# Dilan Kusuma Final Project

**Video Game Sales** 













# Final Project / Video\_Games\_Sales.csv - Executive Summary





We can conclude that the Video Games Sales data has served a company which have around 16.700 users. In response it has feature such as Name, Platform, Release Date, Genre, Publisher, Sales, Critics, Users, Developers and Ratings



An immediate needs of treatment regarding the sharp decline of sales since the year of 2010



Figure the effecting factor and possibilities regarding the matter of declining sales



## Proposed Solutions

The deploying of Machine Learning (ML) in predicting a possible leverage from the data in a mission to raise the sales that's been declining, also provide a fit assistance to the problem.



#### **Result:**

#### **Analysis Results:**

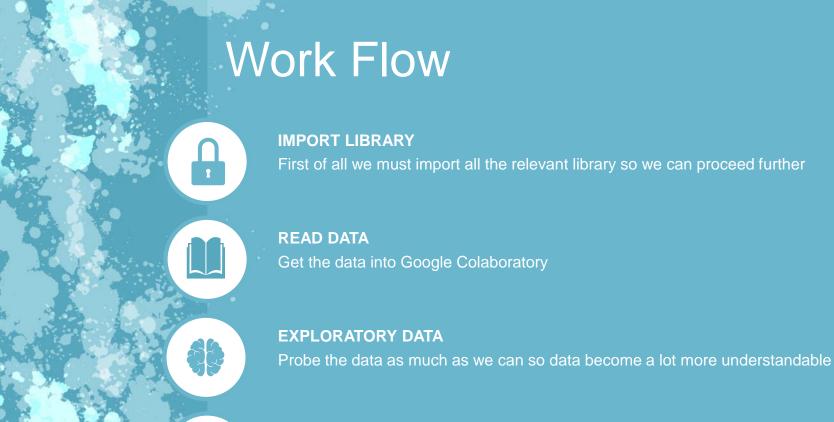
- > As for the Sales, NA are by far the best sales
- ➤ EA and Activision are the most promising Publisher
- ➤ The most hyped genre are Action and Sport genre as
- ➤ the have the most sales in comparison to other genre Points mentioned above require appropriate treatment

#### ML Result:

 Methods of regression used are Linear Regression bears the result of 97% R Square along with MSE score of 0.0016 accuracy

## **Sq** Business Benefit

- It is possible to be used as a bas eline of product treatment
- The Data have been dealt and an alyzed in regards to the User Beh avior, Interest, and Preference of Games
- ❖ Lay a data with definitive prove regarding the Game Sales as of 1991 until 2016, and are qualified to use for further Marketing Plan
- ❖ Found a provable solution in which causing the declining of sales



### **REGRESI**

Find the most befitting R square and MSE

```
'pandas.core.frame.DataFrame'>
    Int64Index: 7365 entries, 1366 to 10826
    Data columns (total 16 columns):
         Column 

                          Non-Null Count
                                          Dtype
                                          object
         Name
                          7365 non-null
        Platform
                          7365 non-null
                                          object
                                          float64
        Year of Release
                         7365 non-null
        Genre
                          7365 non-null
                                          obiect
                          7365 non-null
                                          object
        Publisher
       NA Sales
                          7365 non-null
                                          float64
       EU Sales
                                          float64
                          7365 non-null
        JP Sales
                          7365 non-null
                                          float64
        Other Sales
                          7365 non-null
                                          float64
        Global Sales
                                          float64
                          7365 non-null
    10 Critic Score
                          7365 non-null
                                          float64
    11 Critic Count
                                          float64
                          7365 non-null
     12 User Score
                          7365 non-null
                                          object
     13 User Count
                          7365 non-null
                                          float64
    14 Developer
                          7365 non-null
                                          object
     15 Rating
                          7365 non-null
                                          object
    dtypes: float64(9), object(7)
    memory usage: 978.2+ KB
46] print(modified_value.shape)
    (7365, 16)
```

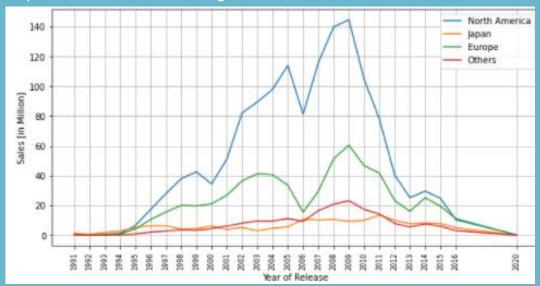
As we know that encountering impure d ata are common in data science, therefore we must clean the data before we proceed. Though unfortunate, our data seems to be a little underperformed as it has many null value.

Thus I decide to do the outlier first because I believe that doing so later would cause a disrupt in the data By doing the outlier first enable us to fill the null or nan value using *bfill* method when handling the missing value as the methods used Means to process the missing value, thus if there's still outlier, it will cause the Means to spread too much

