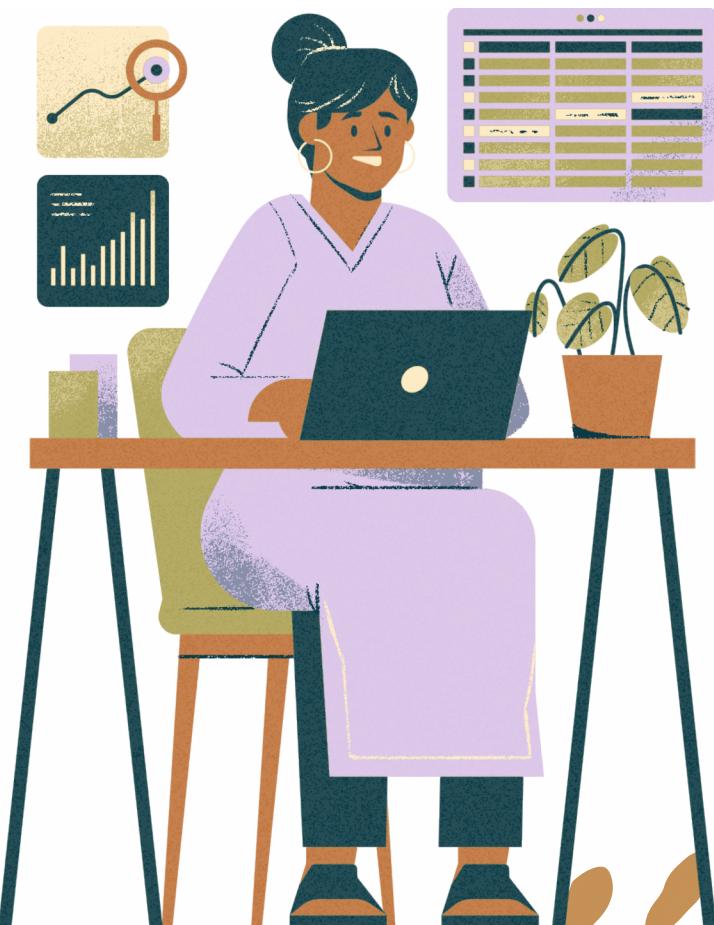


Data Analysis Portfolio

Prepared By:
Bansiben Prajapati



Professional Background

Currently in my 3rd Year pursuing B.Tech CSE. I have secured 7.26 CGPA (till 5th sem) and have several skills including Machine Learning, Deep Learning, Data Analysis, Python.

I have done an AICTE Internship on AI: Transformative Learning with TechSaksham, a joint CSR initiative by Microsoft & SAP during the four-week internship it emphasized on developing essential skills in AI technologies through hands-on learning projects, the project aimed to detect plant diseases from leaf images, helping farmers identify issues early and take timely action using Convolutional Neural Networks (CNNs).

As I am a fresher it would be great to experience the real challenges of the corporate world and understand how things work. Being a fresher, I think I am very flexible and adaptive to learn new things. I have theoretical knowledge. But I am waiting to use my theoretical knowledge in a practical way. And I believe by putting significant efforts I will learn.

Table Of Contents

Sr. No.	Name of Project
1.	Data Analytics Process
2.	Instagram User Analytics
3.	Operation Analytics and Investigating Metric Spike
4.	Hiring Process Analytics
5.	IMDB Movie Analysis
6.	Bank Loan Case Study
7.	Analyzing the Impact of Car Features on Price and Profitability
8.	ABC Call Volume Trend Analysis



Project - 1

Data Analytics

Process

Applications in Real Life Scenario

1. We book the tickets of movie on bookmyshow

Plan

We decide which movie to watch before booking it. Whether a comedy, thriller, romantic genre we want to watch.

Prepare

Next we will check how much I am willing to spend.

Process

Then we need to check which movie we want to watch and how much the seat cost-normal seat or recliner seat.

Analyze

Then we will check which movie is recently released and what is its genre.

Share

Now we will decide the movie and see the available seats and decide the theatre which is nearby.

Act

We then finally book the tickets.

2. We use Blinkit to buy grocery

Plan

We first decide things to buy from the application of blinkit.

Prepare

Next we check how much are we in need for and how much it costs.

Process

Then we check what is available such as vegetables, fruits, rice flour etc.

Analyze

Then we check what we need according to the pantry requirements and how much it costs in total.

Share

Now we add the items to the cart for final checkout.

Act

Then we finally buy it.

3. We use google maps to go to the places whose path is unknown and which path takes minimum time to reach destination.

Plan

We first decide a place where to go and by which means of transport we can go.

Prepare

Then we see which modes of transport are available, how much it costs and time taken to reach the destination.

Process

Then we compare the modes of transport which would be preferred according to number of passengers, time taken to reach the destination and cost of travel.

Analyze

According to the kilometers and traffic situations google map shows us the best route which takes minimum time to travel.

Share

We then finally decide the route to reach our destination according to the time taken to reach and cost.

Act

Then we finally start our journey to reach the destination.

4. We use Ola to travel around the city.

Plan

First we decide where we have to go and plan the destination.

Prepare

Then we see the routes from where we can go and how much time it will take to travel.

Process

Then we see the best suited vehicle according to number passengers and the route.

Analyze

Then we analyze the route what are the conditions and how much time it will take to reach the destination and what it will cost.

Share

Then we search the available vehicle and which is best suitable for the travel.

Act

Then we finally book it.

5. What we should watch on Netflix

Plan

We decide what we want to watch. Is it a fiction, drama, anime, sci-fi, horror etc.

Prepare

Then we check on what device we want to watch such as mobile, laptop or TV.

Process

Then we see what we want to watch from the available movies and series.

Analyze

Then according to the recent movies and series we watch which is freshly released and analyze what we want to watch according to our likings.

Share

Then we explore which is best suitable for us to watch.

Act

Then finally we start watching.

Project – 2

Instagram User

Analytics

Project Description

The aim of this project is to analyze Instagram user engagement and take insights through which we will be able to take informed decisions about future directions of Instagram. By using MySQL workbench and SQL queries we will be able to handle tasks and answer key questions.

Approach

- First loaded the provided dataset into MySQL workbench.
- Then reviewed the table schema and the keys associated to it to understand the relationship between each table and columns.
- Further we analyzed the problem statement given and wrote SQL queries for each task and repeated the process of writing the SQL queries until we found an accurate answer.
- Verified accuracy of queries by validating results against expected patterns.

Tech-Stack Used

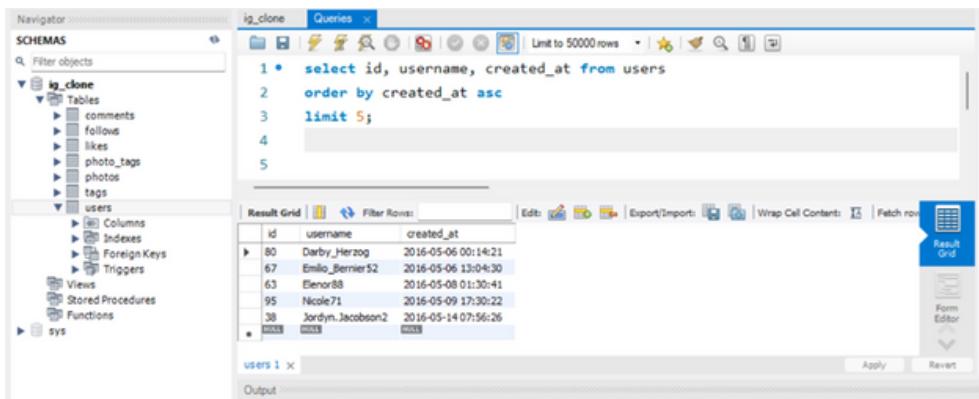
- Used MySQL workbench Version 8.0.41.0.
- Choose MySQL workbench as it can be used for database setup, querying, and performing commands for filtering, aggregating and joining data to have insights.

Insights

A)Marketing Analysis:

1. Loyal User Reward

We found 5 most loyal users by accessing users table and arranging them in ascending order and by printing the 5 users who have made account first from the given dataset.



The screenshot shows the MySQL Workbench interface. The Navigator pane on the left displays the 'ig_clone' schema with its tables: comments, follows, likes, photo_tags, photos, and users. The 'Tables' section under users contains columns, indexes, foreign keys, and triggers. The Queries tab at the top has a query editor with the following SQL code:

```
1 • select id, username, created_at from users
2   order by created_at asc
3   limit 5;
```

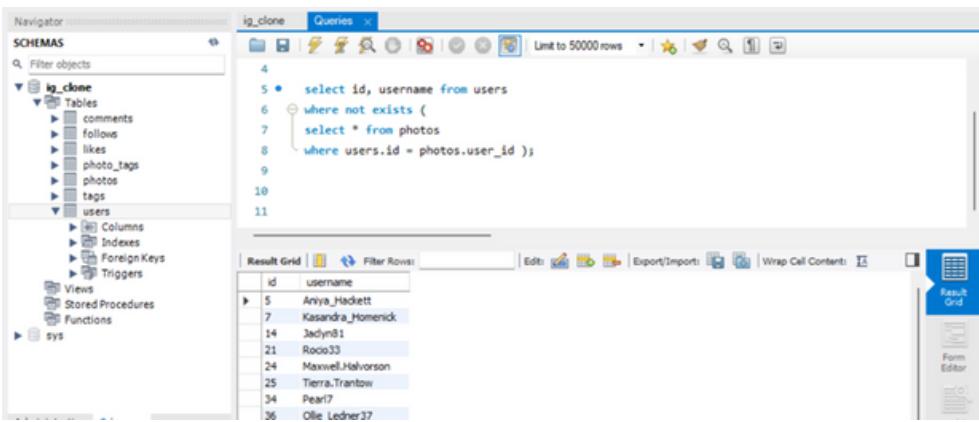
The Result Grid below shows the output of the query:

	id	username	created_at
1	80	Darby_Herzog	2016-05-06 00:14:21
2	67	Emilio_Bernier52	2016-05-06 13:04:30
3	63	Elenor88	2016-05-08 01:30:41
4	95	Nicole71	2016-05-09 17:30:22
5	38	Jordyn.Jacobson2	2016-05-14 07:56:26
	NULL	NULL	NULL

Insight- we found most loyal users by finding who has been using the Instagram for the longest time and found 5 oldest users on Instagram which are given above in output table.

2. Inactive User Engagement

We found inactive user by finding who have not posted any photo. We found it from photos table where we searched which user id was not present.



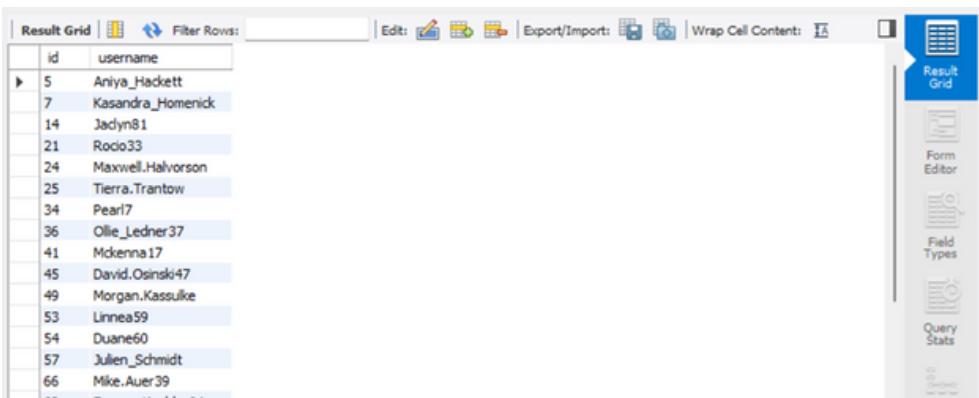
```

SELECT id, username
FROM users
WHERE NOT EXISTS (
    SELECT *
    FROM photos
    WHERE users.id = photos.user_id
);

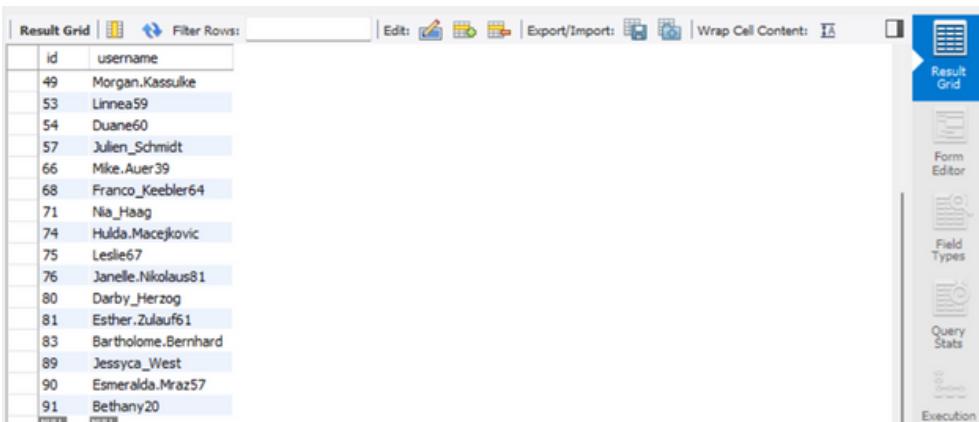
```

The Result Grid shows the following data:

	id	username
5	5	Aniya_Hackett
7	7	Kassandra_Homenick
14	14	Jadyn81
21	21	Rocio33
24	24	Maxwell.Halvorson
25	25	Tierra.Trantow
34	34	Pearl7
36	36	Ollie_Ledner37



	id	username
5	5	Aniya_Hackett
7	7	Kassandra_Homenick
14	14	Jadyn81
21	21	Rocio33
24	24	Maxwell.Halvorson
25	25	Tierra.Trantow
34	34	Pearl7
36	36	Ollie_Ledner37
41	41	Mckenna17
45	45	David.Olszki47
49	49	Morgan.Kassulke
53	53	Linnea59
54	54	Duane60
57	57	Julien_Schmidt
66	66	Mike.Auer39

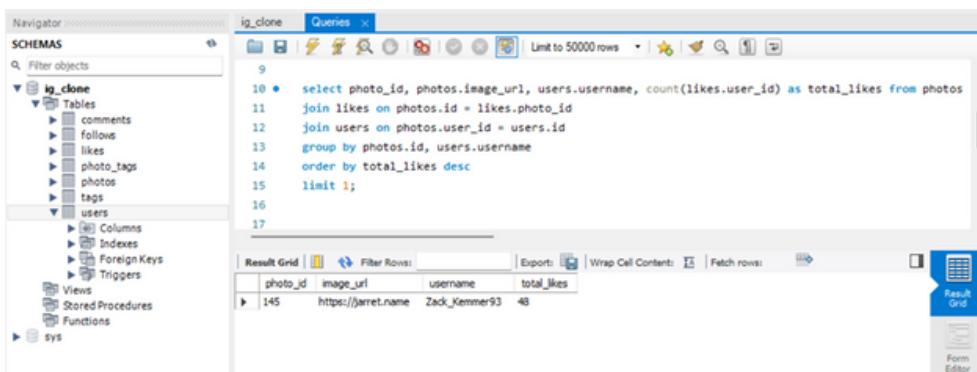


	id	username
49	49	Morgan.Kassulke
53	53	Linnea59
54	54	Duane60
57	57	Julien_Schmidt
66	66	Mike.Auer39
68	68	Franco_Keebler64
71	71	Nia_Haag
74	74	Hulda.Macejkovic
75	75	Leslie67
76	76	Janelle.Nikolaus81
80	80	Darby_Herzog
81	81	Esther.Zulauf61
83	83	Bartholome.Bernhard
89	89	Jessyca_West
90	90	Esmeralda.Mraz57
91	91	Bethany20
*	HULLS	HULLS

Insight - list of users who have never posted a single photo on Instagram this helps team to encourage inactive users to start engaging. The list is given above in the output table.

3. Contest Winner Declaration

We found contest winner by finding the most liked photo from likes table and joining it with photos table that gives as number of likes per photo and then we return the details of user with most liked photos from users table.



The screenshot shows the MySQL Workbench interface. The Navigator pane on the left displays the schema 'ig_clone' with its tables: comments, follows, likes, photo_tags, photos, tags, and users. The Queries pane at the top has a tab labeled 'ig_clone'. Below it is a code editor with the following SQL query:

```
9
10 •    select photo_id, photos.image_url, users.username, count(likes.user_id) as total_likes from photos
11     join likes on photos.id = likes.photo_id
12     join users on photos.user_id = users.id
13     group by photos.id, users.username
14     order by total_likes desc
15     limit 1;
16
17
```

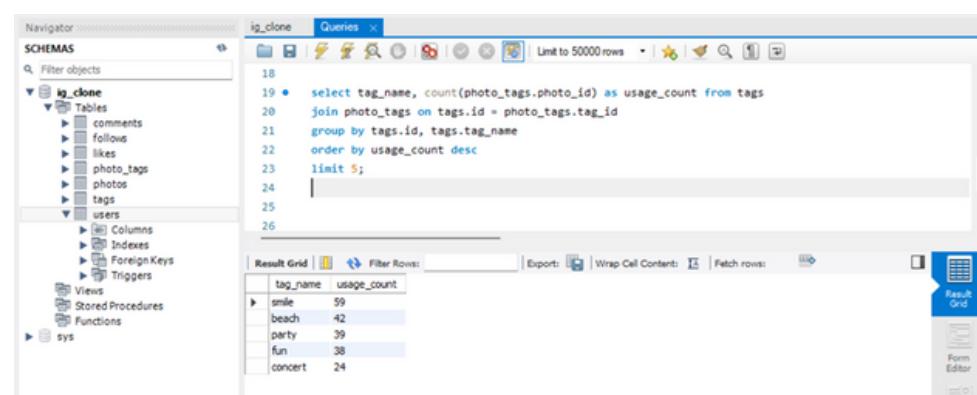
The Result Grid below the code editor shows one row of data:

photo_id	image_url	username	total_likes
145	https://jarret.name	Zack_Kemmer93	48

Insight - found the person who has most likes on the post and identified the details about them. The person is Zack having username Zack_Kemmer93 and he has 48 likes.

4. Hashtag Research

We found five most commonly used photo by accessing photo_tags table where we counted count tags by photo_id from photo_tags table and then ordering it in descending order and finding the top 5 hashtags.



The screenshot shows the MySQL Workbench interface. The Navigator pane on the left displays the schema 'ig_clone' with its tables: comments, follows, likes, photo_tags, photos, tags, and users. The Queries pane at the top has a tab labeled 'ig_clone'. Below it is a code editor with the following SQL query:

```
18
19 •    select tag_name, count(photo_tags.photo_id) as usage_count from tags
20     join photo_tags on tags.id = photo_tags.tag_id
21     group by tags.id, tags.tag_name
22     order by usage_count desc
23     limit 5;
24
25
26
```

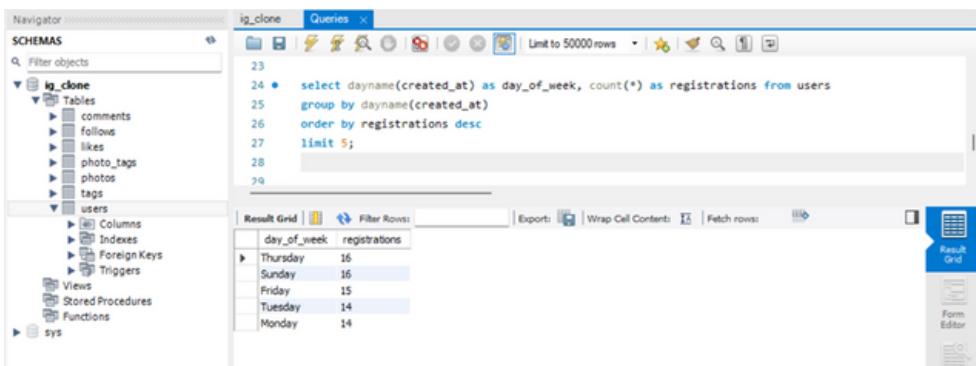
The Result Grid below the code editor shows five rows of data:

tag_name	usage_count
smile	59
beach	42
party	39
fun	38
concert	24

Insight - identified five most used hashtags. This will help the users to maximize their reach on post by using most used hashtags. The hashtags are smile, beach, party, fun and concert.

5. Ad Campaign Launch

We found most users registration from users table where we counted the created_at which is day at which a user created account and then arrange it in descending order and got two most registered days.



The screenshot shows the MySQL Workbench interface. The left pane displays the Navigator with the 'ig_clone' schema selected, showing tables like comments, follows, likes, photo_tags, photos, and tags. The main pane shows a query editor with the following SQL code:

```
23
24 • select dayname(created_at) as day_of_week, count(*) as registrations from users
25 group by dayname(created_at)
26 order by registrations desc
27
28
29
```

The result grid shows the following data:

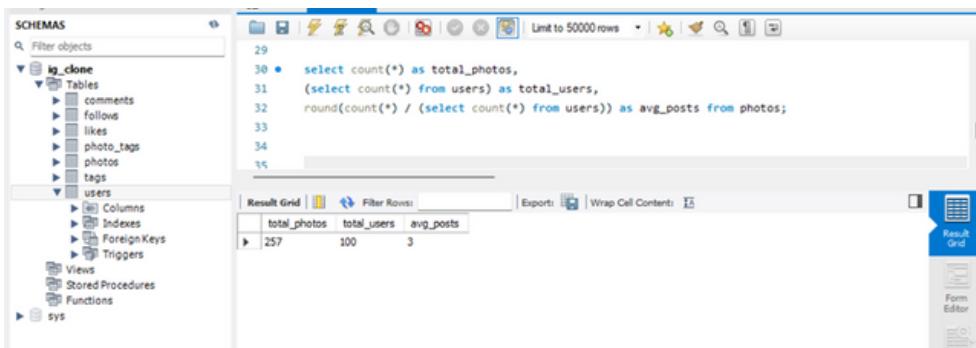
day_of_week	registrations
Thursday	16
Sunday	16
Friday	15
Tuesday	14
Monday	14

Insight - found the day on which the maximum registration was received which will help the team to schedule ad campaign. The days are Thursday and Sunday.

