**Exploratory Data Analysis on Video Games Sales Dataset** • This is a personal project for the online course Data Analysis with Python: Zero to Pandas by Jovian. • In this project, I used Python open-source libraries NumPy , Pandas , Matplotlib , seaborn , opendatasets and os . • As a learner of data analysis/data science and also a video game player, I choose the video games sales dataset to perform exploratory data analysis. Besides I need a close-to-business-world dataset to practice my Python skills, I thought this topic would be interesting and I was also excited to find some insights into video games and related businesses. • I would like to take this project as a showcase of my Python analysis skills. And at the same time, I would love to hear questions, comments, ideas, or feedback from readers. By reading this notebook, you will know (I hope): Some usages and examples of some common-use Python libraries and functions. The basic process of exploratory data analysis. • Some ideas of how to handle and visualize different categories of data. • Some insights into the global video games and related businesses. Some interesting facts of video games. **Dataset Infomation** Before we actually started, the very first thing I should do (I hope you can do also) is to understand the dataset we will use. The description of the source dataset, these 16 columns/variables are defined as follow: • Name - The game's title • Platform - Platform of the games release (i.e. PC, PS2, Wii, Xbox360 etc.) Year\_of\_Release - Year of the game's release • Genre - Genre of the game • Publisher - Publisher of the game • NA\_Sales - Cumulative Units sold in North America since the game was released (in millions) • EU Sales - Cumulative Units sold in Europe since the game was released (in millions) • JP\_Sales - Cumulative Units sold in Japan since the game was released (in millions) • Other Sales - Cumulative Units sold in the rest of the world since the game was released (in millions) Global\_Sales - Cumulative Units sold worldwide since the game was released (in millions) Critic\_Score - Weighted average score by Metacritic base on all published critic reviews (0-100 scale) • Critic\_Count - The number of published critic reviews used in the Critic\_Score User\_Score - Average score by users reviews on Metacritic (0-10 scale) • User\_Count - The number of scores used in the User\_Score - Developer - Developer of the game • Rating - The ESRB rating of the game. (Ratings Guide) Note: All data are as of December 22nd, 2016. Source:\ Video Games Sales Dataset\ Metascore Downloading the Dataset • Because the source dataset is contributed by the user from Kaggle, I will download it to my local directory first. Let me import the os library and create a new directory called data where later I can store the dataset. import os os.makedirs('./data', exist ok = True) Then download the Video Games Sales Dataset , which was contributed by SID\_TWR from Kaggle , using the download function from opendatasets library. Source: Video Games Sales Dataset import opendatasets as od url = 'https://www.kaggle.com/sidtwr/videogames-sales-dataset?select=Video Games Sales as at 22 Dec 2016.csv' od.download(url, './data', force = True) | 507k/507k [00:00<00:00, 3.39MB/s] Downloading videogames-sales-dataset.zip to ./data/videogames-sales-dataset Let's check what has been downloaded and extracted using the listdir function. In [4]: os.listdir('./data/videogames-sales-dataset') Out[4]: ['PS4 