind="box")
```

```
Visualizing Autumn Global_Sales
```

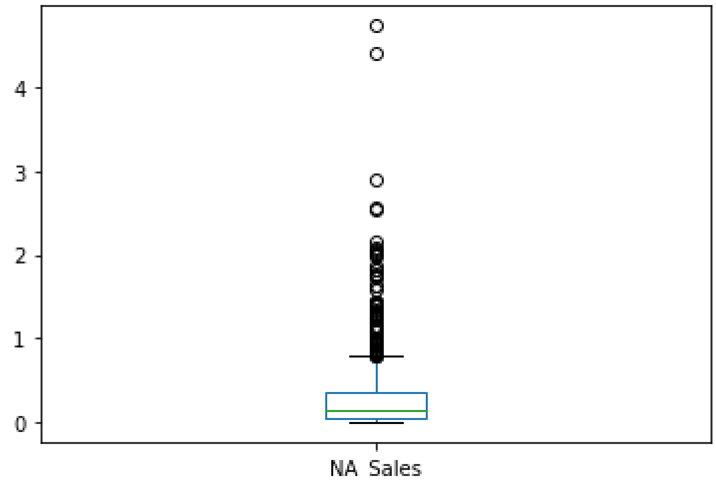
Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x11c176370>



In [49]:
```
#4 Create plots to visualize the results
# Winter NA_Sales
print("Visualizing Winter NA_Sales")
na_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'NA_Sales']
na_winter2.plot(kind="box")
```

```
Visualizing Winter NA_Sales
```

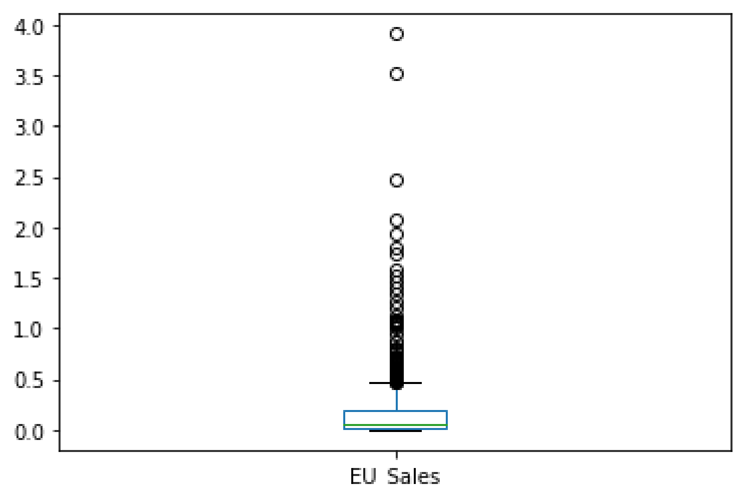
Out[49]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c10d310>
```



In [50]:
```
#4 Create plots to visualize the results
# Winter EU_Sales
print("Visualizing Winter EU_Sales")
eu_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'EU_Sales']
eu_winter2.plot(kind="box")
```

```
Visualizing Winter EU_Sales
```

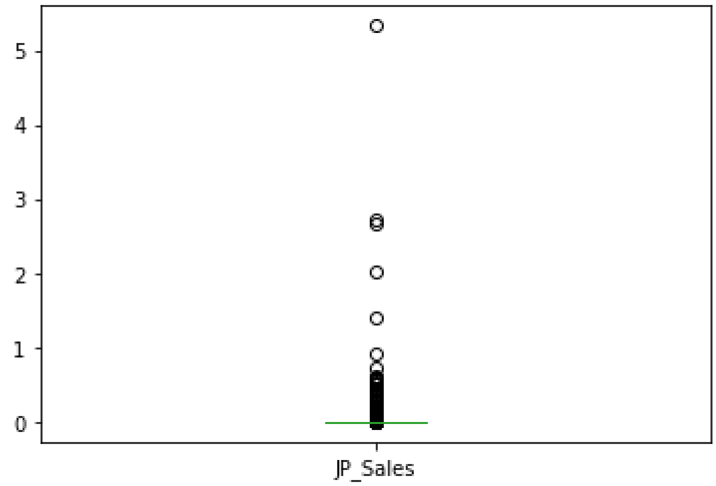
Out[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c3b6580>
```



In [51]:
```
#4 Create plots to visualize the results
# Winter JP_Sales
print("Visualizing Winter JP_Sales")
jp_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'JP_Sales']
jp_winter2.plot(kind="box")
```

```
Visualizing Winter JP_Sales
```

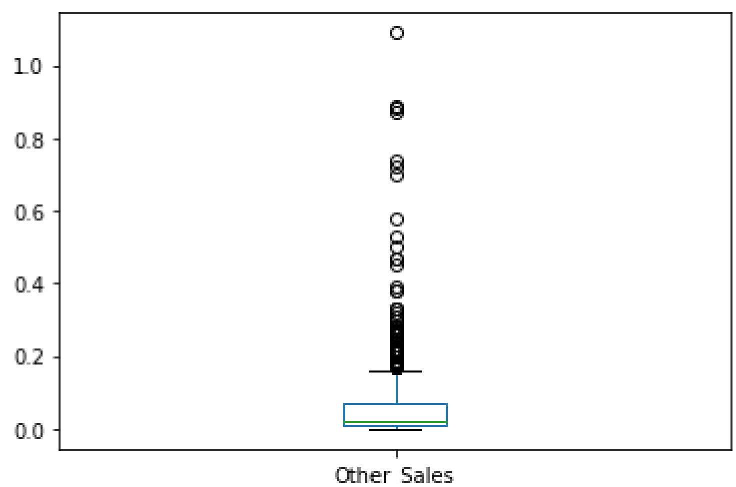
Out[51]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c2e30a0>
```



In [52]:
```
#4 Create plots to visualize the results
# Winter Other_Sales
print("Visualizing Winter Other_Sales")
oth_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Other_Sales']
oth_winter2.plot(kind="box")
```

```
Visualizing Winter Other_Sales
```