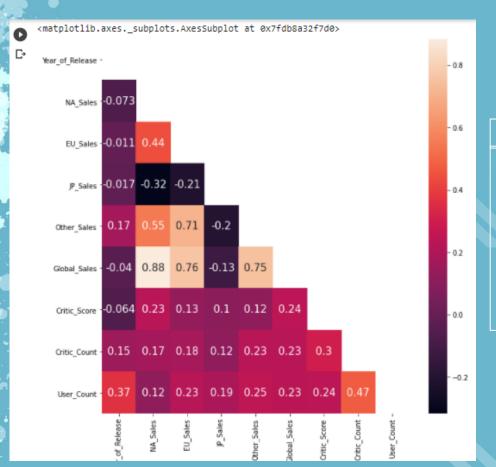
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       Year of Release
                          7365 non-null
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                          7365 non-null
                                           object
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                          7365 non-null
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                                           float64
       EU Sales
                          7365 non-null
                                           float64
      JP Sales
                                           float64
                          7365 non-null
        Other Sales
                          7365 non-null
                                           float64
        Global Sales
                          7365 non-null
                                           float64
     10 Critic Score
                          7365 non-null
                                           float64
     11 Critic_Count
                          7365 non-null
                                           float64
     12 User_Score
                          7365 non-null
                                           object
     13 User Count
                          7365 non-null
                                           float64
        Developer
                          7365 non-null
                                           object
         Rating
                          7365 non-null
                                           object
    dtypes: float64(9), object(7)
    memory usage: 978.2+ KB
46] print(modified_value.shape)
    (7365, 16)
```

# GRAPH OF SALES DISTRIBUTION

Graph based on the Years the game launched



From this graph we can conclude that there's been a sharp decline in Japan Sales.



#### **HEATMAP CORRELATION**

From what I have tested and observed I believe that we can exclude JP\_Sales as it not a significant Variable for our *used feature* later in order to further improve my analysis

```
# Evaluasi Model dengan Mean Square Error (MSE) dan R squared
print("MSE :", metrics.mean_squared_error(y_test,y_test_pred))
print("R squared :", metrics.r2_score(y_test,y_test_pred))
```

MSE : 3.15843608838748e-05 R squared : 0.9994666376262938 With JP\_ Sales

[228] # Evaluasi Model dengan Mean Square Error (MSE) dan R squared
 print("MSE :", metrics.mean\_squared\_error(y\_test,y\_test\_pred))
 print("R squared :", metrics.r2\_score(y\_test,y\_test\_pred))

MSE : 0.001680154702264934

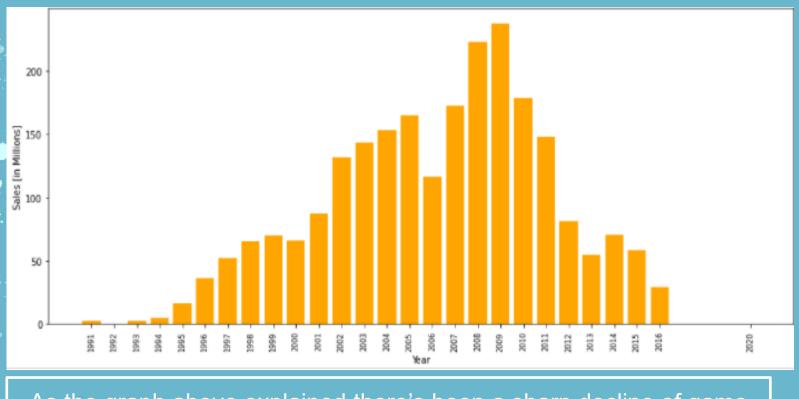
R squared : 0.9716273726896582



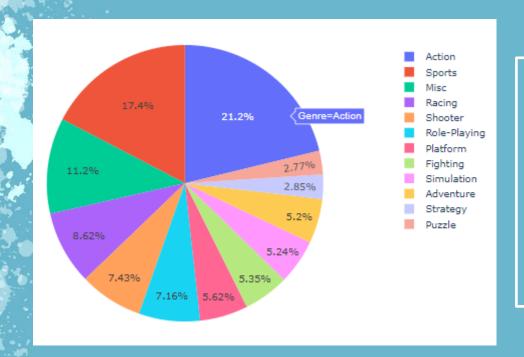
Without JP\_Sales



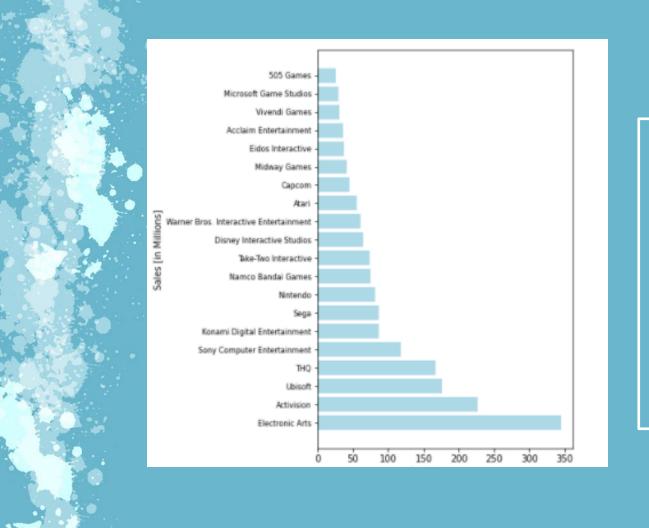
The removal of JP\_Sales has caused a drastic improvement for MSE and R Squared leading to a reliable and accurate result



As the graph above explained there's been a sharp decline of game sales ever since year of 2010 up to the end of the data. Signaling for an immediate response and treatment



This pie graph shows an overwhelming disparity in the Genre Feature. It also suggest that the Action and Sport Genre are what majoring the most hyped Genre, thus contributing in Sales



I believe there are some factor in which possibly affect the sales, such as Publisher. The graph shows the most contributing Publisher are EA (Electronic Art) by a far margin, followed by Activision







# Thank you

I'm very grateful for your enthusiastic attention