B) Investor Metrics:

1. User Engagement

We found average number of posts per user by finding the count of total photos divided by count of total number of users.



The screenshot shows the MySQL Workbench interface. The left pane displays the Navigator with the 'ig_clone' schema selected, showing tables like comments, follows, likes, photo_tags, photos, and tags. The main pane shows a query editor with the following SQL code:

```
29
30 • select count(*) as total_photos,
31 (select count(*) from users) as total_users,
32 round(count(*) / (select count(*) from users)) as avg_posts from photos;
33
34
35
```

The result grid shows the following data:

total_photos	total_users	avg_posts
257	100	3

Insight -found average number of posts on Instagram which is 3.

2. Bots & Fake Accounts

We found dummy and fake accounts by finding out the user who has liked every single photo we did it by joining user and likes table and counted number of likes per user and compared it with total number of photos and the accounts which were equal are printed.

The screenshot shows a database interface with a 'Queries' tab active. The query is:

```
34 • select users.id, users.username, count(likes.photo_id) as total_likes from users
35 join likes on users.id = likes.user_id
36 group by users.id, users.username
37 having count(likes.photo_id) = (select count(*) from photos);
38
39
```

The results grid displays the following data:

	id	username	total_likes
5	Ananya_Hackett	257	
14	Jadyn81	257	
21	Rocio33	257	
24	MaxwellHalvorson	257	
36	Ollie_Ledner37	257	
41	Mckenna17	257	
54	Duanes60	257	
57	Julien_Schmidt	257	
66	Mike_Auer39	257	
71	Nia_Haag	257	
75	Leslie57	257	
76	Janelle_Nikolaus81	257	
91	Bethany20	257	

Insight – we found user who have liked every post on the site this helps us to understand that the platform is crowded with 13 fake and dummy accounts.

Conclusion Insight

Found that most users who have not posted photos are dummy and fake users.

Result

Through this project we discovered user engagement patterns and behavior which helped us to understand the marketing and investor goals for future Instagram growth. It helped to gain deeper knowledge to analyze the situation and gain more knowledge in SQL querying and relational database.

Project – 3

Operation Analytics and Investigating Metric Spike

Project Description

The project aims to perform operational analytics which helps organizations to analyse their performance and end to end operations. The Job Data Analysis and Investigating Metric Spikes case studies will be used to perform dataset analyses using advanced SQL queries. This will help to extract insights to help decision making in marketing and operations.

Approach

- First we load the dataset provided by importing CSV files using MySQL workbench.
- Then we observe the tables to understand the relationship between each columns and table.
- We then analysed the data as per the situations given by performing optimized SQL queries. It helps to derive key business insights.
- Finally we verify the queries by comparing it to expected outcome and checking its accuracy.

Tech-Stack Used

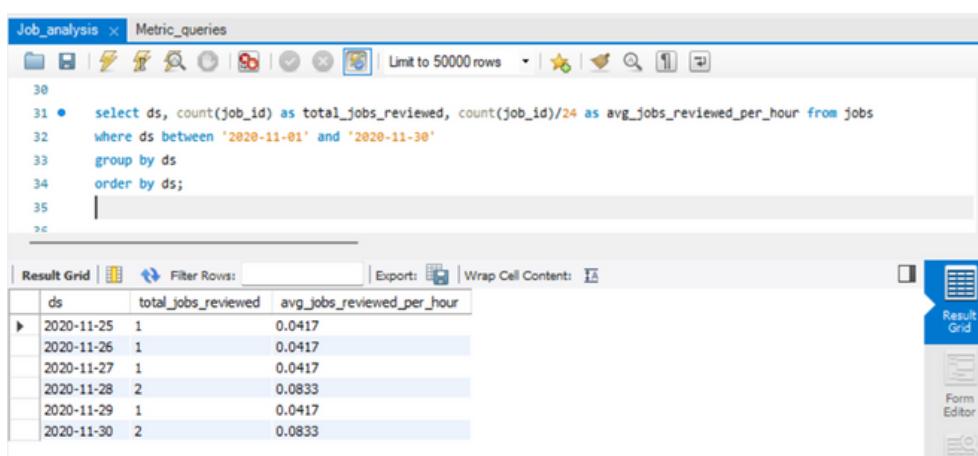
- Used MySQL workbench Version 8.0.41.0 for database management and query execution.
- Excel sheet for data visualization.

Insights

Case Study 1: Job Data Analysis

A.Jobs reviewed over time

We have calculated total number of jobs reviewed per day in November 2020 and the average jobs reviewed per hour by dividing the count by 24. Then it is grouped by date ds and it is then sorted in the ascending order.



The screenshot shows the MySQL Workbench interface with a query editor and a result grid. The query is:

```
30
31 •  select ds, count(job_id) as total_jobs_reviewed, count(job_id)/24 as avg_jobs_reviewed_per_hour from jobs
32  where ds between '2020-11-01' and '2020-11-30'
33  group by ds
34  order by ds;
35
36
```

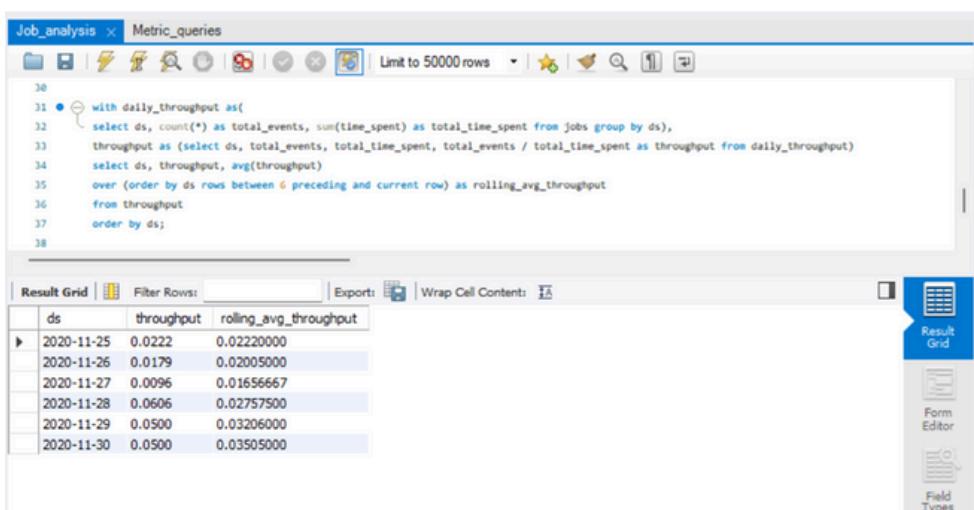
The result grid displays the following data:

ds	total_jobs_reviewed	avg_jobs_reviewed_per_hour
2020-11-25	1	0.0417
2020-11-26	1	0.0417
2020-11-27	1	0.0417
2020-11-28	2	0.0833
2020-11-29	1	0.0417
2020-11-30	2	0.0833

Insights- The above table shows the average jobs reviewed per hour.\

B.Throughput analysis

Daily throughput is calculated by the number of events per total time spent. Then the rolling average throughput is calculated for 7 days considering the current day and previous 6 days. At the end the results are ordered by data ds To have an overview of trends overtime.



The screenshot shows a data analysis interface with a query editor and a result grid. The query is as follows:

```
30
31 • with daily_throughput as(
32     select ds, count(*) as total_events, sum(time_spent) as total_time_spent from jobs group by ds,
33     throughput as (select ds, total_events, total_time_spent, total_events / total_time_spent as throughput from daily_throughput)
34     select ds, throughput, avg(throughput)
35     over (order by ds rows between 6 preceding and current row) as rolling_avg_throughput
36     from throughput
37     order by ds;
38
```

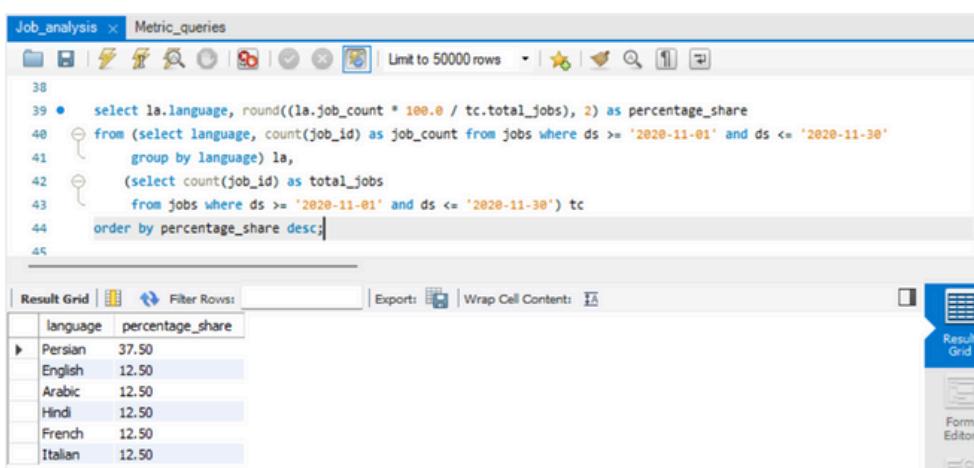
The result grid displays the following data:

ds	throughput	rolling_avg_throughput
2020-11-25	0.0222	0.02220000
2020-11-26	0.0179	0.02005000
2020-11-27	0.0096	0.01656667
2020-11-28	0.0606	0.02757500
2020-11-29	0.0500	0.03206000
2020-11-30	0.0500	0.03505000

Insights - The above table shows the rolling average throughput as per the days.

C.Language share analysis

We have calculated percentage share of each language by counting the number of jobs for each language la and total number of jobs tc. Then we have computed share of each language in percentage by dividing job count to total bs and into 100, then we have rounded it off to two decimal places and at the end we have printed it in descending order.



The screenshot shows a data analysis interface with a query editor and a result grid. The query is as follows:

```
38
39 • select la.language, round((la.job_count * 100.0 / tc.total_jobs), 2) as percentage_share
40     from (select language, count(job_id) as job_count from jobs where ds >= '2020-11-01' and ds <= '2020-11-30'
41             group by language) la,
42     (select count(job_id) as total_jobs
43         from jobs where ds >= '2020-11-01' and ds <= '2020-11-30') tc
44     order by percentage_share desc;
```

The result grid displays the following data:

language	percentage_share
Persian	37.50
English	12.50
Arabic	12.50
Hindi	12.50
French	12.50
Italian	12.50

Insights- The above table shows the percentage of language share and shows that persian has the most percentage share.

D.Duplicate rows detection

We have written this query to identify the duplicate rows in jobs table. We have first grouped the records by columns. We have then counted the number of the group has occurred and then filter it out. We have given the filter to only having more than one occurrence. Through this we are able to find duplicate count.

The screenshot shows a database interface with a query editor and a results grid. The query is:

```
45
46 •  select ds, job_id, actor_id, event, language, time_spent, org, count(*) as duplicate_count from jobs
47   group by ds, job_id, actor_id, event, language, time_spent, org
48   having count(*) > 1;
49
50
51
```

The results grid shows the following columns: ds, job_id, actor_id, event, language, time_spent, org, and duplicate_count. There are no rows present in the grid.

Insights- The above output shows that according to the dataset there is no duplicate rows currently present in the dataset.

Case Study 2: Investigating Metric Spike

A.Weekly user engagement

Here we have aggregated weekly active users by year and month for events which have classified as engagement through this we can extract year and month from the column occurred_at. We have used floor function to calculate the week of the month. Weekly active users are counted by distinct user_id for each week. In the end we have grouped and ordered by year, month and week of month.

```

74
75 •   select year(occurred_at) as year, month(occurred_at) as month,
76     floor((day(occurred_at) - 1) / 7) + 1 as week_of_month,
77     count(distinct user_id) as weekly_active_users
78   from events where event_type = 'engagement'
79   group by year, month, week_of_month
80   order by year, month, week_of_month;

```

year	month	week_of_month	weekly_active_users
2014	5	1	1058
2014	5	2	1068
2014	5	3	1126
2014	5	4	1135
2014	5	5	681
2014	6	1	1186
2014	6	2	1232
2014	6	3	1275
2014	6	4	1264
2014	6	5	416
2014	7	1	1310
2014	7	2	1368

Result 24 x

year	month	week_of_month	weekly_active_users
2014	6	5	416
2014	7	1	1310
2014	7	2	1368
2014	7	3	1373
2014	7	4	1411
2014	7	5	994
2014	8	1	1313
2014	8	2	1233
2014	8	3	1201
2014	8	4	1175
2014	8	5	608

Result 24 x

Insights- The above table shows the weekly active users according to the month.

B. User growth analysis

In this we have retrieved number of users added in each month as an active user and then we have cumulate number of users over time to find user growth. We first have extracted the year and month from the created_at column from user table. To find monthly user we have counted user_id for each month. We have then used sum window function to calculate cumulative total which is ordered by year and month. In the end the result is grouped and ordered by year and month.

The image shows two separate Tableau data sources, both titled "Metric_queries".

Top Source (Year 2013):

```

82 •    select year(created_at) as year, month(created_at) as month, count(user_id) as new_users,
83      sum(count(user_id)) over (order by year(created_at), month(created_at)) as cumulative_users from user
84      group by year, month
85      order by year, month;
86
87
88
  
```

Bottom Source (Years 2013-2014):

year	month	new_users	cumulative_users
2013	10	390	2398
2013	11	399	2797
2013	12	486	3283
2014	1	552	3835
2014	2	525	4360
2014	3	615	4975
2014	4	726	5701
2014	5	779	6480
2014	6	873	7353
2014	7	997	8350
2014	8	1031	9381

Bottom Source Summary:

Result 31 x

Read Only

Insights- The above table shows the number of new users as per the month and then we have added the users to find the growth analysis and 9381 are number of users the growth has been seen.

C. Weekly retention analysis

First to understand we have calculated the overall retention rate of user cohorts over time. By creating subqueries to determine the signup week and activity week for every user. Then the retention_data subquery is used to group user by signup week and then to finally calculate retention rates for each cohort by comparing the number of active users to chort size. Then at the end finally we have calculated the average retention rate across all cohorts.

```

151 •   with user_cohorts as (select user_id, date_format(created_at, '%Y-%u') as signup_week from user),
152   user_activity as (select user_id, date_format(occurred_at, '%Y-%u') as activity_week
153   from events where event_type = 'engagement'),
154
155   retention_data as (
156     select c.signup_week AS cohort_week, a.activity_week,
157     count(distinct c.user_id) as cohort_size, count(distinct a.user_id) as active_users,
158     round(count(distinct a.user_id) * 100.0 / count(distinct c.user_id), 2) as retention_rate
159     from user_cohorts c
160
161     left join user_activity a on c.user_id = a.user_id and a.activity_week >= c.signup_week
162     group by c.signup_week, a.activity_week)
163
164   select round(avg(retention_rate), 2) as overall_retention_rate from retention_data;

```

overall_retention_rate
95.25

Insights- The above output shows that the retention rate is 95.25.

Here we have calculated overall retention rate of users over the time. First we have calculated subqueries first to track user signups second to track activities of users and third retention is made to determine number of retained users per month since signup. Then to find total number of users another query total_users is made. Finally we have calculated overall retention rate by dividing number of retained users by total number of users. Finally we have grouped and ordered the result by months since their signup.

```

126
127 •   with cohort as (select user_id, year(created_at) as signup_year, month(created_at) as signup_month
128   from user),
129
130   activity as (select user_id, year(occurred_at) as activity_year, month(occurred_at) as activity_month
131   from events),
132
133   retention as (
134     select (a.activity_year - c.signup_year) * 12 + (a.activity_month - c.signup_month) as months_since_signup,
135     count(DISTINCT a.user_id) as retained_users from cohort c
136
137     left join activity a on c.user_id = a.user_id
138     where (a.activity_year - c.signup_year) * 12 + (a.activity_month - c.signup_month) >= 0
139     group by months_since_signup),

```

Job_analysis Metric_queries

```

135 count(DISTINCT a.user_id) as retained_users from cohort c
136
137 left join activity a on c.user_id = a.user_id
138 where (a.activity_year - c.signup_year) * 12 + (a.activity_month - c.signup_month) >= 0
139 group by months_since_signup,
140 total_users as (select count(distinct user_id) as total_users from user)
141
142 select r.months_since_signup, r.retained_users, t.total_users,
143 round ((r.retained_users / t.total_users) * 100, 2) as overall_retention_rate from retention r
144
145 cross join total_users t
146 order by r.months_since_signup;
147
148

```

Result Grid | Filter Rows: Export: Wrap Cell Content:

months_since_signup	retained_users	total_users	overall_retention_rate
0	3680	9381	39.23
1	1699	9381	18.11
2	701	9381	7.47
3	587	9381	6.26
4	540	9381	5.76
5	480	9381	5.12

Result 44 x Read Only

140 total_users as (select count(distinct user_id) as total_users from user)

Result Grid | Filter Rows: Export: Wrap Cell Content:

months_since_signup	retained_users	total_users	overall_retention_rate
5	480	9381	5.12
6	415	9381	4.42
7	365	9381	3.89
8	325	9381	3.46
9	335	9381	3.57
10	281	9381	3.00
11	251	9381	2.68
12	218	9381	2.32
13	187	9381	1.99
14	187	9381	1.99
15	182	9381	1.94
16	169	9381	1.80
17	119	9381	1.27
18	69	9381	0.74
19	29	9381	0.31

Result 44 x Read Only

Insights- The above table shows the retention rate as per the month since signup which will help to understand when the retention rate was high.

Here we have aimed to calculate retention time. By first creating subqueries to calculate cohort for tracking user signups then activity to track activities done by users and finally retention to calculate number of retained users per cohort. After this we have join the retention and cohort to obtain cohort size and then calculate retention rate which is obtained by dividing retained users by cohort size. Finally the result are then grouped and ordered by signup year and month and then months since signup.

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

signup_year	signup_month	signup_month_name	months_since_signup	retained_users	cohort_size	retention_rate
2013	3	March	17	33	150	22.00
2013	4	April	13	51	181	28.18
2013	4	April	14	55	181	30.39
2013	4	April	15	52	181	28.73
2013	4	April	16	45	181	24.86
2013	5	May	12	50	214	23.36
2013	5	May	13	45	214	21.03
2013	5	May	14	56	214	26.17
2013	5	May	15	40	214	18.69
2013	6	June	11	45	213	21.13
2013	6	June	12	41	213	19.25
2013	6	June	13	52	213	24.41
2013	6	June	14	37	213	17.37
2013	7	July	10	66	284	23.24
2013	7	July	11	**	**	**
2013	7	July	12	**	**	**
2013	7	July	13	39	284	13.73
2013	8	August	9	86	316	27.22
2013	8	August	10	79	316	25.00
2013	8	August	11	82	316	25.95
2013	8	August	12	61	316	19.30
2013	9	September	8	69	330	20.91
2013	9	September	9	82	330	24.85
2013	9	September	10	72	330	21.82
2013	9	September	11	60	330	18.18
2013	10	October	7	87	390	22.31
2013	10	October	8	**	**	**
2013	10	October	9	**	**	**
2013	10	October	10	64	390	16.41
2013	11	November	6	80	399	20.05
2013	11	November	7	88	399	22.06
2013	11	November	8	100	399	25.06
2013	11	November	9	72	399	18.05
2013	12	December	5	108	486	22.22
2013	12	December	6	106	486	21.81
2013	12	December	7	99	486	20.37
2013	12	December	8	65	99	13.37
2014	1	January	4	128	552	23.19
2014	1	January	5	120	552	21.74
2014	1	January	6	**	**	**
2014	1	January	7	91	552	16.49
2014	2	February	3	136	525	25.90
2014	2	February	4	126	525	24.00
2014	2	February	5	129	525	24.57
2014	2	February	6	94	525	17.90
2014	3	March	2	182	615	29.59
2014	3	March	3	141	615	22.93
2014	3	March	4	160	615	26.02
2014	3	March	5	123	615	20.00
2014	4	April	1	379	726	52.20
2014	4	April	2	168	726	23.14
2014	4	April	3	100	726	21.17

Result 41 x Read Only

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

signup_year	signup_month	signup_month_name	months_since_signup	retained_users	cohort_size	retention_rate
2013	6	June	14	37	213	17.37
2013	7	July	10	66	284	23.24
2013	7	July	11	64	284	22.54
2013	7	July	12	66	284	23.24
2013	7	July	13	39	284	13.73
2013	8	August	9	86	316	27.22
2013	8	August	10	79	316	25.00
2013	8	August	11	82	316	25.95
2013	8	August	12	61	316	19.30
2013	9	September	8	69	330	20.91
2013	9	September	9	82	330	24.85
2013	9	September	10	72	330	21.82
2013	9	September	11	60	330	18.18
2013	10	October	7	87	390	22.31
2013	10	October	8	**	**	**
2013	10	October	9	**	**	**
2013	10	October	10	64	390	16.41
2013	11	November	6	80	399	20.05
2013	11	November	7	88	399	22.06
2013	11	November	8	100	399	25.06
2013	11	November	9	72	399	18.05
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2013	12	December	6	106	486	21.81
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2013	12	December	8	65	99	13.37
2014	1	January	4	128	552	23.19
2014	1	January	5	120	552	21.74
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2014	1	January	7	91	552	16.49
2014	2	February	3	136	525	25.90
2014	2	February	4	126	525	24.00
2014	2	February	5	129	525	24.57
2014	2	February	6	94	525	17.90
2014	3	March	2	182	615	29.59
2014	3	March	3	141	615	22.93
2014	3	March	4	160	615	26.02
2014	3	March	5	123	615	20.00
2014	4	April	1	379	726	52.20
2014	4	April	2	168	726	23.14
2014	4	April	3	100	726	21.17

Result 41 x Read Only

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

signup_year	signup_month	signup_month_name	months_since_signup	retained_users	cohort_size	retention_rate
2013	10	October	7	87	390	22.31
2013	10	October	8	91	390	23.33
2013	10	October	9	95	390	24.36
2013	10	October	10	64	390	16.41
2013	11	November	6	80	399	20.05
2013	11	November	7	88	399	22.06
2013	11	November	8	100	399	25.06
2013	11	November	9	72	399	18.05
2013	12	December	5	108	486	22.22
2013	12	December	6	106	486	21.81
2013	12	December	7	99	486	20.37
2013	12	December	8	65	99	13.37
2014	1	January	4	128	552	23.19
2014	1	January	5	120	552	21.74
2014	1	January	6	135	552	24.46
2014	1	January	7	91	552	16.49
2014	2	February	3	136	525	25.90
2014	2	February	4	126	525	24.00
2014	2	February	5	129	525	24.57
2014	2	February	6	94	525	17.90
2014	3	March	2	182	615	29.59
2014	3	March	3	141	615	22.93
2014	3	March	4	160	615	26.02
2014	3	March	5	123	615	20.00
2014	4	April	1	379	726	52.20
2014	4	April	2	168	726	23.14
2014	4	April	3	100	726	21.17

Result 41 x Read Only

Result Grid | Filter Rows: | Export: | Wrap Cell Content:

signup_year	signup_month	signup_month_name	months_since_signup	retained_users	cohort_size	retention_rate
2014	1	January	4	128	552	23.19
2014	1	January	5	120	552	21.74
2014	1	January	6	135	552	24.46
2014	1	January	7	91	552	16.49
2014	2	February	3	136	525	25.90
2014	2	February	4	126	525	24.00
2014	2	February	5	129	525	24.57
2014	2	February	6	94	525	17.90
2014	3	March	2	182	615	29.59
2014	3	March	3	141	615	22.93
2014	3	March	4	160	615	26.02
2014	3	March	5	123	615	20.00
2014	4	April	1	379	726	52.20
2014	4	April	2	168	726	23.14
2014	4	April	3	100	726	21.17

Result 41 x Read Only

Insights- The table shows the retention rate as per the month and according to the month since sign up which helps to understand in which month and for how days until signup has retention rate.

