



# **MSDS 694 Distributed Computing**

## **EDA on Amazon Review Data**

**By: Jih-Chin Chen, Wei He, Zhipeng Hong, Kaihang Zhao**

- **Data Description**
- **Analytics Goals and Content**
- **EMR Performance Discussion**
  - **Efficiency Improvement**
  - **Cluster Setting and Execution Time**
- **Conclusion**



## Overview of Amazon Review Data

**11,095,239** observations in total

**5** digital product categories

**15** relevant columns

**No extra data**



Review content and other relevant features, including star rating, vote and verified purchase across five categories; ebook, video games, video downloads, music and software.

# Analytical Goals



Find Interesting and Meaningful Patterns from different dimensions of Amazon Digital Products Review

- Jin-Chin Chen: Review Content and Sentimental Score
- Wei He: Review with other features across category level
- Zhipeng Hong: Review with other features across time level
- Kaihang Zhao: Review with other features across time and category level

Our presentation will discuss features one by one, from univariate to multivariate level



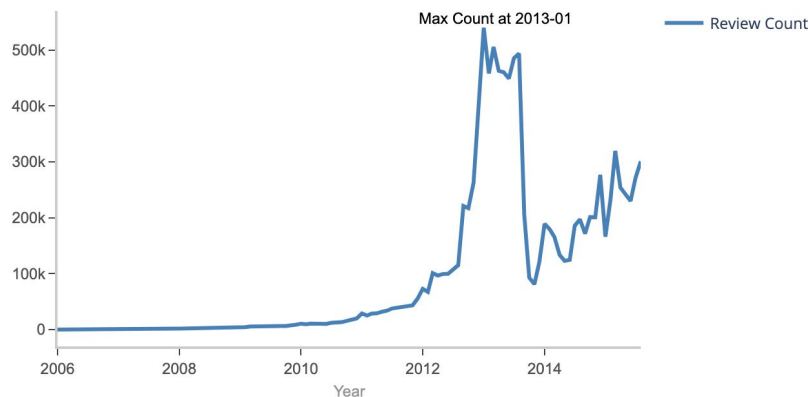
# Review Count and Star Rating Analysis

## Avg. Customer Review



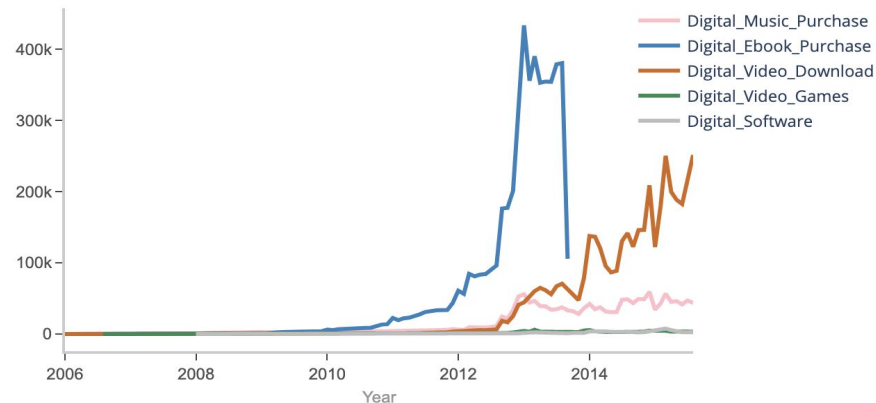
# Review Count Across Time and Category

## Review Count by Month



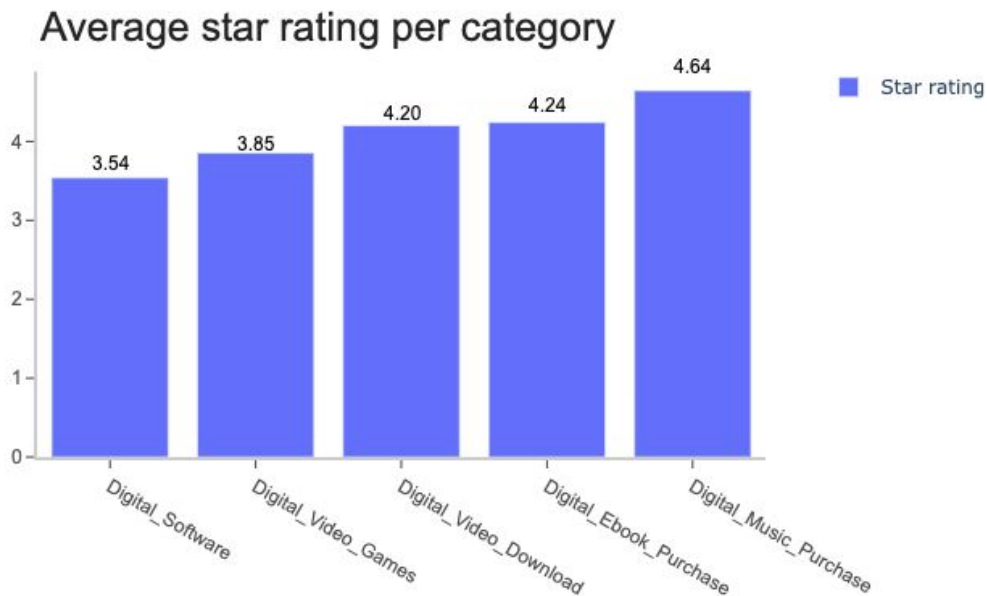
- This plot shows that the number of review increase sharply at from 2012-2013

## Review Count for Each Category



- Boom of Ebook Review
- Video Download Review took over the main trend after 2013

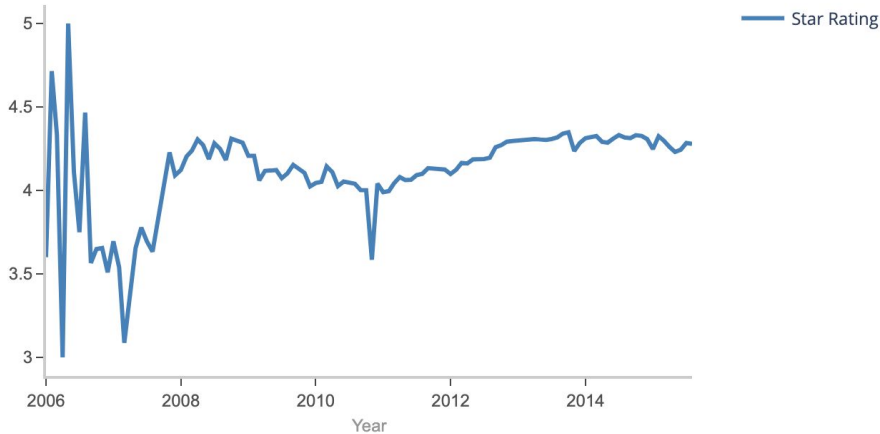
# Star Rating



This is plot of star rating for each category. We calculate each average star rating of each category. Music category has highest rating, software has the lowest.

# Star Rating Across Time and Category

Star Rating By Month



Star Rating for Each Category



- These two plots show the star rating change by month.
- The sharp change of star rating from 2006 to 2008 is caused by small amount of data. With exponential growth afterwards, star rating is around 4 to 4.5.