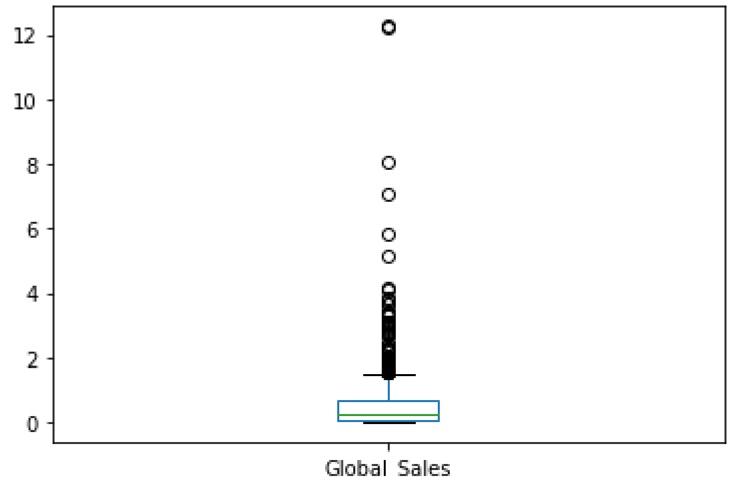
Out[52]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c5b54c0>
```



In [53]:
```
#4 Create plots to visualize the results
# Winter Global_Sales
print("Visualizing Winter Global_Sales")
glo_winter2 = data.loc[data['Season_Number'].isin(["3"]), 'Global_Sales'
]
glo_winter2.plot(kind="box")
```

```
Visualizing Winter Global_Sales
```

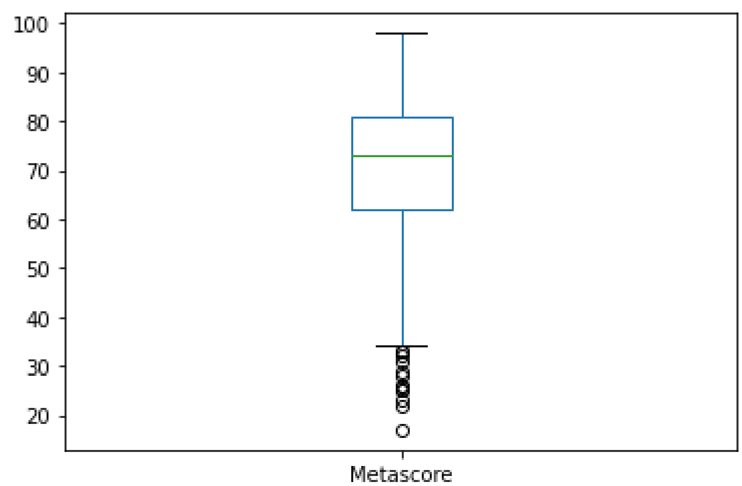
Out[53]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c7b2610>
```



In [54]:
```
#4 Create plots to visualize the results
# Spring Metascore
print("Visualizing Spring Metascore")
spring_meta2 = data.loc[data['Season_Number'].isin(["0"]), 'Metascore']
spring_meta2.plot(kind="box")
```

```
Visualizing Spring Metascore
```

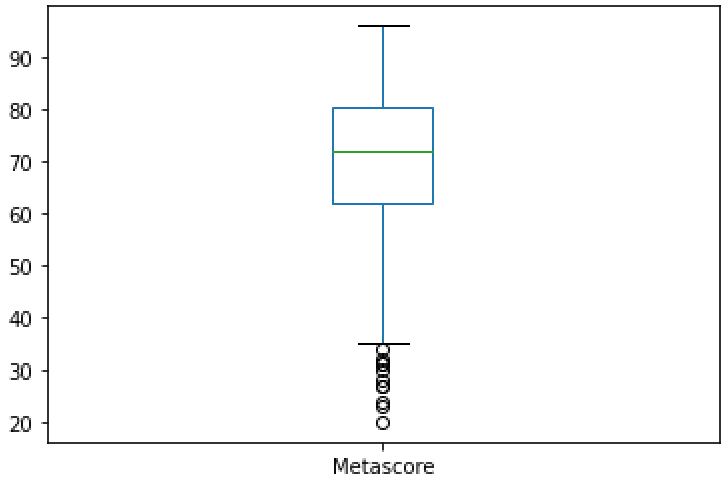
Out[54]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c751490>
```



In [55]:
```
#4 Create plots to visualize the results
# Summer Metascore
print("Visualizing Summer Metascore")
summer_meta2 = data.loc[data['Season_Number'].isin(["1"]), 'Metascore']
summer_meta2.plot(kind="box")
```

```
Visualizing Summer Metascore
```

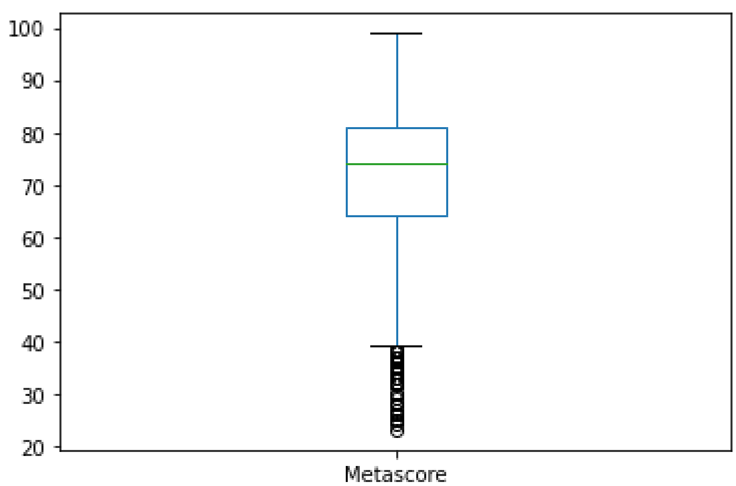
Out[55]: <matplotlib.axes._subplots.AxesSubplot at 0x11c882d60>



In [56]:
```
#4 Create plots to visualize the results
# Autumn Metascore
print("Visualizing Autumn Metascore")
autumn_meta2 = data.loc[data['Season_Number'].isin(["2"]), 'Metascore']
autumn_meta2.plot(kind="box")
```