D. Weekly engagement per device

Here first to understand we have counted number of engagement events for each type of device. Then the result is grouped by device and is then ordered by engagement count to arrange in descending order to see the most used devices first.

The screenshot shows a data analysis interface with two result grids. The top grid displays the total engagement count for various devices, ordered by engagement_count in descending order. The bottom grid displays the average weekly engagement count for the same devices, also ordered by average weekly engagement in descending order. Both grids include a sidebar with navigation links for Result Grid, Form Editor, Field Types, and Query Stats.

device	engagement_count
macbook pro	57295
lenovo thinkpad	36978
macbook air	26786
iphone 5	25883
dell inspiron notebook	19669
samsung galaxy s4	18653
nexus 5	16502
iphone 5s	15929
dell inspiron desktop	10141
iphone 4s	9615
asus chromebook	9542
ipad air	9469
acer aspire notebook	8930
hp pavilion desktop	8881
nexus 7	6540
nokia lumia 635	5612
ipad mini	5501

device	average weekly engagement
nexus 7	6540
nokia lumia 635	5612
ipad mini	5591
acer aspire desktop	5173
nexus 10	5139
mac mini	4454
htc one	4276
kindle fire	4090
windows surface	3451
samsung galaxy note	2677
amazon fire phone	2168
samsung galaxy tablet	1811

Insights- The table above table shows the total engagement count of users per device.

Here we have calculated average weekly engagement for every device. First we have created weekly _engagement subquery to group events by device, year and week. It is done to count engagement. Then we have averaged out the weekly engagement counts for each device. At the end we have ordered it by average weekly engagement in descending order.

Job_analysis Metric_queries

```

156
157 • ⊖ with weekly_engagements as (
158     select device, year(occurred_at) as year, week(occurred_at, 1) as week, count(*) as engagement_count
159     from events
160
161     group by device, year(occurred_at), week(occurred_at, 1))
162
163     select device, avg(engagement_count) as avg_weekly_engagement
164     from weekly_engagements
165
166     group by device
167     order by avg_weekly_engagement desc;
168

```

Result Grid | Filter Rows: Export: Wrap Cell Content: Result Grid Form Editor Field Types Query Stats Read Only

device	avg_weekly_engagement
macbook pro	3183.0556
lenovo thinkpad	2054.3333
macbook air	1488.1111
iphone 5	1437.9444
dell inspiron notebook	1092.7222
samsung galaxy s4	1036.2778
nexus 5	916.7778
iphone 5s	884.9444

Result 63 x

Result Grid | Filter Rows: Export: Wrap Cell Content: Result Grid Form Editor Field Types Query Stats Read Only

device	avg_weekly_engagement
macbook pro	3183.0556
lenovo thinkpad	2054.3333
macbook air	1488.1111
iphone 5	1437.9444
dell inspiron notebook	1092.7222
samsung galaxy s4	1036.2778
nexus 5	916.7778
iphone 5s	884.9444
dell inspiron desktop	563.3889
phone 4s	534.1667
asus chromebook	530.1111
ipad air	526.0556
acer aspire notebook	496.1111
hp pavilion desktop	493.3889
nexus 7	363.3333
nokia lumia 635	311.7778
ipad mini	310.6111

Result 63 x

Result Grid | Filter Rows: Export: Wrap Cell Content: Result Grid Form Editor Field Types Query Stats Read Only

device	avg_weekly_engagement
asus chromebook	530.1111
ipad air	526.0556
acer aspire notebook	496.1111
hp pavilion desktop	493.3889
nexus 7	363.3333
nokia lumia 635	311.7778
ipad mini	310.6111
acer aspire desktop	287.3889
nexus 10	285.5000
mac mini	247.4444
htc one	237.5556
kindle fire	227.2222
windows surface	191.7222
samsung galaxy note	148.7222
amazon fir phone	120.4444
samsung galaxy tablet	100.6111

Result 63 x

Insights- The above table shows the average user engagement per week. This will help to understand the growth and take operational decision.

In this we have calculated number of engagement events for each device on weekly basis. Then we have grouped the data by device, year and week. After that number of engagements for each group is counted. At the end the result is ordered by year, device and week to observe the trend of engagement over the time period for each device.

Job_analysis Metric_queries

```
151
152 •  select device, year(occurred_at) as year, week(occurred_at, 1) as week, count(*) as engagement_count
153   from events
154   group by device, year(occurred_at), week(occurred_at, 1)
155   order by device, year, week;
156
```

Result Grid | Filter Rows: Export: Wrap Cell Content: Result Grid Form Editor Field Types Query Stats Read Only

device	year	week	engagement_count
acer aspire desktop	2014	18	71
acer aspire desktop	2014	19	300
acer aspire desktop	2014	20	252
acer aspire desktop	2014	21	228
acer aspire desktop	2014	22	318
acer aspire desktop	2014	23	261
acer aspire desktop	2014	24	258
acer aspire desktop	2014	25	279
acer aspire desktop	2014	26	278
acer aspire desktop	2014	27	308
acer aspire desktop	2014	28	326
acer aspire desktop	2014	29	268
acer aspire desktop	2014	30	231
acer aspire desktop	2014	31	408
acer aspire desktop	2014	32	370
acer aspire desktop	2014	33	377

Result 58 x

Result Grid | Filter Rows: Export: Wrap Cell Content: Result Grid Form Editor Field Types Query Stats Read Only

device	year	week	engagement_count
acer aspire desktop	2014	33	377
acer aspire desktop	2014	34	362
acer aspire desktop	2014	35	278
acer aspire notebook	2014	18	215
acer aspire notebook	2014	19	386
acer aspire notebook	2014	20	399
acer aspire notebook	2014	21	487
acer aspire notebook	2014	22	480
acer aspire notebook	2014	23	407
acer aspire notebook	2014	24	474
acer aspire notebook	2014	25	526
acer aspire notebook	2014	26	599
acer aspire notebook	2014	27	327
acer aspire notebook	2014	28	605
acer aspire notebook	2014	29	590
acer aspire notebook	2014	30	539

Result 58 x

Result Grid | Filter Rows: Export: Wrap Cell Content: Read Only

device	year	week	engagement_count
acer aspire notebook	2014	30	539
acer aspire notebook	2014	31	662
acer aspire notebook	2014	32	554
acer aspire notebook	2014	33	604
acer aspire notebook	2014	34	482
acer aspire notebook	2014	35	594
amazon fire phone	2014	18	84
amazon fire phone	2014	19	179
amazon fire phone	2014	20	149
amazon fire phone	2014	21	104
amazon fire phone	2014	22	26
amazon fire phone	2014	23	48
amazon fire phone	2014	24	193
amazon fire phone	2014	25	145
amazon fire phone	2014	26	125
amazon fire phone	2014	27	137

Result 58 × Read Only

Result Grid | Filter Rows: Export: Wrap Cell Content: Read Only

device	year	week	engagement_count
asus chromebook	2014	24	704
asus chromebook	2014	25	442
asus chromebook	2014	26	461
asus chromebook	2014	27	609
asus chromebook	2014	28	528
asus chromebook	2014	29	547
asus chromebook	2014	30	570
asus chromebook	2014	31	494
asus chromebook	2014	32	677
asus chromebook	2014	33	590
asus chromebook	2014	34	616
asus chromebook	2014	35	563
dell inspiron desktop	2014	18	198
dell inspiron desktop	2014	19	700
dell inspiron desktop	2014	20	426
dell inspiron desktop	2014	21	516

Result 58 × Read Only

Insights- The above table shows the number of engagement count per week according to the sign up week and according to the device.

E.Email engagement analysis

In this we have exam

Result Grid | Filter Rows: Export: Wrap Cell Content: Read Only

device	year	week	engagement_count
amazon fire phone	2014	27	137
amazon fire phone	2014	28	109
amazon fire phone	2014	29	52
amazon fire phone	2014	30	94
amazon fire phone	2014	31	185
amazon fire phone	2014	32	147
amazon fire phone	2014	33	163
amazon fire phone	2014	34	117
amazon fire phone	2014	35	111
asus chromebook	2014	18	286
asus chromebook	2014	19	498
asus chromebook	2014	20	286
asus chromebook	2014	21	467
asus chromebook	2014	22	565
asus chromebook	2014	23	639
asus chromebook	2014	24	704

Result 58 × Read Only

ine email events to determine unique users and number of actions for each action type. Then we have counted total number of occurrences of each action as action_count. Unique_users are printed as distinct users performing each action. At the end the results are grouped and ordered by action count in descending order as to see most frequent actions first in place.

```
1/8
179 •  select action, count(*) as action_count, count(distinct user_id) as unique_users
180   from emailevents
181   group by action
182   order by action_count desc;
183
184
```

The screenshot shows a database query editor with a results grid. The query counts the number of actions and the number of unique users for each action type. The results are as follows:

action	action_count	unique_users
sent_weekly_digest	57267	4111
email_open	20459	5927
email_clickthrough	9010	5277
sent_reengagement_email	3653	3653

Insights – The above table shows the total count of action of email as per user. The action is counted per user and the unique user. This will help to analyse the email engagement and it would be helpful to analyse the email performance.

Here we have analyzed user engagement of email events dataset. Here we have extracted occurred_at for month and year. Then they are grouped by month-year and action. For each group the number of distinct engaged users, engagement rate and total actions are calculated. And they are ordered by month year and action.

The screenshot shows a database query editor with a results grid. The query extracts the month and year from the occurred_at timestamp, groups by month-year and action, and calculates the number of engaged users, total actions, and engagement rate. The results are as follows:

month_year	action	engaged_users	total_actions	engagement_rate
2014-August	email_clickthrough	1804	1992	29.20
2014-August	email_open	3879	5978	62.78
2014-August	sent_reengagement_email	1073	1073	17.37
2014-August	sent_weekly_digest	4111	16480	66.53
2014-July	email_clickthrough	2267	2721	36.69
2014-July	email_open	3457	5611	55.95
2014-July	sent_reengagement_email	933	933	15.10
2014-July	sent_weekly_digest	3685	15902	59.64
2014-June	email_clickthrough	1915	2274	30.99
2014-June	email_open	3037	4658	49.15
2014-June	sent_reengagement_email	889	889	14.39
2014-June	sent_weekly_digest	3231	13155	52.29
2014-May	email_clickthrough	1703	2023	27.56
2014-May	email_open	2681	4212	43.39
2014-May	sent_reengagement_email	769	769	17.77

Insights- the above table shows the action and according to that total actions are given to find engagement rate is given. It helps to increase the performance of email as a platform.

Result

Through this project we learned to analyse the operations related to retention, user engagement, user activity and email interactions. Using MySQL workbench we found:

- User growth per month of new users
- Retention rate based on sign up cohorts weekly
- Usage of device per active user
- Average weekly activity engagement per device
- User monthly growth analysis
- Email engagement with email services

It helped to gain deeper knowledge to analyze the situation and gain more knowledge in SQL querying and relational database.

Project – 4

Hiring Process

Analytics

Project Description

This project aims to analyse the hiring process within an organization. Here in this project we have analysed gender distribution, salary analyses, salary distribution understanding, department properties visualization and position tier distribution visualization. In conclusion we have gained insights into company's salary structure and hiring trends using excel as data analytics tool.

Approach

- Dataset was downloaded and imported into Microsoft excel
- Ensured dataset was clean and free of missing values
- Then we started with analysis using pivot tables and its function.
- For gender distribution we used pivot tables to count and compare the number of females and males hired.
- For salary analysis we calculated average salary using pivot tables.
- Then for salary distribution we used if function to first form salary range column and then by using pivot table we calculated the salary distribution.
- Then we analysed proportion of employees in different departments using pivot graphs and we plot the pie chart to show the distribution.
- To show the position tier analysis we used pivot graph to the position across different tiers using bar graph.

Tech-Stack Used

Microsoft® Word 2019 MSO (Version 2501 Build 16.0.18429.20132) 64-bit for data analysis, pivot table creation and chart generation.

Insights

A.Hiring Analysis

Analysed proportion of males and females hired. Here 2675 female and 4085 males are hired revealing the gender imbalances.

A screenshot of Microsoft Excel showing a PivotTable titled "Gender Distribution". The PivotTable Fields pane on the right shows the fields: application_id, Interview Taken on, Status, event_name (selected), Department, and Post Name. The Rows area is set to "event_name" and the Values area is set to "Gender Distribution". The data in the PivotTable is as follows:

	Gender Distribution
Don't want to say	393
Female	2675
Male	4085
Grand Total	7153

B.Salary Analysis

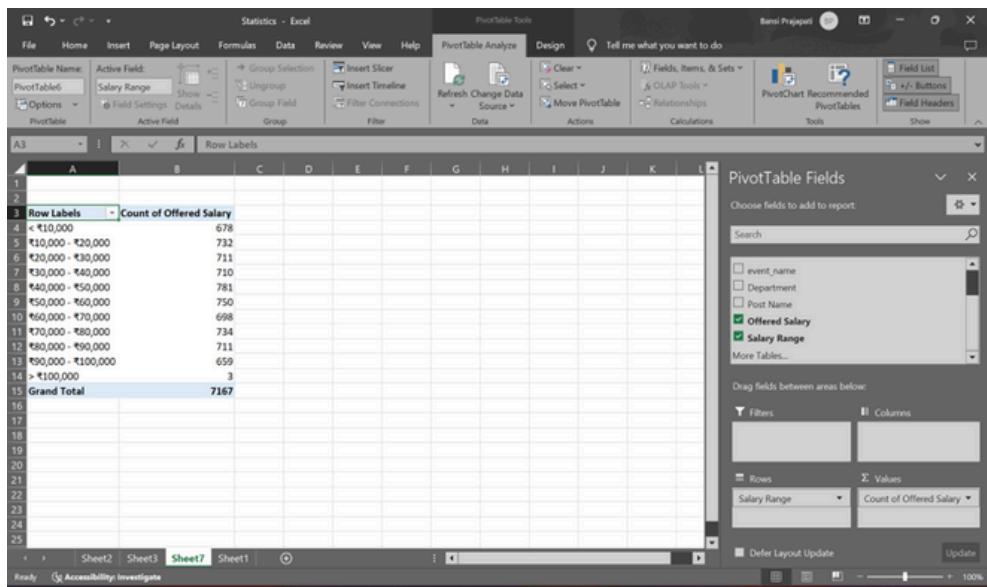
Average salary offered by the company is 49983/-.

A screenshot of Microsoft Excel showing a PivotTable titled "Average of Offered Salary". The PivotTable Fields pane on the right shows the fields: Status, event_name, Department, Post Name, and Offered Salary (selected). The Rows area is set to "Offered Salary" and the Values area is set to "Average of Offered Sal". The data in the PivotTable is as follows:

	Average of Offered Salary
	49983.02902

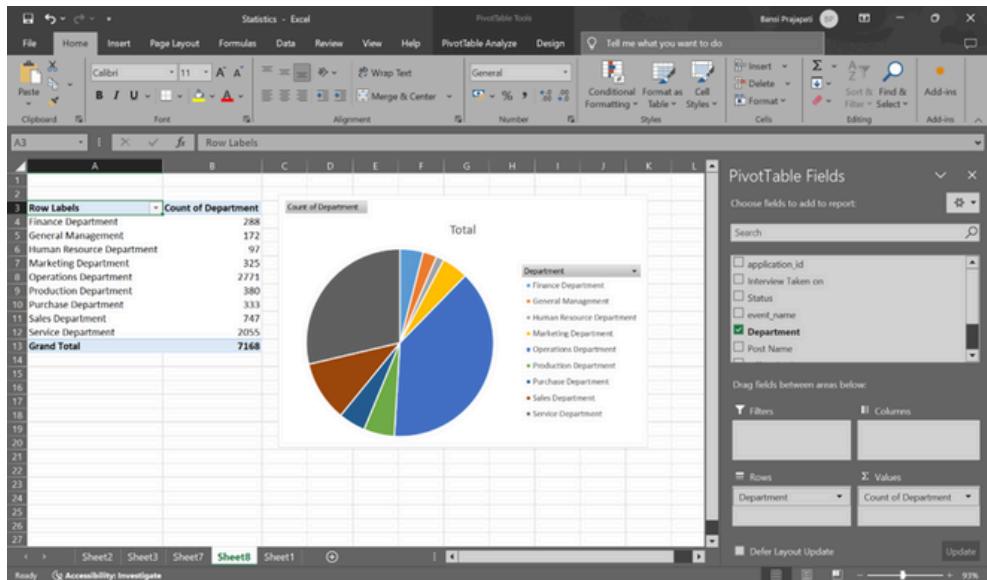
C.Salary Distribution

Visualized how salaries are distributed across different intervals. Here most people have salaries between 40,000-50,000. Which also tells that it is average salary among the company.



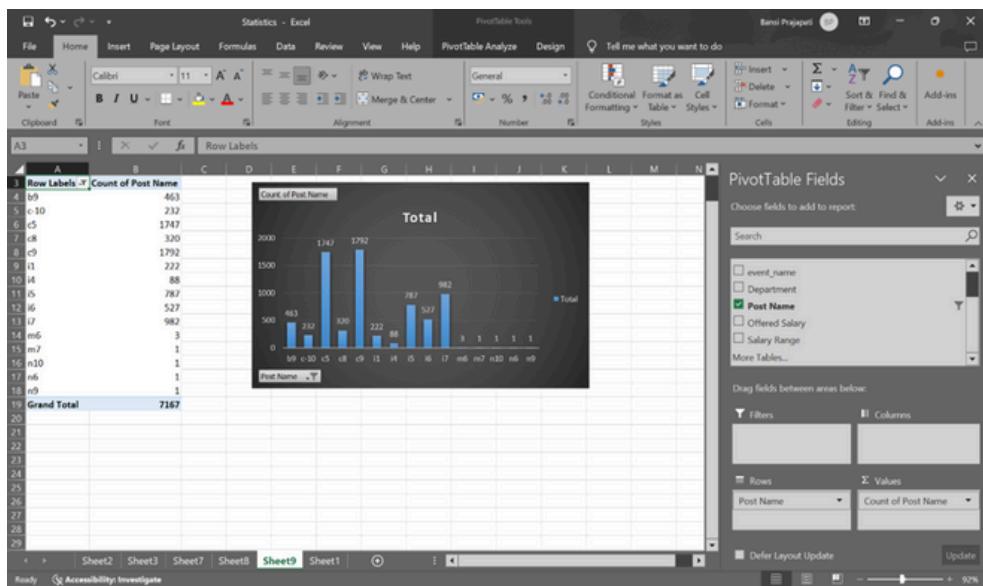
D. Departmental Analysis

Identified that operation department has most employees and human resource department has least number of employees.