GamesSales.csv', 'Video Games Sales as at 22 Dec 2016.csv', 'XboxOne GameSales.csv'] There are three csv files and I will maily focus on the Video\_Games\_Sales\_as\_at\_22\_Dec\_2016.csv since it included not only the sales data but also the score data by critics and users on Metacritic. **Data Preparation and Cleaning** • The first thing I would like to do before the data analysis is to read and load the dataset into Pandas DataFrame, then try to know and understand the dataset by getting some basic information about it. Then do some data cleaning and handle the invalid values as well. Before load and read the dataset into a dataframe, we should install the NumPy and Pandas library. !pip install numpy --upgrade --quiet !pip install pandas --upgrade --quiet Then import both NumPy and Pandas library and alias them as np and pd respectively. import numpy as np, pandas as pd Then read the csv file using read\_csv function from Pandas library.\ The file will be read and stored as a Pandas DataFrame object and I name it vgs\_df. vgs df = pd.read csv('./data/videogames-sales-dataset/Video Games Sales as at 22 Dec 2016.csv') We can check the vgs\_df dataframe with some functions for more basic information. In [9]: # check the number of rows and columns vgs df.shape Out[9]: (16719, 16) vgs\_df has 16,719 rows and 16 columns which means there are 16,719 observations and 16 variables in the dataframe. # check the top 10 rows vgs df.head(10) Name Platform Year\_of\_Release Genre Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Critic\_Score Wii Sports Wii 2006.0 Nintendo 41.36 28.96 3.77 82.53 76.0 Sports 8.45 Super Mario NES 1985.0 Platform Nintendo 29.08 3.58 6.81 0.77 40.24 NaN Bros. Mario Kart 2 Wii 2008.0 15.68 12.76 3.79 3.29 35.52 82.0 Racing Nintendo Wii Wii Sports 3 10.93 2.95 32.77 80.0 Wii 2009.0 Sports Nintendo 15.61 3.28 Resort Pokemon Role-Red/Pokemon GB 1996.0 Nintendo 11.27 8.89 10.22 1.00 31.37 NaN Playing 5 4.22 0.58 Tetris GB 1989.0 Puzzle Nintendo 23.20 2.26 30.26 NaN New Super 2006.0 Platform DS Nintendo 11.28 9.14 6.50 2.88 29.80 89.0 Mario Bros. Wii Play 2006.0 Nintendo 13.96 2.93 2.84 28.92 58.0 Misc **New Super** 8 Wii Nintendo 28.32 87.0 Mario Bros. 2009.0 Platform 14.44 6.94 4.70 2.24 **Duck Hunt NES** 1984.0 Shooter Nintendo 26.93 0.63 0.28 0.47 28.31 NaN # # check the last 10 rows vgs df.tail(10) NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Cri Name Platform Year\_of\_Release Genre Publisher DTP 16709 Adventure 15 Days PC 2009.0 0.00 0.01 0.00 0.0 0.01 Entertainment Men in Black 16710 II: Alien GC 2003.0 Shooter Infogrames 0.01 0.00 0.00 0.0 0.01 Escape Aiyoku no dramatic 16711 2014.0 Misc 0.00 0.01 Eustia create Woody Woodpecker 16712 **GBA** 2002.0 Platform 0.01 0.00 0.00 0.0 0.01 Kemco in Crazy Castle 5 SCORE International 16713 Baja 1000: PS2 2008.0 Activision 0.00 0.00 0.00 0.0 0.01 Racing The Official Game Samurai 16714 Warriors: PS3 2016.0 0.00 0.00 0.01 0.0 0.01 Action Tecmo Koei Sanada Maru LMA 0.01 16715 X360 2006.0 Codemasters 0.00 0.01 0.00 0.0 Manager Sports 2007 Haitaka no 0.01 16716 PSV 2016.0 Adventure Idea Factory 0.00 0.00 0.01 0.0 Psychedelica Spirits & 16717 **GBA** 2003.0 Platform Wanadoo 0.01 0.00 0.00 0.0 0.01 Spells Winning Post 16718 **PSV** 0.01 2016.0 Simulation Tecmo Koei 0.00 0.00 0.01 0.0 # take a sample look vgs df.sample(10) Name Platform Year\_of\_Release Genre Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Tom Clancy's 7916 Splinter Cell: PC 2013.0 Ubisoft 0.04 0.13 0.00 0.01 