```
Visualizing Autumn Metascore
```

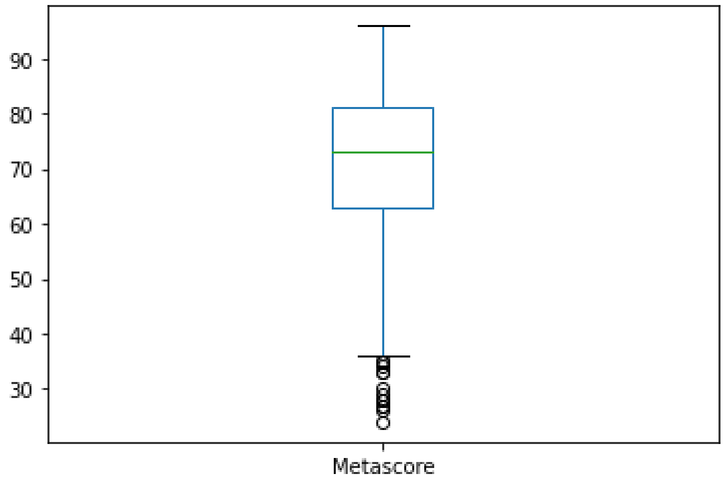
Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x11c933e80>



In [57]:
```
#4 Create plots to visualize the results
# Winter Metascore
print("Visualizing Winter Metascore")
winter_meta2 = data.loc[data['Season_Number'].isin(["3"]), 'Metascore']
winter_meta2.plot(kind="box")
```

```
Visualizing Winter Metascore
```

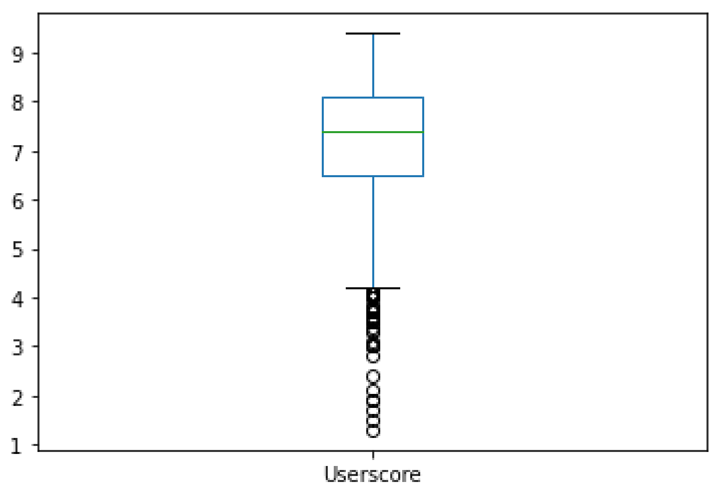
Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x11c3c1ee0>



In [58]:
```
#4 Create plots to visualize the results
# Spring Userscore
print("Visualizing Spring Userscore")
spring_user2 = data.loc[data['Season_Number'].isin(["0"]), 'Userscore']
spring_user2.plot(kind="box")
```

```
Visualizing Spring Userscore
```

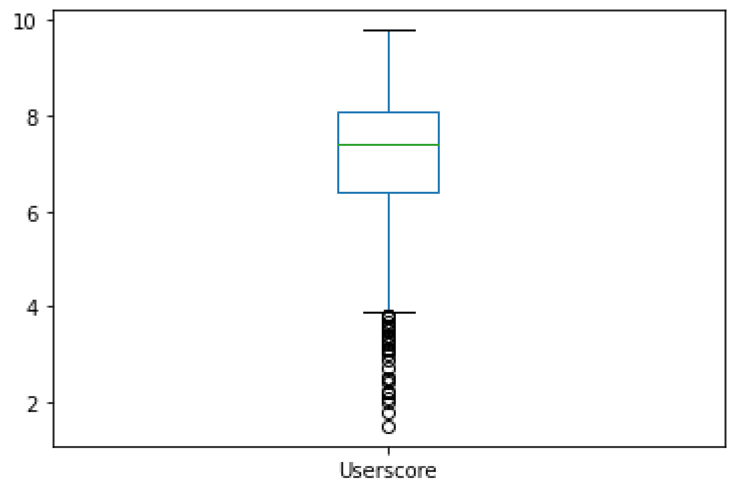
Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x11bf65700>



In [59]:
```
#4 Create plots to visualize the results
# Summer Userscore
print("Visualizing Summer Userscore")
summer_user2 = data.loc[data['Season_Number'].isin(["1"]), 'Userscore']
summer_user2.plot(kind="box")
```

Visualizing Summer Userscore

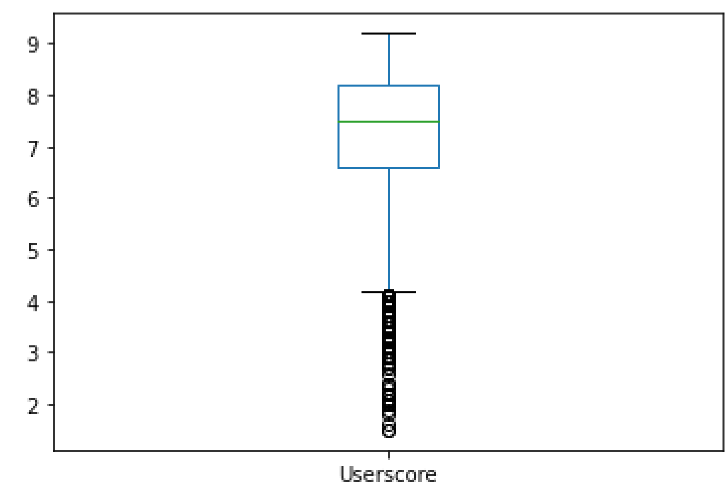
Out[59]: <matplotlib.axes._subplots.AxesSubplot at 0x11c697670>



In [60]:
```
#4 Create plots to visualize the results
# Autumn Userscore
print("Visualizing Autumn Userscore")
autumn_user2 = data.loc[data['Season_Number'].isin(["2"]), 'Userscore']
autumn_user2.plot(kind="box")
```

Visualizing Autumn Userscore

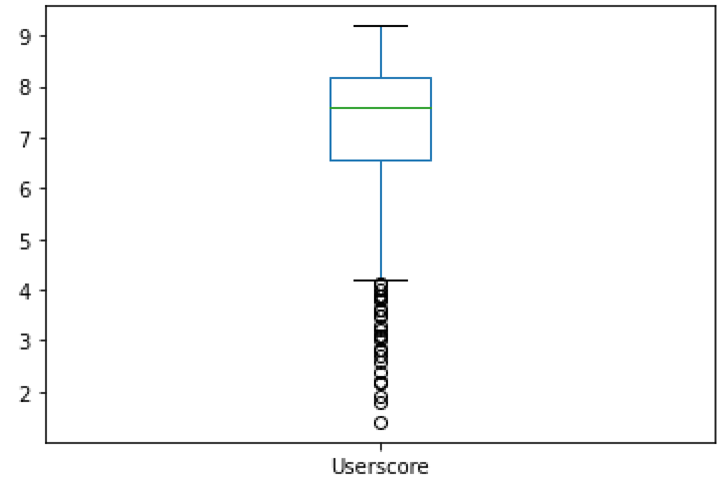
Out[60]: <matplotlib.axes._subplots.AxesSubplot at 0x11cd10340>



In [61]:
```
#4 Create plots to visualize the results
# Winter Userscore
print("Visualizing Winter Userscore")
winter_user2 = data.loc[data['Season_Number'].isin(["3"]), 'Userscore']
winter_user2.plot(kind="box")
```