E. Position Tier Analysis

Examined distribution of positions among the various tiers and it shows that c9 has most positions in company's hierarchical structure.



Result

In this project we were able to derive key trends and patterns in salary structure, gender distribution and departmental composition. This insights help HR and management team to take an informed decisions regarding the salary adjustments, hiring practices and departmental resource allocation. Hence project helps to provide comprehensive understanding of hiring process within organization.

Drive link of Excel Sheet

Refer sheet 2, 3, 7, 8, 9 for the answers.

[https://docs.google.com/spreadsheets/d/17NBk8-FEd5TLBjCXOQkAX5PN4gKKA-jf/edit?](https://docs.google.com/spreadsheets/d/17NBk8-FEd5TLBjCXOQkAX5PN4gKKA-jf/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

Project – 5

IMDB Movie Analysis

Project Description

This project aims to investigate "What factors influence the success of a movie on IMDB?" Here in this project we will analyze movie genre, duration, language, director and budget analysis defined by high IMDB ratings. This analysis is crucial for movie producers, directors, and investors to make informed decisions regarding future projects.

Approach

- Dataset was downloaded and imported into Microsoft excel
- Ensured dataset was clean and free of missing values
- Then we started with analysis using pivot tables and its function.
- For genre analysis we calculated no_of_movies, mean_imdb, max_imdb, min_imdb, StdDev_imdb and var_imdb from pivot table function and we derived the median_imdb, mode_imdb and range_imdb using function in excel sheet.
- Then we generated graph of no_of_movies v/s genre to understand the distribution and a line graph of imdb_score v/s genre to see the trend between there descriptive statistical function.
- For movie duration analysis we analyze the distribution of movie durations and identify the relationship between movie duration and IMDB score using the scatter plot and by observing the trend line.
- For language analysis we have determined the most common languages used in movies and analyzed their impact on the IMDB score using descriptive statistics.
- For director analysis we have calculated the average IMDB score for each director. Used excel's percentile function to identify the directors with the highest scores. Then we compared the scores of these directors to the overall distribution of scores.
- For budget analysis we calculated the correlation coefficient between movie budgets and gross earnings using excel's correl function. Then we calculated the profit margin for each movie and identified the movies with the highest profit margin using excel's max function.

Tech Stack Used

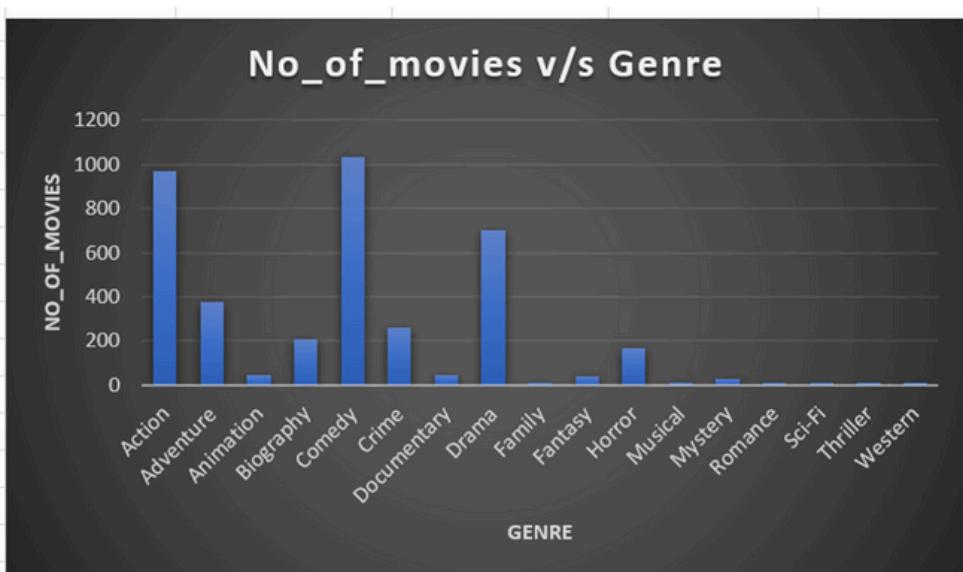
Microsoft® Word 2019 MSO (Version 2501 Build 16.0.18429.20132) 64-bit for data analysis, pivot table creation and chart generation.

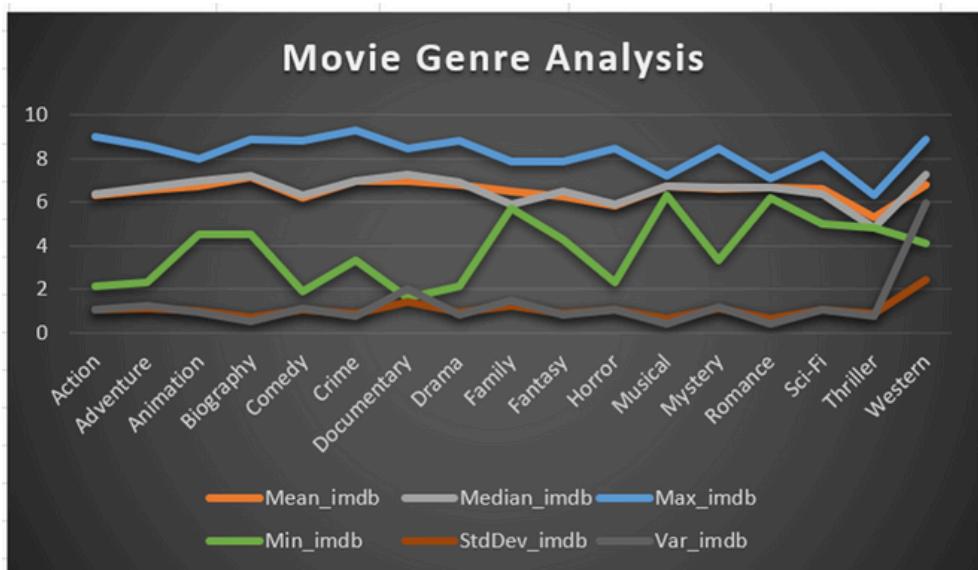
Insights

A. Movie Genre Analysis:

- Most common movie genre includes comedy with 1036 no. of movies and then action, drama and adventure with 9770, 700 and 378 no. of movies respectively.
- Least common genres include musical, romance, thriller and western.
- Highest mean imdb score is of biography, documentary and crime.
- #N/A appears when no single rating appers more than once in that genre.
- Documentary is having most rating of 7.5 which is highest and most repeated.
- The highest rated movie is having crime genre with 9.3 imdb score and lowest rated movie is genre having action and horror with 2.1 imdb score.
- Higher standard deviation means more unpredictable in audience reception.
- Western movies have most inconsistent ratings while animation and musical movies tend to have stable ratings.

Genre	No_of_movies	Mean_imdb	Median_imdb	Mode_imdb	Max_imdb	Min_imdb	Range_imdb	StdDev_imdb	Var_imdb
Action	970	6.290618557	6.35	6.6	9	2.1	6.9	1.038020576	1.07748672
Adventure	378	6.555291005	6.7	7.3	8.6	2.3	6.3	1.114308219	1.24168281
Animation	46	6.763043478	7	7.1	8	4.5	3.5	0.972593028	0.9459372
Biography	208	7.153846154	7.2	7	8.9	4.5	4.4	0.696564805	0.48520253
Comedy	1036	6.166409266	6.3	6.4	8.8	1.9	6.9	1.040657096	1.08296719
Crime	259	6.944787645	7	7.4	9.3	3.3	6	0.864548238	0.74744366
Documentary	43	6.951162791	7.3	7.5	8.5	1.6	6.9	1.41612686	2.00541528
Drama	700	6.814428571	6.9	6.7	8.8	2.1	6.7	0.905146841	0.8192908
Family	3	6.5	5.9	#N/A	7.9	5.7	2.2	1.216552506	1.48
Fantasy	37	6.281081081	6.5	6.8	7.9	4.3	3.6	0.894066191	0.79935435
Horror	165	5.850909091	5.9	5.9	8.5	2.3	6.2	1.032083979	1.06519734
Musical	2	6.75	6.75	#N/A	7.2	6.3	0.9	0.636396103	0.405
Mystery	24	6.608333333	6.7	7.1	8.5	3.3	5.2	1.0898411	1.18775362
Romance	2	6.65	6.65	#N/A	7.1	6.2	0.9	0.636396103	0.405
Sci-Fi	8	6.5875	6.35	#N/A	8.2	5	3.2	1.031555691	1.06410714
Thriller	3	5.3	4.8	4.8	6.3	4.8	1.5	0.866025404	0.75
Western	3	6.766666667	7.3	#N/A	8.9	4.1	4.8	2.444040371	5.97333333

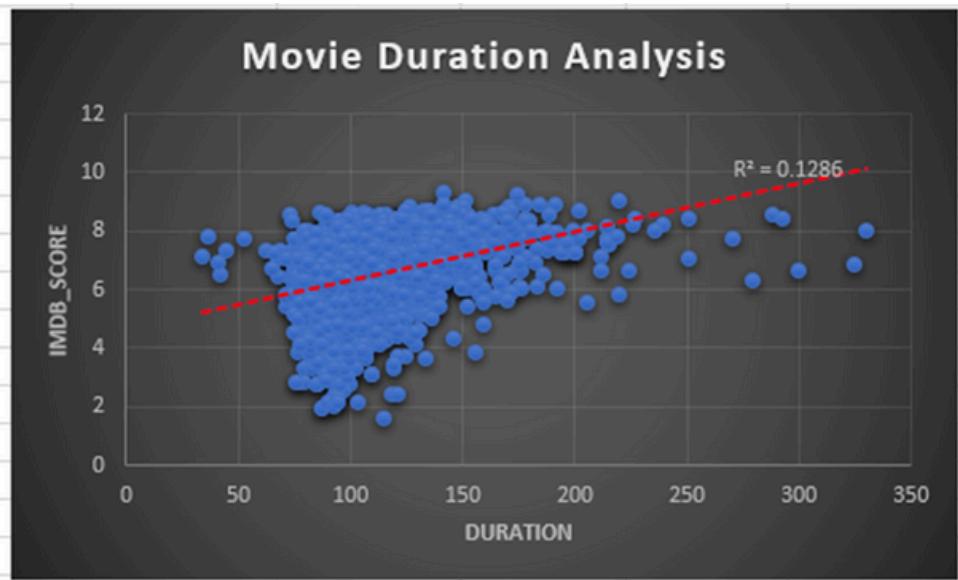




B.Movie Duration Analysis:

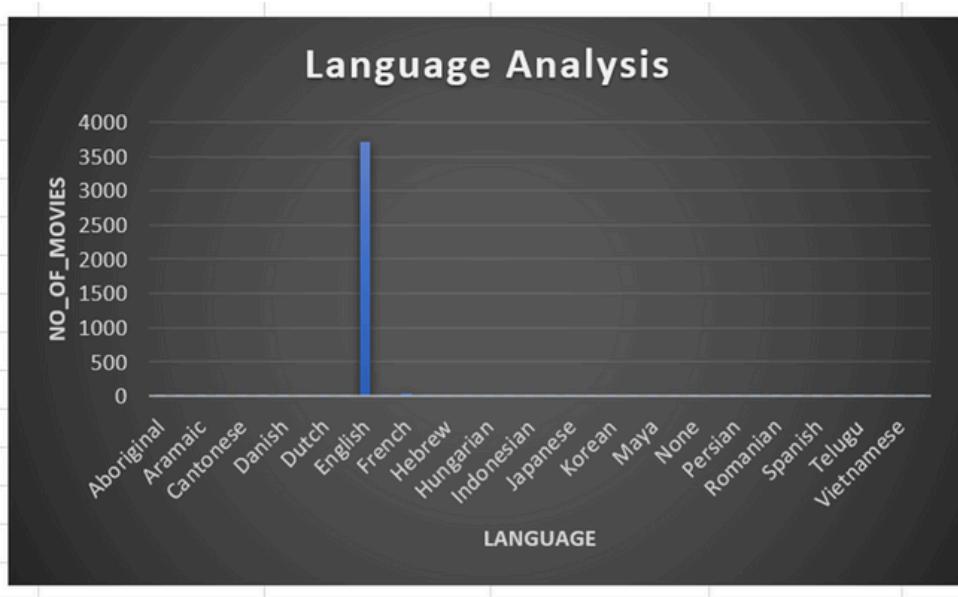
- The scatter plot shows positive correlation between movie duration and IMDB score.
- The R² value shows that the impact of duration of a movie has less impact on IMDB score and it is not a strong predictor.
- Most movies have duration around 100-110 minutes.
- Longer movies might tend to have slightly higher ratings, but duration only cannot determine IMDB score.

Operations	Values
Mean	109.901981
Median	106
Mode	101
Standard Devat	22.7125612
Variance	515.8604361



C. Language Analysis:

- With 3706 movies English is the dominating language.
- English movies have mean of 6.42 of imbd score which is lower it might be due larger dataset that contains both high and low rated movies.
- In conclusion we can observed that smaller language dataset might be biased towards high quality films, while English movies would cover wider spectrum including lower rated films.



Language	No_of_Movies	Average_imdb	Median_imdb	Var_imdb	StdDev_imdb
Aboriginal	2	6.95	6.95	0.605	0.777817459
Arabic	1	7.2	7.2	#DIV/0!	#DIV/0!
Aramaic	1	7.1	7.1	#DIV/0!	#DIV/0!
Bosnian	1	4.3	4.3	#DIV/0!	#DIV/0!
Cantonese	8	7.2375	7.3	0.194107143	0.440575922
Czech	1	7.4	7.4	#DIV/0!	#DIV/0!
Danish	3	7.9	8.1	0.28	0.529150262
Dari	2	7.5	7.4	0.542205882	0.736346306
Dutch	3	7.566666667	7.8	0.163333333	0.404145188
Dzongkha	1	7.5	7.5	#DIV/0!	#DIV/0!
English	3706	6.42172619	6.5	1.104471754	1.050938511
Filipino	1	6.7	6.7	#DIV/0!	#DIV/0!
French	37	7.286486486	7.2	0.31509009	0.561328861
German	13	7.692307692	7.7	0.410769231	0.640912811
Hebrew	3	7.5	7.3	0.19	0.435889894
Hindi	10	6.76	7.05	1.236	1.111755369
Hungarian	1	7.1	7.1	#DIV/0!	#DIV/0!
Icelandic	1	6.9	6.9	#DIV/0!	#DIV/0!
Indonesian	2	7.9	7.9	0.18	0.424264069
Italian	7	7.185714286	7	1.334761905	1.155318962
Japanese	12	7.625	7.8	0.809318182	0.899621132
Kazakh	1	6	6	#DIV/0!	#DIV/0!
Korean	5	7.7	7.7	0.325	0.570087713
Mandarin	15	7.08	7.4	0.596	0.772010363
Maya	1	7.8	7.8	#DIV/0!	#DIV/0!
Mongolian	1	7.3	7.3	#DIV/0!	#DIV/0!
None	1	8.5	8.5	#DIV/0!	#DIV/0!
Norwegian	4	7.15	7.3	0.33	0.574456265
Persian	3	8.133333333	8.4	0.303333333	0.550757055
Portuguese	5	7.76	8	0.958	0.978774744
Romanian	1	7.9	7.9	#DIV/0!	#DIV/0!
Russian	1	6.5	6.5	#DIV/0!	#DIV/0!
Spanish	26	7.05	7.15	0.6826	0.826196103
Swedish	1	7.6	7.6	#DIV/0!	#DIV/0!
Telugu	1	8.4	8.4	#DIV/0!	#DIV/0!
Thai	3	6.633333333	6.6	0.203333333	0.450924975
Vietnamese	1	7.4	7.4	#DIV/0!	#DIV/0!
Zulu	1	7.3	7.3	#DIV/0!	#DIV/0!

D.Director Analysis:

- The average IMDB score of highest rated directors is 7.5 percentile.
- By filtering the data we can identify top directors and which help to understand contributors to higher movie ratings.

Percentile
7.5

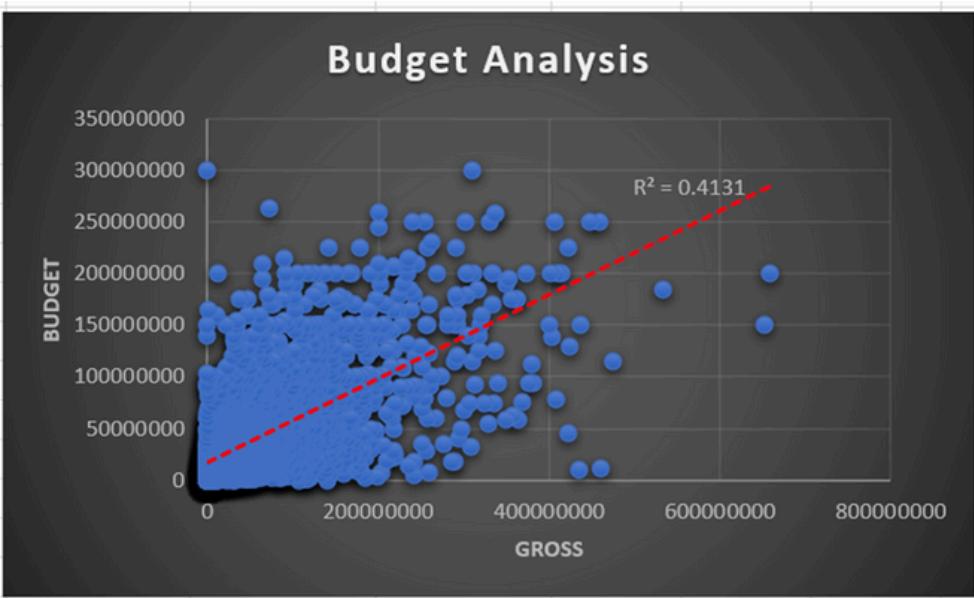
l'Amour	8.9
r.Haigh	7.7
r.Sternen	7.79333333
taylor	7.9
y.Powell	7.6
z	8
Ferhadi	8.4
V.Bluemel	7.6
lock	7.6
je.Bertolucci	7.8
lder	8.3
rd	7.58
erson	7.7
urcio	7.6
e Link	7.7
rock Park	7.63333333
Chaplin	8.6
J.Pergola	7.6
ing Liu	7.6
ak	7.6
ana	7.7
in.Ciaran	7.8
ph.Bertolucci	7.9
pher.Nolan	8.425
ir	7.7
i.Mangia	7.9
i.Chewie	8.5
roy	7.9
incher	7.75
zem	8
anch	7.53333333
engton	8.1
stlock	7.76666667
thermese	7.76666667
leland	7.7
it	7.9
udl	7.6
l.Jones	7.56666667
night	7.6
an	8.2
re	7.7
j.Darboe	7.6
i.Bifilmky	7.9
do.LéA de.Arenou	7.7
do.Meille	7.6
dis.Girard	7.7
Ford.Coppola	7.65555556
leabot	7.975
re	8.3
Ernest	7.6
Coker	7.9
Roy.Hill	8.2
pe.Torres	7.8
Myakka	8.225
Max.Rubin	7.8
Joint	7.6
roma	7.55
i.Perrin	7.9
Ugur	7.55
Cameron	7.914285714
Marsch	7.75
Geng	8.1
Robbins	7.6
schauss	7.8
ezra	7.65
in.Dayton	7.6
am.Kirer.Sukru	7.7
rene	7.8
Oppenheimer	8.2
Tickell	7.6
heron	7.925
SA.©.Campanile	8.2
lak	7.6
pidan	7.6
hadomild	7.7
utch	8.3
ibrahimyan	8.3
acon	7.7
zuri	7.6
Reed	8.5
A.Marcuseia.	8.4
erman	7.8
slowne	2.2
andrich	7.8
McDonagh	7.6
Scorseve	7.675
aron	7.6
w.Vaughn	7.65
roks	7.63333333
nom	7.76666667
J.McGowan	7.6
J.Moore	7.75
E.Rosmer	8.1
J.Waddingh	8.1
marawarikus	8
in.Zhou	7.8
ormen	8.1313131313
Tyldom	7.85
Grano	7.8
Belles	7.7
in	7.6
orantino	7.7
empress	7.585714296
ggis	7.73333333
omas.Anderson	7.51666667
icter	8.23333333
adow	7.675
far	7.225
SA.©.sa	7.6
aduhan	7.65
arko	7.7
Joffin	7.6
i.Tarantino	8.2
lmen	7.8
zore	7.8
i.Curtis	7.75
J.Marquand	8.4
orn	7.7
fatna	7.8
Shremson	7.8
che	8.5
zoglar	7.6
amudi	8.4
asme	8.4313131313
shadows	7.7
in	7.95
lare.Aubine	7.9
Kramer	7.6
Kubrick	7.8
n.Chobock	8
n.Chow	7.55
enes	7.55
h.Qures	7.7
Spierling	7.544
Chomai	7.8
mume	7.6
zorge	8.1
harroch	7.6
v.Winterberg	7.66666667
Cardes	7.6
Inaki	8.1
old	7.55
shouldi	7.45
ed	7.6
paper	7.73333333
i.Gerthy	7.9
Moor	7.7

E.Budget Analysis:

- Avatar is having the highest profit margin of \$523,505,847 which was calculated by gross earnings – budget.
- The correlation coefficient is 0.0408 indicating very weak relationship between budget and gross earnings. This means higher budget does not guarantee higher revenue always.
- We have plotted scatter plot by filtering some outliers to observe the values visually and R² suggest that 42% of variance in gross earnings can be explained by budget.
- In short lower budget movies may achieve exceptional financial success, while some expensive production may sometimes underperform.