0.19 Action Blacklist 3rd Super Namco Role-7117 Robot Wars Z PS3 2014.0 Bandai 0.00 0.00 0.23 0.00 0.23 Playing Jigoku Hen Games Namco Mobile Suit 5193 PS 1997.0 0.00 0.00 0.34 0.02 0.36 Action Bandai **Z-Gundam** Games **Guilty Gear** Majesco PSP 8498 2006.0 Fighting 0.13 0.00 0.02 0.01 0.16 Entertainment Judgment Kurohyou: Ryu ga **PSP** 0.00 0.00 0.29 0.00 0.29 5957 2010.0 Adventure Sega Gotoku Shinshou Army Men: 12154 GC 2004.0 Strategy Global Star 0.05 0.01 0.00 0.00 0.07 Yattaman DS: BikkuriDokkiri DS 2008.0 0.00 0.00 0.12 0.00 0.12 Action Takara Tomy Daisakusen da Koron Kawaii Koinu 15466 2010.0 Simulation 0.00 0.00 0.02 0.00 0.02 DS MTO DS 3 Role-Metal Xicat 14668 ΧB 2002.0 0.02 0.01 0.00 0.03 Dungeon Playing Interactive 7288 0.06 0.00 0.02 0.22 The Crew X360 2014.0 Ubisoft 0.14 Racing # check the columns name vgs df.columns Out[13]: Index(['Name', 'Platform', 'Year\_of\_Release', 'Genre', 'Publisher', 'NA\_Sales', 'EU\_Sales', 'JP\_Sales', 'Other\_Sales', 'Global\_Sales', 'Critic\_Score', 'Critic Count', 'User Score', 'User Count', 'Developer', 'Rating'], Then let's check if there is any NaN (Not a Number) value which is missing value in each columns. In [14]: vgs df.isna().any() Out[14]: Name True Platform False Year of Release True Genre True Publisher True NA Sales False EU Sales False JP Sales False Other Sales Global Sales False Critic\_Score True Critic\_Count True User Score True User Count True Developer True Rating True We can know that all the columns have NaN values except Platform , NA\_Sales , EU\_Sales , JP\_Sales , Other\_Sales , Global\_Sales . vgs\_df.isna().sum() 2 Out[15]: Name Platform 0 Year of Release 269 2 Genre Publisher 54 NA Sales 0 EU Sales JP Sales Other Sales Global Sales Critic Score Critic Count 8582 User\_Score 9129 User Count Developer 6623 6769 Rating dtype: int64 • There are 2 observations have missing values in Name. 269 observations have missing values in Year\_of\_Release. 2 observations have missing values in Genre. 54 observations have missing values in Publisher. 8582 observations have missing values in Critic\_Score and Critic\_Count. 9129 observations have missing values in User\_Score and User\_Count. • 6623 observations have missing values in **Developer**. 6769 observations have missing values in Rating. It is time to do some data cleaning, but I would save a copy of the dataframe before doing that in case something goes wrong. vgs\_copy = vgs\_df # Let's check the two which has NaN in Name vgs df[vgs df['Name'].isna()] Name Platform Year\_of\_Release Genre Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Critic\_Score Acclaim 659 NaN **GEN** 1993.0 1.78 0.53 0.00 0.08 2.39 NaN NaN Entertainment Acclaim 14246 NaN GEN 1993.0 0.00 0.00 0.03 0.00 0.03 NaN Entertainment # also check the two which has NaN in Genre. vgs df[vgs df['Genre'].isna()] # They are the same two rows. Out[18]: Name Platform Year\_of\_Release Genre Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Critic\_Score Acclaim 659 NaN 1993.0 1.78 0.53 0.00 0.08 2.39 NaN NaN Entertainment Acclaim 14246 NaN **GEN** 1993.0 0.00 0.00 0.03 0.00 0.03 NaN Entertainment # I will drop these two rows which with index of 659 and 14246 and store back to the dataframe # since they are missing names and many others values. vgs df.drop([659,14246], inplace = True) # check after data cleaning vgs df[['Name', 'Genre']].isna().any() Out[20]: Name False False dtype: bool Also drop the 269 observations which have NaN in Year\_of\_Release. vgs