```
Visualizing Winter Userscore
```

Out[61]: <matplotlib.axes._subplots.AxesSubplot at 0x11ce54af0>



In [62]:
```
# Add dummy variables
dummy = data[['Platform', 'Genre', 'Season']]
dummy = pd.get_dummies(data=dummy)
dummy.head()
```

Out[62]:

	Platform_3DS	Platform_DS	Platform_Dreamcast	Platform_Game Boy Advance	Platform_GameCube	Platforn
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	1	0	0	0	
4	0	0	0	0	0	

5 rows × 34 columns

In [63]:
```
# Concatenate new dataframe with old dataframe (minus some variables)
X = pd.concat([data.drop(columns=['Name', 'Platform', 'Genre', 'Publishe
r', 'Release_Date', 'Season', 'Season_Number', 'Global_Sales']), dummy],
axis=1)
Y = data['Global_Sales']
X.head()
```

Out[63]:

	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Metascore	Userscore	Platform_3DS	Platform_DS
0	41.49	29.02	3.77	8.46	76	8.0	0	(
1	15.85	12.88	3.79	3.31	82	8.4	0	(
2	15.75	11.01	3.28	2.96	80	8.1	0	(
3	11.38	9.23	6.50	2.90	89	8.5	0	-
4	14.59	7.06	4.70	2.26	87	8.3	0	(

5 rows × 40 columns

In [64]:
```
# Explore the dataset
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5733 entries, 0 to 5732
Data columns (total 40 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   NA_Sales                      5733 non-null   float64
 1   EU_Sales                      5733 non-null   float64
 2   JP_Sales                      5733 non-null   float64
 3   Other_Sales                   5733 non-null   float64
 4   Metascore                     5733 non-null   int64  
 5   Userscore                     5733 non-null   float64
 6   Platform_3DS                  5733 non-null   uint8  
 7   Platform_DS                   5733 non-null   uint8  
 8   Platform_Dreamcast            5733 non-null   uint8  
 9   Platform_Game Boy Advance     5733 non-null   uint8  
 10  Platform_GameCube             5733 non-null   uint8  
 11  Platform_Nintendo 64          5733 non-null   uint8  
 12  Platform_PC                   5733 non-null   uint8  
 13  Platform_PSP                  5733 non-null   uint8  
 14  Platform_PlayStation          5733 non-null   uint8  
 15  Platform_PlayStation 2        5733 non-null   uint8  
 16  Platform_PlayStation 3        5733 non-null   uint8  
 17  Platform_PlayStation 4        5733 non-null   uint8  
 18  Platform_PlayStation Vita     5733 non-null   uint8  
 19  Platform_Wii                  5733 non-null   uint8  
 20  Platform_Wii U                5733 non-null   uint8  
 21  Platform_Xbox                 5733 non-null   uint8  
 22  Platform_Xbox 360             5733 non-null   uint8  
 23  Platform_Xbox One             5733 non-null   uint8  
 24  Genre_Action                  5733 non-null   uint8  
 25  Genre_Adventure               5733 non-null   uint8  
 26  Genre_Fighting                5733 non-null   uint8  
 27  Genre_Misc                    5733 non-null   uint8  
 28  Genre_Platform                5733 non-null   uint8  
 29  Genre_Puzzle                  5733 non-null   uint8  
 30  Genre_Racing                  5733 non-null   uint8  
 31  Genre_Role-Playing            5733 non-null   uint8  
 32  Genre_Shooter                 5733 non-null   uint8  
 33  Genre_Simulation              5733 non-null   uint8  
 34  Genre_Sports                  5733 non-null   uint8  
 35  Genre_Strategy                5733 non-null   uint8  
 36  Season_Autumn                 5733 non-null   uint8  
 37  Season_Spring                 5733 non-null   uint8  
 38  Season_Summer                 5733 non-null   uint8  
 39  Season_Winter                 5733 non-null   uint8  
dtypes: float64(5), int64(1), uint8(34)
memory usage: 503.9 KB
```

In [65]:
```
# Partition the dataset into a training set and a validation set using t
he holdout method
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.
25,train_size = 0.75,random_state = 0)
X_train, X_vals, Y_train, Y_vals = train_test_split(X_train, Y_train, te
st_size = 0.25, train_size = 0.75,  random_state = 0)
```

In [66]:
```
# Standardize the training set and the validation set (NOT RECOMMENDED F
OR DUMMY VARIABLES)
scaler = StandardScaler()
scaler.fit(X_train)
x_train_scaled = scaler.transform(X_train)
x_vals_scaled = scaler.transform(X_vals)
```

In [67]:
```
# Build a LASSO regression model to predict 'Global_Sales'
fitted_model = linear_model.Lasso(alpha = 1).fit(X = x_train_scaled[:,
:], y = Y_train)
print(fitted_model.coef_)
```

```
[ 0.72576583  0.55357641  0.          0.          0.          0.
 -0.          0.         -0.         -0.         -0.          0.
 -0.         -0.          0.          0.          0.          0.
 -0.          0.          0.         -0.          0.          0.
  0.         -0.         -0.          0.          0.         -0.
 -0.         -0.          0.         -0.          0.         -0.
  0.         -0.         -0.         -0.        ]
```

In [68]:
```
# Use the LASSO regression model to predict 'Global_Sales'
predicted = fitted_model.predict(x_vals_scaled[:, :])

# Compute the coefficient of determination of the LASSO regression model
corr_coef = np.corrcoef(predicted, Y_vals.values)[1, 0]
R_squared = corr_coef ** 2
print(R_squared)
```

```
0.9866737820950376
```

In [69]:
```
# Build a linear regression model to predict 'Global_Sales'
model = linear_model.LinearRegression().fit(X = x_train_scaled[:, [0, 1,
2, 3, 15, 24, 33]], y = Y_train)