# Ratio Analysis

Helpful Rate and Vote Rate

30 people found this helpful

Helpful

| Report abuse





# Helpful Vote Rate and Click Vote Rate

## Helpful and Click Rate

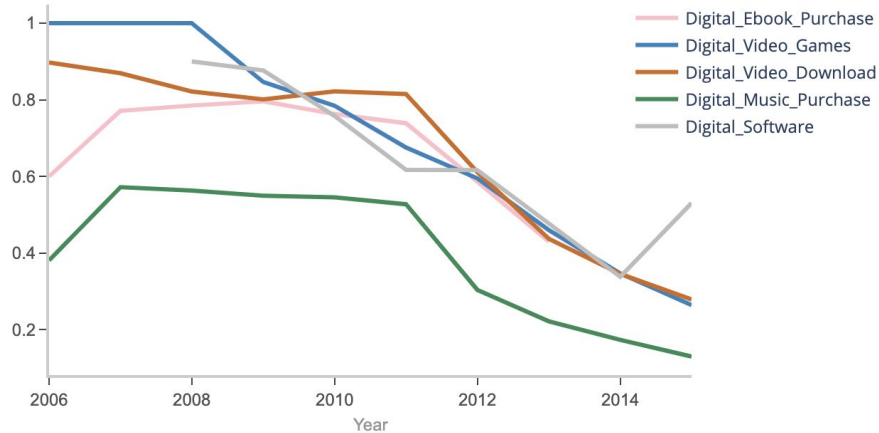


This plot shows that the decrease of the helpful rate and click rate. It means that people unlikely to click their votes. And since helpful rate is decreasing, people think most of review is unhelpful.

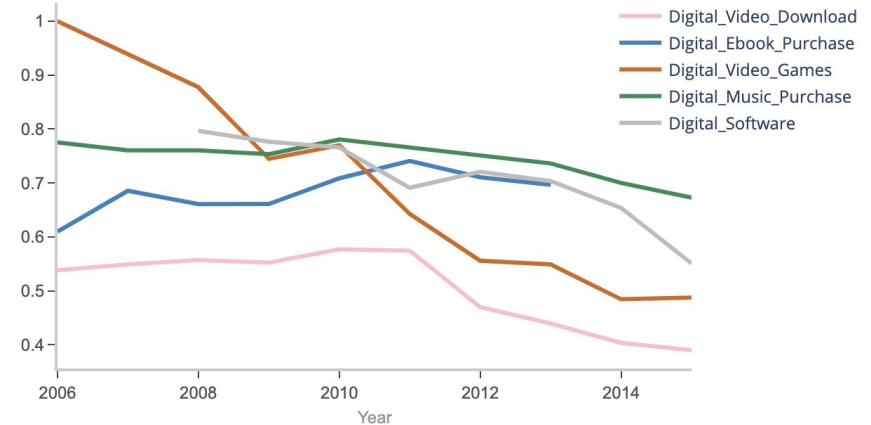
The reason of sudden decrease of click rate in 2012 is because the number of review decrease sharply at this time.