df.dropna(axis = 0, subset = ['Year of Release'], inplace = True) #check the result vgs df['Year of Release'].isna().sum() Out[22]: 0 # Since the dataset was only as of December 22th, 2016 # let me check the games released after 2016. vgs df[vgs df.Year of Release > 2016] Name Platform Year\_of\_Release Genre Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Critic\_Sco Imagine: 5936 Makeup DS 2020.0 Simulation Ubisoft 0.27 0.0 0.00 0.02 0.29 Νć Artist Phantasy Star Online 2 Role-14086 PS4 2017.0 0.00 0.0 0.04 0.00 0.04 Νá Episode Sega Playing 4: Deluxe Package Phantasy Star Online 2 Role-16222 Episode **PSV** 2017.0 Sega 0.00 0.0 0.01 0.00 0.01 Νć Playing Deluxe Package **Brothers** Conflict: Idea PSV 0.00 0.0 0.00 0.01 16385 2017.0 Action 0.01 Νa Precious Factory Baby Seems these four video games have invalid values in Year\_of\_Release, I will drop them directly as these four observations will not much affect our dataframe. In [24]: vgs\_df.drop(vgs\_df[vgs\_df.Year\_of\_Release > 2016].index, inplace = True) vgs df['Year of Release'].agg(['min', 'max']) min 1980.0 2016.0 Name: Year\_of\_Release, dtype: float64 Now the dataframe is only for the games that were released from 1980 to 2016. For the NA\_Sales , EU\_Sales , JP\_Sales , Other\_Sales and Global\_Sales five columns, based on the description of the priginal dataset,\ their values should follow this equation: NA\_Sales + EU\_Sales + JP\_Sales + Other\_Sales = Global\_Sales # Let me check vgs\_df[(vgs\_df.NA\_Sales + vgs\_df.EU\_Sales + vgs\_df.JP\_Sales + vgs\_df.Other\_Sales) != vgs\_df.Global\_Sales] Publisher NA\_Sales EU\_Sales JP\_Sales Other\_Sales Global\_Sales Critic\_ Name Platform Year\_of\_Release Genre 0 Wii Sports 2006.0 Sports Nintendo 41.36 28.96 3.77 8.45 82.53 Mario Kart 2008.0 2 Wii 35.52 Racing Nintendo 15.68 12.76 3.79 3.29 Wii Pokemon Role-Red/Pokemon GB 1996.0 11.27 8.89 10.22 1.00 31.37 Nintendo Playing Blue 5 1989.0 23.20 2.26 4.22 0.58 30.26 Tetris GB Puzzle Nintendo 7 Wii Play Wii 2006.0 Misc 13.96 9.18 2.93 2.84 28.92 Nintendo 16238 0.00 0.01 Vanark PS 1999.0 Shooter Jaleco 0.01 0.01 0.00 Bratz: 16256 PS2 2006.0 Adventure THQ 0.01 0.01 0.00 0.00 0.01 Forever Diamondz K-1 Grand 16292 PS 1999.0 0.01 0.01 0.00 0.00 0.01 Fighting Jaleco Prix G1 Jockey 4 Tecmo 16680 PS3 2008.0 Sports 0.00 0.00 0.00 0.00 0.01 2008 Koei SCORE International 16713 Baia 1000: PS2 2008.0 Racing Activision 0.00 0.00 0.00 0.00 0.01 The Official Game 6686 rows × 16 columns Seems these 6,686 rows are not correct in Global\_Sales, maybe there are typos when rounding. I will fix them using the same equation above. # subset these rows sub = vgs\_df[(vgs\_df.NA\_Sales + vgs\_df.EU\_Sales + vgs\_df.JP\_Sales + vgs\_df.Other\_Sales) != vgs\_df.Global\_Sales # calculate their Global Sales using the equation total = sub.NA Sales + sub.EU Sales + sub.JP Sales + sub.Other Sales # replace the wrongs values with corret values according to wrong rows index in vgs df vgs df.loc[sub.index, 'Global Sales'] = total # check whether all values are fixed ((vgs df.NA Sales + vgs df.EU Sales + vgs df.JP Sales + vgs df.Other Sales) == vgs df.Global Sales).all() Out[30]: True Since the value of Year\_of\_Release is in numeric format, we can conver it into datetime format and only use the year value. vgs\_df['Year\_of\_Release'] = pd.to\_datetime(vgs\_df['Year\_of\_Release'], format = '%Y').dt.year vgs df.shape # After cleaning, there are 16,444 obsevations (16444, 16)vgs df['Name'].nunique() # there are 11,426 unique obsevations Out[33]: 11426 I will work on these 16,444 obervations and 16 variables, note that only 11,426 among of them are unique, because some video games may release different platform versions. Which means there are around 5,000 observations in our dataframe are the same game title but in different platform. We can start the next part for explorary analysis and visulization.\ I am not going to handle the missing values in Publisher, Critic\_Score, Critic\_Count, User\_Score, User\_Count, Developer and Rating right now, maybe we will do that later. **Exploratory Analysis and Visualization** Then we can actually start the exploratory data analysis and visualization by data manipulation and others more. For more statistics information of each numeric column, call the describe function to check, it will ignore the NaN values which is missing values in each column. In [34]: vgs df.describe() Year\_of\_Release NA\_Sales **EU\_Sales** JP\_Sales Other\_Sales Global\_Sales Critic\_Score Critic\_Count Out[34]: User\_{ count 16444.000000 16444.000000 16444.000000 16444.000000 16444.000000 16444.000000 7983.000000 7983.000000 7463.00 0.264012 2006.486256 0.145930 0.078487 0.047594 0.536023 68.994363 26.441313 mean 0.818378 0.506716 0.311100 0.188005 13.920060 19.008136 std 5.875525 1.558786 1.49 1980.000000 0.000000 0.000000 0.000000 0.000000 0.000000 13.000000 3.000000 0.00 min 2003.000000 25% 0.000000 0.000000 0.000000 0.000000 0.060000 60.000000 12.000000 6.40 0.020000 0.170000 50% 2007.000000 0.080000 0.000000 0.010000 71.000000 22.000000 7.50 2010.000000 0.110000 0.040000 0.470000 79.000000 36.000000 75% 0.240000 0.030000 8.20 2016.000000 41.360000 28.960000 10.220000 10.570000 82.540000 98.000000 113.000000 9.70 max # install the matplotlib and seaborn libraries. !pip install matplotlib seaborn --upgrade --quiet # import and alias them import matplotlib import matplotlib.pyplot as plt, seaborn as sns # set plot basic styles %matplotlib inline sns.set style('darkgrid') matplotlib.rcParams['font.size'] = 14 matplotlib.rcParams['figure.figsize'] = (10, 6) matplotlib.rcParams['figure.facecolor'] = '#00000000' Histogram for the Number of Video Games Released Per 5-year We can compare the number of video games released per 5-year from 1980 to 2016 by generating a histogram. plt.hist(vgs df.Year of Release, bins = [1980, 1985, 1990, 1995, 2000, 2005, 2010, 2016], color = 'orange', alpha = 0.8)# add axis labels plt.xlabel('Year of Release') plt.ylabel('Number of Video Games Released') # add title plt.title('Number of Video Games Released per 5-year from 1980 to 2016', pad = 20);Number of Video Games Released per 5-year from 1980 to 2016 6000 Number of Video Games Released 5000 4000 3000 2000 1000 0 1980 1985 1990 1995 2015 2000 2005 2010 Year of Release Known from the plot, there are about 6,000 video games released between 2005 and 2010 which is the highest 5 years in our dataset, following by 2010 to 2016, this 6-year has about 5,200 games released. Pie Chart of Global Sales by Region We can compare cumulative units sold since the games were released till December 22th, 2016 in NA\_Sales, EU\_Sales, JP\_Sales , Other\_Sales four regions by a pie plot. In [39]: # create a subset of sales data for these four regions region\_df = vgs\_df[['NA\_Sales','EU\_Sales','JP\_Sales','Other\_Sales']] In [40]: # generate and style a pie plot with the above regional subset data subtotal = region df.sum() # calculate the sales for each region label = ['North America', 'Europe', 'Japan', 'Rest of the World'] # to inverse the autopct for the actual values def make autopct(subtotal): def inverse autopct(pct): return ' $\{p:.2f\}$ % ( $\{v:.2f\}$  m)'.format(p = pct, v = pct\*sum(subtotal)/100) # plot and style pie = plt.pie(subtotal, # values labels = label, # label for each section autopct = make autopct(subtotal), # show data in percentage and values with two decimal places explode = [0.06, 0.05, 0, 0], # to slice the particular sections textprops = {"fontsize" : 12}, # set the fontsize of the plot shadow = True, # set to show shadow startangle = 90) # set the angle for the first section # add title plt.title('Cumulative Units Sold by Region of Video Games that Released from 1980 to 2016 (in % and number)'); Cumulative Units Sold by Region of Video Games that Released from 1980 to 2016 (in % and number) Rest of the World Japan North America 9.25% (4341.42 m) 27.22% (2399.68 m) Europe We can see that for the games released from 1980 to 2016, almost half of them have sold in North America, followed by Europe with a percentage of 27, which is more than half of the portion left by North America. • That is, over three-fourths of the video games have sold in North America and Europe. These two regions are two important markets for video games and related businesses. Bar Plot for Global Sales by ESRB Rating I will generate a bar plot to show the cumulative global units sold for each ESRB rating. In [41]: sales by rating = vgs df.groupby('Rating')['Global Sales'].sum().sort values(ascending = False).to frame() sales by rating['Perc'] = round(sales by rating['Global Sales'] / sales by rating['Global Sales'].sum() \* 100, sales by rating = sales by rating.reset index() In [42]: # genreate the bar plot using sns bar sales by rating = sns.barplot(y = 'Global Sales', x = 'Rating', data = sales by rating)# set title and axis labels bar sales by rating.set title ('Cumulative Global Units Sold of Video Games between 1980 and 2016 by ESRB Rating pad = 40)bar\_sales\_by\_rating.set\_ylabel('Cumulative Global Units Sold (in millions)') bar\_sales\_by\_rating.set\_xlabel('ESRB Rating') # add pecentage for each rating bar using sns.annotate function for i in range(sales\_by\_rating.shape[0]): bar\_sales\_by\_rating.annotate(str(round(sales\_by\_rating['Global\_Sales'][i],2)) + '\n ('+ str(sales\_by\_rating xy = (i, sales\_by\_rating['Global Sales'][i] + 30), fontsize = 12, horizontalalignment = 'center'); Cumulative Global Units Sold of Video Games between 1980 and 2016 by ESRB Rating (in millions) 2500 (40.18%)Cumulative Global Units Sold (in millions) 2000 1462.53 1473.08 (24.58%)1500 (24.41%)1000 640.98 (10.7%)500 4.32 0.04 (0.07%)(0.03%)(0.03%)(0.0%)0 Т E10+ EC RP K-A ΑO **ESRB** Rating • Seems about 90% of the games are rated as E, T, and M based on the ESRB rating. Bar Plot for Global Sales by Genre Now I am interested in what are the popular genres of video games. I will generate a bar plot to show the cumulative global units sold for each genre. In [43]: # check what are the genres of games vgs df['Genre'].unique() Out[43]: array(['Sports', 'Platform', 'Racing', 'Role-Playing', 'Puzzle', 'Misc', 'Shooter', 'Simulation', 'Action', 'Fighting', 'Adventure', 'Strategy'], dtype=object) In [44]: # check how many of them vgs df['Genre'].nunique() Out[44]: 12 In [45]: # create a subset and calculate the subtotal global sales and percentage by genre sales by genre = vgs df.groupby('Genre')['Global Sales'].sum().sort values(ascending = False).to frame() sales\_by\_genre['Perc'] = round(sales\_by\_genre['Global\_Sales'] / sales\_by\_genre['Global\_Sales'].sum() \* 100, 2) sales\_by\_genre = sales\_by\_genre.reset\_index() In [46]: sales\_by\_genre Out[46]: Genre Global\_Sales Perc 0 1716.52 19.47 Action 1309.67 14.86 1 Sports 1041.36 11.81 Shooter Role-Playing 931.08 10.56 4 Platform 825.55 9.37 5 Misc 790.29 8.97 723.49 8.21 Racing 7 Fighting 442.66 5.02 387.96 8 Simulation 4.40 9 Puzzle 239.89 2.72 10 Adventure 233.33 2.65 11 Strategy 172.57 1.96 In [47]: # genreate the bar plot using sns bar sales by genre = sns.barplot(x = 'Global Sales', y = 'Genre', data = sales by genre, ci = None) # set title and axis labels bar sales by genre.set title ('Cumulative Global Units Sold of Video Games between 1980 and 2016 by Genre (in mi bar sales by genre.set xlabel('Cumulative Global Units Sold (in millions)') bar sales by genre.set ylabel('Genre') # add pecentage for each genre bar using sns.annotate function for i in range(sales by genre.shape[0]): bar\_sales\_by\_genre.annotate(str(round(sales\_by\_genre['Global\_Sales'][i],2)) + ' (' + str(sales\_by\_genre['Pe xy = (sales by genre['Global Sales'][i]+10, i), fontsize = 12, verticalalignment = 'center'); Cumulative Global Units Sold of Video Games between 1980 and 2016 by Genre (in millions) 1716.52 (19.47%) Action Sports 1309.67 (14.86%) 1041.36 (11.81%) Shooter 931.08 (10.56%) Role-Playing 825.55 (9.37%) Platform 790.29 (8.97%) Misc 723.49 (8.21%) Racing 442.66 (5.02%) Fighting 387.96 (4.4%) Simulation 239.89 (2.72%) Puzzle Adventure 233.33 (2.65%) Strategy 172.57 (1.96%) 1500 1750 250 1000 1250 Cumulative Global Units Sold (in millions) It seems that action, sports, shooter and role-playing are the top four genres among all video games because their percentages are all over 10%. Line Chart for Number of Video Games Released Each Year from 1980 to 2016 Now I want to see the trend of number of games relesed each year among these four genres from these years. Note: I was intended to check the sales trend but realized that the sales data are not yearly sales data. The sales data are cumulative units sold as of December 22th, 2016. In [48]: subset the observations that are the top four genres we found above top genre = vgs df.query("Genre == ('Action', 'Sports', 'Shooter', 'Role-Playing')") In [49]: # calculate the number of games released each year for each genre action = top genre[top genre.Genre == 'Action'].groupby('Year of Release')['Name'].count() sports = top genre[top genre.Genre == 'Sports'].groupby('Year of Release')['Name'].count() shoot = top genre[top genre.Genre == 'Shooter'].groupby('Year of Release')['Name'].count() role = top genre[top genre.Genre == 'Role-Playing'].groupby('Year of Release')['Name'].count() # plot and style lines for each genre using above pandas.series plt.plot(action.index, action.values,'-o') plt.plot(sports.index, sports.values, '--s') plt.plot(shoot.index, shoot.values, '-.^') plt.plot(role.index, role.values, ':X') # add legend plt.legend(['Action','Sports','Shooer','Role-Playing']) # add labels for axis plt.xlabel('Year') plt.ylabel('Number of Video Games Released') plt.title('Number of Video Games Released Each Year among Top Four Genres from 1980 to 2016', pad = 20);Number of Video Games Released Each Year among Top Four Genres from 1980 to 2016 Action 250 Sports Shooer Number of Video Games Released Role-Playing 200 150 100 50 1985 1990 1995 1980 2000 2005 2010 2015 Year