# 0 - NA Sales, 1 - EU Sales, 2 - JP Sales, 3 - Other Sales,
# 15 - PS2 (Platform), 24 - Action (Genre), 33 - Simulation (Genre)
# Compute evaluation metrics for the validation set and report your resu
lts.
Rsqr_val = model.score(X = x_vals_scaled[:, [0, 1, 2, 3, 15, 24, 33]], y
= Y_vals)
print(Rsqr_val)
```

```
0.9999870770319683
```

In [70]:
```
# Explore categorical variables
print("Platforms:",data.Platform.unique())
print("Quantity", data.Platform.unique().size)
print("Genres:", data.Genre.unique())
print("Quantity", data.Genre.unique().size)
print("Publishers:", data.Publisher.unique())
print("Quantity", data.Publisher.unique().size)
print("Seasons:",data.Season.unique())
print("Quantity", data.Season.unique().size)
```

```
Platforms: ['Wii' 'DS' 'Xbox 360' 'PlayStation 3' 'PlayStation 2' '3DS'
 'PlayStation 4' 'Nintendo 64' 'PlayStation' 'Xbox' 'PC' 'PSP' 'GameCub
e'
 'Wii U' 'Game Boy Advance' 'Xbox One' 'PlayStation Vita' 'Dreamcast']
Quantity 18
Genres: ['Sports' 'Racing' 'Platform' 'Misc' 'Action' 'Shooter' 'Fighti
ng'
 'Simulation' 'Role-Playing' 'Adventure' 'Strategy' 'Puzzle']
Quantity 12
Publishers: ['Nintendo' 'Microsoft Game Studios' 'Take-Two Interactive'
 'Sony Computer Entertainment' 'Activision' 'Ubisoft' 'Bethesda Softwor
ks'
 'Electronic Arts' 'Sega' 'SquareSoft' 'GT Interactive'
 'Konami Digital Entertainment' 'Sony Computer Entertainment Europe'
 'Square Enix' 'LucasArts' 'Virgin Interactive' '505 Games'
 'Warner Bros. Interactive Entertainment' 'Universal Interactive'
 'RedOctane' 'Capcom' 'Atari' 'Vivendi Games' 'Eidos Interactive'
 'Namco Bandai Games' 'THQ' 'MTV Games' 'Acclaim Entertainment'
 'Midway Games' 'Disney Interactive Studios' 'Deep Silver' 'NCSoft'
 'Tecmo Koei' 'Valve Software' 'Infogrames' 'Valve' 'Mindscape'
 'Hello Games' 'Global Star' 'Gotham Games' 'Codemasters' 'TDK Mediacti
ve'
 'Sony Online Entertainment' 'RTL' 'Black Label Games' 'SouthPeak Game
s'
 'Mastertronic' 'City Interactive' 'Russel' 'Play It'
 'Slightly Mad Studios' 'Tomy Corporation' 'Focus Home Interactive'
 'Game Factory' 'Unknown' 'Titus' 'Empire Interactive'
 'Marvelous Entertainment' 'Genki' 'SCi' 'Crave Entertainment'
 'Rage Software' 'Ubisoft Annecy' 'Atlus' 'Square EA' 'Touchstone' 'Spi
ke'
 'Nippon Ichi Software' 'Majesco Entertainment' 'Illusion Softworks'
 'Interplay' 'Metro 3D' 'Rondomedia' 'Sony Computer Entertainment Ameri
ca'
 'Rising Star Games' 'PQube' 'Trion Worlds' 'Ignition Entertainment'
 'Square' 'D3Publisher' 'System 3 Arcade Software' 'Activision Blizzar
d'
 'Pack In Soft' 'Wanadoo' 'NovaLogic' 'Tetris Online'
 'Harmonix Music Systems' 'Psygnosis' 'GungHo' '3DO' 'Jester Interactiv
e'
 'Enix Corporation' 'Ghostlight' 'Zoo Digital Publishing'
 'Home Entertainment Suppliers' 'Oxygen Interactive' 'Hudson Soft'
 'Banpresto' 'Kalypso Media' 'Wargaming.net' 'Destineer'
 'BAM! Entertainment' 'PopCap Games' 'Indie Games' 'Liquid Games' 'FuRy
u'
 'Gathering of Developers' 'Kemco' 'Marvelous Interactive'
 'AQ Interactive' 'CCP' 'Milestone S.r.l.' 'Black Bean Games' 'Gamebrid
ge'
 'Zushi Games' 'Gremlin Interactive Ltd' 'Agatsuma Entertainment'
 'Mad Catz' 'Xplosiv' 'Rebellion Developments' 'TDK Core'
 'Performance Designed Products' 'Media Rings' 'Xseed Games'
 'JoWood Productions' 'DTP Entertainment'
 'Midas Interactive Entertainment' 'Playlogic Game Factory' 'Funcom'
 'Jaleco' 'Fox Interactive' 'Sammy Corporation' 'Nordic Games'
 'White Park Bay Software' 'Daedalic' 'EA Games' 'Falcom Corporation'
 'Swing! Entertainment' 'Paradox Interactive' 'Hip Interactive'
 'Tripwire Interactive' 'Sting' 'Havas Interactive' 'Funsta' 'Gust'
 'Telltale Games' 'From Software' 'NDA Productions' 'Ackkstudios'
```

```
 'Acquire' 'O-Games' 'SNK Playmore' 'Brash Entertainment' 'Funbox Medi
a'
 'Screenlife' 'Microids' 'Phantom EFX' 'Evolved Games' '03 Entertainmen
t'
 'Aspyr' 'Sunsoft' 'The Adventure Company' 'Telegames' 'Koch Media'
 'Hudson Entertainment' 'Agetec' 'Reef Entertainment' 'Yacht Club Game
s'
 'Daedalic Entertainment' 'Myelin Media' 'Enterbrain' 'SNK'
 'Avalon Interactive' 'Gamecock' 'Revolution Software' 'Groove Games'
 'Nobilis' 'Insomniac Games' 'Aksys Games' 'Ascaron Entertainment GmbH'
 'Mastiff' 'Destination Software, Inc' 'Graffiti' 'Phantagram'
 '1C Company' 'Idea Factory' 'Team17 Software' 'Navarre Corp' 'Max Fiv
e'
 'Conspiracy Entertainment' 'Monte Christo Multimedia'
 'DreamCatcher Interactive' 'XS Games' 'Zoo Games' '2D Boy' 'Just Fligh
t'
 'bitComposer Games' 'Dusenberry Martin Racing' 'Headup Games' 'Pinnacl
e'
 'Number None' 'Xicat Interactive' 'Strategy First' 'GOA' 'Astragon'
 'Graphsim Entertainment' 'Introversion Software' 'Natsume'
 'Codemasters Online' 'Iceberg Interactive' 'Avanquest'
 'MC2 Entertainment' 'Visco' 'Blue Byte' 'Stainless Games']
Quantity 215
Seasons: ['Autumn' 'Spring' 'Summer' 'Winter']
Quantity 4
```

In [71]:

```
# Factorize class labels (Platform)
factor = pd.factorize(data['Platform'])
print(factor[0])
```

```
[ 0  0  0 ... 14 10  7]
```

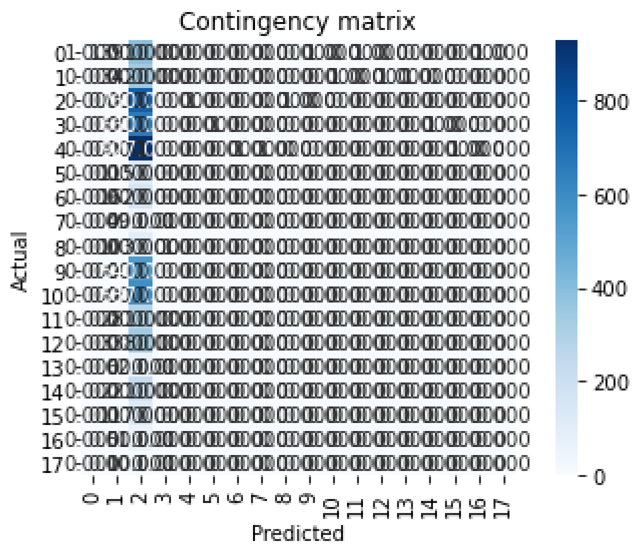
In [72]:

```
# Partition the dataset
X = data[['NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sal
es', 'Metascore', 'Userscore']]
Y = factor[0]

# Standardize the dataset
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
```

In [73]:
```
# Hierarchical Clustering (Platform)
clustering = linkage(X_scaled, method = "single", metric = "euclidean")
clusters = fcluster(clustering, 18, criterion = "maxclust")

cont_matrix = metrics.cluster.contingency_matrix(Y, clusters)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [74]:
```
# Results
adjusted_rand_index = metrics.adjusted_rand_score(Y, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaled, clusters, me
tric = "euclidean")
print([adjusted_rand_index, silhouette_coefficient])
```

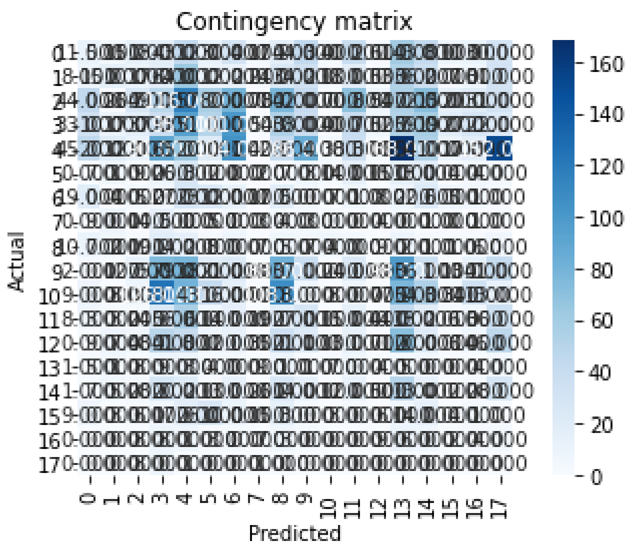
```
[-6.122630755566976e-05, 0.7112680768480899]
```

In [75]:
```
# Compute evaluation metrics for the true clusters of the data (Platfor
m)
silhouette_coefficient = metrics.silhouette_score(X_scaled, Y, metric =
"euclidean")
print(silhouette_coefficient)
```

```
-0.21322323301041163
```

In [76]:
```
# K-Means Clustering (Platform)
clustering2 = KMeans(n_clusters = 18, init = 'random', n_init = 1, rando
m_state = 2).fit(X_scaled)
clusters2 = clustering2.labels_

# Plot contingency matrix
cont_matrix2 = metrics.cluster.contingency_matrix(Y, clusters2)
sns.heatmap(cont_matrix2, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```

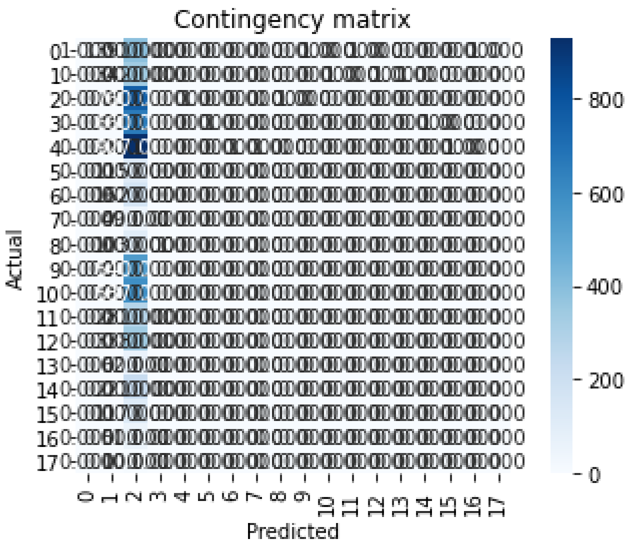


In [77]:
```
# Results
adjusted_rand_index2 = metrics.adjusted_rand_score(Y, clusters2)
silhouette_coefficient2 = metrics.silhouette_score(X_scaled, clusters2,
metric = "euclidean")
print([adjusted_rand_index2, silhouette_coefficient2])
```

```
[0.016878197320543496, 0.20714708203607976]
```

In [78]:
```
# DBSCAN Clustering (Platform)
clustering3 = DBSCAN(eps = 18, min_samples = 5, metric = "euclidean").fi
t(X_scaled)
clusters3 = clustering3.labels_

# Plot contingency matrix
cont_matrix3 = metrics.cluster.contingency_matrix(Y, clusters3)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [79]:
```
# Results
adjusted_rand_index3 = metrics.adjusted_rand_score(Y, clusters3)
silhouette_coefficient3 = metrics.silhouette_score(X_scaled, clusters3,
metric = "euclidean")
print([adjusted_rand_index3, silhouette_coefficient3])
```

```
[-3.246246077930463e-05, 0.9584354230541922]
```