# Helpful Vote Rate and Click Vote Rate

Click Vote Ratio for Each Category



Helpful Vote Ratio for Each Category

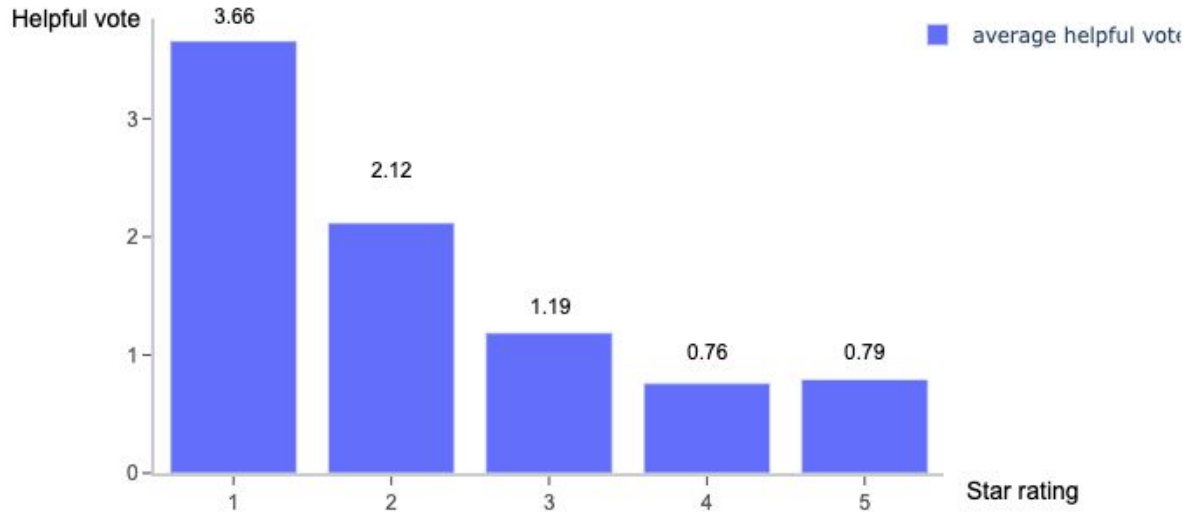


- These two plot shows the click rate and helpful rate between 5 category.
- Helpful Rate and Click Rate is consistent decreasing

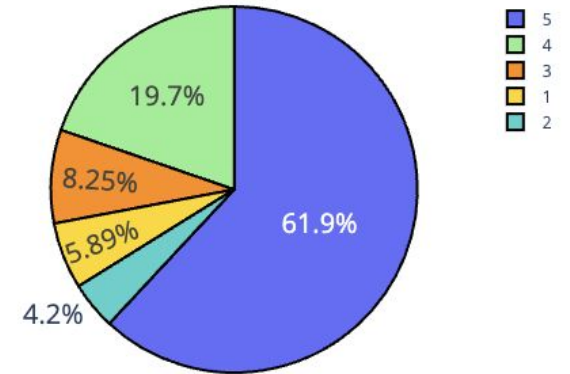
# Helpful Vote VS Star Rating



Relationship between star rate and helpful vote



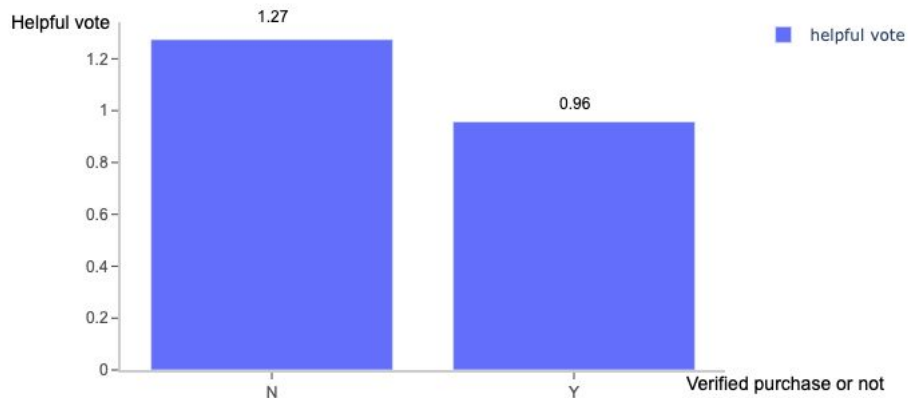
Percentage of each star ratings



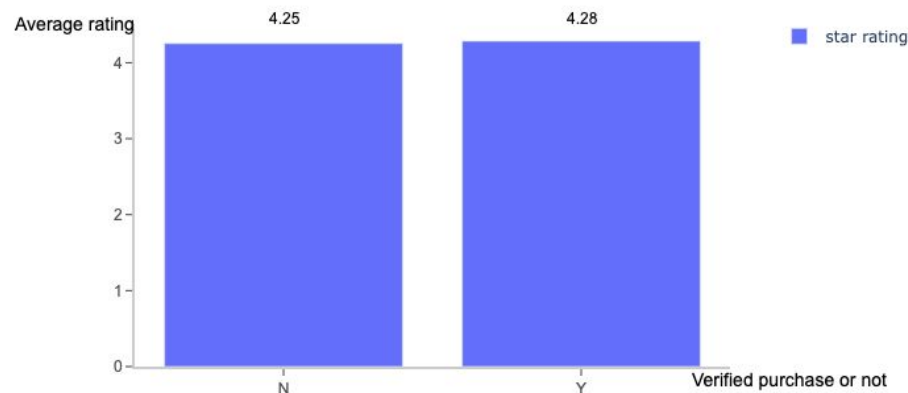
# Helpful Vote, Star Rating and Verified Purchase

Amazon Verified Purchase review: Amazon have verified that the person writing the review purchased the product at Amazon and didn't receive the product at a deep discount.