movie_title	gross	budget	Profit margin
Avatar	760505847	237000000	523505847
Jurassic World	652177271	150000000	502177271
Titanic	658672302	200000000	458672302
Star Wars: Episode IV - A New Hope	460935665	11000000	449935665
E.T. the Extra-Terrestrial	43494959	10500000	424449459
The Avengers	623279547	220000000	403279547
The Avengers	623279547	220000000	403279547
The Lion King	422783777	45000000	377783777
Star Wars: Episode I - The Phantom Menace	474544677	115000000	359544677
The Dark Knight	533316061	185000000	348316061
The Hunger Games	407999255	78000000	329999255
Deadpool	363024263	58000000	305024263
The Hunger Games: Catching Fire	424645577	130000000	294645577
Jurassic Park	356784000	63000000	293784000
Despicable Me 2	368049635	76000000	292049635
American Sniper	350123553	58800000	291323553
Finding Nemo	380838870	94000000	286838870
Shrek 2	436471036	150000000	286471036
The Lord of the Rings: The Return of the King	377019252	94000000	283019252
Star Wars: Episode VI - Return of the Jedi	309125409	32500000	276625409
Forrest Gump	329691196	55000000	274691196
Star Wars: Episode V - The Empire Strikes Back	290158751	18000000	272158751
Home Alone	285761243	18000000	267761243
Star Wars: Episode III - Revenge of the Sith	380262555	113000000	267262555
Spider-Man	403706375	139000000	264706375
Minions	336029560	74000000	262029560
The Sixth Sense	293501675	40000000	253501675
Jaws	260000000	8000000	252000000
Frozen	400736600	150000000	250736600
The Secret Life of Pets	323505540	75000000	248505540

Movie_title	Max_Profit
Avatar	523505847
Correl	0.040837208



Result

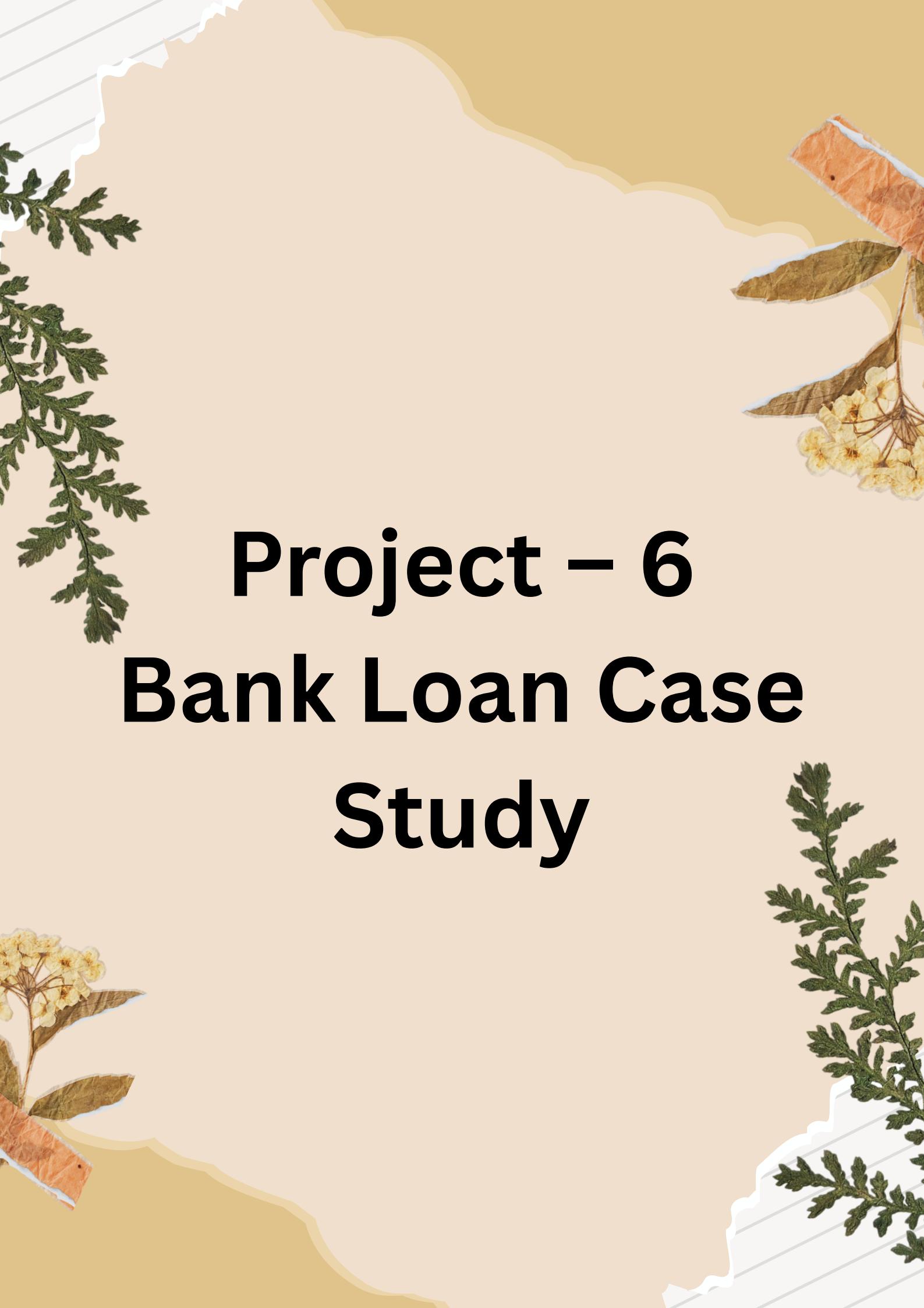
In this project we were able to derive key trends and patterns in factors that influence the success of a movie on IMDB. This insights help movie producers, directors, and investors who want to understand what makes a movie successful to make informed decisions in their future projects. Hence project helps to provide comprehensive understanding of factors that influence success of a movie.

Drive link of Excel Sheet

[https://docs.google.com/spreadsheets/d/1nG343gLUPXV4S1TqFZwNE9gRNVbkg3j/edit?
usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/1nG343gLUPXV4S1TqFZwNE9gRNVbkg3j/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

Loom video link

[https://www.loom.com/share/234580d50bcc4375a2d3c936e650908b?
sid=ef1238f6-d24e-4e0a-8233-ca887d15aba2](https://www.loom.com/share/234580d50bcc4375a2d3c936e650908b?sid=ef1238f6-d24e-4e0a-8233-ca887d15aba2)



Project – 6

Bank Loan Case

Study

Project Description

The main aim of this project is to identify patterns that indicate if a customer will have difficulty paying their installments. This information can be used to make decisions such as denying the loan, reducing the amount of loan, or lending at a higher interest rate to risky applicants. The company wants to understand the key factors behind loan default so it can make better decisions about loan approval.

Approach

- Dataset was downloaded and imported into Microsoft excel
- Then clean the dataset finding the blanks and missing values ,imputing the missing values with the appropriate method(mean, median ,mode).
- Then I found the outliers in the dataset.
- After all these I used pivot tables and basic charts to visualise the data.
- Then I found top 10 correlation between the columns of repayer and defaulters

Tech-Stack Used

Microsoft® Word 2019 MSO (Version 2501 Build 16.0.18429.20132) 64-bit for data analysis, pivot table creation and chart generation.

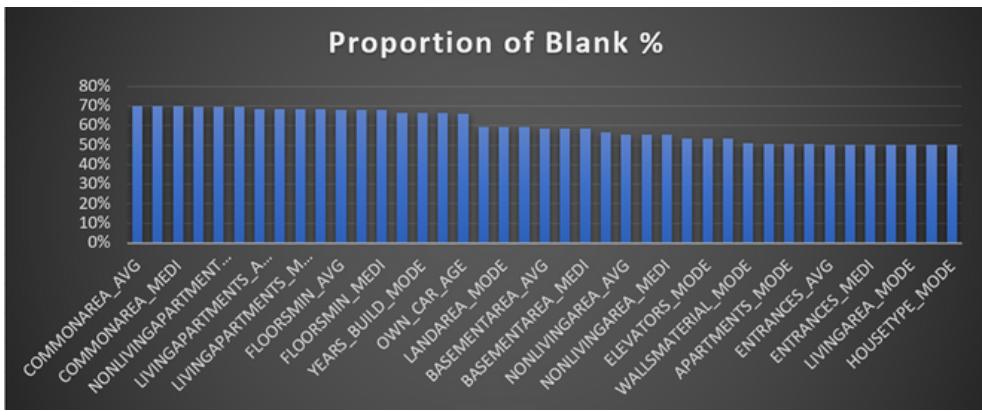
Insights

FOR CURRENT APPLICATION

A.Identify Missing Data and Deal with it Appropriately:

- Initially there were 122 columns and 50000 rows including header row in loan application dataset.
- First we used count blank formula to count all the blank cells in column
- Then we converted it into percent to plot the bar graph by transposing it into new sheet.
- Then we filled null values of numerical column with median as data contains outliers therefore mean is inappropriate.
- For non numerical data we deleted whole column
- Columns removed are:

COMMONAREA_AVG
COMMONAREA_MODE
COMMONAREA_MEDI
NONLIVINGAPARTMENTS_AVG
NONLIVINGAPARTMENTS_MODE
NONLIVINGAPARTMENTS_MEDI
LIVINGAPARTMENTS_AVG
LIVINGAPARTMENTS_MODE
LIVINGAPARTMENTS_MEDI
FONDKAPREMONT_MODE
FLOORSMIN_AVG
FLOORSMIN_MODE
FLOORSMIN_MEDI
YEARS_BUILD_AVG
YEARS_BUILD_MODE
YEARS_BUILD_MEDI
OWN_CAR_AGE
LANDAREA_AVG
LANDAREA_MODE
LANDAREA_MEDI
BASEMENTAREA_AVG
BASEMENTAREA_MODE
BASEMENTAREA_MEDI
EXT_SOURCE_1
NONLIVINGAREA_AVG
NONLIVINGAREA_MODE
NONLIVINGAREA_MEDI
ELEVATORS_AVG
ELEVATORS_MODE
ELEVATORS_MEDI
WALLSMATERIAL_MODE
APARTMENTS_AVG
APARTMENTS_MODE
APARTMENTS_MEDI
ENTRANCES_AVG
ENTRANCES_MODE
ENTRANCES_MEDI
LIVINGAREA_AVG
LIVINGAREA_MODE
LIVINGAREA_MEDI
HOUSETYPE_MODE



B.Identify Outliers in the Dataset:

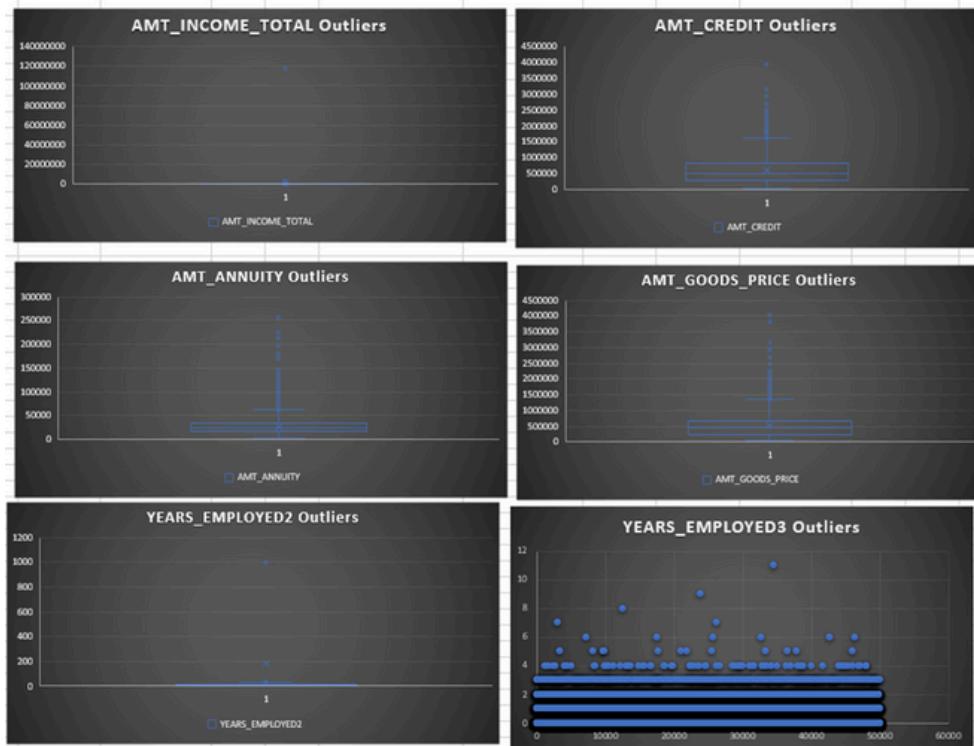
Outliers are the datapoints which deviate significantly from the rest of the datapoints.

So to analyze the datapoints we have used box plot and scatter plot to find out the outliers.

	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE
Mean	170763	599708	27107	539002
Median	145800	514778	24939	450000
Standard Deviation	531833.55	402424.25	14563.2	369729.26
IQR	90000	538650	18140	441000
Lower Bound	-22500	-537975	-10752.75	-423000
Upper Bound	337500	1616625	61805.25	1341000

We also used statistical formula to find upper bound manually to highlight the values greater than the upper bound value

AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE
202500	406597.5	24700.5	351000
270000	1293502.5	35698.5	1129500
67500	135000	6750	135000
135000	312682.5	29686.5	297000
121500	513000	21865.5	513000
99000	490495.5	27517.5	454500
171000	1560726	41301	1395000
360000	1530000	42075	1530000
112500	1019610	33826.5	913500
135000	405000	20250	405000
112500	652500	21177	652500
38419	148365	10678.5	135000
67500	80865	5881.5	67500
225000	918468	28966.5	697500
189000	773680.5	32778	679500
157500	299772	20160	247500
108000	509602.5	26149.5	387000
81000	270000	13500	270000
112500	157500	7875	157500
90000	544491	17563.5	454500
135000	427500	21375	427500
202500	1132573.5	37561.5	927000
450000	497520	32521.5	450000
83250	239850	23850	225000
135000	247500	12703.5	247500
90000	225000	11074.5	225000
112500	979992	27076.5	702000
112500	327024	23827.5	270000
270000	790830	57676.5	675000
90000	180000	9000	180000
292500	665892	24592.5	477000
112500	512064	25033.5	360000
90000	199008	20893.5	180000
360000	733315.5	39069	679500
135000	1125000	32895	1125000
112500	450000	44509.5	450000



Insights

·AMT_TOTAL_INCOME

By the box plot we can understand that most of the values are below the 40,00,000.

The only value which seems unrealistic is 11,70,00,000. As it is outlier it affects the measure of central tendency.

·CNT_CHILDREN

In few cases there are errors in data entry as some have count upto 11 childrens which seems unrealistic in today's world.

·YEARS_EMPLOYED2

By observing the scatter plot we can analyse that some values are above 1000 years which is clearly not possible and is an outlier.

·AMT_GOOD_PRICES

Some the client are applying for loan with extremely high prices and not realistic. Therefore treated as outliers.

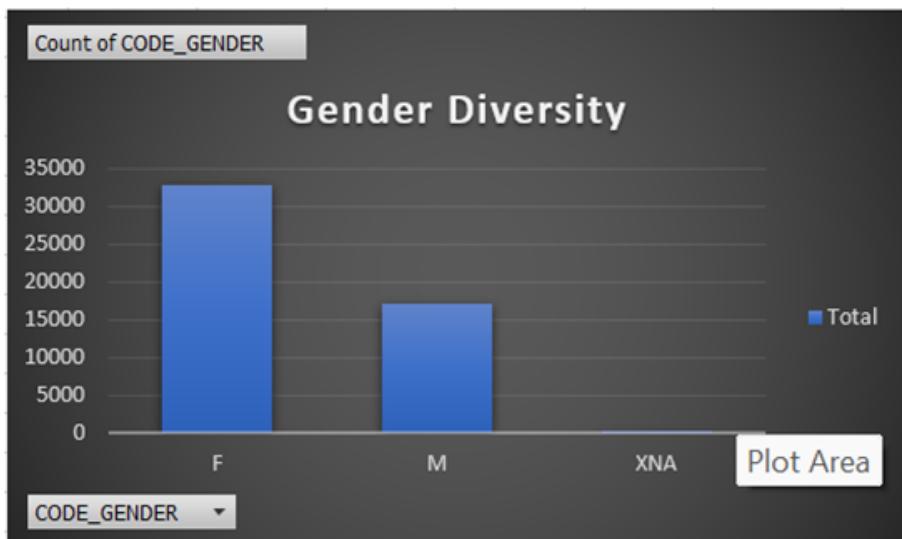
·AMT_ANNUITY

As there is very few chances of having annuity more than 200000 the points observed in box plot above the upper bound are treated as outliers.

·AMT_CREDIT

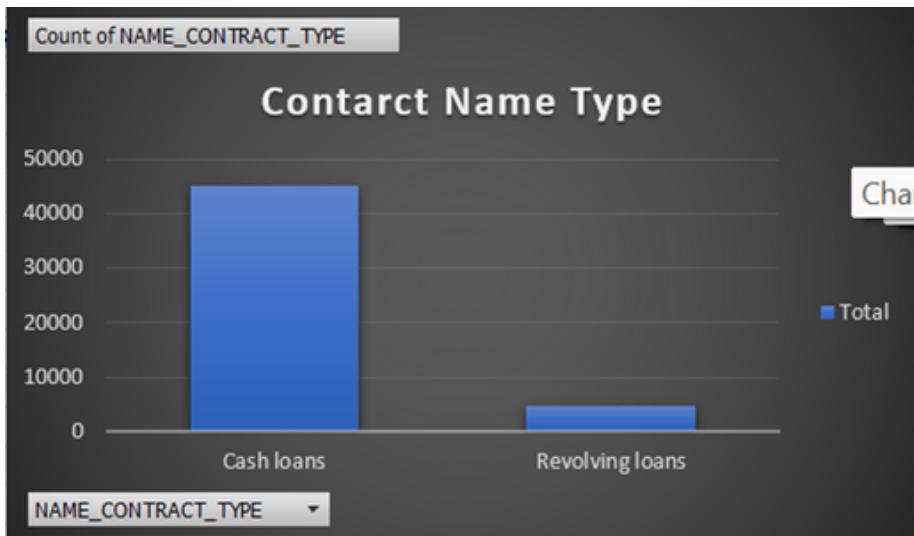
As there is very few chances that a client has this much credit more than 200000 the points above the upper bound are treated as outliers.

C. Analyze Data Imbalance:



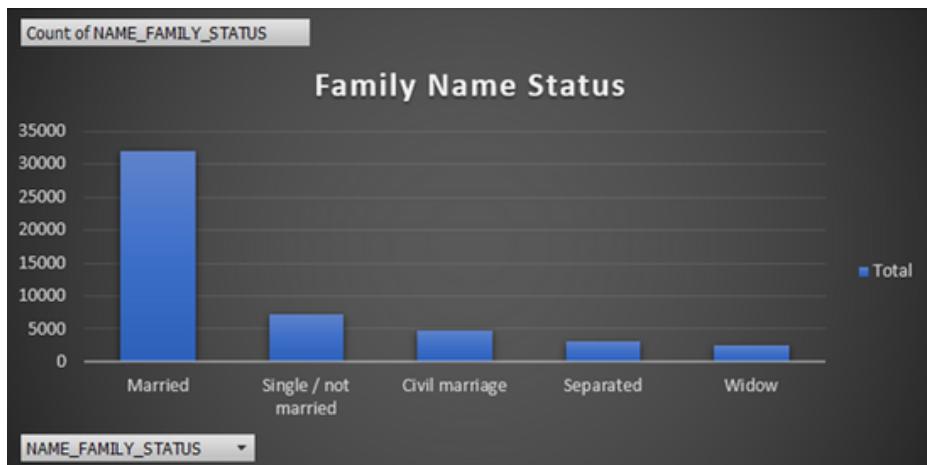
Gender Diversity:

The dataset displays that number of females is much higher than males and also the imbalanced distribution in number of xna.



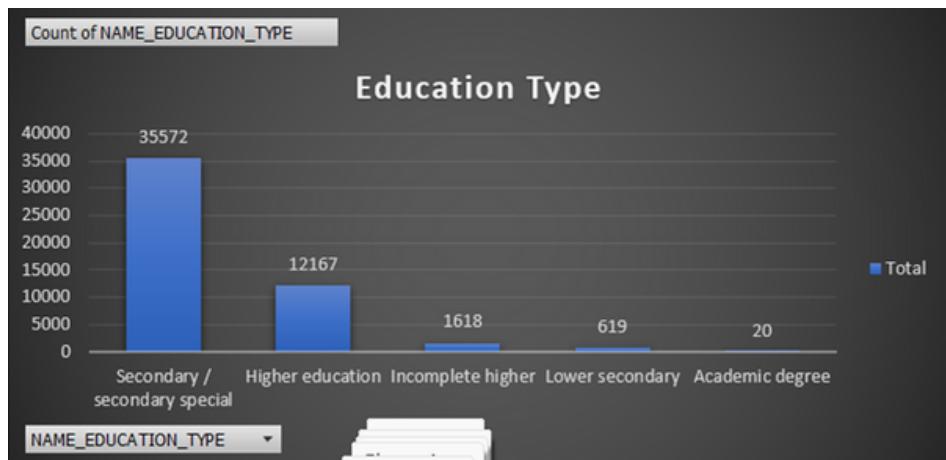
Contract name type:

The frequency of cash loans is much greater than the revolving loans. The revolving loan has small fraction of part out of the total number which is 10.4%.