In [80]:
```
# Factorize class labels (Genre)
factor = pd.factorize(data['Genre'])
print(factor[0])
```

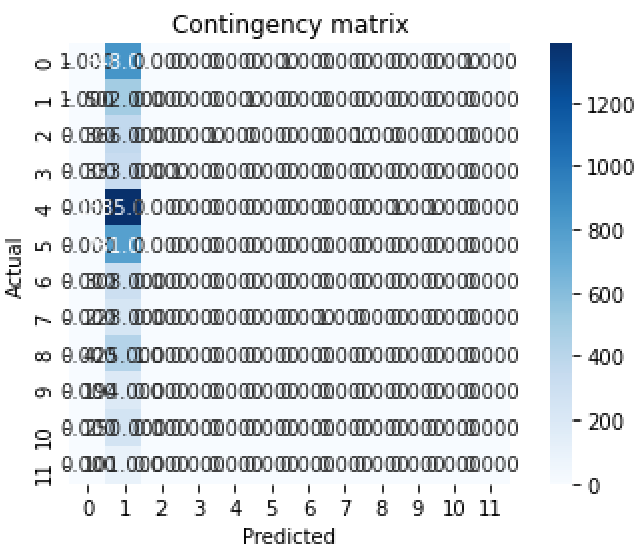
```
[0 1 0 ... 6 5 0]
```

In [81]:
```
# Partition the dataset
X = data[['NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sal
es', 'Metascore', 'Userscore']]
Y = factor[0]

# Standardize the dataset
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
```

In [82]:
```
# Hierarchical Clustering (Genre)
clustering = linkage(X_scaled, method = "single", metric = "euclidean")
clusters = fcluster(clustering, 12, criterion = "maxclust")

cont_matrix = metrics.cluster.contingency_matrix(Y, clusters)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [83]:
```
# Results
adjusted_rand_index = metrics.adjusted_rand_score(Y, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaled, clusters, me
tric = "euclidean")
print([adjusted_rand_index, silhouette_coefficient])
```

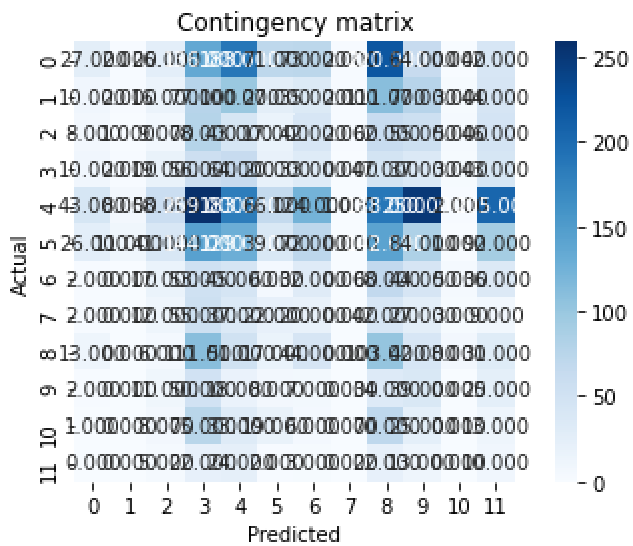
```
[0.00010145584877614118, 0.7933273262483781]
```

In [84]:
```
# Compute evaluation metrics for the true clusters of the data (Genre)
silhouette_coefficient = metrics.silhouette_score(X_scaled, Y, metric =
"euclidean")
print(silhouette_coefficient)
```

```
-0.1674298209428505
```

In [85]:
```
# K-Means Clustering (Genre)
clustering2 = KMeans(n_clusters = 12, init = 'random', n_init = 1, rando
m_state = 2).fit(X_scaled)
clusters2 = clustering2.labels_

# Plot contingency matrix
cont_matrix2 = metrics.cluster.contingency_matrix(Y, clusters2)
sns.heatmap(cont_matrix2, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```

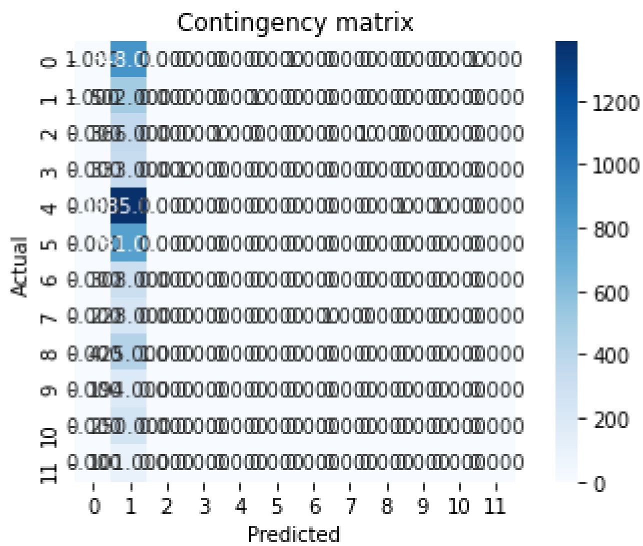


In [86]:
```
# Results
adjusted_rand_index2 = metrics.adjusted_rand_score(Y, clusters2)
silhouette_coefficient2 = metrics.silhouette_score(X_scaled, clusters2,
metric = "euclidean")
print([adjusted_rand_index2, silhouette_coefficient2])
```

```
[0.0038821079586146014, 0.21260704430522095]
```

In [87]:
```
# DBSCAN Clustering (Genre)
clustering3 = DBSCAN(eps = 12, min_samples = 5, metric = "euclidean").fi
t(X_scaled)
clusters3 = clustering3.labels_

# Plot contingency matrix
cont_matrix3 = metrics.cluster.contingency_matrix(Y, clusters3)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [88]:
```
# Results
adjusted_rand_index3 = metrics.adjusted_rand_score(Y, clusters3)
silhouette_coefficient3 = metrics.silhouette_score(X_scaled, clusters3,
metric = "euclidean")
print([adjusted_rand_index3, silhouette_coefficient3])
```