Helpful vote for verified purchase or not



Average star rating for verified purchase or not





# Review Analysis

# Review Text



## Description:

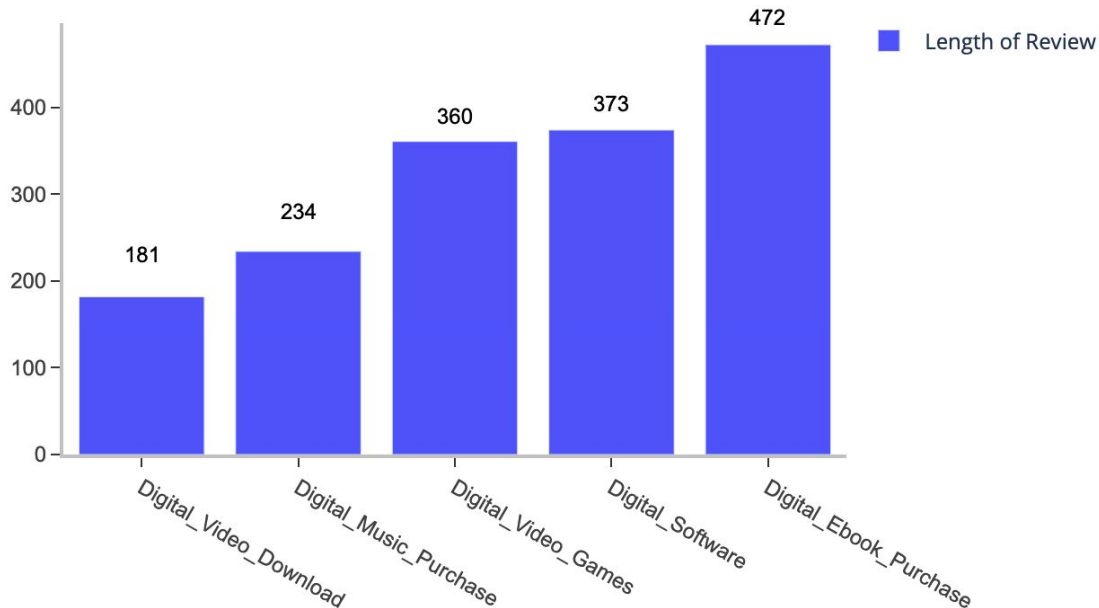
This plot shows the average length of review across different categories.

## Phenomenon:

People who purchase digital ebook are more likely to share their review on product.

People who purchase digital video are less likely to share their review.

Average review length per category



# Review Text



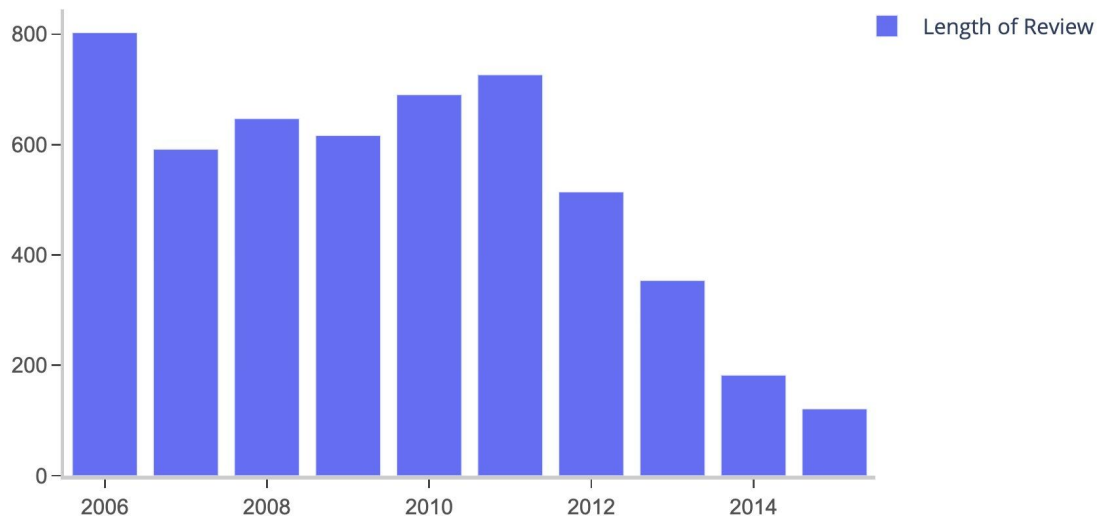
## Description:

This plot shows the average length of review across different years.

## Phenomenon:

There is a obviously decrease trend in this plot after 2011.

Average review length per year



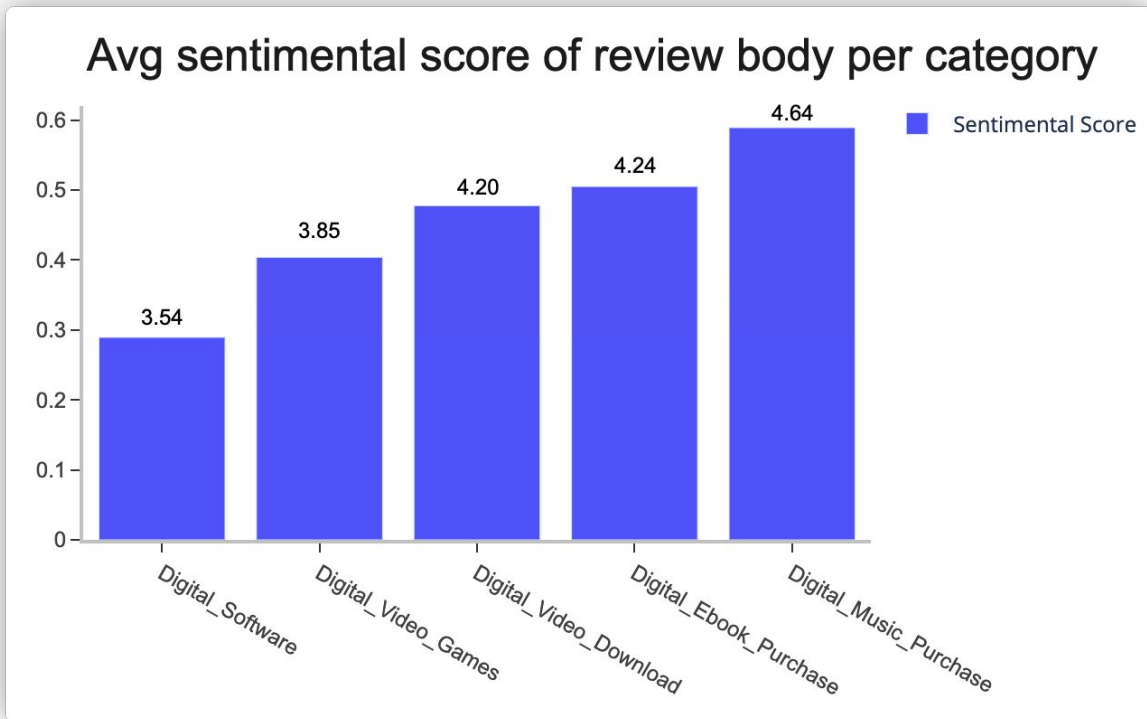
# Review Text

## Description:

This plot shows the average sentimental score of review across different categories. (the number above the bar is star rating)

## Phenomenon:

There is a perfect match between the distribution of sentimental score of review and the distribution of star rating on product.







## EMR Performance Discussion

▶ <a href="#">ig-28DQ175R6HAZ7</a>	Running	<b>CORE</b> Core - 2	<b>m5.xlarge</b> 4 vCore, 16 GiB memory, EBS only storage EBS Storage: 64 GiB	2 Instances <a href="#">Resize</a>
▶ <a href="#">ig-1U8Z9O451PH1Z</a>	Running	<b>TASK</b> Task_m5.xlarge_SP OT_By_Managed_ Scaling	<b>m5.xlarge</b> 4 vCore, 16 GiB memory, EBS only storage EBS Storage: 64 GiB	2 Instances <a href="#">Resize</a>
▶ <a href="#">ig-3FVR6HYM330FX</a>	Running	<b>MASTER</b> Master - 1	<b>m5.xlarge</b> 4 vCore, 16 GiB memory, EBS only storage EBS Storage: 64 GiB	1 Instances

3 instance group in EMR  
5 instances m5.xlarge total

# EMR Performance Discussion: Efficiency

Use rdd.cache() to persist our initial rdd,  
Before **197** seconds; After **82** seconds  
**58%** efficiency improvement

```
: import time
start = time.time()#put this at the beginning

# focus on the review which total vote >0, for those total vote=0 we dont know whether these are helpful
helpful_rate=rdd.map(lambda x:(int(x[8]),int(x[9]),x[-1][:4])).filter(lambda x:x[1] != 0).filter(l
helpful_rate=helpful_rate.map(lambda x:(x[0]/x[1],x[2]))
helpful_rate=helpful_rate.map(lambda x:(x[1],(x[0])))
helpful_rate_countbykey=helpful_rate.sortByKey().countByKey()
helpful_rate=helpful_rate.groupByKey().mapValues(lambda x:mean(x)).sortByKey()
# total review number
total_review=rdd.map(lambda x:x[-1][:4]).filter(lambda x:x > '2005').sortBy(lambda x:x[0],ascendin

print('second' , time.time() - start) #put this at the end we'd like to test/ in the end
```

▶ Spark Job Progress

second 197.72533893585205

```
: import time
start = time.time()#put this at the beginning

# focus on the review which total vote >0, for those total vote=0 we dont know whether these are helpful
helpful_rate=rdd.map(lambda x:(int(x[8]),int(x[9]),x[-1][:4])).filter(lambda x:x[1] != 0).filter(lambda x:x[2] > '2005')
helpful_rate=helpful_rate.map(lambda x:(x[0]/x[1],x[2]))
helpful_rate=helpful_rate.map(lambda x:(x[1],(x[0])))
helpful_rate_countbykey=helpful_rate.sortByKey().countByKey()
helpful_rate=helpful_rate.groupByKey().mapValues(lambda x:mean(x)).sortByKey()
# total review number
total_review=rdd.map(lambda x:x[-1][:4]).filter(lambda x:x > '2005').sortBy(lambda x:x[0],ascending=False).countByValue

print('Second', time.time() - start) #put this at the end we'd like to test/ in the end
```

▶ Spark Job Progress

Second 82.01012682914734

# EMR Performance Discussion: Cluster Setting

```
%configure -f
{
"conf":{
    "spark.pyspark.python": "python3",
    "spark.pyspark.virtualenv.enabled": "true",
    "spark.pyspark.virtualenv.type":"native",
    "spark.pyspark.virtualenv.bin.path":"/usr/bin/virtualenv",

    "spark.executor.heartbeatInterval":"10800s",
    "spark.network.timeout":"24h",

    "spark.driver.memory": "8G",
    "spark.executor.memory": "8G",
    "spark.executor.cores":"4",

    "livy.server.session.timeout" : "5h",

    "spark.app.name":"msds694"
}
}
```

Final Execution Time:

Jih-Chin Chen: 63 minutes 30 seconds

Wei He: 2 minutes 1 seconds

Zhipeng Hong: 3 minutes 35 seconds

Kaihang Zhao: 3 minutes 29 seconds

# Conclusion



- Review Count: mainly from ebooks and video downloads
- Review Rate: Ebooks highest around 4.5; Software only 3.5
- Helpful rate and Click rate are decreasing.
- Review Length: Start to decrease in 2011
- Helpful rate: People are more caring about the weakness or shortcomings of the products.
- Review Sentimental Score: perfectly matches with the star rating