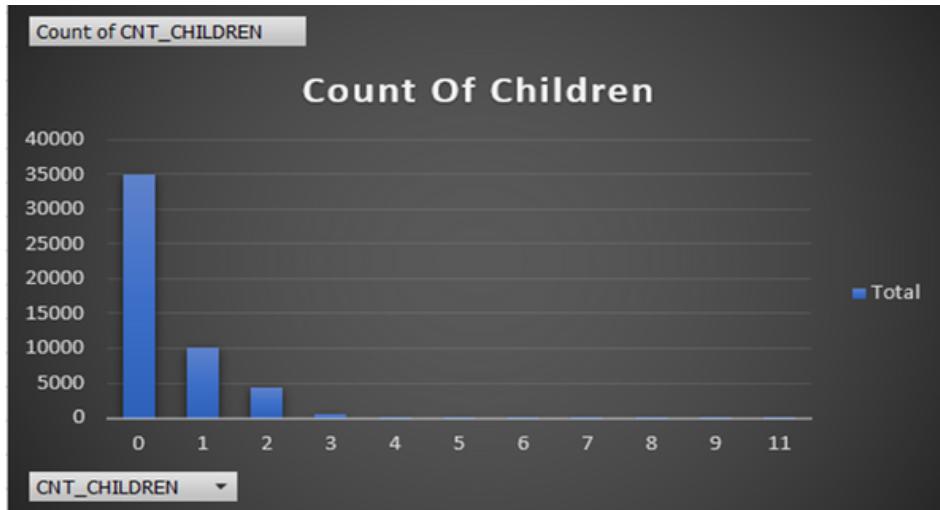
Family Name status:

Married people have taken most of the loans followed by Single/not married and civil marriage.



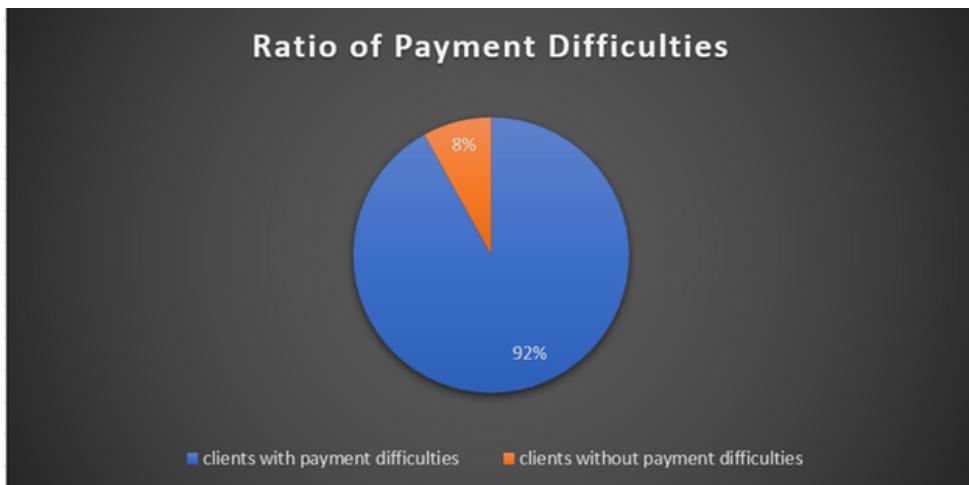
Education Type:

Secondary/secondary special education is of majority clients then followed by Higher education. Clients having academic degree has very small number.



Count of Children:

Clients with no children have higher frequency while other are less. It shows the imbalanced distribution in number of children feature.



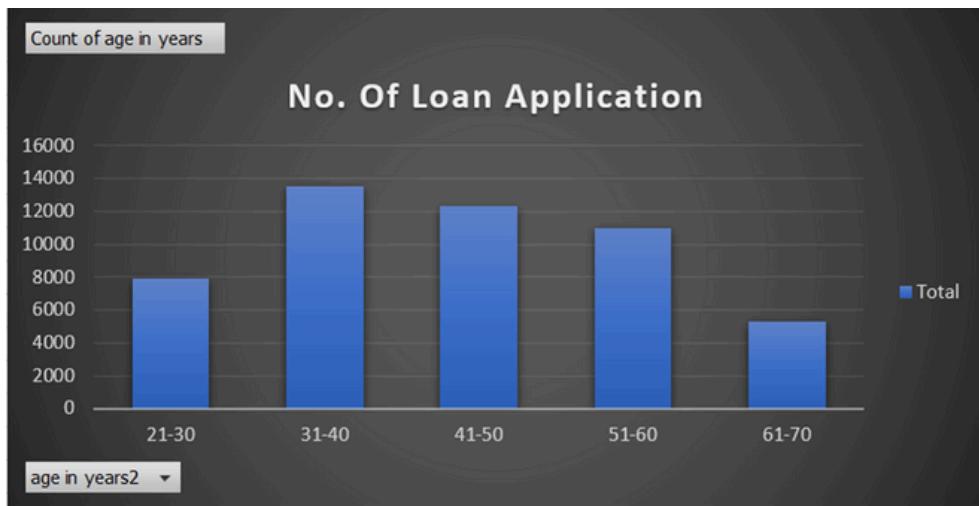
Ratio of Payment Difficulties:

We observe that most of the clients are facing difficulties in payment which 92% and only 8% are able to do payment without any difficulties. This shows that the data is imbalanced as the one class is under represented.

A. Perform Univariate, Segmented Univariate, and Bivariate Analysis:

Univariate:

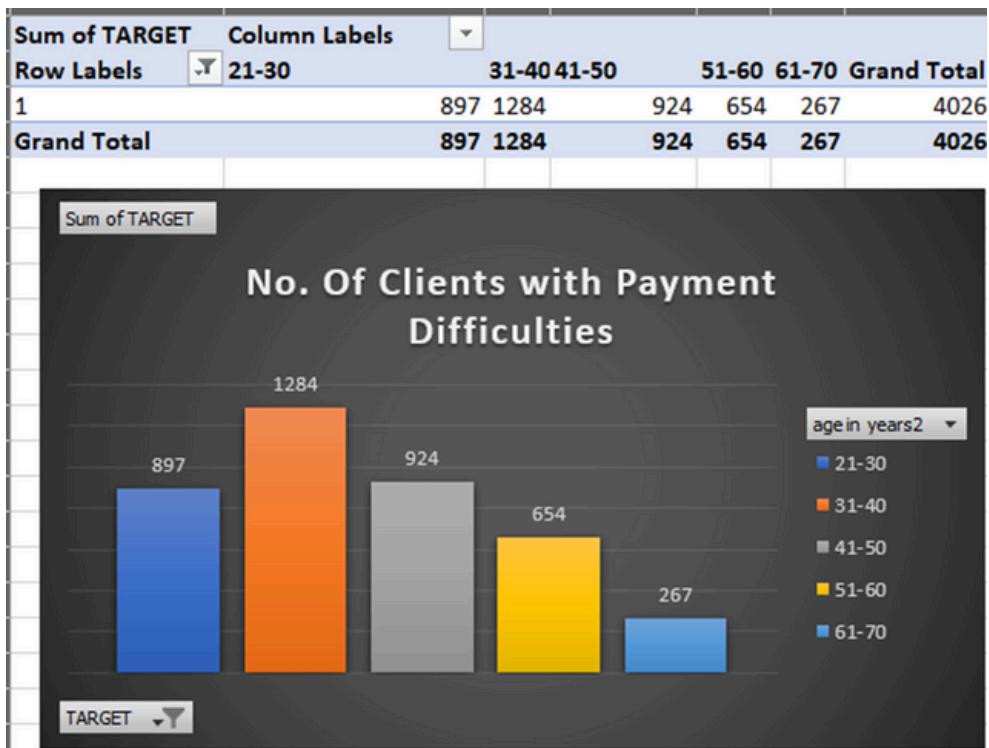
Row Labels	Count of age in years
21-30	7928
31-40	13505
41-50	12327
51-60	10973
61-70	5263
Grand Total	49996



Insight:

Data shows that majority of loan applicants fall within 31-60 age group.

Bivariate:



Insight:

The data shows that after age of 31 the number of clients with payment difficulties decreases as age increases. This gives us a insight that older clients may have more financial stability and experience in managing finances so they have less difficulties in payment of loan.

E. Identify Top Correlations for Different Scenarios:

The top 10 correlation between different variables and client who are defaulter is:

variable 1	variable 2	correlation
OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.998064837
AMT_GOODS_PRICE	AMT_CREDIT	0.982267963
CNT_FAM_MEMBERS	CNT_CHILDREN	0.892521875
DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.890496348
AMT_ANNUITY	AMT_CREDIT	0.749665201
AMT_GOODS_PRICE	AMT_ANNUITY	0.74950403
YEARS_EMPLOYED2	age in years	0.587858433
OBS_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.367887288
DEF_30_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.364900071
DEF_60_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	0.301256981

The top 10 correlation between different variable and clients who are repayer

variable 1	variable 2	coreelation
OBS_60_CNT_SOCIAL_CIRCLE	OBS_30_CNT_SOCIAL_CIRCLE	0.998355351
AMT_GOODS_PRICE	AMT_INCOME_TOTAL	0.987001704
CNT_FAM_MEMBERS	CNT_CHILDREN	0.879243419
DEF_60_CNT_SOCIAL_CIRCLE	DEF_30_CNT_SOCIAL_CIRCLE	0.850952847
AMT_GOODS_PRICE	AMT_ANNUITY	0.775843488
AMT_ANNUITY	AMT_INCOME_TOTAL	0.77077712
YEARS_EMPLOYED2	age in years	0.623250115
AMT_ANNUITY	AMT_INCOME_TOTAL	0.451148293
AMT_GOODS_PRICE	AMT_INCOME_TOTAL	0.384621454
AMT_CREDIT	AMT_INCOME_TOTAL	0.377985089

	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE	age_in_years	YEARS_EMPLOYED	YEARS_REGISTRATION	YEARS_ID_PUBLISH	CNT_FAMILY_MEMBERS	CNT_SOCIAL_CRF5	CNT_SOCIAL_CRF6	CNT_SOCIAL_CRF8	CNT_SOCIAL_CRF9	CNT_SOCIAL_CRF10	last_phone_change
CNT_CHILDREN	0.03625454															
AMT_INCOME_TOTAL	0.05932097	0.37795859														
AMT_CREDIT	0.05932097		0.7707772													
AMT_ANNUITY	0.05932098	0.4594829	0.7707772													
AMT_GOODS_PRICE	0.05932097	0.36425454	0.7707772	0.77594548												
age_in_years	0.05751028	0.07434306	0.0932097	0.0932097	0.04428556											
YEARS_EMPLOYED	-0.16547478	0.4767672	-0.074743	-0.12630745	-0.072459	0.621259										
YEARS_REGISTRATION	-0.1625988	-0.08933584	-0.079501	-0.05423275	-0.059454	0.23496371	0.20858639									
YEARS_ID_PUBLISH	0.05255076	-0.02226718	0.077418	-0.09659568	-0.09678293	0.2764957	0.27574944	0.0723295								
CNT_FAMILY_MEMBERS	0.07434549					0.044958	0.0464859	0.0777942	0.03820727	0.2462455	-0.2174202	0.07038348	0.0254257			
CBG_01_CNT_SOCIAL_C	0.06769705	0.03223542	-0.3932-0.05	0.000354	-0.02953	0.0052937	-0.0060404	0.0089572	0.02497102							
CBG_01_CNT_SOCIAL_C	0.06769705	0.03223542	-0.3932-0.05	0.000354	-0.02953	0.0052937	-0.0060404	0.0089572	0.02497102							
DEF_01_CNT_SOCIAL_C	0.0291976	0.02847722	0.00980	-0.02953	0.00586884	0.00792459	-0.00245358	0.00956868	-0.00239093	0.20573224						
CBG_01_CNT_SOCIAL_C	0.06292709	0.03223542	-0.3932-0.05	0.000354	-0.02953	0.013765-0.02953	0.0054907	0.03057744	0.02445264	0.98020351				0.30930444		
DEF_01_CNT_SOCIAL_C	0.0291976	0.02847722	0.00980	-0.02953	0.00586884	0.00792459	-0.00245358	0.00956868	-0.00239093	0.20573224						
last_phone_change	-0.04340803	0.03223542	-0.08985	-0.02953	0.00586884	0.00792459	-0.00245358	0.00956868	-0.00239093	0.0220878	-0.0647208	0.2375559	0.05495447	0.23087082		
last_phone_change	-0.04340803	0.03223542	-0.08985	-0.02953	0.00586884	0.00792459	-0.00245358	0.00956868	-0.00239093	0.0220878	-0.0647208	0.2375559	0.05495447	0.23087082		
0.03848325	0.04593574	0.070515	0.04444501	0.03223542	0.02732079	0.07242687	-0.02575254	0.04777224	0.03850077	0.02505624	0.0332555	0.03279759	0.01434545	-0.00252539		

Drive link:

[https://docs.google.com/spreadsheets/d/14lAwEXxC09Dxz_GluOaeyzTIn3rLk5YT/edit?
usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/14lAwEXxC09Dxz_GluOaeyzTIn3rLk5YT/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

FOR PREVIOUS APPLICATION

Similarly performing all the tasks for previous application dataset

Drive Link:

[https://docs.google.com/spreadsheets/d/1uSWZS87SSBVZpexxlr2B6UEDpoiA7lu_/edit?
usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/1uSWZS87SSBVZpexxlr2B6UEDpoiA7lu_/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

Conclusion

- The dataset was observed to be imbalanced with one class as being underrepresented.
- The major demographic age group for seeking loan were observed to be between 31-60.
- The age group of 31-60 where observed to have higher incomes which suggests the prime stage of earning in life.
- The clients having higher incomes generally did not face difficulties in payment of loan.
- It was observed cash loans were the most common loan type which gave us insight of liquidity needs among the clients.
- Clients with secondary/secondary special education were more likely to take loans which showed us correlation between education level and loan dependency.
- Married individuals are more likely to apply for loan which suggest greater financial obligations or goals.
- Largest occupation group of loan applicants is observed of labourers which tells financial need in this sector.
- There large amount of repeat clients suggesting customers returning more often for additional loans.
- Age group between 31-60 tend to have more credit score, further establishing this age group as financially stable and reliable.

Project – 7

Analyzing the Impact of Car Features on Price and Profitability

Project Description

This project aims to analyse the relationship between a car's features, market category, and pricing, and identifying which features and categories are most popular among consumers and most profitable for the manufacturer. By using data analysis techniques such as regression analysis and market segmentation, the manufacturer could develop a pricing strategy that balances consumer demand with profitability, and identify which product features to focus on in future product development efforts. This could help the manufacturer improve its competitiveness in the market and increase its profitability over time.

Approach

- First I have cleaned the data to ensure accurate results. I observed that columns having null values where Engine HP, Engine fuel type, Engine cylinders, Market Category and Number of doors.
- Engine fuel type had three blank cells so we filled it with 'regular unleaded'.
- Then we removed the null value rows from Engine HP, Engine cylinders and Number of doors.
- Then for better visualization and understanding we converted MSRP into \$ currency.
- Afterwards using pivot table, regression analysis and different types of charts such as bar chart, scatter chart, bubble chart, stacked bar chart, line chart and combo chart we have explored the relationships between different features.
- This helped us to build an interactive dashboard which shows the relationship between car features, market categories, popularity, fuel efficiency, manufacturers and engine power.

Tech-Stack Used

Microsoft® Word 2019 MSO (Version 2501 Build 16.0.18429.20132) 64-bit for data analysis, pivot table creation and chart generation.

Insights

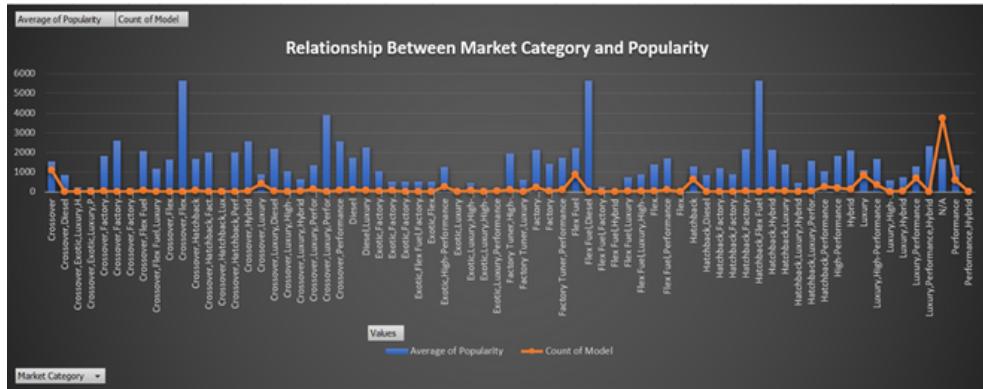
Tasks: Analysis

Insight Required: How does the popularity of a car model vary across different market categories?

- Task 1.A: Create a pivot table that shows the number of car models in each market category and their corresponding popularity scores.

Popularity of Car Model		
Market Category	Average of Popularity	Count of Model
Crossover	1529.030825	1103
Crossover,Diesel	873	7
Crossover,Exotic,Luxury,High-Performance	238	1
Crossover,Exotic,Luxury,Performance	238	1
Crossover,Factory Tuner,Luxury,High-Performance	1823.461538	26
Crossover,Factory Tuner,Luxury,Performance	2607.4	5
Crossover,Factory Tuner,Performance	210	4
Crossover,Flex Fuel	2073.75	64
Crossover,Flex Fuel,Luxury	1173.2	10
Crossover,Flex Fuel,Luxury,Performance	1624	6
Crossover,Flex Fuel,Performance	5657	6
Crossover,Hatchback	1675.694444	72
Crossover,Hatchback,Factory Tuner,Performance	2009	6
Crossover,Hatchback,Luxury	204	7
Crossover,Hatchback,Performance	2009	6
Crossover,Hybrid	2563.380952	42
Crossover,Luxury	884.5487805	410
Crossover,Luxury,Diesel	2195.848485	33
Crossover,Luxury,High-Performance	1037.222222	9
Crossover,Luxury,Hybrid	630.9166667	24
Crossover,Luxury,Performance	1344.849558	113
Crossover,Luxury,Performance,Hybrid	3916	2
Crossover,Performance	2585.956522	69
Diesel	1730.904762	84
Diesel,Luxury	2275	51
Exotic,Factory Tuner,High-Performance	1046.380952	21
Exotic,Factory Tuner,Luxury,High-Performance	517.5384615	52
Exotic,Factory Tuner,Luxury,Performance	520	3
Exotic,Flex Fuel,Factory Tuner,Luxury,High-Performance	520	13
Exotic,Flex Fuel,Luxury,High-Performance	520	11
Exotic,High-Performance	1261.571429	252
Exotic,Luxury	112.6666667	12
Exotic,Luxury,High-Performance	467.0759494	79
Exotic,Luxury,High-Performance,Hybrid	204	1
Exotic,Luxury,Performance	217.0277778	36
Factory Tuner,High-Performance	1941.415094	106
Factory Tuner,Luxury	617	2
Factory Tuner,Luxury,High-Performance	2133.367442	215
Factory Tuner,Luxury,Performance	1413.419355	31
Factory Tuner,Performance	1733.101124	89
Flex Fuel	2217.302752	872
Flex Fuel,Diesel	5657	16
Flex Fuel,Factory Tuner,Luxury,High-Performance	258	1
Flex Fuel,Hybrid	155	2
Flex Fuel,Luxury	746.5384615	39
Flex Fuel,Luxury,High-Performance	878.9090909	33
Flex Fuel,Luxury,Performance	1380.071429	28
Flex Fuel,Performance	1702.358025	81
Flex Fuel,Performance,Hybrid	155	2
Hatchback	1292.998371	614
Hatchback,Diesel	873	14
Hatchback,Factory Tuner,High-Performance	1205.153846	13
Hatchback,Factory Tuner,Luxury,Performance	886.8888889	9
Hatchback,Factory Tuner,Performance	2159.045455	22
Hatchback,Flex Fuel	5657	7
Hatchback,Hybrid	2121.25	72
Hatchback,Luxury	1379.5	46
Hatchback,Luxury,Hybrid	454	3
Hatchback,Luxury,Performance	1566.131579	38
Hatchback,Performance	1039.646825	252
High-Performance	1821.447236	199
Hybrid	2105.569106	123
Luxury	1107.553467	851
Luxury,High-Performance	1668.017964	334
Luxury,High-Performance,Hybrid	568.8333333	12
Luxury,Hybrid	724.6875	48
Luxury,Performance	1292.615156	673
Luxury,Performance,Hybrid	2333.181818	11
N/A	1670.430984	3731
Performance	1371.080479	584
Performance,Hybrid	155	1

Task 1.B: Create a combo chart that visualizes the relationship between market category and popularity.

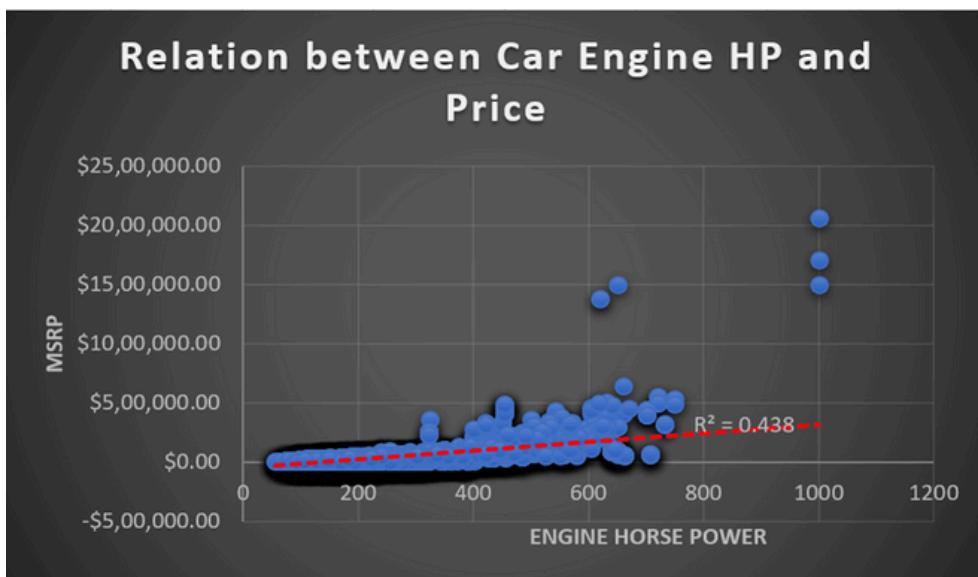


Insight:

The popularity of car model varies across different market categories based on various factors. Here the most popular market categories for car models are Crossover, flex fuel, diesel, hatchback, and performance.

Insight Required: What is the relationship between a car's engine power and its price?

- Task 2: Create a scatter chart that plots engine power on the x-axis and price on the y-axis. Add a trendline to the chart to visualize the relationship between these variables.



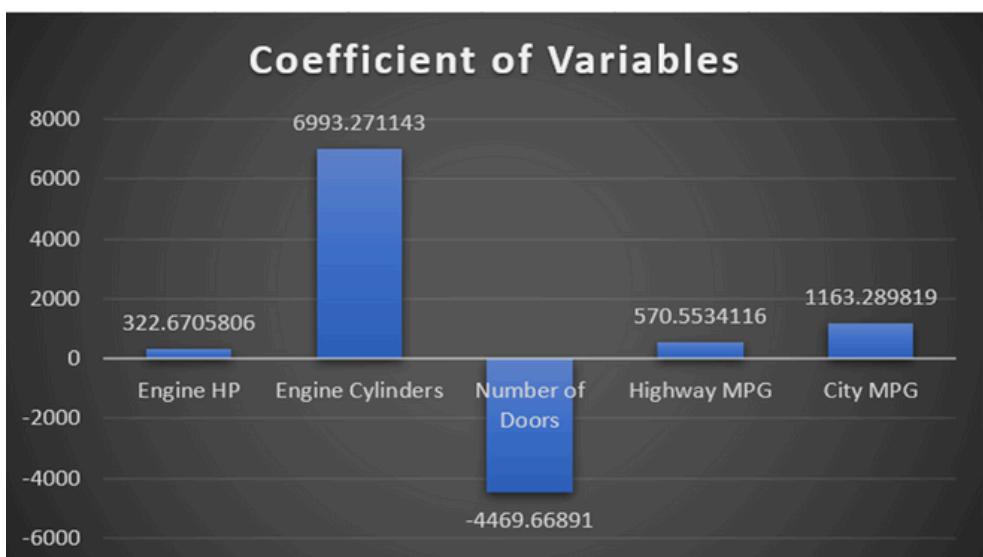
Insight:

We can observe the positive correlation between engine power and price, which means that as engine power increases the price of car tends to increase as well. This is because higher engine power requires more advanced technology and components which increases the cost of production.

Insight Required: Which car features are most important in determining a car's price?

- Task 3: Use regression analysis to identify the variables that have the strongest relationship with a car's price. Then create a bar chart that shows the coefficient values for each variable to visualize their relative importance.

SUMMARY OUTPUT								
Regression Statistics								
Multiple R	0.680713809							
R Square	0.463371289							
Adjusted R Square	0.463144077							
Standard Error	44165.59385							
Observations	11815							
ANOVA								
	df	SS	MS	F	Significance F			
Regression	5	1.98901E+13	3.97802E+12	2039.38084		0		
Residual	11809	2.30346E+13	1950599680					
Total	11814	4.29247E+13						
	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	-101612.1812	3683.853676	-27.58312088	2.3253E-162	-108833.1419	-94391.2206	-108833.1419	-94391.2206
Engine HP	322.6705806	6.014842757	53.64572169	0	310.880497	334.4606642	310.880497	334.4606642
Engine Cylinders	6993.271143	439.5089745	15.91155482	2.02935E-56	6131.761081	7854.781204	6131.761081	7854.781204
Number of Doors	-4469.66891	465.6339314	-9.599104809	9.68047E-22	-5382.388195	-3556.949626	-5382.388195	-3556.949626
Highway MPG	570.5534116	105.7686551	5.394352522	7.0098E-08	363.2294072	777.8774161	363.2294072	777.8774161
City MPG	1163.289819	121.9795585	9.536760372	1.76081E-21	924.1897715	1402.389867	924.1897715	1402.389867



Insight:

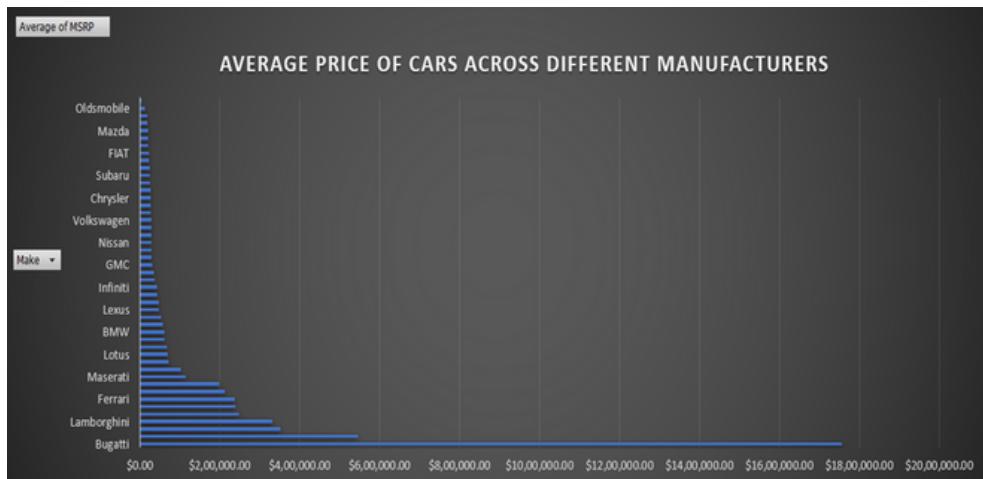
We can observe that engine cylinders is the most important feature to determine the price of a car, then followed by City MPG and Highway MPG.

Insight Required: How does the average price of a car vary across different manufacturers?

- Task 4.A: Create a pivot table that shows the average price of cars for each manufacturer.

Row Labels	Average of MSRP		
Bugatti	\$17,57,223.67	Acura	\$34,887.59
Maybach	\$5,46,221.88	GMC	\$30,493.30
Rolls-Royce	\$3,51,130.65	Toyota	\$28,946.15
Lamborghini	\$3,31,567.31	Volvo	\$28,541.16
Bentley	\$2,47,169.32	Nissan	\$28,513.37
McLaren	\$2,39,805.00	Chevrolet	\$28,273.36
Ferrari	\$2,37,383.82	Buick	\$28,206.61
Spyker	\$2,13,323.33	Volkswagen	\$28,076.20
Aston Martin	\$1,97,910.38	Saab	\$27,413.50
Maserati	\$1,14,207.71	Ford	\$27,393.42
Porsche	\$1,01,622.40	Chrysler	\$26,722.96
Mercedes-Benz	\$71,537.81	Honda	\$26,629.82
Lotus	\$69,188.28	Kia	\$25,112.39
Land Rover	\$67,823.22	Subaru	\$24,827.50
Alfa Romeo	\$61,600.00	Hyundai	\$24,597.04
BMW	\$61,546.76	Dodge	\$22,390.06
Cadillac	\$56,231.32	FIAT	\$22,206.02
Audi	\$53,452.11	Mitsubishi	\$21,215.47
Lexus	\$47,549.07	Scion	\$19,932.50
Genesis	\$46,616.67	Mazda	\$19,719.06
Lincoln	\$42,494.37	Pontiac	\$19,321.55
Infiniti	\$42,394.21	Suzuki	\$17,907.21
HUMMER	\$36,464.41	Oldsmobile	\$11,542.54
Acura	\$34,887.59	Plymouth	\$3,122.90

- Task 4.B: Create a bar chart or a horizontal stacked bar chart that visualizes the relationship between manufacturer and average price.

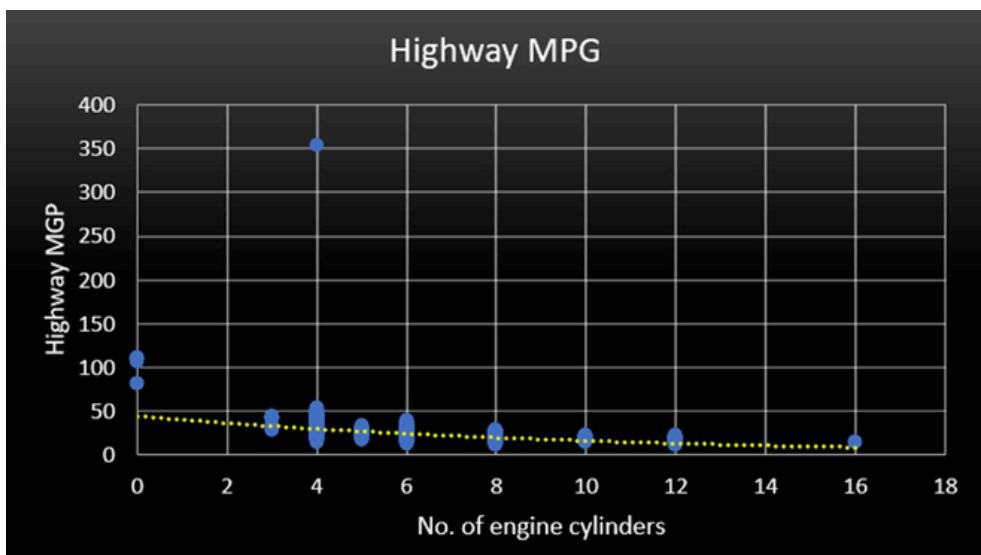


Insight:

Average price of a car depends on the manufacturers as they vary significantly, as each manufacturer has its own pricing strategy, market target, product offerings and brand positioning. Which contributes in variations in average prices. Here we can observe that Bugatti has highest average price and Oldsmobile has the lowest average price.

Insight Required: What is the relationship between fuel efficiency and the number of cylinders in a car's engine?

- Task 5.A: Create a scatter plot with the number of cylinders on the x-axis and highway MPG on the y-axis. Then create a trendline on the scatter plot to visually estimate the slope of the relationship and assess its significance.



- Task 5.B: Calculate the correlation coefficient between the number of cylinders and highway MPG to quantify the strength and direction of the relationship.

Correlation -0.62032

=CORREL(A2:A11816,B2:B11816)

Insight:

It is observed that Number of Engine Cylinders increases and the Highway MPG decreases. So it shows that both of them have negative relationship.

The correlation coefficient between them is -0.62032 which also tells they have negative correlation which means as one will increase the other will decrease and vice versa.

Building the Dashboard:

Task 1: How does the distribution of car prices vary by brand and body style?

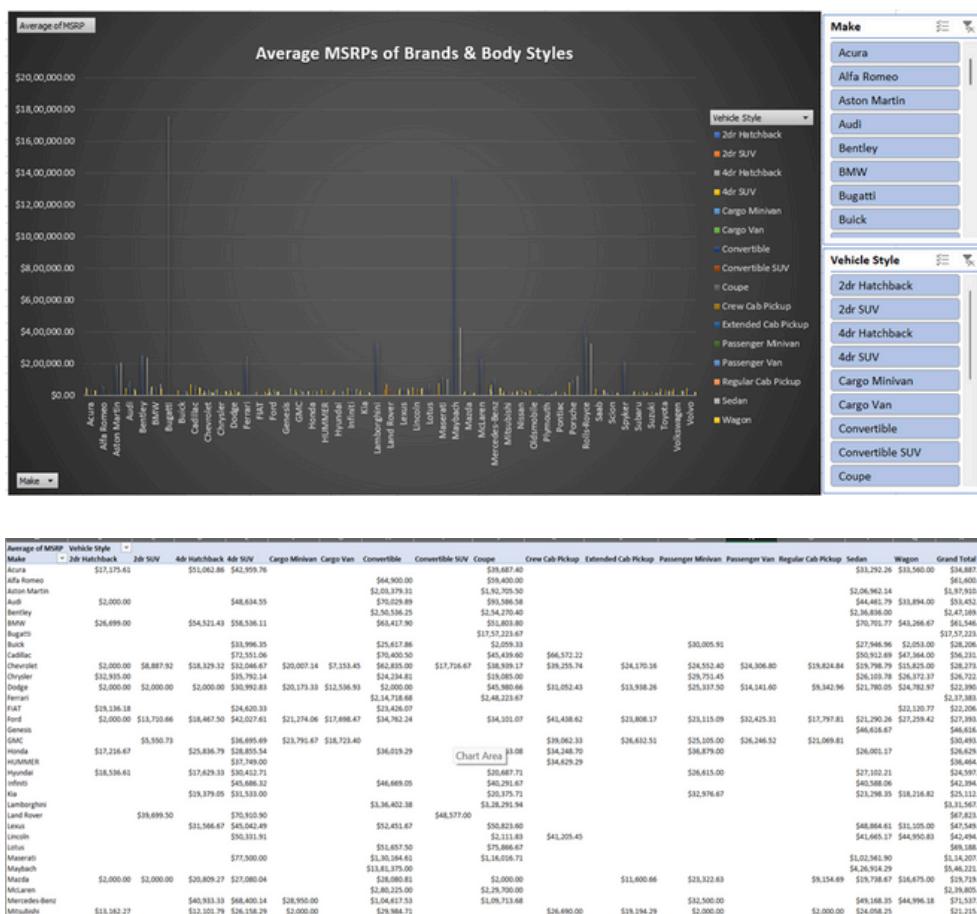


Result:

Chevrolet has the highest price distribution by body style. The price distribution of automobile by brand and body type depends on market trends such as:

- Pricing differs on the basis of target audience and brand positioning such as high end brands have premium feature and cutting edge technology which makes it higher at price point while cost effective brands focus on affordability.
 - Pricing is also influenced and affected by the branding. The well known brands with reputation has quality products which are dependable due to which cost is higher.
 - Body type of vehicle also influence the price point as the increased size and perceived prestige influence the prices at higher end.

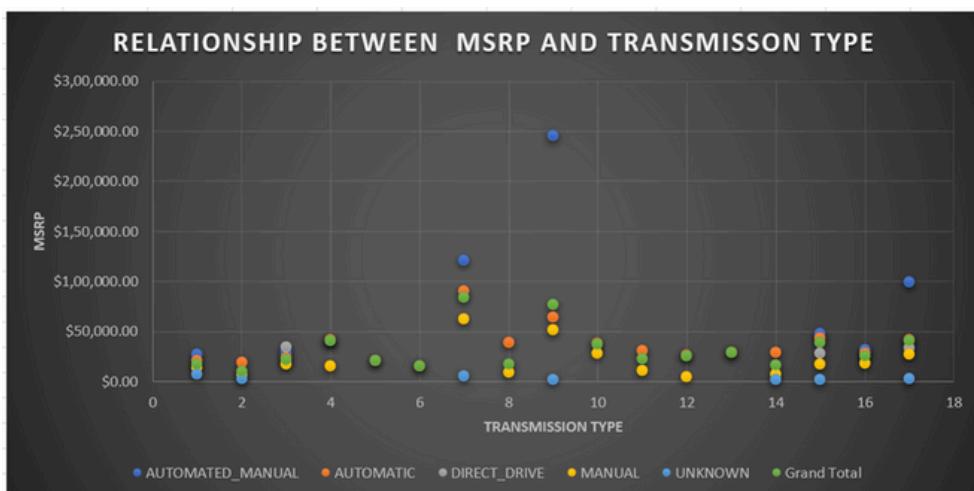
Task 2: Which car brands have the highest and lowest average MSRP, and how does this vary by body style?



Result:

- Bugatti has highest average MSRP which suggests it as luxury brand. This luxury brands are known for its high end product with cutting edge technology.
- On the other hand Plymouth has lowest MSRP which tell it as a budget brand that offers reasonable prices depending on the model and body type.
- The tendencies of brand may be seen as which cars are frequently bought according to their model, material used, engine type and technology used.
- The mainstream companies provide variety of compact and midsize sedans and hatchbacks. This all cars seems to be more economical solution for daily use.

Task 3: How do the different feature such as transmission type affect the MSRP, and how does this vary by body style?



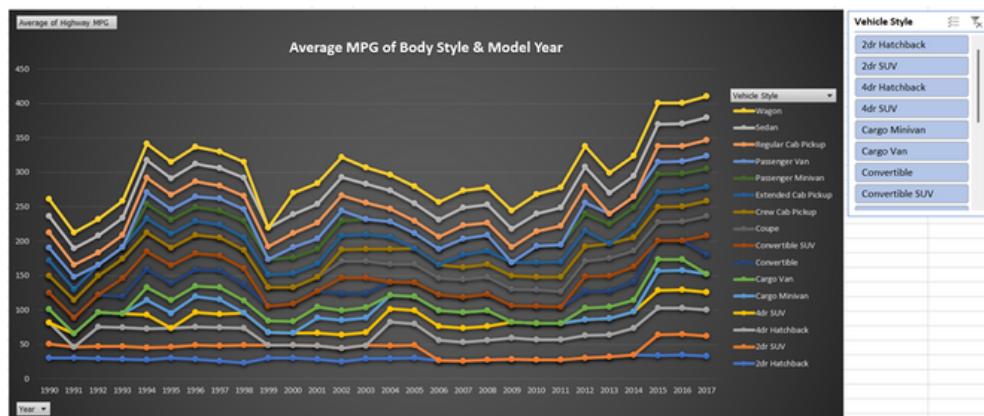
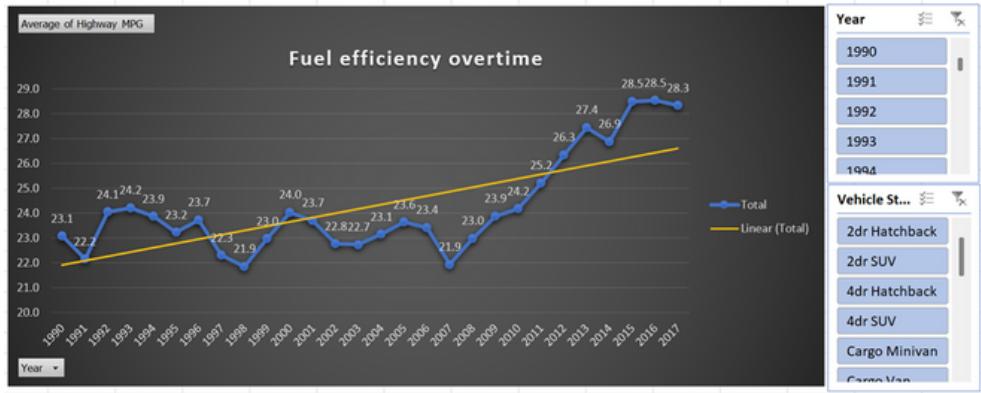
Average of MSRP	Transmission Type	AUTOMATED_MANUAL	AUTOMATIC	DIRECT_DRIVE	MANUAL	UNKNOWN	Grand Total
Vehicle Style	AUTOMATED_MANUAL	\$27,180.96	\$20,926.46	\$13,353.66	\$7,361.50	\$16,778.65	
2dr Hatchback			\$18,615.20		\$6,303.81	\$2,371.00	\$10,115.19
2dr SUV			\$29,249.07	\$23,833.68	\$34,511.92	\$17,594.41	\$22,086.30
4dr Hatchback			\$40,451.15	\$41,555.19		\$15,426.46	\$40,426.82
4dr SUV					\$20,910.86		\$20,910.86
Cargo Minivan					\$15,280.22		\$15,280.22
Cargo Van					\$1,21,256.64	\$90,637.39	\$62,357.76
Convertible					\$38,925.50	\$9,233.14	\$17,424.14
Convertible SUV					\$2,45,588.36	\$63,852.01	\$51,070.48
Coupe					\$37,744.07	\$28,360.53	\$76,900.71
Crew Cab Pickup					\$30,637.35	\$10,884.19	\$37,220.47
Extended Cab Pickup					\$26,392.00	\$4,405.33	\$22,488.78
Passenger Minivan					\$29,015.20		\$25,591.51
Passenger Van					\$28,536.82	\$7,557.77	\$29,015.20
Regular Cab Pickup					\$47,498.71	\$43,760.61	\$2,000.00
Sedan					\$31,985.28	\$27,613.19	\$15,953.71
Wagon						\$17,844.14	\$38,969.06
Grand Total		\$99,195.58	\$41,129.06	\$33,620.00	\$26,671.40	\$3,040.74	\$40,554.37

Result:

- The most expensive transmission is automated manual and also the automatic is one of the most popular transmission.
- The transmission type of a vehicle can vary also on body type of the vehicle such as for sedan cars they have higher trim levels and automatic transmission levels which generally offers comfortable driving options.
- Which suggests us that sedan having automatic transmission have expensive MSRP than equivalent model with manual transmissions.
- Generally the MSRP have an important feature which is transmission type. It varies according to the body style of a vehicle. As automated transmission provides more comfort and ease to use it has higher price than manual transmission.

Task 4: How does the fuel efficiency of cars vary across different body styles and model years?

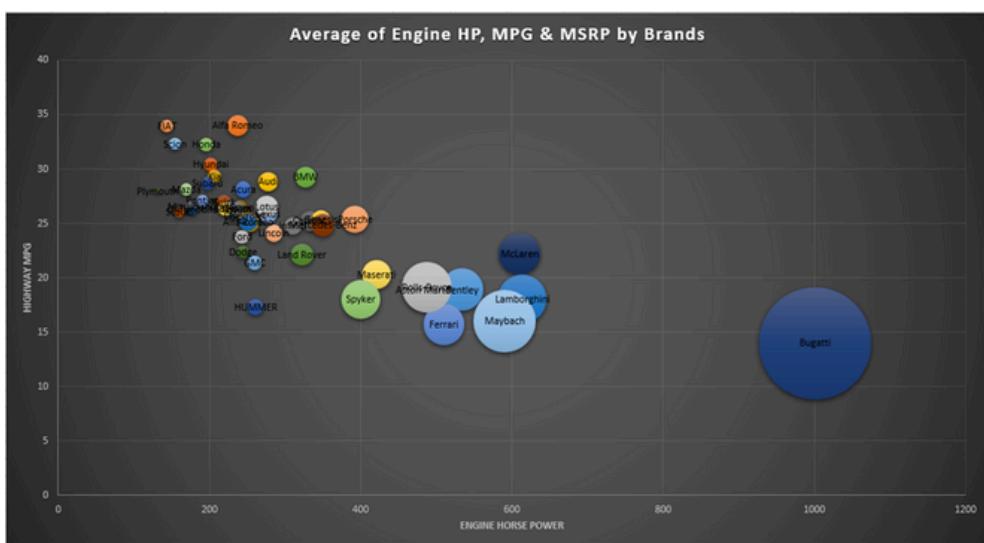
Row Labels	Average of Highway MPG
1990	23.1
1991	22.2
1992	24.1
1993	24.2
1994	23.9
1995	23.2
1996	23.7
1997	22.3
1998	21.9
1999	23.0
2000	24.0
2001	23.7
2002	22.8
2003	22.7
2004	23.1
2005	23.6
2006	23.4
2007	21.9
2008	23.0
2009	23.9
2010	24.2
2011	25.2
2012	26.3
2013	27.4
2014	26.9
2015	28.5
2016	28.5
2017	28.3
Grand Total	26.3



Result:

- Overall fuel efficiency has increased after 2007 at slower rate.
 - Car's fuel efficiency range as per the body type and model years. It can be seen that different body style have impact on fuel efficiency.
 - As most efficient engines have been developed by automakers which later improves fuel economy.
 - As the year passes the manufacturer improves their design and use of technology so it is observed that there is seen the increase in fuel economy after 2007.

Task 5: How does the car's horsepower, MPG, and price vary across different Brands?

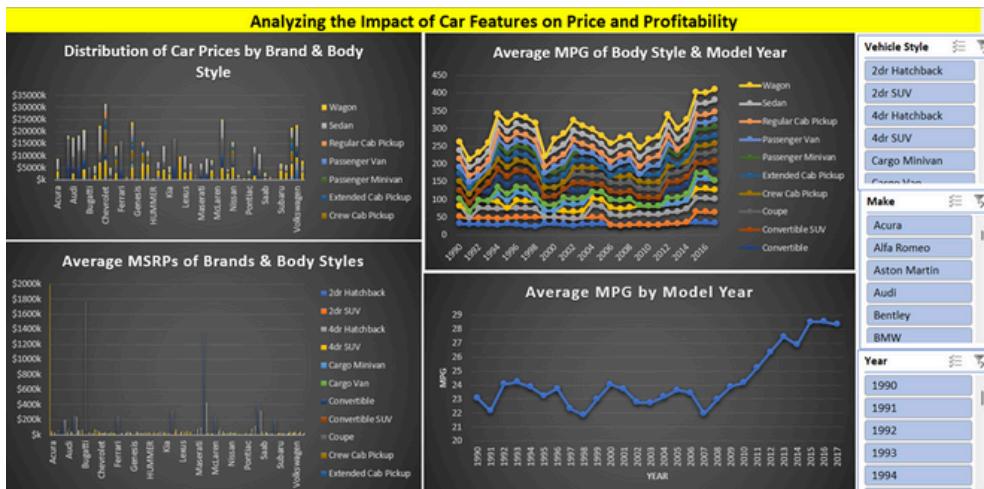


Row Labels	Average of Engine HP	Average of Highway MPG	Average of MSRP
Acura	245	28	\$34,888
Alfa Romeo	237	34	\$61,600
Aston Martin	484	19	\$1,97,910
Audi	278	29	\$53,452
Bentley	534	19	\$2,47,169
BMW	327	29	\$61,547
Bugatti	1001	14	\$17,57,224
Buick	219	27	\$28,207
Cadillac	332	25	\$56,231
Chevrolet	247	26	\$28,273
Chrysler	229	26	\$26,723
Dodge	244	22	\$22,390
Ferrari	510	16	\$2,37,384
FIAT	144	34	\$22,206
Ford	243	24	\$27,393
Genesis	347	25	\$46,617
GMC	260	21	\$30,493
Honda	196	32	\$26,630
HUMMER	261	17	\$36,464
Hyundai	202	30	\$24,597
Infiniti	310	25	\$42,394
Kia	207	29	\$25,112
Lamborghini	614	18	\$3,31,567
Land Rover	322	22	\$67,823
Lexus	277	26	\$47,549
Lincoln	285	24	\$42,494
Lotus	276	27	\$69,188
Maserati	421	20	\$1,14,208
Maybach	591	16	\$5,46,222
Maybach	591	16	\$5,46,22
Mazda	169	28	\$19,71
McLaren	610	22	\$2,39,80
Mercedes-Benz	350	25	\$71,53
Mitsubishi	174	27	\$21,21
Nissan	240	26	\$28,51
Oldsmobile	177	26	\$11,54
Plymouth	132	28	\$3,12
Pontiac	190	27	\$19,32
Porsche	393	25	\$1,01,62
Rolls-Royce	488	19	\$3,51,13
Saab	221	26	\$27,41
Scion	154	32	\$19,93
Spyker	400	18	\$2,13,32
Subaru	197	29	\$24,82
Suzuki	160	26	\$17,90
Toyota	236	26	\$28,94
Volkswagen	190	32	\$28,07
Volvo	231	27	\$28,54
Grand Total	249	26	\$40,55

Result:

- It is observed as the engine horse power increases the highway MPG decreases and the price goes up.
- It helps us to see how different manufacturers design and price their vehicles.
- Such as Bugatti, Maybach, Lamborghini have high performance automobiles. This brands manufacturers mainly focuses on acceleration, speed and track performance. It provides varied horsepower numbers.
- On the other hand large amount of manufacturers focuses on mass market such as Toyota, Honda, and ford as they mainly focuses on utility and fuel economy.
- There are two types of automakers one is luxury which are like Rolls Royce, Bently, Bugatti and many more this focuses on creating expensive automobiles that have cutting edge technology.
- And the another one is mainstream brands which includes Toyota, Honda, Ford and many more this all provides affordable options and also offers higher end priced models with advanced features which offers varied price range.

Dashboard



Result:

This interactive dashboard helps stakeholders to explore different aspects of dataset. It helps to visualize distribution of car prices by brand and body style, average MSRPs of brands and body styles, average MPG by model year and average MPG of body style and model year. This helps to understand the relationship between horsepower, MPG and price across different car brands. This information helps the manufacturers to make informed decisions of pricing, product development, marketing and competitiveness of market. Manufacturers by optimizing the factors as discussed can optimize maximum profitability while keeping in mind the needs of consumer demand.

Drive Link

[https://docs.google.com/spreadsheets/d/184tjYBAI2fvYnGquVBQgMvfo8xwjjnK/edit?
usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true](https://docs.google.com/spreadsheets/d/184tjYBAI2fvYnGquVBQgMvfo8xwjjnK/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

Loom Link

<https://www.loom.com/share/d6cf481072664eb09872f0d7243e3600>

Project – 8

ABC Call Volume

Trend Analysis

Project Description

In this project we have done analysis of inbound call data for ABC Insurance Company, which focuses on optimizing call handling efficiency and improving customer service. The analysis is done by performing certain analysis which will give us useful insights. This begins by performing average call duration analysis which provides us insights into efficiency of call handling process throughout the day. Then using visualization call volume analysis is presented to show the trends in call over time. Then we have proposed a detailed manpower strategy which aims to reduce abandon rate to 10% this is done by calculating minimum number of agents required in each time bucket. Then at last we have addressed the issue of unanswered calls during night shifts, where also we have proposed manpower plan to make sure customer satisfactory experience. Overall this project highlights the assumptions, methodologies and recommendations, that provides actionable insights for ABC Insurance Company's management team to optimize call centre operations and increase the customer satisfaction.

Approach

- We begin by importing and preprocessing the dataset.
- We then ensured that data is cleaned to have accurate outcomes and results.
- Then using descriptive statistics and visualization we have calculated the average call duration for each time bucket.
- For call volume analysis, using visualization through graphs we have plotted the bar chart which shows the temporal distribution of call volume.
- Then after we have plotted the graph to display the phone number counts, ratio distribution and average call durations. This is done to present the manpower allocation plan for each time bucket which ensures adequate coverage to meet service level targets.
- Then we have analyzed the distribution of calls during night shift period. This helps to determine manpower requirements for calls to handle which maintains the abandon rate. This helps to propose manpower plan for night shift according to the availability and scheduling of the agents.

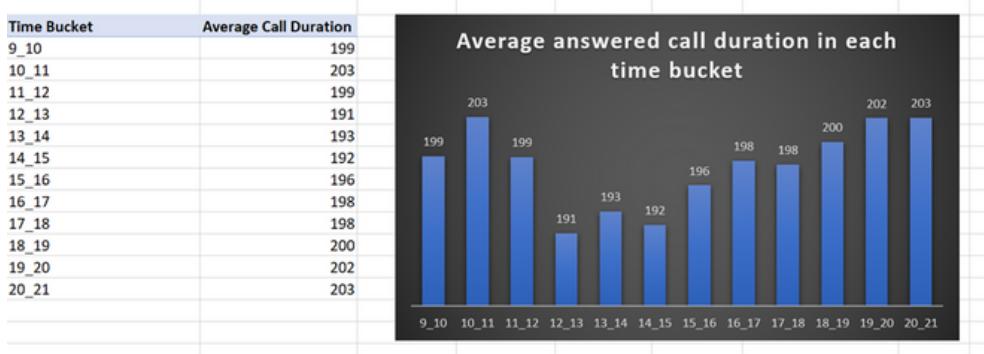
Tech-Stack Used

Microsoft® Word 2019 MSO (Version 2501 Build 16.0.18429.20132) 64-bit for data analysis, pivot table creation and chart generation.

Insights

1. Average Call Duration: Determine the average duration of all incoming calls received by agents. This should be calculated for each time bucket.

Your Task: What is the average duration of calls for each time bucket?

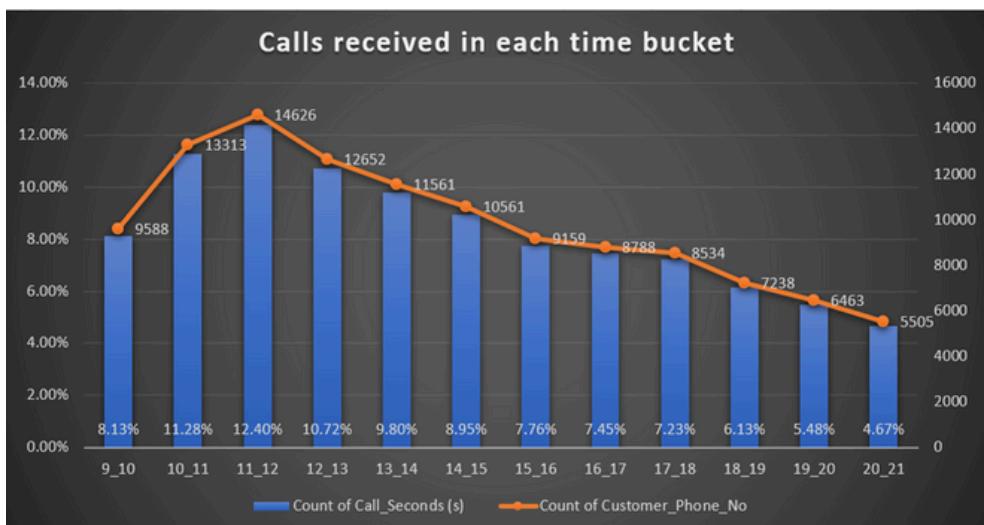


Highest Average Call Duration: 10_11

Lowest Average Call Duration: 12_13

1. Call Volume Analysis: Visualize the total number of calls received. This should be represented as a graph or chart showing the number of calls against time. Time should be represented in buckets (e.g., 1-2, 2-3, etc.).

Your Task: Can you create a chart or graph that shows the number of calls received in each time bucket?

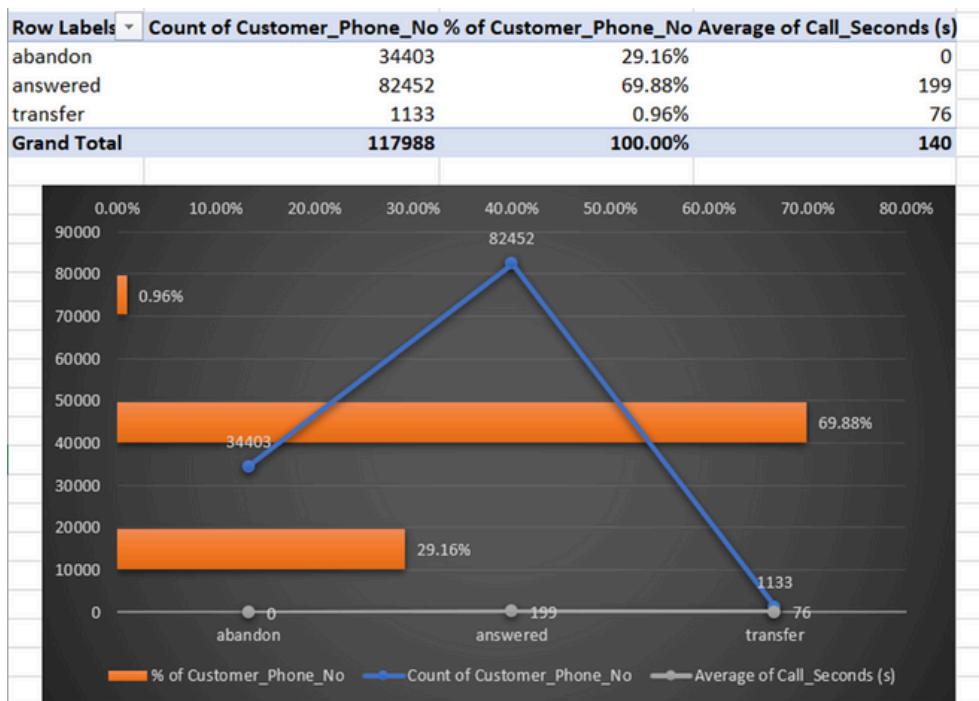


Max number of calls answered in duration: 11_12

Min number of calls answered in duration: 20_21

1. Manpower Planning: The current rate of abandoned calls is approximately 30%. Propose a plan for manpower allocation during each time bucket (from 9 am to 9 pm) to reduce the abandon rate to 10%. In other words, you need to calculate the minimum number of agents required in each time bucket to ensure that at least 90 out of 100 calls are answered.

Your Task: What is the minimum number of agents required in each time bucket to reduce the abandon rate to 10%?



For January the total sum of call duration = 676664s			
Sum of call records(sec)	676664		
Sum of call records(hr)	187.9622222		
Abandon rate = 30%			
Efficiency rate = 60% as it is mentioned agent works for 6 hours per day			
Total number of agents working in a day	31.32703704		
This means 31 agents work in a day			
Efficiency should be 90% in order to reduce abandon rate to 10%			
Total number of agents required for above condition	46.5		
Row Labels	Count of Call_Seconds (s)	Row Labels	% Count of Call_Seconds (s)
10_11	11.28%	9_10	8.13%
11_12	12.40%	10_11	11.28%
12_13	10.72%	11_12	12.40%
13_14	9.80%	12_13	10.72%
14_15	8.95%	13_14	9.80%
15_16	7.76%	14_15	8.95%
16_17	7.45%	15_16	7.76%
17_18	7.23%	16_17	7.45%
18_19	6.13%	17_18	7.23%
19_20	5.48%	18_19	6.13%
20_21	4.67%	19_20	5.48%
9_10	8.13%	20_21	4.67%
Grand Total	100.00%		

Total agents required to reduce the abandon rate to 10% is 47. The distribution according to each hour is given in the table (agent required) column.

1. Night Shift Manpower Planning: Customers also call ABC Insurance Company at night but don't get an answer because there are no agents available. This creates a poor customer experience. Assume that for every 100 calls that customers make between 9 am and 9 pm, they also make 30 calls at night between 9 pm and 9 am. The distribution of these 30 calls is as follows:

Your Task: Propose a manpower plan for each time bucket throughout the day, keeping the maximum abandon rate at 10%.

Assumptions: An agent works for 6 days a week; On average, each agent takes 4 unplanned leaves per month; An agent's total working hours are 9 hours, out of which 1.5 hours are spent on lunch and snacks in the office. On average, an agent spends 60% of their total actual working hours (i.e., 60% of 7.5 hours) on calls with customers/users. The total number of days in a month is 30.

Distribution of 30 calls coming in night for every 100 calls coming in between 9am - 9pm (i.e. 12 hrs slot)														
9pm- 10pm	10pm - 11pm	11pm- 12am	12am- 1am	1am - 2am	2am - 3am	3am - 4am	4am - 5am	5am - 6am	6am - 7am	7am - 8am	8am - 9am			
3	3	2	2	1	1	1	1	3	4	4	5			

Count of Call_Status	Column Labels	Row Labels	Time Buckets	Distribution of calls	Distribution of time	Agents required	
	abandon	answered transfer Grand Total					
01-01-2022	4117	526	1	4644	9_10	1	
02-01-2022	869	2478	4	3351	10_11	1	
03-01-2022	935	3791	63	4789	11_12	1	
04-01-2022	1494	3567	52	5113	12_13	1	
05-01-2022	559	4166	65	4790	13_14	0	
06-01-2022	1113	3755	83	4951	14_15	0	
07-01-2022	1209	3676	63	4948	15_16	0	
08-01-2022	2099	2543	30	4672	16_17	0	
09-01-2022	897	2746	9	3652	17_18	1	
10-01-2022	965	3937	81	4983	18_19	2	
11-01-2022	3524	1113	4637	4637	19_20	2	
12-01-2022	3807	836	4643	Total	20_21	2	
13-01-2022	1685	2433	5	4123		11	
14-01-2022	264	2885	6	3155			
15-01-2022	339	2707	12	3058	The average of incoming calls from 01-01-2022 to 23-01-2022 is 5129.91304 In 30 days, average of 5130 calls are coming in a day and as we know a day's 30% calls are coming at nights.		
16-01-2022	1413	3685	44	5142	Average number of calls coming at night is 1539		
17-01-2022	2737	19140	470	22347	From Task 1, We have already got the average duration of all calls(in s) that is 199. And we will have to answer 90% calls(means upto 10% call can be abandoned).		
18-01-2022	1232	4451	91	5774			
19-01-2022	682	3987	34	4708			
20-01-2022	2586	1735	1	4922			
21-01-2022	945	2721	9	3675			
22-01-2022	619	2668	4	3291			
23-01-2022	313	2906	6	3225			
Grand Total	34403	82452	1133	117988	Additional Time Required (in seconds):	275635	
				\$129.913	Additional Time Required (in hours):	77	
					Since an agent works for 6 hours, For additional 77 hours of work, number of additional agents required will be:	13	
					This is Total number of estimated additional agent required is 13. Total number of additional agents required in practical is 11.		

Total number of additional agents required is 11. Discrete number of agents required for each time interval from 9PM to 9AM is given in the table (agent required) column.

Result

In analyzing the inbound call data for ABC Insurance Company, we found that the average call duration varies across different time buckets throughout the day. Call volume follows a distinct pattern, with peaks and troughs corresponding to different hours. To reduce the abandon rate from 30% to 10%, we determined the minimum number of agents required during each time bucket, ensuring that at least 90 out of 100 calls are answered. Additionally, to address nighttime calls and provide a better customer experience, we proposed a manpower plan for each time bucket, maintaining the abandon rate at or below 10%. These solutions are based on specific calculations and assumptions regarding agent availability and call distribution patterns.

Drive Link for Excel

[https://docs.google.com/spreadsheets/d/1WxiyxMxCuUH4O93kNWwY8RG_BwE5aSdfU/edit?](https://docs.google.com/spreadsheets/d/1WxiyxMxCuUH4O93kNWwY8RG_BwE5aSdfU/edit?usp=sharing&ouid=109001208060904860088&rtpof=true&sd=true)

<https://www.loom.com/share/b0048433361c4d148c21f1aef65ae9b6?sid=0dd2e282-f75f-40ff-8ebc-851bb75b75f2>