```
[-0.00010801774896538767, 0.9584354230541922]
```

In [89]:
```
# Factorize class labels (Season)
factor = pd.factorize(data['Season'])
print(factor[0])
```

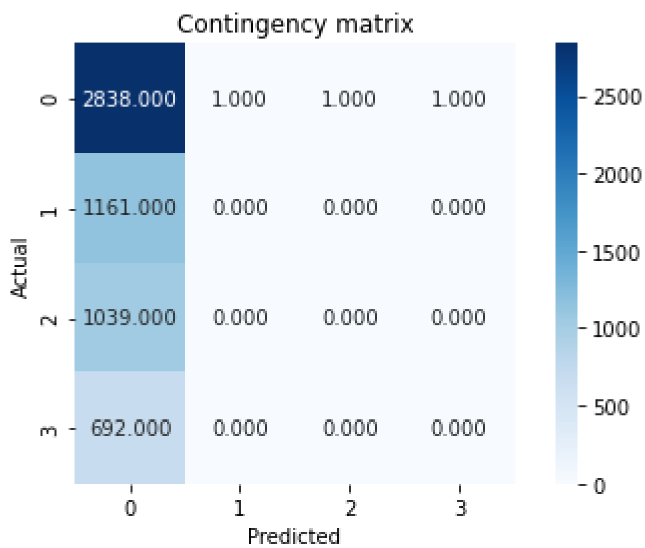
```
[0 1 2 ... 0 1 2]
```

In [90]:
```
# Partition the dataset
X = data[['NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sal
es', 'Metascore', 'Userscore']]
Y = factor[0]

# Standardize the dataset
scaler = StandardScaler()
scaler.fit(X)
X_scaled = scaler.transform(X)
```

In [91]:
```
# Hierarchical Clustering (Season)
clustering = linkage(X_scaled, method = "single", metric = "euclidean")
clusters = fcluster(clustering, 4, criterion = "maxclust")

cont_matrix = metrics.cluster.contingency_matrix(Y, clusters)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [92]:
```
# Results
adjusted_rand_index = metrics.adjusted_rand_score(Y, clusters)
silhouette_coefficient = metrics.silhouette_score(X_scaled, clusters, me
tric = "euclidean")
print([adjusted_rand_index, silhouette_coefficient])
```

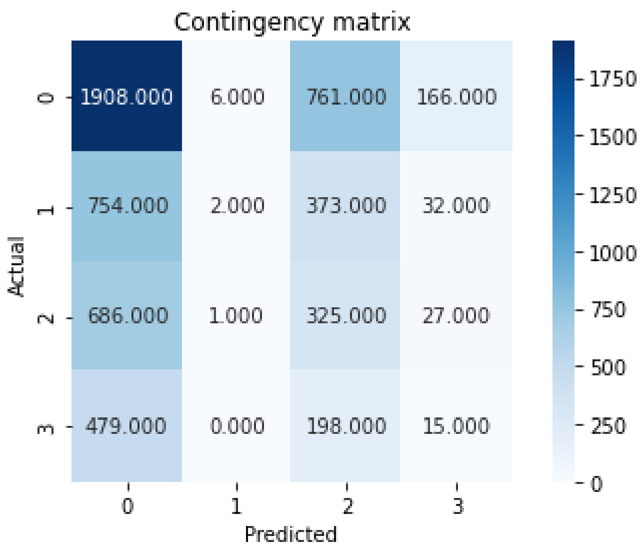
```
[-0.0005076416865963497, 0.8936972565745791]
```

In [93]:
```
# Compute evaluation metrics for the true clusters of the data (Season)
silhouette_coefficient = metrics.silhouette_score(X_scaled, Y, metric =
"euclidean")
print(silhouette_coefficient)
```

```
-0.05658855435231134
```

In [94]:
```
# K-Means Clustering (Season)
clustering2 = KMeans(n_clusters = 4, init = 'random', n_init = 1, random
_state = 2).fit(X_scaled)
clusters2 = clustering2.labels_

# Plot contingency matrix
cont_matrix2 = metrics.cluster.contingency_matrix(Y, clusters2)
sns.heatmap(cont_matrix2, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```

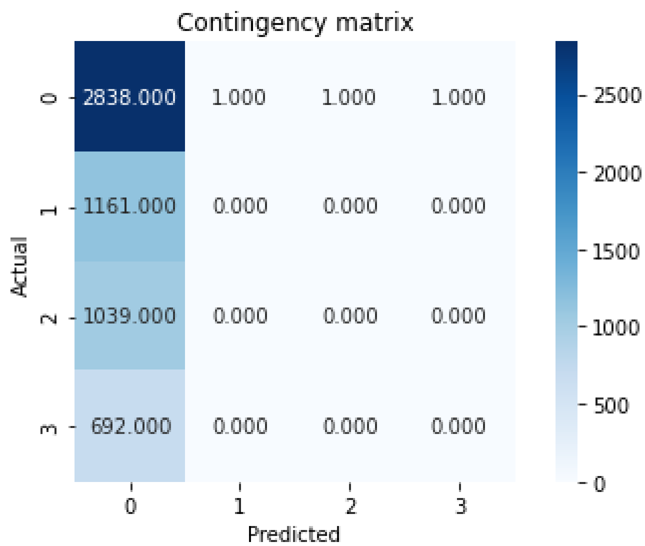


In [95]:
```
# Results
adjusted_rand_index2 = metrics.adjusted_rand_score(Y, clusters2)
silhouette_coefficient2 = metrics.silhouette_score(X_scaled, clusters2,
metric = "euclidean")
print([adjusted_rand_index2, silhouette_coefficient2])
```

```
[-0.0033549284193847015, 0.37422908879066746]
```

In [96]:
```
# DBSCAN Clustering (Season)
clustering3 = DBSCAN(eps = 4, min_samples = 5, metric = "euclidean").fit
(X_scaled)
clusters3 = clustering3.labels_

# Plot contingency matrix
cont_matrix3 = metrics.cluster.contingency_matrix(Y, clusters3)
sns.heatmap(cont_matrix, annot = True, fmt = ".3f", square = True, cmap
= plt.cm.Blues)
plt.ylabel('Actual')
plt.xlabel('Predicted')
plt.title('Contingency matrix')
plt.tight_layout()
```



In [97]:
```
# Results
adjusted_rand_index3 = metrics.adjusted_rand_score(Y, clusters3)
silhouette_coefficient3 = metrics.silhouette_score(X_scaled, clusters3,
metric = "euclidean")
print([adjusted_rand_index3, silhouette_coefficient3])
```

```
[-0.0007031295469137511, 0.9143189708365329]
```

In [ ]: